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Volatility Contagion from Bulk Shipping and Petrochemical Industries to Oil Futures Market during the Economic Uncertainty

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Abstract: The purposes of the research have evidenced the spillover effects of oil-related factors in the oil market and the leading indexes of petrochemical commodities and the bulk shipping markets. The research gap was fitted and explored the effects associated with leading indexes for the shipping and petrochemical markets on the oil market during the US-China trade war, which is seldom bridged with significant relations in the history of oil. The scope of data for the period from 4 January 2016, through 31 August 2022, were analyzed using a generalized autoregressive conditional heteroskedastic mixed data sampling model as methodology of mix frequency to examine volatility spillover of four research hypotheses from the bulk shipping and petrochemical markets to the oil market. Main contributions revealed that spillover from the bulk shipping and petrochemical commodity markets transmitted significant volatility to West Texas Intermediate (WTI) oil returns after the US-China trade war began, a trend that has continued throughout the COVID-19 era until Ukraine–Russia war. These rare events indicate that the realized volatility derived from these market variables can be used to track the more significant contagions on WTI futures volatility in this empirical research than the weak relation in past studies.

Keywords: oil; bulk shipping; petrochemical markets; volatility; contagion; generalized autoregressive conditional heteroskedastic mixed data sampling model; US-China trade war; COVID-19

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1. Introduction

The novelty of the paper compared to other studies is to bridge the significant spillover effect from two markets to WTI with new evidence of empirical research and reasons as below.

Firstly, this study discovered that the volatility contagion from the Chinese petrochemical industry to WTI futures was significant after the trade war began, a finding will be the research gap seldom demonstrated by the comparisons of previous academic studies that have shown only weak correlations between the plastic commodity markets and oil prices during economic crises. Mansur M. et al. [1] discussed the price dynamics between regional ethylene markets and crude oil.

Secondly, no research on port congestion in COVID-19 has investigated and composited the various problems faced by shipments and supply chains between upstream and downstream due to the US–China trade war extended to Ukraine–Russia war. In particular, Yantian Port in Shenzhen was congested because dock workers had COVID-19. Problems with transporting oil—due to the pandemic and trade war—have driven up oil prices and induced volatility in the oil and freight markets as the risk of uncertainty. Considering this context, this study examined data on the Baltic Dirty Tanker Index and Baltic Clean Tanker Index covering the period of the US-China trade war; these indexes are leading indexes of bulk shipping submarkets of WTI.

Thirdly, the important role of China in crude oil market share should be researched by the interconnections between their specific indices of transportation and futures of petrochemical markets, because China is the world's largest crude oil importer with 72% of its crude coming from imports in 2018. With China's rapid urbanization and industrialization, the country's dependence on foreign crude oil is estimated to reach 80% by 2030. Although world oil markets have recovered from the considerable COVID-19-induced demand shock, an extreme degree of volatility continues to challenge the industry as never before. China imports a substantial volume of oil. Empirical studies have linked international trade and domestic entrepreneurial activities by using tariff differences between industries during the US–China trade war. Scholars discovered that the increase in US import tariffs is related to the rate at which Chinese companies had been established and encountered how large the negative impact of the trade war is on a given US-export-dependent industry. Consequently, Chinese consumption decreased, reducing domestic oil demand, which caused oil prices to remain low [2]. According to the International Energy Agency [3], crude oil is the major source of global energy. Moreover, crude oil is the most critical commodity in the world, accounting for a major part of the Dow Jones commodity index in the energy industry [4].

Fourthly, the methodology of past works by the same frequency data only found weak correlations between the abovementioned markets. This research pioneered the adoption of the generalized autoregressive conditional heteroskedastic mixed data sampling (GARCH-MIDAS) model to investigate an amalgamation of low- and high-frequency data sources pertaining to the link between monthly hedge and arbitrage of the petrochemical and transportation markets on dairy trade of WTI before and after the US-China trade war extended to Ukraine-Russia war.

Fifthly, the aforementioned studies have seldom considered the relationship of key indexes for interregional oil tanker transportation caused by problems of epidemic alert on the volatility contagion of oil prices during the COVID-19 period; thus, I investigated this topic in the present study to meet the new research gap. Will freight of oil tankers become the leading index of the oil market by mix frequency methodology during turmoil?

In addition, the sample data after the trade war in this research suggest that plastic markets transmit considerable price volatility to the oil market, indicating that shocks to the Chinese petrochemical industry influence the oil market. In the past ten years, many financial derivatives related to the petrochemical market have been launched in China. However, investigating the relationship between the plastic commodity and oil markets remains challenging for researchers. Given the importance of crude oil, oil prices strongly influence many other commodities and financial markets; this is because of oil's extensive use as the main driver in the production process for petrochemicals and shipping [5]. China is the world's largest importer of crude oil, causing high global oil demand. Notably, the world's largest petrochemical enterprises are located in the United States, but the major growth in production capacity is in China. Trade between the US and Chinese petrochemical industries may affect oil prices during the bilateral US-China conflict. Therefore, understanding oil price fluctuations and the influence of trade in the Chinese petrochemical and bulk shipping markets, the leading indices of both industries may provide further insight into the investment of the oil market. Co-movement such as directional spillover between the Chinese petrochemical industry and the oil market is affected by the degree of demand in the oil-importing country, which is mainly determined by the supply chain upstream and downstream of the oil industry; this warrants further interesting research.

The remainder of the paper is organized as follows: Section 2 presents a literature review that supplements what is already provided in the Introduction. Section 3 provides descriptive statistics of the database used in this work and a description of the MIDAS-GARCH methodology; Section 4 presents the empirical results obtained using the aforementioned models; Section 5 compares and contrasts our results with those of other authors; and Section 6 presents conclusions and some discussions.

2. Literature Review

Section 2.1 reviewed the literature on volatility contagion from bulk shipping and petrochemicals to oil prices; the other, I reviewed the literature on volatility spillover and the methodology at the center of Sections 2.2 and 2.3 of the research.

2.1. Review of Petrochemical and Shipping Industries' Influence on Oil Markets

In our review of the prior literature on the petrochemical and shipping industries' influence on oil markets, I first surveyed petrochemical commodities and oil prices. Mansur et al. [1] reported a cointegration relationship between West Texas Intermediate (WTI) crude oil and regional ethylene spot prices. Jiang et al. [6] studied changes in US biomass policy that have driven spillover fluctuations among WTI crude oil futures, corn futures, and high-density polyethylene (HDPE) spot prices. Using the vector error correction model, they noted that corn futures and the plastic market [7] exhibit a significant bidirectional spillover relationship. Long-term plastic prices and corn futures are also linked, and the relationship between corn futures and crude oil futures markets has been strengthened since the 2007 Energy Independence and Security Act.

Crude oil price fluctuations affect the petrochemical industry's production costs, and petrochemical companies' higher operating costs are reflected in their stock prices. Gu et al. [8] used the value-at-risk dynamic conditional correlation GARCH (VAR-DCC-GARCH) model to study Brent crude oil prices, HDPE, polyethylene terephthalate, and polypropylene (PP)—three common recycled plastics in China from 2010 to 2018—as well as China's plastics stock index over time. Crude oil is the raw material most essential to plastic products. Fluctuations in crude oil prices exert a significant influence on investment in China's plastics industry.

The crude oil and tanker markets are also closely related. The tanker is the main transportation method for crude oil and refined oil in the world and plays a vital role in the energy supply chain. The oil tanker market is divided based on the two types of oil tankers: dirty oil tankers and clean oil tankers. Crude oil tankers (dirty) transport unrefined crude oil, and product tankers (clean) transport oil refined from crude oil. Tanker freight rates indicate the global supply and demand for oil products at a given time. Roar and Kevin [9] and Alizadeh et al. [10] observed that the tanker market is vulnerable to international crude oil and crude oil product price fluctuations, which in turn affect the net profit and cash flow of tanker shipping. Poulakidas and Joutz [11] studied the leading, inverse, and causal relationships among crude oil prices, crude oil inventories, and tanker freight rates, discovering that the demand for tankers comes from the demand for oil and tanker freight rates are strongly correlated with oil prices. From 2008 through 2016, the financial crisis influenced the shipping market, and analyzing crude oil price volatility and tanker freight rates has attracted more attention. Chen et al. [12] used multifractal detrended cross-correlation analysis (MF-DCCA) to study the correlation between WTI crude oil and the Baltic tanker freight index, empirically demonstrating a stronger short-term than long-term correlation. The dry bulk shipping market is an indispensable factor in a proper evaluation of the global economic cycle. Wang et al. [13] used the BDI, the leading indicator of global economic activity and the demand for raw materials, to construct Killian's index of global real economic activity (REA) [14] and other variables to empirically predict the spot price of WTI crude oil. Ruan et al. [15] used statistical verification and the MF-DCCA model to confirm the noteworthy multifractal characteristics of the BDI and crude oil prices. Lin and Chang [3] studied the volatility transmission between the United States Oil Fund (USO) and BlackRock World Energy Fund A2 (BGF) before and after the US-China trade war's commencement, determining that the BDI catalyzes the transmission of volatility from the bulk shipping index to the oil market.

This study explored the volatility contagion of bulk shipping and Chinese petrochemical markets to the oil futures market during the ongoing COVID-19 pandemic, an abnormal period of oil history. Our objective was to explore the leading index among tanker shipping and the petrochemical industry during the current turmoil. Because not all oil price shocks are similar, I also analyzed the reasons explaining why several instances of port congestion caused ocean freight and oil prices to markedly rise during the COVID-19 pandemic. By using the GARCH-MIDAS model after the onset of the US–China trade war and extending the analysis to the COVID-19 era, I discovered empirical evidence verifying that the Baltic Dirty Tanker Index (BDTI) and Baltic Clean Tanker Index (BCTI) have exerted significant volatility spillover effects on the WTI futures. Notably, the econometrics of GARCH-MIDAS were advantageous in combining high- and low-frequency data to elucidate the volatility contagion between various markets and WTI oil future prices. In this paper, I present the influence of the US–China trade war, which has now extended throughout the COVID-19 pandemic era, on the WTI crude oil futures contract, three world shipping indexes (the BDI, BDTI, and BCTI), and the petrochemical plastic industry's pure terephthalic acid (PTA), polyvinyl chloride (PVC), linear low-density polyethylene (LLDPE), and polypropylene (PP) futures. Thus, I employed the GARCH-MIDAS model to study the volatility spillover among these submarkets. The contributions of this study are twofold. First, I adapted the research of a single author [3], who was the first to combine both daily oil exchange-traded fund (ETF) data and energy mutual fund data with monthly data on equities and bulk shipping; in this paper, I extended this author's model by including variables for bulk shipping and plastic commodities to distinguish the long-term versus short-term components of oil volatility. Second, limited literature has investigated the volatility contagion from transportation and interregional petrochemical trade, such as tanker shipping and plastic commodities, to the associated crude oil market. The previous literature on the key WTI index seldom reported on the bulk shipping submarkets and only analyzed the BDI computed from the freight of five submarkets [16]. This paper addresses one of the research gaps by investigating the correlation of financial activity in the bulk tanker shipping industry with oil prices during financial disturbances. Using the key data of the BDTI and BCTI, representative of the world's dirty and clean oil tanker shipping industry, this research compares the effects of financial contagion on the WTI index in the short and long terms. To our knowledge, no literature published in this journal has combined data from the key indexes of the tanker shipping and petrochemical industries and used GARCH-MIDAS to analyze these contagion effects on oil prices. Our findings suggest that investors can use the leading index of the shipping and petrochemical industries to predict the co-movement of WTI oil prices during periods of both tranquility and crisis.

2.2. Review of Volatility Spillover

Several studies have discussed volatility contagion, which focuses on the mechanisms underlying the transmission of volatility from one financial market to another. Forbes and Rigobon [17] defined volatility contagion as a significant increase in cross-market linkages after an economic shock, which is a change to the economy or relationships between two markets that have a substantial effect on the macroeconomic outcome. Moreover, Guesmi et al. [18] defined contagion effects as excessive correlations among financial markets. These authors also emphasized oil's pivotal role in financial contagion. The analysis of the volatility of crude oil prices and tanker freight rates has attracted much attention. Chen et al. [12] used multifractal detrended cross-correlation analysis (MF-DCCA) to examine the correlation between WTI crude oil and the Baltic tanker freight index. Empirically, the short-term correlations were observed to be stronger than the long-term correlations.

Lin et al. [16] investigated the cross-market volatility transmission between the BDI and the commodities futures before and after the critical crisis. The BDI serves as a transmission factor in the shipping financial market. Kavussanos and Nomikos [19] argued that understanding the spillover volatility of the shipping market is of great importance for portfolio diversification, hedging strategies, the forecasting of shipping price indices, and improvements to the pricing efficiency of shipping derivatives. Tsouknidis [20] used the DCC-MGARCH model and spillover indicators to investigate the dynamic spillover volatility between dry bulk shipping and tanker shipping, discovering that a large spillover volatility (varying across time) could be observed across the shipping markets. The spillover effect became more intense after the global financial crisis.

The fluctuations in crude oil prices disturb the production costs of the petrochemical industry, in which a company's operating performance is reflected by its stock price. Gu et al. [8] used the VAR-DCC-GARCH model to examine Brent crude oil prices and high-density prices from 2010 to 2018. HDPE, PET, and PP are the three most common recycled plastics in China and the status of their markets has been related to China's plastics stock index over time. Crude oil is an indispensable ingredient in plastic production. The instability of crude oil prices has considerably affected investment behavior in China's plastics industry, which is becoming more influential in Asia. Regarding volatility contagion during the US–China trade war, Bouri et al. [21] analyzed the importance of the US–China trade war by forecasting the out-of-sample daily realized volatility of Bitcoin returns and revealed that the main Google Trends–based measure of the US-China trade war improves forecast accuracy for various configurations of random forests and forecast horizons.

2.3. Review of the GARCH-MIDAS Model

The following three main methodologies instead of GMM, 2SLS, or the PLS-SEM are generally used to investigate volatility contagion during the chaos of turmoil. Because research on inter-market contagions is seldom explored by GMM, 2SLS, or PLS-SEM in energy-related markets. In mathematics or applied mathematical field, I only found one article (in Applied Mathematics and Nonlinear Sciences, 2022) from 2019 until now when keywords (energy GMM spillover contagion) were searched in Google Scholar. Furthermore, I cannot find any article (in Applied Mathematics or your journal) from 2019 until now when keywords (energy 2SLS spillover contagion) were hunted in Google Scholar. The same situation occurred when keywords (energy PLS-structured equations method spillover contagion) were questioned in Google Scholar. So, my study still came to the three main methodologies of volatility analysis as below and finally adopted the MIDAS GARCH method.

(1) Copula models: Gong et al. [22] used a three-variable Markov regime transition copula model to study the dynamic dependence between shipping and freight and the stock market. In most cases, the decrease in US-China trade increases the risk of contagion between the two markets;

(2) The value-at-risk method: For example, Yang et al. [23] adopted the value-at-risk method to better understand the dry bulk shipping market, measuring the risk of the dry bulk shipping market in terms of the BDI. The risk of investment in the two reference markets of the stock market and crude oil market was used, and the risk spillover effect of the global stock market and crude oil market on the dry bulk market was discussed;

GARCH models: In the present study, I used a GARCH model, which has also been used by the following studies. Conrad et al. [24] used the GARCH-MIDAS model to study long-term Bitcoin volatility and discovered that the realized volatility of the S&P 500 index had a significant negative correlation with long-term Bitcoin volatility and has a strong positive association with the BDI, which demonstrates that Bitcoin fluctuations are linked to global economic activities. Wang et al. [25] investigated the influence of asymmetric and extreme volatility effects on the volatility of the S&P 500 index in the short and long term. The in-sample data revealed that extreme shocks greatly affected the volatility of the S&P 500 index. Over the long term and short term, the influence of asymmetry is greater than that of extreme volatility.

Salisu et al. [26] adopted a GARCH-MIDAS model to analyze the predictive power of six indicators of global economic activity in forecasting crude oil market volatility. Salisu et al. [27] adopted GARCH-MIDAS and verified that global economic conditions significantly influence gold market volatility, albeit with mixed outcomes.

Shi et al. [28] examined whether the US–China trade war has affected the linkage between the Chinese and US stock markets over time by using the DCC-GARCH (1,1) model. In addition, a structural breakpoint test revealed that most of the structural breakpoints in the linkage between China, Hong Kong, and the US stock markets occurred after 6 July 2018, when US-China relations tensions came to a head, accompanied by a volatility spillover.

3. Materials and Methods

3.1. Volatility Transmission and Methodology

3.1.1. Volatility Transmission

Both energy ETFs (e.g., the USO) and energy funds (e.g., the BGF) have exhibited high volatility since the trade war extended into the COVID-19 pandemic era due to the erratic oscillations in the volatility of oil prices, which occur mainly due to global oil supply and demand shocks and particular oil demand shocks [29,30]. Both the fluctuation in the global supplies of plastic commodities and the growth in the aggregate demand for all petrochemical commodities trigger a general oil demand shock. An increase in the demand for crude oil in response to increased uncertainty about a future oil supply shortfall causes a specific oil demand shock [31].

Volatility transmission is also known as volatility spillover or volatility contagion [32]. Studies have suggested that during the global financial crisis in 2008, volatility contagion caused increasing uncertainty across various financial markets, highlighting the importance of elucidating channels of volatility transmission [6,33–35]. Arouri et al. [36] contended that the threat of volatility transmission increased substantially during the financial crisis due to financial instability and economic uncertainty. Zhang and Wang [34] asserted that observing high-intensity volatility transmission helps investors forecast oil prices.

3.1.2. Choice of Methodology: GARCH-MIDAS Model

Previously, I employed GARCH models that were later elaborated by Engle et al. [37] to analyze time series data; the resultant GARCH model can effectively explain the volatility transmission of an analyzed time series.

In many empirical studies, the sum of parameter estimates (except α_0; given the regularity conditions of $\alpha_0 > 0$, $\alpha_1 \geq 0$, and $\beta_1 \geq 0$, the required stationarity condition is $\alpha_1 + \beta_1 < 1$) used in the standard GARCH model is almost 1, making the variance highly persistent. Hence, Engle and Rangel [38] proposed the integrated GARCH (IGARCH) model, which takes the form of an equation where $\alpha_1 + \ldots + \alpha_q + \beta_1 + \ldots + \beta_p = 1$. A shock to the conditional variance in the IGARCH model is persistent in the sense that it remains significant for forecasts of all horizons. The analysis in previous literature was limited to classes of the AR (1)—GARCH (1,1) model with single-frequency data largely because processing order selection autoregression at the AR (1) level and the GARCH process at the GARCH (1,1) level was deemed sufficient to capture the autoregressive effect and heteroskedasticity [37]. Our empirical results suggest that the present model represents the optimal solution for combining low- and high-frequency data with GARCH-MIDAS rather than GARCH (1,1).

A particularly noteworthy application of GARCH models is the description and forecasting of volatility, which is understood as a measure of uncertainty. In the case of GARCH models, such a measure of uncertainty is conditional variance or conditional standard deviation. GARCH models are the most commonly used models of variation, primarily because they can describe most empirical properties of an analyzed time series [39].

Using a machine learning method, Fałdzinski, Fiszeder, and Orzeszko [40] compared the performance of GARCH-type models with that of support vector regression to predict the futures contracts of selected energy commodities, namely crude oil, natural gas, heating oil, gas oil, and gasoline, without petrochemical commodity or tanker shipping data. Volatility contagion has often been predicted using a series of GARCH models, but GARCH-MIDAS is the optimal method for the data fusion of daily and monthly data, which is advantageous in simultaneous econometric analysis of spot prices and futures markets.

3.2. Description of the GARCH-MIDAS Model

The GARCH-MIDAS model is expressed similarly to the Equation (1). The following MIDAS regression formula was derived by an author of this paper (A.J. Lin) and published in this journal [3]:

$$Y_{t+h} = \beta_0 + \beta_1 B\left(L^{1/m}; \omega\right) X_t^{(m)} + \varepsilon_t^{(m)} \quad (1)$$

I followed the model of Engle and Rangel [38] as follows:

$$r_{i,t} - E_{i-1,t}(r_{i,t}) = \sqrt{g_{i,t} \times \tau_t}\varepsilon_{i,t} \quad (2)$$

where the volatility is decomposed into two components: The $g_{i,t}$, which explains a short daily fluctuation, and the long-term component τ_t. This equation primarily indicates that the same favorable or unfavorable results may exert varying effects depending on the prevailing economic conditions. I assume that the $g_{i,t}$ relates to daily liquidity concerns and other short-term factors. By contrast, I assume that the macroeconomic τ_t variable can provide information on the volatility of the oil futures market.

I then use Equation (2) to consider the return for day i of any month as period a, which may follow t, and define $r_{i,t}$ as the return on day i of month t. The return on the i_{th} day of month t is obtained as follows:

$$r_{i,t} = \mu + \sqrt{\tau_t \times g_{i,t}}\varepsilon_{i,t}\,, \quad \forall_i = 1, \ldots, Nt, \quad (3)$$

In Equation (3), the conditional variance equation can be divided into two parts: (1) explaining short-term everyday volatility as $g_{i,t}$ which follows GARCH (1,1), and (2) that explain long-term everyday volatility as τ_t, in which MIDAS regression captures every market and explains the realized volatility of variables from the shipping and petrochemical industries. In this equation, $\varepsilon_{i,t}|\Phi_{i-1,t} \sim N(0,1)$ and $\Phi_{i-1,t}$ is the information for the i_{th} day of month t. Following Engle and Rangel [38], I used the volatility dynamics of the component $g_{i,t}$ in a daily univariate GARCH (1,1) process as follows:

$$g_{i,t} = (1-\alpha-\beta) + \alpha\frac{(r_{i-1,t}-\mu)^2}{\tau_t} + \beta g_{i-1,t} \quad (4)$$

$$\tau_t = m + \theta\sum_{k=1}^{K}\varphi_k(\omega_1,\omega_2)X_{t-k} \quad (5)$$

$$E_{t-1}\left[(r_{i,t}-\mu)^2\right] = \tau_t E_{t-1}(g_{i,t}) = \tau_t \quad (6)$$

I then follow Engle et al. [37] in specifying the τ component (instead of merely measuring the realized volatility of a single month) by using MIDAS regression and filtering to smooth the realized volatility.

Monthly volatility is represented as X_t. In Equation (5), X_t is the time when the financial markets of the shipping and petrochemical industries explain the realized monthly volatility of the variable, k is the lagged period, X_{t-k} is the volatility of period k when the period t has a lagged effect in relation to period k. K is the maximum lagged period, which is usually determined by a likelihood function or the Bayesian information criterion (BIC). The parameter θ measures the effect of the explanatory variable on the long-term volatility of WTI future prices. The $\varphi_k(\omega_1,\omega_2)$ function is the weighted scheme of MIDAS regression screening with an aggregate weight of 1.

Therefore, the conditional variance equation explains everyday volatility long-term τ_t, in which MIDAS regression captures every market explaining the realized volatility of the variable and is determined according to the expected value of Equation (6) set at period $t-1$. In the present study, I adopted the GARCH-MIDAS fixed window to represent the long-term τ_t value that does not change over *t* months.

The component $\varphi_k(\omega_1, \omega_2)$ is then specified to finalize the model as follows.

$$\varphi_k(\omega_1, \omega_2) = \frac{\left(\frac{k}{K}\right)^{\omega_1 - 1} \times \left(\frac{1-k}{K}\right)^{w_2 - 1}}{\sum_{j=1}^{K} \left(\frac{j}{k}\right)^{\omega_1 - 1} \times \left(\frac{1-j}{K}\right)^{\omega_2 - 1}} \tag{7}$$

The weight is defined as $\varphi_k(\omega_1, \omega_2) \geq 0,\ k = 1, 2, 3, \ldots, K$, sum to one.

Furthermore, to apply the model, I follow Conrad et al. [41] in imposing a restriction of $\omega_1 = 1$, which suggests that this weighting scheme is monotonically decreasing. In this specification, I take volatility as our variance in the long-term component τ_t.

This study used daily observations on returns before and after the trade war and monthly frequency within the MIDAS equation to predict the long-term component of volatility. I then employed realized volatility as our measure of the monthly variance and applied the aforementioned model with an estimation window adopted on the basis of the assumptions of Javed et al. [42]. The selection of the lag period parameter K was based on the Bayesian criteria information and log-likelihood. The τ_t indicated our quasi-maximum likelihood estimates from the MIDAS model to predict the long-term variance. Restricted by the daily basis of τ_t, I adopted the method of Javed et al. [42] to multiply τ_t by the number of trading days within every month. The prediction of short-term variance was estimated using σ_t^2, the estimated daily total variance.

4. Data, Hypothesis, and Results

4.1. Data Description

4.1.1. Dependent Variables in High-Frequency Data

In this study, the WTI futures prices, based on the daily closing prices, were obtained from the US Energy Information Administration and were checked against the Bloomberg database for missing data. Our volatility spillover analysis of the first period was applied to a data sample from the period from 4 January 2016, through 31 August 2022. Assume r_t is the percentage return of a variable at period t. P_t is the price of the variable at period t. Let $r_t = \ln(P_t/P_{t-1}) \times 100$. The first analysis period lasted from 4 January 2016, through 29 March 2018 (597 business days). The second period, which spanned from 2 April 2018, through 26 February 2021 (844 observations) was evidenced by the spillover effect of the US–China trade war. The third period was extended to 31 August 2022, pertained to the Ukraine–Russia War which has now extended throughout the US-China war era. WTI futures are the most liquid energy futures contracts, with an average daily volume of nearly 1.1–2 million contracts written [8,25]. WTI is also considered the key benchmark for global oil prices.

According to An et al. [29], in 2008, Brent prices were affected by contagion from the WTI crude market; however, in 2015, the opposite situation was the case. A graphical representation of the networking effect is presented. Therefore, in stage 1, I conducted research on the contagion of WTI volatility instead of BRT because the level of contagion of WTI in the COVID-19 pandemic has been as intense as that recorded in 2008. In future studies, I will investigate the contagion between Brent and WTI prices since the 2015 small-scale global financial contagion, in which WTI was affected by contagion from Brent.

4.1.2. Independent Variables in Low-Frequency Data

Our study of the global shipping industry used BDI, BDTI, and BCTI data collected from the DataStream platform. I also investigated four independent variables of futures contracts in the petrochemical industry from the Wind database as follows: (1) PTA futures as quoted in China's Zhengzhou Commodity Exchange and (2) PVC, (3) LLDPE, and (4) PP futures (detailed as Figure 1) as quoted in the Dalian Commodity Exchange. Petrochemicals are the chemical products refined from petroleum. Some chemical compounds are produced from petroleum. The two most common petrochemical classes are olefins (e.g., ethylene and propylene-derived acrylic acid) and aromatics (e.g., benzene, toluene, and xylene isomers).

Olefins and aromatics are the building blocks of a wide range of materials such as solvents, detergents, and adhesives. Olefins are the basis of polymers and oligomers used in plastics, resins, fibers, elastomers, lubricants, and gels.

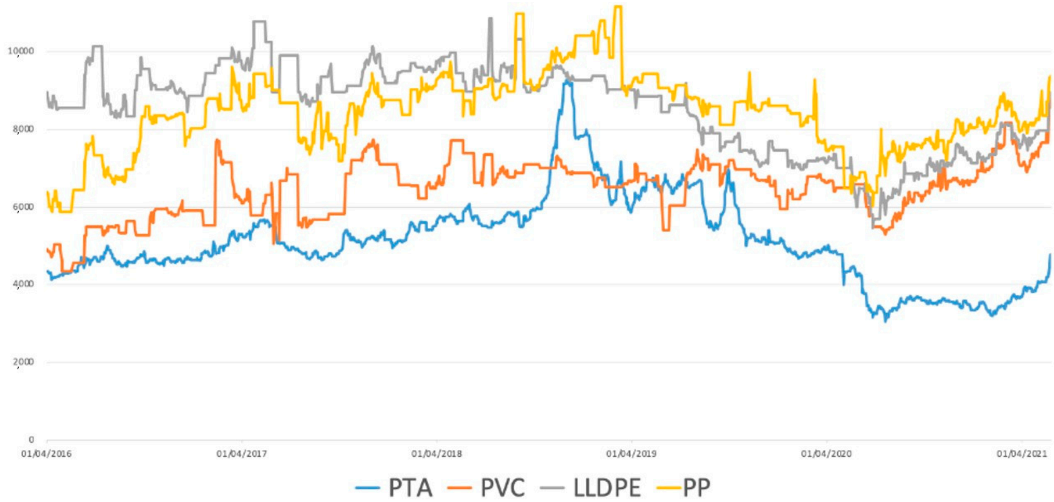

Figure 1. Run chart (C) of PTA, PVC, LLDPE, and PP futures prices. Notes: The four independent variables of futures contracts were the daily closing price in the petrochemical industry from the Wind database. (1) PTA futures as quoted in China's Zhengzhou Commodity Exchange (2) PVC, (3) LLDPE, and (4) PP futures as quoted in the Dalian Commodity Exchange.

The GARCH-MIDAS model was used to describe the contagions of the four independent variables of Chinese petrochemical markets on WTI futures. It seems the co-movement among PTA, PVC, LLDPE, and PP of the leading index in Figure 1. This study found spillover evidence of four leading indexes from the Chinese petrochemical to oil market. Global investment institutions sometimes ignored those four leading indices perhaps due to the data source from different Commodity Exchange in varied provinces of China. Each source of data was described in the notes of Figure 1.

4.2. Descriptive Statistics

I used R version 3.2.0 software to obtain descriptive statistics for all variables in the sample, as detailed in Table 1. The BDI, BDTI, BCTI, and PTA data exhibited right-tailed distributions; the other variables exhibited left-tailed distributions. The minimum recorded WTI value was −37.63, occurring on 20 April 2020.

Table 1. Descriptive analysis.

	Mean	**Median**	**Sd**	**Skew**	**Kurt**	**ADF**	**PP**	**JB**
WTI	−0.004	0.003	0.129	−19.452	442.537	−41.441 ***	−41.565 ***	5,889,872 ***
BDI	−0.018	0.019	0.361	0.828	6.341	−17.902 ***	−17.897 ***	420.56 ***
BDTI	0.003	0.010	0.245	0.016	4.760	−22.461 ***	−23.189 ***	93.736 ***
BCTI	0.005	0.088	0.321	−1.210	7.129	−21.795 ***	−22.517 ***	692.84 ***
PTA	0.008	0.027	0.086	−0.750	3.929	−32.652 ***	−32.988 ***	94.207 ***
PVC	0.000	−0.004	0.093	0.564	4.357	−36.543 ***	−36.534 ***	55.738 ***
PP	−0.001	−0.006	0.069	0.009	3.264	−37.135 ***	−37.170 ***	40.587 ***
LLDPE	0.003	−0.009	0.067	0.318	3.151	−36.829 ***	−36.851 ***	12.915 ***

Notes: This table reports the mean, median, standard deviation (Sd), skewness (Skew), kurtosis (Kurt), and test statistics of the Augmented Dickey–Fuller (ADF), Phillips–Perron (PP), and Jarque–Bera (JB) normality tests, respectively. *** denotes 1% significant level.

The descriptive analysis of relevant tests is made below. A positive value for kurtosis indicates a distribution more peaked than normal. Analogous to skewness, the general guideline is that if the kurtosis is greater than 2, the distribution is too peaked. Both skew and kurtosis can be analyzed through descriptive statistics. Acceptable values of Kurtosis are appropriate from a range of −10 to +10 when utilizing the GARCH model. High Kurtosis in the WTI dataset is an indicator that data has heavy tails or outliers. Because the COVID-19 pandemic triggered an unprecedented demand shock in the oil industry, leading to a collapse in oil prices. The May 2020 contract futures for WTI plummeted from USD 18 a barrel to around USD −37 a barrel. But WTI recovered and finished 2020 at a price of USD 49 per barrel, the extremely low and negative peak of WTI was a temporary phenomenon in oil history. If there is a high Kurtosis, past studies in Energy Economics suggest choosing the GARCH model instead of the VAR model without implementing the Bootstrap Method which is able to resample a single dataset to create many simulated samples. The correlation analysis and the VIF test are detailed in Table A1 of Appendix A for verifying the collinearity and avoidance of dependence among the indices.

4.3. Stationarity and Unit Root Test

The stationarity test of the independent and dependent variables followed the same process as in previous research [39]. To analyze the volatility contagion and to determine whether the variables were stationary, we used the Augmented Dickey–Fuller (ADF), PP, and KPSS tests, respectively (Table 2). Therefore, testing whether the data were stationary was necessary before analyzing the time series data. If not, the data would be different until stationary characteristics were exhibited.

Table 2. The results of unit root analysis by the ADF and PP test (lag = 6).

Variables/Test	ADF	PP	KPSS
ΔWTI	−41.441 ***	−41.565 ***	0.182
ΔBDI	−17.902 ***	−17.897 ***	−36.851 ***
ΔBDTI	−22.461 ***	0.533 **	0.136
ΔBCTI	−21.795 ***	−23.189 ***	0.644 **
ΔPTA	−32.652 ***	−22.517 ***	0.447 *
ΔPVC	−36.543 ***	−32.988 ***	0.379 **
ΔLLDPE	−37.135 ***	−36.534 ***	0.24
ΔPP	−36.829 ***	−37.170 ***	0.296

Note: ΔN represents the return of variables in the ADF, PP, and KPSS test. *** denotes 1% significant level, ** denotes 5% significant level, and * denotes 10% significant level.

The numbers in the table are the results of the returns of the variables in the ADF, PP, and KPSS Tests, and ΔN represents the return of variables. After the collection of data and before using the GARCH-MIDAS model in further empirical analysis, we must determine whether the data are stationary. Steady-state data indicate that the impact of an exogenous shock lasts only over the short term. If the time series data are nonstationary data, the data must be made stationary by using the difference method.

4.4. Research Hypotheses

This literature-based study reviewed the impact of the petrochemical industries and shipping industries on the oil market. However, literature exploring the volatility contagion from plastic commodities futures and shipping freight indexes on oil prices is scant. Thus, I proposed hypotheses to determine the volatility spillover from Chinese plastic commodity futures in the petrochemical industry and Baltic shipping indexes into the global shipping industry; I tested that spillover by using a two-subsample division based on distinct time periods. Therefore, to verify the influence of the seven selected indices (pertaining to two key industries) on WTI futures before and after the commencement of the trade war, I developed the following hypotheses:

H1. *No volatility contagion would have been transmitted from the Baltic shipping industries (BDI, BDTI, and BCTI) to oil market returns (WTI) before the trade war.*

H2. *No volatility contagion would be transmitted from the Baltic shipping industries (BDI, BDTI, and BCTI) to oil market returns (WTI) after the trade war's commencement.*

H3. *No volatility contagion would have been transmitted from the Chinese petrochemical industry (PTA, PVC, LLDPE, and PP futures) to oil market returns (WTI) before the trade war.*

H4. *No volatility contagion would be transmitted from the Chinese petrochemical industry (PTA, PVC, LLDPE, and PP futures) to oil market returns (WTI) after the commencement of the trade war.*

5. Empirical Results of GARCH-MIDAS

5.1. Results before the US-China Trade War

The results of the GARCH-MIDAS-based empirical analysis of WTI futures before and after the US–China trade war are presented in Tables 3 and 4.

Table 3. Results of GARCH-MIDAS model for WTI before the U.S.–China trade war (K = 24).

Variable	M	α	β	m	θ	ω_2	BIC
BDI	0.166 (0.189)	0.000 (0.120)	0.360 (0.243)	−1.269 (1.416)	0.083 (0.064)	5.334 *** (1.046)	260.488
BDTI	0.180 (0.180)	0.000 (0.144)	0.350 (0.287)	−0.388 (0.709)	0.064 (0.048)	5.290 *** (1.148)	264.304
BCTI	0.133 (0.206)	0.000 (0.152)	0.964 *** (0.077)	0.262 (15.113)	−0.051 (0.472)	3.161 (12.077)	265.751
PTA	0.170 (0.189)	0.000 (0.169)	0.351 (0.283)	3.274 (2.743)	−0.589 (0.579)	11.461 ** (5.163)	264.210
PVC	0.134 (0.175)	0.000 (0.118)	0.980 *** (0.070)	0.303 (6.203)	−0.054 (0.200)	3.644 *** (0.165)	264.351
LLDPE	0.202 (0.138)	0.000 (0.101)	0.799 *** (0.112)	7.797 *** (2.693)	−0.805 *** (0.292)	1.697 *** (0.471)	260.453
PP	0.175 (0.185)	0.000 (0.100)	0.330 (0.267)	0.713 (0.839)	−0.008 (0.044)	1.000 (2.616)	266.811

Note: The maximum lag period was set to 2 MIDAS years (K = 24). The figures in the table are the estimated values of the model parameters for the explanatory variables, and the standard error HAC is written in parentheses. *** denotes 1% significant level, ** denotes 5% significant level.

I analyzed the long- and short-term components of WTI based on the monthly volatility of the petrochemical industry in China. The results indicate that the coefficients (θ) of all variables were nonsignificant except that of LLDPE (Table 3).

For LLDPE, the mean return (7.797) is significant. The estimate of α (0.0000) is nonsignificant, but the estimate of GARCH β (0.799) is significant. The sum of α and GARCH β is less than one, which confirms the covariance stationarity. Moreover, long-term volatility is associated with decreased short-term volatility persistence. The estimated coefficient θ (-0.805) is significant, indicating that the monthly volatility of LLDPE significantly affected the daily WTI futures returns before the US–China trade war. The results also suggest that the daily WTI futures returns were significantly influenced by the LLDPE monthly volatility during the past 24 months. Thus, H3 is partially rejected, implying that only one volatility contagion from the Chinese LLDPE market on the WTI oil returns occurred in the analysis period before the US–China trade war. Because the model's weighting scale converged to approximately 0, model stability (i.e., when K = 24) was optimized according to the approach proposed by Conrad et al. [43].

Table 4. Results of the GARCH-MIDAS model for WTI after the U.S.–China trade war (K = 24).

	M	**α**	**β**	**m**	**θ**	**ω_2**	**BIC**
BDI	0.279 ** (0.113)	0.080 (0.067)	0.878 *** (0.029)	8.568 *** (2.474)	−0.117 *** (0.037)	1.784 *** (0.281)	1419.643
BDTI	0.251 ** (0.107)	0.091 *** (0.003)	0.894 *** (0.003)	1.803 *** (0.236)	0.008 *** (0.002)	3.140 ** (3.705)	1415.199
BCTI	0.268 ** (0.114)	0.052 * (0.027)	0.913 *** (0.025)	5.864 *** (1.390)	−0.069 *** (0.025)	1.078 *** (0.370)	1403.580
PTA	0.272 ** (0.124)	0.041 (0.026)	0.929 *** (0.031)	0.395 (0.468)	0.108 *** (0.028)	21.491 *** (4.494)	1409.485
PVC	0.285 ** (0.111)	0.138 *** (0.000)	0.861 *** (0.0006)	−5.206 (1.925)	0.852 ** (0.338)	2.810 *** (0.968)	1410.148
LLDPE	0.254 ** (0.115)	0.147 *** (0.0006)	0.850 *** (0.000)	−4.393 (3.416)	0.783 *** (0.290)	1.000 *** (0.168)	1416.732
PP	0.261 ** (0.120)	0.144 *** (0.0001)	0.856 *** (0.0008)	9.940 *** (2.898)	−0.286 * (0.167)	2.730 * (1.463)	1415.243

Note: The maximum lag period was set to 2 MIDAS years (K = 24). The figures in the table are the estimated values of the model parameters for the explanatory variables, and the standard error HAC is written in parentheses. *** denotes 1% significant level, ** denotes 5% significant level, and * denotes 10% significant level.

For the Baltic shipping industry, all of the coefficient values θ, m, and α are nonsignificant, and only the estimate of GARCH β (0.964) in BCTI is significant, indicating that the monthly volatility of the Baltic shipping industry (in terms of BDI, BCTI, and BDTI data) did not exert a significant impact on the WTI futures daily returns before the US-China trade war. Hence, H1 is supported. No volatility contagion was transmitted from the Baltic shipping industries (BDI, BCTI, and BDTI) to the oil market (WTI futures) during the analysis period before the US–China trade war. Hence, the exogenous shock of financial activity in the global shipping industry was not significant before the key event.

5.2. Results after Commencement of the US–China Trade War

Table 4 shows that the BIC of the GARCH-MIDAS model is less than that of GARCH (1,1), implying that the mixed data sampling version of the GARCH model fits the data better than GARCH (1,1). All of the β parameters are nearly 1 and futures. According to Table 3, the contagion arising from the monthly volatility of the Baltic shipping market to the daily WTI oil returns differed extensively, with all θ and β values significant after the trade war commenced. Additionally, the α of the BDTI (0.091) and BCTI (0.052) indicate significant effects on the daily WTI returns. However, the α of the BDI data (0.091) has a nonsignificant influence on the daily WTI returns. Thus, H2 is rejected, and I conclude that volatility originating from the Baltic shipping industries (BDI, BDTI, and BCT significant at the 1% level, indicating a high degree of volatility persistence in the daily returns of WTI) was transmitted to oil market returns (WTI) after the trade war's commencement. Nevertheless, the BDI results did not suggest any volatility transmission to WTI returns in the long term. The shipping rates of bulk carriers fluctuate greatly, as is evident in the data from BDI; this is reportedly associated with oil demand because 60% of variable costs in transportation are attributed to the cost of oil.

The tests of volatility contagion between the Chinese petrochemical industry and WTI returns are detailed in Table 4.

The significant transmission of contagion from four plastic commodity markets to the oil market (WTI) differed depending on whether the θ comparisons were made before or after the trade war was initiated. The estimated α (0.041) is nonsignificant, whereas the estimated GARCH β (0.929) is significant for the PTA market. This confirms that the PTA results did not influence WTI futures in the long term; the sum of the α and GARCH β is less than 1, which proves the covariance stationarity. Moreover, long-term volatility reduces the persistence of short-term volatility. The estimated coefficient θ (0.4728) of the four markets is significant, indicating that the monthly volatility contagion of PTA, PVC, LLDPE, and PP futures exerted a significant influence on the daily WTI returns that increased after the US-China trade war commenced. Thus, H4 is rejected, and I conclude that volatility contagion was transmitted from the Chinese petrochemical industry (PTA, PVC, LLDPE, and PP futures) to oil market returns (WTI) after the US-China trade war's commencement. In addition, strong short-term volatility persistence between the seven variables and WTI returns was noted, with the β at the 1% significance level.

5.3. Results after the US–China Trade War Extended to the Ukrainian–Russian War

These results extended to Ukrainian–Russian War, revealing that PTA and PP had no significant spillover effects on WTI. Because the shocks had switched from China to Ukraine–Russia war, the impact on Chinese petrochemical markets became weakened than US–China trade war. Meanwhile, The BCTI had no significant spillover effect on WTI, since the problems of port congestions and COVID-19 had been solved. The freight from the shipment of clean oil did not influence the WTI at all. Only BDTI still affects the WTI directly due to the demand for crude oil cannot find another substitution. But the demand for clean oil can be substituted by a Circular Economy and renewable energy.

The results after US-China war had extended to Ukrainian-Russian War from 2 December 2019 to 31 August 2022 in Table 5. According to Table 5, the spillover being contagious from the monthly volatility of the Baltic shipping market to the daily WTI oil returns fluctuated expansively, with all θ of BDI, BDTI, PVC, and LLDPE significant after the trade war extended to the Ukrainian–Russian War. Furthermore, the α of the BDI (2.310) and BDTI (2.655) indicate significant effects on the daily WTI. However, the α of the two global shipping indexes has a significant impact on the daily WTI. Thus, I conclude that volatility initiated by the Baltic shipping industries (BDI and BDT) was transmitted to WTI after the extended war. This is supposedly connected with oil demand due to the majority of transportation costs are attributed to the expense of oil. The tests of volatility contagion between the global shipping industry and WTI returns are detailed in Table 5.

Table 5. Results of the GARCH-MIDAS model WTI during the Ukrainian–Russian War (K = 24). Period: 2 December 2019–31 August 2022.

Variable	M	α	B	m	θ	ω_2	BIC
BDI	−0.001 (0.003)	0.000 (0.099)	0.483 (0.656)	−6.906 *** (0.128)	2.310 *** (0.422)	217.363 *** (28.467)	274.477
BDTI	0.005 ** (0.002)	0.000 (0.035)	0.968 *** (0.042)	−7.047 *** (0.229)	2.655 ** (1.147)	45.263 (38.276)	1118.216
BCTI	0.002 (0.002)	0.338 *** (0.011)	0.661 *** (0.012)	−2.727 (1.811)	16,216 (13.375)	1.319 ** (0.530)	642.168
PTA	0.002 (0.002)	0.347 *** (0.072)	0.652 *** (0.073)	−3.031 (2.341)	28.049 (26.240)	1.000 *** (0.286)	2167.535
PVC	0.003 (0.002)	0.137 ** (0.063)	0.844 *** (0.053)	−6.529 *** (0.812)	−5.928 ** (3.003)	274.160 *** (20.564)	2187.396
LLDPE	0.004 (0.002)	0.149 * (0.090)	0.826 *** (0.062)	−6.413 *** (1.361)	−11.652 ** (5.244)	223.870 *** (76.000)	2579.454
PP	0.003 (0.002)	0.175 *** (0.067)	0.810 *** (0.061)	−5.910 *** (0.962)	−112.156 (95.244)	2.644 *** (0.661)	2606.940

Note: The maximum lag period was set to 2 MIDAS years (K = 24). The figures in the table are the estimated values of the model parameters for the explanatory variables, and the standard error HAC is written in parentheses. *** denotes 1% significant level, ** denotes 5% significant level, and * denotes 10% significant level.

The transmission of contagion from two plastic commodity markets to WTI persisted significantly after the extended war. The estimated coefficient θ of PVC (0.4728) and LLDPE

(−11.652) of the two plastic markets is significant, indicating that the monthly volatility transmission of PVC and LLDPE futures wielded a significant impact on the daily WTI that increased after the extended war. Thus, I conclude that volatility transmission from the Chinese petrochemical industry (PVC and LLDPE) to WTI after the extended war. Moreover, strong short-term volatility persistence between those five variables (BCTI, PTA, PVC, LLDPE, and PP) returns was proved, with the α at the 1% significance level. It seems those five variables had short-term influences from the news and emotional side. The β of all variables at the 1% significance level seemed those seven variables had long-term influences from co-movement of the spillover effect.

6. Conclusions

6.1. Findings of Empirical Results

In summary, the leading indexes from the Baltic shipping and Chinese petrochemical industries transmitted significant volatility to WTI futures after the trade war began in 2018 (Table 5). No indexes pertaining to the Baltic shipping or Chinese petrochemical industries transmitted significant volatility to WTI futures before the trade war except that of LLDPE futures. However, using the GARCH-MIDAS model, I discovered that the volatility contagion of these two industries' submarkets increased after the trade war was initiated and has continued through the COVID-19 era. The BDI, BDTI, and BCTI from the global shipping industry have all exerted significant volatility contagion on WTI futures since the trade war began. Table 6 compares the respective volatility transmission effects of the BDI, BDTI, BCTI, PTA, PVC, LLDPE, and PP futures on WTI oil returns.

Table 6. Comparison of volatility contagion from Baltic shipping and petrochemical industries to WTI futures.

	WTI		
	Before the U.S.-China Trade War (K = 24)	**After the U.S.-China Trade War Extended to COVID-19 (K = 24)**	**Extended to Ukraine-Russia War (K = 24)**
BDI	Insignificant	Significant ***	Significant ***
BDTI	Insignificant	Significant **	Significant **
BCTI	Insignificant	Significant ***	Insignificant
PTA	Insignificant	Significant ***	Insignificant
PVC	Insignificant	Significant ***	Significant **
LLDPE	Significant ***	Significant ***	Significant **
PP	Insignificant	Significant *	Insignificant

*** denotes 1% significant level, ** denotes 5% significant level, and * denotes 10% significant level.

Previous studies have shown that the BDI can predict oil prices because bulk shipping rates reflect economic activity earlier than other financial markets, including the oil market [44,45]. Ji and Fan [46] observed that the crude oil price transmitted significant volatility to nonenergy commodity markets such as the bulk shipping market. However, in this study, H2 was supported based on the adverse contagion from the BDI, BDTI, and BCTI to WTI futures after the US-China trade war commenced.

This study also discovered that the volatility contagion from the Chinese petrochemical industry to WTI futures was significant after the trade war began, a finding as the research gap seldom demonstrated by the comparisons of previous academic studies that have shown only weak correlations between the plastic commodity markets and oil prices during economic crises. Mansur M. et al. [1] discussed the price dynamics between regional ethylene markets and crude oil. Co-movement such as directional spillover between the Chinese petrochemical industry and the oil market is affected by the degree of demand in the oil-importing country, which is mainly determined by the supply chain upstream and downstream of the oil industry; this warrants further interesting research.

A comparison of the coefficients of volatility between Tables 3 and 4 indicates that the α of the BDTI and BCTI is significant, but that of the BDI is nonsignificant. This indicates that the leading indexes of the tanker shipping market are superior predictors of arbitraging trade than the BDI during chaos. Furthermore, the α of all variables was nonsignificant before the US-China war, meaning that the seven variables related to the Baltic shipping and Chinese petrochemical industries except LLDPE did not transmit volatility to WTI futures in the long term before the US-China trade war. By contrast, all of the tanker shipping and petrochemical indexes (except PTA) exerted long-term volatility transmission to WTI futures after the trade war commenced. Before the trade war, the β of the BCTI, PVC, and LLDPE was significant, but that of the BDI, BDTI, PTA, and PP is nonsignificant. For the purpose of arbitraging by short-term news, the freight index of clean oil tankers (BCTI) transmitted only shorter-term volatility, unlike the others in the shipping market. After the trade war's commencement, all variables were superior predictors of short-term volatility for hedging than they were before.

6.2. Practical Implications and Discussions

Our findings are potentially attributable to the fact that before the trade war began, the global shipping markets and WTI fluctuated steadily, with low volatility. Moreover, the volatility contagions from the Baltic shipping and Chinese petrochemical industries to the energy market were nonsignificant. However, the trade war's commencement in March 2018 signified a major economic disturbance. The demand in the petrochemical supply chain for oil decreased in China, and the COVID-19 pandemic triggered price competition between the recycled and new plastic industries. The new plastic commodity industry has necessitated substantial crude oil imports by global shipping services. It is a key time to hedge the petrochemical and oil prices. Economic slowdowns caused by COVID-19 lockdowns in Chinese cities and foreign countries have markedly reduced oil demand, thereby reducing the price of new plastic. China, which used to import over half the world's traded plastic waste, banned imports of most plastic in 2018. At that time, the trade war also commenced. Chinese plastic products exported to the US were adversely affected by US-imposed tariffs. Variable demand and supply shocks affected WTI futures. The key indices of four plastic commodity markets declined due to the downturn in China's economy, which is the world's major oil-importing country. The ensuing volatility of the PVC, LLDPE, PTA, and PP futures from the Chinese petrochemical industry transmitted significant volatility to oil market demand, emphasizing the need to understand the drivers of WTI price volatility from the Chinese petrochemical industry in times of economic turmoil. The principles of investment were suggested to buy the WTI futures according to the five leading indices of the above-mentioned commodities earlier. Every crisis and economic event for example the Subprime crisis (2008), the Greek government's bonds (2012), the crude oil price plunging from USD 100 to USD 60 per barrel (2014–2016), etc. had their different shocks to specific markets. Investors had better search out the possibilities of predicting critical variables and profiting from arbitrage in each turmoil. This study rarely found the four Chinese petrochemical commodities as the leading index on the WTI during the extended period of the US–China trade war. Those who need to rely on the stability of crude oil prices shall arbitrage and hedge the cost of WTI according to the time-lag effect and direction of co-movement of the critical leading index. Before the price of oil is adjusted to the point of equilibrium, enterprises are able to purchase the derivatives of oil in advance for arbitraging the gain of trade and hedging the limited risk.

Regarding practical implications, firstly, this study examined volatility contagion across and within intra-industrial segments among shipping freight and petrochemical markets to WTI. The results revealed that large volatility spillovers across Chinese Petrochemical markets became more distinct during and after the US–China war. Those traders who utilized the four-leading index of Chinese petrochemical markets to arbitrage and hedge the oil price will take advantage of this war by that intangible information in the domestic exchange bureau. The volume and price of local trade in Chinese petrochemical markets will be information-leaking and contagious to global financial markets. Those who trigger the arbitrage in advance before the other traders will win the gain in this Turmoil. Secondly, significant volatility was transmitted from the Baltic shipping markets to WTI futures, as indicated by the volatility contagion of the BDTI and BCTI (insignificant before the trade war and the Ukraine–Russia war) to WTI futures noted in this study. Congestion at China's east coast oil ports increases costs for shipping enterprises. Bad news from the tanker shipping markets, such as reports of how many million barrels of crude oil were waiting to be discharged from Chinese ports, caused the oil price fluctuations. Thirdly, because of the volatility contagion demonstrated in this paper, investors in the banking industry and fund managers of asset management companies can use the three leading indexes from the Baltic shipping industry submarkets to predict fluctuations in oil futures. Hence, the effect of these leading bulk shipping indexes of various tanker vessels on oil prices should be further verified by future research. Fourthly, because of the lagged effect of the BDI, BDTI, BCTI, PTA, PVC, PP, and LLDPE markets on WTI futures, institutional investors in the future trading industry and financial managers in energy companies can profit through arbitrage. Fifthly, the volatility contagions of PVC, LLDPE, PTA, and PP futures to the WTI futures were transmitted more often after the trade war. These phenomena were more noticeable when the two principal actors, the United States and China, engaged in a political conflict. The fluctuations in the demand and supply of the petrochemical industry due to the trade war caused shocks that affected oil prices significantly; these were influenced by the four plastic commodity markets. Consequently, these markets diffused unpredictable volatility contagion to the WTI futures in the period leading into the COVID-19 era.

Other implications of management and policy warrant discussion below. Sixthly, the governments of various countries had better learn from China's futures regulatory authorities to establish tradable futures commodities for the upstream, midstream, and downstream products of the petrochemical industry. These findings encourage market stakeholders to observe the volatility spillover of the petrochemical supply chain on the arbitrage of oil derivatives. In addition, the futures of petrochemical products in the vertical supply chain can be bought and sold to hedge oil price fluctuations. Seventhly, I suggest that key petrochemical producers monitor bulk shipping indicators, such as the BCTI, BDTI, and BDI, to predict the directional movements of oil price fluctuations. Eighthly, The MNC should monitor every intervention in advance (e.g., the measures announced by President Biden on 13 October 2021) when the bulk shipping indicators sharply increase to avoid the high freight and oil prices caused by port congestion.

The present study has some limitations. First, in this study, the differences in the leading factors of oil price spillover before versus after the US-China trade war were analyzed, but this did not constitute a sufficiently long study period and may thus not provide a complete picture of oil price volatility contagion. Future studies should analyze a longer period to verify whether our findings hold in the long term and whether markets stabilize over time.

Thus, our findings reflect outlier phenomena affected by the US-China trade war that extended into the COVID-19 pandemic period. Because not all oil price shocks are similar, the phenomena observed in this study are unlikely to play out again in the oil market. In the second limitation, an econometric method like regression or panel with fixed effect estimation or random effect estimation is still waiting for other scholars to test by same frequency data. Because regression or cointegration is not specialized in inter-market research for testing the spillover effect during the chaos of crisis or war, past studies demonstrated only weak correlations among variables of each market.

Future studies should investigate the following. First, studies should investigate differences in oil prices (e.g., Brent and WTI prices) between various cities or regions, such as Daqing, Cintas, Dubai, Minas, Oman, Tapis, and Duri, during different periods of crisis. Second, studies should investigate the spillover of the network effect of volatility contagion on various oil price indexes in different regions. As mentioned, Brent price was affected by contagion from the WTI in 2008, whereas the opposite situation was the case in 2015 [32]. In future research, the network effect of volatility contagion will be a gap among distinct oil price indices from various regions and thus identify the leading index and the consequence of interaction, which are crucial in the network, especially during the COVID-19 pandemic extended to new events.

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Appendix A

The correlation analysis and the VIF test are very important in this research for verifying the collinearity and avoidance of dependence among the indices. When each variable is independent, the value of VIF becomes 1. The bigger value of VIF indicates the higher possibility of collinearity. The VIF (4.43990) of PP and LLDPE reveal a higher possibility of collinearity, but it's not terrible due to a VIF of less than 10. According to Table A1 in the Appendix A, the other variables are approaching 1. It discloses a low correlation among each variable. For example, the spillover effect between PP and LLDPE is different during the USA–China war and the Ukraine–Russia war.

Table A1. The correlation analysis and the VIF test.

	WTI	BDI	BDTI	BCTI	PTA	PP	PVC	LLDPE
WTI	Infinite	1.000003	1.000017	1.016676	1.002712	1.004539	1.001010	1.000668
BDI	1.000003	Infinite	1.003605	1.012390	1.000342	1.022479	1.034121	1.005752
BDTI	1.000017	1.003605	Infinite	1.495456	1.023608	1.013466	1.089766	1.024890
BCTI	1.016676	1.012390	1.495456	Infinite	1.023130	1.004730	1.092122	1.010473
PTA	1.002712	1.000342	1.023608	1.023130	Infinite	1.223917	1.147003	1.293724
PP	1.004539	1.022479	1.013466	1.004730	1.223917	Infinite	1.777048	4.433990
PVC	1.001010	1.034121	1.089766	1.092122	1.147003	1.777048	Infinite	1.854945
LLDPE	1.000668	1.005752	1.024890	1.010473	1.293724	4.433990	1.854945	Infinite

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