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Volatility Transmission from Equity, Bulk Shipping, and Commodity Markets to Oil ETF and Energy Fund—A GARCH-MIDAS Model

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Abstract: Oil continues to be a major source of world energy, but oil prices and funds have experienced high volatility over the last decade. This study applies the generalized autoregressive conditional heteroskedasticity-mixed-data sampling (GARCH-MIDAS) model on data spanning 1 July 2014 to 30 April 2020 to examine volatility transmission from the equity, bulk shipping, commodity, currency, and crude oil markets to the United States Oil Fund (USO) and BlackRock World Energy Fund A2 (BGF). By dividing the sample into two subsamples, we find a significant volatility transmission from the equity market to the oil ETF and energy fund both before and after the 2018 U.S.–China trade war. The volatility transmission from the bulk shipping, commodity, and crude oil markets turns significant for the oil ETF and energy fund after the 2018 U.S.–China trade war, extending into the COVID-19 pandemic in early 2020. The results suggest that investors can use the equity market to predict the movement of oil and energy funds during both tranquil and turmoil periods. Moreover, investors can use bulk shipping, commodity, and crude oil markets in addition to the equity market to forecast oil and energy funds' volatility during the turmoil periods. This paper benefits investors against the high volatility of the energy funds.

Keywords: oil industry; oil ETF; energy mutual fund; volatility transmission; contagion; GARCH-MIDAS model; U.S.–China trade war; commodities

1. Introduction

Crude oil is a major source of energy in the world, accounting for approximately 32% of global energy needs in 2018, according to the International Energy Agency [1]. IEA further projects that crude oil will continue to supply 30% of the world's energy by 2030 [2]. Moreover, crude oil is the most important commodity in the world, with a weight above 50% in the general commodity index. Nearly all nations around the world spend more money on oil than they do on all other commodities, such as gold, iron ore, and coal [3].

Given the importance of crude oil, oil prices exert a strong influence on many other commodities and the financial markets. The impact stems from the fact that oil has been extensively used as the main propeller in the production process for petrochemicals, vehicles, aviation, and shipping [2]. In addition, oil directly influences the economies of oil-importing and -exporting countries. For example, the U.S. was the sixth biggest oil-exporting country in 2019 [4]. On the other hand, China was the largest crude oil-importing nation in the same year, creating high demand for oil [5]. More importantly, the relationship between the two countries may impact the price of oil [6]. Therefore, understanding oil price movements with a consideration of the U.S. and China may provide further insights into the oil market.

Many investors desire to add oil in some form of a financial product to their investment portfolios, simply because oil is one of the world's largest industries [7]. However, selecting the right oil stocks can be difficult due to the sector's volatility and complexity. Therefore, investors can choose to participate in the oil market through exchange-traded funds (ETFs) or mutual funds as an investment strategy rather than choosing a particular stock of an oil company [7,8]. However, the risk and uncertainties associated with oil price volatility usually affect investors and fund managers who seek to maximize investors' returns [9].

The United States Oil Fund (USO) is the largest and most traded oil ETF denominated in USD, with an asset value of over USD 4.7 billion as of July 2020. USO tracks the West Texas Intermediate (WTI) crude oil futures contract delivered to Cushing, Oklahoma [10].

Another popular way for investors to participate in the oil market is to buy equity energy mutual funds. Investors may benefit from the knowledge and experience of mutual fund managers who decide when to buy and sell energy stocks to maximize returns [8]. The BlackRock World Energy Fund (BGF), denominated in USD, is the largest energy mutual fund in the world as of 2020. BGF invests in equity securities of companies with their primary business activities in the exploration, development, production, and distribution of energy. Over 80% of BGF is invested in listed companies of the oil industry. BGF's size reached USD 1.775 billion in May 2020 [11].

Oil prices have experienced a high level of volatility over the last decade. Their large fluctuations have affected the oil ETFs and energy mutual funds. For example, the price of USO plunged by nearly 80% from USD 101.04 in December 2019 to USD 20.56 in April 2020. The value of BGF dropped by 38% from USD 15.66 in December 2019 to USD 9.76 in April 2020 [12]. Figure 1 shows the value of USO denominated in USD from 10 April 2006 to 10 April 2020.

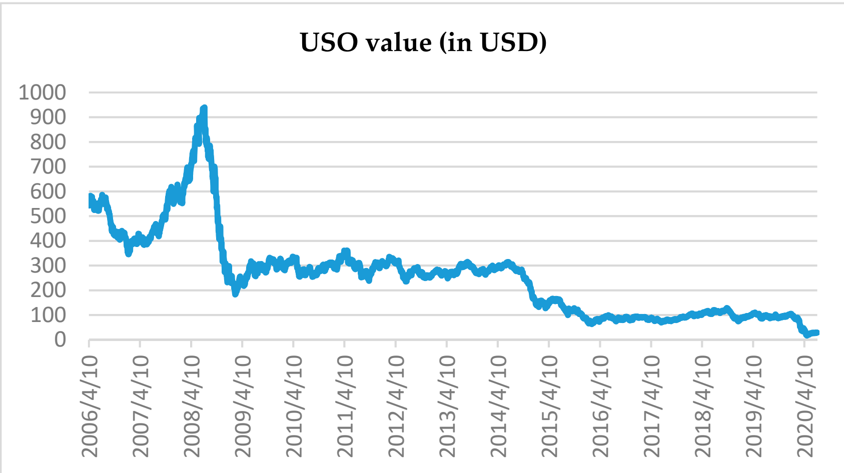

Figure 1. The price of the United States Oil Fund (USO) from 10 April 2006 to 10 April 2020.

The high volatility of USO and BGF leads to a question of volatility transmission, because financial markets around the world have become increasingly connected due to globalization [13]. Volatility transmission is also known as volatility spillover or volatility contagion [13]. Forbes and Rigobon [14] defined financial contagion as a significant increase in cross-market linkages after a shock to one market or a group of markets. The spread of financial disturbances can therefore be traced by the correlations among financial markets [15]. In addition, prior studies found that volatility transmission becomes more pronounced during a financial crisis [8,9,15,16]. Nazlioglu [17] argued that understanding the direction of volatility transmission from one financial market to another is critical for diversifying long-term portfolios and hedging strategies.

Prior studies suggested that cross-market correlation volatility during a financial crisis is heightened [13,15,18]. We used the U.S.–China trade war as the significant economic event in this study. The U.S. and China are large oil-exporting and oil-importing countries, respectively [4,5]. The trade war broke out between the U.S. and China in 2018, with the implementation of tariffs by the U.S. on Chinese products leading to lower sales and employment in China. As a result, consumption in China dropped, causing demand for oil to fall. The lower demand for oil has caused its price to remain low [19].

The extant literature focused mainly on the relationship between crude oil prices and the equity markets [20–24]. Scant literature has investigated the direction and intensity of volatility transmissions from related financial markets, such as equity, bulk shipping, commodities, currency, and crude oil, to oil ETFs and mutual funds. This paper fills the gap by investigating the causal relationship between five financial markets and oil ETF and one energy mutual fund.

The purpose of the study is to investigate the volatility transmission from the equity, bulk shipping, commodity, currency, and crude oil markets to USO and BGF. We applied the generalized autoregressive conditional heteroskedasticity–mixed-data sampling (GARCH-MIDAS) model proposed by Engle et al. [25] on data spanning July 2014 to April 2020. The data are separated into two subsamples, with the U.S.–China trade war inception date as the breakpoint. The advantage of the GARCH-MIDAS model is that it can combine high-frequency data, such as the daily value of oil ETF, with low-frequency data, such as the monthly crude oil price.

The results of this study indicate that the equity market has a significant volatility transmission effect on USO and BGF both before and during the U.S.–China trade war. The bulk shipping, commodity, and crude oil markets have a significant volatility transmission effect on USO and BGF only after the U.S.–China trade war began. The results help investors and fund managers execute hedging strategies to avoid possible losses from the oil ETF and energy mutual funds, in case of downward movements in related financial markets.

This paper contributes to the literature in three ways. First, we are the first to combine the daily values of an oil ETF and an energy mutual fund and the monthly data of equity, bulk shipping, commodity, currency, and crude oil markets using the GARCH-MIDAS model, which can distinguish the long-term and short-term components of the oil ETF and energy fund volatility. Second, this study is the first to analyze the volatility transmission effect on the largest oil ETF and energy mutual fund. Third, this study scrutinizes the volatility transmission effect before and after the breakout of the U.S.–China trade war in 2018. The results of this study benefit individual, institutional investors, and mutual fund managers in predicting the movements of the oil ETF and energy mutual fund.

The remainder of this paper is organized as follows. Section 2 provides a review of the related literature. Section 3 describes the samples and methodology. Section 4 includes the empirical results. Section 5 discusses the results and implications. Section 6 concludes the paper.

2. Literature Review

Commodities have become increasingly important over the last decade in financial markets. Among them, oil has received more attention because it has a weight of 50% in the general commodity index [26]. Oil has economic significance for three reasons. First, oil has remained the largest source of world energy, accounting for over 30% of world energy supply for the last decade [1]. The International Energy Agency [2] projects that oil will continue to provide 30% of global energy by 2030, despite the rapid development of renewable energy [2,21]. Second, oil prices affect consumers and producers. When oil prices rise, the consumers are affected by the higher prices on final goods and services. Lower demand then challenges the oil producers that are faced with shrinking profits. However, oil-exporting companies generate higher profits due to rising oil prices, and thus, their stock prices increase [20]. Third, crude oil and its related financial products, such as the stock prices of oil companies, futures, forward prices, oil ETFs, and energy mutual funds, are traded extensively in international financial markets [27]. Therefore, the risk and uncertainties associated with oil price volatility usually affect investors' portfolios. Similarly, portfolio managers who seek to maximize investors' returns track the movements of oil price carefully [9,20].

2.1. Oil ETF and Energy Mutual Fund

With the growth of commodity markets, an increasing number of investors are engaging in global trading strategies, adding commodities such as oil to their portfolios to achieve optimal risk diversification [28]. USO is the largest crude oil ETF traded on the New York Stock Exchange (NYSE). Established on 10 April 2006, USO seeks to provide investors with easy access to the oil market. USO holds the near-month WTI futures and tracks their daily price changes in US dollars. WTI futures are the most liquid energy futures contracts, with an average daily volume of nearly 1.1 million to 2 million contracts written [10,26]. WTI refers to oil extracted from wells in the U.S. and sent via pipeline to Cushing, Oklahoma. WTI is sweet because it contains 0.24% sulfur and is light (low density), which makes it ideal for the refining of gasoline. WTI is also considered the benchmark for oil prices [29]. Currently, Victoria Bay Asset Management compiles the index and manages USO, with its asset value reaching USD 3.489 billion as of 30 April 2020 [30].

Mutual funds play a crucial role in the global financial markets. A large population utilizes mutual funds as their primary investment vehicles, which affect the equity, bond, and commodities markets [31]. Investors can benefit from the knowledge of fund managers and reduce costs through investing in energy mutual funds. Most energy mutual funds hold a substantial amount of stocks in various oil sectors, even though they diversify their holdings for alternative energy [32]. These fund managers prefer companies that operate within the oil industry for their sheer size and revenue. The largest energy mutual fund is BGF. Established on 15 May 2001, BGF has a fund size of USD 1.775 billion as of May 2020. BGF invests at least 70% of its total assets in the equity securities of companies that are involved in the exploration, development, production, and distribution of energy, mainly oil. The top five holdings of BGF are Chevron Corporation, British Petroleum Company plc (BP plc), Royal Dutch Shell plc., Total S.A. Company, and ConocoPhillips [11].

2.2. Volatility Transmission

Both USO and BGF have experienced high volatility over the last decade due to the tremendous change in the price of oil. It changes mainly due to supply oil shocks, demand oil shocks, and oil-specific demand shocks [29,33]. A change in global oil production causes a supply oil shock. An increase in the aggregate demand for all industrial commodities causes a demand oil shock. An increase in the demand for crude oil in response to increased uncertainty about a future oil supply shortfall causes an oil-specific demand shock [34]. The value of USO plunged from USD 312 in June 2014 to USD 71.76 in January 2016, representing a 77% decline. During the same period, the net asset value (NAV) of BGF dropped from USD 28.05 to USD 14.85, signifying a decrease of 47%. Subsequently, the value of USO plummeted from USD 101.04 in December 2019 to USD 20.56 in April 2020, signifying a decrease of 80%. During the same period, the NAV of BGF declined 38% from USD 15.66 to USD 9.76 [12].

The high volatility of oil ETFs and mutual funds has raised the question of volatility transmission. It is beneficial for investors and mutual fund managers to forecast the movements of funds by understanding the way in which volatility is transmitted from financial markets to these funds [35,36]. Zhang and Li [37] claimed that the volatility of financial markets affects investors' portfolios. Zhang and Li [37] further argued that understanding volatility transmission is an essential issue in risk management and portfolio optimization.

Prior studies discussed volatility transmission, which focuses on the pathways through which volatility is transmitted from one financial market to another. Volatility transmission is also known as volatility spillover or volatility contagion [13]. Forbes and Rigobon [14] 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 has a substantial effect on the macroeconomic outcome. Moreover, Guesmi et al. [15] defined contagion effects as an excess of correlations. These authors claimed that when the common source of risk explains co-movements, the portion of risk not explained by the fundamental part is the financial contagion effect. These authors also emphasized that oil plays an important role in financial contagion. In addition, oil price fluctuations amplify volatility transmission in regions that are strongly associated with the U.S. market.

Prior studies discovered that during the global financial crisis in 2008, volatility transmission caused increasing uncertainly across various financial markets, highlighting the importance of gaining a deeper understanding of volatility transmission channels [15,23,38,39]. Arouri et al. [9] claimed that the transmission increased substantially during the financial crisis due to the effects of financial instability and economic uncertainty. Zhang and Wang [39] claimed that the observation of increased intensity in volatility transmission helps investors forecast oil prices.

2.3. Equity and Commodities Markets and Oil

A large body of the literature examined the relationship between oil price and equity markets [9,20–22,40–42]. Mensi et al. [43] studied the volatility transmission between the Standard and Poor's 500 Index (S&P 500) and the commodity markets. The results showed a significant volatility transmission between the oil and stock markets.

Mensi et al. [43] continued to verify the interdependence between oil prices and major stock indices such as S&P 500 and Dow Jones Industrial Average (DJIA). Other studies also identified the return spillover from S&P 500 to WTI [42,44]. Moreover, Zhou et al. [45] evaluated the co-movement between the volatility of the equity market proxied by S&P 500 and the oil market proxied by USO from 2007 to 2016. These authors found a difference between long-term and short-term data. Their results showed that the volatilities of the oil and stock markets become more correlated in long-term (yearly) than in short-term (several days) data. Ewing et al. [8] investigated the volatility transmission between oil prices and emerging market mutual funds using the GARCH model. The results of their study highlighted a significant risk spillover from the energy markets to mutual funds with increased volatility contagion during the 2008 financial crisis.

Prior studies probed into the relationship between oil prices and commodities. Zhou et al. [45] reported an increasing number of investors who participate in the commodities markets, which strengthens the impact of oil price on commodity futures prices. Robe and Wallen [46] found a significant relationship between oil prices and the commodity futures market. Moreover, previous studies scrutinized the connection between commodity futures markets and stock markets. Gorton and Rouwenhorst [47] argued that adding commodities to an equity portfolio improves the risk and return ratios due to the fundamental differences between commodity futures markets with oil being the largest component and equity markets in nature. These authors found a negative correlation between commodities and the stock market. Other studies noted that commodity markets, proxied mostly by the Standard and Poor's Goldman Sachs Commodity Index (S&P GSCI), significantly affect the returns on stock markets [48,49].

The S&P 500 is a major index among the various stock markets in the U.S. SPGSCI is a major index of the commodity market. It tracks the prices of 24 commodities, with oil accounting for over 50% of the index. This index is traded on the Chicago Mercantile Exchange. It was originally developed by Goldman Sachs in 1991. In 2007, the Standard & Poor company acquired ownership of the fund. The fund was thus renamed SPGSCI.

2.4. Bulk Shipping and Oil

The Baltic Dry Index (BDI) tracks the stock prices of shipping companies that transport bulk dry commodities, such as steel, coal, ore, and grain. The shipping rates of the bulk carriers fluctuate greatly, which is captured by BDI [50]. The London-based Baltic Exchange reports the value of BDI on a daily basis. BDI is often regarded as an overall economic indicator.

Previous studies showed that BDI can predict stock exchanges because bulk shipping rates reflect economic activities before other financial markets, including the oil market [46,51,52]. Ji and Fan [53] found that crude oil price has a significant volatility transmission on non-energy commodity markets such as the bulk shipping market. The results also indicated that the correlation strengthened after the 2008 financial crisis. Evidence also reveals a connection between the bulk shipping and commodity markets, because bulk shipping rates move in tandem with commodities in business cycles [54,55]. Lin et al. [56] examined the spillover effect of BDI on the commodity futures, currency, and stock markets by combining trivariate (VAR), Baba, Engle, Draft, and Kroner (BEKK) matrix, and the GARCH model with cross-sectional market volatility (GARCH-X), which is the VAR-BEKK-GARCH-X model, on a dataset from 1 October 2007 to 31 October 2018. The results revealed the spillover effect of the BDI was insignificant during the whole sample period, but significant during the 2008/2009 global financial tsunami, and its influence increased during the 2014–2016 economic slowdown in China. BDI serves as a short-term rather than long-term indicator for the commodity, currency, and equity markets, especially during financial crises.

2.5. Currency and Oil

Oil price is associated with the currency market because the values of the commodities are typically denominated in US dollar [40,45,54,57]. The value of the US dollar is frequently indicated by the U.S. Dollar Index (USDX). USDX measures the exchange of the US dollar in the international foreign exchange market. This index is a weighted geometric mean of the value of the US dollar relative to a basket of six currencies: Euro (EUR) 57.6%, Japanese yen (JPY) 13.6%, British pound (GBP) 11.9%, Swedish krona (SEK) 4.2%, and Swiss franc (CHF) 3.6%.

Prior studies discovered that oil price increases lead to significant appreciation in the US dollar in emerging markets [40,57]. Diebold and Yilmaz [16] studied the connection across stock, bond, currency, and commodity markets. Dimpfa and Peter [28] analyzed the volatility spillover among the oil, stock, gold, and currency markets from 2008 and 2017 using the transfer entropy method. These authors revealed that oil and stock market volatilities are most affected by past volatilities in the currency and commodity markets, especially gold [16,28]. Basher et al. [40] indicated that oil-importing nations experience depreciation in their currencies relative to the US dollar in the long run due to rising oil prices. However, no evidence is found that oil prices respond to exchange rate movements in the short run.

2.6. Crude Oil and Energy Fund

Previous studies found a significant relationship between crude oil price and the NAV of mutual funds, because the energy mutual funds invest in stocks of companies engaged in energy-related activities, with oil being the largest component. Ordu and Soytas [58] found that oil price fluctuations produce a significant effect on energy firms in a direct matter. The rising oil prices increase the profits of the energy-producing firms. Gormus et al. [32] identified a significant impact of crude oil prices on energy mutual funds. In particular, these authors also highlighted that energy mutual funds with better investment performance show higher interactions with the oil markets for both price and volatility [32].

2.7. U.S.–China Trade War

A major economic event that occurred in March 2018 is the trade war between the world's two largest economies, the U.S. and China, which escalated subsequently. From 6 July 2018, the U.S. government officially imposed a 25% tariff on USD 34 billion worth of Chinese exports to the U.S. [59]. Since this time, China has experienced tariff turbulence. The coronavirus disease (COVID-19) breakout during December 2019 further aggravated the economic downturn of China [60,61]. During this period, institutional investors held a negative sentiment toward the U.S. and China equity market [59]. The USO value started as high as USD 104.72 in March 2018, but plunged to USD 19.12 by April 2020, representing a striking decline of 81%.

The U.S. government officially claimed that the trade war was unavoidable due to China's unfair competition strategy. This unfair competition caused lower output, factory closures, and job losses in American industries. To cope with the situation, the U.S. imposed trade tariffs against Chinese products and companies [62]. As the largest oil-importing country in the world, China's demand for oil declined due to the economic downturn caused by the U.S.–China war. The imposition of tariffs by the U.S. on Chinese products lowered sales and employment in China. As a result, China's lower demand for oil due to its economic downturn caused the oil price to fall, thus affecting the value of oil ETFs and energy mutual funds [61].

2.8. Selection of GARCH-MIDAS Model

Prior studies mostly focused on financial contagion between financial markets, and oil prices and financial markets. These studies utilized various versions of the GARCH model to analyze high-frequency data (daily data) with asymmetric contagion. Asymmetric financial contagion refers to the co-movement of two markets in the opposite direction. For example, when one market has positive returns, another market has negative returns.

Bonga-Bonga [23] examined the financial contagion between South Africa and Brazil, Russia, India, and China (BRICS) during 1996–2012. Bonga-Bonga [23] built on the DCC-GARCH model proposed by Engle [63], and applied the GARCH framework with a multivariate vector autoregressive dynamic conditional correlation GARCH (VAR-DCC-GARCH) model to access the correlations of stock returns across financial markets using high-frequency (daily) data. Xu et al. [64] used the asymmetric generalized dynamic conditional correlation (AG-DCC) to investigate the time-varying asymmetric volatility spillover between the oil and stock markets in the U.S. and China from 2007 to 2016. Xu et al. [64] found the existence of asymmetric contagion.

Zhou et al. [45] used the super-efficiency data envelopment analysis (DEA) model to evaluate the performance of the forecasting models for crude oil prices. Dimpfl and Peter [28] analyzed the transmission of volatility between the oil, stock, gold, and currency markets using the transfer entropy method. Basher et al. [40] utilized a structural vector autoregression (SVAR) model to investigate the relationship between oil prices, exchange rates, and emerging stock market prices. Chiang et al. [41] examined the degree to which the equity markets can be explained by oil prices using the capital asset pricing model (CAPM).

Salisu and Oloko [44] studied the spillover effect between the U.S. stock market (S&P 500) and oil market (WTI and Brent crude oil) from 2002 to 2014 and found a significant positive return spillover between the two markets. Salisa and Oloko [44] employed a vector autoregressive moving average–asymmetric generalized conditional heteroscedasticity (VARMA-AGARCH) model, developed by McAleer et al. [65], implemented within the context of a BEKK (Baba, Engle, Kraft, and Kroner over parameterization) framework. The VARMA-BEKK-AGARCH model analyzes the returns and volatility spillovers across markets. Chang et al. [27] applied the diagonal version of the multivariate extension of the univariate GARCH model, namely, the Diagonal BEKK proposed by Engle [66], to analyze the conditional correlations, conditional covariances, and co-volatility spillovers between international crude oil (WTI and Brent) and financial markets from 1988 to 2016. Similarly, Mensi et al. [43] used the VAR-GARCH model to detect the volatility spillover between markets. Marashdeh and Afandi [7] also used the VAR-GARCH model to understand whether oil price changes can predict stock market returns in the largest oil-producing countries, namely, Saudi Arabia, Russia, and the United States. Lin et al. [67] employed the VAR-AGARCH model proposed by McAleer et al. [65] and the DCC-GARCH model proposed by Engle [63] to capture the asymmetric relationship between returns. The advantage of these models is that they can capture asymmetric return and volatility transmission across markets. The disadvantage of these models is that they are unable to process a combination of high-frequency and low-frequency data.

MIDAS sampling is a mixed-frequency time-series regression model proposed by [68]. Subsequently, some studies have used different variations of the GARCH model to investigate volatility across multiple components [69–72]. Engle et al. [25] proposed the GARCH-MIDAS model to process high-frequency data (daily) and low-frequency data (monthly or quarterly) simultaneously.

Zhang and Wang [39] explained the advantages of the GARCH-MIDAS model. Equity market data on a daily basis can be used to forecast monthly or quarterly crude oil prices. Zhang and Wang [39] used the GARCH-MIDAS model and selected high-frequency equity market data (S&P 500 and FTSE 100 Index) to forecast monthly international crude oil prices (WTI). Their study found the GARCH-MIDAS model to be superior to other GARCH models. Prior studies [36,73] also found that the GARCH-MIDAS model proposed by Engle et al. [25] is more useful in analyzing the volatility relationship between high-frequency independent variables, such as daily stock returns or exchange rate, and low-frequency explanatory variables, such as the monthly oil price or macroeconomic factors. Conrad and Kleen [73] compared the forecast performance of GARCH-MIDAS models with many other models such as heterogeneous autoregression (HAR), realized GARCH, high-frequency-based volatility (HEAVY), and Markov-switching GARCH. Conrad and Kleen [73] found that the GARCH-MIDAS outperforms all other models at forecasting.

3. Sample and Methodology

3.1. Sample Collection

This study examined the volatility transmission effects of the five financial markets on USO and BGF. The five financial markets were equity market (proxied by S&P 500), bulk shipping market (proxied by BDI), commodity market (proxied by SPGSCI), currency market (proxied by USDX), and crude oil market (proxied by WTI).

This study used USO and BGF as the dependent variables. We obtained the daily volatility of USO from the Bloomberg database and BGF from the BlackRock official website. The independent variables were S&P 500, BDI, SPGSCI, USDX, and WTI. We obtained the monthly volatilities of S&P 500, BDI, SPGSCI, USDX, and WTI from the Bloomberg database.

This study aimed to identify the degree of volatility transmission from financial markets to oil ETFs and energy mutual funds, with the U.S.–China trade war as the major financial event. Vivian and Wohar [74] investigated the existence of structural breaks, which refer to structural changes in the volatility series derived from a GARCH model. Vivian and Wohar [74] found structure breaks in commodity return volatility using an iterative cumulative sum of squares procedure. High volatility may not persist after structural breaks [43]. Following previous studies [43,44,74], we divided our sample into two subsamples based on structural breaks.

The first subsample included data before the U.S.–China trade war beginning in mid-March 2018. The second subsample included data after the outbreak of the U.S.–China trade war. The second subsample covered the data ranging from 1 April 2018 to 30 April 2020, extending into the COVID-19 pandemic, because the U.S.–China trade war began in mid-March 2018.

To determine the data period for the first subsample, we followed Salisu and Oloko's [44] and Vivian and Wohar's [74] work. We separated the sample for pre- and post-break periods. The main distinction is that the return spillover effect from one financial market to another disappears with the structural break, as shown by the insignificant coefficient. We collected and tested the data of S&P 500, BDI, SPGSCI, USDX, and WTI before 1 April 2018 with a minimum of 500 historical data points (daily index point based on 500 trading days) and found insignificant coefficients. The data collection process shows that the period covering the 500 historical data points before the U.S.–China trade war falls from 1 July 2014 to 30 March 2018. In short, based on Salisu and Oloko's and Vivian and Wohar's (2012) studies, we obtained the first subsample time period from 1 July 2014 to 30 March 2018, with at least 500 historical data points in each financial market. This study set a lag of 12 months (K = 12) to track the impact of independent variables on dependent variables.

3.2. GARCH-MIDAS Model

Bollerslev [75] proposed the GARCH model in 1986. In a conventional autoregressive conditional heteroskedasticity (ARCH) time-series model, a dependent variable is assumed to be homoscedastic, which refers to constant volatility. However, in financial markets, volatility can change. Volatility clustering exists for price and rate of return. Periods of low volatility can follow periods of high volatility. Similarly, periods of high volatility can follow periods of low volatility. The financial markets exhibit heteroskedasticity, showing an irregular pattern of variation of a variable. Financial markets can become more volatile during financial crises and remain calm during steady economic growth periods.

In this study, we used a new class of component GARCH models based on MIDAS regression. MIDAS regression models were introduced by Ghysels et al. [68]. MIDAS offers a framework to incorporate energy-fund-related variables from financial markets sampled at different frequency along with the time series. This research adopted the GARCH-MIDAS model and selected high-frequency financial data from S&P 500, BDI, SPGSCI, USDX, and WTI to forecast the monthly prices of the oil ETF and energy mutual fund (USO and BGF).

The MIDAS regression model is expressed as follows:

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

Here, Y is the dependent variable at time $(t + h)$. It is known as the h-step-ahead forecast. Y has a higher frequency than X.

m denotes the number of higher frequencies.

$X_t^{(m)}$ is the frequency of the independent variable at time t.

$\varepsilon_t^{(m)}$ denotes the random error term of sampling frequency m at time t.

$B\left(L^{1/m};\theta\right)$ denotes the lagged distributed operator.

The structure of the distributed lag $B(\bullet)$ is expressed as:

$$B\left(L^{1/m};\omega\right) = \sum_{k=0}^{K} \varphi(k;\omega)L^{k/m} \tag{2}$$

where $L^{k/m}$ is the lag operator, which is $L^{k/m}X_t^{(m)} = X_{t-k/m}^{(m)}$, $k = 0, 1, 2, \cdots, K$.

$\varphi(k;\omega)$ denotes the parameterized weight function.

$\omega = [\omega_1, \omega_2, \cdots, \omega_T]$ is the weight vector of parameter $(1 \times T)$ and T is the number of parameters.

The common probability density function of the two-parameter beta distribution is expressed as:

$$f\left(\frac{k}{K};\omega_1,\omega_2\right) = \frac{\Gamma(\omega_1+\omega_2)}{\Gamma(\omega_1)\Gamma(\omega_2)}\left(\frac{k}{K}\right)^{\omega_1-1}\left(1-\frac{k}{K}\right)^{\omega_2-1} \tag{3}$$

The GARCH model includes a lag variance term, s, which is the number of observations if modeling the white noise residual errors of another process, together with lag residual errors from a mean process, m.

The GARCH model is expressed as:

$$\begin{gathered} Y_t = E(Y_t|\Omega_{t-1}) + \varepsilon_t \\ \varepsilon_t = Z_t\sqrt{\sigma_t^2} \\ \sigma_t^2 = \alpha_0 + \sum_{j=1}^{s}\alpha_j\varepsilon_{t-j}^2 + \sum_{k=1}^{m}\beta_k\sigma_{t-k}^2, \end{gathered} \tag{4}$$

where Z_t is the standard white noise—that is, $Z_t \overset{i.i.d}{\sim} (0, 1)$, $\forall t$.

ε_t is the error term; Z_t and the past error term ε_{t-j}, $j = 1, 2, \cdots, s$ are independent of one another.
Ω_{t-1} is the information shown as $t-1$.
$E(Y_t|\Omega_{t-1})$ is the conditional mean of Y_t.
σ_t^2 is the conditional variance of Y_t.
$t = \max(m, s), \max(m, s) + 1, \cdots, T$.
α_j, $j = 1, 2, \cdots, s$ is the ARCH parameter.
β_j, $k = 1, 2, \cdots, m$ is the GARCH parameter.
$\alpha_0 > 0$, $\alpha_i \geq 0$, $\beta_i \geq 0$, and $\sum_{j=1}^{s} \alpha_j + \sum_{k=1}^{m} \beta_k < 1$.

Based on the GARCH-MIDAS model by Engle et al. (2013), which processes high-frequency data (daily) and low-frequency data (monthly) simultaneously, the equation for the GARCH-MIDAS model is expressed as follows:

$$Y_{i,t} = E\left(Y_{i,t}\middle|\Omega_{i-1,t}\right) + \varepsilon_{i,t} \tag{5}$$

$$\varepsilon_{i,t} = Z_{i,t}\sqrt{h_{i,t}\tau_t}$$

The subscript t denotes the time period for low-frequency data, $t = 1, 2, \cdots, T$.

The subscript i denotes the time period for high-frequency data, $i = 1, 2, \cdots, N_t$.

In the GARCH-MIDAS model, the volatility of the energy fund's return is decomposed into two components: long-term volatility and short-term volatility. Here, $\gamma_{i,t}$ is the return on day i of month t. The short-run volatility of inter-market variables changes at the daily frequency i, and long-run volatility changes at the period frequency t.

Engle [25] decomposed the conditional variance σ_t^2 multiplicatively into two components—long-term volatility and short-term volatility:

$$\sigma_t^2 = h_{i,t}\tau_t.$$

The first component is a short-term component, $h_{i,t}$, for high-frequency data. The second component is a long-term component, τ_t, for low-frequency data, and is a function of an observable explanatory variable.

For the short-term component, the equation shows that $h_{i,t}$ follows unit-variance in the GARCH model. The equation is expressed as:

$$h_{i,t} = (1 - \alpha - \beta) + \alpha\frac{\varepsilon_{i-1,t}^2}{\tau_t} + \beta h_{i-1,t},$$

where the coefficients are $\alpha > 0$, $\beta \geq 0$, and $\alpha + \beta < 1$.

$\varepsilon_{i-1,t}^2$ is the square of the error term for transaction $i-1$ in time t.

To facilitate the discussion of the GARCH-MIDAS model, the GARCH model based on the same frequency data is described as follows:

$$\gamma_t - E_{t-1}(\gamma_t) = \varepsilon_t$$

$$\varepsilon_t = \sqrt{\sigma_t^2 z_t}$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\varepsilon_{t-1}^2, \tag{6}$$

where γ_t is the natural logarithmic rate of the return of the energy fund, τ_t is for long-term data, $t = 1, 2, \cdots, T, i = 1, 2, \cdots, N_t$, and τ_t is defined as smoothed realized volatility in the MIDAS regression.

$E_{t-1}(\gamma_t)$ is its conditional mean, ε_t is the residual, z_t is innovation, σ_t^2 is the conditional variance, and ω, α, and β are the model coefficients.

We modified the equation to involve the international financial variables along with X in order to study the impact of these financial indices on the long-term return variance.

The long-term component in the MIDAS regression is expressed as:

$$\tau_t = \mathrm{m} + \theta \sum_{k=1}^{K} \mathrm{W}_k(w_1, w_2)\mathrm{X}_{t-k},$$

where m is a constant.

X_{t-k} is the k-length lag of the macro-level variable on day t.

X_{t-k} denotes the observable explanatory variable for multiple markets (for example, crude oil, shipping market, etc.) in lag k, where K is the maximum lag of the international financial variable, of which we smooth out the volatility, and $\varphi_k(\omega_1, \omega_2)$ is a weighting equation based on the Beta function:

$\omega(k; \theta_1, \theta_2)$ is the weighting scheme.

The abovementioned weighting scheme is commonly used and described by the two-parameter beta lag polynomial. It is expressed as:

$$\varphi(k; \omega_1, \omega_2) = \frac{f\left(\frac{k}{K}; \omega_1, \omega_2\right)}{\sum\limits_{k=1}^{K} f\left(\frac{k}{K}; \omega_1, \omega_2\right)} = \frac{\frac{\Gamma(\omega_1+\omega_2)}{\Gamma(\omega_1)\Gamma(\omega_2)}\left(\frac{k}{K}\right)^{\omega_1-1}\left(1-\frac{k}{K}\right)^{\omega_2-1}}{\sum\limits_{k=1}^{K}\frac{\Gamma(\omega_1+\omega_2)}{\Gamma(\omega_1)\Gamma(\omega_2)}\left(\frac{k}{K}\right)^{\omega_1-1}\left(1-\frac{k}{K}\right)^{\omega_2-1}}. \tag{7}$$

This study used the GARCH-MIDAS model as expressed in equation 8:

$$r_{i,t} = \mu + \varepsilon_{i,t}$$

$$\varepsilon_{i,t} = Z_{i,t}\sqrt{h_{i,t}\tau_t} \tag{8}$$

4. Empirical Results

4.1. Descriptive Statistics

This study uses the R 3.2.0 version for statistical computing to obtain descriptive statistics for all variables in the whole sample. The numbers for the samples, mean value, standard deviation, kurtosis coefficient, skewness coefficient, minimum value (min), and maximum value (max) are in Table 1.

Table 1. Descriptive statistics for the whole sample.

Variable	Number of Samples	Mean	Standard Deviation	Kurtosis Coefficient	Skewness Coefficient	Min	Max
S&P 500	3098	−0.00023	0.013292	14.8519	0.333595	−0.135577	0.115887
BDI	3098	0.000846	0.02571	3.033844	−0.142663	−0.146401	0.120718
SPGSCI	3098	0.000278	0.015316	6.114918	0.553907	−0.076829	0.125228
USDX	3098	-8.62×10^{-5}	0.005086	2.601659	0.022252	−0.027344	0.030646
WTI	3098	0.000121	0.029341	27.0928	−0.966676	−0.319634	0.282206
USO	3098	0.001112	0.024636	16.52257	1.303312	−0.154151	0.291891
BGF	3098	4.27×10^{-5}	0.012729	8.698855	0.619081	−0.078193	0.10351

4.2. Stationary Test

To perform stationary analysis on the data, this study first performed the augmented Dickey–Fuller (ADF) unit root test on S&P 500, BDI, SPGSCI, USDX, WTI, USO, and BGF. The ADF unit root test is expressed as follows:

$$DF - t = \frac{\hat{\delta}}{\sqrt{\widehat{var(\hat{\delta})}}}.$$

Through the ADF unit root test, we can identify whether a transaction is stationary. This study converted the time-series data to stationary series data using the difference method. We then performed another unit root test, the Phillips-Perron (PP) test on the converted time-series data. Table 2 shows that the ADF values were at the 1% significance level. The results rejected the null hypothesis, which referred to the existence of a single root. The outcome indicated that all the data possess stationary status. Table 2 shows the results of the ADF unit root tests.

Table 2. The results of unit root tests for the variables.

Unit Root Test/Variable	S&P 500	BDI	SPGSCI	USDX	WTI	USO	BGF
ADF	−8.6736 ***	−8.7668 ***	−8.952 ***	−10.602 ***	−11.599 ***	−7.6277 ***	−10.726 ***
PP	−1060.6 ***	−1059.8 ***	−1055 ***	−957.29 ***	−903.67 ***	−294.73 ***	−873.55 ***

Note: 1. *** means the results reject the null hypothesis of the existence of unit root at the 1% significance level.
2. The augmented Dickey-Fuller (ADF) test, a unit root test, has the equation $\Delta Y_t = \omega + \alpha_u Y_{t-1} + \sum_{i=1}^{p} \beta_i \Delta Y_{t-1} + \varepsilon_t$.
3. The Phillips-perron (PP) test is another unit root test.

4.3. Test Results of USO before the U.S.–China Trade War

The results of the data analysis for USO before the U.S.–China trade war (K = 12) using the GARCH-MIDAS model are presented in Table 3.

Table 3. Results of the GARCH-MIDAS model for USO before the U.S.–China trade war (K = 12).

Variable	μ	α	β	m	θ	ω_2
S&P 500	0.0039 (0.0693)	0.0000 (0.0146)	0.9370 *** (0.0130)	0.1706 (0.4547)	0.3268 ** (0.1353)	1.1306 ** (0.5570)
BDI	0.0125 (0.1137)	0.0000 (0.0266)	0.9583 *** (0.0202)	0.0616 (1.1527)	0.0676 (0.1200)	2.3830 (1.6247)
SPGSCI	0.0094 (0.0723)	0.0000 (0.0221)	0.9410 *** (0.0060)	0.4180 (1.7871)	0.1300 (0.3486)	1.0000 (0.9149)
USDX	−0.0227 (0.0836)	0.0000 (0.0129)	0.9527 *** (0.0008)	2.3128 (1.4238)	−0.6347 (0.5955)	4.1284 (3.1095)
WTI	0.0033 (0.0713)	0.0000 (0.0191)	0.9388 *** (0.0046)	0.4501 (1.1001)	0.0697 (0.1154)	1.0001 (0.6121)

Note: *** denotes 1% significant level; ** denotes 5% significant level.

Our study analyzed the long-term component and short-term component of USO and BGF using the GARCH-MIDAS model based on the S&P 500 monthly volatility. The results showed the mean value of S&P 500 was 0.0039, which was insignificant.

For S&P 500, the mean return (0.0039) was insignificant. The estimate of α (0.0000) was insignificant, but the estimate of GARCH β (0.9370 ***) was significant. The sum of α and GARCH β was less than one, which confirmed covariance stationarity. Moreover, long-term volatility reduced the persistence of short-term volatility. The estimated coefficient θ (0.3268 **) was significant. The results indicated that the USO daily return was significantly influenced by the S&P 500 monthly volatility during the past 12 months. Because the weighting of the model converged to approximately 0, model stability (when K = 12) was optimized according to the approach proposed by Conrad et al. [6]. The results indicated that the monthly volatility of S&P 500 had a significant effect on the USO daily return before the U.S.–China trade war.

For BDI, the mean return (0.0125) was insignificant. The estimate of α (0.0000) was insignificant, while the estimate of GARCH β (0.9583 ***) was significant. The sum of α and GARCH β was less than one, which confirmed covariance stationarity. Moreover, long-term volatility reduced the persistence of short-term volatility. The estimated coefficient θ (0.0676) was insignificant, indicating that BDI monthly volatility had no significant impact on the USO daily return before the U.S.–China trade war.

For SPGSCI, the mean return (0.0094) was insignificant. The estimate of α (0.0000) was insignificant, but the estimate of GARCH β (0.9410 ***) was significant. The sum of α and GARCH β was less than one, which verified covariance stationarity. Moreover, long-term volatility reduced the persistence of short-term volatility. The estimated coefficient θ (0.1300) was insignificant, indicating that the SPGSCI monthly volatility had no significant impact on the USO daily return before the U.S.–China trade war.

For USDX, the mean return (−0.0227) was insignificant. The estimate of ARCH α (0.0000) was insignificant, while the estimate of GARCH β (0.9527 ***) was significant. The sum of α and GARCH β was less than one, which signified covariance stationarity. Moreover, long-term volatility reduced the persistence of short-term volatility. The estimated coefficient θ (−0.6347) was insignificant, indicating that the USDX monthly volatility had no significant impact on the USO daily return before the U.S.–China trade war.

For WTI, the mean return (0.0033) was insignificant. The estimate of α (0.0000) was insignificant, while the estimate of GARCH β (0.9388 ***) was significant. The sum of α and GARCH β was less than one, which confirmed covariance stationarity. Moreover, long-term volatility reduced the persistence of short-term volatility. The estimated coefficient θ (0.0697) was insignificant, indicating that the WTI monthly volatility had no significant impact on the USO daily return before the U.S.–China trade war.

4.4. Test Results of USO during the U.S.–China Trade War

The results of MARCH-MIDAS analysis for USO during the U.S.–China trade are in Table 4.

Table 4. Results of the GARCH-MIDAS model for USO during the U.S.–China trade war.

Variable	μ	α	β	m	θ	ω_2
S&P 500	−0.1967 (0.1452)	0.0099 (0.0249)	0.4263 ** (0.1841)	1.3237 *** (0.3400)	0.1346 *** (0.0190)	104.1241 *** (7.9875)
BDI	−0.0871 (0.1618)	0.0592 (0.0659)	0.5129 ** (0.2209)	−4.3287 (3.2970)	0.4728 ** (0.2300)	1.4207 ** (0.3293)
SPGSCI	−0.2005 (0.1601)	0.0073 (0.0225)	0.4517 *** (0.1429)	1.0209 ** (0.4280)	0.1743 *** (0.0403)	34.0588 (36.6924)
USDX	0.1744 (0.7725)	0.0000 (0.0436)	0.9219 *** (0.1300)	−0.0589 (3.5322)	−0.0560 (0.0965)	2.9007 (2.1368)
WTI	−0.1868 (0.1628)	0.0104 (0.0215)	0.4440 *** (0.1325)	1.3293 *** (0.4105)	0.0644 *** (0.0142)	46.2931 (106.2170)

Note: *** denotes 1% significant level; ** denotes 5% significant level.

The mean return of S&P 500 (−0.1967) was insignificant. The estimate of α (0.0099) was insignificant, while the estimate of GARCH β (0.4263 **) was significant. The sum of α and GARCH β was less than one, which confirmed covariance stationarity. Thus, long-term volatility reduced the persistence of short-term volatility. The estimated coefficient θ (0.1346 ***) was significant, which was similar to that of USO before the U.S.–China trade war. Because the weighting of the model converged to approximately 0, the stability of the model (when K = 12) was optimized according to the approach by Conrad et al. [6]. The results indicated that the S&P 500 monthly volatility had a significant effect on the USO daily return during the U.S.–China trade war (the past 12 months).

For BDI, the mean return (−0.0871) was insignificant. The estimate of α (0.0592) was insignificant, while the estimate of GARCH β (0.5129 **) was significant. The sum of α and GARCH β was less than one, which proved covariance stationarity. Moreover, long-term volatility reduced the persistence of short-term volatility. The estimated coefficient θ (0.4728 **) was significant, indicating that the BDI monthly volatility had a significant impact on the USO daily return during the U.S.–China trade war. The outcome suggested that the volatility transmission from BDI to USO became significant after the U.S.–China trade war began.

For SPGSCI, the mean return (−0.2005) was insignificant. The estimate of α (0.0073) was insignificant, while the estimate of GARCH β (0.4517 ***) was significant. The sum of α and GARCH β was less than one, which showed covariance stationarity. Moreover, long-term volatility reduced the persistence of short-term volatility. The estimated coefficient θ (0.1743 ***) was significant, indicating that the SPGSCI monthly volatility had a significant impact on the USO daily return during the U.S.–China trade war. The outcome suggested that the volatility transmission from SPGSCI to USO became significant after the outbreak of the U.S.–China trade war.

For USDX, the mean return (0.1744) was insignificant. The estimate of α (0.0000) was insignificant, while the estimate of GARCH β (0.9219 ***) was significant. The sum of α and GARCH β was less than one, which showed covariance stationarity. Moreover, long-term volatility reduced the persistence of short-term volatility. The estimated coefficient θ (−0.0560 ***) was insignificant, indicating that the USDX monthly volatility had no significant impact on the USO daily return during the U.S.–China trade war.

For WTI, the mean return (−0.1868) was insignificant. The estimate of α (0.0104) was insignificant, while the estimate of GARCH β (0.4440 ***) was significant. The sum of α and GARCH β was less than one, which confirmed covariance stationarity. Moreover, long-term volatility reduced the power of short-term volatility. The estimated coefficient θ (0.0644 ***) was significant, indicating that the WTI monthly volatility had a significant impact on the USO daily return during the U.S.–China trade war. This outcome suggested the increase in volatility transmission from SPGSCI to USO became significant after the outbreak of the U.S.–China trade war.

4.5. Test Results of BGF before the U.S.–China Trade War

The results of GARCH-MIDAS analysis for BGF before the U.S.–China trade are in Table 5.

Table 5. Results of the GARCH-MIDAS model for BGF before the U.S.–China trade war.

Variable	μ	α	β	m	θ	ω_2
S&P 500	−0.0249 (0.0454)	0.1259 ** (0.0610)	0.7602 *** (0.1340)	−0.0075 (0.2655)	0.2302 *** (0.0757)	1.0177 (1.0698)
BDI	−0.0168 (0.0461)	0.0775 *** (0.0161)	0.8958 *** (0.0235)	0.3855 (1.1039)	0.0338 (0.1250)	1.000 (7.4308)
SPGSCI	−0.0173 (0.0465)	0.0854 *** (0.0088)	0.8919 *** (0.0024)	1.0465 *** (0.3754)	−0.0638 (0.0560)	13.1374 *** (4.7568)
USDX	−0.0184 (0.0475)	0.0881 *** (0.0314)	0.8834 *** (0.0442)	0.3390 (1.2343)	0.1852 (0.5746)	1.000 (8.4940)
WTI	−0.0169 (0.0464)	0.0842 *** (0.0061)	0.8928 *** (0.0002)	0.9228 *** (0.0644)	−0.0223 (0.0173)	10.2715 * (5.7363)

Note: *** denotes 1% significant level; ** denotes 5% significant level; * denotes 10% significant level.

The mean return of S&P 500 (−0.0249) was insignificant. The estimate of α (0.1259 **) and the estimate of GARCH β (0.7602 ***) were both significant, but the sum of α and GARCH β was less than one, confirming covariance stationarity. Therefore, long-term volatility reduced the persistence of short-term volatility. The estimated coefficient θ (0.2302 ***) was significant. Such an outcome suggested that the monthly volatility of S&P 500 significantly influenced the BGF daily return during the past 12 months, which was similar to that of USO before the U.S.–China trade war. Because the weighting of the model converged to approximately 0, the stability of the model (when K = 12) was optimized based on the approach by Conrad et al. [6]. The results indicated that the S&P 500 monthly volatility had a significant effect on the BGF daily return before the U.S.–China trade war.

For BDI, the mean return (−0.0168) was insignificant. The estimate of α (0.0775 ***) and the estimate of GARCH β (0.8958 ***) were both significant. The sum of α and GARCH β was less than one, which indicated covariance stationarity. Moreover, long-term volatility reduced the persistence of short-term volatility. The estimated coefficient θ (0.0338) was insignificant, suggesting that the BDI monthly volatility had no significant impact on the BGF daily return before the U.S.–China trade war.

For SPGSCI, the mean return (−0.0173) was insignificant. The estimate of α (0.0854 ***) and the estimate of GARCH β (0.8919 ***) were both significant. The sum of α and GARCH β was less than one, which confirmed covariance stationarity. Moreover, the long-term volatility reduced the persistence of short-term volatility. The estimated coefficient θ (−0.0638) was insignificant, indicating that the SPGSCI monthly volatility had no significant impact on the BGF daily return before the U.S.–China trade war.

For USDX, the mean return (−0.0184) was insignificant. The estimate of α (0.0881 ***) and the estimate of GARCH β (0.8834 ***) were both significant. The sum of α and GARCH β was less than one, which confirmed covariance stationarity. Hence, long-term volatility reduced the persistence of short-term volatility. The estimated coefficient θ (0.1852) was insignificant, indicating that the USDX monthly volatility had no significant impact on the BGF daily return before the U.S.–China trade war.

For WTI, the mean return (−0.0169) was insignificant. The estimate of α (0.0842 ***) and the estimate of GARCH β (0.8928 ***) were both significant. The sum of α and GARCH β was less than one, which proved covariance stationarity. Hence, long-term volatility reduced the persistence of short-term volatility. The estimated coefficient θ (−0.0223) was insignificant, indicating that the WTI monthly volatility had no significant impact on the BGF daily return before the U.S.–China trade war.

4.6. Test Results of BGF during the U.S.–China Trade War

The results of GARCH-MIDAS analysis for BGF during the U.S.–China trade are in Table 6.

Table 6. Results of the GARCH-MIDAS model for BGF during the U.S.–China trade war.

Variable	**μ**	**α**	**β**	**m**	**θ**	**ω_2**
S&P 500	0.0626 (0.1222)	0.4698 *** (0.0541)	0.4743 *** (0.0759)	1.5931 *** (0.6139)	0.1089 * (0.0681)	12.9503 (8.2904)
BDI	0.0023 (0.1426)	0.3083 (0.2340)	0.0004 (1.0040)	−30.1550 *** (6.2932)	2.7549 *** (0.5438)	1.0000 *** (0.2348)
SPGSCI	0.0995 (0.1273)	0.3107 *** (0.0119)	0.6623 *** (0.0022)	−7.4466 *** (2.2623)	1.6939 *** (0.4590)	1.0000 *** (0.3793)
USDX	0.0383 (0.1268)	0.1801 *** (0.0088)	0.8076 *** (0.0000)	13.7362 (8.7690)	−8.5123 (5.7973)	1.0717 *** (0.2641)
WTI	0.0902 (0.1178)	0.4113 *** (0.0043)	0.5518 *** (0.0052)	−2.8688 (2.4343)	0.5088 ** (0.2550)	1.0000 *** (0.2981)

Note: *** denotes 1% significant level; ** denotes 5% significant level; * denotes 10% significant level.

The mean return of S&P 500 (0.0626) was insignificant. The estimate of α (0.4698 ***) and the estimate of GARCH β (0.4743 ***) were both significant. The sum of α and GARCH β was less than one, indicating covariance stationarity. Therefore, long-term volatility reduced the persistence of short-term volatility. The estimated coefficient θ (0.1089 *) was significant, which was similar to that of S&P 500 before the U.S.–China trade war. The results indicated that the monthly volatility of S&P 500 had a significant effect on the BGF daily return during the U.S.–China trade war.

For BDI, the mean return (0.0023) was insignificant. The estimate of α (0.3083) and the estimate of GARCH β (0.0004) were both insignificant. The sum of α and GARCH β was less than one, which confirmed covariance stationarity. Moreover, long-term volatility reduced the persistence of short-term volatility. The estimated coefficient θ (2.7549 ***) was significant, indicating that the BDI monthly volatility had a significant impact on the BGF daily return during the U.S.–China trade war. Similar to the test results of USO, the volatility transmission from BDI to BGF became significant after the outbreak of the U.S.–China trade war.

For SPGSCI, the mean return (0.0995) was insignificant. The estimate of ARCH α (0.3107 ***) and the estimate of GARCH β (0.6623) were both significant. The sum of ARCH α and GARCH β was less than one, which confirmed covariance stationarity. Moreover, long-term volatility reduced the persistence of short-term volatility. The estimated coefficient θ (1.6939 ***) was significant, indicating that the SPGSCI monthly volatility had a significant impact on the BGF daily return during the U.S.–China trade war. Similar to the test results of USO, the volatility transmission from SPGSCI to BGF became significant after the U.S.–China trade war began.

For USDX, the mean return (0.0383) was insignificant. The estimate of α (0.1801 ***) and the estimate of GARCH β (0.8076) were both significant. The sum of α and GARCH β was less than one, which showed covariance stationarity. Moreover, long-term volatility reduced the persistence of short-term volatility. The estimated coefficient θ (−8.5123) was insignificant, indicating that the USDX monthly volatility had no significant impact on the BGF daily return during the U.S.–China trade war.

For WTI, the mean return (0.0902) was insignificant. The estimate of α (0.4113 ***) and the estimate of GARCH β (0.5518 ***) were both significant. The sum of α and GARCH β was less than one, which confirmed covariance stationarity. Hence, long-term volatility reduced the persistence of short-term volatility. The estimated coefficient θ (−0.5088 **) was significant, indicating that the WTI monthly volatility had a significant impact on the BGF daily return before the U.S.–China trade war. Similar to the test results of USO, the volatility transmission from WTI to BGF became significant after the outbreak of the U.S.–China trade war.

In summary, S&P 500 had a significant volatility transmission to USO and BGF both before and during the U.S.–China trade war (including the period of the COVID-19 pandemic). BDI, SPGSCI, USDX, and WTI had insignificant volatility transmission to USO and BGF before the U.S.–China trade war. However, the volatility transmission of these factor markets increased after the outbreak of the U.S.–China war. BDI, SPGSCI, USDX, and WTI all produced significant volatility transmission to USO and BGF during the U.S.–China trade war (including the COVID-19 pandemic period). Table 7 presents the comparison of the volatility transmission effect from S&P 500, BDI, SPGSCI, USDX, and WTI to USO and BGF, respectively.

Table 7. Comparison of volatility transmission effect from S&P 500, BDI, SPGSCI, USDX, and WTI to USO and BGF.

	USO		**BGF**	
	Before the U.S.–China Trade War	**During the U.S.–China Trade War**	**Before the U.S.–China Trade War**	**During the U.S.–China Trade War**
S&P 500	Significant **	Significant ***	Significant ***	Significant *
BDI	Insignificant	Significant **	Insignificant	Significant ***
SPGSCI	Insignificant	Significant ***	Insignificant	Significant ***
USDX	Insignificant	Insignificant	Insignificant	Insignificant
WTI	Insignificant	Significant ***	Insignificant	Significant **

Note: *** denotes 1% significant level; ** denotes 5% significant level; * denotes 10% significant level.

5. Discussion

This study found that the volatility transmission effect from S&P 500 to USO and BGF was significant both before and during the U.S.–China trade war, which is consistent with previous academic studies that show a strong correlation between oil prices and the equity markets during a long period. S&P 500 includes 26 stocks of energy companies, which comprise more than 4% of the index by market capitalization [76]. Therefore, when S&P 500 increases, the prices of the component stocks are likely to increase. Such co-movement is reflected in the NAV of both USO and BGF, which mainly consists of oil companies, in the next period.

The results of this study did indicate a difference in the impact of BDI, SPGSCI, and WTI on USO and BGF. Before the U.S.–China trade war, BDI, SPGSCI, and WTI had no significant volatility transmission effect on USO and BGF. After the U.S.–China trade war began, BDI, SPGSCI, and WTI showed a significant volatility transmission on USO and BGF.

The possible reason for such an outcome is that before the U.S.–China trade war began, the global BDI, SPGSCI, and WTI moved up and down steadily with low volatility. In addition, no severe economic disruptions occurred except for the June 2015 stock market crash in China, which ended shortly in February 2016. Therefore, the volatility transmissions from BDI, SPGSCI, and WTI to the oil ETF and energy mutual fund represented by USO and BGF, respectively, were insignificant. However, the outbreak of the U.S.–China trade war in March 2018 signified a major economic event. The demand for oil decreased in China. Chinese products exported to the U.S. were severely impacted due to the imposed tariffs. Larger demand and supply shocks affected oil prices. BDI, SPGSCI, and WTI indices declined due to the downturn of China's economy, which was the largest oil-importing country. Such volatility was significantly transmitted to USO and BGF.

The USDX volatility contrarily had no significant impact on USO and BGF both before and during the U.S. trade war. The reason is probably that the USO holdings as of 30 April 2020 consisted of 51% WTI and 49% U.S. government bonds and cash. Therefore, the USDX volatility had no impact on the value of USO because the index points of the two markets increase and decrease at a similar rate. Similarly, BGF invests in U.S. dollar-denominated stocks. As a result, USO and BGF, which are both traded in US dollars, did not experience an exchange rate gain or loss during the two sample periods. Therefore, the changes in USDX had an insignificant impact on USO and BGF.

The study produces four implications. First, a significant volatility transmission exists from the equity market (S&P 500) to the oil ETF (USO) and mutual fund (BGF) both before and during the U.S.–China trade war. This finding signifies that the equity market precedes oil ETFs and mutual funds at all times, regardless of the financial/economic crisis. This shows that the oil ETF and energy mutual fund are most connected with the equity market because they are all traded on NYSE. A rise or fall in the equity market is always reflected in the oil ETFs and energy mutual funds subsequently in the same direction. This implies that when investors hold a pessimistic view about the future economy, they first sell corporate stocks, causing the stock markets to fall. The decline in the equity market triggers the investors into believing the deterioration of the future economy, thus lowering the demand for oil. Subsequently, the investors tend to sell the oil ETFs and energy mutual funds to reflect their pessimistic views. Consequently, the values of oil ETFs and energy mutual funds which consist mostly of oil companies would decline. Such a relationship is evidenced by the lagged effect of the S&P 500 on USO and BGF in this study. Investors and fund managers may therefore regard the equity market as a suitable leading indicator of oil ETFs and energy mutual funds. Investors and fund managers may always use equity markets to predict the movement of oil ETF and BGF.

Second, other financial markets (BDI, SPGSCI, WTI) produce a time-varying influence on oil ETF and energy mutual funds. BDI, SPGSCI, and WTI have an insignificant influence on oil ETF and energy mutual funds during the tranquil periods with no major financial events found. In contrast, BDI, SPGSCI, and WTI have a significant impact on oil ETF and energy mutual funds during turmoil periods with the occurrence of major financial events, such as the U.S.–China trade war in this study. It is worth noting that the U.S. and China are major oil-exporting and -importing countries, respectively. Thus, the conflict between the two countries affects the demand and supply of oil considerably. Specifically, the U.S.–China trade war decreases China's demand for oil due to tariff restrictions and reduces the U.S. supply for oil accordingly. Because the U.S.–China trade war affects the global demand and supply of oil, BDI, SPGSCI, and WTI started to have a significant impact on oil ETF and energy mutual funds after the trade war began. Therefore, investors can use BDI, SPGSCI, and WTI to predict the movements of oil ETFs and energy mutual funds during the U.S.–China trade war. Moreover, investors and fund managers may expect the volatility transmission from BDI, SPGSCI, and WTI on oil ETFs and energy mutual funds to persist so long as the U.S.–China trade war continues.

Third, the results of this study indicate that oil ETF (USO) and energy mutual fund (BGF) move in the same direction relative to the equity, BDI, SPGSCI, and WTI markets. This finding allows investors and fund managers to manage oil ETF and energy mutual funds in a similar fashion. For example, if investors and fund managers hold both oil ETF and energy mutual funds at the same time, they may decide to buy or sell oil ETF and energy mutual funds simultaneously. Investors could make such decisions when they foresee the future movements of these two funds based on the movements of the equity, BDI, SPGSCI, and WTI markets in the U.S.–China conflict.

Fourth, the results of this study enable investors and fund managers to formulate hedging and arbitrage strategies. This study suggests that investors may use the equity, BDI, SPGSCI, and WTI markets to predict oil ETFs and energy mutual funds. When the equity, BDI, SPGSCI, and WTI markets decline, the values of oil fund and energy mutual funds are likely to drop. Thus, investors may protect the value of their investments in oil with the understanding of such co-movement. For example, investors could consider selling USO and BGF when they see a fall in all or some of the equity, BDI, SPGSCI, and WTI markets. Furthermore, the results of this study suggest that there is a seven-day lag for oil ETF and mutual funds that fall after the financial markets. This finding allows experienced investors to formulate an arbitrage strategy. For instance, when institutional investors see a drop in the equity, BDI, SPGSCI, and WTI markets, they may short sell oil ETF or energy funds. In other words, institutional investors may borrow oil ETF and mutual funds and sell them immediately when they see a drop in the equity, BDI, SPGSCI, and WTI markets. At that time, institutional investors could expect to sell oil ETF and mutual funds at a higher price. After the oil ETF and mutual fund drop in values in a few days later, the investors may buy these funds at a lower price and return them to the lenders. Thus, institutional investors can earn a profit through arbitrage due to the lagged effect.

6. Conclusions

Oil prices and funds have experienced high volatility over the last decade. This study applies the GARCH-MIDAS model on data from 1 July 2014, to 30 April 2020 to detect the direction and magnitude of volatility transmission from the equity (S&P 500), bulk shipping (BDI), commodity (SPGSCI), currency (USDX), and crude oil (WTI) markets to the largest oil ETF (USO) and energy mutual fund (BGF). We compared the two subsamples before and after the 2018 U.S.–China trade war.

This paper concludes that transmission volatility exists from the equity market (S&P 500) to the oil ETF and energy mutual fund during both tranquil and turmoil periods. The effect of transmission volatility from BDI, SPGSCI, USDX, and WTI to the oil ETF and energy mutual fund became significant after the major financial event of the U.S.–China trade war. The results of the study benefit investors and fund managers in optimizing their portfolio returns.

This paper is limited by the data period ending at April 2020, thus unable to analyze the whole period covering the U.S.–China trade war and COVID-19 pandemic. Future research may include a comparison of energy mutual fund performance and the factors affecting the movements before, during, and after the trade war and the COVID-19 pandemic.

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