Does Something Change in the Oil Market with the COVID-19 Crisis ?

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Dan Zhang[a,b,*], Arash Farnoosh[b], Frédéric Lantz[b]

a China University of Petroleum (Beijing), 18 Fuxue Road , Changping District , 102249 Beijing, China

b IFPEN, IFP School, 232 Avenue Napoléon Bonaparte, 92852 Rueil-Malmaison, France

***Corresponding author.**

Email addresses:

danzhang.424@gmail.com (Dan zhang);

arash.farnoosh@ifpen.fr (Arash Farnoosh);

frederic.lantz@ifpen.fr (Frédéric Lantz);

Abstract:

This paper examines the price discovery of three international crude oil futures markets (WTI, Brent, INE) before and after the outbreak of the COVID-19 with the application of the information share and component share model. Our study shows that there is a structural break of the date of March 6, 2020, in each price series with Zivot and Andrew's unit root tests. Using Gregory and Hansen cointegration tests, cointegration relationships with the structural break in May 2020 are detected. According to results of Information Share (IS) and Component Share (CS) measures Brent futures price mainly plays a leading role in WTI and INE futures prices and occupies an absolutely dominant position all the time in the three crude oil futures markets systems. In the post-covid period, the price discovery efficiency of INE has been improved slightly but is still weak compared with other two markets. After the outbreak of COVID-19, the dominant position in price contribution in the relationship with INE has transferred from Brent to WTI. These findings offer practical implications for regulators and portfolio risk managers during the unprecedented uncertainty period provoked by the COVID-19 pandemic.

Keywords: Oil Market, Price discovery, Structural Break

JEL Code: C32, C53, Q41

Introduction

Shanghai Crude oil futures market, known as a new international crude oil futures market in China, was officially built in the Shanghai International Energy Exchange (INE) on March 26, 2018. It has experienced an increasing trading volume which

even exceeded Dubai to become the third crude oil futures market in the world since 2018. Specially, world oil demand fell sharply because of the COVID-19 in 2020. Thus, crude oil prices fluctuated drastically during this period from 2019-2021. On April 20, 2020, the US oil benchmark West Texas Intermediate (WTI) fell to negative for the first time. Meanwhile, China's outbreak was considered under control and its economy began to recover due to the government's strict confinement policy while the confirmed cases in Europe still went up and crude oil demand remains depressed. Based on the existing facts, we suppose that these market changes have a significant impact on crude oil price fluctuations and the relationships between different oil markets. We also wonder what changes have happened in oil markets from 2019 to 2021 and how new information around the Covid-19 is reflected in international oil markets. If the underlying market is the first one to reflect new information about fundamental value, it will be considered to dominate price discovery. Price discovery is the process by which security markets attempt to identify permanent changes in equilibrium transaction prices.

In fact, many previous studies have shown that epidemics, geopolitical conflicts, natural disasters, and other exogenous events have a significant impact on economic markets (Nippani & Washer, 2004; Wang & Kutan, 2013). In the field of the international crude oil market, there is a significant body of literature to explore the impact of the pandemic shock on oil prices. The results of Bakas and Triantafyllou (2020) show that the economic uncertainty of pandemics has a strong negative impact on the volatility of commodity prices, especially crude oil markets. Bourghelle, Jawadi, and Rozin (2021) analyze the dynamics of oil price volatility in the context of the COVID-19 and find pandemic shock affected oil price volatility significantly. However, the research focuses on price discovery of crude oil futures with the COVID crisis is so far insufficient. As the results of Ewing, Hammoudeh, and Thompson (2008) show, the impact of supply and demand shocks on one region quickly affects other regional markets and they prove the evidence of cointegration in four oil benchmark prices (WTI, Brent, Dubai, and Maya). There is no doubt that the COVID-19 pandemic brings huge supply and demand shocks to the whole crude oil market. Hence, it is safe to induce that the price discovery mechanics will change between the first three international crude oil futures markets (WTI, Brent, INE) because of the COVID-19.

Our paper aims to test whether there is a structural break in crude oil prices and to explore the price discovery of international crude oil markets (WTI, Brent, INE) under the background of the COVID-19. The two methods we applied here to explore price discovery of different crude oil markets are information share (IS) and component share (CS). Hasbrouck (1995b) proposed Information share (IS) to measure 'who moves first in the process of price adjustment' by the price proportion

of the variance in the common efficient price innovations. Component Share (CS) is a method put forward by Gonzalo and Granger (1995) where a cointegrated price series is decomposed into a permanent component and a temporary component. The permanent component is interpreted as a common efficient price and the temporary component refers to the deviation between prices series due to market noise.

Our study contributes to the literature along several important dimensions. First, we add to a rapidly expanding body of literature exploring the financial implications of the COVID-19 pandemic, especially in the field of crude oil markets analyses. Second, by unit root test and cointegration test with the structural break, a breakpoint in crude oil price series due to pandemic from 2019 to 2021 can be observed. It is helpful for us to make a deep exploration about the influence of exogenous shocks to price discovery process. Third, since the recent launch of Shanghai Crude oil futures, comparative research between INE and other benchmark prices is still insufficient. Yang and Zhou (2020) have analyzed at 5-minute intervals the first three months of the INE oil futures trading to document evidence of cointegration relationships among the Chinese INE futures and the Brent, WTI, and Oman futures markets. Palao, Pardo, and Roig (2020) use multiple regression models to study the impact of the new Chinese oil futures contract compared with the WTI and Brent for an analysis period from March 26, 2018, to June 5, 2020. They find that INE futures contract still plays a minor role in the market at a worldwide level. Due to the pandemic and lockdown over the world, significant changes have taken place in the crude oil markets as we mentioned before. Our paper could enrich literature based on empirical analysis of three different crude oil futures markets. Apart from empirical contributions, our findings offer practical implications for regulators, policymakers, and portfolio risk managers during the unprecedented uncertainty period provoked by the COVID-19 pandemic.

Overall, we first find that there is a breakpoint which is tested as of March 6, 2020 in WTI, Brent, and INE price time series. Take the cointegration relationships two by two, the structural break occurred on May 12 because of the impact of negative WTI price in April. We consider that of March 6, 2020, to divide the whole sample into two sub-samples (the pre-covid period and the post-covid one). For the whole sample, both IS and CS results show that the Brent futures market contributes more share than the other two markets. Although information share and component share of the INE market is the smallest among these three markets, they increased slightly after the pandemic outbreak, which means the price discovery efficiency has improved due to the COVID-19. Between the group WTI and Brent, Brent plays a dominant role in price discovery in the whole period but when it comes to subperiod (both pre-covid and post-covid period), the IS and CS of WTI surpass those of Brent.

The plan of the paper is as follows: Section 1 presents the economic context of the worldwide economic activity and the oil market in 2019-2021. Section 2 provides a description of the related studies in this domain. Section 3 introduces the empirical methodology and tests applied in this paper. In section 4, empirical results and interpretation are presented to show the changes in the price discovery of WTI, Brent, and INE futures market before and after the COVID-19 outbreak. Finally, we summarize the results in the conclusion, and we give some policy implications.

1. Economic Context of the Oil Market in 2019-2021

Since the widespread of the COVID-19 all over the world, this pandemic has caused unprecedented effects on public health and safety, industrial production, and economic activities. Due to new virus mutations and the accumulating human toll raise, there is emerging uncertainty around global prospects as growing vaccine coverage lifts sentiment. When it comes to the global economy, as Table 1 shows, gross domestic product (GDP) fell by -3.3% by 2020 according to the latest World Economic Outlook issued by IMF (International Monetary Fund). For most countries, except China in 2020, the GDP growth experienced a negative value affected by the pandemic and the whole world may enter recovery in 2021. This situation aligns with the growth rate of oil consumption. Most regions witness a considerable decrease in growth rate of oil consumption. In contrast, the figure of China is still positive, and the oil consumption of China has increased slightly under the COVID-19. Therefore, the after-effects of the COVID-19 have aroused wide concern among scholars and policymakers.

Table 1. World economic growth and oil consumption

	Growth Rate of GDP		Growth Rate of Oil Consumption	
Countries and Regions	2019	2020	2019	2020
World	2.90	-3.30	0.30	-9.70
United States	2.30	-3.50	-0.03	-12.70
Euro Area	1.20	-6.60	0.50	-14.10
China	6.10	2.30	5.30	2.00
India	4.20	-8.00	4.60	-10.10
ASEAN-5	4.80	-3.40	-0.40	-13.60
Latin America and the Caribbean	0.10	-70	-1.68	-10.50
Middle East and Central Asia	1.20	-2.90	1.50	-7.80
Saudi Arabia	0.30	-4.10	2.50	-2.30
South Africa	3.10	-1.90	1.20	-13.80

Source：Growth Rate of GDP (%): World Economic Outlook issued by IMF (International Monetary Fund); Growth Rate of Oil consumption (%): BP Statistics Review of all the energy 1965-2020

About crude oil markets, crude oil futures market has changed a lot all over the world in recent years. The Shanghai crude oil futures market has developed rapidly since its launch, especially after the outbreak of the pandemic. In the first half of 2020, the average daily trading volume of crude oil futures in Shanghai was about 18 thousand lots, up by 3% and 286% respectively from the same period last year. It replaced Dubai and became the third largest crude oil futures after WTI and Brent crude oil futures in terms of trading volume. On April 20, 2020, US oil benchmark West Texas Intermediate (WTI) fell from $17.85 at the start of the trading day to negative $37.63 by the close. Without any doubt that is the biggest black swan event in crude oil markets in 2020 after the pandemic outbreak. In other words, we can't help but wonder how these crude oil futures markets react to the COVID-19 crisis? Does something change in the oil market with the pandemic? Whether different crude oil markets behave differently with the arrival of new information?

So far, according to Shanghai International Energy Exchange, in total there are 120 thousand accounts opened in Shanghai crude oil futures market. In 2019, the trading volume of corporate clients in the INE market increased from 23% to 35% and open interest of corporate clients increased from 47% to 63%. Volume of overseas customers increased 106.5% year on year, and the proportion increased from 7% to 15%. The open interest of overseas customers increased 122.1% year on year and the proportion increased from 14% to 22%. Trading volume and open interest data reflect a sharp rise in institutional and foreign investors engagement, which means the market is gradually maturing and becomes more independent. The INE volumes picked up significantly, especially in May and June when the WTI negative price event just happened in April as described in Figure 1. At the height of the demand collapse and the stress felt by several oil benchmarks, we can reasonably doubt that something changed in international oil markets before and after the COVID-19 outbreak. Intuitively, in Figure 2 we see that the spread of trading volume between INE and WTI, Brent has decreased after 2020, which is arousing our interest in exploring the price discovery with a structural break in world oil markets.

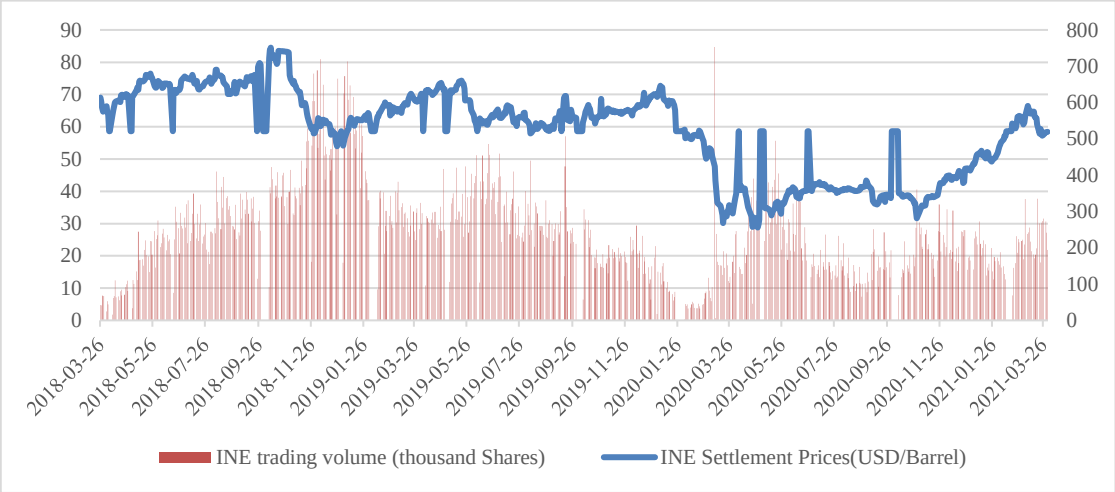

Figure 1. INE crude oil contract: settlement prices and volumes

Source: Shanghai Energy International Exchange

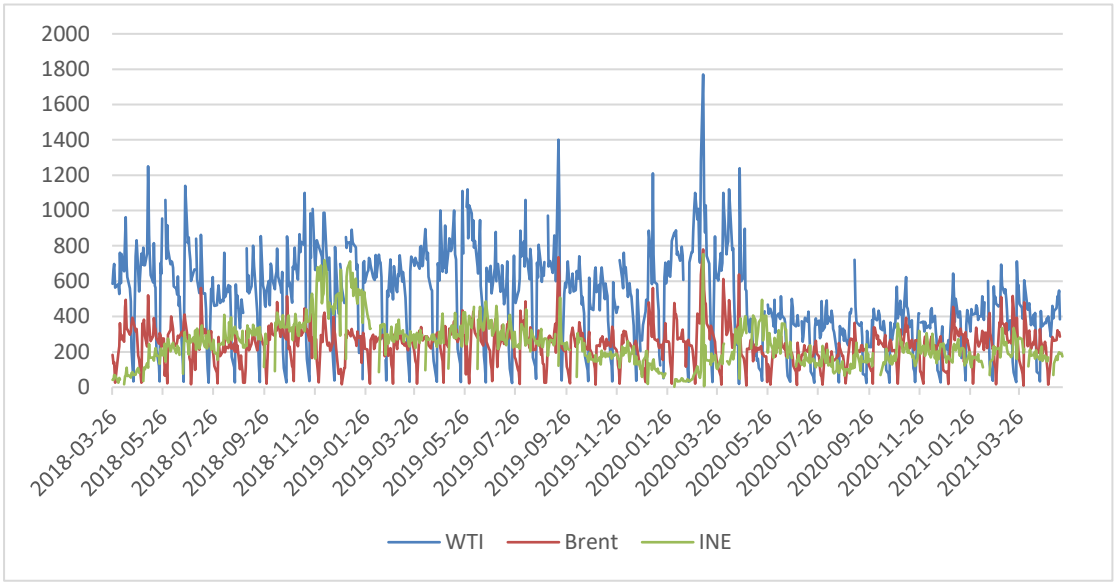

Figure 2. Trading volume (thousand shares) of WTI, Brent, INE (Nymex)

Source: CME group

2. Review of Literature

Despite many price discovery studies to date, there is still not a strict definition of price discovery. The concept of price discovery is complex and subject to different interpretations. For example, in the early discussion of price discovery, Irwin (1933) reveals that the essence of the price discovery is to explore which market product moves closer to the intrinsic value. Garbade and Silber (1983) consider price discovery to reflect one of the major contributions of futures markets to the organization of economic activity. Their research introduces the concept of dominant

and satellite markets. The market where the price discovery takes place primarily is considered to be the dominant market. Schwarz and Szakmary (1994) interpret the price discovery as a process of searching for an equilibrium price. However, these descriptions are not explicit and do not make clear what exactly price discovery of a price series measures.

With the increasing trials of measuring price discovery, researchers try to specify the meanings of "dominant in price discovery", "the contribution to price discovery". Hasbrouck (1995) put forward the "who moves first" view of price discovery which is widely accepted by subsequent research. Booth, So, and Tse (1999a) state that "price discovery is typically documented by noting except the speed at which prices react to new information". Lehmann (2002) sees price discovery as involving an "efficient and timely incorporation of the information implicit in the investor trading impact on market prices". Here, Putniņš (2013) thinks about efficient and timely implication of the speed and noise of incorporation of information and interprets the price discovery in two aspects: the relative speed of price adjustment and the relative absence of noise. In summary, the common sense of price discovery means which price series incorporates information into fundamental value first (Cabrera, Wang, & Yang, 2009; Chakravarty, Gulen, & Mayhew, 2004; Mizrach & Neely, 2008; Rittler, 2012).

From previous literature, many methods can be used to measure price discovery between markets. For instance, Garbade and Silber (1983) use the vector autoregressive (VAR) model to analyze the price discovery for wheat, corn, oats, orange juice, copper, gold, and silver. They find empirical evidence that price discovery mainly takes place in the futures markets. Bopp and Sitzer (1987) use cost pass through regression, polynomial distributed lag model, and some forecasting models to analyze monthly data on heating oil and find that 1-month futures price contains significant information about the cash price. Wlazlowski, Hagstromer, and Giulietti (2011) apply Granger causality tests to study the price dependence of 32 crudes in order to find out which crudes drive other prices and which ones simply follow general market trends.

Since the prices in different markets are normally found to be non-stationary (unit-root), processes with the number of cointegrating vectors equal to the number of markets minus one in recent years, price discovery measures are defined based on a framework of cointegration. The prices series usually deviate from each other in the short run and converge in the long run. Vector error correction models (VECM) (Engle & Granger, 1987) are therefore used to analyze the price adjustment under the assumption that such cointegrated prices share a common random work efficient walk. Bentzen (2007) uses an error correction model approach to compare several different crude oils — WTI, Brent, Alaska North Slope, Dubai Fateh, and the Indonesian Arun and finds that there is a tight link between the world oil markets.

Derived from VECM models, two commonly used metrics were introduced to measure price discovery: Hasbrouck's (1995) information share (IS) and Gonzalo and Granger's (1995) component share (CS). Both IS and CS are used to directly measure the contributions to market implicit value. Information share measures each market's relative contribution to innovations variance while Component share measures each market's contribution to the common factor, where the contribution is defined to be a function of the markets' error correction coefficients. These two metrics are typically interpreted to be the extent to which it is the first to reflect new information about the 'true' underlying asset value. Higher IS and CS means the higher speed of the price series reflecting new information. However, there are some limitations in these two metrics. For example, when price innovations across markets are correlated, the attribution of efficient price innovation variance is not unique and instead one can estimate an upper and lower bound on a price series' information share. As the linear coefficient vector can be shown to be orthogonal to the error correction coefficient matrix, one of the limitations of component share is the fact that it ignores the innovation variances.

To address these problems of IS and CS, many researchers make efforts to reconcile and extend the setups of the "share" of price discovery. Lien and Shrestha (2009) proposed modified information share (MIS) leads to a unique measure of price discovery instead of the upper and lower IS. Generalized information share (GIS) is developed by Lien and Shrestha (2014) since not only it yields a unique measure of information share but also it could be applied to the situation where the cointegrating relation is not one-to-one. Lehmann (2002) points out that IS and CS are not always clear because they are dependent on the structural model of price formation. Yan and Zivot (2007) interpret IS and CS in the context of a structural cointegration model to solve this problem directly. Putniņš (2013) states that inferences made from the IS and CS metrics will be biased when the noise levels are different. Therefore, he extends the work of Yan and Zivot (2010) and develops an alternative measure, the information leadership share (ILS), which is not influenced by differences in the levels of noise. Ozturk, Wel, and van Dijk (2016) point out that the implicit assumption of constant price discovery contributions is not always true over the sample period. Thus, Lien and Wang (2019) Lien and Wang (2019) construct quantile information share (QIS) analytically based on the method of Chakraborty (2003). In our study, we take both IS and CS metrics to compare the contribution of price discovery before and after the COVID-19 for the sake of the robustness of the results.

3. Methodology and Tests

The data employed in this study to explore price discovery in the oil market consists of daily log closing prices of the WTI, Brent, INE futures. INE crude oil futures are

quoted in RMB, so we need to adjust the price by the USD-RMB exchange rate so that its price would become on par with WTI and Brent. The samples are over the period from March 26, 2018, to March 31, 2021. For the negative price of WTI on April 20, 2020, we replace it with a moving average before applying the logarithm approach. Intuitively, we can observe the characteristics of the log price of three international crude oil prices from Figure 3. An observable linkage between these three time-series is shown, and the degree of deviation between these series has gradually decreased since the launch of the INE crude oil futures in 2018. We induce that the pricing design of INE contracts was firmly tracking international oil prices at the early stage of the market when there is a lack of vitality and the Chinese international crude oil is not mature enough. In the first half-year of 2020 when COVID-19 spread across the whole world, the logarithmic price fluctuates obviously and then the deviation degree of the three is magnified to a certain extent. A drastic fluctuation can be observed from March to June 2020. During this period, WTI price went negative at closing and brought a huge panic to the crude oil markets. From this time onwards, the linkage relationship is closer and there is remarkable volatility in INE return in the second half-year of 2020.

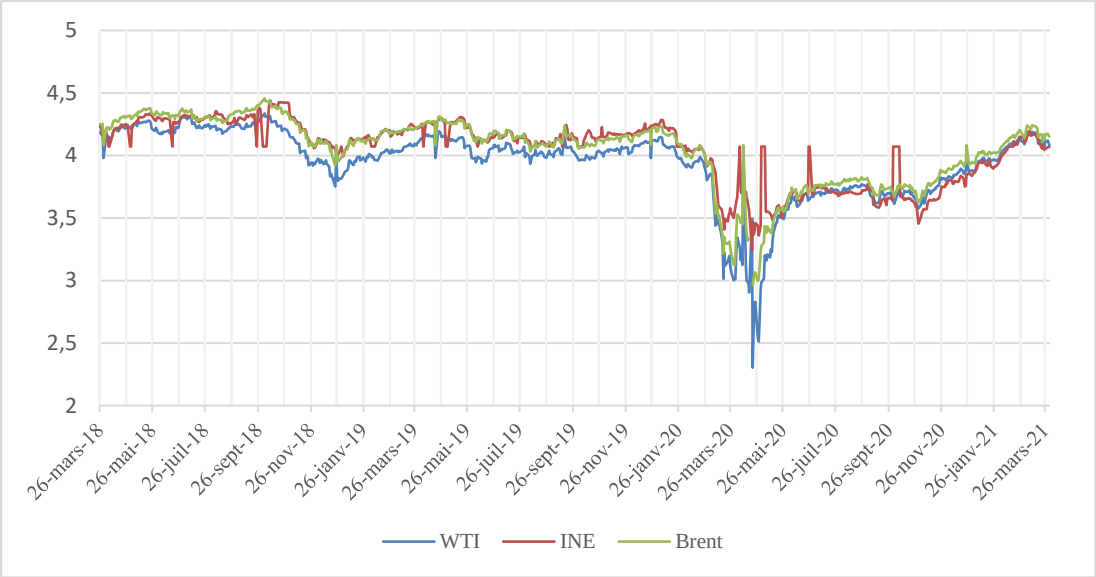

Figure 3. Price of three international crude oil futures in logarithm

Source: CME group

Based on the above fact, we can guess that there is a structural break in these time series. The standard Dickey-Fuller and Philips-Perron tests which lead to the non-rejection of a unit root may become suspicious when the sample under consideration incorporates economic events capable of causing shifts in the regime. Similar to the COVID-19 crisis, Perron (1989) carried out tests of the unit root hypothesis against the alternative hypothesis of stationary trend with a break in the trend occurring at the

Great Crash of 1929 or the oil price shock of 1973. He proposed introducing into the Dickey-Fuller regression a dummy variable specifying the existence of a structural break. However, Zivot and Donald (1992) argued that Perron's choice of breakpoints is based on the pre-observation of the data and hence problems associated with pre-testing are applicable to his methodology. Therefore, they questioned this exogeneity assumption and conducted a unit root test which treats the structural break as an exogenous occurrence. Here, we apply the Zivot-Andrews unit root test to confirm the structural break as the specific point of the COVID-19 outbreak. The null hypothesis is that the price series is integrated without an exogenous break.

After unit root tests, it is a common practice to look for long-term equilibrium relationships between different variables in financial markets. However, if there is a structural break, the hypothesis that the residuals of the Engle and Granger model are I(1) will not be rejected, and therefore there is a non-cointegration, and may be a shift in regime in the cointegration relationship. To solve this problem, Gregory and Hansen (1996) used a modified approach of the Engle and Granger model to allow a change in structure in the long-term relationship. In this test, the null hypothesis is non-cointegration while the alternative hypothesis is a cointegration relation with a structural change in the constant and/or the slope of a linear trend follows a major shock.

Once a cointegration relationship with structural break does exists, the vector error correction could be estimated to describe the evolution of the variables in the short-term and long-term for each sub-period sample. Under the framework of VECM, Information Share (IS) defined by Hasbrouck (1995) and Component Share (CS) proposed by Gonzalo and Granger (1995) could be used to calculate and evaluate price discovery for multiple markets. They are two intuitive metrics to indicate the speed of market prices impounding new information. IS and CS share a lot in common because both are closely related to the same combination of the reduced form error correction coefficients. IS focuses on the variance of the efficient price innovation, and measures what proportion of efficient price variance can be attributed to the innovations of each individual market. The CS approach, on the other hand, focuses on the composition of efficient price innovation and measures a market's contribution to price discovery and also its contribution to the efficient price innovation. Lastly, we compare the difference between IS and CS for subperiods which were divided based on the break date tested out, to summarize and conclude the impact of COVID-19 on the crude oil future market.

3.1 Zivot and Andrews Unit Root Tests

We will now briefly review the procedures and tests of Zivot and Andrews (1992) which were extended from Perron (1989).They developed a procedure to test the null hypothesis that the time series $Y_{t,\ t\in[1,T]}$ is characterized by the existence of a unit

root and possibly a null constant with a structural break occurring at time T_B, *(1 $< T_B <$ T)* versus the alternative hypothesis that the series is stationary around a linear trend with a structural break at T_B in this trend. The authors also propose to distinguish between a sudden change (denoted AO for Additive Outlier) and a transition effect (denoted IO for Innovational Outlier). For each of the effects AO and IO, they consider three models for the alternative hypothesis.

For the AO version, the models take the following form:

$$Y_t = \mu + \beta t + \gamma DU_t(\lambda) + \widetilde{Y}_t \qquad (A^{AO})$$

$$Y_t = \mu + \beta t + \theta DT_t^*(\lambda) + \widetilde{Y}_t \qquad (B^{AO})$$

$$Y_t = \mu + \beta t + \gamma DU_t(\lambda) + \theta DT_t^*(\lambda) + \widetilde{Y}_t \quad (C^{AO})$$

Where $\widetilde{Y}_t$ is the series Y_t, from which the deterministic trend has been removed, $DU_t(\lambda) = 1$ if $t > T_B$, otherwise 0, $DT_t^*(\lambda) = (t - T_B)$ if $t > T_B$, otherwise 0, with $T_B = \lambda T$ where λ denotes the location of the structural break T_B, for the sample of size T.

The IO type models, in the alternative hypothesis, take the form:

$$Y_t = \mu + \beta t + \Phi(L)(e_t + \theta DU_t(\lambda)) \qquad (A^{IO})$$

$$Y_t = \mu + \beta t + \Phi(L)(e_t + \gamma DU_t^*(\lambda)) \qquad (B^{IO})$$

$$Y_t = \mu + \beta t + \Phi(L)(e_t + \theta DU_t(\lambda)\gamma DU_t^*(\lambda)) \quad (C^{IO})$$

Where $\Phi(L) = (1 - \alpha L)^{-1} A(L)^{-1} B(L)$ with $A(L)$ and $B(L)$ are two polynomials with a lag operator L, with a finite number of degrees of freedom. These three versions indicate the way in which the transition takes place after the structural break.

And regarding the date of the structural break T_B, it was determined endogenously from the data, using the sequential procedures of Zivot and Andrews (1992). This method consists in estimating the regression models A, B and C version AO and IO for $T_B = 2, \ldots, T-1$, which amounts to considering the possible relative structural breaks $\lambda = T_B/T$ from $2/T$ to $(T-1)/T$. For a given model, the time of the selected structural break is when the t-statistic for $\alpha = 0$ denoted $t_{\widetilde{\alpha}}(1)$ is minimal. $\lambda \in \Lambda$, Λ a closed interval of (0,1), for the different models A, B and C associated with the effects AO and IO. In our study we have used the location interval L = [0.15;0.85] proposed by Zivot and Andrews.

3.2 Gregory and Hansen Tests

To test the existence of a cointegration relation that allows for the possibility of regime shifts, Gregory and Hansen (1996) propose ADF-, Z-, and Z-type tests designed to test the null of no cointegration against the alternative of cointegration in the presence of a possible regime shift. In their article, to estimate the structural effect, they introduced the dummy variable $D_{t\tau} = 0\ if\ t \leq [n\tau]$ and otherwise 1， and [.] represents the integer part, where the unknown parameter $\tau \in (0,1)$ denotes the (relative) timing of the change point. Assuming that the observed data is $Y_t = (Y_1, Y_2)$ where Y_1 is real-valued and Y_2 is a vector with m components. They considered three alternative types of regression models where the intercept and/or slope coefficients have a single break of unknown timing. The standard cointegration model of Engle and Granger is:

$$Y_{1t} = \mu_1 + \alpha' Y_{2t} + \varepsilon_t \quad (1)$$

The alternative models are:

(i) A model with level shift (C)

$$Y_{1t} = \mu_1 + \mu_2 D_{t\tau} + \alpha' Y_{2t} + \varepsilon_t \quad (2)$$

(ii) A model with a liner trend incorporating a change in level(C/T)

$$Y_{1t} = \mu_1 + \mu_2 D_{t\tau} + \beta t + \alpha' Y_{2t} + \varepsilon_t \quad (3)$$

(iii) Regime shift(C/S)

$$Y_{1t} = \mu_1 + \mu_2 D_{t\tau} + \beta t + \alpha' Y_{2t} + \alpha' Y_{2t} D_{t\tau} + \varepsilon_t \quad (4)$$

When it comes to test statistics, Gregory and Hansen use modified values of the Z_α and Z_t statistics of Phillips (1987) and of augmented Dickey-Fuller (ADF). Their statistics are the smallest values of the preceding statistics, across all values of $\tau \in T$. These statistics are:

$$Z_\alpha^* = \inf_{(\tau \in T)} Z_\alpha(\tau) \quad (5)$$

$$Z_t^* = \inf_{(\tau \in T)} Z_t(\tau) \quad (6)$$

$$ADF^* = \inf_{(\tau \in T)} ADF(\tau) \quad (7)$$

Where τ located the shift in regime and T is a closed interval of (0,1). In our research, we used the interval T= [0.15,0.85] proposed by Gregory and Hansen.

3.3 Vector Error Correction Model

Let $P_t = \left(p_{1,t}, p_{2,t}\right)'$ denote a two dimensions vector of log price for the asset from the two markets. The basic assumption of these prices is that they contain a random walk component which means P_t is integrated with order 1. In addition, the prices in P_t are for the same security in different markets as Hasbrouck mentioned in 1995. In his research in 2003, the condition of the same underlying asset is relaxed, prices such as futures contracts and their corresponding exchange-traded funds could be involved as long as the quantity $p_{1,t} - p_{2,t}$ does not diverge over time. Under the precondition of cointegration, meaning that we assume P_t is cointegrated with known cointegrating vector $\beta = (1, -1)'$, $\beta' P_t = p_{1,t} - p_{2,t}$ is integrated of order zero, or $I(0)$. This means that the two markets are fully integrated because the prices in logarithm terms have the same evolution. Consequently, based on Engle and Granger (1987), the representation of the vector error correction model can be written as follows:

$$\Delta p_t = \alpha(\beta' p_{t-1} - \mu) + \sum_{k=1}^{k-1} \Gamma_k \Delta p_{t-k} + e_t \tag{8}$$

Where $\mu = \mathrm{E}(\beta' p_{t-1})$. The vector α is a matrix of error correction coefficients which implies the adjustment speed to the deviations from the long-run equilibrium. For a bivariate case, α contains two coefficients, α_1 and α_2, for market 1 and market 2. If α_2 is larger than α_1, it implies that market 1 leads market 2 in the long run. Market 2 leads market 1 if the other way around. Γ_k contains coefficients for short-term adjustment. e_t is a zero-mean vector of serially uncorrelated innovations with covariance matrix Ω such that:

$$\Omega = \begin{pmatrix} {\sigma_1}^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{pmatrix} \tag{9}$$

Here ${\sigma_1}^2, \sigma_2^2$ are respectively the variance of e_{1t} and e_{2t} and ρ is the correlation between e_{1t} and e_{2t}.

3.4 Information Share (IS)

Information Share was interpreted as a measurement of "who moves first in the process of price adjustment". Hasbrouck (1995) decomposes the variance of the common factor innovations, ψe_t. According to Hasbrouck (1995) information share, we transform the VECM in Equation (8) into a vector moving average (VMA):

$$\Delta p_t = \Psi(L) e_t \tag{10}$$

And its integrated form is

$$p_t = \Psi(1)\sum_{s=1}^{t} e_s + \Psi^*(\mathrm{L})e_t \quad (11)$$

Where $\Psi(1)$ is the impact matrix of the innovation e_t on all future price movements which represents the sum of all moving average coefficients. $\Psi(1)e_t$ is the long-run impact of an innovation on each of the prices. Because $\beta = (1,-1)'$ and $\beta'\Psi(1) = 0$, the rows of impact matrix are identical, the long-run impact is the same for all market. This has been proved by Baillie, Booth, Tse, and Zabotina (2002), de Jong (2002) and Hasbrouck (1995). We denote $\psi = (\psi_1, \psi_2)$ as the common row vector in $\Psi(1)$. Therefore, the permanent innovation n_t can be defined as:

$$n_t = \psi' e_t = \psi_1 e_{1,t} + \psi_2 e_{2,t} \quad (12)$$

The variance of permanent innovation is $\psi\Omega\psi'$ and the proportion of information contribution of market *i* is defined as:

$$IS_i = \frac{\psi_i^2 \Omega_{ii}}{\psi\Omega\psi'} \quad (13)$$

where Ω_{ii} is the element (i,i) of Ω. When Ω is a diagonal matrix, this means there are no correlations between markets. Thus, the IS of market i is defined in this case as:

$$IS_i = \frac{\psi_i^2 \sigma_i^2}{\psi\Omega\psi'} = \frac{\psi_i^2 \sigma_i^2}{\psi_i^2 \sigma_i^2 + \psi_2^2 \sigma_2^2}\ ,\ i\ = 1{,}2 \quad (14)$$

Where ψ_i is the i th element of Ψ. By construction, $IS_1 + IS_2 = 1$, it is clear that a low (high) information share for market *i* implies a small (large) reaction to the arrival of new information about fundamental value.

If Ω is non-diagonal, Hasbrouck (1995) suggested to compute the Cholesky decomposition of Ω and measure the IS using the orthogonalized innovations. In fact, Cholesky factorization depends the orders of variables. Hence, we need to take into account different variable orders to obtain the upper and lower bounds for information share of each market. For a bivariate case, let F be a lower triangular matrix such that FF' $= \Omega$, then the IS for the *i* th market is:

$$IS_i = \frac{([\psi F]_i)^2}{\psi\Omega\psi'} \quad (15)$$

Where $[\psi F]_i$ is the i th element of the row of matrix ψF:

$$\mathrm{F} = \begin{pmatrix} f_{11} & 0 \\ f_{12} & f_{22} \end{pmatrix} = \begin{pmatrix} \sigma_1 & 0 \\ \rho\sigma_2 & \sigma_2(1-\rho^2)^{\frac{1}{2}} \end{pmatrix} \quad (16)$$

When market one is in the first variable, the calculated information share is its upper limit and when it is in the last variable, the calculated information share is its lower

limit. The average of the upper and lower limits is its average share of information (Yan & Zivot, 2007).

Upper bound of information share of Market1 is:

$$IS_u = \frac{(\alpha_2\sigma_1 - \alpha_1\sigma_2\rho)^2}{\alpha_2^2\sigma_1^2 - 2\rho\alpha_1\alpha_2\sigma_1\sigma_2 + \sigma_2^2\alpha_1^2} \tag{17}$$

And lower bound of information share of Market1 is:

$$IS_l = \frac{\alpha_2^2\sigma_1^2(1-\rho^2)}{\alpha_2^2\sigma_1^2 - 2\rho\alpha_1\alpha_2\sigma_1\sigma_2 + \sigma_2^2\alpha_1^2} \tag{18}$$

Where α_1 and α_2 are defined is the same way as they are defined in VECM: the error correction coefficients imply the adjustment speed to the deviations from the long-run equilibrium.

3.5 Component Share (CS)

Component Share was proposed by Gonzalo and Granger (1995) and first applied by Booth, So, and Tse (1999), Chu, Hsieh, and Tse (1999), and Harris, McInish, and Wood (2009) to measure one market's contribution to price discovery by using the permanent-transitory (PT) component decomposition. The PT decomposition of p_t is defined as follows:

$$p_t = Af_t + Z_t \tag{19}$$

Where $f_t \sim I(1)$ is a permanent common factor and Z_t is the transitory component which is a short-term stationary factor. A is a coefficient matrix. Z_t does not Granger causes f_t. Following Gonzalo and Granger(1995), f_t can be expressed as a linear combination of prices. Thus,

$$f_t = \gamma' p_t \tag{20}$$

As Gonzalo and Granger (1995) defined,

$$\gamma = (\alpha_\perp'\beta_\perp)^{-1}\alpha_\perp' \tag{21}$$

where $\alpha_\perp$ is an orthogonal matrix to the error-correction coefficient matrix α which can be used to measure the contribution of each market to the price discovery process. $\beta_\perp$ is an orthogonal matrix to the co-integrating matrix β. $\alpha_\perp$ and $\beta_\perp$ are scaled vectors to 1. For two markets case, $\alpha_\perp$ and $\beta_\perp$ are 2*1 vectors such that $\alpha_\perp'\alpha = 0$ and $\beta_\perp'\beta = 0$, Since $\beta = (1,-1)^{'}$, one choice for $\beta_\perp$ is $\mathbf{1} = (1,1)^{'}$, implying $\gamma = \left(\alpha_\perp^{'}\mathbf{1}\right)^{-1}\alpha_\perp^{'}$ so that the permanent component weights $\gamma_i = \frac{\alpha_{\perp,i}}{\alpha_{\perp,1}+\alpha_{\perp,2}}$ for i=1, 2 is a weighted average of observed prices with component weights. The Component Share

(CS) which was proposed by Booth, So, and Tse (1999), Chu, Hsieh, and Tse (1999), and Harris, McInish, and Wood (2009) measures price discovery in market i:

$$CS_i = \frac{\alpha_{\perp,i}}{\alpha_{\perp,1}+\alpha_{\perp,2}}, i = 1, 2 \quad (22)$$

Since the vector of long-run impact coefficients ψ is equal up to a scale factor, the CS measures can also be expressed in terms of ψ (Baillie et al., 2002):

$$CS_i = \frac{\psi_i}{\psi_1+\psi_2} \quad (23)$$

Equation (23) shows that the IS is a variance-weighted version of CS when market innovations are uncorrelated.

4. Empirical Analysis

Before discussing more in-depth the interpretation of the IS and CS between three crude oil futures markets, we perform the unit root test and cointegration test with the structural break. On this basis, we can establish the IS and CS model to study the contribution of different crude oil markets to the price discovery process before and after the outbreak of COVID-19.

4.1 Unit Root Test and Stationary Tests

To check the stationarity of the three crude oil futures time series, the study performs the Augmented Dickey–Fuller (ADF) unit root test, Phillips–Perron (PP) unit root test, and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test. The null hypothesis for ADF and PP tests is that the time series has one unit root and hence, not stationary while the null hypothesis for KPSS test is that the time series is stationary. The results of classic unit root tests are summarized in Table 2. From the tests for log price series, we cannot reject the null hypothesis of ADF and PP and reject the null hypothesis of KPSS, which means that these three crude oil prices are all not stationary. The post oil crash literature provided alternative arguments following the paper of Perron (1989), which has shown that the unit tests have low power in applications to processes with level shifts. We mentioned before that there is a drop in oil prices, and it's known that the unit root tests do not distinguish between the stationary processes with local trends and non-stationary processes with global trends. Thus, the unit root tests tend to accept the null hypothesis.

Table 2. Unit root test and stationary tests for log price series

	Ln(P_WTI)	Ln(P_Brent)	Ln(P_INE)
Augmented Dickey-Fuller Test (H0: Ln(P_X) has a unit root)			

Exogenous: Constant, Linear Trend			
t- statistic	-2.91	-1.90	-2.51
Phillips–Perron (PP) Test (H0: Ln(P_X) has a unit root			
Exogenous: Constant, Liner Trend			
t- statistic	-2.82	-2.34	-3.77
Kwiatkowski-Phillips-Schmidt-Shin Test (H0: Ln(P_X) is stationary)			
Exogenous: Constant, Linear Trend			
t-statistic	0.22***	0.23***	0.21**

Note: The superscript '***' '**' '*'indicate the test statistic to be significant at 1%,5%, and 10% significance levels, respectively.

A simple way to solve the problem is to conduct the Zivot-Andrews unit root test to confirm the structural break as the specific point of the COVID-19 breakout. The null hypothesis is that the price series is integrated without an exogenous break. From the Zivot-Andrews test results in Table 3, it shows that the t statistics favor the rejection of the null hypothesis at 1% level of significance for the price series and the break date is the 6th of March, 2020. We also used each sub-sample to conduct Zivot-Andrews test and didn't find other common break dates which occurred during COVID-19 (see Appendix 1).

Table 3. Zivot-Andrews unit root test

Null Hypothesis: Ln(P_X) has a unit root with a structural break in both the intercept and trend

Variables	Ln(P_WTI)	Ln(P_Brent)	Ln(P_INE)
Zivot-Andrews T-Statistics	-5.34***	-6.53***	-6.72***
Break Date	March 6, 2020	March 6, 2020	March 6, 2020

Note: The critical value for Zivot Andrews tests are -5.57, -5.08, -4.82 at 1%, 5%, 1 0% significant level. The superscripts'***' '**' '*' indicate the degree of significance associated with rejection of null hypothesis at the level of 1%, 5%, and 10% respectively.

4.2 Cointegration Tests with Structural Break

Table 4 gives the results of the Gregory and Hansen tests with the determination of the structural breakpoint for WTI, Brent, and INE during the period from 2018 to 2021. The three statistics ADF*, Z_α^* , and Z_t^* clearly indicate that there is cointegration with the three alternative models (C), (C/T), and (C/S). According to the ADF*, Z_α^* , and Z_t^*, the structural break date, estimated on the basis of the three models, is mainly May 12th, 2020. We noticed that most cities, including Wuhan, have lift the lockdown restrictions in China by May, 2020. Many tourist attractions reopened and the national economy has entered the stage of recovery, which drives oil demand without any doubt. However, concerning Europe, the European Commission invited the Schengen Member States and the Schengen Associated States to extend the temporary

restriction on non-essential travel for another 30 days at the beginning of May. At this point, after the negative price at the end of April, WTI was still under high volatility in America. Based on these facts, it is not hard to realize why the structural break dates in cointegration relationship tested by ADF*, Z_α^* and Z_t^* are mainly refered to April or May.

Table 4. Testing for regime shifts in crude oil markets with Gregory and Hansen's cointegration tests

Dependent Variable: Brent; Independent Variable: INE						
	ADF*	ADF Break	Z_α^*	Z_α Break	Z_t^*	Z_t Break
C	-7.12	May 12, 2020	-233.35	May 12, 2020	-11.85	May 12, 2020
C/T	-7.21	May 12, 2020	-240.07	May 12, 2020	-12.06	May 12, 2020
C/S	-7.72	May 12, 2020	-274.11	May 12, 2020	-13.05	May 12, 2020
Dependent Variable: WTI; Independent Variable: INE						
C	-6.68	May 22, 2020	-204.95	May 12, 2020	-11.08	May 12, 2020
C/T	-6.72	May 22, 2020	-206.48	May 12, 2020	-11.15	May 12, 2020
C/S	-7.33	May 22, 2020	-257.87	May 12, 2020	-12.63	May 12, 2020
Dependent Variable: WTI; Independent Variable: Brent						
C	-4.72	May 27, 2020	-103.20	May 12, 2020	-7.40	May 12, 2020
C/T	-4.70	May 27, 2020	-98.01	May 29, 2020	-7.22	May 12, 2020
C/S	-4.99	May 27, 2020	-105.55	May 12, 2020	-7.53	May 12, 2020
Dependent Variable: INE ; Independent Variable: Brent						
C	-8.15	May 12, 2020	-265.28	May 8, 2020	-12.69	May 8, 2020
C/T	-13.09	May 12, 2020	-274.85	May 11, 2020	-12.96	May 8, 2020
C/S	-13.29	May 12, 2020	-284.52	May 11, 2020	-13.21	May 12, 2020
Dependent Variable: INE ; Independent Variable: WTI						
C	-9.15	Apr 28, 2020	-233.27	May 8, 2020	-11.82	May 12, 2020
C/T	-9.14	Apr 28, 2020	-236.48	May 8, 2020	-11.92	May 12, 2020
C/S	-11.08	May 12, 2020	-267.20	May 12, 2020	-12.78	May 12, 2020
Dependent Variable: Brent ; Independent Variable: WTI						
C	-4.63	May 27, 2020	-92.47	May 12, 2020	-6.99	May 12, 2020
C/T	-4.50	May 27, 2020	-89.24	May 12, 2020	-6.86	May 12, 2020
C/S	-4.94	May 26, 2020	-102.94	May 12, 2020	-7.43	May 12, 2020

Note: The critical values for Gregory and Hansen's cointegration tests are listed in Table 5.

Table 5. The critical value of Gregory and Hansen's cointegration tests

	1% Critical Value	5% Critical Value	10% Critical Value
ADF^* , Z_t^*			

C	-6.05	-5.56	-5.31
C/T	-6.36	-5.83	-5.59
C/S	-6.92	-6.41	-6.17
Z_{α}^{*}			
C	-70.18	-59.40	-54.38
C/T	-76.95	-65.44	-60.12
C/S	-90.35	-78.52	-72.56

Note: Critical value are taken from Gregory and Hansen (1996).

4.3 Choice of Break Date

Although both Zivot-Andrews unit root tests and Gregory-Hansen cointegration tests could detect breakpoints for price time series, we select the break date corresponding to the Zivot and Andrews tests because it corresponds to the starting point for the slowdown (2020 Q1) of the worldwide oil demand (See figure 4). Therefore, this study only considers one break of March 6, 2020 as a breakpoint to explore the impact of the COVID crisis.

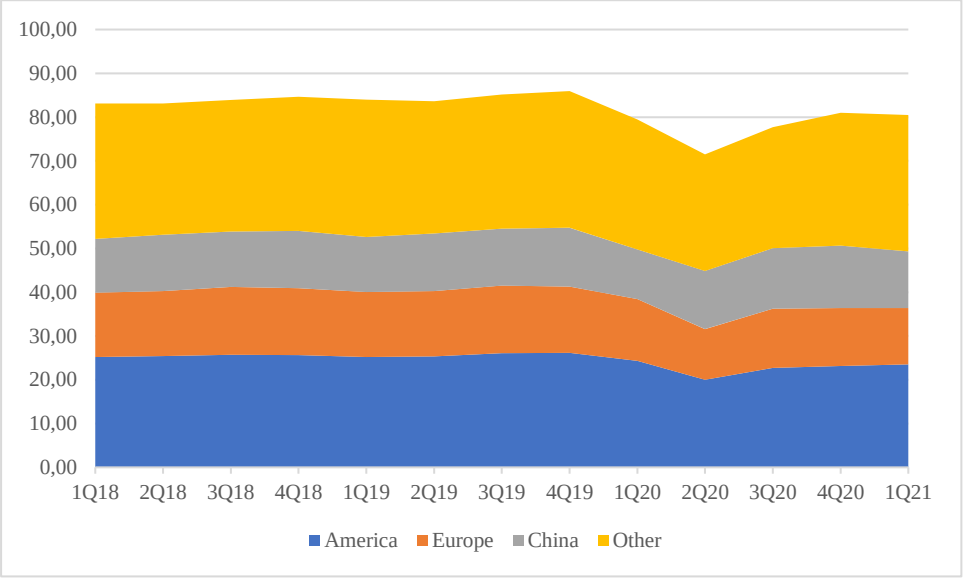

Figure 4. Quarterly world oil demand from 2018 to 2021 (Units: mb/d)

Source: OPEC

As a result, we take this date as a turning point to split our research sample into two subperiods: Pre-COVID (March 26, 2018 - March 5, 2020) and Post-COVID (March 6, 2020 - March 31, 2021). We compared the difference between the three international crude oil markets before and after the breakout of the COVID-19. In table 6 we list the descriptive statistics of specific variables.

Table 6. Descriptive statistics of daily price

Variable	Ln(P_INE)			Ln(P_WTI)			Ln(P_Brent)		
	Whole Sample	Pre-COVID	Post-COVID	Whole Sample	Pre-COVID	Post-COVID	Whole Sample	Pre-COVID	Post-COVID
Mean	4.04	4.20	3.76	3.94	4.09	3.68	4.05	4.20	3.77
Maximum	4.44	4.44	4.20	4.34	4.34	4.19	4.46	4.46	4.24
Minimum	3.36	3.91	3.36	2.30	3.75	2.30	2.96	3.91	2.96
Std. Dev.	0.25	0.10	0.20	0.29	0.12	0.33	0.28	0.11	0.27
Skewness	-0.80	0.05	0.54	-1.84	-0.01	-1.18	-1.28	0.01	-0.55
Kurtosis	2.44	2.54	2.38	7.66	2.26	4.91	4.51	2.30	3.31

In table 6 we show the descriptive statistical analysis results of the logarithmic price of the three crude oil markets respectively. As we expected, the results show that after the outbreak of the COVID-19 the mean of three crude oil futures markets decreases on account of the decreased demand while the standard deviation of log price increases obviously, which means that the market fluctuates significantly due to the COVD-19. From the Standard Deviation results, we can see that the WTI price series fluctuate the most, especially in the post-COVID period, which also fits well the real situation.

4.4 IS and CS Measures

So far, we have identified a breakpoint of March 6, 2020, using unit root tests with a structural break (Zivot and Andrews, 1992). We have also established that there exist cointegration relationships with the structural break between the price time series of WTI, INE, and Brent using cointegration test with a structural break (Gregory and Hansen, 1996). Therefore, we have satisfied the conditions necessary for the use of IS and CS measures on each subsample. As we discussed in the previous section, both Information share and Component share are calculated from the specification of parameters from VECM. In our study, we estimate a VEC model for each sub-period and the detailed results are in the appendix （see Appendix 2.

Table 7. Information share for international crude oil markets

		Upper bound	Lower bound	Midpoint
Whole sample (March 26, 2018 - March 31, 2021)				
(WTI, INE)	WTI	72.47%	57.41%	64.94%
	INE	42.59%	27.53%	35.06%
(Brent, INE)	Brent	96.35%	88.22%	92.29%
	INE	11.78%	3.65%	7.71%
(WTI, Brent)	WTI	46.71%	22.95%	34.83%

	Brent	77.05%	53.29%	65.17%
The pre-covid period (March 26, 2018 - March 5, 2020)				
(WTI, INE)	WTI	99.90%	98.37%	99.14%
	INE	1.63%	0.10%	0.87%
(Brent, INE)	Brent	99.37%	96.87%	98.12%
	INE	3.13%	0.63%	1.88%
(WTI, Brent)	WTI	99.94%	7.74%	53.84%
	Brent	92.26%	0.06%	46.16%
The post-covid period (March 6, 2020 - March 31, 2021)				
(WTI, INE)	WTI	96.85%	93.93%	95.39%
	INE	6.07%	3.15%	4.61%
(Brent, INE)	Brent	88.38%	86.52%	87.45%
	INE	13.48%	11.62%	12.55%
(WTI, Brent)	WTI	96.62%	17.09%	56.86%
	Brent	82.91%	3.38%	43.15%

The estimated Information Shares are summarized in Table 7 where we present the maximum, minimum, and average IS of WTI, Brent, INE. We use the automatic lag selection based on the AIC criterionand specify an upper bound for the maximum number of lags to be used for VECM estimation. Here, we set the maximum number of lags 120 following Aggarwal and Thomas (2019). For the sake of robustness of results, we also run the model by setting the number of lags as 60. The results are attached in the appendix (see Appendix 3 and 4). The empirical results of full samples indicate that the price discovery capability (average information share, Yan and Zivot (2007) of WTI and Brent is stronger than the INE market. Table 7 shows, in the group of (Ln(P_WTI), Ln(P_INE)), the average information share of the WTI market accounts for 64.94% and that of the INE market is 35.06%. That means in the long run, a coordinated movement between the two markets is dominated by WTI futures markets. In other words, the WTI futures market contributes to 64.94% of the price discovery and the INE futures market up to 35.06%. Similarly, in the group of (Ln(P_Brent), Ln(P_INE)), it is the Brent market that plays a leading role. Between the group of (Ln(P_WTI), Ln(P_Brent)) which are two main worldwide benchmarks, Brent contributes more than WTI in the long run. The above results show that since the launch of INE crude oil futures, Brent price mainly plays a leading role in price discovery in international crude oil price.

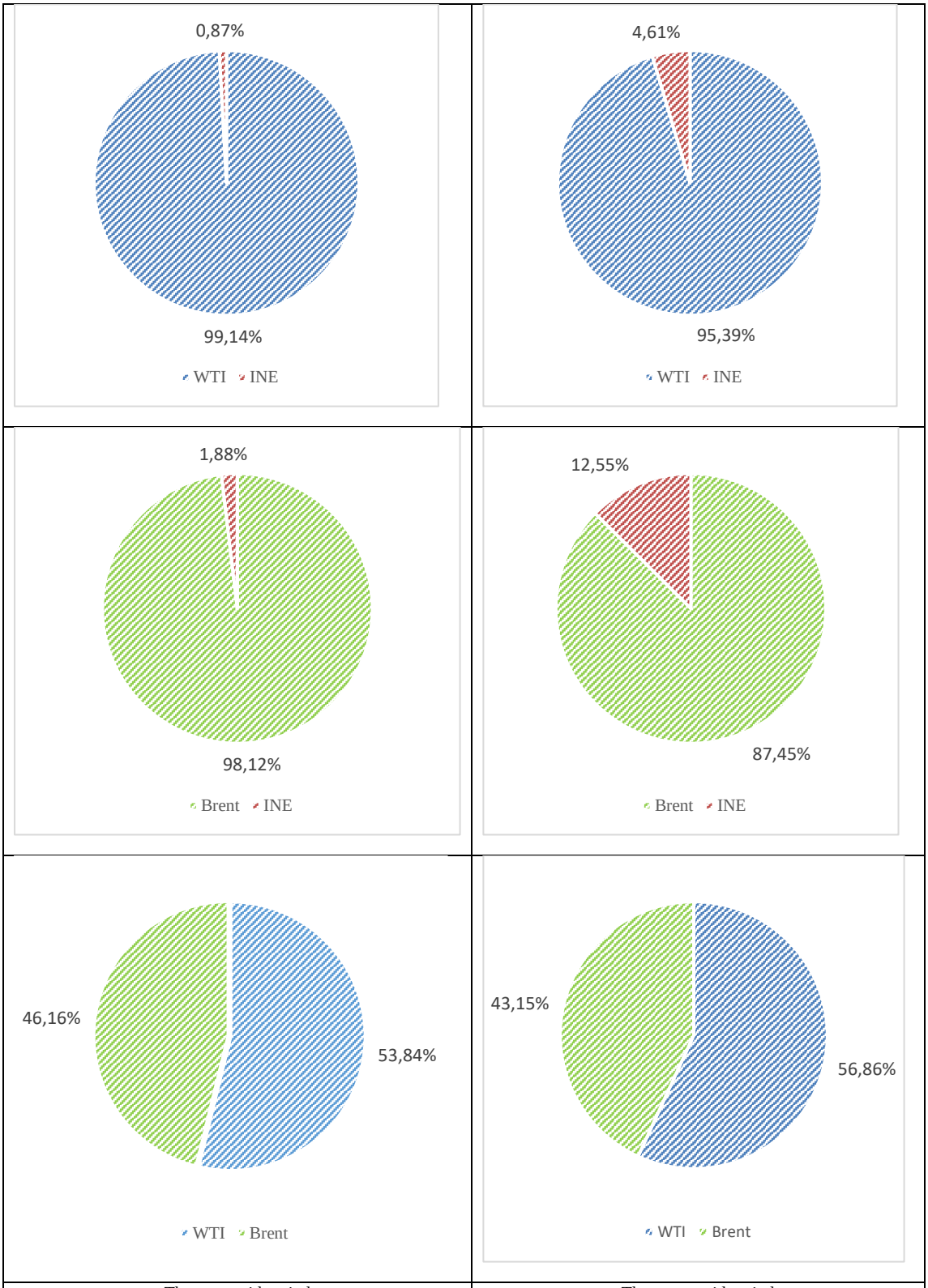

Figure 5. Comparison of IS of three markets before and after the COVID-19

In addition, we further analyzed the difference in information share before and after the outbreak. We took March 6, 2020, as the turning point to divide the whole sample

into two subsamples. As is shown in figure 5, we found that the information share of the INE market has increased slightly in the post-covid period compared with the pre-covid period. Although limited by the number of samples, it also proves that its price discovery function has been improved after the outbreak of COVID. After this outbreak, the effective implementation of epidemic prevention measures by the Chinese government has increased market confidence as well as the trading volume of crude oil futures in INE, thus enhancing the realization of price discovery function in the Shanghai crude oil futures market. On the contrary, the information share of WTI and Brent crude oil futures market has decreased in the three combined markets, indicating that the information advantage of WTI and Brent futures market has decreased after the epidemic, but they still occupy an absolute dominant position. These results can be supported by the change of world oil demand before and after the COVID-19 outbreak. As previewed by GDP growth and the oil demand changes by regional areas (Table 1 and Figure 4), we observe a significant change in world oil demand in 2020 Q1 and Q2. Since the end of 2019, oil demand has experienced an obvious decrease in America, Europe, and China because of the pandemic. Among that, the slowdown of oil demand in Europe is larger than in America. After 2020 Q2, the Word oil demand has been increasing and the oil demand of China has increased more rapidly than America and Europe, which can be used to explain why the IS of INE increased slightly after the COVID.

In the group of (Ln(P_WTI), Ln(P_Brent)), the information share of the WTI market is always larger than the Brent market no matter before or after the outbreak of COVID, which means WTI price becomes more important than the Brent price after the crisis in 2020. Additionally, the IS of WTI is larger in the post-covid period than in the pre-covid period probably because the oil demand recovery speed of Europe is slower than that of America as shown in Figure 5. The variability of the results of the average information share model on the full sample point out the importance to detect the changes and compare the IS before and after the COVID. This points out the consequences of the sudden external shock caused by the epidemic which plays a regulatory role in the price discovery of the three major international crude oil markets.

Table 8. Component share for international crude oil markets

	(WTI, INE)		(Brent, INE)		(WTI, Brent)	
	WTI	INE	Brent	INE	WTI	Brent
Whole sample (March 26, 2018 - March 31, 2021)	58.80%	41.20%	85.91%	14.09%	34.89%	65.11%
The pre-covid period (March 26,	97.59%	2.41%	94.57%	5.43%	91.26%	8.74%

2018 - March 5, 2020)						
The post-covid period (March 6, 2020 - March 31, 2021)	85.20%	14.80%	80.97%	19.03%	69.66%	30.34%

When it comes to component share, the results of CS in Table 8 are generally similar to those of IS. For the whole sample, Brent contributes more share than WTI followed by INE. It means that during the process of price discovery, the Brent market moves to the equilibrium price faster than Brent. INE is the market that moves to implicit efficient prices most slowly. Compared with the pre-covid period (See Figure 6), the component share of INE increased slightly no matter in the WTI and INE group or the Brent and INE group after the outbreak of COVID-19. In the group of WTI and Brent, we can also notice the phenomenon of the dominant role transfer from Brent to WTI in the short run compared to within the long run. After the negative oil price event, the information share of the WTI futures market did not reduce but increased after the pandemic. We believe that the low price and high volatility of futures markets of WTI may be conducive to attracting more market participants to speculate and hedge, so it's likely that the price discovery function of futures markets is improved because of the large trading volume in the short-term.

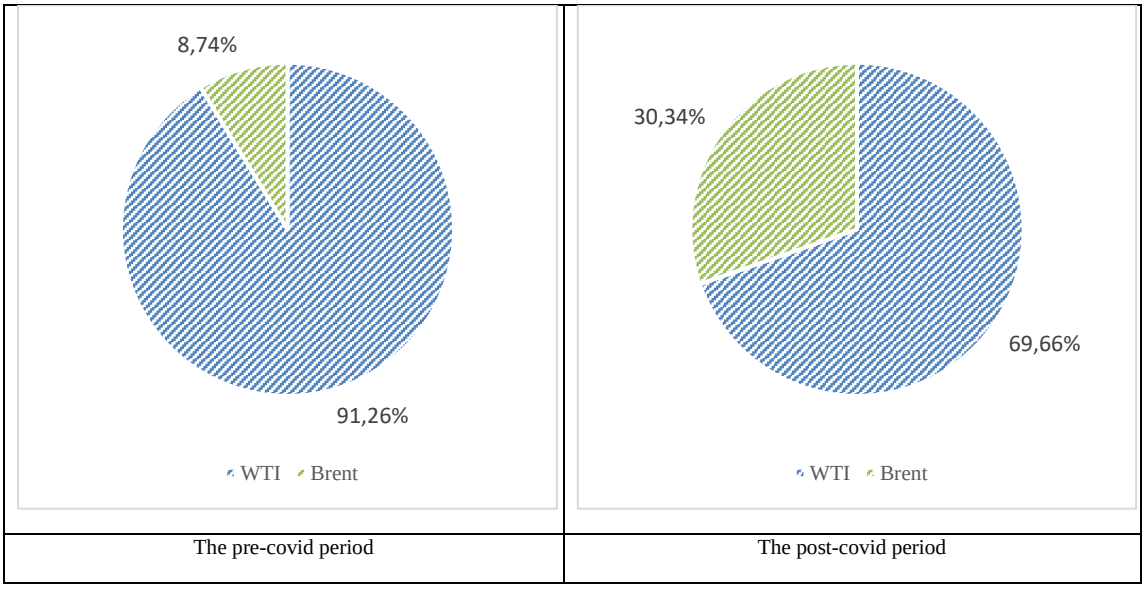

Figure 6. Comparison of CS of three markets before and after the COVID-19

5. Conclusion

In this paper, we provided a comprehensive empirical analysis on the price discovery of three international crude oil futures markets (WTI, Brent, INE) before and after the outbreak of the COVID-19, using various econometrics approaches. We applied both the information share model and the component share model to test the price discovery between these three futures markets. In our study, we took March 6, 2020 as the breakpoint based on the results of the Zivot-Andrews unit root test. Additionally, we proved the existence of cointegration relationships with the structural break in May between these three international oil markets.

Employing complementary econometric approaches, we have an additional insight into the price discovery of international oil prices. For the whole sample, we find that Brent price mainly contributes most information share in these three markets system, which means Brent futures price plays a leading role for WTI and INE futures price. After the breakpoint, the information advantage of Brent and WTI futures markets has decreased following the epidemic while the information share contributed by the INE market has slightly increased. We are persuaded that the increased price discovery capability of the INE market is due to the Chinese government's policy to control the pandemic which gives more confidence to the crude oil futures trading market. Consequently, the Chinese oil demand increased rapidly. However, the absolute value of Brent's and WTI's information share is still larger, occupying an absolute dominant position. Additionally, in the group of Brent and WTI, WTI plays the lead-lag role of Brent in the international oil market in both subperiods.

These conclusions, apart from offering a much better understanding of the price discovery of WTI, Brent, INE crude oil markets, may have important implications for helping the traders to manage risk and react rapidly in the trade of physical and

financial contracts during external shocks. These findings offer practical implications for regulators, policymakers, and portfolio risk managers during the unprecedented uncertainty period provoked by the COVID-19 pandemic. They could also be useful for regulators to take different market supervision measures on traders' behavior in the INE futures market because we could see the efficiency of price discovery and price information transmission still needs to be improved. It will also bring some constructive advice to help INE prices to become a potential benchmark price in Asia.

Of course, there are also some limitations in our empirical analysis. When we study the international crude oil market, we analyze every two markets of three respectively. As Yan and Zivot (2007) show, when the level of noise between two markets is different, the two typical information share measures (IS and CS) result in an overstatement of the price discovery contribution of the market with lower levels of noise. Hence, we could extend the IS and CS measures and take the noise into account, for exampleby using "information leadership metric" (ILS) (Putniņš, 2013). It's a robust measure to identify the price series that is first to impound new information at different noise levels. In addition, price discovery is a dynamic process of incorporating innovation into efficient values. Therefore, paths of information share and component share will be the direction of the later studies. Based on the complicated and variable international situation, we could extend the changes of IS and CS in crude oil markets in a wider range of settings, for instance, in quantile information share (Lien & Wang, 2019) or quantile information share under the Markov regime-switching (Lien, Wang, & Yu, 2020). Another interesting subject for future research would be the price relationship analysis between crude oil futures markets and many other financial markets such as stock, currency, and so on. Taking the global financial system and exogenous shocks into account will help us to know the internal logic of crude oil price formation. Therefore, during the process of price discovery, more factors could be taken into consideration to make the research more comprehensive and objective.

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Appendix

Appendix 1. Zivot-Andrews unit root test on subsamples

Null Hypothesis: Ln(P_X) has a unit root with a structural break in both the intercept and trend

	Ln(P_WTI)	Ln(P_Brent)	Ln(P_INE)
March 26, 2018 - March 5, 2020			
Zivot-Andrews T-Statistics	-3.41	-3.03	-5.97
Break Date	October 10, 2018	October 10, 2018	November 1, 2018

March 5, 2020 - March 31, 2021			
Zivot-Andrews T-Statistics	-4.08	-4.91	-7.47
Break Date	July 23, 2020	September 2, 2018	October 9, 2020

Note: The critical value for Zivot Andrews tests are -5.57, -5.08, -4.82 at 1%, 5%, 1 0% significant level.

Appendix 2. The parameters estimated results of the VECM

VECM before the break date					
	CE1	D (Ln(P_Brent(-1))	D (Ln(P_Brent(-2))	D (Ln(P_INE(-1))	D (Ln(P_INE(-2))
D (Ln(P_Brent))	0.0060 (0.0255)	-0.3090 (0.0479)	-0.1003 (0.0465)	0.0179 (0.0324)	-0.0051 (0.0304)
D (Ln(P_INE))	-0.2951 (0.0364)	0.0863 (0.0682)	0.0756 (0.0663)	0.0863 (0.0683)	0.0756 (0.0663)
	CE1	D (Ln(P_WTI(-1))	D (Ln(P_WTI(-2))	D (Ln(P_INE(-1))	D (Ln(P_INE(-2))
D (Ln(P_WTI))	-0.0111 (0.0252)	-0.3448 (0.0476)	-0.1128 (0.0463)	0.0432 (0.0343)	0.0048 (0.0325)
D (Ln(P_INE))	-0.2580 (0.0340)	0.0686 (0.0640)	0.0582 (0.0621)	-0.0495 (0.0460)	0.0156 (0.0436)
	CE1	D (Ln(P_Brent(-1))	D (Ln(P_Brent(-2))	D (Ln(P_WTI(-1))	D (Ln(P_WTI(-2))
D (Ln(P_Brent))	0.0253 (0.0342)	-0.3953 (0.1444)	-0.2963 (0.1436)	0.0769 (0.1349)	0.1921 (0.1335)
D (Ln(P_WTI))	-0.0037 (0.0367)	-0.1605 (0.1553)	-0.2273 (0.1545)	-0.1933 (0.1451)	0.1031 (0.1436)
VECM after the break date					
	CE1	D (Ln(P_Brent(-1))	D (Ln(P_Brent(-2))	D (Ln(P_INE(-1))	D (LnP_INE(-2))
D (Ln(P_Brent))	0.0230 (0.0373)	-0.2642 (0.0626)	-0.0397 (0.0621)	0.0525 (0.0554)	0.0525 (0.0536)
D (Ln(P_INE))	-0.2100 (0.0417)	0.1607 (0.0700)	0.1140 (0.0695)	0.0419 (0.0619)	0.0064 (0.0599)
	CE1	D (Ln(P_WTI(-1))	D (Ln(P_WTI(-2))	D (Ln(P_INE(-1))	D (Ln(P_INE(-2))
D (Ln(P_WTI))	0.0207 (0.0447)	-0.2957 (0.0617)	-0.1261 (0.0618)	0.0491 (0.0746)	0.0722 (0.0722)
D (Ln(P_INE))	-0.1633 (0.0365)	0.1519 (0.0504)	0.1118 (0.0505)	0.0153 (0.0610)	-0.0044 (0.0590)

	CE1	D (Ln(P_Brent(-1))	D (Ln (P_Brent(-2))	D (Ln (P_WTI(-1))	D (Ln (P_WTI(-2))
D (Ln(P_Brent))	0.0600 (0.0654)	-0.1824 (0.1855)	-0.0985 (0.1907)	-0.0642 (0.1376)	0.0532 (0.1378)
D (Ln(P_WTI))	-0.0079 (0.0886)	-0.6115 (0.2515)	0.1245 (0.2585)	0.1304 (0.1864)	-0.1941 (0.1868)

Note: The standard error is in the parentheses.

Appendix 3. Information share for international crude oil markets (override. Lags=60)

		Upper bound	Lower bound	Midpoint
Whole sample (March 26, 2018 - March 31, 2021)				
(WTI, INE)	WTI	37.93%	25.37%	31.65%
	INE	74.63%	62.07%	68.35%
(Brent, INE)	Brent	71.66%	56.82%	64.24%
	INE	43.18%	28.34%	35.76%
(WTI, Brent)	WTI	48.33%	22.01%	35.17%
	Brent	77.99%	51.67%	64.83%
The pre-covid period (March 26, 2018 - March 5, 2020)				
(WTI, INE)	WTI	63.25%	51.61%	57.43%
	INE	48.39%	36.75%	42.57%
(Brent, INE)	Brent	99.88%	99.27%	99.57%
	INE	0.73%	0.12%	0.43%
(WTI, Brent)	WTI	46.42%	21.44%	33.93%
	Brent	78.56%	53.58%	66.07%
The post-covid period (March 5, 2020 - March 31, 2021)				
(WTI, INE)	WTI	66.99%	62.87%	64.93%
	INE	37.13%	33.01%	35.07%
(Brent, INE)	Brent	84.18%	73.34%	78.76%
	INE	26.66%	15.82%	21.24%
(WTI, Brent)	WTI	90.91%	30.18%	60.55%
	Brent	69.82%	9.09%	39.45%

Appendix 4. Component share for international crude oil markets (override. lags = 60)

	(WTI, INE)		(Brent, INE)		(WTI, Brent)	
	WTI	INE	Brent	INE	WTI	Brent
Whole sample (March 26, 2018 - March 31, 2021)	37.21%	62.79%	62.98%	37.02%	34.57%	65.43%
The pre-covid period (March 26, 2018 - March 5, 2020)	61.63%	38.37%	97.61%	2.39%	42.56%	57.44%
The post-covid period (March 5, 2020 - March 31, 2021)	70.14%	29.86%	76.58%	23.42%	64.60%	35.40%