Fresh evidence on connectedness between prominent markets during COVID-19 pandemic

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Abstract
Various empirical studies have examined the nexus between financial markets, but this study focused on the comovement among prominent markets. Our study examines the interrelationship among main financial markets, i.e., stock, oil, and commodity during the recent pandemic. The interconnections among the selected markets are investigated using a battery of wavelet coherence tools and the Granger causality test. From the wavelet coherence analysis, our findings indicate strong co-movements among the VIX, oil volatility, and commodity prices during pandemic and localized in all scales and over the sample period. The dependency strength among the considered economies is noted to increase in pandemic, which implies increased short- and long-term benefits for the investors. Moreover, Our result exhibits a feedback causality between OVIX and crude oil, VIX and S&P 500, and gasoline and VIX. Interestingly, a unidirectional causality exists between VIX and crude oil, S&P 500 and crude oil, Brent and crude oil, gasoline, crude oil, and VIX and OVIX. We advocate that the findings will be helpful for portfolio managers, investors, and officials around the world.

Keywords VIX · OVIX · S&P500 · Energy · Commodities market · COVID-19 · Wavelet approach

Introduction
It is no denying fact that Covid-19 has a variety of negative consequences for energy stocks, agriculture, industry, financial markets, the economy, and the environment. It is worth noting that energy resources are among the most important natural resources that countries use as inputs in various economic sectors, such as industry (Albulescu et al. 2020), transportation, and others ensuring economic stability and national security (Su et al. 2019) where oil, natural gas, and coal are the most regularly traded energy commodities across countries (Ahmed and Sarkodie 2021a). While energy is always a valuable commodity in the overall economy, it also appeals to a large number of industrial
users and financial investors who want to allocate energy assets in the financial market to earn a profit and hedge risks (Comodi and Rossi 2016). The correlation between energy and stock markets has been widely researched to understand better energy market price volatility and investment features (Lin and Su 2020). The meteoric rise of Covid-19 and its far-reaching consequences may be seen on a global scale. Recent research made by (Qureshi 2021) concludes that, unlike previous devastating crises, the COVID-19 pandemic directly and severely impacts the world economy. It is worth noting that it is largely proved that prominent markets respond significantly to extreme events. Especially, many studies (Uddin et al. 2021) and Zhang et al. 2021 among others revealed that the 2008 financial crisis and Covid-19 pandemic generated significant volatility in global stock markets (Uddin et al. 2021). That is why analysis and prediction of the impact of extreme events and shocks on markets’ volatility is crucial to all market’ participants (investors and portfolio managers) as well as policy makers. Investors and portfolio managers will be interested in optimizing their portfolio decision-making in an uncertain context and minimizing the risk exposure in their investments. Furthermore, from a theoretical point of view, contagion among prominent markets occupies a central stage in empirical studies in finance field. More precisely, the evidence on co-movements across prominent markets prompts that it is a significant occurrence that has happened in various crises. Considering the COVID-19 havoc worldwide, a growing body of literature recently studied the impact of the pandemic on stock markets (Baker et al. 2020a; Zhang et al. 2020a; Gormsen and Koi-jen 2020; Yilmazkuday 2020; Corbet et al. 2020; Liu et al. 2020a). Moreover, it has been witnessed that the COVID-19 pandemic has caused a massive shock in the energy markets (Zhang et al. 2021). The crude oil market, for instance, has been suffering from substantial fluctuations over the last decade mainly caused by economic and political factors and the recent pandemic outbreak. According to Heinlein et al. (2021), the consequences of the COVID-19 pandemic on the world economy have been estimated to be much worse than the sub-prime turmoil and economic growth in upcoming years is expected to be lower as a consequence of the pandemic.1 In addition, the pandemic has also affected the

\[1\] Furthermore, due to the global pandemic, the S&P 500 entered a bear market for the first time on March 12, 2020, and had the most single-day percentage point drop. Sharif et al. 2020. “COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: Fresh evidence from the wavelet-based approach.” International Review of Financial Analysis, 101, 496. The stocks market jumped 18 times in the last 22 trading days between February 24 to March 24, and 16 out of 18 jumps were due to bad news associated with COVID-19 and US policy in response to the disease Baker et al. 2020b. “Covid-induced economic uncertainty.” National Bureau of Economic Research.
In view of all the above, we may presume the considerable effects of the COVID-19 epidemic on the interconnections across the market volatility index (VIX), S&P stock price index, and different commodities market products. Thus, in this study, our goal is to investigate the interrelationships across the VIX index, the US financial stock market index, and commodities (e.g., Gasoline, heating and natural gas, Brent, and crude oil) and assess whether this interrelationship varies across scales and over time.

This paper contributes to the literature in four significant ways: first, this paper explores the time-varying response of market volatility (VIX) index, S&P stock prices, and different commodities market products (e.g., gasoline, heating and natural gas, Brent, and crude oil) to the COVID-19 outbreak. There is significant evidence that financial markets are interconnected. Understanding better market performance and investment opportunities during turmoil necessitates a further investigation of market trends and interconnections during crises. Second, this paper highlights the lead-lag relationship between the different variables based on wavelet coherence analysis during the Covid-19 crises over dissimilar time scales. Compared to previously applied techniques, wavelet coherence approach decomposes energy price changes into positive and negative shocks (Chowdhury et al. 2021). It provides lead-lag separate estimations for the impact of positive and negative changes among VIX, OVIX, S&P 500 stock price, and energy commodities. Earlier, scientists have used time-series instruments such as correlation, GARCH models, and copula models (Joyo and Lefen 2019; Wen et al. 2012). The wavelets coherence analysis tool suggested by (Torrence and Compo 1998; Torrence and Webster 1999) has appeared as an active tool in diverse systematic applications, such as medication (Qassim et al. 2013; Hassan et al. 2010; Donner et al. 2012), astrophysics (Li et al. 2009; Bloomfield et al. 2004; Donner and Thiel 2007; Kelly et al. 2003), and geophysics (Liu et al. 2005; Zamani et al. 2013; Grinsted et al. 2004). Specifically, wavelet approaches such as continuous wavelet spectrum (hereafter, CWT), cross-wavelets transformation (hereafter, XWT), and wavelet coherence (hereafter, WCOH) have been used to determine the co-movements between stock market couples in financial markets (Crowley and Mayes 2009; Aguiar-Conraria et al. 2008; Rua and Nunes 2009). Such models have identified diverse frequencies and are interpreted based on the scalogram color. WCOH has the extra ability to identify high co-movement regions over time and across different scales (Aguiar-Conraria et al. 2008; Rua and Nunes 2009). Second, the standard time series estimation methods used to analyze VIX, OVIX, S&P 500 stock price and energy prices relations provide only time-domain information while missing critical information from the frequency domain can be detected using wavelet tools. However, in time-series analysis, the hidden information on the frequency domain is one of the leading reasons for nonlinearity (Manimaran et al. 2009). The use of wavelet analysis helps to evaluate the relationship among VIX, OVIX, S&P 500 stock market and energy price by incorporating information from both time and frequency domain (Goupillaud et al. 1984; Habiba and Zhang 2020). According to Aguiar-Conraria et al. (2008), the wavelet approaches help estimate the spectral specifications of time series as a time function, thus exhibiting how the various periodic components of this time series swing through time. This approach allows for capturing the slow and persistent movements of time series.

In addition, the wavelet Granger causality test is used as a robustness test to assess the relationships between the variable over time, decomposing time-series into a bidimensional time-frequency sphere, can identify the regime-switching behavior and evaluate short- and long-run dynamics between stock markets and energy commodities. Third, we understand between pre-COVID-19 and COVID-19 samples to provide a more comprehensive evaluation of the asymmetric relationship between the US stock market and energy prices. Although the research on Covid-19 outbreak effects is rapidly growing, still limited research has been done on the causal effects of Covid-19 spread on both financial and commodity markets cumulatively.

Fourth, to do this, this paper specifically focuses on testing the response of the USA stock market, oil volatility, market level volatility, and commodities prices to the spread of Covid-19 pandemic. The study utilizes the implied volatility index (VIX), also known as the fear index of investors’ nervousness and the ex-ante measure of volatility (Shaikh and Padhi 2015). There are different sources of VIX, such as economic environment, uncertainty related to the market, institutional issues (Hartwell 2018), and economic policy uncertainty (Mei et al. 2018; Kalyvas et al. 2020; Tiwari et al. 2019; Chen and Chiang 2020). At the end of 2019, the Covid-19 epidemic is the latest source of market volatility, which has severely affected markets worldwide. During this outbreak, the S&P index also dropped to 11% in a week. The equity market in the USA and Europe had caused the loss of up to 35% of their value between February 19 and March 23 (Ampudia et al. 2020). Therefore, it can be inferred that Covid-19 epidemic could be the most recent source of market volatility (Onali 2020; Liu et al. 2020a). In addition to the theoretical contribution, the rapid change in the growth of economic uncertainty, the US stock market, energy prices and political consequences justify the economic significance of this study.

From an empirical standpoint, the findings exhibit that, during the COVID-19 outbreak, there is a substantial dynamic connectedness between VIX, OVIX, S&P 500 prices, and energy commodities are quite high at low and high scales. On the one hand, the highest interrelationships between both volatility indexes and S&P 500 index prices,
crude oil, natural gas, and gasoline energy commodities market generally occur at large scales for every stock market.
It is worth noting that most stock markets show a strong co-movement during the COVID-19 pandemic and financial crisis. The evidence of this relationship is shown over time and across different horizons. This variation provides important information about the portfolio management decision-making of the investors operating in different horizons (Bashir 2022; Syed and Bouri 2022).

Stockholders typically choose equities with high unpredictability while pushing toward low instability to be safe in a crisis (Chitteddi 2015). Furthermore, this study looks at the relationship between the VIX, OVIX, and the US stock market and energy commodities, which could result in an unusual premium for investors. These findings provide important implications for portfolio managers and create places where co-movement between the two can be considered. Investors should think about frequency and time frame when constructing their portfolios.

The rest of the paper is organized as follows: In segment 2, concise literature and theoretical background is discussed; in segment 3, methods and data are presented; in segment 4, findings are depicted; and segment 5 gives some concluding remarks.

**Literature and theoretical framework**

Hkiri et al. (2019) revealed that market interrelationships can be divided into interdependence and contagion. While the interdependence is related to a situation of continuous “tranquil-period” relations between markets which are generally due to common fundamentals driven by financial market integration or real linkages, the contagion is defined as a substantial upsurge in cross-market links after a shock to one country or group of countries (Forbes and Rigobon 2002). The interdependency and contagion between financial markets were especially important during the crisis period. Several academics have made useful theoretical and empirical arguments about how stock markets are linked across time. Pretorius (2002), for instance, presents three sorts of hypotheses for why there is co-movement between different stock markets worldwide. According to (Pretorius 2002), the first two categories are dependent on the fundamental approach. However, the contagion is not described by the fundamental method. Economic interconnectedness serves as a conduit for financial market links. As a result of the two economies’ economic interdependence, their stock markets are likewise linked (Phylaktis and Ravazzolo 2002). Another explanation for stock market connection is contagion effects or the notion of contingent crisis. Since the Asian financial crisis of 1997, which impacted several countries, there has been a surge in interest in studies on the transmission of financial shocks (Chancharat 2009). Turmoil can occur due to institutional elements influencing investor behavior or informational reasons that cause investors to alter their conduct (Wolf 1998).

Concerning direct investigations on COVID-19’s impact on financial markets, it discovered that global financial market risks have increased during COVID-19 and that probable non-conventional policy responses may be riskier than the pandemic itself (Zhang et al. 2020). In this pandemic, energy commodities have seen significant price movements and unexpected events (Huang and Zheng 2020). Similarly, Gharib et al. (2021) indicated that the correlations between oil and other commodity prices had shifted considerably during the epidemic. These changes are relevant to financial techniques like cross-hedging and cross-speculation. A recent study made by (Goodell 2020) highlighted the economic cost of Covid-19 and its importance in the field of finance and anticipated a few unanswered questions regarding the impact of Covid-19 on financial markets, cost of equity, the efforts to protect the financial system, and provide a future agenda for researchers. Considering the adverse effect on the overall economy and commodity markets, researchers keenly investigated how these markets behaved during this pandemic. In this regard, subsequent studies examine the response of stock markets and the corporate sector to Covid-19, mainly focusing on market volatility, trading volume and return (Onali 2020; Chen et al. 2020), and firm liquidity (De Vito and Gomez 2020). The literature covered three main channels on the pandemic; first, the effect on economic uncertainty; second, the effect on the financial market; third, the impact on the commodity market.

The sudden attack of the novel Covid-19 has dramatically increased the uncertainty that has a massive effect on the real economy and the financial sphere. This severe effect of the pandemic is attributed to the interruption of demand and supply related to economic activity. In a recent report on the economic effects of Covid-19, (Fernandes 2020) discussed several scenarios regarding the effect of the pandemic. In the first case, the GDP growth rates in 2020 are expected to decline by up to –2.8% for the sample of 30 countries. In the second scenario, the GDP would fall more than 10% in some countries. Countries reliant on service industries and tourism are among the top affected counties. Several empirical studies have been done to examine the economic effect of the pandemic. For instance, (Baker et al. 2020b) found that the US GDP has been dramatically affected by the Covid-19 outbreak inducing thus economic uncertainty.

They used wavelet coherence and wavelet-based Granger causality tests to investigate the link with Covid-19, oil price volatility, stock market volatility, geological risk, and economic policy uncertainty in the USA. The findings show that the emergence of Covid-19 significantly affects the US geopolitical risk as well as the US.
economic uncertainty during the pandemic negatively affects commodity price volatility, particularly the adverse effect on the oil price (Bakas and Triantafyllou 2020). Focusing on the association between the world industrial production index and Covid-19-induced uncertainty, Caggiano et al. (2020) predict a decline of 14% in world industrial production over one year.

In addition to the economic effects of Covid-19 pandemic, a growing literature has also discussed the impact of the pandemic on financial markets (Liu et al. 2020a; Chen et al. 2020; Ashraf 2020). The risk of global financial markets substantially increased in response to the pandemic (Zhang et al. 2020) and the short-term impact of the Covid-19 outbreak is clearly revealed in major affected countries. After using the event study method, Liu et al. (2020a) found that all the stock market indices quickly fell after the virus outbreak. The number of increased death cases as a proxy for the effect of Covid-19 has negatively reacted to the stock market due to losses (Ashraf 2020). The individual stock market reaction to the pandemic has shown severe signs in many countries like China, the USA, Italy, Spain, South Korea, and Iran (Zhang et al. 2020).

Moreover, the Covid-19 crisis also affected liquidity risk at the firm level (De Vito and Gomez 2020). Using a sample of 26 countries, the findings of De Vito and Gomez (2020) study revealed that up to 75% reduction in sales is witnessed, and the current liabilities increased up to eight times in the presence of distress condition. The S&P 500 index decreases by 0.01% daily and about 0.03% monthly in response to a 1% increase in daily Covid-19 cases. The historical analysis of the market indicates a negative effect of Covid-19 cases on the S&P 500 index during March 2020. Onali (2020) studies the impact of Covid-19 on the volatility and return of the US stock market. The findings were somewhat mixed as the effect of Covid-19 infected cases in the USA does not affect market returns. However, the market volatility increased up to three times in response to the infection cases at the end of February 2020.

The spread of Corona and its influence on people’s social life and the lockdown of the supply chain has already affected the demand and supply of commodity market products. The pandemic also indirectly affects the market due to global response in terms of slow growth than anticipated and global recessions (Bretscher et al. 2020). The effect is particularly severe on commodities and the transportation industry. The crude oil prices plunged to a historical decrease from January to April 2020. Other energy products, such as natural gas and coal prices also reduced, although there is an anticipation of a rebound in the next year. According to Meng et al. (2020), there is a strong return volatility linkage and spillover between the oil and Chinese commodity markets.

Moreover, this dynamic volatility connection between the oil and commodity market lasts for an extended period. Similar findings were observed in the study of (Jiang et al. 2019). Moreover, (Bakas and Triantafyllou 2020) found that the economic uncertainty created due to Covid-19 has also negatively affected commodity and oil market volatility. The main channel through the Covid-19 reduces commodity prices is the disturbance in global demand for the commodity market, particularly the demand for oil. The behavior of S&P 500 stocks in response to Covid-19, focusing on the March 2020 market crash. Using panel data techniques shows that around 90% of the S&P 500 stocks showed Asymmetry negative returns. Specifically, firms in the crude oil industry were severely affected with up to a 60% decline in their value.

On the other hand, firms in the chemical and natural gas industries increased their market value by 10% (Ibikunle and Rzayev 2020; Nyga-Lukaszewska and Aruga 2020). The empirical findings from the Markov-copula model revealed by Tiwari et al. (2020), oil price dynamics have a greater impact on G-7 stock market returns in the volatility regime than in the serenity regime. During the financial crisis, a significant positive association existed between crude oil price and stock-implied volatility return index, (Liu et al. 2020b). A well, a significant correlation between crude oil and stock market price volatility is also recorded in Asia (Sarwar et al. 2020).

Likewise, prospects and choices on VIX, OVIX, and the USA stock market with energy commodities markets give new speculation benchmarks. They can turn into another monetary instrument to support unpredictability hazards during Covid-19, similar to those items on VIX and OVIX in the stock market. Investors in the energy commodities, explicitly oil and stock markets, can express their disposition on additional unpredictability of raw petroleum costs. The stock market costs huge risks by exchanging choices on VIX, OVIX and the USA to get benefit opportunities in return for energy and oil commodities markets. As a result, this research may appeal to investors interested in using new financial tools to hedge stock price volatility and oil price volatility risk, such as futures and options trading on VIX, OVIX, the S&P 500, and energy commodities. Understanding the dynamics between VIX, OVIX, S&P 500, and major energy commodities indices is important for investors to develop instability-related portfolios, including diversifying risk during the COVID-19 pandemic. During the Covid-19 period, few studies have examined the spillover effect between market volatility and the commodity market. Commodity-dependent economies, particularly oil-exporting countries, are among the most affected economies due to the Covid-19 outbreak. Therefore, this study is one of the few studies investigating the response of market volatility, oil price, and the spillover effect on other commodity products.
The authors revealed a lack of correlation between energy prices and stock markets in terms of volatility. Additionally, the empirical findings indicate few correlations between stock market volatility and traditional energy commodities. Therefore, this study is one of the few studies investigating the response of market volatility, oil price, and the spillover effect on other commodity products. Against this background, this study aims to add to the literature by examining the static and dynamic interdependence across financial markets, including energy, VIX, OVIX and the US stock markets. The investigation has important policy implications for adopting optimal diversification measures in the prominent markets, particularly in light of the COVID-19 pandemic.

Procedures and materials

Data and primary analysis

The variables used in this study are the volatility index (VIX), the Oil volatility index (OVIX), and S&P500 stock prices of energy commodities, mainly Brent oil, Crude oil, Heating oil, natural gas, and gasoline. The daily data of all variables are collected from the Nasdaq database. The Oil volatility index data was collected from DataStream from December 2016 to September 2021. We remove observations in which data for at least one market is unavailable due to holidays or other factors. By taking log differences, all price data is converted to returns. Notably, the considered information covers the most important stock emergencies date during the Covid-19 pandemic. In these periods, the strains in the worldwide markets were recorded to be high in mid of December 2019, end of January, and from March to April 2020.

Figure 1 shows that investors respond firmly to fears of a worldwide monetary downturn driven by Covid-19 and energized by the conflict of the world’s significant oil-exporting nations. Most investors had dropped their investment in VIX and OVIX during the first two quarters of 2020 to recover their losses. While small fluctuations in VIX and OVIX are indicating uncertainties in two quarters of 2019. S&P 500 has a safe zone role for investors and attempted to respond to the worldwide vulnerability by pushing stock costs up and recovering their sudden losses during Covid-19. S&P 500 prices and commodities markets have the same trend, except natural gas shows more volatile trend. The downward trends in different commodities markets are witnessed due to commodity-dependent economies. The oil-exporting countries are among the most affected economies due to the Covid-19 outbreak and the decline in industrial production. The demand and supply imbalance during the Covid-19 pandemic has further affected the commodity market due to the world lockdown and disturbance. The prices of the USA economy and energy commodities decrease the volatility of the fear index and oil upward. On March 09, 2020, the vertical pattern was disturbed as rising oil costs news sent USA stock costs and commodities markets in defeat, leaving investors confounded.

Table 1 reports the elementary statistics of the investigated indexes. First, all the indices’ mean returns are positive, demonstrating a generally expanding stock price pattern for all periods. Similarly, all markets’ standard deviation indicates a small but increasing dispersion from their mean in these three panels. Second, the scope of returns demonstrates that the ware prices are exceptionally unpredictable. It is not surprising that for all indices except for S&P500, the cost has higher unpredictability given that it is not storable and request supply factors create shocks in the prices. Third, the standard deviations of the 7 months of all indices indicated that the returns of the energy commodities prices are more erratic than that of the 7-month S&P 500, further consistent with the “Samuelson effect” in the unpredictability of futures contracts (Jaekel and Lautier 2016). The Samuelson effect implied the maturity effect, which is the empirical evidence that a commodities contract’s volatility increases as it approaches maturity. The skewness value of VIX and OVIX has a slight variation and negative value of the S&P 500 market. The skewness values of Brent commodity have positive sign in penal A and negative sign in penal B & penal C. At the same time, Crude and Gasoline are negative, and natural gas positive in all these sample panels. Fourth, some returns exhibit negative skewness and are inconsistent with earlier findings (Deaton and Laroque 1992; Gorton et al. 2013).

The negative skewness is compatible with an oversupplied market because adverse interest shocks drive the cost to fall more than spikes in frequency or size. The kurtosis value of VIX and S&P 500 stock market has normal, but OVIX and crude brent commodities markets are increasing from panel A to C, indicating high variation. Similarly, the kurtosis values of the commodities market Natural gas and Heating oil indicate the same pattern in all panels. In contrast, the gasoline kurtosis value has increased in panel C. Fifth, the item returns are leptokurtic, with a lower kurtosis than the S&P 500 index. Leptokurtosis suggests that a Student t-distribution is fitting for experimental demonstration. The correlation between VIX and S&P500 is negative, as shown in panels A and B, indicating thus a strong inverse relationship. At the same time, it is revealed to be positive in panel C. Similarly, VIX and OVIX have a significant strong positive relationship in panels A and C. All the commodities markets...
have a strong inverse correlation with VIX and OVIX stock markets, while they show positive and robust correlations with S&P500. These findings indicate that the increases in commodities prices have adversely affected the VIX and OVIX stock market returns while increasing the S&P500 market returns.

The economic uncertainty has negatively affected the commodity price, especially the oil price during the pandemic (Bakas and Triantafyllou 2020). The world industrial production index and COVID-19 uncertainty predict a decline of 14% in total production in one year (Cagiano et al. 2020). Similarly, all the commodities markets have significantly and positively connected and directly affect their returns. These preliminary findings indicate that all commodities markets have strongly and adversely affected the volatility of the major world stock markets during the Covid-19 outbreak. Hence, investors need to liquidate their position or find safe investment alternatives during unexpected events in the future.

**Methodology**

In order to comprehend market behavior and investment opportunities utilizing stock market data, there has been a rising body of study on the link between the stock market. A suitable substitute for other time series models, aside from these models, has been the Wavelet model. In particular, wavelet model variations such as continuous wavelet transform (CWT), wavelet coherence (WCOH), cross wavelets transformation (XWT), and wavelet correlation analysis (WCA) have been utilized to study the co-movements between the pairings of stock markets (Rua and
### Table 1 Descriptive statistics

#### Panel A
Dec 2019 to Sep 2020

|                  | VIX  | OVIX | S&P 500 | BRENT CRUDE | CRUDE OIL | HEATING OIL | NATURAL GAS | GASOLINE |
|------------------|------|------|---------|-------------|-----------|-------------|--------------|----------|
| **Mean**         | 1.4138 | 1.7401 | 3.4913 | 1.9122 | 1.5830 | 0.1048 | 0.2879 | 0.0689 |
| **Median**       | 1.4289 | 1.6594 | 3.5039 | 1.7835 | 1.6086 | 0.0885 | 0.2667 | 0.0839 |
| **Maximum**      | 1.9174 | 2.5120 | 3.5537 | 2.5464 | 1.8011 | 0.3141 | 0.4329 | 0.2515 |
| **Minimum**      | 1.0827 | 1.3816 | 3.3497 | 1.2862 | 0.9571 | -0.1583 | 0.1708 | -0.3056 |
| **Std. Dev**     | 0.1977 | 0.2538 | 0.0393 | 0.4258 | 0.1585 | 0.1154 | 0.0601 | 0.1317 |
| **Skewness**     | 0.1352 | 0.8540 | -1.2673 | 0.4269 | -1.0529 | 0.2373 | 0.4875 | -0.7983 |
| **Kurtosis**     | 2.6105 | 2.7791 | 4.2785 | 1.5593 | 4.0963 | 2.3488 | 2.1468 | 2.9558 |
| **Jarque–Bera**  | 1.9861 | 26.201 | 71.192 | 49.795 | 5.7363 | 14.829 | 22.539 |
| **Probability**  | 0.0003 | 0.0000 | 0.0000 | 0.0000 | 0.0568 | 0.0000 | 0.0000 |
| **Sum**          | 299.72 | 368.91 | 740.157 | 405.40 | 335.60 | 22.219 | 61.036 | 14.627 |
| **Sum Sq. Dev**  | 8.2542 | 13.594 | 0.3272 | 38.262 | 5.3061 | 2.8125 | 0.7631 | 3.6643 |

#### Panel B
Dec 2020 to Sep 2021

|                  | VIX  | OVIX | S&P 500 | BRENT CRUDE | CRUDE OIL | HEATING OIL | NATURAL GAS | GASOLINE |
|------------------|------|------|---------|-------------|-----------|-------------|--------------|----------|
| **Mean**         | 1.2967 | 1.5728 | 3.6132 | 1.8168 | 1.7964 | 0.2772 | 0.5033 | 0.2855 |
| **Median**       | 1.2878 | 1.5714 | 3.6198 | 1.8340 | 1.8116 | 0.2930 | 0.4681 | 0.3153 |
| **Maximum**      | 1.5707 | 1.8123 | 3.6568 | 1.9005 | 1.8777 | 0.3689 | 0.7684 | 0.3682 |
| **Minimum**      | 1.1781 | 1.4955 | 3.5620 | 1.6760 | 1.6488 | 0.1295 | 0.3627 | 0.0865 |
| **Std. Dev**     | 0.0707 | 0.0447 | 0.0283 | 0.0562 | 0.0608 | 0.0585 | 0.0970 | 0.0746 |
| **Skewness**     | 0.7067 | 1.0935 | -0.2100 | -0.8662 | -0.8052 | -0.7976 | 0.8923 | -1.2197 |
| **Kurtosis**     | 3.4728 | 6.5645 | 1.7218 | 2.7308 | 2.6450 | 2.5548 | 2.8208 | 3.2193 |
| **Jarque–Bera**  | 19.341 | 152.301 | 15.763 | 26.767 | 23.683 | 23.887 | 28.015 | 52.237 |
| **Probability**  | 0.0001 | 0.0000 | 0.0004 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| **Sum**          | 271.01 | 328.71 | 755.157 | 379.72 | 375.44 | 57.94 | 105.20 | 59.66 |
| **Sum Sq. Dev**  | 1.04  | 0.42  | 0.17  | 0.66  | 0.77  | 0.71  | 1.96  | 1.16  |

#### Panel C
Dec 2016 to Sep 2021

|                  | VIX  | OVIX | S&P 500 | BRENT CRUDE | CRUDE OIL | HEATING OIL | NATURAL GAS | GASOLINE |
|------------------|------|------|---------|-------------|-----------|-------------|--------------|----------|
| **Mean**         | 1.2251 | 1.5485 | 3.474  | 1.7637 | 1.7292 | 0.2398 | 0.4393 | 0.2136 |
| **Median**       | 1.2033 | 1.5168 | 3.457  | 1.7917 | 1.7455 | 0.2735 | 0.4488 | 0.2232 |
| **Maximum**      | 1.9174 | 2.5120 | 3.6567 | 1.9360 | 1.9101 | 0.4065 | 0.8002 | 0.3812 |
| **Minimum**      | 0.9609 | 1.2518 | 3.3406 | 1.2862 | 0.9571 | -0.1583 | 0.1708 | -0.3057 |
| **Std. Dev**     | 0.1681 | 0.1586 | 0.0801 | 0.1037 | 0.1116 | 0.0988 | 0.1010 | 0.1075 |
| **Skewness**     | 0.87  | 2.2787 | 0.684  | -1.3895 | -2.0027 | -1.2247 | 0.0798 | -1.4971 |
| **Kurtosis**     | 3.8707 | 10.799 | 2.581  | 5.6674 | 9.8420 | 4.1860 | 4.0280 | 6.3480 |
| **Jarque–Bera**  | 192.4 | 3603  | 104.05 | 754.2000 | 3195 | 376.55 | 55.01 | 1025.00 |
| **Probability**  | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| **Sum**          | 1494.0 | 1889.0 | 4239.0 | 2156.0 | 2109.0 | 292.6 | 536.0 | 260.5 |
| **Sum Sq. Dev**  | 34.48 | 30.689 | 7.831 | 13.112 | 15.185 | 11.903 | 12.424 | 14.076 |

#### Correlation matrix

**Panel A**  
Dec 2019 to Sep 2020

|      | VIX  | OVIX | S&P 500 | BRENT CRUDE | CRUDE OIL | HEATING OIL | NATURAL GAS | GASOLINE |
|------|------|------|---------|-------------|-----------|-------------|--------------|----------|
| **VIX** | 1    |      |         |             |           |             |              |          |
| **OVIX** | 0.8458*** | 1    |         |             |           |             |              |          |
| **S&P 500** | -0.7563*** | -0.8552*** | 1    |             |           |             |              |          |
| **BRENT CRUDE** | -0.2519*** | -0.5754*** | 0.6693*** | 1    |           |             |              |          |
| **CRUDE OIL** | -0.7837*** | -0.9312*** | 0.6968*** | 0.4093*** | 1    |             |              |          |
| **HEATING OIL** | -0.7862*** | -0.8026*** | 0.4942*** | 0.1455*** | 0.9019*** | 1    | | |
When compared to Fourier analysis, wavelet-based techniques have a number of benefits. The wavelet coherence analysis displays how time series’ periodic constituents fluctuate with time and assesses time series’ spectral features as a time function. More interestingly, the wavelet coherence graphs allow us to understand the co-movement between variables across different frequencies and over time and the lead-lag relationships between these variables simultaneously during the different bands of scales (short, middle, and long-term run) and over time. One of the main advantages of wavelet coherence analysis is its capacity to visualize the exact timing and scale of shocks and provide an insightful understanding of trends related to financial and economic time series during shocks and extreme events. The wavelet graphs displayed as color spectra capture the time dynamics across many frequencies. WCOH, as compared to wavelet correlation analysis, provides more ability to discover high co-movement zones in a time and frequency space (Rua and Nunes 2009).

**Cross wavelet transform, wavelet coherence and phase difference**

The XPW (cross wavelet power) is utilized to recognize the highest market value comovement areas in the event of frequency sphere (Aguiar-Conraria et al. 2008). The 2-signal XPW can be characterized with the help of a range of cross wavelets ($W_{XY}^n(s)$), specified as

$$W_{XY}^n(s) = W_X^n(s)W_Y^n*(s)$$  \hspace{1cm} (1)

here $W_X^n(s)$ addresses the complex conjugate of $W_X^n(s)$. $W_{XY}^n(s)$, the CWP assists with securing the co-variance of the variables. The theoretical dispersion of the XPW of 2-signals with power bands $P_X^k$ and $P_Y^k$ are expressed as follows:

$$B\left(\frac{|W_X^n(s)W_Y^n*(s)|}{\sigma_X\sigma_Y} < p\right) = \frac{Z_p(p)}{\sqrt{P_X^k P_Y^k}}$$  \hspace{1cm} (2)

This table provides summary statistics of VIX, OVIX. Stock price and commodity factors, as well as pairwise correlations. The asterisks *, **, and *** denotes rejections of null hypothesis at 10%, 5%, and 1% significance levels, respectively. According to [52], positive skewness in commodity prices can be explained by the theory of storage in which a low level of inventory causes positive price spikes that exceed in magnitude the negative price spikes at times of a high level of inventory.
where \( \sigma^2 X \) and \( \sigma^2 Y \) denotes the SD of \( x \) and \( y \). \( Z_s(p) \). The probability density function (pdf), well-defined as the root squared \( \chi^2 \) dispersal, is represented by the confidence interval, where \( p \) indicates the possibility of a probability density function (pdf). The wavelet coherence is calculated as the outright squared value of the leveled cross wavelet bands standardized by the result of the leveled individual wavelet power spectra of each time sequence, as shown in (Torrence and Webster 1999)

\[
R^2(u, s) = \frac{ \left| S(s^{-1}W_{xy}(u, s)) \right|^2 }{ S\left(s^{-1}\left| W_x(u, s) \right|^2 \right) \ast S\left(s^{-1}\left| W_y(u, s) \right|^2 \right)}, \tag{3}
\]

In the equation, \( S \) stands for the smoothing parameter. The disparity state is satisfied by the CSWC (coefficient of squared wavelet-coherence) of \( 0 \leq R^2(u, s) \leq 1 \). A \( R^2(u, s) \) value approaches one indicates a higher association, and if \( R^2(u, s) \) approaches to zero, it suggests correlation is weak. The wavelet-coherence method is used as the most suitable technique for the above reasons for variable examination concerning frequency and time. The two-phase time-series differences variable, i.e., \( \phi_{s, x, y} \) could be used to differentiate their phase connection. The phase differences characterized underneath decide the situations in the pseudo-cycle, and it is determined as:

\[
\phi_{s, x, y} = \tan^{-1}\left( \frac{\mathbb{I}\{W_{xy}^n\}}{R\{W_{xy}^n\}} \right) \text{ with } \phi_{s, x, y} \in [-\pi, \pi] \tag{4}
\]

The stage relationship has been described by arrow directions. If arrows are coordinated to one side, then two variables have a positive correlation and vice versa. In addition, when arrows approach from the right and up, the variable \( X \) is leading, and the two variables are positively correlated; when arrows approach from the right and down, the variable \( X \) is trailing, and the two variables are positively linked. If the arrows travel up to one side, the principal variable \( X \) lags, and the relationship is negative. If the arrows travel to one side and down, the relationship is negative since the major variable \( X \) is leading.

For all wavelet charts beneath, the frequency is changed over to time unit (every day) on the vertical axis and time (month) addressed by the horizontal axis. In all plots, the dark shape addresses the more critical area at 5% level again the red noise. The powerful area is delimited by the coin of impact (COI), which is shown by a lighter tint. The arrow bearing captures the stage disparities between the double-cross series. The variables in-phase (anti-phase) were shown by arrows to the right and up (down), the principal variable leading(lagging) was shown by arrows to the left and up (down), and the primary variable lagging was shown by arrows to the left and up (down).

**Findings and discussion**

**Wavelet estimations**

**Cross wavelet analysis**

When localized similarities are present, characteristic features are extracted using the cross wavelet transform (XWT) approach. This methodology has the benefit that it can distinguish between normal and abnormal classes with fewer parameters than previous methods for classifying time-frame features (Younis et al. 2020). When few similarities are observed in data patterns, the cross wavelet transform (XWT) approach is employed to extract the characteristic element. While determining the absolute worth of the adjacent covariance between the double-cross series, the data about the phase-dependent on the nonexistent component is lost. As a result, value indices of double cross series with the same high power areas may be challenging to identify. Figure 2 shows how the cross-wavelet transform of value indices helps solving this problem by revealing if stock value indices' variations differ over time and across scales. We can see that the co-movements of all pairings vary among unspoiled areas. The VIX co-variations with commodity indexes are displayed in Fig. 2b, c, d, and e. The VIX index shows an anti-phase relationship with heating oil, gasoline, natural gas indexes, and crude oil, indicating a negative relationship between the VIX index and commodity indexes. The most important areas of co-variation are localized in the medium and long runs. This result indicates that the higher “the fear index,” the greater the level of uncertainty will be in the commodity market; if commodity market indexes suffer sharp drops, the expected volatility increases.

In Fig. 2f, h, i, OVIX-Gasoline, OVIX-Heating oil, and OVIX-Crude oil price indices co-movements are localized over the period starting from the end of January to March 2020, showing a high level of covariances between pairs. While the covariances between OVIX index, Brent, Crude Oil, and Natural gas respectively is not significant, the couples show anti-phase relationships, which are especially perceived in the 16–32 and 32–64 band of scales corresponding to the middle and long horizons and these results are similar with the findings of (Gharib et al. 2020; Sharif et al. 2020). Further, the OVIX index has leading Gasoline index in the middle and long runs.

The co-variations between the S&P 500 and the five energy commodities price indices are reported in Fig. 2k
The S&P 500 and Brent crude oil (Fig. 2k) did not show a substantial co-variation, while the S&P 500 and Crude Oil couple exhibits a mixed relationship in the middle and long horizons. Although the S&P 500 is driven the crude oil over the (16–32) positive, negative relationship perceived in the long horizon. In the medium and long terms, a positive and significant relationship is revealed for the couples S&P 500-Heating Oil (Fig. 2m), S&P 500-Gasoline (Fig. 2o), and S&P 500-Natural gas (Fig. 2n) over the period January–May 2020 (Jeris and Nath 2020). These results indicate that the shocks of Covide-19 are transmitting from S&P 500 stock market to the commodities and further increases the volatility of commodities markets. Additionally, in March 2020, the stock market was adversely impacted by the dramatic breakdown of oil prices due to the conflict between Saudi Arabia and Russia over oil supply and prices (Ma et al. 2021), providing significant implications for stock market investors.

According to panel B Fig. 3a, b, c, d, and e, the couples indices of VIX-Brent, VIX-Crude, VIX-Heating oil, VIX-Natural gas, and VIX-Gasoline at the high-frequency region have indicated positive leading patterns. The increasing energy commodities demand is due to the rising VIX market uncertainties and affecting investors’ returns during (32–64 days). Crude is the substitute for coal, and natural gas creates another upside risk and downside risk for oil demand during outbreaks of Covid-19. Due to the pandemic, this imbalance of demand and supply has also affected the commodity market. Because of the unpredictability of the US economic policy and market volatility, the disease’s probability of causing financial crises is high (Sharif et al. 2020).

Similarly, in Fig. 3f, g, h, i, and j, the couples indices of OVIX-Gasoline, OVIX-Natural Gas, OVIX-Heating oil, OVIX-Crude, and OVIX-Brent have negative and leading patterns at the high-frequency regions respectively. While in Fig. 3k, l, m, o, and n), S&P500 with Brent, Crude, Heating oil, and Gasoline have negative-lagging and positive-lagging patterns with Natural gas indicated respectively. The increasing OVIX and S&P500 market volatility tends to increase energy commodities’ risks and prices in (57–64 days). The oil substitutes have upward risk, and if high commodity prices remain longer, it can decrease the energy growth of importing countries and push the food insecurity in underdeveloped countries (Baker et al. 1998; Meng et al. 2020; Syed and Bouri 2022).

In panel C Fig. 4a, b, and c, VIX with -Brent, Crude, and Heating oil have indicated a negative and leading pattern at high frequencies. But in Fig. 4d and e, VIX-Naturel gas and gasoline have shown negative leading-lagging patterns during (64–128 days). The soaring energy prices of brent, crude, heating oil, and gasoline have been due to the VIX market volatility. Natural gas tends to zero the market return due to covid-19 uncertainties indicated at the higher frequency islands. These higher prices adversely affect other commodities’ production and create supply chain disruptions by increasing demand (Meng et al. 2020).

Consistently in Fig. 4, h, i, and j, the OVIX with -Gasoline, Heating oil, Brent, and Crude have a negative-leading pattern during (64–128 days). The leading and inverse relationship between the VIX market and energy commodities is declining market returns with increasing volatilities for investors in the long run. But, in Fig. 4k, l, m, n, and o, S&P 500 with Brent Crude, Heating, Natural gas, and Gasoline...
Fig. 3  Panel B Cross wavelet
Fig. 3 (continued)

Fig. 4 Panel C Cross wavelet
have positive-lagging patterns at high-frequency. The energy commodities Brent, crude, heating oil, natural gas, and gasoline higher prices not leading the S&P 500 market in long-horizon (64–128 days). S&P 500 index has adjusted the price volatilities of the energy commodities indices in the long run by providing a safe zone for the investor’s investment returns in the financial market.

Hence, as shown in panels A and B, all commodities markets have significantly affected the volatility of the VIX, OVIX, and S&P 500 stock markets during Covid-19. The
study of Ahmed and Sarkodie (2021a) reported a strong return volatility linkage and interesting spillover between the oil and Chinese commodity markets. However, the emotional volatility connection between oil and the commodity market lasts for an extended period (Jiang et al. n.d.; Syed and Bouri 2022). According to the World Bank report on the energy and commodities market, the commodities prices will further be increased in the future, and agriculture goods prices increased by 22% in 2021 and stabilize in 2022 (Chen et al. 2022). Hence, investors can predicate to plan and move to the safe zones in the financial market by reducing their investment risks and a significant loss in the future.

Wavelet coherence findings

Because of visible and clear findings, further investigations are directed through wavelet intelligibility. We resort to the WCOH which delivers a robust measurement for synchronizing the considered variables over the long haul and across frequency bands. The wavelet intelligibility analysis generates the confined relationship coefficient between two variables. Obviously, the wavelet lucidity can reliably provide the co-movements between variables over various investment horizons. In addition, this method also works productively in a noisy climate where we require the main amendment of the baseline of the stock value indices for greater measurement exactness, and regardless of whether the baseline distortion persists, the classification precision is moderately acceptable. The unique relationship between double-cross series is portrayed through the island's colors. The tone goes from blue (low power of coherency) to red (high power of coherency) between time series.

Based on the prior findings, it is worth looking into whether one variable’s instability causes another's instability or if it is just a coincidence. The wavelet rationality, as mentioned earlier, quantifies the close link between time series. An ideal connection among VIX, OVIX, and S&P 500 stock market indices with considered energy commodities market indices at low, medium, and high-frequency bands for a specific time are seen when the nearby relationship is equivalent to 1. When the value approaches zero, the neighborhood relationship becomes less interesting. The estimated wavelet for VIX, OVIX, and S&P 500 with the relevant energy commodities is shown in Fig. 5. We can see that the indices change a lot across all frequency bands and time intervals, which provides interesting information. A look at Fig. 5f, h, and i, panel A demonstrates a strong coherency between OVIX and the corresponding set of commodity prices. OVIX index highly co-move negatively with Gasoline, Heating oil, and Crude oil indices at high scales (January-ended to April 2020) and at low scales (16-day, 32-day, and 32–64 day of scales) over the sample period. It indicates that Gasoline, Heating oil, WTI crude oil, and Brent crude price indices are leading the OVIX index. These findings identified a rapid increase in financial stress during and after the Covid-19 and substantial nonlinearity in a spread. It is worth noting that the nonlinear impact, which can be attributed to investors’ varied expectations over short and long investment horizons and information timeliness, is a basic commonsense issue (Fetzer et al. 2020; Jeris and Nath 2020).

Figure 5k, l, m, n, and o represents the WCOH between S&P 500 and energy commodities prices. At low scales, the stock market index moves in a positive relationship with Brent crude oil (Fig. 5k), WTI (Fig. 5l), and Natural gas (Fig. 5n), where the arrows are up-down, indicating a follower of the stock market. From January to March 2020, the oil market’s volatility shocks are conveyed to the financial stock market. However, we believe that the rapid drop in oil prices and concerns about COVID-19 has had a greater impact on the US economy, which is projected to have a long-term negative impact. The VIX is principally identified with the drawn-out US economy and how the world will respond to the remarkable volatility rise during COVID-19 (Sharif et al. 2020). A close correlation ranging from 0.9 to 1 and scattered over the sample period and across scales band is reported in (Fig. 5o) corresponding to S&P 500 vs. Gasoline coherency and indicating that the Gasoline index drives the US financial market index fluctuation. The VIX index also drives the financial stock market change over the whole sample period and at low and high scales when the time series demonstrate a negative relationship. The US volatility index leads to the financial stock market index change.

According to panel B Fig. 6a and b, the wavelet coherence plot among VIX-Brent and VIX-Crude oil is in anti-phase lagging (leading) at (days 4–8) in a higher frequency band during May–August 2021 (Fig. 6c). The wavelet coherence plot VIX-Heating oil has an anti-phase-lagging (leading) pattern during Jan–Feb 2021 and May–August 2021, but in Fig. 6d, VIX-natural gas in phase leading pattern during December 2020 and July 2021 at (days1–8). Our finding indicates the existence of substantial volatility spillover from Heating Oil to the VIX index during the considered sub-periods, which correspond to the negative heating oil price period. This result exhibit that the uncertainty in the oil market propagated to the US financial market and is expressed by shocks in the common volatility measure of this market. This finding corroborates those of (Corbet et al. 2021). Corbet et al. (2021) used a TVP-VAR model to assess the inter-relationship between crude oil and other US energy prices, stock prices, and exchange rate markets during the COVID-19 pandemic. They revealed a spillover among markets. Interestingly, their findings exhibited that WTI is identified as a volatility receiver from all considered markets during the sample period as well as a volatility transmitter during
Fig. 5  Panel A Wavelet coherence
shock price events. In Fig. 6e, VIX-gasoline has in the phase leading during April 2021 days (1–4) and in the anti-phase-lagging (leading) pattern during May–August 2021 (days 4–10). The wavelet coherence analysis indicates that the VIX market has negatively reacted to energy commodities brent, crude, heating oil, and gasoline variations. In contrast, it reacts positively to natural gas change in the short run during covid-19 (May–August 2021). These small fluctuations have been due to the increasing demand in the world market and reduced world production during the covid-19 outbreak.

Similarly, in Fig. 6f OVIX-gasoline, an anti-phase lagging (leading) pattern is perceived in high frequencies during the sub-period April–September 2021. Figure 6g shows the relationship between OVIX-Natural Gas positive during December 2020, while in Feb–Mar 2021 negative at short frequency bands. Again in Fig. 6h, i, and j, the OVIX have a native relationship with Heating, Crude, and Brent oil during Feb–August 2021 at short frequency bands. The OVIX market was inversely affected but did not lead the energy commodities market in a short time. The uncertainty of energy commodities increased due to the decreasing level of investment in oil production firms during the Covid-19 pandemic.

The plots in panel B, Fig. 6k, l, m, o, and n) correspond to the wavelet coherence of S&P 500 with Brent, crude, heating oil, and gasoline, respectively. These couples demonstrated phase-leading patterns from Dec. 2020 to Mar. 2021 and in phase-lagging pattern (Fig. 6) from June–September 2021 in the short run. Whereas S&P 500 and natural gas are in phase and lagging from Jan–August 2021 in the medium horizon (16–64 days of scale- Fig. 6). The S&P 500 and commodities market are in a line making the same risk-returns for investors due to the fast adoption of the lockdown system and better health policy during Covid-19. All the countries worldwide are fighting a health emergency. But the increase in lockdown has also
affected the supply and demand of the commodities (Baker et al. 2020b; Bretscher et al. 2020).

In panel C, Fig. 7a, b, and c, the wavelet coherence of VIX with Brent, Crude, and Heating oil, respectively, has indicated an anti-phase relationship in a high-frequencies during the years 2019–2021. However, as revealed in Fig. 7d and e, the VIX-Naturel gas indices indicate a weak relationship, whereas VIX-Gasoline indicates an anti-phase relationship. Again, the VIX market has driven and inversely reacted to changes in energy commodities, especially Brent, Crude, Heating oil, and Gasoline by increasing the demand, prices, and risks to the commodities market investors operating in long horizons.

Correspondingly, in Fig. 7f, h, i, and j, the OVIX coherency with Gasoline, Heating, Brent, and Crude oil, respectively, indicate anti-phase relationships in the median and long-term scales over the sub-period 2019–2021 while Fig. 7g corresponding to OVIX-Natural gas co-movements reveal a positive relationship in the medium scales which is especially scattered before 2019. These commodities indices have adversely affected the OVIX market during Covid-19 due to lockdown, increasing demand and decreasing supply of commodities, and shifting the investors’ attitude to minimize a significant loss in the financial market.

We are looking now at the wavelet coherencies reported in Fig. 7k, l, m, and o between S&P 500 and Brent, crude, heating oil, and gasoline, respectively. The graphs indicate positive relationships between pairs indicating that the contagion effect between financial stock market and commodities markets. Similarly, in Fig. 7n, S&P 500 and natural gas show a weak relationship where the S&P 500 is lagging in (16–32 days of scale) during the sub-period 2018–19. These findings again indicate that S&P 500 and commodities markets have declining demand/supply and adjusting the risk-returns patterns for investors during the outbreak of Covid-19. It is the most current source of market volatility in various studies (Onali 2020; Liu et al. 2020a).

Overall, all the couples, including the VIX index, depict an anti-phase relationship over time and across frequency bands. Especially, high levels of coherency range from 0.9 to 1, spread in the short and middle horizons during the sub-periods December 2020- March 2020 and June 2020 to August 2020. When recognizing the wavelet coherencies between the VIX index and commodity prices indexes, a strong and significant long-term co-movement is exhibited between the VIX index and Gasoline. The ascending arrows suggest that commodities prices contributed to stock market volatility in the USA during the COVID-19 epidemic. Because of movement restrictions and low expected yield development in China and European countries, this result shows that stock market volatility, oil volatility, and S&P 500 volatility due to the Covid-19 pandemic appear to have severe implications on oil cost and energy commodity unpredictability through the interesting side. In any event, it appears that calculating the impact of the current infectious illness flare-up on long-term future oil prices is ahead of schedule. Undoubtedly, the oil markets are in a perplexing situation due to the unusual combination of rising supply and dropping demand. This might explain the fluctuation of oil unpredictability in the time–frequency space as well as the oil interrelationship in the last three months of the pandemic.

In crisis places, the Covid-19 crisis effects were substantially revealed. The financial devastation brought on by the Covid-19 outbreak worldwide has prompted many similarities to the Incomparable Recession of 2008–09. While the previous crisis began in the financial sector and spread across the economy, this recent outbreak was ushered in by a worldwide healthcare crisis, which brought the entire economy to a halt, disrupting supply chains, industries, enterprises, small businesses, and consumers in unusual ways. The public authority and national bank have responded to this crisis like the global financial crises. During a crisis, risks create investing opportunities, but stock return predictability and price volatility increase in the worst-case scenario. The fear indexes fluctuate over time but show a general downward trend (Sun et al. 2021). Stock market performance and epidemic distress indexes have varying links over time. Covid-19 identified long-run interdependence between the markets under investigation as well as substantial evidence of pure stock market contagion. The such crisis has the potential to have dire effects similar to those observed during the global financial crisis (Junor et al. 2021). However, there are signs that the relief and strategy measures will be distributed unevenly as they were during the previous crisis, resulting thus in an even greater pay gap in the USA.

Robustness evidence on wavelet granger causality

The wavelet-based Granger Causality tests are used to assess the robustness of the wavelet coherence analysis results. Three frequency domains are used in the causality testing (D1 to D5). Based on the wavelet coherence findings, the periods will be classified into three major periods: namely, short-run (D1 = 4 days + D2 = 8 days), medium-run (D3 = 16 days + D4 = 32 days), and D5 (64 days), revealing the long-run. The results are conveyed in Table 2. We first examined the causality between VIX and OVIX, S&P 500, and considered energy commodities returns in the first bring series. We looked at the causality further by using the wavelet transformation to look at the time-scaled components of the first series. The findings reported in Table 2 provide evidence of causality among independent and dependent variables at the 1%, 5%, and 10% significance levels.

In contrast, the results of Granger causality tests, as shown in Table 3, reveal that D1 exhibits unidirectional causation from the VIX, OVIX, and S&P 500 indices to
heating oil and gasoline. At the same time, it demonstrates a bidirectional causality relationship between Crude oil and OVIX and S&P 500, respectively.

The Granger causality test results for different time scales in the short term (D2) exhibit a bidirectional causality among VIX, OVIX, S&P 500, Crude, Heating oil, and Gasoline. This evidence is also consistent with the idea that impermanent oil value shocks little affect energy commodities prices and impact dampens rapidly extends to shorter horizons. We notice that, unsurprisingly, oil price unpredictability is bidirectional, causing the S&P 500, oil instability and dread indices for each selected frequency. This finding supports prior research of [57, 58]. These studies found the S&P 500 was extremely sensitive to unexpected oil shocks. Over extremely short term investment horizons (D1 + D2), the impact of oil prices on the S&P500 can be clearly perceived. Furthermore, a wavelet-based finding about VIX and S&P 500 for the short-run (D1) to the long-run (D5) has unique frequency patterns. Significantly, the VIX has caused unidirectional and OVIX bidirectional risks at all levels and at the same time, it affects the S&P 500 index at D1 and D5 differently. This could be due to US investors viewing the COVID-19 flare-up as a financial catastrophe first and foremost. Since the three exogenous shocks are dependent, VIX, OVIX, and the S&P 500 index significantly impact oil, natural gas, and gasoline prices over the remaining frequency domains. However, we discovered an evidence of causality at longer time scales to the couple indices, crude-heating oil and crude gasoline. Also, the causality tests from heating oil, crude oil and gasoline energy indices to crude oil prices have provided evidence of unidirectional and bidirectional causality. Furthermore, evidence on bidirectional causality, primarily at intermediate scales (D3 + D4), is consistent with the assumption that each market gives data about other markets that has been valuable in modifying prices for a long time. When oil price shocks persist, the impact of these shocks is conveyed to Brent, crude, heating oil, and gasoline energy prices to certain lags.

Table 3 reports results for causality between VIX, OVIX, S&P 500, and five energy commodities markets. Our results provide evidence on the existence of non-direct causality at unsurpassed scales. We found consistent evidence of causality going from VIX, OVIX, and the US markets to oil prices for each frequency band at the short run. While (from D1 to D5), causality consecutively from oil to energy commodities markets was somewhat mixed. Except for the Gasoline and crude oil indices, there was no Granger connection among oil and energy commodity prices in short-run time scales.

In contrast, Granger causality runs from oil to all energy commodities indices, save Brent crude, for a long period. Evidence on bidirectional causation, primarily at lower frequencies, suggests that the oil market does not always lead the energy commodities market in the long run. Our findings imply that the oil and energy commodities markets are intimately intertwined and that the success of energy commodities is highly dependent on oil price behavior. These results are in line with our earlier wavelet covariance and wavelet analysis findings. The coherencies over (8–16 days) frequency band show a strong relationship between S&P

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Fig. 6 Panel B Wavelet coherence
500-Crude oil. Undeniably, the oil markets are in a difficult situation due to the unusual combination of rising supply and dropping demand due to Covid-19. It could explain the S&P 500-Crude oil interrelationship’s change over the last seven months. It's worth noting that the S&P 500-Heating oil pairs have a poor correlation and it indicates that heating oil prices lead (lagging) the S&P 500 prices during these sub-periods. As a result, as we move from higher...
frequencies to lower frequencies, the scope of risk diversification decreases. Similarly, the evolution of risks around the latest episode of the Covid-19 problem is critical. The co-movement of risks was significant practically around the globe in the newest episode of a dark swan. However, this is only true for dangers at lower frequencies and not always for risks at higher frequencies. There is evidence of correlation in short-term risk co-movements between VIX, OVIX, S&P 500, Brent, Crude oil, heating oil, natural gas, and Gasoline. Risks’ volatility transmission occurs more frequently among VIX, OVIX, S&P 500, and five energy commodities indices (Fig. 3) and is moderately frail. This evidence is documented in the new episode of the COVID-19 crisis in which the developed stock market and five energy commodities indices dropped together and is not necessarily apparent at the long-term risks level. The wavelets’ findings suggest that the unpredictability spillovers were mostly limited during this period, even while stock value indices’ spillover is significant.

Conclusions and policy implications

This study analyzed the relationship between the prices of VIX, OVIX, S&P 500, and energy commodities during the recent pandemic. We performed a period-frequency analysis based on the cross-wavelet, wavelet rationality, and Granger causality-based wavelet (horizons) to investigate this link at various time scales. Except for the two pairs VIX-Heating oil and S&P 500-Heating oil markets, the wavelet rationality results suggest the co-movement between VIX, OVIX, S&P 500 prices, and energy commodities markets is quite high at low and high frequency. From the findings, it can be deduced that the co-development of the VIX, S&P 500,
Fig. 7 (continued)
| Independent variables | Dependent variables |
|-----------------------|---------------------|
| **D1**                |                     |
| VIX                   | 2.06322*            |
| OVIX                  | 3.51134***          |
| S&P500                | 3.59585***          |
| Brent Crude           | 1.04625             |
| Crude oil             | 0.29299             |
| Heating oil           | 0.02466             |
| Natural gas           | 0.33158             |
| Gasoline              | 0.05593             |
| S&P500                | 1.96754***          |
| Brent Crude           | 0.66000             |
| Crude oil             | 1.04605             |
| Heating oil           | 0.02466             |
| Natural gas           | 0.33158             |
| Gasoline              | 0.05593             |
| VIX                   | 2.07212***          |
| OVIX                  | 0.90193             |
| S&P500                | 1.21019             |
| Brent Crude           | 0.76724             |
| Crude oil             | 0.02466             |
| Heating oil           | 0.02466             |
| Natural gas           | 0.33158             |
| Gasoline              | 0.05593             |
| VIX                   | 2.37252***          |
| OVIX                  | 0.99425             |
| S&P500                | 1.21019             |
| Brent Crude           | 0.76724             |
| Crude oil             | 0.02466             |
| Heating oil           | 0.02466             |
| Natural gas           | 0.33158             |
| Gasoline              | 0.05593             |
| VIX                   | 2.40697***          |
| OVIX                  | 0.76957***          |
| S&P500                | 1.27961             |
| Brent Crude           | 0.76724             |
| Crude oil             | 0.02466             |
| Heating oil           | 0.02466             |
| Natural gas           | 0.33158             |
| Gasoline              | 0.05593             |
| VIX                   | 2.90100***          |
| OVIX                  | 2.04088             |
| S&P500                | 5.79657***          |
| Brent Crude           | 1.27961             |
| Crude oil             | 0.02466             |
| Heating oil           | 0.02466             |
| Natural gas           | 0.33158             |
| Gasoline              | 0.05593             |
| VIX                   | 2.43756***          |
| OVIX                  | 4.47329***          |
| S&P500                | 4.43648***          |
| Brent Crude           | 3.60870***          |
| Crude oil             | 1.55348             |
| Heating oil           | 1.79875             |
| Natural gas           | 1.27324             |
| Gasoline              | 2.42488***          |
| VIX                   | 2.38937***          |
| OVIX                  | 2.40697***          |
| S&P500                | 4.47329***          |
| Brent Crude           | 3.60870***          |
| Crude oil             | 1.55348             |
| Heating oil           | 1.79875             |
| Natural gas           | 1.27324             |
| Gasoline              | 2.42488***          |
| VIX                   | 3.85188***          |
| OVIX                  | 1.62591             |
| S&P500                | 3.79067***          |
| Brent Crude           | 0.56589             |
| Crude oil             | 0.42519             |
| Heating oil           | 0.48726             |
| Natural gas           | 0.26734             |
| Gasoline              | 1.18558             |

This table provides summary Wavelet based Granger causality of VIX, OVIX US Stock price and commodity factors, *, ** and *** denotes rejections of null hypothesis at 10%, 5% and 1% significance levels, respectively.
### Table 3 Wavelet Granger causality outcomes

| Null hypothesis | Direction of causality | Null hypothesis | Direction of causality | Null hypothesis | Direction of causality |
|-----------------|------------------------|-----------------|------------------------|-----------------|------------------------|
| D1 VIX ≠ OVIX   | ↔                      | OVIX ≠ Crude oil | ↔                      |                |                        |
|                 |                        | VIX ≠ > S&P500   | ↔                      | Crude oil ≠ Natural gas | →                      |
|                 |                        | VIX ≠ Brent Crude| →                      | Gasoline ≠ Crude oil | →                      |
|                 |                        | VIX ≠ Crude oil  | →                      | Natural gas ≠ > Heating oil | →                      |
|                 |                        | VIX ≠ > Heating oil | →                      | S&P500 ≠ > Crude oil | ↔                      |
|                 |                        | VIX ≠ Gasoline   | →                      | S&P500 ≠ > Heating oil | →                      |
|                 |                        | OVIX ≠ > S&P500 | →                      |                |                        |
| D2 VIX ≠ OVIX   | ↔                      | OVIX ≠ > S&P500 | →                      | Crude oil ≠ Gasoline | ↔                      |
|                 |                        | VIX ≠ > S&P500   | →                      | Crude oil ≠ Natural gas | →                      |
|                 |                        | VIX ≠ > Gasoline | →                      | Heating oil ≠ > Natural gas | ↔                      |
|                 |                        | VIX ≠ > Crude oil | ↔                      | Gasoline ≠ > Crude oil | →                      |
|                 |                        | VIX ≠ > Heating oil | ↔                      | S&P500 ≠ > Heating oil | →                      |
|                 |                        | OVIX ≠ > Crude oil | ↔                      | S&P500 ≠ > Gasoline | →                      |
|                 |                        | OVIX ≠ > Gasoline | ↔                      |                |                        |
| D3 VIX ≠ OVIX   | →                      | OVIX ≠ > Natural gas | →                      | Crude oil ≠ > Heating oil | ↔                      |
|                 |                        | VIX ≠ > S&P500   | ↔                      | Crude oil ≠ > Natural gas | →                      |
|                 |                        | VIX ≠ Brent Crude| →                      | Crude oil ≠ > Gasoline | ↔                      |
|                 |                        | VIX ≠ > Crude oil | ↔                      | Heating oil ≠ > Natural gas | ↔                      |
|                 |                        | VIX ≠ > Heating oil | ↔                      | S&P500 ≠ > Natural gas | ↔                      |
|                 |                        | VIX ≠ > Gasoline | ↔                      | S&P500 ≠ > Gasoline | ↔                      |
|                 |                        | OVIX ≠ > S&P500 | ↔                      |                |                        |
|                 |                        | OVIX ≠ > Crude oil | ↔                      | Heating oil ≠ > Brent crude | →                      |
| D4 VIX ≠ OVIX   | ↔                      | OVIX ≠ > Crude oil | ↔                      | Heating oil ≠ > Crude oil | →                      |
|                 |                        | VIX ≠ > S&P500   | ↔                      | Crude oil ≠ > Natural gas | →                      |
|                 |                        | VIX ≠ > Natural gas | ↔                      | S&P500 ≠ > Heating oil | →                      |
|                 |                        | VIX ≠ > Crude oil | ↔                      | S&P500 ≠ > Crude oil | ↔                      |
|                 |                        | VIX ≠ > Heating oil | ↔                      | S&P500 ≠ > Natural gas | ↔                      |
|                 |                        | VIX ≠ > Gasoline | ↔                      | S&P500 ≠ > Gasoline | ↔                      |
|                 |                        | OVIX ≠ > S&P500 | ↔                      |                |                        |
| D5 VIX ≠ OVIX   | ↔                      | OVIX ≠ > Heating oil | ↔                      | Brent oil ≠ > Gasoline | →                      |
|                 |                        | VIX ≠ > S&P500   | ↔                      | Natural gas ≠ > Brent oil | →                      |
|                 |                        | VIX ≠ > Crude oil | ↔                      | Crude oil ≠ > Gasoline | ↔                      |
| Brent Crude ≠ VIX | →                     | S&P500 ≠ > Crude oil | ↔                      | Natural gas ≠ > Heating oil | →                      |
|                 |                        | VIX ≠ > Gasoline | ↔                      | Heating oil ≠ > S&P500 | ↔                      |
|                 |                        | OVIX ≠ > S&P500 | ↔                      | Heating oil ≠ > S&P500 | ↔                      |
|                 |                        | OVIX ≠ > Crude oil | ↔                      | Brent oil ≠ > S&P500 | →                      |
| Original VIX ≠ OVIX | →                      | OVIX ≠ > Gasoline | →                      |                |                        |
|                 |                        | VIX ≠ > S&P500   | ↔                      | S&P500 ≠ > Crude oil | ↔                      |
|                 |                        | VIX ≠ > Crude oil | ↔                      | S&P500 ≠ > Heating oil | ↔                      |
|                 |                        | VIX ≠ > Heating oil | ↔                      | S&P500 ≠ > Gasoline | →                      |
|                 |                        | VIX ≠ > Gasoline | ↔                      | Brent crude ≠ > S&P500 | →                      |
|                 |                        | OVIX ≠ > S&P500 | ↔                      | Crude oil ≠ > Natural gas | →                      |
|                 |                        | OVIX ≠ > Crude oil | ↔                      | Gasoline ≠ > Heating oil | →                      |

***, *, and ** stands for 0.01, 0.05, and 0.10 significance level. ≠ > symbolized “does not Granger cause”. ↔ represents bidirectional (feedback) causality and → represents unidirectional causality.

Sources: Author’s computation 2020
and Brent crude stock markets is powerless in the short and medium-term but extremely powerful in the long term. The energy commodities and stock markets do not respond to S&P 500 value shocks over the long run and occasionally in the medium run. The fact that S&P 500 value shocks do not instantly affect financial markets is a clear advantage for energy commodities stock markets. This time frame of inaction may provide energy commodities regulators more flexibility to respond to the unpredictability of VIX, OVIX, and S&P 500 prices and their potential negative effects on energy commodities stock markets and trade finance. The oil price continued to decline during the Covid-19, which indicated that the energy commodities market was becoming more volatile. As energy is always a valuable commodity in the technology economy, it also attracts many industrial users and financial investors looking to profit and hedge risks by allocating energy assets in the financial market.

Indeed, the Covid-19 epidemic has demonstrated the real-world consequences of a stock market drop on back-trading access. If the shocks persist in the stock markets consequently, markets will be affected. The cost of the S&P 500 has been falling since the end of January 2020, while the VIX and OVIX indexes have been rising, indicating that the hypothesis association between S&P 500 prices and stock market unpredictability is valid. In this situation, the US financial markets, strategists, and managers should pursue various local and global economic reforms and policies to reap the benefits of a diversified and large stock market. In addition, authorities in both developed and developing markets should bolster adjacent financial institutions. Even during the Covid-19 outbreak’s instability, this study recommends that countries and investors stay on a long-term path toward sustainable growth that improves stock market and commodity market performance across the economy, even being the most susceptible.

These stock markets do not instantly reflect shocks and provide flexible investors due to sustainable development. Investors can rebalance their short- and long-term diversification strategies when designing stock market and energy commodity asset portfolios based on the dynamic risk co-movements and time–frequency domains to reduce risks and maximize returns. Even during the Covid-19 outbreak’s instability, this study suggests that countries and investors stay on a long-term path toward sustainable growth that improves stock market and commodity market performance across the economy, even being the most susceptible. But these international stock markets and prices of energy commodities are exhibiting high-risk co-movements during Covid-19. Hence, governments and policymakers could design better strategies to overcome these shocks and investors could hedge their investments in alternative stock markets, where low-risk co-movements occur during Covid-19. This study adds to the literature on Covid-19 and its economic ramifications by concentrating on global stock markets and the pricing of energy commodities as prospective investment opportunities in this pandemic event.

This study recommends that investors continue on a long-term path toward sustainable growth that enhances the performance of the stock market and commodity markets in light of the Covid-19 outbreak’s short-term market instability. In such an economy where the Covid-19 pandemic is prevalent and its policy consequences for a country’s economic development and prosperity, the government should concentrate on carbon emission and environmental policies and real estate and eco-friendly stock markets risks and risks return strategeis in the short term. The scope of this analysis is restricted to a few of the most important international stock markets and energy commodity price co-movements in Covid-19. Further research can expand the impact of global and Islamic stock indices and the recent Russian-Ukrainian war consequences on these stock market performances.

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Author contribution All authors have contributed to the study. Ijaz Younis developed the contextual framework of the study and prepared the original draft. Miss Besma Hkiri assisted in the methodological formulation and data analysis. Mr. Waheed Ullah Shah and Fiza Qureshi helped with the software analysis and result interpretation. Mr. Muhammad Ilyas reviewed and improved the initial draft. Mr. Cheng Longsheng provided valuable supervision and arranged funding’s for the study.

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