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Storm after the Gloomy days: Influences of COVID-19 pandemic on volatility of the energy market

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ABSTRACT

Volatility is a common phenomenon in the energy market, but COVID-19 has cast a dark shadow over this characteristic. In light of this observation, individuals might have an incorrect impression of the impact of this shock on the energy markets. By applying a time-varying parameter vector autoregression (TVP-VAR) in combination with an extended joint connectedness approach to identify the sources of the energy market’s volatility, we characterize the influences of COVID-19 health crisis and the volatility of the crude oil and precious metals (including gold and silver) market on the volatility of the energy market starting from January 1, 2020, to December 31, 2021. The total connectedness index, the net total, and pairwise directional connectedness measures obtained from the extended TVP-VAR allow us to monitor interlinkages from various variables in a designed network. The novel method has the benefit of distinguishing between a net recipient and a net transmitter. Our results demonstrate that the COVID-19 pandemic shocks first absorb the volatility from the energy and precious market to cause lagged but more severe consequences returning to these markets. Furthermore, there is a time-variant of system-wide interlinkages. Net total directional connectedness suggests that the oil and gold markets consistently appear to be a net transmitter of spillover shocks in the energy market. The COVID-19 pandemic shock first plays the role of shock receiver from other markets. However, this uncertainty shock acts as a shock transmitter, and its effects seem to be delayed but persistent for an extended period, thus making the energy and precious metal markets more volatile.

1. Introduction

An individual might assume that a pandemic has nothing to do with the energy sector. Yet, the uncertainty resulting from the pandemic is expected to affect the energy market. Coronavirus disease 2019 (COVID-19), a virus that began in Wuhan, China, in 2019 and spread quickly to Europe and the United States, led to significant economic losses in the global economy. Several symptoms were associated with this pandemic, including its rapid impact on economic activity and the spread of acute uncertainty across the globe. As a result of this uncertainty combined with the current financial turmoil, firms and individuals have been advised to exercise caution. The first step was to minimize spending in order to prepare for upcoming challenges if any.

An assortment of factors, most notably the daily news regarding deaths and illnesses, negatively affected consumer psychology, including financial difficulties. As reported by Chiaramonti and Maniatis (2020), it was inevitable that oil demand would decline, which in turn would cause the price of iron ore to decline. Global electricity consumption fell by an average of 15% during the first two years of the outbreak, resulting in a drop in crude oil and natural gas prices. More than other industries, the energy industries suffer severe damage from the pandemic due to blockage and surplus. This can be attributed to the rapid decrease in oil demand and the decline in oil prices. Kalyuzhnova and Lee (2020) discussed the relationship between the pandemic and oil demand and the implications for the oil industry. As a result of their findings, once the oil demand resumed, the built-up oil stock would have a detrimental effect on prices. Moreover, businesses are cutting their budgets, which could negatively impact oil production capacity in the near future. Due to imbalances in the energy market, there are expected to be consequences beyond health crises, resulting in a decline in the demand for oil relative to predictions before the epidemic began (Kalyuzhnova & Lee, 2020). While the oil market may be alleviated due to the Organization of the Petroleum Exporting Countries (OPEC) negotiations, geopolitical risks remain a major concern (Sharif et al., 2020).

In this regard, it is important to note that the COVID-19 pandemic...
phase did not exhibit the same characteristics of previous economic transitions brought about by a slowing or overheating economy. Therefore, COVID-19 response approaches should be tailored accordingly. Regardless of how the restrictions were imposed, they tended to restrict the freedom of movement of people. Travel restrictions were primarily imposed within countries rather than between them. As a consequence of these restrictions on the movement of goods and people, fuel consumption was reduced significantly, further harming the energy sector. Organizations and states around the world acted swiftly and took steps to limit the economic consequences of the pandemic. By combining historical experience with the tools made available by technology, policymakers can formulate more complex decisions that are more effective. The primary objective of this initiative is to protect private residences throughout the globe and to prevent a partial economic lockdown. However, there has been a severe lack of empirical studies that explore the consequences of the COVID-19 pandemic on the energy sector. It is more likely that the current silence of the energy market catches people off guard about a storm that is about to break out later.

Furthermore, the previous studies mostly utilized the asymmetric slope Conditional Autoregressive Value-at-Risk (CARV) to estimate the risk in a particular sector (Gkillas et al., 2021; Wu & Yan, 2019). The time-varying property of the specific role of each market has not been considered by these methods. Lastly, the literature has only exploited the linkage between crude oil, heating oil, and gasoline prices while still abstracting the dynamic connectedness from the different markets to the energy market. That is to say, the efficiency of the energy market is not only affected by itself but also constrained by other market factors (Abu-Rayash & Dincer, 2020; Wang et al., 2011). More recently, the study by Hoang et al. (2021) and Wang et al. (2022) are among the very few that exploit the impact of the COVID-19 pandemic on the specific sector, such as oil and coal. However, the effects of COVID-19 on the energy sector’s volatility and dynamic interlinkages between different sectors have still been kept silent thus far in the literature.

This article is primarily concerned with assessing the effects of COVID-19 on the energy sector’s volatility. The main research question of this paper is whether the COVID-19 pandemic shock acts as a net recipient or a net transmitter to other markets, especially the energy market. These findings are expected to aid policymakers in accurately understanding the impacts of the COVID-19 pandemic shock and designing and implementing policies to limit the energy market volatility. Energy is essential to the economy’s functioning and human welfare (Le et al., 2022). When economic conditions are uncertain, policies that minimize the adverse effects of the COVID-19 health crisis on the energy market are more effective in enabling countries to grow and prosper.

This article makes at least three contributions to the literature. Our research is the first of its kind to investigate the dynamic connectedness of the COVID-19 crisis and the energy as well as precious metal market (including the energy, crude oil (WTI), gold, and silver). The literature discusses the effects of the COVID-19 crisis on the financial market. The importance of evaluating the impact of individual oil shocks increased during the first wave of the pandemic when reduced travel and a drop in industrial production led to a significant reduction in demand for oil. The world witnessed geopolitical tensions between Saudi Arabia and Russia in early March 2020, which could be thought to have contributed to price shocks (Corbet, Larkin, et al., 2020), which might be represented by the risk component of oil price shocks (Akranc, 2020). As an essential part of our study, we examine the impact of COVID-19 health shocks on the energy sector, integrated into the interconnected network of the oil and precious metal markets.

Second, this paper’s methodological approach significantly differs from those employed by prior scholars. In line with Balcilar et al. (2021), we employ a time-varying parameter autoregression (TVP-VAR), as well as an extended joint connectivity approach. The advantages of this method are numerous, especially in the case of limited observations. Additionally, the presence of an outlier does not significantly alter our results, and this method can be adjusted to parameter changes more efficiently. The most important of our employed strategy is to compute the net pairwise connectedness, which detects transmission mechanisms among these commodity and financial markets. As a result of this report’s findings, investors and authorities can benefit from critical, insightful knowledge and warnings that utilize the daily data to explore the impacts of the COVID-19 pandemic on the energy sector.

An additional contribution of this paper is our dataset. In this paper, we present the daily figures for COVID-19 confirmed cases and death cases, the volatility of energy, crude oil (WTI), gold, and silver, which starts from January 1, 2020, to December 31, 2021. Our concentration is on exploring the sources of the energy market volatility. Our study reveals critical findings. There is a shift in the role of each market within our designed system over time. The crude oil, gold, and silver market appear consistently as a net transmitting of volatility shocks into the volatility of the energy market. Since the first days of COVID-19 introduction, the energy market is still relatively stable, and the health shock only plays the role of shock receiver from other markets. However, the COVID-19 then appears to be a shock transmitter to cause the energy market to be more volatile, and the effects seem to last for an extended period.

We organize the remaining of this paper as follows. While Section 2 provides a discussion of the related works on the interlinkages between the COVID-19 pandemic and the energy sector, the methodology, and the dataset are presented in Section 3. Section 4 provides the empirical results, and we will wrap the paper by providing a summary and policy implications in Section 5.

2. Literature review

The impact of COVID-19 on the financial market and in the macroeconomic sector has been extensively documented in the literature. In general, these studies in the literature provide valuable information, and the impact of the pandemic will be a prominent topic of discussion. However, the influences of the COVID-19 pandemic on the energy sector have not gained enough attention of scholars, while this sector plays a critical role in sustaining economic and social development (Hoang et al., 2021). Dutta (2018) contended that the implied volatility indexes of the U.S. energy market are influenced by the global oil market. The implied volatility indices of oil and the stock market have been established as having a long-term relationship. Additionally, Xu et al. (2020) stated that crude oil could be employed as a hedge against stock market volatility in the U.S., Japan, China, and Hong Kong. Wavelet coherence analysis suggests that crude oil cannot be used for long-term hedging but may be used during periods of anxiety, such as the pandemic period. Bouri et al. (2019) investigated the predictive value of a daily newspaper-based uncertainty index in the context of the oil market volatility epidemic using a heterogeneous autoregressive realized volatility model. They significantly improved forecast accuracy by incorporating such data into their model.

The global health crisis COVID-19 has caused severe damage to the energy sector and to the global economy (Abu-Rayash & Dincer, 2020; Chakraborty & Maity, 2020). In the COVID-19 health shocks, the energy sector is highly volatile due to both a fluctuating demand and a fluctuating supply of energy. There have been significant reductions in the personal use of automobiles and other primary modes of transportation due to containment measures such as travel restrictions, border closures and the increased use of remote learning and employment (Elavarasan et al., 2020). A decline in worldwide demand has resulted in a significant reduction in nuclear energy production and natural gas in Europe and the United States in the first quarter of 2020 (Hoang et al., 2021).

On a global level, renewable energy production has steadily increased, resulting in a greater share of renewable energy in the world’s energy mix in China, Japan, Southeast Asia, and Africa. As reported by the International Energy Agency (IEA), global energy consumption has decreased as a result of pandemic-related freezes on renewable energy
projects. At the same time, countries’ governments focus their efforts on the fight against the virus (IEA, 2020). Due to the current economic crisis in the worldwide energy market, which is the worst in the last 30 years, many renewable energy companies are in danger of bankruptcy. As contended by Ivanov and Dolgui (2021), the worldwide supply chain of renewable energy sources has been negatively affected by an unexpected production halt. This effect would not only be felt by the present project but also by future renewable energy projects (Newburger, 2020). As a result of the epidemic, many of the central wind turbine manufacturing facilities have been shut down (Eroglu, 2021). Solar industry sales are expected to decline by 28% in 2020 as a result of a pandemic-induced decline in demand (IEA, 2020). Coal production is gradually being phased out and de-emphasized in Germany due to the country’s position as a significant renewable energy source. The decline in overall energy demand has negatively affected renewable energy and carbon trading pricing schemes. Carbon prices per unit have declined dramatically since the pandemic began in both the United States and Europe’s carbon cap and trade systems (Allowance Price Ex, 2020).

Additionally, Hoang et al. (2021) indicate that decreasing the global demand for energy leads to considerable revenue losses for both conventional and renewable energy producers due to lower energy pricing for systems with a higher proportion of renewable energy. The lockdown that was triggered by the epidemic has had a significant effect on the deployment of renewable energy sources. A number of renewable energy projects have been halted due to supply chain delays and the cessation of non-essential industrial operations. According to Bloomberg New Energy Finance, the number of solar and wind projects will decline by 8% and 12% in 2020. As a result of the COVID-19 outbreak, China, the world’s largest producer of solar photovoltaic modules, has had to shut down many of its manufacturing facilities. Furthermore, the distribution system operators have been slow to integrate new renewable energy projects into the grid (Energy Community and Energy, 2020). As a result of the pandemic’s impact on production and manufacturing, there may be a shortage of electrical components. As a result of the outbreak, several planned projects have been suspended, including the construction of 3500 MW of wind and solar energy in India (Oxford Business Group, 2020) and up to 25 GW of wind energy in the United States (Weko et al., 2020). Frangoul (2020) anticipated that approximately 150 GW of renewable energy projects in Asia would be delayed or halted if the recession persists beyond 2024. Many European countries have chosen to freeze or restrict the amount of renewable energy that will be auctioned in the near future (Wigand et al., 2020). To overcome these challenges, the Global Wind Energy Council, a leading industry organization, has advocated for legislative objectives such as feed-in tariffs, tax refunds, and round auction extensions (GWEC, March 11, 2022).

Additionally, nation- and policy-related vulnerabilities may originate and exacerbate these threats. It is critical to remember that changes in public opinion and legislation, as well as shifts in the market itself, may produce a new sense of insecurity and danger in these unstable times (Monasterolo et al., 2020). Several stakeholders are concerned that the government may retroactively alter current policy frameworks. Poor market conditions and changes in incentive structures may substantially affect how renewable energy sources are financed (Ji et al., 2020). A large part of the funds available for the support of renewable energy projects was diverted to state-sponsored loans for struggling businesses during the pandemic. Most funds available to support renewable energy projects have been diverted to help struggling businesses throughout the pandemic. The most vulnerable and exposed developers and owners are those with a high price tag after the financial crisis. As part of the economy’s recovery plan, green investment projects may contribute to alleviating the difficulties that renewable energy financing schemes may encounter due to global loss-absorption efforts by governments. After hindsight, it appears that the global demand for fossil fuels peaked in 2019 rather than 2020 (Uhlmann et al., 2019). In light of COVID-19’s perfect storm nature, it is likely that the COVID-19 health crisis has expedited the extinction of fossil fuels. As a result, the question of how to achieve a more sustainable energy future remains unresolved. The post-pandemic recovery program includes investments in clean energy infrastructure and production capacity as well as a novel commercial model for renewable energy. In spite of these possibilities, COVID-19’s impact on the clean energy sector continues to reverberate due to its historical momentum (Edomah & Ndulue, 2020). As a result of the outbreak, there have been significant delays in production and supply chain operations, as well as in the deployment of renewable energy resources. A lack of access to funding programs and government incentives has worsened the sector’s difficulties over the previous year (Armani et al., 2020; Capelle-Blancard & Desroizers, 2020). Siddique et al. (2021) also argue that recent gains in renewable energy are likely to be reversed by the impact of a pandemic.

Many recent studies have emphasized on the volatilities of energy market in response to the COVID-19 pandemic. Christopoulos et al. (2021) explores the correlation between oil price volatility and COVID-19 pandemic volatility. COVID-19 appears to be a new risk component on top of economic and market uncertainty that has an impact on oil prices and volatility. According to Szczygieliski et al. (2022), COVID-19 related uncertainty can be assessed by measuring the number of searches for information related to COVID-19 as captured by Google search trends. The findings of this study show that countries further west from the outbreak of the virus in China are more adversely affected by COVID-19-related uncertainty. Similar observations are made regarding net energy and oil exporters compared to importers. As the pandemic evolved, the impact of uncertainty on most national energy sectors intensified and then weakened as it evolved.

Based on our discussion, we hypothesize as follows:

H1. The COVID-19 health crisis and the volatility of the crude oil and precious metals (including gold and silver) market influence the volatility of the energy market.

3. Data and methodology

3.1. Data description

The daily data sample of COVID-19 confirmed cases (COVID19C), and COVID-19 death cases (COVID19D) from CEIC Global premium database is collected from January 1, 2020, to December 31, 2021. Regarding the energy sector, the data is available from the Chicago Board of Options Exchange (CBOE). Based on the energy sector volatility index (VOL_VXXLE), we can determine the implied volatility level of the energy sector. In order to calculate this index, weights are assigned to companies based on their market capitalization in the S&P 500 index. In the case of crude oil, we use the crude oil volatility index (VOL_OVX), which measures the estimated volatility of the future contract price of crude oil over the next 30 days. Regarding the precious metal market, we collect the daily data for the COMEX gold volatility index (VOL_GVX) and the silver ETF volatility index (VOL_VXXSLV), which represent the expected 30-day ahead volatility of Comex Gold futures and implied volatility for silver. In this paper, we calculate the percentage change of these four indexes and apply a time-varying parameter vector autoregression (TVP-VAR) in combination with an extended joint connectedness approach. Since our analyzed variables are non-stationary processes based on Elliott et al. (1996)’s unit-root test statistics, we create the first log-differenced series interpreted as a percentage change in respective variables. The pattern of these series is seen in Fig. 1.

Table 1 summarizes all series’ main statistics, which have a positive average level. In addition, with the variance of VOL_VXXLE being the highest, followed by VOL_OVX, these energy and crude oil markets are stated to be the two riskiest among the sample. Notably, this paper finds that all series are significantly leptokurtic, which means that the tails of the distributions are fatter than those of a normal distribution. Jarque &
Bera (1980) contended that asset distributions are significantly non-normal. It is concluded that all variables are stationary at least on a 1% significance level based on results obtained from the ERS unit root test of Elliott et al. (1996). Finally, the weighted portmanteau test of Fisher and Gallagher (2012) demonstrates that the percentage changes of \( \text{VOL\_VXXLE}, \text{VOL\_OVX}, \text{VOL\_GVX}, \text{VOL\_VXSLV} \) and their squares are autocorrelated, suggesting that the TVP-VAR technique with time-varying variance-covariance structure is suitable for modeling the interconnectedness of the series. Our ultimate goal is to explain the sources of the volatility of the energy market due to the COVID-19 health crisis and the crude oil volatility, and the precious metal volatility as well as the influences of the energy market on those of other markets. Hence, we attempt to examine changes in the interconnectedness between the COVID-19 pandemic and various market volatility and the energy market. Since the Public Health Organization formally announced the COVID-19 to the world for the first time on December 31, 2019 (WHO, 2020), our data cover from January 1, 2020 to December 31, 2021.

### Table 1

|                   | Whole sample         | VOL\_VXXLE | VOL\_OVX | VOL\_GVX | VOL\_VXSLV |
|-------------------|----------------------|------------|----------|----------|------------|
| **Mean**          | 0.0623               | 0.057      | 0.0211   | 0.0296   |
| **Variance**      | 40.581               | 62.085     | 28.3985  | 34.4892  |
| **Skewness**      | 0.965***             | 2.027***   | 0.648*** | 1.521*** |
| **Kurtosis**      | 4.210***             | 25.817***  | 3.288*** | 11.650***|
| **JB**            | 893.815***           | 28456.559***| 520.582***| 6040.806***|
| **ERS**           | -12.678***           | -14.752*** | -7.284***| -5.271***|
| **Q(20)**         | 36.070**             | 30.369*    | 44.529***| 20.872***|
| **Q^2(20)**       | 264.328***           | 98.562***  | 440.594***| 203.498**|

In this part, Antonakakis et al. (2020) present their TVP-VAR connectedness technique, which is combined with the approach of Diebold & Yilmaz, 2012. The Bayesian information criterion (BIC) suggests that the TVP-VAR model be estimated with a lag length of order one in our article:

\[
y_t = \sum_{l=0}^{\infty} N_l \psi_l \epsilon_i \sim N(0, \sigma)
\]  

where \( \sigma \) and \( \sum_{l=0}^{\infty} N_l \psi_l \) are \( f \times 1 \) dimensional matrices, whereas \( y_t, y_{t-1}, \ldots \) and \( \psi_l \) are \( f \times 1 \) dimensional vectors. \( R_t \) is a \( f^2 \times f^2 \) dimensional matrix, whereas \( \text{vec}(Q_i) \) and \( u_t \) are \( f^2 \times 1 \) dimensional vectors. This method includes all indices \( (Q_i) \) to change throughout time, as well as the connection between series. Moreover, the \( \sum_{l=0}^{\infty} N_l \psi_l \) variance-covariance matrices are considered to be time-varying. While practically all prior research has proven that variances and covariances change over time, particularly in the financial market, this shows the altering market and risk ratio.

According to the Wold representation theorem, we turn TVP-VAR into a TVP-VMA model in the next step:

\[
y_t = \sum_{l=0}^{\infty} N_l \psi_l \epsilon_i \sim N(0, \sigma)
\]  

where \( Q_t \) and \( \sum_{l=0}^{\infty} N_l \psi_l \) are \( f \times f \) dimensional matrices, whereas \( y_t, y_{t-1}, \ldots \) and \( \psi_l \) are \( f \times 1 \) dimensional vectors. \( R_t \) is a \( f^2 \times f^2 \) dimensional matrix, whereas \( \text{vec}(Q_i) \) and \( u_t \) are \( f^2 \times 1 \) dimensional vectors. This method includes all indices \( (Q_i) \) to change throughout time, as well as the connection between series. Moreover, the \( \sum_{l=0}^{\infty} N_l \psi_l \) variance-covariance matrices are considered to be time-varying. While practically all prior research has proven that variances and covariances change over time, particularly in the financial market, this shows the altering market and risk ratio.
with a forecast error covariance matrix equal to:

\[
E((\mathbf{b}_i(\mathbf{\Gamma}))^\prime i(\mathbf{\Gamma})) = N_i N_i^\prime
\]

The suggested approach is based on (Koop et al., 1996; Pesaran & Shin, 1998)’s \(\bar{N}\)-step forward generalized forecast error variance decomposition (GFEVD). The (scaled) GFEVD, \(q\mathbf{\Delta}_{ij}\), can be read as the impact of a shock in indicator \(j\) on indicator \(i\) and is written as:

\[
q\mathbf{\Delta}_{ij} = \frac{\sum_{t=0}^{\bar{N}} (e_i N_i e_j)^2}{e_i N_i e_j}
\]

where \(e_j\) is a \(\bar{N} \times I\) zero selection vector with unity on its \(i\)th location and \(q\mathbf{\Delta}_{ij}\) is the decreased level of indicator \(i\)’s \(\bar{N}\)-step prediction error variance owing to controlling for unexpected shocks of indicator \(j\).

(Diebold & Yilmaz, 2012) suggested standardizing the \(\sum_{t=0}^{\bar{N}} q\mathbf{\Delta}_{ij}(\mathbf{\Gamma}) \neq 1\) to unity using the row sum, leading to the generalized spillover panel, \(gST_{ij}\).

The generalized spillover table is the foundation for numerous spillover summary estimates like total directional connectedness from others to indicator \(i\) and total directional connectedness from a shock in indicator \(i\), which show how much the system impacts indicator \(i\) and how much indicator \(i\) impact the whole system, respectively. This statistic may be expressed as follows:

\[
q\mathbf{\Delta}_{ij} = \sum_{t=0}^{\bar{N}} q\mathbf{\Delta}_{ij}(\mathbf{\Gamma})
\]

The net total directional connectedness of indicator \(i\), which shows whether indicator \(i\) impact the system more than it is affected by it, is among the core metrics of the connectedness approach: \(q\mathbf{\Delta}_{ij}^{gen}\). If \(q\mathbf{\Delta}_{ij}^{gen} > 0 (q\mathbf{\Delta}_{ij}^{gen} < 0)\), indicator \(i\) is a net transmitter (receiver) of shocks meaning that indicator \(i\) is driving (driven by) the system.

The total connectedness index (TCI) is at the heart of the connectedness center, displaying system interlinkages or, in our instance, market risk, which is a critical signal for portfolio and risk administrators. The total directional connectedness index (TCI) is meant to be the average total directional connectedness from (to) others and is calculated as follows:

\[
q\mathbf{\Delta}_{ij} = \frac{\sum_{i=1}^{\bar{N}} q\mathbf{\Delta}_{ij}^{gen}\Delta_{ij}^{gen}}{\bar{N}}
\]

where a large value implies large market risk and thus a large degree of system spillovers, whereas a small value implies small market risk and thus that shocks in one indicator mainly affect its own volatility without influencing others, which is informative from the perspective of portfolio diverseness.

Lastly, the connectedness method gives evidence of the pairwise interrelationships of two indicators through the idea of net pairwise directional spillovers, which are described as: \(q\mathbf{\Delta}_{ij}^{gen} = q\mathbf{\Delta}_{ij}^{gen} - q\mathbf{\Delta}_{ij}^{gen}\). If \(q\mathbf{\Delta}_{ij}^{gen} > 0 (q\mathbf{\Delta}_{ij}^{gen} < 0)\), indicator \(i\) has a larger effect on indicator \(j\) than vice versa, meaning that indicator \(i\) dominates indicator \(j\).

### 3.2.2. Extended joint connectedness approach

The major purpose is to determine the \(q\mathbf{\Delta}_{ij}^{gen}\) equivalence for the mutual connectedness method, called \(j\mathbf{\Delta}_{ij}\), that meets these criteria:

\[
j\mathbf{\Delta}_{ij} = \sum_{f=1}^{\bar{N}} j\mathbf{\Delta}_{ij}(\mathbf{\Gamma})
\]

To do this, we must adapt the technique of (Lastrepes & Wiesen, 2021a). As a result, the recommended computation of equation (12) must be correct. Because the row total of the original and joint connectedness tables must equal 1, the joint connectedness table’s diagonal components must also remain the same. As a result, the scaling factor varies per row, yielding the given formula:

\[
\eta_i = \sum_{j=1}^{\bar{N}} j\mathbf{\Delta}_{ij}(\mathbf{\Gamma})
\]

The sole difference between our \(\eta\) soaring and the one that arises from the joint connectedness technique is that our method allows greater flexibility because each row has its own soaring element. Then, the steps below must be arranged:

\[
\bullet j\mathbf{\Delta}_{ij} = \eta_i j\mathbf{\Delta}_{ij}
\]

Furthermore, by varying the soaring parameter by row, the net total and pairwise directional connectedness metrics may be calculated based:

\[
q\mathbf{\Delta}_{ij}^{gen} = q\mathbf{\Delta}_{ij}^{gen} - q\mathbf{\Delta}_{ij}^{gen}
\]

Our findings are more precise because it solves the drawbacks of the row sum normalization technique, although the explanations are equal to those of the original connectivity approaches Caloia et al. (2019). Overall, this strategy resolves a number of concerns with the previously suggested connectedness approach, including: (i) no arbitrary rolling-size must be chosen, (ii) the predicted results are not outlier delicate due to the multivariate Kalman filter approach, which contains the Kalman gain, (iii) we enable the VAR coefficients to fluctuate over time, (iv) variances and covariances are also permitted to fluctuate over time to improve observe energy market volatility, which is important for portfolio and risk administrators, (v) solution of Lastrepes & Wiesen (2021b) to the row sum normalization problem has been implemented and (vi) in a special manner, we have enlarged the joint connectedness method that is in line with the directional joint connectedness study but enables for more flexibility and the computation of the net total and pairwise directional connectedness measures, which are one of the core features and are very important because they show the comparative...
bilateral power of indicators.

4. Results

This paper starts by reporting the average TCI values. In the following step, we also analyze results for total net connectedness and net pairwise connectedness, which help us achieve a more deeply insightful knowledge about the consequences of the COVID-19 pandemic and the role of each market within our proposed system. It is worth noting that each market can play a role of either a net shock transmitter or net shock receiver. Finally, for comparison purposes, we then follow Lastrapes & Wiesen (2021) to quantify the joint spillover index, which can be useful to explore the insights behind changes in interlinkages of these markets within the system.

4.1. Time-variant of average dynamic connectedness

Using the full observations and specific observational data when the COVID-19 epidemic first broke out, Table 2 presents average results regarding connectedness within the network of diverse markets. In this table the feature of this table is that the metrics on the diagonal are the impact on their own. In contrast, the elements off the diagonal represent the level of transmitting and receiving. The rows in Table 2 contribute each individual market’s volatility to the forecast error variance of one specific type of market in the system. By contrast, columns correspond to one particular type of market’s effect on all other markets separately. In this table, the volatility of the indexes is accounted by its own shocks is reported by the diagonal element, and a contribution of this market to others’ volatility (FROM) and others to this market’s volatility (TO) are summarized in off-diagonal elements.

Interlinkage metrics show that the TCI average value is 34.63%, suggesting that fluctuations within this network can elucidate 34.63% of the variant in our network of considered markets. Similarly, the forecast error variance of indices is also determined by the variation of the elements on the diagonal. This further suggests that idiosyncratic effects account for nearly 65% of the forecast error variance of the system, supporting the view that the volatility of these markets tends to co-move substantially. Put it differently, and other markets play a critical role in contributing to the volatility of the energy market and vice versa. Average results outlined in Table 2 further suggest that the energy market (VOL_VXXLE) is a net transmitter of shocks in the specific system, meaning that on net terms, the volatility arising in the energy market tends to impact other markets rather than be impacted by others. Similarly, oil (VOL_OVX) and gold (VOL_GVX) are net transmitters of respective shocks. The only exception for the data set is the silver market (VOL_VXXSLV), which is the net receiver of shocks. Among all transmitters, the energy market (VOL_VXXLE) is the most crucial net transmitter, while the oil market (VOL_OVX) followed to be the sample’s second most significant net transmitter. The findings of our study are consistent with Wang et al. (2022), which indicate that the efficiency of the energy market decreases during uncertain times. They also reveal the risk transmission between coal and WTI crude oil markets. However, their study is still quite limited when they just demonstrate the linkage between coal and oil. Our method approach is more advantageous since we suggest that the interconnectedness between markets can be time-variant. Put it differently, each market’s role can be exchanged at a certain time.

4.2. Time-variant of total connectedness

This paper starts with the dynamic total connectedness results presenting the intertemporal evolution of the TCI as illustrated in Fig. 2. The TCI values do not fluctuate substantially over the studied periods. However, 2020 witnessed a rise in the first quarter of the mentioned year, peaking at around 70% of total connectedness. The figure then decreased gradually and steadily without any significant fluctuation during the span of the sample. It would be worth noting that small TCI values typically suggest low spillovers between the diverse types of the market of interest. Prior studies also indicate the rise in the connectedness in some commodity markets during uncertain times such as the global financial crisis (2007–2009), such as Balcilar et al. (2021) and Zhang and Broadstock (2020). The greater values of TCI mean larger contagions between the diverse types of markets, but these high TCI values only happen in a very short period since the point marked by the first appearance of the COVID-19 pandemic. Similar evidence is also found in the study of Balcilar et al. (2021), in which total connectedness values reach a new remarkable peak due to the COVID-19 pandemic. Ji et al. (2020) also advocate that specific commodity markets should be regarded as safe-haven for investors in uncertain times like the COVID-19 pandemic.

4.3. Time-variant of net total and pairwise directional connectedness

Although average results show the most fundamental trends in the interaction between markets, it also ignores a lot of the interesting effects of each factor when there is the COVID-19 crisis. Hence, it is vital to employ a more dynamic analysis framework, which considers the TCI evolution. The TCI also reflects how critical the particular markets within the analyzed network might be time-varying. For example, it is necessary to consider changes from a net receiver to a net transmitter or vice versa. Put it differently, the roles played by a specific market as a net shock receiver and a net shock transmitter in the system at different times will be conditional on the time interval and the particular types of the market within the studied network.

| Whole sample | VOL_VXXLE | VOL_OVX | VOL_GVX | VOL_VXXSLV | FROM |
|--------------|-----------|---------|---------|------------|------|
| VOL_VXXLE    | 68.26     | 13.07   | 12.87   | 5.80       | 31.74|
| VOL_OVX      | 12.90     | 76.81   | 6.38    | 3.91       | 23.19|
| VOL_GVX      | 13.13     | 6.90    | 54.56   | 25.41      | 45.44|
| VOL_VXXSLV   | 6.04      | 4.63    | 27.49   | 61.84      | 38.16|
| TO           | 0.33      | 24.59   | 46.75   | 35.12      | TCI  |
| NET          | 2.00      | 1.40    | 1.31    | –3.04      | 34.63|

Source: Authors’ calculations

Fig. 2. Time-variant of total connectedness.

Notes: We follow Balcilar et al. (2021) to set up the lead (20 leads) and lag length (1 lag) order of forecast error variance decomposition in our TVP-VAR system. The robustness checks were also conducted by changing these values. We display the joint interlinkages (the black shaded area) and the original interlinkages (the red line).
Fig. 3 shows the time-variant net total directional connectedness that fluctuates through the periods. For each market, positive values indices mean the net transmitters while others mean the net receivers. In all cases, the joint and original interlinkages tend to differ. That shows that the volatility of the markets is highly dependent on external shocks. By examining the data from the beginning of 2020 to the end of 2021 (December 31, 2021), it can be seen that for most of the time, the energy market has proven itself to serve as the net transmitter of shock with a few exceptions and small fluctuations in the beginning months of 2020 and a few months toward the end of the 2021’s data. The oil market also mainly served as the net transmitter of shock, consistent with the average joint connectedness of the whole sample. Especially for the first way of the pandemic, the oil market was a major factor affecting and creating spillovers, peaking at around 20%. While the energy market remained at a constant rate for a long period of time toward the end of 2020, the oil market has proven its role as a net transmitter by starting to be the net transmitter for all 2020 and the majority of the 2021’s sample with only an exception toward the end of 2021. The directional connectedness of both VOL_VXXLE and VOL_OVX fosters the previous conclusion regarding the two as the two main transmitters of shocks. Although also being stated as a net transmitter according to the whole sample analysis, VOL_GVX is not seen as a significant transmitter as fluctuation occurred quite frequently. During most of the studied time, the VOL_GVX was even reported as a net shock receiver. One very significant and consistent market in the role is the silver market (VOL_VXSLV), as this market reported being a net receiver of shocks throughout the studied period with no change in its role.

The results suggest more information about the energy market’s volatility sources during uncertain times. Both the oil and gold market plays a critical role in transmitting the impacts of respective shocks on the energy market. Since we concentrate on the consequences of the COVID-19 pandemic on the volatility of the energy and precious metal market, the interlinkages between the energy market’s volatility and the COVID-19 health crisis, the time-variant net pairwise directional interlinkages between the COVID-19 pandemic and the specific market are presented in Fig. 4.

Our results reveal some exciting findings. It is more likely that the energy, crude oil, and precious metal market caused the COVID-19 health crisis to become more volatile as the COVID-19 pandemic first appeared at the beginning of 2020. The net pairwise directional interlinkage values between COVID-19 confirmed cases and the volatility of each market are negative and substantial during this time. From the beginning of 2021, the emergence of variants posed an increased risk to the global economy and public health. Our results report that COVID-19 plays a different role compared to the previous period. The COVID-19 pandemic shock appears to be a transmitter of respective shocks to the energy, crude oil, and precious metal. Among the considered market, crude oil is less likely to be affected by the COVID-19 pandemic when these shocks only contribute a small proportion to this market’s volatility. Furthermore, the consequences of COVID-19 to other markets seem to last longer in the subsequent period. Our results suggest that the COVID-19 pandemic does not immediately influence the energy and precious metal markets. Instead, their effects seem to be delayed but persistent for a long period, thus making the energy and precious metal markets more volatile.

4.4. Robustness check

To confirm the findings in this paper, we conduct robustness checks by using other proxies for the uncertainty shocks. In particular, we employ a percentage change in the COVID-19 death case and CBOE Volatility Index (VIX). VIX index is an indicator of expected market volatility. We then apply a similar empirical approach to the new sets of variables. The results are displayed in Figures A.1-A.3 in Appendix. Using the different measures of uncertainty shocks, we reach similar conclusions, thus our findings are robust and reliable.

5. Conclusions and policy implications

Our research focuses on identifying the sources of volatility in the energy, crude oil, and precious metal markets.
energy market, especially the influences of uncertainty shocks like the COVID-19 pandemic. Using a TVP-VAR approach, we estimate the interlinkages between the COVID-19 pandemic and four commodity markets, namely, energy, crude oil, gold, and silver, in a time-varying manner. This approach provides more flexibility and is capable of achieving the net pairwise connectivity measures. In this regard, we can understand how the uncertainty shocks, including macroeconomic, financial, and health shocks, affect the energy sector. In this paper, we collect the daily data for the COVID-19 confirmed cases and death cases, the volatility level of the energy, crude oil (WTI), gold, and silver, starting from January 1, 2020, to December 31, 2021.

Our results show that there is a dynamic connectedness between the COVID-19 health crisis (as well as the volatility of the precious metal and commodity markets) and the energy sector’s volatility. The TCI value is approximately 35%. By using the time-variant of net total and pairwise directional connectedness analysis, we indicate the shift in the role of COVID-19 shock within our designed system over time. The COVID-19 pandemic shock first plays the role of shock receiver from other markets. However, this uncertainty shock acts as a shock transmitter, and its effects seem to be delayed but persistent for an extended period, thus making the energy and precious metal markets more volatile. The findings are similar when applying the empirical approach to other uncertainty shocks. Another finding is that the crude oil, gold, and silver market appear consistently as a net transmitting of volatility shocks into the volatility of the energy market during uncertain times like COVID-19.

On the policy front, our study indicates that uncertainty shocks such as the COVID-19 health crisis may have a lag effect on energy market volatility. These uncertainty shocks absorb the volatility from the energy and precious market to cause more severe consequences returning to these markets. The findings are evidence of the nexus between COVID-19 and the energy market. Our findings are crucial for policymakers and authorities to design policies to combat uncertainty shocks and mitigate the lagged and lasting consequences of these shocks on the energy market. Investors and managers should be more careful, realize that there are contagions of uncertainty and risk, and regard these as an early warning signal to reconsider investment strategies. Furthermore, the findings of this paper can also be useful for policy and enhancing public welfare, given the lagged and lasting impacts of uncertainty shocks and the fact that energy is vital for economic development and human welfare. Hence, it is a prerequisite to consider them when designing policies for a vulnerable group to enhance society’s welfare.

Three limitations should be considered when interpreting the findings of this study. First and foremost, it is essential to note that there is no universal law or general pattern of the impact of risk events on the overall, net, or pairwise spillovers. A second point to consider is the extent of spillover in the context of market integration. A spillover effect will result in a market system being heavily influenced by fluctuations and shocks occurring in other markets. In order to reduce the negative effects of external shocks, various measures must be taken by the authorities. Risk sources should be analyzed according to frequency. In accordance with international regulation policy, the coordination of regulation for different markets should aim to counteract the negative effects of short-term return spillovers and long-term volatility spillovers. Finally, since many scholars have examined the spillover effect across different markets, quantifying the portfolio benefits of diversification is a useful extension of the study. It is left as an exercise for future research.

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Compliance with ethical standards

- Disclosure of potential conflicts of interest
- Research involving Human Participants and/or Animals
- Informed consent

Contributions

Le Thanh Ha was equally contributed to all stages of preparing, drafting, writing and revising this review article. All authors listed have made a substantial, direct, and intellectual contribution to the work during different preparation stages. All authors read, revised and approved the final version of this manuscript.
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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix

Fig. A.1. Time-variant of total connectedness.

Notes: We follow Balcilar et al. (2021) to set up the lead (20 leads) and lag length (1 lag) order of forecast error variance decomposition in our TVP-VAR system. The robustness checks were also conducted by changing these values. We display the joint interlinkages (the black shaded area) and the original interlinkages (the red line).

Fig. A.2. Time-variant of net total directional connectedness.

Notes: We follow Balcilar et al. (2021) to set up the lead (20 leads) and lag length (1 lag) order of forecast error variance decomposition in our TVP-VAR system. The robustness checks were also conducted by changing these values. We display the joint interlinkages (the black shaded area) and the original interlinkages (the red line).
Fig. A.3. Time-variant net pairwise directional connectedness: Energy market to other markets

Notes: We follow Baclier et al. (2021) to set up the lead (20 leads) and lag length (1 lag) order of forecast error variance decomposition in our TVP-VAR system. The robustness checks were also conducted by changing these values. We display the joint interlinkages (the black shaded area) and the original interlinkages (the red line).

References

Abu-Rayash, A., Dincer, I., 2020. Analysis of the electricity demand trends amidst the COVID-19 coronavirus pandemic. Energy Research & Social Science 68, 101682. https://doi.org/10.1016/j.erss.2020.101682.

Akramc, F., 2020. Oil price drivers, geopolitical uncertainty and oil exporters' currencies. Energy Economics 89, 104801.

Antonakakis, N., Chatziantoniou, I., Gabaour, D., 2020. Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. Journal of Risk and Financial Management 13 (4), 84. https://doi.org/10.3390/jrfm13040084.

Armani, A.M., Hurt, D.E., Hwang, D., McCarthy, M.C., Scholtz, A., 2020. Low-tech solutions for the COVID-19 supply chain crisis. Nature Reviews Materials 5 (6), 403–406. https://doi.org/10.1038/s41578-020-0205-1.

Baclier, M., Gabaour, D., Umar, Z., 2021. Crude Oil futures contracts and commodity markets: New evidence from a TVP-VAR extended joint connectedness approach. Resources Policy 73, 102219. https://doi.org/10.1016/j.resourpol.2021.102219.

Caloia, F.G., Cipollini, A., Muzzioli, S., 2019. How do normalization schemes affect net spillovers? A replication of the diebold and Yilmaz (2012) study. Energy Economics 84, 104536. https://doi.org/10.1016/j.eneco.2019.104536.

Capelle-Blancard, G., Desroziers, A., 2020. The stock market is not the economy? Insights from the covid-19 crisis. Covid Economics 28, 29–69.

Chiaromonti, D., Maniatis, K., 2020. Security of supply, strategic storage and Covid19: Which lessons learnt for renewable and recycled carbon fuels, and their future role in decarbonizing transport? Applied Energy 271, 115216. https://doi.org/10.1016/j.apenergy.2020.115216.

Christopoulos, A.G., Kalantonis, P., Katsampoxakis, I., Vergos, K., 2021. COVID-19 and the energy price volatility. Energies 14 (20), 6496. https://doi.org/10.3390/en14206496.

Corbet, S., Larkin, C., Lucey, B., 2020. The contagion effects of the COVID-19 pandemic: Evidence from gold and cryptocurrencies. Finance Research Letters 35, 101554. https://doi.org/10.1016/j.frl.2020.101554.

Diebold, F.X., Yilmaz, K., 2012. Better to give than to receive: Predictive directional spillovers? A replication of the diebold and Yilmaz (2012) study. Energy Economics 34, 104536. https://doi.org/10.1016/j.eneco.2012.04.016.

Dutta, A., 2018. Oil and energy sector stock markets: An analysis of implied volatility indexes. Journal of Multinational Financial Management 44, 61–68. https://doi.org/10.1016/j.mulfin.2017.12.002.

Edomah, N., Ndalu, G., 2020. Energy transition in a lockdown: An analysis of the impact of COVID-19 on changes in electricity demand in Lagos Nigeria. Global Transitions 2, 127–137. https://doi.org/10.1016/j.gtrans.2020.07.002.

Elliott, G., Rothenberg, T.J., Stock, J.H., 1996. Efficient tests for an autoregressive unit root. Econometrica 64 (4), 813–836. https://doi.org/10.2307/2171846.

Erol, H., 2021. Effects of Covid-19 outbreak on environment and renewable energy sector. Environment, Development and Sustainability 23 (4), 4782–4790. https://doi.org/10.1007/s10668-020-00327-4.

Fisher, T.J., Gallagher, C.M., 2012. New weighted portmanteau statistics for time series goodness of fit testing. Journal of the American Statistical Association 107 (498), 777–787. https://doi.org/10.1080/01621459.2012.688465.

Gillkas, K., Konstantatos, C., Tsagkaros, A., Siriopoulos, C., 2021. Do economic news releases affect tail risk? Evidence from an emerging market. Finance Research Letters 40, 101727. https://doi.org/10.1016/j.frl.2021.101727.

Gillkas, K., Konstantatos, C., Tsagkaros, A., Siriopoulos, C., 2021. Do economic news releases affect tail risk? Evidence from an emerging market. Finance Research Letters 40, 101727. https://doi.org/10.1016/j.frl.2021.101727.

Kalyuzhnova, Y., Lee, J., 2020. Will COVID-19 change oil markets forever? In: A new world post COVID-19. Foscari - Digital Publishing, Venezia, pp. 165–175. https://doi.org/10.30687/978-88-6963-452-4/012.

Koop, G., Pesaran, M.H., Potter, S.M., 1996. Impulse response analysis in nonlinear multivariate models. Journal of Econometrics 74 (1), 119–147. https://doi.org/10.1016/0304-4076(96)00684-8.

Lastrapes, W.D., Wiesen, T.F.P., 2021a. The joint spillover index. Economic Modelling 94, 681–691. https://doi.org/10.1016/j.econmod.2020.02.010.

Lastrapes, W.D., Wiesen, T.F.P., 2021b. The joint spillover index. Economic Modelling 94, 681–691. https://doi.org/10.1016/j.econmod.2020.02.010.

Lee, T.H., Hoang, P.D., To, T.T., 2022. Is product proximity a driver for better energy security? Global evidence of nonlinear relationships between product proximity and energy security, 0(0). The International Journal of Sustainable Development and World Ecology 1–21. https://doi.org/10.1016/j.ijsde.2022.2025500.

Maduni Elavarasan, R., Shafiiullah, G., Raju, K., Naveed, W., Ali, B., Jamil, T., Subramanian, S., Srirojan Balaguru, V.S., Reddy, K.S., Subramanian, U., 2020. COVID-19: Impact analysis and recommendations for power sector operation. Applied Energy 279, 115739. https://doi.org/10.1016/j.apenergy.2020.115739.

Pranesh N. Menon, A., Billio, M., Battistion, S., 2020. The importance of compound risk in the nexus of COVID-19, climate change and finance (Working Paper 2020:15). Department of Economics, University of Venice “Ca’ Foscari”. https://ecompass.venice.unive.it/paper/viewpaper/2020/02/35348.

Newburger, E., 2020, March 13. Coronavirus could weaken climate change action and hit clean energy investment, researchers warn. CNBC. https://www.cnbc.com/2020/03/13/coronavirus-could-weaken-climate-change-action-hit-clean-energy.html.

Pesaran, H.H., Shin, Y., 1998. Generalized impulse response analysis in linear multivariate models. Economics Letters 58 (1), 17–29. https://doi.org/10.1016/0165-1765(97)00214-0.

Sharif, A., Aloui, C., Varovaya, L., 2020. 2019 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 70. https://doi.org/10.1016/j.irfa.2019.101496.

Siddique, A., Shahzad, A., Lawler, J., Mahmoud, K.A., Lee, D.S., Ali, N., Bilal, M., Rasool, K., 2021. Unprecedented environmental and energy impacts and challenges of COVID-19 pandemic. Environmental Research 193, 102219. https://doi.org/10.1016/j.envres.2020.110443.

Szczygielski, J.J., Brzeszczynski, J., Charteris, A., Bwanya, P.R., 2022. The COVID-19 storm and the energy sector: The impact and role of uncertainty. Energy Economics 109, 105258. https://doi.org/10.1016/j.eneco.2021.105258.
Uhlmann, E.L., Ebersole, C.R., Chartier, C.R., Errington, T.M., Kidwell, M.C., Lai, C.K., McCarthy, R.J., Riegelman, A., Silberzahn, R., Nosek, B.A., 2019. Scientific utopia III: Crowdsourcing science. Perspectives on Psychological Science 14 (5), 711–733. https://doi.org/10.1177/1745691619850561.

Wang, Y., Wei, Y., Wu, C., 2011. Analysis of the efficiency and multifractality of gold markets based on multifractal detrended fluctuation analysis. Physica A: Statistical Mechanics and its Applications 390 (5), 817–827. https://doi.org/10.1016/j.physa.2010.11.002.

Wang, Q., Yang, X., Li, R., 2022. The impact of the COVID-19 pandemic on the energy market – a comparative relationship between oil and coal. Energy Strategy Reviews 39, 100761. https://doi.org/10.1016/j.esr.2021.100761.

Wigand, F., Brückmann, R., Jimeno, M., Bünker, F., Breitschopf, B., Anatolitis, V., Kitzing, L., Duda, M., Del Rio, P., Fitch-Roy, O., Laszlo, S., Menzies, C., 2020. Policy brief: Impact of COVID-19 on renewable energy auctions. https://doi.org/10.13140/RG.2.2.192332.335206.

Wu, Q., Yan, X., 2019. Capturing deep tail risk via sequential learning of quantile dynamics. Journal of Economic Dynamics and Control 109, 103771. https://doi.org/10.1016/j.jedc.2019.103771.

Xu, S., Du, Z., Zhang, H., 2020. Can crude oil serve as a hedging asset for underlying securities?—research on the heterogenous correlation between crude oil and stock index. Energies 13 (12), 3139. https://doi.org/10.3390/en13123139.

Zhang, D., Broadstock, D.C., 2020. Global financial crisis and rising connectedness in the international commodity markets. International Review of Financial Analysis 68, 101239. https://doi.org/10.1016/j.irfa.2018.08.005.