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Risk transmission from the COVID-19 to metals and energy markets

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ABSTRACT

We examine the risk transmission from the COVID-19 to metal (precious and industrial) and energy markets using the BEKK-MGARCH model. The findings reveal the significant and negative volatility transmission from the COVID-19 to gold, palladium, and brent oil markets, suggesting the safe-haven properties of these markets. The COVID-19 risk is not transmitted to the industrial metal market, whereas the rise in COVID-19 volatility leads to an increase in WTI oil market volatility. These results provide useful insights to investors and policymakers regarding risk management, asset pricing, and financial market stability during the COVID-19 pandemic.

1. Introduction

The COVID-19 has considerably affected the majority of financial markets around the globe (Zhang et al., 2020; Goodell, 2020; Baker et al., 2020; Salisu and Vo, 2020; Yaroyava et al., 2020; Yousaf and Ali, 2021). On Jan 12, 2021, the total number of coronavirus cases and deaths are 90 million and 1.94 million, respectively.1 Due to the COVID-19, almost all countries are enforcing the SOP of coronavirus to avoid the spread of this virus, and social distancing is one of the majorly suggested precautions. The social distancing severely disturbed the financial markets (Ashraf, 2020), and no one is sure about the end of this virus effect. Although many companies have prepared the vaccine for coronavirus, it will take time to provide this vaccine to the whole world population. There is huge uncertainty in the markets due to the different cycles/waves of the coronavirus, i.e., the first wave of corona cases and then the second. This fluctuation in corona cases and deaths creates uncertainty in human beings, and ultimately this uncertainty is transmitted to financial markets (Baek and Lee, 2020). Therefore, it is important to analyze the transmission of uncertainty/risk from the COVID-19 to the financial markets. It has important implications for investors and policymakers regarding diversification, safe-haven investments, and financial markets stability.

With respect to methodology, most of the studies examine the relationship between two financial markets before and during the COVID-19 pandemic using panel logit, GARCH (1,1), dynamic network, Diebold, and Yilmaz approaches (Salisu et al., 2020a; Corbet et al., 2020a; Guo et al., 2020; Ben Amar et al., 2020; Le et al., 2021). Moreover, some studies also examined the impact of the COVID-19 on the dynamic correlations/spillovers between different pairs of markets using network analysis, TVP-VAR model, and DCC-GARCH model (So et al., 2021; Adekoya and Oliyide, 2020; Mariana et al., 2021; Dutta et al., 2020; Akhtaruzzaman et al., 2021; Conlon and McGee, 2020). However, fewer studies have investigated the relationships/spillovers between the COVID-19 proxies and different financial markets using the multifractal analysis, OLS, panel quantile regression, and fixed effect model (Mensi et al., 2020; Albulescu, 2021; Cepoi, 2020; Salisu et al., 2020b). Baek and Lee (2020) use the BEKK-MGARCH model to measure the risk transmission from the COVID-19 deaths to the US stock market. Following Baek and Lee (2020), we examine the risk spillover from the COVID-19 to commodity markets. However, we are using the global fear index of the COVID-19 index proposed by Salisu and Akanni (2020) as a proxy of the COVID-19, which incorporated both cases and deaths of coronavirus, instead of using only deaths data as used by (Baek and Lee, 2020).

With respect to commodity markets, several studies have examined the impact of coronavirus on different types of financial markets, like stocks (Topcu and Gulal, 2020; Ashraf, 2020a; Phan and Narayan, 2020; Liu et al., 2020), bonds (Halling and Zechner, 2020; Falato et al., 2020), cryptocurrencies (Goodell and Goutte, 2021; Yousaf and Ali, 2020a, 2020b), currencies (Umar and Gubareva, 2020), gold (Salisu et al.,...
2020b; Corbet et al., 2020b; Yousaef et al., 2021), and oil markets (Mensi et al., 2020; Bouri et al., 2020). It can be noticed from the above-mentioned studies that the literature is missing on the impact of the COVID-19 on some precious metals, industrial metals, and the natural gas market. Therefore, we focus on examining the risk transmission from the COVID-19 to metals (precious and industrial) and energy markets using the multivariate BEKK-GARCH model. Our study contributes to the literature of “the COVID-19/crisis and commodity markets nexus”.

The study’s findings reveal that risk transmission is significantly negative from the COVID-19 to gold, palladium, and Brent oil markets, suggesting the safe-haven properties of these markets during the pandemic. The volatility transmissions are insignificant from the COVID-19 to the industrial metal market, indicating that investors can diversify their risk by adding industrial metals to their portfolios. Lastly, the COVID-19 volatility is positively transmitted to the WTI oil market, indicating that the WTI oil market is adversely affected by the COVID-19 pandemic. These results provide valuable insights to investors and policymakers regarding risk management, asset pricing, and financial market stability during the COVID-19 pandemic. The remaining paper is structured as follows: Section 2 describes the data and methodology, Section 3 provides the results and analysis, and Section 4 concludes the whole study.

2. Data and methodology

2.1. Data

We use the daily data of metals and energy markets from January 22, 2020, to January 04, 2021. More specifically, this study uses the data of four precious metals (Gold, Silver, Platinum, Palladium), five industrial metals (Aluminum, Copper, Lead, Nickel, Zinc), and three energy markets (Brent, WTI, Natural Gas). Following Yousaef and Hassan (2019), and Yousaef et al. (2020), the data of precious metals, industrial metals, and energy indices are taken from the London Bullion Market Association website, US Energy Information Administration website, and investing.com website, respectively. All indices are in the US dollar. The daily data of coronavirus cases and deaths are taken from https://ourworldindata.org (Erdem, 2020).

2.2. Methodology

This study’s methodology consists of two stages. In the first stage, we construct the COVID-19 index based on the data of coronavirus cases and deaths. We use the BEKK-MGARCH model to examine the risk transmission from the COVID-19 index to metal and energy markets in the second stage.

We follow the process of Salisu and Akanni (2020) to construct the COVID-19 index. The global panic/fear index of COVID-19 incorporates the incubation period (14 days), coronavirus cases, and deaths. The global fear index (GFI) the average of two indices, namely reported cases index (RCI) and reported death index (RDI). According to Salisu and Akanni (2020), “RCI measures how far expectations from reported cases in a 14-day period ahead veered from the present reported case”. The choice of 14-day expectations represents the highest number of incubation days as defined by the WHO 2020. “RDI relates the number of daily reported deaths to expectations from the reported number of deaths in a 14-day period ahead in line with the assumption for RCI based on WHO declaration”. The RCI, RDI, and GFI indices are calculated as:

\[ RCI = \left[ \frac{\sum_i^n \text{Corona virus cases}_{t,i}}{\sum_i^n \text{Corona virus cases}_{t,i} + \text{Corona virus cases}_{t-14,i}} \right] \]  

\[ RDI = \left[ \frac{\sum_i^n \text{Corona virus deaths}_{t,i}}{\sum_i^n \text{Corona virus deaths}_{t,i} + \text{Corona virus deaths}_{t-14,i}} \right] \]  

\[ GFI = [0.50(RCI + RDI)] \]

\[ \sum_i^n \text{Corona virus cases}_{t,i} \] and \[ \sum_i^n \text{Corona virus deaths}_{t,i} \] represent the total number of cases and deaths, respectively, of coronavirus for all countries at time t, specified as N. Corona virus cases \( c_{t,i} \) and Corona virus deaths \( d_{t,i} \) denotes the number of cases and deaths, respectively, reported at the beginning of the incubation period, t-14.

In the second stage, we measure the risk spillover from the GFI index of COVID-19 to metal and energy markets using the BEKK-MGARCH model of Engle and Kroner (1995). Several studies have employed the BEKK-GARCH model to examine the volatility transmission between different types of markets (Sadorsky, 2012; Arouiri et al., 2015; Khalifaoui et al., 2015; Batten et al., 2017; Katsiampa et al., 2019; Yu et al., 2020; Yousaf and Ali, 2021). The main advantage of the BEKK-GARCH model is the positive definiteness of the variance-covariance matrix. BEKK-GARCH model is more stable than the other GARCH models (Engle and Kroner, 1995). The BEKK-GARCH model is better than other connectedness models (Choudhry and Wu, 2008; Yong Fu et al., 2011; Vo and Ellis, 2018) because it has lesser convergence issues (Chng, 2009). In a multivariate setting to estimate spillovers, the BEKK-GARCH model is more relevant than the univariate models (Arouiri et al., 2011). Apart from BEKK-GARCH model, several other models are also available for the connectedness analysis like Wavelet approach and Diebold & Yilmaz approach etc., (Umair et al., 2021; Naeem et al., 2020). Moreover, Baek and Lee (2020) use the BEKK-MGARCH model to examine the volatility/risk transmission from the COVID-19 deaths to the US stock market. For risk spillover, the multivariate BEKK-GARCH (1,1) model is used, which necessitates positive definiteness restrictions for \( H_t \), is given by:

\[ H_t = C + A \epsilon_{t-1} \epsilon_{t-1}^\prime A + B H_{t-1} B \]  

Where A and B are square matrices, and C is a lower triangular matrix expressed as follows:

\[ C = \begin{pmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{pmatrix}, A = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}, B = \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} \]

Variable order is the COVID-19 (1) and the commodity market (2) in our analysis. The elements of matrix \( A \) represent the coefficients of the ARCH term. As this study focuses on examining the impact of the COVID-19 on commodity (metal and energy) markets, thus the relevant coefficients are \( a_{12} \) and \( b_{12} \). The coefficient \( a_{12} \) represents the effect of the past shocks in the COVID-19 on the current conditional volatility of the commodity market. The coefficient \( b_{12} \) denotes the effect of past volatility in the COVID-19 on the current conditional volatility of the commodity market. Moreover, we also report the results of coefficients \( a_{22} \) and \( b_{22} \), which indicates the effect of past shocks and volatility, respectively, in the commodity market on their current volatility. The parameters of the multivariate BEKK-AGARCH are estimated by the ML (maximum likelihood) method using the algorithm of BFGS.

3. Results

3.1. Summary statistics

Table 1 reports the summary statistics of the returns of metals and energy markets during the COVID-19 pandemic. The average daily returns are observed to be highest in silver and lowest in the WTI market. The WTI market observed a huge decline and negative prices
During the COVID-19 due to a decrease in consumer demand globally (Corbet et al., 2020), also indicated by the minimum value of WTI (-301.966%). The unconditional volatility is highest in WTI and lowest in aluminium. Overall, gold, silver, copper, and nickel provide high returns with low risk. The skewness is negative in majority of the metals (silver, platinum, palladium, copper, lead, and Zinc) and WTI market, implies that there are frequent small gains and few large losses in these markets. The highest negative skewness is noted in WTI because this market observed the losses, and WTI became negative during the COVID-19. Moreover, the skewness is positive in a few metals (gold, aluminium, nickel) and energy (Brent and Natural Gas) markets, indicating the few large gains in these markets during the COVID-19. The kurtosis is greater than 3 in the majority of the markets, in some cases, it is much higher, which indicates the high level of investment risk in these markets. During the COVID-19, a high level of risk can be expected due to extremely large and small returns in the majority of markets.

Jarque-Bera statistics are statistically significant for all series, indicating the normally distributed returns in commodity and energy markets. As ARCH test is significant in all series, indicating that the volatility is not constant in all markets. Moreover, the presence of ARCH effects in all series allow us to apply the BEKK-GARCH model. The Augmented Dickey Fuller test’s coefficients are negative and significant, showing the stationarity of all series. Fig. 1 illustrates the returns of metals and energy markets during the COVID-19 pandemic. It can be noticed that all precious and industrial metals reached their highest negative peaks during the first quarter of 2020, whereas huge negative returns are observed at the start of the second quarter of 2020 in the Brent and WTI markets. Overall, these returns show that the COVID-19 pandemic adversely affects these markets in the first and second quarters of 2020.

3.2. Risk spillovers

Table 2 provides the results of risk transmission from the COVID-19 to precious metals. The coefficient \(a_{22}\) is significant and positive in gold, silver, and platinum markets, implying that past shocks of precious metals significantly influence the current volatility of the majority of precious metals. The coefficient \(a_{12}\) is significant and positive in the palladium market, showing that the lag shocks in the COVID-19 index

|               | Mean | Maximum | Minimum | Std. Dev. | Skewness | Kurtosis | Jarque-Bera | ARCH | ADF |
|---------------|------|---------|---------|-----------|----------|----------|-------------|------|-----|
| Gold          | 0.099| 7.026   | -5.258  | 1.250     | 0.199    | 8.204    | 267.846***  | 24.697*** | -13.808*** |
| Silver        | 0.216| 10.748  | -17.787 | 2.782     | -0.788   | 11.341   | 708.526***  | 16.976*** | -8.740***  |
| Platinum      | 0.063| 9.871   | -10.986 | 2.239     | -0.440   | 8.576    | 313.352***  | 62.660*** | -7.466***  |
| Palladium     | 0.032| 12.473  | -12.911 | 2.851     | -0.070   | 8.216    | 267.868***  | 42.928*** | -10.541*** |
| Aluminium     | 0.028| 3.967   | -2.967  | 1.019     | 0.360    | 3.544    | 8.018**     | 5.055*  | -13.999*** |
| Copper        | 0.103| 3.908   | -7.024  | 1.461     | -0.731   | 5.813    | 98.850***   | 19.335*** | -13.929*** |
| Lead          | 0.020| 4.075   | -6.274  | 1.535     | -0.161   | 3.802    | 7.347**     | 8.229***| -16.654*** |
| Nickel        | 0.108| 4.741   | -4.797  | 1.589     | 0.053    | 3.496    | 2.529       | 6.181** | -15.873*** |
| Zinc          | 0.052| 3.253   | -4.284  | 1.400     | -0.369   | 3.260    | 6.013**     | 5.843*  | -14.294*** |
| Brent         | 0.067| 50.987  | -47.465 | 7.186     | 0.554    | 23.970   | 4336.0***   | 63.721***| -15.988*** |
| WTI           | -1.325| 53.086  | -301.966| 22.561    | -10.664  | 138.791  | 185791.2*** | 27.066***| -11.307*** |
| Natural Gas   | -0.114| 16.769  | -9.813  | 3.359     | 0.639    | 5.432    | 74.210***   | 5.087*  | -14.812*** |

Notes: WTI- West Texas Intermediate, Std Dev-standard deviation, ARCH- autoregressive conditional heteroscedasticity model, ADF-Augmented Dickey-Fuller test. ***,**,* denote the 1%, 5%, and 10% level of significance.
significantly increase the conditional volatility of the palladium market. However, previous shocks in the COVID-19 index do not affect the conditional volatility of gold, silver, and platinum markets. The effect of past volatility is significant and negative (positive) on the current volatility of gold (silver, platinum, and palladium), as indicated by \( \beta_{a2} \) and \( \beta_{b2} \). Moreover, the effect of past own volatility is higher compared to the past own shock in precious metals, indicating the importance of current volatility in forecasting the future volatility of precious metals. Regarding cross volatility transmissions, the coefficient \( \beta_{b3} \) is found to be negative in all precious metals. However, the coefficient \( \beta_{b2} \) is significant and negative only in gold and palladium markets, indicating that gold and palladium. It shows that a rise in the volatility of the COVID-19 index leads to a decrease in the volatility of gold and palladium markets, implying the safe-haven properties of gold and palladium during the COVID-19 pandemic. Dutta et al. (2020) and Ji et al. (2020) also report gold as a safe-haven against different financial markets.

Table 3 provides the results of risk transmission from the COVID-19 to the industrial metals market. Refer to coefficient \( \alpha_{12} \), the own shock spillovers are significant and positive (negative) in copper (Nickel) market. The coefficient \( \alpha_{12} \) is significant and positive in the case of Lead and Nickel, showing that the past shocks of COVID-19 significantly affect the current volatility of Lead and Nickel markets. Moreover, the coefficient \( \alpha_{22} \) is significant in aluminum, copper, and lead, indicating that past volatility significantly influences the current volatility of aluminum, copper, and lead. The comparison of \( \alpha_{22} \) and \( \beta_{22} \) coefficients show that the impact of past volatility is higher compared to past shocks on the current volatility of industrial metals. The coefficient \( \beta_{12} \) is not significant in all industrial metals, which indicates the influence of COVID-19 on the volatility of all industrial metals, indicating that investors can diversify the risk through investing in industrial metals during the COVID-19 pandemic.

Table 4 presents the findings of risk spillover from the COVID-19 to energy markets. The coefficient of \( \alpha_{22} \) is significant and positive in brent, WTI, and natural gas markets, showing that past shocks significantly and positively influence the current volatility of energy markets. The coefficient \( \alpha_{12} \) is found to be significantly negative, indicating that past shocks of the COVID-19 index directly influence the current volatility of WTI market. Refer to coefficient \( \beta_{b2} \), the past volatility significantly affects the current volatility in brent and natural gas markets, indicating the possibility of future volatility forecasting through past own volatility in brent and natural gas market. Regarding the \( \beta_{b2} \) coefficient, the results reveal that the risk transmission is significantly positive (negative) from the COVID-19 to WTI (brent), whereas insignificant in the natural gas market. In fact, the WTI market is inversely affected by the COVID-19 because the volatility of WTI rises due to the increase in volatility of the COVID-19 index. Lin and Su (2021) also find that the COVID-19 significantly affects the crude oil markets. Lastly, brent also provides strong safe-haven features against the risk of the COVID-19 pandemic.

4. Conclusion

We examine how much daily COVID-19 cases and deaths related news contributes to the volatility of metal (precious and industrial) and energy markets. Firstly, we construct the global fear index of the COVID-19, which incorporates factors like coronavirus cases and deaths. Secondly, we apply the multivariate BEKK-GARCH model to examine the risk transmission from the global fear index of COVID-19 to the metals and energy markets. The findings show that volatility transmission is significantly negative from the COVID-19 to gold, palladium, and Brent oil markets, indicating the safe-haven properties of these markets therefore investors and portfolio managers are suggested to invest in these markets to maximize risk adjusted returns during the pandemic. The volatility transmissions are insignificant from the COVID-19 to the industrial metal market, indicating that investors can diversify their risk by adding industrial metals to their portfolios. Lastly, the COVID-19 volatility is positively transmitted to the WTI oil market, indicating that the WTI oil market is adversely affected by the COVID-19 pandemic. In fact, the crude oil prices crash is widely linked to the national and international economic states including among others interest rates, inflation, fiscal policy, economic activity, exchange rates, and the geopolitical events. The US is the producer of WTI crude oil therefore the US policy makers are suggested to consider the pandemic risk as one of the important risk factors, for the market stability, while devising the policies for the oil sector and economy. Moreover, the US governments should be more cautious in taking preventive measures against the

| Table 2 | Risk transmission from the COVID-19 to Precious Metals. |
|---------|---------------------------------------------------------|
| GDP     | SILVER | PLATINUM | PALLADIUM |
| \( \beta_{22} \) | 0.133  | 0.923*** | 1.090*** | 0.000  |
|         | (0.283) | (0.001)  | (0.000)  | (0.190) |
| \( \alpha_{12} \) | 0.002  | -0.002   | 0.000    | 0.004*  |
|         | (0.331) | (0.562)  | (0.603)  | (0.085) |
| \( \alpha_{22} \) | 0.333*** | 0.546*** | 0.541*** | 0.004  |
|         | (0.000) | (0.000)  | (0.000)  | (0.503) |
| \( \beta_{12} \) | -0.004* | -0.001   | -0.005   | -0.009*** |
|         | (0.083) | (0.535)  | (0.332)  | (0.010) |
| \( \beta_{22} \) | -0.908*** | 0.809*** | 0.647*** | 0.983*** |
|         | (0.000) | (0.000)  | (0.000)  | (0.000) |

Notes: \( \beta_{a2} \) denotes the constant terms of the market metal-based variance equation. \( \alpha_{22} \) and \( \beta_{22} \) represents the past own shocks and volatility spillovers, respectively, in the metal market. \( \alpha_{12} \) indicates the shock transmission from the COVID-19 to the metal market, whereas \( \alpha_{22} \) denotes the volatility transmission from the COVID-19 to the metal market. Parenthesis includes the p-values. ***, **, * denote the 1%, 5%, and 10% level of significance, respectively.

| Table 3 | Risk transmission from the COVID-19 to Industrial Metals. |
|---------|----------------------------------------------------------|
| ALUMINUM | COPPER | LEAD | NICKEL | ZINC |
| \( \beta_{22} \) | 0.000  | 0.579** | 0.112  | 1.334*** | 0.000  |
|         | (0.079) | (0.018) | (0.813) | (0.000)  | (0.969) |
| \( \alpha_{12} \) | -0.001 | 0.001  | 0.003** | 0.002*** | -0.002 |
|         | (0.699) | (0.760) | (0.029) | (0.008)  | (0.487) |
| \( \alpha_{22} \) | 0.278  | 0.297** | -0.038 | -0.344** | 0.068  |
|         | (0.171) | (0.015) | (0.211) | (0.012)  | (0.177) |
| \( \beta_{12} \) | 0.001  | -0.001 | 0.000  | 0.001    | 0.002  |
|         | (0.565) | (0.301) | (0.920) | (0.919)  | (0.150) |
| \( \beta_{22} \) | 0.628** | 0.859*** | 0.983*** | 0.398   | 0.239  |
|         | (0.023) | (0.000) | (0.000) | (0.174)  | (0.237) |

Notes: \( \beta_{a2} \) denotes the constant terms of the market metal-based variance equation. \( \alpha_{22} \) and \( \beta_{22} \) represents the past own shocks and volatility spillovers, respectively, in the metal market. \( \alpha_{12} \) indicates the shock transmission from the COVID-19 to the metal market, whereas \( \alpha_{22} \) denotes the volatility transmission from the COVID-19 to the metal market. Parenthesis includes the p-values. ***, **, * denote the 1%, 5%, and 10% level of significance, respectively.

| Table 4 | Volatility transmission from the COVID-19 to Energy Market. |
|---------|------------------------------------------------------------|
| BRENT   | WTI | NATURAL GAS |
| \( \beta_{22} \) | 0.399 | -0.023*** | 0.000  |
|         | (0.021) | (0.000)  | (0.981) |
| \( \alpha_{12} \) | 0.015  | 0.052*  | 0.005  |
|         | (0.201) | (0.087)  | (0.536) |
| \( \alpha_{22} \) | 0.413*** | 3.433*** | 0.414*** |
|         | (0.000) | (0.000)  | (0.009) |
| \( \beta_{12} \) | -0.014* | 0.082*** | 0.004  |
|         | (0.095) | (0.009)  | (0.459) |
| \( \beta_{22} \) | 0.904*** | -0.151   | 0.759*** |
|         | (0.000) | (0.104)  | (0.000) |

Notes: \( \beta_{a2} \) denotes the constant terms of the market metal-based variance equation. \( \alpha_{22} \) and \( \beta_{22} \) represents the past own shocks and volatility spillovers, respectively, in the energy market. \( \alpha_{12} \) indicates the shock transmission from the COVID-19 to the energy market, whereas \( \alpha_{22} \) denotes the volatility transmission from the COVID-19 to the energy market. Parenthesis includes the p-values. ***, **, * denote the 1%, 5%, and 10% level of significance, respectively.
health crisis to save the energy sector from falling into a more profound crisis. The US oil exploration and production companies are also advised to add pandemic risk in their risk assessments to stabilize cashflows in the pandemic type emergencies. The WTI crude oil investors are advised to diversify their portfolio by adding safe haven assets in their WTI oil based portfolio, especially during the COVID-19. Overall, these results provide valuable insights to investors and policymakers regarding portfolio risk management, asset pricing, and financial market stability during the COVID-19 pandemic.

Author statement

Imran Yousaf: Conceptualization; Data curation; Formal analysis; Funding acquisition; Investigation; Methodology; Project administration; Resources; Software; Supervision; Validation; Visualization; Roles/ Writing - original draft; Writing - review & editing.

Appendix

Fig. 1A. Conditional Volatilities.

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