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Research paper

Shanghai crude oil futures: Flagship or burst?

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ABSTRACT

This study examines the potential of Shanghai crude oil (SCO) futures as a benchmark in the Asian market. We investigate the market efficiency and long-term equilibrium of SCO futures in comparison with global benchmarks, such as West Texas Intermediate, Brent, and Dubai crude oil futures. Despite the weak market integration between SCO futures and other international benchmarks, we find strong evidence that their market efficiency and long-term equilibrium do not significantly differ. We explain how current market properties are achieved using the information flow from international crude oil to the SCO futures market. Our findings present implications for investors and policymakers based on the unilateral information flow at the level and rise–fall pattern in the price series: (1) investors could exploit this pattern's predictability in their investment strategy, and (2) regulators could implement open trading policies that would enable SCO futures to integrate with global benchmarks.

1. Introduction

"***China eyes new energy exchange to expand global oil and gas trade***"*—Forbes, December 9, 2019*.

On March 26, 2018, China launched its first crude oil futures contract through the Shanghai International Energy Exchange (INE). The country opened its crude oil futures market for domestic investors in 1993, which it closed down in the subsequent year because of low liquidity. After nearly two decades of preparation, yuan-denominated oil futures contracts were reintroduced to domestic and foreign investors. China designated heavy high-sulfur oil as an underlying asset to avoid direct competition with the well-known West Texas Intermediate (WTI) and Brent futures, both of which are based on light low-sulfur oil. Heavy high-sulfur oil is majorly imported oil mainly controlled by Northeast Asian countries, though it has no representative price index. Consequently, the price of oil flowing into the Asia-Pacific region has increased, which has long been known as the "Asian premium" (AlKathiri et al., 2017; Zhang et al., 2018). Thus, other Asian countries including China have made several attempts to establish the oil price benchmark. For example, Japan and Singapore have attempted to set oil price standards, but none of them has succeeded to date (Ji and Zhang, 2019).

Accordingly, we examine whether China's Shanghai crude oil (SCO) futures can become the benchmark in the Asian market by comparing and contrasting it with other global benchmarks, particularly in terms of market integration and market properties, such as market efficiency and long-term equilibrium.[1] Furthermore, we provide the reasons behind their similarities and differences by employing information flows between SCO futures and other markets. First, we investigate the degree of market integration in the short run by comparing the sensitivity of each crude oil futures with WTI. Second, we use the Hurst exponent and test the weak-form efficient market hypothesis (EMH) to characterize the market efficiency of each crude oil futures (Fama, 1965; Samuelson, 1965).[2] Third, we calculate the average level of uncertainty inherent in the time-varying patterns of each crude oil futures by the monthly average of the Shannon entropy, which describes the degree of long-term equilibrium. Fourth, we explain *how current market properties are achieved* using the transfer entropy (TE), that is, a proxy for information flow between SCO futures and each of the others.

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[1] Long-term equilibrium has the same meaning as statistical equilibrium. Statistical equilibrium is a concept that is commonly used in physics and information theory and is derived by maximizing the entropy of the system, which refers to the most likely state of the system (Jaynes, 1957).

[2] Multifractal detrended fluctuation analysis is a good choice for examining whether the multifractality degree for uptrends is stronger or weaker than that for downtrends (Shahzad et al., 2020). However, we use the Hurst exponent and provide evidence that the degree of market efficiency for SCO futures is not significantly different compared with those for international benchmarks. All markets, including SCO futures, have a Hurst exponent of approximately 0.5 within two standard errors, implying that the log-prices of all crude oil futures are not persistent, but follow a random walk.

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Numerous studies have investigated the crude oil market because crude oil is closely linked to economic activities (Brown and Yucel, 2002). Two groups of previous studies, intensively examining market properties in terms of market efficiency and long-term equilibrium, are related to our study. The first group used rescaled range analysis to examine global oil market and provided evidence that market efficiency increased along with market policy deregulation (Tabak and Cajueiro, 2007; Alvarez-Ramirez et al., 2008). The second group explored the long-term equilibrium of the WTI crude oil market using the entropy approach (Martina et al., 2011; Ortiz-Cruz et al., 2012; Joo et al., 2020). They documented that the decline in crude oil demand, particularly after the 2007–2008 financial crisis (Joo et al., 2020), reduced the diversity of market operations, thereby simplifying the pricing mechanism. This condition resulted in a low level of disorder in the marketplace and reduced randomness of the crude oil market: the crude oil prices became more predictable.

However, prior studies on the crude oil market primarily focused on developed markets rather than emerging markets. Accordingly, the literature on SCO futures is considerably limited.[3] Thus, our study aims to (1) enrich market studies on current SCO futures and (2) resolve the ambiguity regarding whether SCO futures can become a benchmark in the Asian market. Moreover, previous studies mainly concentrated on the change in market properties by historical shocks, such as the 2007–2008 financial crisis (Alvarez-Ramirez et al., 2008; Ortiz-Cruz et al., 2012; Lahmiri et al., 2017; Joo et al., 2020), OPEC actions (Tabak and Cajueiro, 2007; Martina et al., 2011), and the COVID-19 pandemic (Bouri et al., 2020, 2021; Dutta et al., 2021; Norouzi et al., 2020). Thus, our study uncovers the fundamental cause of current market properties through a new perspective: the information flow between SCO futures and international benchmarks. Subsequently, we present the implications for investors and policymakers. First, considering the unilateral information flow, at the level and rise–fall pattern in the price series, from global markets to the SCO futures market, investors could exploit this pattern's predictability in their investment strategy. Second, as the SCO futures market cannot fully interact with other markets, regulators would devise an open trading policy to integrate further the SCO futures market into the global markets when SCO achieves its initial growth goal.

2. Data and methodology

2.1. Data

The samples in this study were collected from four crude oil markets, namely, WTI, Brent, Dubai, and SCO. The first three are considered primary benchmarks of global oil markets (Liu et al., 2018; Xiao and Huang, 2018). As a newcomer to the crude oil market, our study focuses on SCO futures established in 2018. All crude oil futures experience increased trading volume as maturity approaches, and the closest contract is commonly the most liquid. For SCO, Brent, and Dubai futures, the front month contract is the most actively traded; therefore, front month contract prices are used. However, for WTI futures, the most liquid contracts are second front contracts. Nonetheless, if we select the contract with the largest trading volume, the price series may switch between the front and second front contracts, resulting in a mismatch with the three other price series. Therefore, we still select the prices of the front month contract for WTI futures (Han et al., 2013). The daily closing prices of SCO futures were obtained from the Shanghai INE, and the others were retrieved from Bloomberg. The price series spanned from March 26, 2018, to April 15, 2019,[4] starting from the opening date of SCO futures. Subsequently, the price series were transformed into logarithmic returns to generate stationary time series data for further analysis.

WTI futures and Dubai futures are traded in electronic platforms, namely, Chicago Mercantile Exchange (CME) Globex, and open outcry markets. CME offers electronic trading almost 24 h/6 days a week (Sunday–Friday 18:00–17:00 EST with a 60-minute break each day at 17:00 EST), whereas open outcry markets open from 9:00 to 14:30 on business days only. Brent futures contracts can be traded through the Intercontinental Exchange (ICE) electronic platform. Brent futures market opens at 20:00 EST on Sunday–Friday and closes at 18:00 EST on the following day. However, SCO futures, the primary focus of our study, can be traded only during three segments in time: (1) from 9:00 to 11:30, (2) from 13:30 to 15:00, and (3) from 21:00 to 2:30. Moreover, the contract policy for SCO futures differs from that of the other three. For example, SCO's trading currency is the Chinese renminbi (RMB). However, the other three crude oil futures use the US dollar as the trading currency. Hereafter, we provide the results considering the exchange rate risk: SCO futures prices are converted into US dollars based on the foreign exchange rate.[5]

Table 1 documents the descriptive statistics for the log-returns of our samples. Overall, each oil futures market does not significantly differ. The mean, standard deviation, and spread between the minimum and maximum values are similar. The skewness of all crude oil futures has a negative value, as with other financial assets (Ekholm and Pasternack, 2007). In addition, the four crude oil futures markets have a kurtosis of approximately 3, similar to the Gaussian distribution. Thus, the frequency of the extreme outliers of the four markets does not differ significantly.

Table 1
Summary statistics of the daily log-return.

	Obs.	Min	Max	Mean	Std.	Skewness	Kurtosis
SCO	276	−0.084	0.045	8.79×10^{-5}	1.68×10^{-2}	−0.507	2.727
WTI	276	−0.080	0.083	1.12×10^{-4}	1.97×10^{-2}	−0.689	3.244
Brent	276	−0.071	0.076	6.53×10^{-5}	1.88×10^{-2}	−0.806	3.179
Dubai	276	−0.076	0.074	2.18×10^{-4}	1.93×10^{-2}	−0.832	3.766

2.2. Hurst exponent

The Hurst exponent is widely used as the "index of dependence". It quantifies the relative tendency of a time series either to regress strongly to the mean or cluster in a direction. The Hurst exponent was employed to test the weak-form EMH of each crude oil futures (Jang et al., 2020; Joo et al., 2020).

First, data were plotted and analyzed using the reconstructed R/S statistic following Hurst (1951, 1955) and Mandelbrot and Wallis (1968, 1969) as follows:

$$(R/S)_n = c \times (n)^{HE} .$$

[3] Yet, there are some literatures about the SCO futures market: (1) Huang and Huang (2020) reported the comovement strength between the Shanghai International Exchange and international crude oil futures; (2) Yang et al. (2020) investigated the equilibrium relationship between Shanghai crude oil futures and the representative spot markets; and (3) Yang and Zhou (2020) examined return and volatility transmission between the newly established crude oil futures in China and international major crude oil futures markets.

[4] We exclude the COVID-19 period as the pandemic outbreak can cause heterogeneous consequences to different crude oil futures markets. The SCO futures market is mainly driven by the economic motives, such as supply and demand, because of the unique feature of contract policies. However, other global futures markets are influenced by both the economic motives and speculative trading activities after the financialization of the commodity market in 2000 (Joo et al., 2020). Yet, we extend our dataset to the recent period and further provide evidence of the robustness of our results in Appendix A.1.

[5] We further provide an analysis of whether the exchange rate risk matters in terms of market integration, market efficiency, and long-term equilibrium in Appendix A.2.

Subsequently, the Hurst exponent was estimated by the slope of the regression line according to the following:

$$\log(R/S)_n = \log c + HE \log n,$$

where n is the length of partial time series, c is a constant, and HE is the Hurst exponent. R/S statistic and standard deviation S_n were obtained as follows:

$$(R/S)_n = \frac{1}{S_n}\left[\max_{1\le t\le n}\sum_{k=1}^{t}(r_k - \bar{r}_n) - \min_{1\le t\le n}\sum_{k=1}^{t}(r_k - \bar{r}_n)\right],$$

$$S_n = \left[\frac{1}{n}\sum_{k=1}^{t}(r_k - \bar{r}_n)^2\right]^{1/2},$$

where t is a specific time, r_k is the return at time k, and $\bar{r}_n$ is the average return with a length of n.

The Hurst exponent ranges between 0 and 1. Based on the estimated HE value, the spreading process of time series can be largely classified into three categories[6]: (1) $HE = 0.5$ for a random walk process (geometric Brownian motion); (2) $0 < HE < 0.5$ for a mean reversion process (anti-persistence series); and (3) $0.5 < HE < 1$ for a persistent series with long-run memory.

2.3. Entropy

Entropy is widely used to examine the degree of randomness and uncertainty in a financial time series (Franses and Ghijsels, 1999; Rousseeuw and Hubert, 2011; Ahn et al., 2019b). The entropy was calculated through a symbolic time series analysis (STSA) to explore the association from the long-term equilibrium of each crude oil futures' market. STSA is robust to noise and is commonly applied in the fields of physics, information theory, and finance (Daw et al., 2000; Ahn et al., 2019b).

The sequence of S consecutive returns of each crude oil futures was symbolized by 0 and 1; each positive return was converted to 1, and 0 otherwise. Subsequently, each sequence with a length S was converted to a decimal number X^S. Accordingly, by applying this conversion process to the entire return series with a daily moving window, the Shannon entropy of the discrete variable X^S was computed as follows:

$$H(X^S) = -\sum_{i=1}^{M-(S-1)} p(x_i^S)\log_2 p(x_i^S),$$

where M is the number of outcomes in the entire series, and $p\left(x_i^S\right)$ is defined as the probability assigned to state x_i^S. To offset $H\left(X^S\right)$ increases through S increases, we normalized the following:

$$h\left(X^S\right) = \frac{1}{S}H\left(X^S\right).$$

Hereafter, when we mention "Shannon entropy", or simply "entropy", it refers to a normalized one, that is, $h\left(X^S\right)$.

[6] Different forms of stochastic differential equations are used to model various phenomena exhibiting stochastic behavior in the financial market, e.g., stochastic volatility (Ji et al., 2020b), jump process (Dai et al., 2018; Jang et al., 2018; Lee et al., 2020b), controlled growth process (Kim et al., 2017), process evolving according to a size-independent proportional growth rate after an exponentially distributed period of time (Ji et al., 2020a), and quantum harmonic oscillator (Ahn et al., 2018; Lee et al., 2020a; Ryu et al., 2021).

2.4. Transfer entropy

Transfer entropy directly estimates from data and does not require any insight into the relationship between two time series data. Moreover, it does not suffer from any noisy measurements of coupled dynamic systems. Therefore, transfer entropy is apt for analyzing non-linear dependencies between dynamically coupled systems (Jang et al., 2019; Storhas et al., 2020; Yi et al., 2021).[7]

Transfer entropy between two variables, namely, X_t and Y_t for $X_t^{(k)} = \{X_t, X_{t-1}, \ldots, X_{t-(k-1)}\}$ and $Y_t^{(l)} = \{Y_t, Y_{t-1}, \ldots, Y_{t-(l-1)}\}$, respectively, can be expressed as follows (Schreiber, 2000):

$$TE_{Y\to X} = H(X_{t+1}|X_t^{(k)}) - H(X_{t+1}|X_t^{(k)}, Y_t^{(l)}),$$

where $H(X_{t+1}|\Delta_t)$ denotes the degree of uncertainty for predicting X_{t+1} for a given Δ_t, which is expressed by conditional entropy. Therefore, transfer entropy $TE_{Y\to X}$ is an asymmetric measure that enables us to estimate the information flow transmitted from $Y_t^{(l)}$ to X_{t+1}.

We further considered effective transfer entropy (ETE) to correct the bias induced by the finite sample size. ETE was calculated as follows (Sandoval, 2014):

$$ETE_{Y\to X} = TE_{Y\to X}(k,l) - \frac{1}{M}\sum_{i=1}^{M} TE_{Y_{(i)}\to X}(k,l),$$

where $Y_{(i)}$ indicates the randomly shuffled variable Y, and M is the number of random shuffling. Accordingly, ETE is calculated by subtracting the arithmetic mean of the randomized TEs from the estimated TE value.

3. Results and discussion

3.1. Market integration

Fig. 1 presents the scatter plot of each crude oil futures versus WTI crude oil futures: the benchmark for the international crude oil that has the largest transaction volumes (Hsu et al., 2014). According to the Futures Industry Association (FIA), WTI futures and options led the trading volume of energy futures and options contracts from 2007 to 2012.[8] Accordingly, we further conducted a linear regression analysis of each crude oil futures with WTI crude oil futures.[9] The regression coefficient of WTI against SCO significantly differs from that against Brent and Dubai. The regression coefficients against Brent and Dubai are 0.96 ± 0.03 and 0.89 ± 0.03, respectively. Therefore, both regression coefficients

[7] Barnett et al. (2009) proved that for Gaussian variables, Granger causality and transfer entropy are entirely equivalent and, thus, bridged autoregressive and information-theoretic approaches to data-driven causal inference. Granger causality is a statistical notion of causal influence based on prediction via vector autoregression. However, transfer entropy is an information-theoretic measure of time-directed information transfer between jointly dependent processes. Granger causality test has been used to identify the causal relationship between two time series but in a limited sense. We even use the expression "A Granger causes B" instead of "A causes B" when finding a significant relationship between the two time series data through the Granger causality test. In particular, despite its common use to identify couplings between two systems, the Granger causality test is not free from criticism for its structural restrictions. Accordingly, its use is always accompanied by a caution that the results should be carefully considered and interpreted (Friston et al., 2014; Gencaga, 2018).

[8] The FIA annual report is available at the official website (http://www.futuresindustry.org/volume.asp).

[9] An effective way to measure the market co-integration process is to examine the degree of convergence through price trends rather than levels (O'Rourke and Williamson, 2004). The convergence and divergence of the two prices can be estimated by a logarithmic linear regression of the relative price or price gaps (Persson, 2004).

Table 2
Market efficiency and long-term equilibrium.

	Hurst exponent $\mu \pm \sigma$	Entropy $\mu \pm \sigma$
SCO	0.53 ± 0.02	0.96 ± 0.03
WTI	0.56 ± 0.04	0.95 ± 0.01
Brent	0.56 ± 0.04	0.93 ± 0.02
Dubai	0.56 ± 0.03	0.95 ± 0.02

Note. We calculated the Hurst exponent and Shannon entropy to test the weak-form EMH and measure the degree of long-term equilibrium, respectively. We also include standard error σ as statistical estimation always brings uncertainty. Accordingly, when we decide on the degree of market efficiency with the Hurst exponent, we rely on the 95% confidence interval, that is, approximately $\mu \pm 2\sigma$, other than the point estimator μ. As the estimated Hurst exponent values are well within the 95% confidence interval, we conclude that the four crude oil futures markets are efficient, at least in the weak-form. In general, the Hurst exponent is estimated by two methods: classical R/S and corrected R/S (Lo, 1991). Since classical R/S significantly deviates from the slope representing Brownian motion (Celeste et al., 2020), prior studies have mostly used the corrected R/S, adjusting the classical rescaled statistics for short-term dependencies. Accordingly, we employed a corrected Hurst exponent with a length of minimum subseries 8. The STSA method was used to capture the spread of time-varying patterns in the price series. Several studies (Ruiz et al., 2012; Ahn et al., 2019b; Joo et al., 2020) have documented that the STSA entropy captures the uncertainty of financial time series more effectively than the histogram-based entropy. We applied $S = 3$ for window size, whereas $S = 2$ and $S = 4$ were also considered to check the robustness of our results.

are not statistically different within two standard errors and close to one. However, the regression coefficient of WTI against SCO is 0.06 ± 0.07, indicating that the return of SCO futures cannot be contemporaneously explained by that of WTI. Thus, the SCO futures market has weak market integration with its global benchmark in the short run (Huang and Huang, 2020).[10] In other words, three crude oil futures markets other than the SCO futures market move in a correlated fashion. This finding further implies that the global oil market has become "one big pool" given the open market environment and improved information transmission technology (Ji and Fan, 2016). However, this condition does not apply to the SCO futures market.

3.2. Market efficiency and long-term equilibrium

Table 2 summarizes the results for the market efficiency and long-term equilibrium, and demonstrates that the market properties of SCO futures do not significantly differ from those of the others. In terms of market efficiency, all markets, including the SCO futures, have a value of Hurst exponent approximately 0.5 within two standard errors. Thus, the log-price of all crude oil futures follows a random walk. Our results are consistent with prior studies (Chen et al., 2019; Yang et al., 2020) demonstrating that SCO futures effectively reflect the fundamental information in price series and exhibit high market efficiency.[11] Moreover, the long-term equilibrium of all crude oil futures markets does not significantly differ as well, similar to market efficiency. Each crude oil market has a similar entropy level of approximately 0.95. Thus, we can conclude that the SCO futures market has

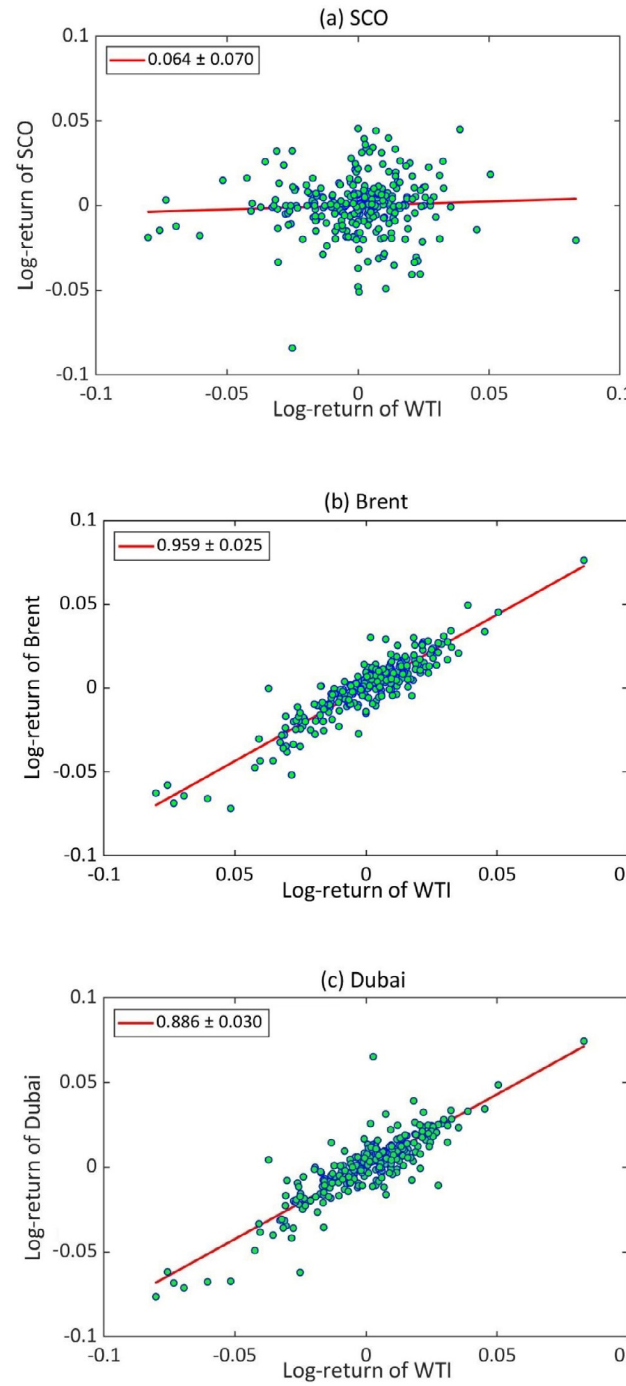

Fig. 1. Scatter plot and regression line. The log-returns of crude oil futures for (a) Shanghai crude oil (SCO), (b) Brent, and (c) Dubai are plotted against that of West Texas Intermediate (WTI). Solid lines represent a regression line.

reached market properties similar to global benchmarks with respect to market efficiency and long-term equilibrium.

3.3. Information flow

SCO futures' similar market properties to those of others can be explained by the information flow between markets: the price fluctuation of China's crude oil futures tends to lag behind that of international crude oil futures (Huang and Huang, 2020). Table 3 demonstrates that transfer entropy, as defined by two different

[10] Yang and Zhou (2020) provided evidence for strong market linkage between the SCO futures and others in the long run; meanwhile, our result is about the market linkage in the short run. We use the result of weak market integration in the short run as a motivation for further investigation about the degree of long-run equilibrium in the marketplace and market efficiency.

[11] Bouri et al. (2020) provided evidence that the SCO futures market is not efficient because a daily newspaper-based index of uncertainty associated with infectious diseases has predictability on realized volatility. Accordingly, it has return predictability on the SCO futures. However, we test the weak-form market efficiency of the SCO futures market.

Table 3
Information flow between crude oil markets.

	Transfer entropy		Effective transfer entropy	
	(1)	(2)	(3)	(4)
(A) Quantile-based	WTI → SCO 0.081***	SCO → WTI 0.009	WTI → SCO 0.063	SCO → WTI 0.000
	Brent → SCO 0.109***	SCO → Brent 0.018	Brent → SCO 0.092	SCO→ Brent 0.000
	Dubai → SCO 0.071***	SCO → Dubai 0.014	Dubai → SCO 0.053	SCO → Dubai 0.000
(B) STSA-based	WTI → SCO 0.7695*	SCO → WTI 0.6974	WTI → SCO 0.0527	SCO → WTI 0.0000
	Brent → SCO 0.8111**	SCO → Brent 0.7015	Brent → SCO 0.0206	SCO → Brent 0.0000
	Dubai → SCO 0.8125**	SCO → Dubai 0.7288	Dubai → SCO 0.0179	SCO → Dubai 0.0000

Note. We show the information flow between each crude oil futures. The arrow indicates the direction, and the number denotes the estimated value of transfer entropy and effective transfer entropy, respectively. The significance level is evaluated by bootstrapping the underlying Markov process (Horowitz, 2003; Dimpfl and Peter, 2013). The estimation results of TE include the significance level, though a statistically significant TE could encounter the finite sample bias. Therefore, we further examine the robustness of our results with ETE. Positive ETE supports the result of statistically significant TE. For example, if TE is statistically significant, but the corresponding ETE is zero, we cannot exclude the possibility that the result is due to the bias of a finite sample size.
*Indicate significance at the 10% level.
**Indicate significance at the 5% level.
***Indicate significance at the 1% level.

measures, namely, a quantile-based measure[12] and STSA, supports our findings. The results in column (1) confirm the information flow into SCO futures from other crude oil markets. However, column (2) shows that the information flow from SCO futures to the others is much weaker compared with the opposite direction and is not statistically significant. In addition, we further calculated the ETE and confirmed the robustness of our results in columns (3) and (4) to overcome sample bias. ETE values flowing from other markets to SCO futures are all positive, whereas they are zero for the opposite direction. This finding suggests that information flow from others to the SCO futures market is not due to random noise (Sandoval, 2014). Moreover, the SCO futures market shares the long-term equilibrium with global benchmarks as documented (Yang et al., 2020). Therefore, the international major futures markets have a leading role in information diffusion compared with the SCO futures market (Huang and Huang, 2020). Accordingly, this unilateral information flow at the level and rise–fall patterns from the global markets to the SCO futures market has contributed to making the similarity of SCO futures' market properties to those of the global benchmarks.

3.4. Market properties and investment constraints

Thus far, we find that the SCO futures' market properties are similar to others and provide evidence that information flow from others to the SCO futures market is significant in all cases. Thus, considering the fact that the SCO futures market shares the long-term equilibrium with global benchmarks (Yang et al., 2020), the SCO futures market effectively reflects unilateral information into its price series and, accordingly, reaches market properties similar to those of other crude oil futures markets. However, the SCO futures market still fails to supply its information to other markets. Hence, we hypothesize that our findings are primarily due to the unique feature of contract policies in the SCO futures market. A legal trading framework affects liquidity (Jun et al., 2003; Gao and Kling, 2006). Thus, we conjecture that the international major futures markets, which have fewer trading restrictions with massive liquidity, have a leading role in information discovery against the SCO futures market (Ahn et al., 2019a).

[12] "Quantile-based" represents a histogram analysis that uses cutoff points to exclude potential outliers. We consider a histogram defined on an equally spaced interval, with 0.1 percentile and 0.9 percentile as cutoff points (Dimpfl and Peter, 2013).

Table 4 demonstrates that the SCO futures market has strict investment constraints. First, regarding trading hours, SCO futures can only be traded during three segments of a trading day,[13] whereas WTI, Brent, and Dubai crude oil futures are accessible at any time for 23 h, 22 h, and 23 h of every trading day, respectively. Second, SCO futures have a daily price limit of approximately ±4%; the price cannot change more than ±4% compared with the previous day's settlement price. By contrast, the remaining markets do not have daily price limits. Third, all other crude oil futures are traded using the US dollar, whereas SCO futures allow only RMB as a trading currency and, therefore, are exposed to currency risk. Thus, the SCO futures market has several tight trading restrictions, including high transaction fees (Ji and Zhang, 2019). Accordingly, this unfavorable investment environment for the SCO futures market is linked to relatively low liquidity, and even then, it is mainly traded by domestic players.[14] Thus, the SCO futures market unilaterally receives information from others rather than providing its information and interacting with the global markets.

4. Conclusion

This study investigates the potential of SCO futures as a benchmark in the Asian market. The market properties (that is, market efficiency and long-term equilibrium) of SCO futures are compared with those of global benchmarks using the Hurst exponent and Shannon entropy. SCO futures have weak market integration with global benchmarks in the short run. Nevertheless, our results indicate that their intrinsic characteristics, such as market efficiency and long-term equilibrium, do not significantly differ from those of others. Our findings are explained by the fact that SCO futures receive unilateral information from global benchmarks, process information inflow on its price effectively, and result in market properties that are similar to those of global benchmarks. Therefore, our findings support the potential of SCO futures as a benchmark in the Asian market despite its brief operating history.

[13] SCO's futures contracts are only available during the trading hours of three segments: from 9:00 to 11:30, 13:30 to 15:00, and 21:00 to 2:30 (Ji and Zhang, 2019).

[14] According to INE data from mid-December in 2018, approximately 92% of trading volume and 80% of open interests were made up by domestic traders in China (S&P Global Platts, 2019).

Table 4
Contract specification for each crude oil futures.

	SCO	WTI	Brent	Dubai
Contract	SCO futures	WTI crude oil futures	Brent crude futures	Dubai crude oil futures
Price quotation (per barrel)	Yuan (RMB)	US dollar	US dollar	US dollar
Trading hour	9:00–11:30 13:30–15:00 21:00–2:30 (GMT +8)	18:00–17:00 (EST)	20:00–18:00 (EST)	18:00–17:00 (EST)
Daily price limit	±4% from the settlement price of the previous trading day	None	None	None
Tick size (per barrel)	RMB 0.1	1 cent	1 cent	1 cent
Grade	Medium sour	Light sweet	Light sweet	Medium sour
Listing exchange	INE	CME	ICE	CME
Underlying origin	Arabian Gulf (main), Shengli, and five others	North America	Norwegian and UK North Sea	Persian Gulf

Note. The specification of each crude oil futures was obtained from the listed exchange in order: INE, CME, ICE, and Dubai mercantile exchange (DME). Dubai crude oil is DME's flagship crude oil benchmark. However, we referred to the Dubai crude oil futures transactions provided by CME because all transactions executed in DME are cleared and guaranteed by CME.

Our findings have implications for investors and policymakers. First, information flow, at the level and rise–fall patterns in the price series, from global markets to the SCO futures market allows investors to forecast the fluctuation of price evolution in the SCO futures market. This condition is likely to be observed in the future unless the SCO market plays a role as an information producer. Accordingly, investors could potentially exploit this pattern's predictability in their investment strategy. Second, strict market policies negatively impact market growth potential, which limits the role of the SCO futures market as an information provider. Hence, regulators should devise an open trading policy to integrate further the SCO futures market into global markets. In addition, as the SCO futures market becomes more liquid, policymakers (regulators) must closely monitor information flow with global benchmarks. When the two markets exchange information in a state with strong market integration, unbalanced regulation between them could lead to market distortion and regulatory arbitrage.

CRediT authorship contribution statement

Kyohun Joo: Software, Validation, Formal analysis, Data curation, Writing - original draft, Visualization. **Minhyuk Jeong:** Software, Validation, Formal analysis, Data curation, Writing - original draft, Visualization. **Yongseok Seo:** Conceptualization, Methodology, Validation, Writing - original draft, Supervision. **Jong Hwan Suh:** Conceptualization, Methodology, Validation, Writing - original draft, Supervision, Funding acquisition. **Kwangwon Ahn:** Conceptualization, Methodology, Validation, Writing - original draft, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

A.1. Extended sample period

We extend our dataset to the recent period, but exclude the turmoil period of the COVID-19 outbreak, that is, from February 2020 to April 2020, as the pandemic outbreak can cause heterogeneous consequences on different crude oil futures markets. Tables A.1–A.3 confirm the robustness of our results: (1) The regression coefficient of WTI against SCO futures overlaps each other at 95% confidence interval regardless of the sample period; (2) The Hurst exponent of each sample period includes "0.5" at 95% confidence interval; and (3) The entropy of each sample period overlaps each other at 95% confidence interval.

Table A.1
Market integration between the SCO futures and WTI.

Sample period	Regression coefficient	Standard error
Sample period for the main analysis March 2018–April 2019	0.06	0.07
Before the COVID-19 outbreak August 2019–January 2020 (6 months)	0.12	0.06
After the COVID-19 outbreak May 2020–October 2020 (6 months)	0.05	0.05

Note. This table reports the regression coefficient of the SCO futures' log-return on the WTI futures' log-return during each sample period.

Table A.2
The efficiency of the SCO futures market.

Sample period	Hurst exponent	Standard error
Sample period for the main analysis March 2018–April 2019	0.53	0.02
Before the COVID-19 outbreak August 2019–January 2020 (6 months)	0.46	0.04
After the COVID-19 outbreak May 2020–October 2020 (6 months)	0.43	0.06

A.2. Impact of exchange rate risk

We analyze whether the exchange rate risk affects market integration, market efficiency, and long-term equilibrium as shown

Table A.3
Long-run equilibrium of the SCO futures market.

Sample period	Entropy	Standard error
Sample period for the main analysis March 2018–April 2019	0.96	0.03
Before the COVID-19 outbreak August 2019–January 2020 (6 months)	0.96	0.01
After the COVID-19 outbreak May 2020–October 2020 (6 months)	0.97	0.01

Table A.4
Market integration between the SCO futures and WTI with currency risk.

Sample period (March 2018–April 2019)	Regression coefficient	Standard error
SCO futures in USD	0.06	0.07
SCO futures in CNY	0.03	0.05

Note. This table reports the regression coefficient of the SCO futures' log-return on the WTI futures' log-return.

Table A.5
The efficiency of the SCO futures market with currency risk.

Sample period (March 2018–April 2019)	Hurst exponent	Standard error
SCO futures in USD	0.54	0.02
SCO futures in CNY	0.54	0.02

Table A.6
Long-run equilibrium of the SCO futures market with currency risk.

Sample period (March 2018–April 2019)	Entropy	Standard error
SCO futures in USD	0.96	0.03
SCO futures in CNY	0.97	0.01

in Tables A.4–A.6. We conclude that three proxies for market integration, market efficiency, and long-term equilibrium do not differ, though we do not adjust the SCO futures price based on the USD/CNY rate.

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