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What Makes the Oil Pricing Center? The Impact of Futures Markets and Production

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Abstract

This study examines the impact of oil futures markets and production on the connectivity and speed of information transmission in a country's spot oil market within the global network. First, we estimate the causal relationships between 12 spot oil markets using the existence and strength of transfer entropy as edges and weights to construct a series of dynamic networks for the global oil market. Second, we use a temporal network model to analyze changes in the connectivity, closeness, and betweenness of each oil market over different periods, and then compare these variations. Our findings indicate that Brent serves as the central hub of the global oil market, followed by the West Texas Intermediate and Minas markets. Moreover, the presence of oil futures markets significantly enhances the connectivity, information transmission speed, and hub role of spot markets. Oil production also positively impacts connectivity and betweenness; however, it does not have a significant relationship with the speed of information transmission.

JEL classification: F3, G1
Keywords: Oil price; Temporal centrality; Financial network; Pricing center

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1 Introduction

Since the 1980s, the presence of the West Texas Intermediate (WTI) and Brent crude oil futures markets has allowed these benchmarks to dominate global oil pricing.[1] Therefore, researchers have traditionally focused on these two benchmark oil prices (Frino et al., 2018; Scheitrum et al., 2018; Elder et al., 2014; Kaufmann and Ullman, 2009). Although electronic trading and capital flows have promoted price convergence between regions, often referred to as the "law of one price" (Bachmeier and Griffin, 2006; Bentzen, 2007), significant differences remain in the influence and price-setting capabilities of various oil markets. Studies using risk spillover effects to measure intermarket relationships have consistently indicated that Brent and WTI exhibit the strongest spillover effects (Chatziantoniou et al., 2023; Cui and Maghyereh, 2023; Lee et al., 2023). Graph theory and complex network analysis have yielded similar conclusions, reinforcing the centrality of these two benchmarks in the global oil market (Ji and Fan, 2016).

The heterogeneity in the oil markets has become more pronounced in recent times. Since 2004, oil prices have begun to reflect demand-driven information from emerging market economies, signaling a significant shift in traditional market dynamics (Ji and Fan, 2015; Ji and Zhang, 2019). In particular, variations in crude oil characteristics—including density, sulfur content, and origin—have led to the emergence of numerous oil products and markets worldwide. For example, the UAE and China launched new oil markets in 2007 and 2018, respectively, establishing benchmark prices distinct from those of Brent and WTI. This trend highlights the evolving competitive landscape of the global oil market, where the importance of oil in industrial activities has driven nations to seek control over oil pricing. Moroever, extreme events such as the Organization of the Petroleum Exporting Countries (OPEC) "Price War" and the COVID-19 pandemic have significantly distorted the competitive structure and supply–demand balance of the oil market. As a result, despite the increasing integration of the global oil market, disparities remain in the influence and pricing power of different oil markets (Ji

[1] WTI crude oil is a light, low-sulfur crude oil primarily sourced from the U.S. and widely traded on the New York Mercantile Exchange. The Brent market is based in the UK and extracts crude oil from the North Sea region.

and Fan, 2016; Cui and Maghyereh, 2023).

These events have heightened the urgency of exploring the fundamental factors underlying the establishment of influential and more stable oil markets, and energy policymakers and market participants have begun to strategically prioritize gaining pricing advantages and enhancing the influence of national oil markets. Achieving dominance in the increasingly competitive global oil market requires a keen understanding of the key factors that determine oil pricing power.

In this connection, two issues need to be addressed to fill the aforementioned research gap. First, an in-depth investigation of whether traditional benchmarks still dominate the global oil pricing system is missing. Second, few empirical studies have investigated the factors underlying the pricing power and centrality of traditional benchmarks in the global market. To address these two issues, we empirically examine the roles of oil futures markets and production in shaping the connectivity and information transmission capacity of global spot oil markets. Drawing on the theory of commodity pricing power within the framework of international political economy (Strange, 1988), we use transfer entropy to quantify the causal relationships and intermarket linkages between 12 spot oil markets, and construct dynamic, temporal network models thereof. Our analysis employs the measures of network centrality—namely, temporal degrees, closeness, and betweenness—to assess connectivity, information transmission speed, and the role of the hub within the global oil network. We use a panel model to distinguish between the impact of oil production and the financialization of oil markets on the pricing power of spot oil markets.

Our findings provide novel insights: the establishment of oil futures markets significantly enhances connectivity, information transmission speed, and hub roles, collectively reinforcing the centrality of spot markets within the global oil network. In contrast, while oil production positively affects market connectivity, it has less significant effects on information transmission speed than financialization. These findings contribute to the understanding of the mechanisms that drive the influence of the oil market; they provide important implications for policymakers and market participants seeking to strengthen their national oil pricing power and ensure energy security.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature, Section 3 outlines the underlying economic theory, and Section 4 describes the research methodology. Section 5 explains our data set, Section 6 presents the empirical results, and Section 7 concludes.

2 Literature Review

Given the significance of oil for consumers and producers, the study and prediction of oil price behavior is a major subject of research. Based on the vector autoregression framework, researchers have employed the Diebold–Yilmaz spillover Diebold and Yilmaz (2009) and time-varying parameter vector autoregression models to analyze the dominance of various markets from the perspective of risk spillovers. Cui and Maghyereh (2023) used paired risk spillovers from 12 spot oil prices to construct a static oil network for their entire sample and analyzed the influence of each market. They showed that the risk spillover capabilities of various oil markets vary over time, revealing the possibility of a change in the influence and benchmark status of the oil markets over time. Moreover, graph theory-based analyses can address complexities arising from the increasing number of nodes in the global oil market. In an innovative approach, Zhang et al. (2014) used the intensity of direct competition between oil markets as an edge weight to establish an oil trade network. They were the first to introduce the role of competition in oil network analysis, suggesting that the economic characteristics of oil markets, countries, and regions can be incorporated into cross-border influence studies. Their findings indicate that Brent and WTI are the most influential markets.

Moreover, Zhu et al. (2023) used panel data to study the impact of internal and external risk spillovers on energy security in 46 economies and found that cross-border spillover effects only induce risks through price channels. Their study is a particularly valuable attempt to analyze cross-border risk spillovers in energy prices from internal economic factors. Zhu et al. (2021) analyzed the impact of oil trade patterns on the effects of transnational systemic risk spillover in the global oil market, using Gaussian graphical models to estimate systemic risk spillovers between the oil sectors in 27 countries and describe oil trade patterns as a complex network. Results from their panel logit model showed that the intensity of bilateral trade and import competition could enhance oil market risk spillovers. Overall, risk events in North America and Europe trigger stronger spillovers than in Asia and vary over time.

Some studies have analyzed the adjustment speeds of multiple global market prices to illustrate the differences between markets. For example, Kaufmann (2016) used an error correction model (ECM) to analyze the adjustment speeds of 33 spot oil prices when deviating from the long-term equilibrium. The deviation of a market's price from the long-term equilibrium owing to national risk was defined as the cost of choosing that market. Accordingly, oil prices from countries with higher national risks adjusted more slowly, and factors such as sulfur content, density, distance between supply ports, and OPEC membership affected the ability to adjust the price of oil markets. Kaufmann's study presents information on the factors that influence the ability to adjust cross-border prices in the oil markets.

Both the financialization of the oil markets and oil production can explain heterogeneity in the oil markets. Financialization is particularly important in the analysis of oil price fluctuations; it reflects the impact of capital flows on oil asset prices, speculation and hedging, and the derivative price discovery function (Feng et al., 2022). The WTI oil market is more financially integrated compared with the Brent oil market, which is mainly influenced by global changes in supply and demand and less influenced by financialization and speculation (Tudor and Anghel, 2021). Hirshleifer (1988, 1989, 1990) focused on the price discovery function and effects of the information spillover of derivative markets, represented by oil futures.

Futures markets are known to be closely linked to spot markets. Silverio and Szklo (2012) used the Kalman filter technique to obtain temporal metrics of the contribution of the WTI oil futures market to the spot price discovery mechanism. Kaufmann and Ullman (2009) demonstrated that the futures prices of WTI and the Dubai crude oil spot prices are Granger-causative factors for a series of oil prices, and contribute to the rigorous definition of oil price influence. Compared with risk spillovers, the existence and strength of causal relationships better explain the influence of oil markets. However, Granger causality tests are not effective in describing the specific strength of causal relationships between time series. Transfer entropy can integrate the advantages of describing influence magnitude, as in net risk spillovers, and explaining causal relationships, as in Granger causality tests. This method has been widely used to study information transmission between financial markets. Zhou et al. (2024) used multiscale entropy methods to analyze interactions between innovative and traditional financial assets on short-, medium-, and long-term scales. Niu and Hu (2021) used transfer entropy networks to measure the transmission of information and the relationships between the Chinese stock market and the commodity futures market on different time scales. They found that the direction and magnitude of information spillovers vary with asset types and time scales. These studies emphasize the superiority of entropy methods in explaining information transmission.

In addition to financialization, the advantages of production are equally important in explaining market heterogeneity. Razek and Michieka (2019) used the vector autoregression model to study the impact of production by OPEC and non-OPEC countries, global and Chinese demand, and oil financial assets on oil prices. They reiterated the importance of production levels in the U.S. and OPEC. De Graaff (2012) found that the expansion and production cooperation of state-owned oil companies from countries such as Russia promoted the multipolarity of the global oil order. Wu et al. (2022) also emphasized the role of production advantages in the multilayered network risk transmission mechanisms of international energy enterprises.

In this study, we employ a dynamic network approach based on transfer entropy, which extends the traditional pairwise causal analysis of transfer entropy to a high-dimensional, multi-node setting. This methodological advancement allows for a more rigorous and nuanced definition of the "pricing center" compared with existing studies. The varying roles of market nodes can also be distinguished using network metrics such as temporal degree, temporal closeness, and temporal betweenness in order to capture the diverse behaviors observed in market dynamics. Importantly, our dynamic network analysis is grounded in graph theory. Unlike the quantile-based risk spillover network in Zhou et al. (2022), our method uncovers the underlying market structure rather than merely assessing the influence of individual markets. Ji and Fan (2016) also employed graph theory, using a minimum spanning tree to analyze connectivity and global market structure. Our study goes beyond simple connectivity by incorporating a broader range of network indicators and examining their respective driving factors. Overall, we comprehensively investigate how financial futures markets and production-related factors influence the role of oil markets within the global oil network.

3 Economic Theory

The price information can flow invisibly and rapidly through electronic systems in different markets worldwide. A country with an efficient oil pricing center can access detailed information about oil price changes in real time, gaining an information advantage over other countries or markets in controlling oil price performance. From the perspective of financial economics, Fama (1970), in the "Efficient Market Hypothesis," proposed that efficient markets quickly reflect all available information, thereby reducing asset pricing errors and optimizing capital allocation. In this regard, all investors hope to trade in a fully efficient market to achieve their investment goals. We use the physical and statistical concept of transfer entropy to measure the directed flow of information between these different oil market nodes (Schreiber, 2000). Specifically, the advantage of statistical information prediction between two price series can be seen as the strength of the transfer entropy. When one market consistently exhibits transfer entropy with respect to another, we can view it as information flowing from that market, and that such a market influences other markets.

We accordingly extend the scenario from two markets to multiple markets, where dynamic networks perfectly meet our needs. In the physical properties of dynamic networks, “temporal degree” represents the average number of information flows from one market to all other nodes in the network, reflecting the connectivity of markets (Kaufmann et al., 2004). The strength of the information flow represented by transfer entropy is used to measure the distance between the nodes in the network. Then, the inverse of the average distance from each market node to the other nodes becomes the “temporal closeness.” From a physical perspective, the market node with the highest temporal closeness is the global oil pricing center, which can exchange and transmit information the fastest. We view this as the most efficient market described by Fama (1970). Another advantage of the network model is that it captures the intermediary role of markets through “temporal betweenness,” which reflects how often a market lies on the shortest information paths between others. Markets with high betweenness act as key bridges in the global oil network, facilitating information flow between otherwise disconnected regions.

We also examine the factors that cause differences in the information transmission and pricing ability of different markets, with financial markets represented by derivatives and production being the most concerning. On the one hand, Strange (1988) summarized the factors that influence a country’s global commodity pricing power from the perspective of political economy: financialization, production, security, and knowledge. Strange (1988) argued that financialization enhances the market’s price discovery function and stability by providing liquidity, risk management tools, and capital flows. Her point of view is highly macroeconomic, while we focus on the oil futures market, which is an aspect of financialization as described by Strange (1988). On the other hand, production structures directly influence prices by controlling supply, production costs, and commodity quality. The combination of these two factors determines a country’s or entity’s pricing power in the global market and shapes the dynamics and influence of commodity prices.

Inspired by Scheitrum et al. (2018), we integrate the widely recognized view in financial economics that futures markets contribute to the discovery of spot prices; we focus on the establishment of the financial futures market, a key aspect of financialization. Garbade and Silber (1983) provided a quantitative method to evaluate the contribution of the information flow from the futures market to the spot price discovery process. Schwarz and Szakmary (1994) combined the statistical methods of Garbade and Silber (1983) and Engle and Granger (1987) to incorporate the influence of the futures market on the spot market in cointegration tests.

These studies used cointegration and the error correction model to examine the relationship between crude oil spot prices and futures prices, and defined the temporal contribution of futures prices to the spot price discovery process.

Following the literature, the contribution of the futures market to the spot market's price discovery process can be measured by representing the relationship between the two variables as a cointegration model with error correction. Assume that S_t and F_t are the logarithms of the spot and futures prices of the commodity at time t, respectively, and β_t synthesizes the elements proposed by the theories discussed earlier. The cointegration relation is expressed as

$$S_t = F_t + \beta_t \tag{1}$$

The error correction model can be written as

$$\Delta F_t = \alpha_F \left(S_{t-1} - F_{t-1} - \beta_{t-1}\right) + c_{F1}\Delta S_{t-1} + c_{F2}\Delta F_{t-1} + \epsilon_{F_t} \tag{2}$$

$$\Delta S_t = \alpha_S \left(S_{t-1} - F_{t-1} - \beta_{t-1}\right) + c_{S1}\Delta S_{t-1} + c_{S2}\Delta F_{t-1} + \epsilon_{S_t} \tag{3}$$

In these equations, S_t and F_t are the logarithms of the WTI spot and first-month futures prices, respectively. α_S and α_F are the adjustment coefficients in the error-correction equations for the spot and futures markets, respectively. c_{F1}, c_{F2}, c_{S1}, and c_{S2} are the coefficients of deterministic terms. ϵ_{F_t} and ϵ_{S_t} are uncorrelated white noise residuals. Caporale et al. (2014) explained the contribution of the futures price to spot market price discovery as δ, which can be calculated as:

$$\delta = \frac{\alpha_S}{\alpha_S + \alpha_F} \tag{4}$$

However, as δ is a point estimate derived from the error correction model, it does not capture the time-varying nature of the market's contribution to the price discovery process. To address this, Foster (1996) and Caporale et al. (2014) proposed using a state–space model combined with the Kalman filter technique to analyze fluctuations in the adjustment coefficients, thereby obtaining a time-varying measure of price discovery (δ_t). The state–space model's transition equations, which describe the evolution of the system's state over time, are as follows:

$$A_{1t} = A_{1t-1} + \eta_{1t} \tag{5}$$

$$A_{2t} = A_{2t-1} + \eta_{2t} \tag{6}$$

By applying the Kalman filter, which is a recursive algorithm, we can dynamically estimate the state variables A_{1t} and A_{2t} over time. The time-varying price discovery metric δ_t can then be calculated through the following steps:

1. Initialization: Set the initial values for the state variables $A1_0$ and $A2_0$ and their covariance matrix.

2. Prediction: Predict the next state variables using the state equation.

$$\begin{pmatrix} A1_{t|t-1} \\ A2_{t|t-1} \end{pmatrix} = \begin{pmatrix} A1_{t-1} \\ A2_{t-1} \end{pmatrix} + \begin{pmatrix} \eta 1_t \\ \eta 2_t \end{pmatrix} \tag{7}$$

3. Update: Update the state variables and covariance matrix using the observation data.

$$\begin{pmatrix} A1_t \\ A2_t \end{pmatrix} = \begin{pmatrix} A1_{t|t-1} \\ A2_{t|t-1} \end{pmatrix} + K_t \begin{pmatrix} \Delta F_t - \Delta F_{t|t-1} \\ \Delta S_t - \Delta S_{t|t-1} \end{pmatrix} \tag{8}$$

where K_t is the Kalman gain, balancing the error between prediction and observation.

4. Compute δ_t: Calculate δ_t using the updated state variables $A1_t$ and $A2_t$:

$$\delta_t = \frac{A2_t}{A2_t + A1_t} \tag{9}$$

By following these steps, the Kalman filter algorithm dynamically assesses the contribution of the futures market to the spot price discovery δ_t at each time point, capturing its time-varying nature.

A higher value of δ indicates that the futures market plays a greater role in price discovery, with futures prices leading spot prices. A lower value of δ suggests that the spot market dominates price discovery. By tracking the time-varying nature of δ, we can dynamically assess the contributions of the futures market. We regard this price discovery function as the flow of information from the futures market to the spot market. Therefore, spot markets with an associated futures market can access more information, allowing faster adjustments. In contrast, spot markets without futures markets are unable to obtain high-frequency supply and demand information, making it difficult to fully reflect the effective information of the global oil market; thus, they are less frequently referenced by investors. The market efficiency driven by this price discovery function is reflected in the dynamic network as a faster information exchange, that is, higher temporal closeness. This also enhances the information connectivity and hub function of the spot market. Therefore, we derive the following hypotheses:

Hypothesis 1: The oil futures market could enhance the information connectivity and transmission speed of spot market prices.

Production is the second factor examined in this study. Within the supply–demand framework, the share of production is the most important factor on the supply side. For example, OPEC holds a major share of global oil production, significantly monopolizing oil production and controlling oil prices. Kilian (2009) used a structural vector autoregression model to define the impact of supply, represented by production, on oil prices and confirmed the influence of production on the oil market. In practice, changes in production are the main regulatory tools that OPEC countries use to influence oil prices. Moreover, production predicts oil prices and alters market behavior. Monge et al. (2017) studied price behaviors in the WTI oil market before and after the U.S. shale oil revolution, confirming that the increase in production owing to this revolution led to a decrease in WTI oil prices in different frequency domains. When the production volume of a country or region increases, its share in the global oil market also increases. This means that the market engages in more transactions with other markets through the export of more oil, thereby enhancing the connections and interactions between markets. While increased production may improve the physical connectivity of the market, the speed of information flow is also influenced by market mechanisms, trading frequency, and information transparency.

Hypothesis 2: An increase in oil production can enhance the information spillover capacity of the oil market.

Thus, we identify two factors, the presence of the futures market and crude oil production, influencing information flows in international markets.

4 Methodology

4.1 Transfer Entropy

Transfer entropy is a nonparametric measure introduced by Schreiber (2000) to quantify the direction and amount of information transfer between two time series. It thus captures causal influence and nonlinear dependencies. For two time series X and Y, the transfer entropy from X to Y ($T_{X\rightarrow Y}$) is defined as:

$$T_{X\rightarrow Y} = \sum_{y_{t+1}, y_t, x_t} p(y_{t+1}, y_t, x_t) \log \frac{p(y_{t+1} \mid y_t, x_t)}{p(y_{t+1} \mid y_t)}$$

where y_t is the state of Y at time t. x_t is the state of X at time t; $p(y_{t+1}, y_t, x_t)$ is the joint probability distribution of Y at $t+1$, Y at t, and X at t. $p(y_{t+1} \mid y_t, x_t)$ is the conditional probability of y_{t+1} given y_t and x_t; $p(y_{t+1} \mid y_t)$ is the conditional probability of y_{t+1} given y_t.

Transfer entropy measures how much knowing the past states of X reduces the uncertainty in predicting the future states of Y, beyond what is already known from the past states of Y. In other words, it reveals the role of X as an information source for Y. If $T_{X \to Y} > 0$, it indicates that X provides additional information about Y, showing a directional influence from X to Y. If $T_{X \to Y} = 0$, it indicates that X does not provide any extra information for Y.

We use the strength of the transfer entropy as a key indicator to assess pricing power. The greater the transfer entropy, the stronger the influence of X as an information source for Y, indicating a higher level of inter-market influence.

4.2 Temporal Complex Network

We employ the complex network temporal centrality indicators developed by Kim and Anderson (2012) to examine the structure of the global crude oil market and changes in key nodes. Each crude oil market is considered as a node in the complex network, with the most representative crude oil product price serving as the data flow. Initially, we define the dynamic network with time parameters as $G^D_{(0,T)} = (V, E_{(0,T)})$ on a time interval $[0, T]$, consisting of a set of vertices (V) and a set of temporal edges $E_{(0,T)}$, where a temporal edge $(u, v)_{(i,j)} \in E_{(0,T)}$ exists between vertices u and (V) on a time interval $[i, j]$ such that $i \leq T$ and $j \geq 0$. In the dynamic network, (V) remains constant, while the set of existing edges may change over time.

When the time information is divided into sequences with a duration of $w = T/n$, we obtain a dynamic network consisting of a series of static graphs. Specifically, the notation G_t ($1 \leq t \leq n$) represents the aggregate graph, which includes a set of vertices V and a set of edges E_t, where an edge $(u, v) \in E_t$ exists only if a temporal edge $(u, v)_{(i,j)} \in E_{(0,T)}$ exists between vertices u and v on a time interval [i, j] such that $i \leq wt$ and $j > w(t-1)$. In other words, G_t is the t^{th} temporal snapshot of the dynamic network $G^D_{(0,T)}$ during the t^{th} time window. In each short snapshot, the directed graph $G = (V, E)$ is set with vertices (v_t) for each $t \in \{0, 1, ..., \infty, n\}$, having edges from $u_{(t-1)}$ to v_t and vice versa for an edge $(u, v) \in E[t]$; and it has edges from $u_{(t-1)}$ to v_t for all $v \in V$ and for all $t \in \{1, ..., n\}$.

Temporal Degree

In a network constructed on the basis of transfer entropy, the degree represents how often a node acts as an information source for other nodes, corresponding to the number of edges directly connected to that node in the graph. In a dynamic network, a higher degree indicates more connections, reflecting the activity and influence of the node within the system.

Since network structures evolve over time, the degree of each node also changes dynamically. The indicator $D_{(i,j)}(v)$ captures the connectivity of a node in a specific time interval, thereby providing information on the temporal evolution of the network.

The formula for temporal degree is defined as follows:

$$D_{(i,j)}(v) = \frac{\sum_{t=i}^{j} 2D_t(v)}{2(|V|-1)m} \tag{10}$$

where $D_{(i,j)}(v)$ denotes the temporal degree of node v within the time interval [i, j]. $D_t(v)$ represents the degree of node v at time point t, indicating the number of edges directly connected to node v at time t. $m = j - i$ is the length of the time interval. $|V|$ denotes the size of the node set.

Temporal degree directly reflects the concept of "connectivity" because a higher temporal degree indicates that a market engages in more frequent and active information exchange with other markets. This suggests that the market is more structurally integrated into the global oil market network and plays a more significant role in the dissemination of price signals. Therefore, temporal degree serves as a key metric to evaluate how a market is connected to and influential over others within the structure of global oil price transmission.

Temporal Closeness

Temporal closeness measures a node's efficiency in disseminating information within a network. Nodes with higher closeness can reach other nodes more quickly, thereby exerting greater influence. Unlike temporal degree, temporal closeness considers not only direct connections but also the inverse of the shortest paths to all other nodes. Nodes with high temporal closeness—often referred to as "centers"—play a critical role in controlling and distributing information throughout the network.

The formula for temporal closeness centrality is defined as

$$C_{(i,j)}(v)' = \sum_{i \le t < j} \sum_{u \in V \setminus v} \frac{1}{\Delta_{(t,j)}(v,u)} \tag{11}$$

where $\Delta_{(t,j)}(v,u)$ represents the temporal shortest-path distance from node v to node u over the time interval [t, j]. If no temporal path exists from node v to node u during the time interval [t, j], $\Delta_{(t,j)}(v,u)$ is defined as ∞. Importantly, $\Delta_{(t,j)}(v,u)$ differs from $\Delta_{(t,j)}(v,u)$, as the time-ordered graph G is a directed graph.

To facilitate the comparison of closeness values across different nodes, we can normalize the values within a standard range by dividing $C_{(i,j)}(v)$ by $(|V|-1)m$. This yields the standardized temporal closeness:

$$C_{(i,j)}(v) = \frac{1}{(|V|-1)m} \sum_{i \le t < j} \sum_{u \in V \setminus v} \frac{1}{\sigma_{(t,j)}(v,u)} \tag{12}$$

where $\sigma_{(t,j)}(v,u)$ represents the temporal shortest-path distance from node v to node u, $|V|$ denotes the size of the node set, and $m = j - i$ is the length of the time interval.

This indicator corresponds to the concept of "information transmission speed" because a higher temporal closeness indicates that a market can reach and influence other markets more quickly through shorter information paths. Such markets can respond more rapidly to global oil price signals and can reflect and transmit price changes in a timely manner. Therefore, temporal closeness serves as a proxy for measuring the speed and efficiency of information transmission within the global oil network.

Temporal Betweenness

Temporal betweenness measures the extent to which a node acts as an intermediary in the network over different time periods—that is, the role it plays as a bridge in the information transmission paths connecting other nodes. It is often used to assess the structural importance of a node within the entire network (Ji and Fan, 2016). The formula is as follows:

$$B_{(i,j)}(v) = \sum_{i \le t < j} \sum_{\substack{s \neq v \neq d \\ s,d \in V}} \frac{\sigma_{(t,j)}(s,d,v)}{\sigma_{(t,j)}(s,d)} \tag{13}$$

where $B_{(i,j)}(v)$ represents the temporal betweenness of node v within the time interval $[i,j]$. Here, $\sigma_{(t,j)}(s,d,v) = |S_{(t,j)}(s,d,v)|$ denotes the number of temporal shortest paths from node s to node d passing through node v during the time interval $[t,j]$. $\sigma_{(t,j)}(s,d)$ represents the number of temporal shortest paths from node s to node d during the time interval $[t,j]$.

Temporal betweenness reflects the concept of a "hub role" because markets with high temporal betweenness frequently lie on the shortest informational paths between other markets, effectively serving as intermediaries or bridges. Such markets play a critical role in connecting otherwise disconnected regions and facilitating the transmission of global oil price signals. Their position within the network grants them structural importance, enabling them to influence the flow and distribution of information across the entire system.

5 Oil Prices

We select 12 crude oil spot prices, covering Brent, WTI, and Russian crude oil, representing Europe and North America, as well as prices from the main oil-producing countries of the Middle East and East Asia. The sample period spans from January 29, 2010, to February 26, 2024, with a total of 734 weekly settlement prices included after removing one outlier. To analyze medium- and long-term changes in the global oil market, the chosen sample period encompasses several critical periods that have had a profound impact on oil prices. For instance, the "Price War" within OPEC in 2014 led to a surge in production and a sharp decline in oil prices. Although the OPEC strategy did not fully achieve its intended objectives, it contributed to the reallocation of global market shares and structural adjustments (Quint and Venditti, 2023; Ma et al., 2021). Another significant event was the COVID-19 pandemic, which led to a sharp contraction in global economic activity and a significant drop in oil demand in 2020, further driving profound changes in the supply–demand dynamics of the oil market. Finally, the Russia–Ukraine war disrupted the security of oil transport between Eastern and Western Europe, with the geopolitical risks arising from the war causing significant pressure on the Brent market, while the WTI market experienced relatively smaller fluctuations. This phenomenon indicates that regional geopolitical risks have, to some extent, distorted the competitive landscape of the global oil market (Almutairi et al., 2025).

We also include the Eastern Siberia–Pacific Ocean (ESPO) crude oil price data, a relatively under-analyzed Russian crude oil primarily exported to China and India. After the Russia–Ukraine war, the exports of Ural blend oil to Europe were significantly reduced; however, Russia increased its oil trade with China, leading to a rise in ESPO crude oil trade volumes. Analyzing the role of ESPO crude oil in the global network is not only novel, but it also provides important policy insights. Figure 1 illustrates the trends of the 12 crude oil spot prices, with extreme price declines observed in the global oil market from 2014 to 2016 and early 2020. Table 1 provides the background information sourced from DataStream.

We process all price series into logarithmic return series (Equation 14) to meet the assumptions and requirements of the statistical analysis. Figure 2 and Table 2 present the trends of the logarithmic return series and the descriptive statistical results, respectively. The kurtosis results are adjusted by subtracting the standard normal distribution kurtosis value of 3, and all are negative. This indicates a higher probability of extreme decreases in oil prices, with more extreme values on the negative side of returns. All return series significantly deviate from the extreme characteristics of the standard normal distribution, which is consistent with the findings of other studies on oil prices and returns (Fan et al., 2008; Zhang et al., 2019). All return samples pass the augmented Dickey—Fuller test at the 1% level, indicating that they can be considered stationary series.

$$R_t = \ln(P_t) - \ln(P_{t-1}) \tag{14}$$

The representation for the return of the oil price at day t is the oil price at day t, and P_{t-1} is the oil price at day $t-1$.

6 Empirical Results

6.1 Full Samples

We will now explore the centrality of a temporal network based on the returns of 12 spot prices for crude oil. First, we apply a 52-week (one-year) window to calculate the pairwise transfer entropy between the returns of 12 prices, with the selection of window size following the study on rolling transfer entropy networks by Choi and Kim (2024).[2] Since the transfer entropy is directional, each window generated 132 sets of transfer entropy results. We evaluate the robustness of the transfer entropy using the bootstrap method (300 times) and retain significant transfer entropy values at the 5% level as directed edges between two markets (Behrendt et al., 2019), with the transfer entropy value serving as the edge weight. This step completes the construction of the static network for the first window period.

Second, we shift the window forward by one week and recalculate the transfer entropy to construct a new network. Using this rolling-window method, we generate 682 networks over the sample period, which consist of 733 return data points. The network structure for each window period is represented by an adjacency matrix, which captures the connections between nodes within a specific time interval. Figure 3 illustrates the specific structures of the 1st, 10th, 100th, and 682nd network slices.

Based on the dynamic network composed of 682 time slices, we calculate the temporal degree, temporal closeness, and betweenness of each node, representing the number of connections, speed of information transmission, and mediating properties within each time window, respectively. To highlight the relative strengths of the network metrics for each node, we apply the min–max normalization to these indices, as shown in Equation (15):

[2]Choi and Kim (2024) employed 20, 60, and 120 days as window lengths to compute transfer entropy, constructing a series of dynamic network slices and verifying the existence of dynamic causal relationships between stock prices and trading volumes. Similarly, we select 52, 56, and 60 weeks as window lengths to demonstrate the robustness of the centrality measures of Brent and WTI under different parameter settings.

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{15}$$

where X represents the original data value, X' the normalized data value, $X_{\min}$ the minimum value in the dataset, and $X_{\max}$ the maximum value in the data set. Normalization converts the data to a common scale, eliminating the dimensional differences between variables, facilitating the comparison of the relative advantages of different market pricing powers at different times. Unlike discrete rankings, min–max normalized data remain continuous while preserving the underlying data distribution, thereby enhancing the precision of the subsequent panel analysis.

Table 3 presents the normalized temporal degree, closeness, and betweenness results for each oil market across the entire sample under different window lengths. First, the connectivity of the Brent, Mexico, and WTI markets consistently ranks among the top four across all three window lengths. That is, these markets exhibit strong connectivity and innovation capabilities, enabling them to effectively exchange information with other markets. Second, as the window length extends from 52 weeks (one year) to 56 weeks (one year and one month), and then to 60 weeks (one year and two months), the Brent market maintains a leading position in closeness, followed by WTI, Minas, and Mexico. This suggests that these markets have the shortest average path length and the highest efficiency of information transmission within the network. In particular, the Mexico market, located in the same production region as WTI, demonstrates faster information transmission between the two markets. Hence, Brent and WTI are the most efficient markets in spreading price innovation information. Third, Brent consistently ranks first in terms of betweenness across all window lengths. Nodes with high betweenness typically act as intermediaries between different clusters, facilitating information flows that exhibit clear directionality and diversity. As a critical intermediary node, the Brent market plays a vital role in integrating and enhancing multidirectional information interactions. These findings underscore the hub-and-spoke roles of Brent and WTI in the global oil market network.

In addition to these prominent nodes, the temporal degree and closeness of the Russian and Minas crude oil spot markets also rank highly. Russia's ESPO oil has become a key export product for the country, primarily transported to China. As a benchmark price in the Far East, Minas crude oil is low in sulfur, easy to process, and predominantly exported to Asian countries such as China and India. Finally, we observe that the information transmission capabilities of individual OPEC member countries are relatively low. Despite leading in total production, OPEC member countries have not yet established an international oil futures market. The total trading volumes of the Oman and Dubai oil futures markets are not comparable to those of Brent and WTI. In practice, OPEC and oil-producing countries such as Russia mainly rely on adjusting production levels to influence oil prices and maximize their national interests. The adjustment capabilities of individual countries are further constrained by geopolitical uncertainties in the Middle East and the operational constraints of OPEC organizations.

6.2 Rolling Samples

Using a rolling-window approach, we present the temporal centrality of various crude oil spot markets across different periods. Similarly to the full-sample analysis, we first calculate the results for each oil market in January 2012, covering the period from February 5, 2010, to January 27, 2012, for a total of 104 weeks (two years).[3] During this sample period, we use a 52-week (one-year) window to calculate transfer entropy and establish 53 networks.

Then, we move the sample window according to the number of weeks in each month, resulting in 146 months of data collected from January 2012 to February 2024. Figures 4, 5, and 6 show the normalized temporal degree, closeness, and betweenness of each crude oil spot market over different periods, respectively. We also calculate the average values of each indicator over the entire sample period and find that the Brent market ranks first across all three metrics, followed closely by the WTI market, whereas some OPEC countries' crude oil spot markets

[3] Ji and Fan (2016) employed the graph theory approach of minimum spanning trees to analyze the evolution of the global oil market network; they used a rolling window of 100 weeks with a step size of 1. Following their methodology, we select a rolling window of 104 weeks (2 years) with a step size of 1 to construct a series of networks.

lag behind those of Brent and WTI. This is generally consistent with the findings for the full sample period.

The performance of each market varies across different periods. For example, between 2016 and 2018, the temporal degree, closeness, and betweenness of the Brent market declined, while the WTI, Minas, and Russian oil markets gained prominence. Specifically, the global oil market experienced a shift from oversupply to a supply–demand balance during this period. The OPEC+ production cut agreements, the resurgence of U.S. shale oil, and geopolitical uncertainties collectively contributed to the recovery of oil prices. However, the formation of OPEC+ did not stabilize the global oil market after 2017, as researchers observed changes in OPEC's behavior (Behar and Ritz, 2017). By early 2024, the centrality of different oil markets had undergone significant changes once again. The Brent market, particularly in Europe, faced geopolitical threats from the Russia–Ukraine conflict, while capital outflows from Europe further increased economic uncertainty. Consequently, the information sources and transmission mechanisms of the global oil market have experienced a structural shift (Zhang et al., 2024). During this phase, Malaysia's low-sulfur Tapis crude oil market briefly emerged as an important source of oil market information.

6.3 Impact of Futures Markets and Oil Production

Although we have assessed the spillover effects of information and pricing power in different markets, empirical discussions remain limited with respect to the economic factors that drive heterogeneity in the connectivity and information transmission capacity of crude oil spot markets. Therefore, before further analysis, we examine the relationship between the presence of futures markets and the concept of financialization.

Initially, we examine the impact of financialization from the perspective of financial derivatives. Our theoretical rationale is that futures markets perform a price discovery function for their corresponding spot markets and, therefore, have the potential to facilitate spot price adjustments. Specifically, if a crude oil spot market is associated with a corresponding futures market, we assign the value of 1; otherwise, it is set to 0. The resulting futures variable is also closely linked to a country's overall level of financial development.

To verify whether the presence of futures markets can serve as an appropriate proxy for financialization, we collected the Financial Development Index (FD) and the Financial Institutions Index (FI) for 12 countries from the IMF covering the period 1980–2021, and calculated their correlations with the futures market variable for each country. The FD index reflects countries' relative rankings in terms of the development, access, and efficiency of their financial institutions and financial markets. The FI index aggregates indicators from sectors such as banking, fund assets, and insurance and is widely used to measure the degree of financialization between countries. The 41-year sample period covers several major shocks to the oil market, including the 2008 financial crisis, the shale oil revolution, the 2014 OPEC "Price War," and the COVID-19 pandemic. Figure 7 presents the Spearman correlation matrix between the futures market variable and the FD and FI indices for the 12 countries. Due to the lack of high-frequency data, the correlations are calculated using annual data, and the background information and descriptive statistics of the two datasets are presented in Table 3 and Table 4, respectively. The results show a significant positive correlation over the 41-year period. The figure shows that it is appropriate to analyze the impact of financialization from the perspective of the corresponding futures markets for spot markets.

Meanwhile, supply-side advantages—such as the ability to influence global crude oil supply through production adjustments—may also have a significant impact on oil prices. Regarding the process of shaping global crude oil pricing hubs, no study has presented a comparative analysis of the relative importance of futures markets and production capacity. To address this gap, we examine the effects of the existence of crude oil futures markets and crude oil production levels on the temporal degree, temporal closeness, and temporal betweenness of crude oil spot markets. This approach draws on the framework of Kaufmann (2016), which investigates how country risk influences the speed of oil price adjustment.

Given that global oil production markets are highly susceptible to geopolitical shocks (Saint Akadiri and Ozkan, 2025; Chiaramonte et al., 2025), we incorporate a geopolitical risk (GPR) index developed by Caldara and Iacoviello (2022), which is constructed based on news-based indicators, as a control variable. This allows us to test the robustness of our findings in the presence of geopolitical disturbances. Note that the GPR index from Caldara and Iacoviello (2022) does not include Kuwait, Oman, Qatar, and the UAE. Therefore, we set the GPR values for these four countries to 0 while applying a first-order difference to the GPR index for all other countries.

For additional control variables, we follow Zhu et al. (2021), who used the change rates of the Consumer Price Index (ΔCPI) and foreign exchange rates (ΔFX) in their study on the impacts of the trade pattern on risk spillover in oil markets. We also include official total reserves in the U.S. dollar (Δln_Liq), published by the IMF, as a control variable. Owing to the "oil–dollar" link, the dollar reserves used for oil purchases constitute a significant item in the balance of payments of countries (Ivan et al., 2022). As such, dollar-based liquidity assets are relevant to our analysis.

Table 4 provides the background information on the panel and correlation data, and Table 5 presents the descriptive statistics for the panel correlation variables. Our regression models are as follows:

$$\text{Degree}_{it} = \alpha_{it} + \beta_1 \text{Future}_{it} + \beta_2(\text{Volume}_{it}) + \gamma \mathbf{X}_{it} + \delta_t + \epsilon_{it} \tag{15}$$

$$\text{Closeness}_{it} = \alpha_{it} + \beta_1 \text{Future}_{it} + \beta_2(\text{Volume}_{it}) + \gamma \mathbf{X}_{it} + \delta_t + \epsilon_{it} \tag{16}$$

$$\text{Betweenness}_{it} = \alpha_{it} + \beta_1 \text{Future}_{it} + \beta_2(\text{Volume}_{it}) + \gamma \mathbf{X}_{it} + \delta_t + \epsilon_{it} \tag{17}$$

where Degree_{it} is the normalized temporal degree of oil market i at time t. Closeness_{it} is the normalized temporal closeness of oil market i at time t. Betweenness_{it} is the normalized temporal betweenness of oil market i at time t. Volume_{it} is the volume of crude oil production in country i at time t. Future_{it} is a dummy variable that equals one if the spot oil market has a corresponding futures market and zero otherwise (Kaufmann, 2016). $\mathbf{X}_{it}$ is a vector of the control variables for country i at time t, ϵ_{it} signifies the stochastic disturbance term.

α_{it}, β_1, β_2, β_3, and γ are coefficients. δ_t is a time dummy.

For the dataset, we have N countries, with data ranging from January 2012 to February 2024, providing a comprehensive overview of the impact of these variables on the oil network.

In the regressions of the indicators, we apply fixed-month effects and clustered standard errors by month. This approach allows for more precise control and adjustment for month-specific effects and correlations in the data, eliminating confounding factors such as seasonal production variations and providing more reliable and accurate results.

Table 6 reports the regression results for the normalized temporal degree using a rolling window of 52 months. We consider fixed-month effects and clustered standard errors by month. In Model 1, the estimated coefficient for the presence of an oil futures market is 0.07, while the coefficient for oil production volume is 0.03. These results indicate that both the development of oil financial markets and increased oil production significantly contribute to the enhancement of the normalized temporal degree of crude oil spot markets within the global oil network. In other words, establishing highly liquid oil futures markets and maintaining substantial production volumes improve the information connectivity across spot markets.

To assess the robustness of this positive relationship and mitigate concerns regarding potential reverse causality, we lag key explanatory variables by one month and re-estimate the model. In Model 6, the lagged futures market variable continues to exhibit a coefficient of 0.07, and the coefficient for lagged production volume remains at 0.03—both nearly identical to the original estimates. Even after incorporating additional controls such as the rate of change in global liquidity and the GPR index, the positive relationship persists across all model specifications. This suggests that the observed effect is not merely driven by contemporaneous shocks, including geopolitical uncertainty, reinforcing the empirical validity of our initial hypothesis.

From a theoretical point of view, cross-border investors can transmit price signals from one market to another through capital flows. The price discovery function of oil futures markets allows spot markets to incorporate domestic demand conditions more rapidly in oil trade. In addition, futures markets act as new nodes in the global oil network, enriching the diversity and structure of the system and linking domestic spot markets to international markets. Consequently, financialization activities—particularly the introduction of oil derivatives—serve to improve the overall connectivity of crude oil spot markets. Our findings provide empirical support for the hypothesis that oil financialization enhances network integration.

We further confirm the positive impact of oil production on the temporal degree of spot markets. Under the supply–demand framework, crude oil, being a physical commodity with limited substitutes, is more susceptible to price control by producers. OPEC, as a representative cartel, illustrates the monopolistic role of suppliers in shaping global oil prices. For net oil exporters, expanding production strengthens their position in global supply and enables profit maximization through output adjustments. For net oil importers, increasing domestic production mitigates dependence on foreign oil and enhances national energy security. A prominent example is the U.S., where the shale oil revolution led to a sustained increase in domestic production, transforming the U.S. into a net oil exporter. This production growth expanded the reach of U.S. crude in global oil trade and elevated the global relevance of WTI crude oil prices. Hence, higher oil production implies greater market share and connectivity, allowing countries to establish more extensive links with other spot markets through trade volume control.

Table 7 presents the regression results for normalized temporal closeness, controlling for fixed-month effects and clustering standard errors at the monthly level. In Model 1, the coefficient for the existence of an oil futures market is 0.07. The lagged specification in Model 6 produces a nearly identical coefficient, reinforcing the robustness of the result. These findings suggest that the presence of oil futures markets significantly increases temporal closeness, indicating faster and more efficient information transmission within the global crude oil spot market network.

In practice, certain spot markets report only one or a limited number of shipment prices per trading day. By contrast, futures markets rely on electronic trading platforms that generate continuous streams of price and volume data throughout the trading day, offering a more consistent and granular reflection of the country's oil market conditions. Through the use of highly liquid capital and high-frequency trading, such information is swiftly transmitted across markets and incorporated into domestic spot prices, thereby facilitating near-instantaneous market adjustments. In this context, the speed of adjustment in oil markets can be interpreted as a proxy for market efficiency. Markets that fail to respond promptly to publicly available information create arbitrage opportunities for speculative trading, which runs counter to the risk-management objectives of both economic policy and energy security (Vansteenkiste, 2011).

Unlike the results for normalized temporal degree, the relationship between oil production and normalized temporal closeness is not statistically significant across all model specifications. This suggests that variations in production levels do not necessarily accelerate the rate at which information is transmitted in spot markets. While we do not dispute OPEC's capacity to influence global oil prices through supply adjustments, the principal objective of pricing for OPEC and other major producers is to maximize national economic returns rather than to provide price signals or hedging instruments for other market participants. Consequently, pricing intentions in key exporting countries, particularly in the Middle East, are largely insulated from information originating in external markets.

This finding is consistent with the operational realities of oil markets, where production levels are relatively rigid in the short to medium term. On the one hand, logistical and storage constraints limit producers' ability to enact substantial output adjustments. On the other hand, price movements generally occur at a much higher frequency than production changes, leading to a mismatch in adjustment intervals between the two variables. Thus, increases in production alone do not directly contribute to faster information flow in spot markets. This interpretation is consistently supported by all model results reported in Table 7.

Table 8 presents the regression results for normalized betweenness centrality. In Model 1, the regression coefficient for the futures market variable is 0.056, while the coefficient for the production variable is 0.061. These results suggest that the establishment of futures markets for spot trading and the increase in oil production both contribute to enhancing a spot market's betweenness centrality within the global oil network. This positive relationship holds consistently across both the baseline regressions and the lagged specifications (Models 6 through 10).

After introducing control variables such as the change in liquidity and the change in the GPR index, the core results remain robust, indicating that the inclusion of these controls does not alter the main hypothesis. The stability of these findings underscores the reliability of the positive association. Betweenness captures the extent to which other nodes depend on a particular node to transmit information or resources. On the one hand, nodes with high betweenness act as critical conduits for markets with asymmetric information, effectively serving as "information bridges" Liu and Gong (2020). On the other hand, betweenness centrality also highlights the structural importance of a node in network security. Removing a key intermediary node can significantly reduce the efficiency of information flow across the entire network.

Nodes with high betweenness are frequently used and relied upon by other markets, becoming the most "busy" nodes within the global oil market network. Therefore, enhancing betweenness through the development of futures markets and increased oil production can increase the importance of a country's spot market in global information exchanges, thus exerting greater influence on international oil pricing.

7 Conclusion

This study systematically analyzes the impact of oil production and financialization, represented by oil futures markets, on the pricing power of crude oil spot markets. We particularly focus on their differential effects on 12 key oil spot markets in the global oil market network. Using weekly settlement prices of crude oil spot markets as data samples, we calculate the transfer entropy between the price returns to measure bidirectional causal relationships. Transfer entropy serves as a proxy for fundamental pricing power. A series of dynamic networks are constructed based on the direction and intensity of transfer entropy, and quantitative analysis is performed using network centrality indicators, including degree, closeness, and betweenness centrality. This approach reveals causal relationships between price information across oil markets, providing a new perspective on the identification of market pricing power. The results of the full sample demonstrate that the Brent and WTI markets occupy key positions in the global oil network.

Moreover, the rolling sample analysis illustrates the dynamic evolution of market centrality indicators (degree, closeness, and betweenness) over a span of 146 months. The results show that after the 2014 "Price War," the pricing power of the global oil market experienced significant turbulence. This suggests that shocks and restructurings from important events may disrupt the spillover of information in the global oil network, highlighting the need for regulators to pay special attention during such periods. The impacts of financialization and oil production on network centrality reveal that, although the establishment of oil futures markets significantly enhances market connectivity, transmission efficiency, and information mediation, increases in oil production do not significantly accelerate the speed of information spillovers. This positive relationship remains unaffected by geopolitical uncertainties and changes in official liquidity reserves. Thus, contrary to the conventional understanding of pricing power (Tudor and Anghel, 2021), our data suggest that futures markets exert a more comprehensive influence on the spillover capacity of information than oil production. The differences in influence channels help explain why Brent and WTI have remained stable centers over the long term, whereas Middle Eastern markets have not: financialization affects market behavior more rapidly and effectively than production levels.

To help enhance risk management capabilities and pricing power in oil spot markets, our findings support three policy recommendations for financial institutions and regulatory bodies involved in international oil trading and investment.

First, we recommend strengthening the construction and regulation of oil financial derivative markets. Governments should increase support for oil futures and options markets, ensuring that these markets have adequate liquidity and security. This will enhance market transparency and information integration, providing more comprehensive and accurate forward-looking information to spot markets. Second, countries should establish stable oil production plans to maintain their influence within the global oil network. Specifically, governments should closely monitor fluctuations in national oil production, evaluate their position in the global oil supply chain, and implement emergency measures to prevent spot market failure in the event of drastic production changes, safeguarding investor interests. Finally, investment and regulatory bodies should enhance their monitoring of the information transmission capacity of key oil markets. Governments and market participants must pay close attention to the spillover capabilities of major oil markets. When these markets lose their reference value, continued reliance on their price signals should be avoided to protect the interests of the national oil market. In particular, during extreme economic conditions, oil market participants and economic information users should select price benchmarks from markets with strong pricing power and efficient information transmission.

Despite the progress made in this study in revealing the impact of oil financial derivative markets and oil production on oil pricing power, several limitations remain. First, the sample period is limited to 2010–2024. Future research could extend the time span to further explore the evolution of oil market pricing power over a longer time horizon. Second, although this study has examined the roles of futures markets and production, future research could incorporate additional financialization indicators to enrich the intrinsic definition of oil financialization and provide more micro-level insight into its impact on oil pricing power.

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Table

Table 1: Background Information of Data

	Country	Full Name	Unit	Future
Brent	UK	Brent Crude Oil Spot	USD/barrel	1
WTI	USA	WTI Crude Oil Spot	USD/barrel	1
Minas	Indonesia	Asia Minas Crude FOB Indonesia Cargo Spot	USD/barrel	0
Russia	Russia	Crude Oil ESPO Blend FOB	USD/barrel	0
Mexico	Mexico	Pemex Mexican Crude Oil Basket Price	USD/barrel	0
China	China	Daqing Crude Spot	USD/barrel	0
Oman	Oman	Oman Crude Spot	USD/barrel	1
Qatar	Qatar	Qatar Cargo Spot	USD/barrel	0
Kuwait	Kuwait	Kuwait Cargo Spot	USD/barrel	0
Tapis	Malaysia	Asia Tapis Crude FOB Kerteh Cargo Spot	USD/barrel	0
Dubai	UAE	Dubai Crude Spot	USD/barrel	1
Saudi Arabia	Saudi Arabia	Arab Light Crude Oil Spot	USD/barrel	0

Notes: The table lists the spot prices for various crude oil benchmarks from different countries and regions.

Table 2: Normalized Temporal Degree, Closeness and Betweenness (Full Samples)

	Br	Me	WT	Ru	Du	Ku	Qa	Om	Sa	Mi	Ta	Cn
Window=52												
Degree	0.785	0.859	0.798	1.000	0.143	0.065	0.143	0.222	0.000	0.337	0.133	0.208
Closeness	0.781	0.609	1.000	0.843	0.017	0.066	0.194	0.252	0.107	0.560	0.000	0.065
Betweenness	1.000	0.766	0.840	0.616	0.000	0.135	0.372	0.116	0.305	0.568	0.192	0.244
Window=56												
Degree	0.818	1.000	0.430	0.310	0.028	0.328	0.018	0.256	0.000	0.744	0.145	0.355
Closeness	1.000	0.487	0.245	0.376	0.319	0.338	0.114	0.623	0.132	0.669	0.129	0.000
Betweenness	1.000	0.571	0.301	0.267	0.000	0.238	0.012	0.162	0.036	0.371	0.059	0.257
Window=60												
Degree	0.667	1.000	0.430	0.387	0.095	0.326	0.071	0.319	0.000	0.754	0.185	0.358
Closeness	1.000	0.713	0.403	0.615	0.565	0.447	0.306	0.873	0.256	0.915	0.257	0.000
Betweenness	1.000	0.783	0.360	0.483	0.080	0.549	0.000	0.451	0.010	0.549	0.228	0.350

Notes: Br - Brent, Me - Mexico, WT - WTI, Ru - Russia, Du - Dubai, Ku - Kuwait, Qa - Qatar, Om - Oman, Sa - Saudi Arabia, Mi - Minas, Ta - Tapis, Cn - China.

Table 3: Panel and Correlation Data

Variable	Label	Definition	Measurement	Source
Degree	Normalized Degree	Rolling calculated degree of each oil spot market	None	Author
Closeness	Normalized Closeness	Rolling calculated closeness of each oil spot market	None	Author
Betweenness	Normalized Betweenness	Rolling calculated betweenness of each oil spot market	None	Author
Future	Future Market	Dummy variable for oil futures market	None	EIA
Volume	Oil Production Volume	Monthly crude oil production (incl. condensate), scaled down by a factor of 10000	kb/d (thousand barrels per day)	EIA
Δ GPR	Δ GPR	Change of Geopolitical risk (GPR) index	None	Caldara and Iacoviello (2022)
Δ CPI	Δ CPI	Change of Consumer Price Index	None	IMF
Δ FX	Δ FX	Change in exchange rates (domestic currency per Euro)	None	IMF
Δ ln_Liq	Δ Ln(returns of Liquidity)	Log returns of Official total reserves	None	IMF
FD	Financial Development Index	Relative ranking of financial institutions and markets development across countries	None	IMF
FI	Financial Institutions Index	Relative ranking of financial institutions across countries	None	IMF

Notes: EIA is the United States Energy Information Administration. IMF is the International Monetary Fund.

Table 4: Descriptive Statistics of the Panel and Correlation Data

Variable	**Mean**	**Std. Dev**	**Min**	**Q1**	**Median**	**Q3**	**Max**
Normalized Degree	0.372	0.322	0.000	0.091	0.293	0.579	1.000
Normalized Closeness	0.490	0.318	0.000	0.226	0.477	0.758	1.000
Normalized Betweenness	0.326	0.333	0.000	0.048	0.197	0.535	1.000
Future	0.333	0.472	0.000	0.000	0.000	1.000	1.000
Volume	0.390	0.377	0.045	0.095	0.255	0.529	1.330
Δln_Liq	0.003	0.037	-0.394	-0.009	0.002	0.015	0.340
ΔGPR	0.002	0.294	-3.972	-0.022	0.000	0.021	3.405
ΔCPI	2.816	2.595	-3.982	1.364	2.495	3.742	17.800
ΔFX	0.000	0.025	-0.232	-0.011	0.001	0.012	0.357
FD	0.442	0.203	0.000	0.302	0.401	0.540	0.956
FI	0.448	0.213	0.000	0.310	0.393	0.563	0.943

Notes: The table provides descriptive statistics for the panel data, including mean, standard deviation, minimum, first quartile (Q1), median, third quartile (Q3), and maximum values for each variable.

Table 5: Descriptive Results

	Obs.	Mean	Std. Dev.	Skewness	Kurtosis-3	J-B	ARCH(20)	ADF
Brent	733	0.0002	0.05	-1.08	15.24	7238.60	264.23	-9.68***
WTI	733	0.0001	0.10	-2.91	226.52	1568134.31	258.95	-10.16***
Minas	733	0.0001	0.06	-0.64	16.95	8829.30	259.10	-8.16***
Russia	733	0.0002	0.05	-0.68	8.76	2399.79	292.89	-9.50***
Mexico	733	0.0002	0.07	0.03	20.34	12629.69	333.61	-9.79***
China	733	0.0002	0.05	-1.25	11.24	4049.78	211.59	-9.12***
Oman	733	0.0002	0.05	-0.67	6.84	1483.71	141.42	-9.46***
Qatar	733	0.0002	0.05	-0.41	7.75	1741.87	158.40	-8.94***
Kuwait	733	0.0002	0.05	-0.54	7.55	1869.82	189.34	-8.99***
Tapis	733	0.0002	0.05	-0.62	5.52	977.27	136.41	-8.91***
Dubai	733	0.0002	0.05	-0.56	6.37	1276.65	122.27	-9.41***
Saudi Arabia	733	0.0002	0.05	-0.48	4.44	631.10	151.29	-8.77***

Notes: ***, **, * denote significance at 1%, 5%, and 10% significance levels, respectively.

Table 6: Regression of Normalized Degree

Variables	Normalized Degree					lag=1	Normalized Degree				
	(1)	(2)	(3)	(4)	(5)		(6)	(7)	(8)	(9)	(10)
Future	0.071^{***}	0.070^{***}	0.070^{***}	0.082^{***}	0.083^{***}	Future_lag	0.069^{***}	0.069^{***}	0.069^{***}	0.082^{***}	0.082^{***}
	(6.79)	(6.62)	(6.62)	(6.71)	(6.72)		(6.67)	(6.51)	(6.53)	(6.60)	(6.59)
Volume	0.031^{*}	0.033^{**}	0.033^{**}	0.018	0.018	Volume_lag	0.030^{*}	0.032^{*}	0.032^{*}	0.017	0.017
	(1.89)	(2.01)	(2.01)	(1.16)	(1.15)		(1.83)	(1.94)	(1.95)	(1.05)	(1.05)
Δln_Liq		0.409	0.408	0.423	0.425	Δln_Liq_lag		0.398	0.396	0.412	0.412
		(1.50)	(1.50)	(1.56)	(1.57)			(1.47)	(1.47)	(1.53)	(1.53)
ΔGPR			-0.010^{*}	-0.009^{*}	-0.012	ΔGPR_lag			-0.017	-0.016	-0.017
			(-0.39)	(-0.34)	(-0.44)				(-0.63)	(-0.57)	(-0.58)
ΔCPI				0.010^{***}	0.010^{***}	ΔCPI_lag				0.011^{***}	0.011^{***}
				(3.63)	(3.66)					(3.76)	(3.76)
ΔFX					-0.165	ΔFX_lag					-0.062
					(-0.45)						(-0.16)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Fixed Effects	Yes	Yes	Yes	Yes	Yes
N	1,752	1,752	1,752	1,752	1,752	N	1,740	1,740	1,740	1,740	1,740
R^2	0.110	0.112	0.112	0.116	0.117	R^2	0.107	0.109	0.109	0.115	0.115

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. T-statistics are in parentheses. Δlog_Liq represents the change in the logarithm of liquidity returns.
Standard errors are clustered at the country level. All models include time fixed effects.

Table 7: Regression of Normalized Closeness

Variables	Normalized Closeness					lag=1	Normalized Closeness				
	(1)	(2)	(3)	(4)	(5)		(6)	(7)	(8)	(9)	(10)
Future	0.069***	0.069***	0.069***	0.098***	0.098***	Future_lag	0.067***	0.067***	0.067***	0.097***	0.097***
	(5.79)	(5.71)	(5.70)	(6.99)	(7.02)		(5.67)	(5.59)	(5.60)	(7.05)	(7.08)
Volume	0.026	0.027	0.027	-0.007	-0.007	Volume_lag	0.026	0.027	0.027	-0.009	-0.009
	(1.41)	(1.46)	(1.46)	(-0.36)	(-0.36)		(1.40)	(1.45)	(1.45)	(-0.44)	(-0.44)
Δln_Liq		0.220	0.220	0.255	0.254	Δln_Liq_lag		0.206	0.205	0.242	0.239
		(1.02)	(1.02)	(1.27)	(1.26)			(1.00)	(0.99)	(1.25)	(1.23)
ΔGPR			0.000	0.003	0.006	ΔGPR_lag			-0.012	-0.008	-0.003
			(0.01)	(0.13)	(-0.22)				(-0.43)	(-0.31)	(-0.10)
ΔCPI				0.025***	0.025***	ΔCPI_lag				0.026***	0.026***
				(7.69)	(7.65)					(8.21)	(8.09)
ΔFX					0.134	ΔFX_lag					0.260
					(0.38)						(0.65)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Fixed Effects	Yes	Yes	Yes	Yes	Yes
N	1,752	1,752	1,752	1,752	1,752	N	1,740	1,740	1,740	1,740	1,740
R^2	0.129	0.129	0.129	0.158	0.159	R^2	0.128	0.129	0.129	0.161	0.162

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. T-statistics in parentheses. Δlog_Liq represents the change in the logarithm of liquidity returns. Standard errors are clustered at the country level. All models include time fixed effects.

Table 8: Regression of Normalized Betweenness

Variables	Normalized Betweenness					lag=1	Normalized Betweenness				
	(1)	(2)	(3)	(4)	(5)		(6)	(7)	(8)	(9)	(10)
Future	0.056***	0.056***	0.056***	0.064***	0.065***	Future_lag	0.054***	0.053***	0.053***	0.063***	0.064***
	(3.84)	(3.78)	(3.78)	(3.89)	(3.97)		(3.70)	(3.60)	(3.60)	(3.86)	(3.92)
Volume	0.061***	0.062***	0.063***	0.053***	0.052***	Volume_lag	0.060***	0.062***	0.062***	0.049***	0.049***
	(3.64)	(3.72)	(3.73)	(3.05)	(3.06)		(3.56)	(3.68)	(3.68)	(2.86)	(2.86)
Δln_Liq		0.216	0.215	0.225	0.233	Δln_Liq_lag		0.359	0.359	0.372	0.377
		(0.94)	(0.94)	(0.98)	(1.01)			(1.53)	(1.53)	(1.58)	(1.60)
ΔGPR			-0.012	-0.012	-0.025	ΔGPR_lag			-0.000	0.001	-0.009
			(-0.35)	(-0.35)	(-0.66)				(-0.01)	(0.03)	(-0.23)
ΔCPI				0.007**	0.007**	ΔCPI_lag				0.009**	0.009**
				(2.07)	(2.06)					(2.59)	(2.59)
ΔFX					-0.668	ΔFX_lag					-0.468
					(-1.58)						(-1.08)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Fixed Effects	Yes	Yes	Yes	Yes	Yes
N	1,752	1,752	1,752	1,752	1,752	N	1,740	1,740	1,740	1,740	1,740
R^2	0.090	0.090	0.090	0.092	0.094	R^2	0.088	0.089	0.089	0.093	0.093

Notes: *** p<0.01, ** p<0.05, * p<0.1. T-statistics are in parentheses.
Standard errors are clustered at the country level. All models include time fixed effects.

Figure

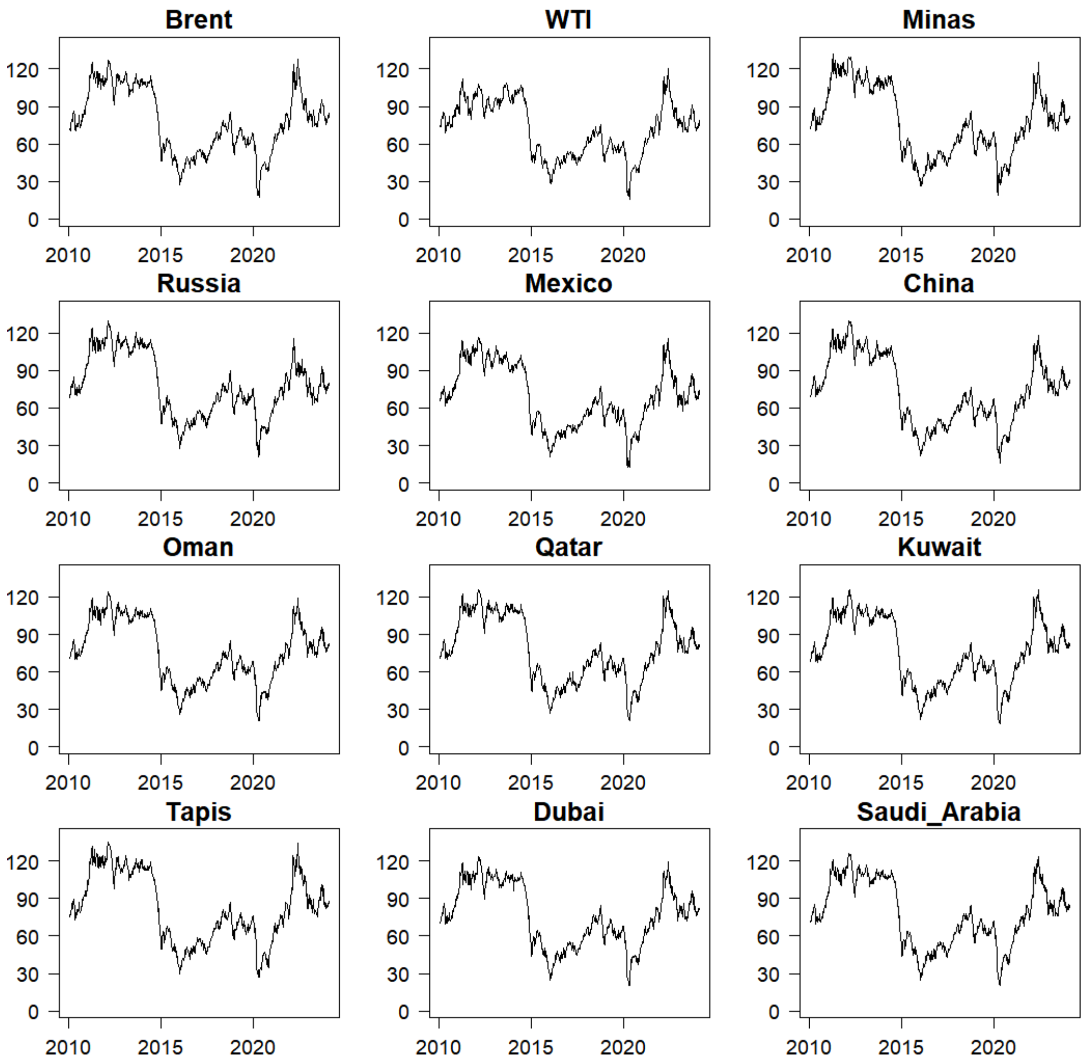

Figure_1. Oil Prices

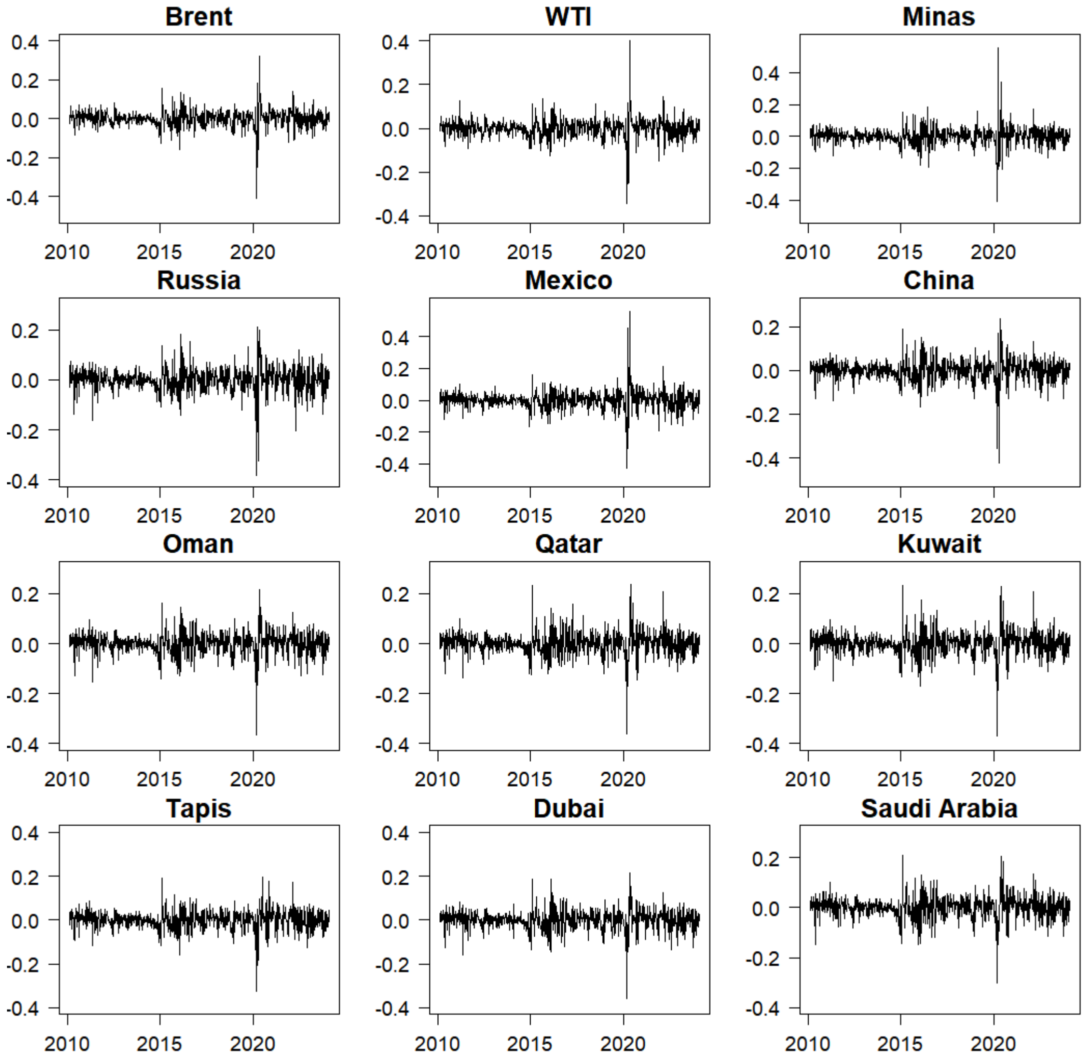

Figure_2. Returns of the Oil Prices

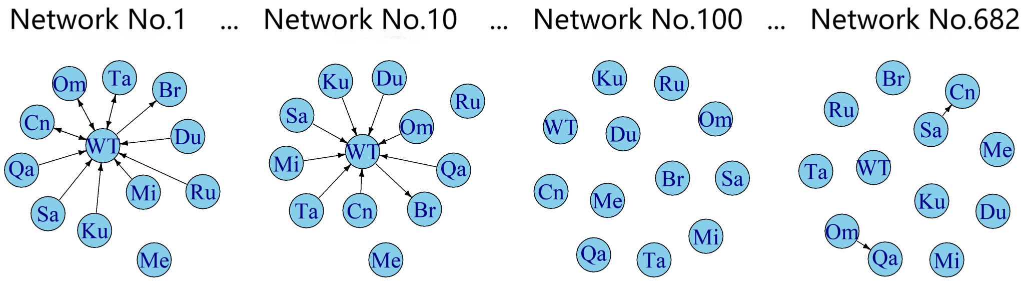

Figure_3. Network Slices

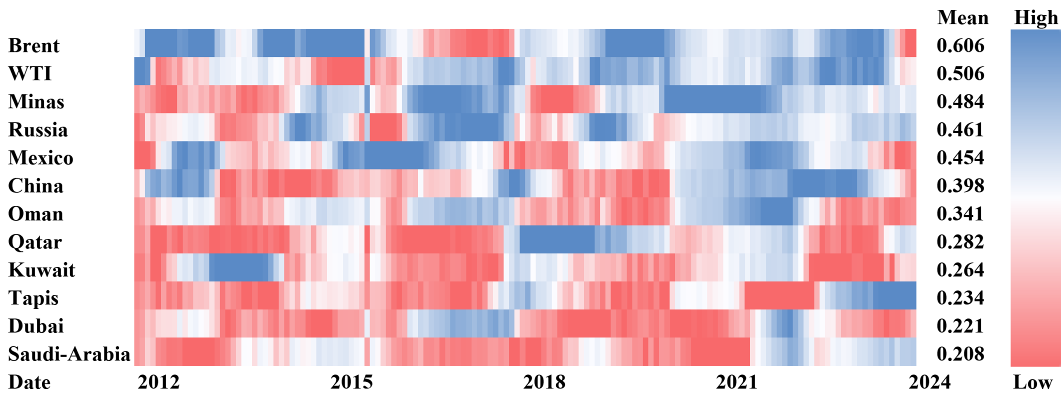

Figure_4. Temporal Degree

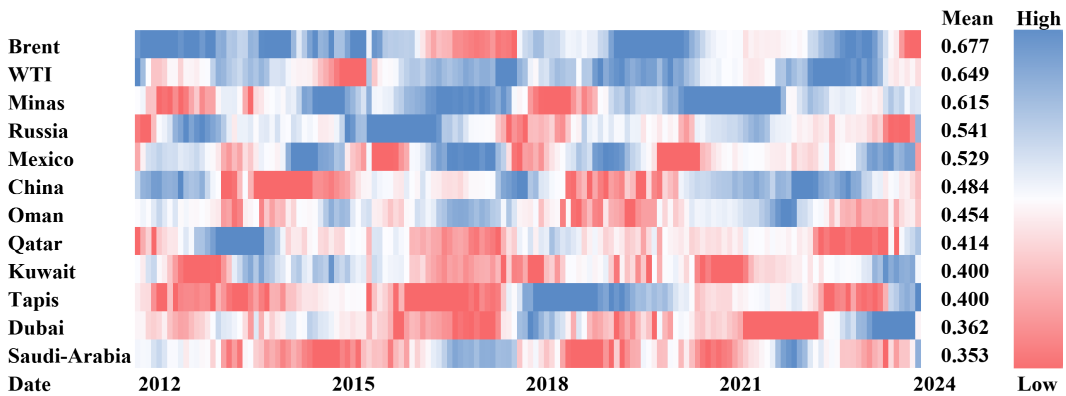

Figure_5. Temporal Closeness

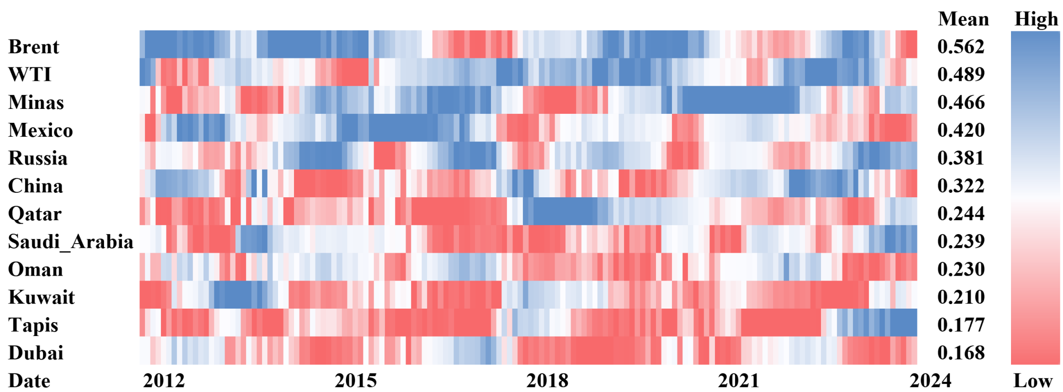

Figure_6. Temporal Betweeness

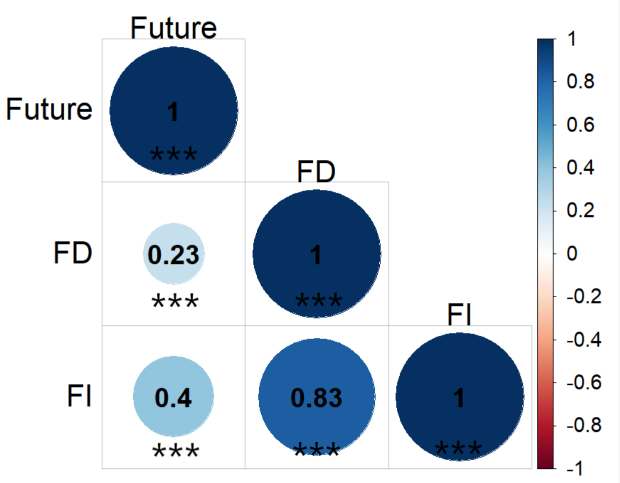

Figure_7. Correlation between the Futures Variable and the FD and FI Index