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Volatility in metallic resources prices in COVID-19 and financial crises-2008: Evidence from global market

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ABSTRACT

The prevalence of uncertainty is evident in natural resources and financial markets almost every period. However, the global financial crisis and the recent Covid-19 pandemic is considered the most distressful event that disturbs the global economic and financial performance. In such crises, natural resource (mineral) prices also fluctuate as a result of demand and supply shocks. Identifying volatility in metallic resource prices is now the time’s need, which consequently leads to implementing appropriate policies for recovery of the global markets. In this sense, the current study analyzed these two period from August 21, 2007, to December 31, 2009 (global financial crisis) and from January 01, 2019, to September 17, 2021 (Covid-19 pandemic). The empirical results obtained via threshold generalized autoregressive conditional heteroscedasticity (TGARCH) and exponential autoregressive conditional heteroscedasticity (EGARCH) model asserted that volatility exists in metallic resource prices in both the crises periods. Concerning the global financial crisis, the metallic resource prices were more volatile in 2008, while such priwere are highly volatile during the Covid-19 pandemic peak year (2020). Additionally, volatility in metallic resources is found higher in the Covid-19 pandemic, relative to global financial crisis. Based on the empirical results, this study suggests the appropriate policy measures that could help tackle the issue of metallic resource price volatility.

1. Introduction

Gold is among the most frequently traded commodities that market participants rarely recognize. In 2011, the expected daily worldwide turnover of gold was approximately 4000 metric tons, which corresponded to an estimated value of nearly $240 billion. This is almost equivalent to the regular dollar volume of trading on all stock exchanges around the world (World Federation of Exchanges, 2011). If gold is considered a currency, its turnover surpasses all but four currency pairings (von Kleist et al., 2010). As with the foreign currency market, gold trading is heavily concentrated, with London (physical, over-the-counter (OTC) spot trade) and the New York Mercantile Exchange Futures Market (COMEX) accounting for 85 percent (78 percent and 7.7 percent, respectively) of worldwide turnover volume (Hauptfleisch et al., 2016). Although, demand for metallic resources such as gold has progressively increased over time due to its limited supply. However, local or external shocks have also widely affected the demand and supply of such resources.

There are many global events occurred that have dramatically changed the world’s economic and non-economic order (Rafique et al., 2022). However, two global events have been responsible for causing more adversity to the worldwide economic conditions in the last two decades. Specifically, the global financial crisis of 2008 and the recent Covid-19 pandemic have created uncertainty in the global economic, financial, and trading markets. Although the influence of these crises has been identified on various economic and non-economic factors, including natural resources, oil price volatility, economic growth, and financial market (Devpura and Narayan, 2020; Bouazizi et al., 2020; Hayat and Tahir, 2021). Still, the focus of researchers and scholars is diverted to other economic issues like economic growth and financial markets. In contrast, volatility in metallic resources –sensitive to such global crises remained unexplored.

Metallic natural resources and especially gold, have progressed with human civilization. It was originally prized for its exquisiteness, but it has since been utilized for trade and exchanged for other products and commodities (Kanjilal and Ghosh, 2017). Gold’s scarcity worldwide, along with its high density and ease of melting and shaping, makes it a natural trading asset. Gold has long been acknowledged as a universally

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accepted currency that retains its buying value despite the deterioration of monetary and financial institutions (Kanjilal and Ghosh, 2017). Although studies have mentioned that gold prices are greatly influenced by gold reserves, financial market indices, energy product prices, and global macroeconomic indicators (Lili and Chengmei, 2013). Still, there is evidence available that demonstrates that volatility in metallic resource prices could be linked to uncertainties in the regional and global markets caused by both the global financial crisis and the Covid-19 pandemic (Kristjanpoller and Minutolo, 2015; Yaya et al., 2016; Sheikh et al., 2020; Wang et al., 2016; Syahri and Robiyanto, 2020; Yousef and Shehadeh, 2020a; Marwanti and Robiyanto, 2021). However, this volatility itself is greatly linked to the declination of many other economic and financial factors such as oil prices volatility, exchange rate, and stock market and stock price volatility (Singhal et al., 2019; Hashim et al., 2017; Syahri and Robiyanto, 2020; Sheikh et al., 2020; Choudhry et al., 2015). Beside the global financial crisis, the volatility of metallic resource prices are also affected by the Covid-19 pandemic. Since the Covid-19 is rapidly spreading across the world, the procedures adopted to battle Covid-19 reflect those that have previously been employed during global wars. Estimates by the OECD indicate that such policies are expected to reduce economic production by 20–25 percent. As increased market volatility has progressively encouraged investors to seek out safe-haven assets, the U.S. dollar has risen on the international currency exchange market. In times of economic uncertainty and turmoil, investors often seek safety in gold. Gold is a liquid, anti-cyclical asset and a long-term store of wealth, enabling investors to achieve their primary goals of liquidity, safety, and return. Consequently, the price of gold has climbed by 12.85 percent from $1517.3 per ounce on January 1, 2020 to $1712.39 per ounce on May 1, 2020, and are anticipated to continue rising (Yousef and Shehadeh, 2020a). This indicates that they are surpassing the U.S. dollar. On the other hand, several researchers mentioned that gold prices have a positive association with that of Covid-19 global new infections (Yousef and Shehadeh, 2020a; Attri et al., 2021). Hence, it cannot be considered as a safe haven due to its changing nature, which is also evident in empirical studies (Chen and Wang, 2018; Bredin et al., 2015; Hood and Malik, 2013). Although, many scholars, as mentioned above, have tried to explore the influence of gold volatility on various economic and financial factors. While the volatility in metallic resource prices still remained out of the researcher’s attention, which this study tends to relive.

The prime objective of this study is to investigate volatility in metallic resource prices. Although many efforts have been made to examine gold price volatility in different periods (Syahri and Robiyanto, 2020; Mishra et al., 2010; Kristjanpoller and Minutolo, 2015; Singhal et al., 2019). Still, these studies ignored volatility in either global financial crisis period or the Covid-19 pandemic period. Hence: another objective of this study is to investigate volatility in metallic resource prices in the global financial crisis. Lastly, the recent pandemic caused a global lock-down – which consequently offset most of the economic and trading sectors of the world. Therefore, another objective of the study is to empirically analyze the volatility of metallic resource prices in the Covid-19 pandemic period. Besides, these two crisis periods could substantially impact metallic resource prices volatility. Hence, the last objective is to identify which crisis event is considered with the greater magnitude of volatility in the said variable. In order to achieve the objective of the study, we have used the traditional threshold generalized autoregressive conditional heteroskedasticity (TGARCH) and exponential autoregressive conditional heteroskedasticity (EGARCH) models, which is a best approach to examine volatility in metallic resource prices.

This study is novel and contributes to the existing literature manifold: firstly, it is one of the pioneering studies investigating volatility in metallic resource prices for the global market. Since there are many studies, as mentioned in the literature, empirically investigated gold prices volatility in different periods. Still, volatility in metallic resource prices remained ignored if considered the two most disastrous events: global financial crisis and the recent Covid-19 pandemic. Therefore, this study fills the literature gap by analyzing metallic resources prices volatility in both periods. Lastly, although the time period for data on the global financial crisis is well established, this study used the most recent dataset for the Covid-19 pandemic crisis, which could provide relevant and updated information regarding the issue. Moreover, this study provides some practical policy insights that could help resolve the issue.

The rest of the study is organized as following: Section-2 provides relevant literature review covering both the global financial crisis and Covid-19 pandemic periods; Section-3 presents data and methodology used for empirical investigation; Section-4 represents empirical results and their discussion in two parts, where the earlier indicates the findings in global financial crisis period while the latter indicates empirical findings in the Covid-19 pandemic period; Section-5 provides conclusion of the study and policy implications.

2. Literature review

The most recent study by Syahri and Robiyanto (2020) investigated the dynamic correlation of gold prices, exchange rate and the stock market in Covid-19 pandemic by using daily data. The study concludes that gold prices and composite stock price index (CSPI) are positively correlated while exchange rate and CSPI are negatively correlated in Covid-19 pandemic. Regarding volatility and weak market efficiency of metallic future prices, Chen and Tang (2004) investigated Chinese copper and aluminium futures and concluded that aluminum futures are more heavily impacted by outside variables than copper futures; both markets have substantial clustering and persistent features. In India’s Gold market volatility and stock market return, Mishra et al. (2010) unveil a bidirectional causal association between the two. In addition, Kristjanpoller and Minutolo (2015) investigated gold price volatility by utilizing the Dow Jones, financial time stock exchange indexes and oil price returns and realized a 25% overall reduction in the mean average percent error. Furthermore, Contuk et al. (2013) investigated the effect of fluctuation in gold prices on ISE-100. The study identified that there is an ARCH effect, whereas the MGARCH model revealed that volatility in both gold prices and ISE-100 have been affected by their own as well as each other’s shocks – validating volatility in metallic resource prices.

On the contrary, the recent study by Singhal et al. (2019) investigated the linkage of volatility and returns between gold prices and international crude oil prices. The study concludes that international gold prices have a beneficial impact on Mexican stock prices, whilst oil prices have a negative impact. Oil prices have a long-term negative impact on the exchange rate, but gold prices have no meaningful impact. Regarding the influence of shock such as Covid-19 pandemic on gold prices, Yousef and Shehadeh (2020b) analyzed daily gold returns and found the existence of positive correlation between Covid-19 cases and gold price increase. Besides, the study concludes that Covid-19 positively impacts the conditional variance equation, which validates the increase in gold price return volatility during the Covid-19 pandemic period.

Regarding the factors affecting gold price volatility, Hashim et al. (2017) investigated five largest gold consumers in the world and concluded a positive association between crude oil prices and gold prices. However, GDP, inflation rate, exchange rate, and real interest rate negatively correlate with gold price volatility. However, the long-run equilibrium relationship exists between oil prices, gold prices and S&P500 market price index (Gokmenoglu and Fazlollahi, 2015), which is 1.2% on daily basis. Still, the external shocks could play a substantial role in analyzing commodity price volatility. In this regard, the recent study of Bakas and Triantafyllou (2020) investigated the economic uncertainty of pandemics and commodity price volatility. The study unveils that pandemics’ related uncertainty exhibit a strong and negative impact on the crude oil market, while positively but less significantly
affecting gold market.

Focusing on the pre and post global financial crisis periods, Yaya et al. (2016) investigated volatility persistence and returns spillover between gold prices and oil prices. They conclude that the gold market volatility is less than the oil market in both periods. The study of Sheikh et al. (2020) examined the asymmetric association between gold prices, oil prices, stock prices and exchange rate in case of Pakistan in the pre and post financial crisis periods. The examined results unveil that in the pre-financial crisis period, the investors react differently only to gold and oil prices, but react to positive shocks in gold prices, oil prices, stock prices and exchange rate in the post crisis period. In addition, Choudhry et al. (2015) tested the gold returns and the stock market volatility in Japan, UK, and the US during the global financial crisis period. The study revealed that the correlation integral based on the bivariate model indicates a non-linear significant feedback effect between variables during the crisis period. The study argued that gold might not be a safe haven in the crisis period because of the bidirectional dependence on gold returns, stock returns and stock market volatility.

In order to investigate the spillover effect of extreme risk in the global gold market in the pre and post-global financial crisis, Wang et al. (2016) examined the four major gold markets and claimed extreme spillover effects of gold market exist between the four markets, where the extreme risk quickly transferred in the post-financial crisis. On the other hand, Marwanti and Robiyanto (2021) conclude that gold and oil price volatility do not posit any influence on the stock returns in the pre and post Covid-19 pandemic crisis period. Therefore, they claimed gold as a safe haven during the financial crisis period in Indonesia. In the same vein, Salsu et al. (2021) investigated both the pre and post pandemic periods. The estimated results unveil that gold is a significant safe haven against the risk in oil prices. That is, hedging of gold is effective with the risk associated with oil. Moreover, the study of Hansun and Suryadibatra (2021), Wen et al. (2017), Kanjilal and Ghosh (2017), Sopipan et al. (2012) provide empirical evidence regarding the effectiveness of an estimator for volatility in gold prices and also to predict the gold prices in future.

Although many studies, as mentioned earlier, have been done regarding volatility in gold or other natural resources price volatility. However, to the best of our knowledge, there is no such study found in the existing literature that empirically investigates metallic resources price volatility especially in the periods of two global crisis, namely: global financial crisis and the recent Covid-19 pandemic, which holds importance as both of these crises substantially disturb global financial and economic activities. Therefore, to fill the gap, an attempt has been made by this study while investigating both of these mentioned periods.

3. Methodology

Natural resources prices and particularly metallic resources prices are very sensitive to external shocks. External shocks in the form global financial crisis and the recent Covid-19 pandemic outbreak have caused changes in the global economic and financial systems. Nonetheless, many attempts have been made on the influence of global financial crisis and Covid-19 pandemic on various natural resources and prices. Still, the matter of volatility, particularly in metallic resources prices remained out of the focus of the researchers, which is important to investigate in the current times. There is a deep relationship between a shock in the economy and metallic resources prices. For instance, any sort of political, financial, or pandemic shock create uncertainty in the market, which influence investors, industrialists, and their choices regarding investment in energy as well as industrial sector. Due to such uncertain circumstances, the investors tend to invest in gold, leading to the price increase as gold is considered a safe haven (Baur and McDermott, 2010, 2016; Baur and Lucey, 2010), whereas another group of scholars argued that gold is not a safe haven due to its variable and volatile structure (Chen and Wang, 2018; Bredin et al., 2015; Hood and Malik, 2013). Therefore, it is important to empirically examine volatility in gold prices and identify the real properties of gold prices (Darehshiri et al., 2022). The data for the said variable is extracted for the mentioned periods from one source, that is the World Gold Council1 (2021). Moreover, the gold prices are measured in the US dollars.

Although there are many global and regional events occurred since the last three decades including Gulf war of 1990s, Asian financial crisis (1997), oil price hike (2004), the global financial crisis 2007–2009, and the recent Covid-19 pandemic are few to mention. These crises have serious effects on natural resources and natural resources prices fluctuations or volatility. Besides, the last two crises have been considered events with higher influence on natural resource price volatility, which consequently affect both the financial markets and the whole economy. Moreover, swings in natural resources prices and metallic resources prices in particular, boost investors’ concern regarding returns, making them more anxious about variability or risk of prices instability. Since, both the global financial crisis and the recent Covid-19 pandemic have created uncertainties in the global financial and economic sectors, and the former caused a global lockdown, which could significantly contribute to volatility in metallic resources prices such as gold prices. Therefore, it is need of the time to investigate the volatility of metallic resources prices during both global financial crisis and Covid-19 pandemic period.

Although there are number of econometric specifications that could identify volatility in the time series variable. For instance, the wavelet power spectrum, multivariate Regime Switching GARCH modelling, among others. Where the former is only limited to graphical representation of the fluctuations and provide ambiguous results. However, the latter is more powerful in forecasting the next period risk on the basis of present data. Whereas, considering the study’s aims, which is identifying volatility in the gold prices during the mentioned two periods, the ARCH, GARCH, TGARCH, and EGARCH could be used as appropriate tools, which are discussed in this section.

In order to identify metallic resources price volatility in both financial crises (2008) and Covid-19, a simple measure to take its value over the time. That is, a data having of metallic resources prices over ‘n’ days period, then simply subtract the mean value of these prices from the value of individual n, square the difference, and divide by the observation’s number to get the variance. Because it is a measurement of

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1 For details and data, visit: https://www.gold.org/goldhub/data/gold-price-volatility.
unconditional variance, which is a single figure for a specific sample, it does not show volatility clustering on its own. Here, the previous metallic resources prices are not taken into account. That is, it ignores the fact that metallic prices fluctuate over time. As a result, autoregressive conditional heteroscedasticity (ARCH) is a criterion that takes into account the past history. In general, the ARCH(1) model calculates the mean and variance at the same time. The simulation of ARCH(1) is provided in Eq. (1) and Eq. (2) below, respectively:

\[ Z_t = \alpha + \beta X_t + \mu_t \]  
\[ \sigma_t^2 = \theta_0 + \theta_1 \mu_{t-1}^2 \]  

Where Eq. (1) is indicated as the mean equation while Eq. (2) revealed the variance equation. Besides, \( \mu_t \) as mentioned above, is the information set. Here, the ARCH(1) model demonstrates that when the shock is bigger as observed in the \( t \) – 1 period, the error term’s \( \mu_t \) values will consequently be larger, which could be obtained in the absolute form because of squaring. Thus, the value variance for next innovation would be greater if the \( \mu_t \) value is greater, and the variance value for the next innovation would be smaller if the \( \mu_t \) value is smaller. Additionally, the \( \theta_1 \) which is the value of estimated coefficient will be positive for the positive variance. Furthermore, this conditional variance could not be kept limited only to one lagged realization. Instead, it is extendable up to q lags, which is known as ARCH(q) model. Generally, the ARCH(q) model could be estimated as following:

\[ \sigma_t^2 = \theta_0 + \theta_1 \mu_{t-1}^2 + \theta_2 \mu_{t-2}^2 + \ldots + \theta_q \mu_{t-q}^2 \]  

Where this general representation could be transformed to the simplest version as following:

\[ \sigma_t^2 = \theta_0 + \sum_{j=1}^{q} \theta_j \mu_{t-j}^2 \]  

Where in the above equations, \( \theta \) s are the estimated coefficients are would provide positive values for positive variance. It must be noted that the ARCH(q) model is more efficient as it allows the series variability to change more slowly than that of ARCH(1) model. Nonetheless, the ARCH(q) models identified variability of the metallic resources’ prices, the method is still challenging to adopt as these models produce negative assessment of \( \theta \). Additionally, as per Engle (1995), the ARCH approach holds a drawback as it is more similar to the moving averages specifications relative to autoregression. Therefore, to overcome the mentioned problem, Bollerslev (1986) come up with a new approach which is known as the generalized ARCH (GARCH) approach. In this method, the author included the lagged conditional variance terms as autoregressive terms. The GARCH(p, q) model could be generally presented as following:

\[ Z_t = \alpha + \beta X_t + \mu_t \]  
\[ \sigma_t^2 = \theta_0 + \sum_{i=1}^{p} \theta_i \mu_{t-i}^2 + \sum_{i=1}^{q} \theta_i \sigma_{t-i}^2 \]  

Where Eq. (6) illustrates that the value of \( \sigma_t^2 \) (variance scaling parameter) not only depends on the values of past shocks presented as the lagged squared residuals, but also depends up on the past values of itself presented as the lagged \( \sigma_t^2 \) terms. Here, it is worth mentioning that the GARCH(p, q) model can be reduced to the ARCH(q) model by taking the coefficient (\( \rho \)) values equal to zero, i.e., \( \rho_i = 0 \). Moreover, in the GARCH(p, q) model, the GARCH(1, 1) is considered as the simplest structure, which is expressed in Eq. (7) below:

\[ \sigma_t^2 = \theta_0 + \rho_1 \sigma_{t-1}^2 \]  

Where, the above-mentioned GARCH(1, 1) model is simple and usually performs well due to three unknown parameters only, that is, \( \theta_0, \theta_1, \) and \( \rho_1 \). Further, the said model is an economical substitution of ARCH(q) estimation. However, the estimation can be achieved by continuously substituting the right sided equation. Hence, the final transformed equation could be expressed in Eq. (8) below:

\[ \sigma_t^2 = \frac{\theta_0}{1-\rho} + \theta_1 \sum_{j=1}^{\infty} \rho^{j-1} \mu_{t-j}^2 \]  

Where the above mentioned equation reveals that GARCH(1, 1) has similar specifications as of infinite ARCH model with geometrically decreasing coefficients. On the basis of this logic, it is important to analyze the GARCH(1, 1) models as an alternative to higher order ARCH models because the GARCH(1, 1) provides few parameters for estimation, which also leads to loss fewer degrees of freedom. Similar to the extendable properties of ARCH, the GARCH(1, 1) model could also be extended to GARCH(6) specifications. This provides in depth investigation of the metallic resource prices variation up to six lagged terms. Apart from the previously mentioned benefits and drawbacks of ARCH and GARCH specifications, one important limitation is that these approaches are symmetric. As the residual terms are squared, this implies that only the absolute value of the innovation is important, whereas the signs make no influence. As a result, if the shocks are of equal magnitude, a large positive or negative shock in ARCH/GARCH models might have a similar effect. In the case of metallic resources prices, however, negative shocks may have a stronger impact on volatility of prices than a positive shock of comparable magnitude. In this sense, the threshold GARCH (TGARCH) model might be a useful tool for capturing asymmetries in terms of both positive and negative shocks. The TGARCH approach is proposed by Zakoian (1994) and Glosten et al. (1993). The influence of negative shock is considerably differentiated in this (TGARCH) model by using multiplicative dummies in the variance equation. Generally, the TGARCH(1, 1) model could be expressed in the equation form as following:

\[ \sigma_t^2 = \theta_0 + \theta_1 \mu_{t-1}^2 + \theta_2 \mu_{t-2}^2 + \ldots + \theta_p \mu_{t-p}^2 + \rho \sigma_{t-1}^2 \]  

Where in the priorly mentioned Eq. (9), when the \( \mu_t < 0 \), the value of \( d_t \) will be equal to one, while remained as 0 if \( \mu_t \geq 0 \). As a result, the influence of negative or positive shock will be differentiated. Here, the impact of negative shock is \( \theta_1 + \theta_2 \), while that of positive shock is \( \theta_1 \) only. This reveals that the influence of shocks is asymmetric. Conversely, if \( \theta_2 = 0 \), this leads to the conclusion that the shocks are symmetric. Furthermore, the TGARCH(1, 1) model is also extendable and adding more lagged terms to Eq. (9) provides higher order TGARCH specification, which could be expressed as following:

\[ \sigma_t^2 = \theta_0 + \sum_{i=1}^{p} (\theta_i + \nu_i d_{t-i}) \mu_{t-i}^2 + \sum_{j=1}^{q} \rho_j \sigma_{t-j}^2 \]  

Despite the fact that the above given specifications offer predicted volatilities: still, they have limitations in that they do not ensure that the variance will not be negative. In this regard, the exponential GARCH (EGARCH) approach is considered as efficient, which is proposed by Nelson (1991). In this specification, the exponential leverage effect has been generated rather than the quadratic – hence, guaranteed the non-negative conditional variance. Generally, the EGARCH specification considers asymmetries and the TGARCH, which is expressed in the following Eq. (11):

\[ \log(\sigma_t^2) = \theta + \sum_{j=1}^{p} \frac{\theta_j}{\sigma_{t-j}^2} \mu_{t-j} + \sum_{j=1}^{q} \nu_j \frac{\mu_{t-j}}{\sigma_{t-j}} + \sum_{j=1}^{q} \rho_j \log(\sigma_{t-j}^2) \]
Where the left side of the above equation is the log variance of the series. On the other hand, \( \theta, \xi, \zeta, \xi, s \), and \( p \) on the right side of equation are the estimating parameters. In addition, if \( \xi_1 = \xi_2 = \xi_3 = \ldots = 0 \) is found, then it will be considered as a symmetric model. Whereas the \( \xi_j < 0 \) if found, it will lead to the conclusion that volatility created by negative shock is greater than that of the positive shock.

4. Results and discussion

We provided empirical results of metallic resources [gold prices (GP)] for the mentioned two periods of data in two sections: firstly, Section-4.1 presents the empirical findings for global financial crisis period, while Section-4.2 provides empirical findings of gold price volatility in the recent Covid-19 pandemic.

4.1. Empirical findings of metallic resource prices volatility in global financial crisis

This section begins empirical estimation of metallic resource price volatility in the period of global financial crisis by evaluating the descriptive statistics of data from August 21, 2007, to December 31, 2009. Descriptive statistics provide data in summarize form. Specifically, it includes the mean, median, range and standard deviation, presented in Table-1. The mean value of GP is reported as US$ 897.2184, while the median value is accounted for US$ 904.9500. However, this value of GP lead to the highest of US$ 1217.400 from the minimum of US$ 656.7. Specifically, the gold prices were found at the minimum level of US$ 656.7 on August 21, 2007, which is an initial period of the global financial crisis. However, after the emergence of the crisis, the gold prices significantly increased daily, reaching the maximum (1217.40) on December 03, 2009. However, a fall in the gold prices is observed after the peak of the mentioned prices. Such substantial difference between the maximum and minimum values indicates a higher standard deviation, which is accounted for US$ 105.4990. Since the standard deviation is a general measure of volatility in a time series. Therefore, the higher standard value reveals the existence of volatility in gold prices.

Once the descriptive statistics are calculated, we further estimated the AR(1) model, which is simply regressing metallic resource prices by its lagged values. The estimated results are obtained for the mean equation are presented in Table-2. Here, the AR(1) model is estimated purposively for obtaining the value of residuals (RSD). The value of RSD further helps in the identification of ARCH effect.

After obtaining the residuals, this study further investigated the presence of ARCH effect. For this, we performed a heteroscedasticity test, the estimated outcomes for which is provided in Table-3. Here, the lagged term of squared RSD (RSD\(^2\)) has been regressed on the RSD\(^2\), which provides highly significant coefficient value of 0.140 at 1% level of significance. Additionally, the Obs*R\(^2\) value obtained is even higher than the ARCH (1), accounting for 22.616, which is highly statistically significant at 1%. As the value of Obs*R\(^2\) is higher, therefore it suggests a substantial rejection of the null hypothesis in GP. As a result, it is concluded that the ARCH effect is present in GP and further allows current study to investigate the ARCH model.

As the ARCH effect has been confirmed by both the ARCH(1) and ARCH(6) effects, therefore it allows to estimate the ARCH(1) model, for which the estimated results are provided in Table-4. The earlier presented model i.e., Eq. (1) and Eq. (2) can be elaborated with the empirical findings as given below:

\[ COP_t = 11.002[0.023] + (0.989)COP(-1)_{t-1}[0.000] + \mu_t, \]

Where \( \mu_t | \Omega_t \sim iid N(0, \sigma^2_t) \), and

\[ \sigma^2_t = 174.016[0.000] + (0.109)\mu^2_{t-1}[0.003] \]

Here, the residual’s coefficient is positive and highly statistically significant, which is in line to the earlier ARCH models. Hence, the null hypothesis if GP being homoscedastic is rejected and it is concluded that the GP is heteroscedastic. Moreover, the values of \( \alpha \) and \( \beta \) The mean equation changed from the earlier values, which are now 11.002 and 0.989, respectively. Further, these coefficient values are highly statistically significant, as suggested by the probability values in the brackets.

Similarly, the ARCH(1) model is extended to ARCH(6) model, which

**Table-1**

Descriptive statistics during financial crises.

| Statistics  | GP (Gold Prices) |
|-------------|------------------|
| Mean        | 897.2184         |
| Median      | 904.9500         |
| Maximum     | 1217.400         |
| Minimum     | 656.7000         |
| Std. Dev.   | 105.4990         |

**Table-2**

Results of a simple AR(1) model for GP.

| Variable | Coefficient | Std. Error | t-Statistic | Prob.  |
|----------|-------------|------------|-------------|--------|
| C        | 168.498***  | 18.5072    | 9.12571     | 0.0000 |
| GP(-1)   | 0.140***    | 0.046257   | 3.449013    | 0.0006 |
| R-squared| 0.019       | F-statistic| 11.839      | 0.0006 |
| Adjusted R-squared | 0.018 | Prob(F-statistic) | 32882.99 |
| F-statistic| 11.839 | Prob(F-statistic) | 0.000000 |

Note: The dependent variable used here is Squared Residual (RSD\(^2\)). ***, ***, * are for 1%, 5% and 10% significance levels.

**Table-3**

Testing for ARCH(1) effects in GP.

| Variable | Coefficient | Std. Error | t-Statistic | Prob.  |
|----------|-------------|------------|-------------|--------|
| C        | 129.458***  | 23.0692    | 5.16122     | 0.0000 |
| GP(-1)   | 0.117***    | 0.041378   | 2.836045    | 0.0047 |
| R-squared| 0.045       | 0.041604   | 1.077787    | 0.2816 |
| R-squared| 0.099**     | 0.041637   | 2.392525    | 0.0171 |
| R-squared| 0.019       | 0.041636   | 0.460231    | 0.6455 |
| R-squared| 0.054       | 0.041599   | 1.289590    | 0.1977 |
| R-squared| 0.011       | 0.041370   | 0.274899    | 0.7835 |
| Adjusted R-squared | 0.028368 | Prob(F-statistic) | 0.000843 |
| F-statistic| 3.872836 | Prob(F-statistic) | 0.000843 |
| Obs*R-squared | 22.61568 | Prob(Chi-Square(6)) | 0.0009 |

Note: The dependent variable used here is Squared Residual (RSD\(^2\)). ***, ***, * are for 1%, 5% and 10% significance levels.

**Table-4**

Testing for ARCH(6) effects in GP.

| Variable | Coefficient | Std. Error | t-Statistic | Prob.  |
|----------|-------------|------------|-------------|--------|
| C        | 129.458***  | 23.0692    | 5.16122     | 0.0000 |
| GP(-6)   | 0.177***    | 0.041378   | 2.836045    | 0.0047 |
| R-squared| 0.054       | 0.041604   | 1.077787    | 0.2816 |
| R-squared| 0.099**     | 0.041637   | 2.392525    | 0.0171 |
| R-squared| 0.019       | 0.041636   | 0.460231    | 0.6455 |
| R-squared| 0.054       | 0.041599   | 1.289590    | 0.1977 |
| R-squared| 0.011       | 0.041370   | 0.274899    | 0.7835 |
| Adjusted R-squared | 0.028368 | Prob(F-statistic) | 0.000843 |
| F-statistic| 3.872836 | Prob(F-statistic) | 0.000843 |
| Obs*R-squared | 22.61568 | Prob(Chi-Square(6)) | 0.0009 |
provides a more comprehensive look into the disturbance by considering six lags of $RSD^2$. The estimated outcomes of ARCH(6) model is presented in Table-6. The estimated results indicate that the coefficient values for all the residuals are positive, but the only three lagged values are found statistically significant at 1% and 5%, which is lag 1st, lag 4th and lag 5th. Nonetheless, the rest of the lagged residuals are insignificant, still the three lags are providing enough support of rejecting the null hypothesis of homoscedasticity and concluding that the GP is heteroscedastic in the study period. Besides, the $\alpha$ and $\beta'$ From the mean equation is reported slightly changed then the ARCH(1) model. Although, the earlier estimates of ARCH(1) and ARCH(6) models provides evidence for the homoscedasticity of GP across the selected time. However, the graphical display of conditional standard deviation and conditional variance (Figure-1 and Figure-2) further clarify the earlier empirical findings. With reference to the figures, the higher volatility can be seen in the late 2007, 2008 and 2009 as a whole. Still, the highest volatility of GP is observed in 2008 and earlier 2009. Hence, these figures confirm the earlier empirical findings of ARCH models. The empirical findings are consistent to the earlier findings of Kristjanpoller and Minutolo (2015), Yaya et al. (2016), Sheikh et al. (2020), Wang et al. (2016) and Marwanti and Robiyanto (2021), which confirmed the volatile behavior of gold and other metallic resource prices in the global financial crisis period.

As mentioned earlier in Section-3, the ARCH models are more contagious to generate negative values and look more like a similar approach to moving averages (Engle, 1995). Therefore, to ignore these issues, we have adopted the GARCH specification provided by Bollerslev (1986). Here, the conditional lagged terms have been included as autoregressive terms, and the GARCH(1) model’s estimated findings are reported in Table-7. Here, the values for $\theta$ and $\rho$ are found 2.250 and 0.990, respectively. These values are found highly statistically significant at 1% level, which indicates that the GP is heteroscedastic during the global financial crisis period. In addition, the values intercept and

| Table-5 |
| --- |
| An ARCH(1, 1) model for GP. |

| Mean Equation |
| --- |
| Variable | Coefficient | Std. Error | z-Statistic | Prob. |
| C | 11.002*** | 4.832692 | 2.276598 | 0.0228 |
| GP(-1) | 0.989*** | 0.005379 | 183.8109 | 0.0000 |

| Variance Equation |
| --- |
| C | 174.016*** | 9.290097 | 18.73132 | 0.0000 |
| $RSD^2(-1)$ | 0.109*** | 0.036181 | 3.007522 | 0.0026 |

Note: The dependent variable used here is GP. ***, **, * are for 1%, 5% and 10% significance levels.

| Table-6 |
| --- |
| An ARCH(1, 6) model for GP. |

| Mean Equation |
| --- |
| Variable | Coefficient | Std. Error | z-Statistic | Prob. |
| C | 12.007*** | 4.248253 | 2.826297 | 0.0047 |
| GP(-1) | 0.988*** | 0.004599 | 214.7503 | 0.0000 |

| Variance Equation |
| --- |
| C | 88.957*** | 11.92012 | 7.462790 | 0.0000 |
| $RSD^2(-1)$ | 0.077*** | 0.028313 | 2.704558 | 0.0068 |
| $RSD^2(-2)$ | 0.078 | 0.047796 | 1.631489 | 0.1022 |
| $RSD^2(-3)$ | 0.065 | 0.051455 | 1.266541 | 0.2053 |
| $RSD^2(-4)$ | 0.119** | 0.049622 | 2.405829 | 0.0161 |
| $RSD^2(-5)$ | 0.176*** | 0.051300 | 3.421399 | 0.0006 |
| $RSD^2(-6)$ | 0.071759 | 0.050147 | 1.430976 | 0.1524 |

Note: The dependent variable used here is GP. ***, **, * are for 1%, 5% and 10% significance levels.

| Table-7 |
| --- |
| A GARCH(1, 1) model for GP. |

| Mean Equation |
| --- |
| Variable | Coefficient | Std. Error | z-Statistic | Prob. |
| C | 8.672** | 3.847058 | 2.254115 | 0.0242 |
| GP(-1) | 0.991*** | 0.004527 | 218.9331 | 0.0000 |

| Variance Equation |
| --- |
| C | 2.250*** | 0.425406 | 5.288594 | 0.0000 |
| GARCH(-1) | 0.990*** | 0.002296 | 431.2928 | 0.0000 |

Note: The dependent variable used here is GP. ***, **, * are for 1%, 5% and 10% significance levels.

lagged GP are also found positive and statistically significant at 5% and 1% levels, respectively. Although, the GARCH(1) provides a more robust estimate than the ARCH model. Still, it shares similarities to the higher order ARCH model. Therefore, to confirm the findings from GARCH model, we expand the simple GARCH(1) model into GARCH(1) model into GARCH(6) model.

The estimated findings of the expended GARCH(1) model into GARCH(6) are presented in Table-8. The coefficient values of the lagged
GARCH are found to be positive up to five lagged values. However, the sixth lagged GARCH is found to posit negative value. Besides, all the lagged coefficient values of GARCH are found highly statistically significant, which further stimulates the rejection of null hypothesis of GP being homoscedastic. Hence the highly significant GARCH lagged values revealed that the GP are volatile in the global financial crisis period.

Moreover, the intercept and slope values for GP(-1) are found to hold a slightly changed value from the GARCH(1) model, which is highly significant at 1% level. Hence, it could be stated that global financial crisis has created uncertainty across the globe, which further fuel the GP prices fluctuate during the crisis period. Further, the estimated findings have been confirmed by providing the graphical representation of the GARCH models with reference to Figure-3 and Figure-4. These figures have demonstrated that GP was more volatile in 2008, a critical year of global financial crisis.

In order to overcome the issue of high order ARCH and GARCH models, this study employed the TGARCH approach provided by Zakoian (1994) and Glosten et al. (1993). As mentioned earlier, both the ARCH and GARCH models are symmetric, which only gives importance to the absolute value of innovation rather than the signs. As a result, both positive and negative shocks in the period of the financial crisis could have the same influence if their magnitude is equal. However, Metallic resource prices, particularly gold prices, are more sensitive to negative shocks than positive ones. Therefore, the authors of this approach add multiplicative dummies to the TGARCH model, which could differentiate the negative shock influence (Shahzad et al., 2022).

The empirical estimates of the TGARCH(1, 1) is provided in Table-9. The examined results unveil that residual and GARCH(-1) coefficients are highly statistically significant. While the interactive dummy holds an insignificant coefficient value, which reveals consistent results to the earlier GARCH model. Although, the results provide evidence of the heteroscedastic behavior of GP in the financial period. Still, the TGARCH does not verify the influence of negative shock. Therefore, to guarantee the influence of negative shock, this study further used EGARCH specification. Besides, the TGARCH estimations are further confirmed by Figure-5 and Figure-6.

Nonetheless, the ARCH, GARCH and TGARCH specifications provide evidence of the heteroscedastic behavior of GP during the financial crisis period. Still, these approaches have ignored the negative variance, which could have a stronger influence than the positive one. In this regard, Nelson (1991) proposed EGARCH specification is a handy tool that generate exponential leverage effect rather than the quadratic and guaranteed non-negative conditional variance. Table-10 provides empirical findings of the EGARCH approach. The examined results reveal that the unveils that the estimate of the mean equation is about 1% level, which validates the volatile behavior of GP across the financial crisis. Also, the EGARCH approach confirms that the negative shock severely influences the price volatility of gold. Current empirical findings are in line with the earlier findings of Kristjansenpoller and Minutolo (2015), Khan et al. (2020), Yaya et al. (2016), Sheikh et al. (2020), Wang et al. (2016) and Marwanti and Robiyanto (2021), which confirmed the volatile behavior of gold and other metallic resource prices in the global financial crisis period. Besides, the

*Table-8*

| Variable | Coefficient | Std. Error | z-Statistic | Prob. |
|----------|-------------|------------|-------------|-------|
| C        | 10.215***   | 2.365621   | 4.318246    | 0.0000|
| GP(-1)   | 0.990***    | 0.002898   | 34.61095    | 0.0000|

Variance Equation

| C        | 0.268***    | 0.018565   | 14.44101    | 0.0000|
| GARCH(-1)| 0.207***    | 0.008823   | 23.4594     | 0.0000|
| GARCH(-2)| 0.440***    | 0.009278   | 47.4710     | 0.0000|
| GARCH(-3)| 0.662***    | 0.010412   | 63.5940     | 0.0000|
| GARCH(-4)| 0.468***    | 0.013052   | 35.8583     | 0.0000|
| GARCH(-5)| 0.264***    | 0.007803   | 33.8477     | 0.0000|
| GARCH(-6)| -1.043***   | 0.007767   | -134.2501   | 0.0000|

Note: The dependent variable used here is GP. ***, **, * are for 1%, 5% and 10% significance levels.

*Figure-3.* Conditional standard deviation (GARCH).

*Table-9*

| Variable | Coefficient | Std. Error | z-Statistic | Prob. |
|----------|-------------|------------|-------------|-------|
| C        | 8.814***    | 2.989688   | 2.948142    | 0.0032|
| GP(-1)   | 0.991***    | 0.003403   | 291.2625    | 0.0000|

Variance Equation

| C        | 2.240***    | 0.790315   | 2.834021    | 0.0046|
| RSD(-1)  | 0.049***    | 0.018900   | 2.607171    | 0.0091|
| RSD(-1)*(RSD(-1)<0) | 0.014 | 0.017738 | -0.768325 | 0.4423|
| GARCH(-1)| 0.949***    | 0.013691   | 69.2881     | 0.0000|
| R-squared| 0.982220    | 0.982165   |             |       |

Note: The dependent variable used here is GP. ***, **, * are for 1%, 5% and 10% significance levels.

*Figure-4.* Conditional variance (GARCH).
volatility of GP is confirmed by the graphical display obtained via EGARCH specifications and provided in Figure-7 and Figure-8. Moreover, the Figure-9 also demonstrates the values of residuals, actual and fitted variance of the GP across the global financial crisis period.

### Table-10
An EGARCH(1, 1) model for GP.

| Mean Equation | Variable | Coefficient | Std. Error | z-Statistic | Prob. |
|---------------|----------|-------------|------------|-------------|-------|
| C             | 9.287*** | 2.444003    | 3.800039   | 0.0001      |
| GP(-1)        | 0.991*** | 0.002788    | 355.3698   | 0.0000      |

| Variance Equation | C     | 0.032  | 0.029766 | 1.058836 | 0.2897 |
|                  | ABS(RESID(-1)/SQRT(GARCH(-1))) | 0.102*** | 0.027519 | 3.723341 | 0.0002 |
|                  | LOG(GARCH(-1)) | 0.979*** | 0.005838 | 167.7738 | 0.0000 |
|                  | R-squared | 0.992946 |
|                  | Adjusted R-squared | 0.992944 |

Note: The dependent variable used here is GP. ***, **, * are for 1%, 5% and 10% significance levels.
4.2. Empirical findings of metallic resource prices Volatility in Covid-19 pandemic

This section provides the empirical results of metallic resource prices volatility during the Covid-19 pandemic from January 01, 2019, to September 17, 2021. Prior to empirical estimations, this study provides descriptive statistics – including the mean, median, range and standard deviation of the data under study. The computed outcomes of descriptive statistics are provided in Table-11. Here, it is noted that the mean and median values are US$ 1669.467 and 1728.650, which are quite high than the GP mean and median values in the financial crisis period. Also, the range value is reported with a minimum value of US$ 1277.900 to the maximum of US$ 2103.200, which is higher than that in global financial crisis period. Specifically, the lowest gold prices are observed in the pre-Covid-19 pandemic period, which is April 19, 2019. However, after the emergence of the pandemic, the gold prices significantly increased and reached the maximum of all time on August 06, 2022, which is regarded as the peak period of the Covid-19 pandemic. In the peak period of the pandemic, the investors postponed their investment in industrial and financial activities and shifted towards a safe or low-risk commodity, gold. In the same line, the standard deviation is reported as 204.0110, which indicates that this value is higher, and the price of gold is not the same across the Covid-19 pandemic period. Hence, it can be concluded that the gold prices fluctuate during the Covid-19 pandemic, which is of higher magnitude than the global financial crisis.

As discussed in Section-4.1, the estimation process of GP in Covid-19 pandemic also holds the same procedure. Firstly, we investigated the presence of an ARCH effect in the data in Covid-19 pandemic period. In this regard, current study performs simple heteroscedasticity test, for which the estimated results are provided in Table-12. The RSD2(−1) examined results are found at 0.074, which is statistically significant at 5% level. Also, the value of Obs*R2 is found 4.040806 with a Chi square value of 0.0444 and statistically significant at 5% level. This leads to the conclusion that the ARCH effect is present in gold prices in the Covid-19 pandemic.

As the ARCH effect is present in the GP data in Covid-19 pandemic, therefore current study estimated the ARCH(1) model, which considers only one lagged value of the GD in the mean equation and one lagged value of RSD2 in the variance equation. The estimated outcomes of the ARCH(1, 1) variables are presented in Table-13. The examined results unveil that the coefficient value of RSD2(-1) is positive and highly statistically significant at 1% level. This leads to the rejection of the null hypothesis of data being homoscedastic in the Covid-19 pandemic. Hence it is assumed that metallic resources are volatile in the Covid-19 pandemic period As the pandemic creates global lock-down, directly affecting every economic and industrial activity. Thus, the demand and supply of metallic resources is also disturbed. This further fuel uncertainty in the metallic resource prices. Moreover, the mean equation reveals that the value of intercept and slope of GP(-1) are positive and statistically significant at 5%, and 1% levels, respectively.

Although, the ARCH(1, 1) empirically provides evidence of the presence of volatility in GP in Covid-19. Still, the higher order ARCH, i. e., ARCH(1, 6) could provide comprehensive estimates of the volatility by considering six lagged values of the RSD2. The ARCH(1, 6) model’s estimated outcomes are presented in Table-14, where the variance equation indicates that the first and last lag of the RSD2 are statistically significant at 1%, 5%, and 10% levels. This further provides strong evidence of the rejection of null hypothesis and leads to the conclusion that metallic resource prices are heteroscedastic during the Covid-19 pandemic period. Regarding the mean equation, the intercept is found insignificant, while the GP(-1) slope is reported positive and highly statistically significant at 1% level. Moreover, to represent the deviation of gold prices from mean value, this study also provides the graphical display of the ARCH findings. With reference to Figure-10 and Figure-11, the graphical display provides conditional standard deviation and conditional variance, respectively. However, from these two figures, it is noted that the highest variation has been observed in the gold prices in the Covid-19 pandemic peak period, which is 2020. Also, the variation in GP is found in the other two years, but the magnitude of the variance is smaller than that in the year 2020. The empirical findings of current study are statistically significant to the earlier findings of Syahri and Robiyanto (2020), Yousef and Shehadeh (2020b), and Marwanti and Robiyanto (2021). Which reported that oil prices were volatile during the period of Covid-19 pandemic. Although, the ARCH models identify volatility in the GP during Covid-19 pandemic. Still, the GARCH model provides more generalized

Table-12
Testing for ARCH(1) effects in GP.

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|----------|-------------|------------|-------------|-------|
| C        | 362.527***  | 39.04228   | 9.28502     | 0.0000|
| RSD2(-1) | 0.074**     | 0.036930   | 2.013046    | 0.0445|
| R-squared| 0.05628     |            |             |       |
| Adjusted R-squared | 0.04239 | Prob(F-statistic) | 0.044484|
| F-statistic | 4.052356 | Prob. | 0.0445     |
| Obs*R2-squared | 4.040806 | Prob Chi-Square | 0.00444|

Note: The dependent variable used here is Residual (RSD). ***, **, * are for 1%, 5% and 10% significance levels.

Table-13
An ARCH(1, 1) model for GP.

| Mean Equation |
|----------------|
| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
| C        | 15.3211***  | 5.944979   | 2.223244    | 0.0263|
| GP(-1)   | 0.992***    | 0.003465   | 286.4178    | 0.0000|

| Variance Equation |
|-------------------|
| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
| C        | 367.674***   | 13.07264   | 281.12546   | 0.0000|
| RSD2(-1) | 0.073***     | 0.024593   | 2.959428    | 0.0031|
| R-squared| 0.9909399    |            |             |       |
| Adjusted R-squared | 0.9909399 | Prob. | 0.0000     |

Note: The dependent variable used here is GP. ***, **, * are for 1%, 5% and 10% significance levels.

Table-14
An ARCH(1, 6) model for GP.

| Mean Equation |
|----------------|
| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
| C        | 1.304       | 6.016448   | 0.216611    | 0.8284|
| GP(-1)   | 0.999***    | 0.003552   | 281.4060    | 0.0000|

| Variance Equation |
|-------------------|
| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
| C        | 218.101***   | 12.61019   | 17.29559    | 0.0000|
| RSD2(-1) | 0.085***     | 0.024250   | 3.540168    | 0.0004|
| RSD2(-2) | 0.311***     | 0.047561   | 6.531408    | 0.0000|
| RSD2(-3) | 0.052**      | 0.023430   | 2.204045    | 0.0275|
| RSD2(-4) | 0.021       | 0.020206   | 1.081961    | 0.3082|
| RSD2(-5) | -0.013      | 0.015245   | -0.838884   | 0.4015|
| RSD2(-6) | 0.036**     | 0.015110   | 2.393047    | 0.0167|
| R-squared | 0.990367 | Prob. | 0.0000     |
| Adjusted R-squared | 0.990353 | Prob. | 0.0000     |

Note: The dependent variable used here is GP. ***, **, * are for 1%, 5% and 10% significance levels.

Table-11
Descriptive statistics for COVID-19.

| Statistics | GP |
|------------|----|
| Mean       | 1669.467|
| Median     | 1728.650|
| Maximum    | 2103.200|
| Minimum    | 1277.900|
| Std. Dev.  | 204.0110|
estimates than that of ARCH models. The estimated outcomes of GARCH (1, 1) model is presented in Table-15. The GARCH(1, 1) model provides two equations, namely: mean equation and the variance equation. Regarding the mean equation, the estimated results unveil that the values of intercept and slope of GP(-1) are about the same as found in ARCH(1, 6) model, which is GARCH(1, 6) and the estimated results are provided in Table-16. Here, the mean equation presents about the same coefficient value and is significant, with slight changes. However, the variance equation reveals that the first four lagged variables of GARCH are positive, while the last two lagged variables are negative. Still, all of these lagged variables are found insignificant, which leads to the acceptance of the null hypothesis that the gold prices are homoscedastic in the Covid-19 pandemic period. Although the results report insignificant estimates, it may be due to the limitations of GARCH specifications.

This would significantly reject the null hypothesis of homoscedasticity.

Table-15
A GARCH(1, 1) model for GP.

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|----------|-------------|------------|-------------|-------|
| C        | 11.629***   | 6.294462   | 1.847424    | 0.0647|
| GP(-1)   | 0.993***    | 0.003690   | 269.2150    | 0.0000|

Variance Equation

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|----------|-------------|------------|-------------|-------|
| C        | 203.823     | 172.0677   | 1.184549    | 0.2362|
| GARCH(-1)| 0.481       | 0.437236   | 1.101051    | 0.2709|
| R-squared| 0.990413    |            |             |       |
| Adjusted R-squared | 0.990400 |          |             |       |

Note: The dependent variable used here is GP. ****, ***, * are for 1%, 5% and 10% significance levels.

Although the GARCH(1, 1) estimates are found insignificant. Still, this study tends to examine the extended version of the GARCH(1, 6) model, which is GARCH(1, 6) and the estimated results are provided in Table-16. Here, the mean equation presents about the same coefficient value and is significant, with slight changes. However, the variance equation reveals that the first four lagged variables of GARCH are positive, while the last two lagged variables are negative. Still, all of these lagged variables are found insignificant, which leads to the acceptance of the null hypothesis that the gold prices are homoscedastic in the Covid-19 pandemic period. Although the results report insignificant estimates, it may be due to the limitations of GARCH specifications. Besides, the graphical display captured the conditional standard deviation and conditional variance, presented in Figure-12 and Figure-13, respectively. The deviation and variance of GP in Covid-19 pandemic can be seen in the figures, which allows us to utilize more robust approaches like TGARCH and EGARCH.

The GARCH(1, 1) and GARCH(1, 6) models provide insignificant estimates due to the possible limitations of the GARCH approach. In this regard, we employed the TGARCH(1, 1) approach, empirical estimates of which are provided in Table-17. The results of the mean equation reveal that the slope of GP(-1) reports approximately the same positive and significant value, while the intercept value is observed to change and decrease up to 2.488, but is found insignificant. On the other hand, unlike the GARCH models, the TGARCH approach unveils that the variance equation provides positive and highly statistically significant estimates. This leads to rejecting the null hypothesis and concludes that GP is heteroscedastic in the Covid-19 pandemic period. Also, the R² and adjusted R² values are very high, demonstrating that the model is best fit.

Besides the TGARCH(1, 1) model, we also analyzed the extended version of TGARCH, which is TGARCH(1, 6). The examined results are reported in Table-18, where the mean equation reveals approximately the same findings as of TGARCH(1, 1) model. While the variance equation demonstrates that except for the RSD²(-3) and RSD²(-4), all the lagged variables are statistically significant at 5% and 10% levels. This would significantly reject the null hypothesis of homoscedastic variance of GP in the Covid-19 and concludes that the metallic resource prices posit volatility during the Covid-19 pandemic period. Hence, the findings of Syahri and Robiyanto (2020), Yousef and Shehadeh (2020b), and Marwanti and Robiyanto (2021) have shown the consistency to the existing findings of volatility in gold prices during the Covid-19 pandemic period.

Moreover, the threshold GARCH has verified the conditional standard deviation and conditional variance in the GP throughout the Covid-19 pandemic, as displayed in Figure-14 and Figure-15, respectively. These figures also confirmed that the volatility is higher during the Covid-19 pandemic peak period, which is the year 2020. While the volatility is also observed in the other two years, but relatively less in magnitude.

Table-16
A GARCH(1, 6) model for GP.

| Variable | Coefficient | Std. Error | z-Statistic | Prob. |
|----------|-------------|------------|-------------|-------|
| C        | 12.311*     | 6.407623   | 1.921272    | 0.0547|
| GP(-1)   | 0.993***    | 0.003736   | 265.7861    | 0.0000|

Variance Equation

| Variable | Coefficient | Std. Error | z-Statistic | Prob. |
|----------|-------------|------------|-------------|-------|
| C        | 180.345*    | 104.7878   | 1.721033    | 0.0852|
| GARCH(-1)| 0.462       | 1.121646   | 0.411617    | 0.6806|
| GARCH(-2)| 0.295       | 1.910565   | 0.154253    | 0.8774|
| GARCH(-3)| 0.157       | 2.636165   | 0.059524    | 0.9525|
| GARCH(-4)| 0.004       | 3.342383   | 0.001172    | 0.9991|
| GARCH(-5)| 0.124       | 2.074736   | 0.059967    | 0.9522|
| GARCH(-6)| 0.229       | 0.679890   | 0.336787    | 0.7363|
| R-squared| 0.990413    |            |             |       |
| Adjusted R-squared | 0.990399 |          |             |       |

Note: The dependent variable used here is GP. ****, ***, * are for 1%, 5% and 10% significance levels.

The GARCH(1, 1) and GARCH(1, 6) models provide insignificant estimates due to the possible limitations of the GARCH approach. In this regard, we employed the TGARCH(1, 1) approach, empirical estimates of which are provided in Table-17. The results of the mean equation reveal that the slope of GP(-1) reports approximately the same positive and significant value, while the intercept value is observed to change and decrease up to 2.488, but is found insignificant. On the other hand, unlike the GARCH models, the TGARCH approach unveils that the variance equation provides positive and highly statistically significant estimates. This leads to rejecting the null hypothesis and concludes that GP is heteroscedastic in the Covid-19 pandemic period. Also, the R² and adjusted R² values are very high, demonstrating that the model is best fit.

Besides the TGARCH(1, 1) model, we also analyzed the extended version of TGARCH, which is TGARCH(1, 6). The examined results are reported in Table-18, where the mean equation reveals approximately the same findings as of TGARCH(1, 1) model. While the variance equation demonstrates that except for the RSD²(-3) and RSD²(-4), all the lagged variables are statistically significant at 5% and 10% levels. This would significantly reject the null hypothesis of homoscedastic variance of GP in the Covid-19 and concludes that the metallic resource prices posit volatility during the Covid-19 pandemic period. Hence, the findings of Syahri and Robiyanto (2020), Yousef and Shehadeh (2020b), and Marwanti and Robiyanto (2021) have shown the consistency to the existing findings of volatility in gold prices during the Covid-19 pandemic period. Moreover, the threshold GARCH has verified the conditional standard deviation and conditional variance in the GP throughout the Covid-19 pandemic, as displayed in Figure-14 and Figure-15, respectively. These figures also confirmed that the volatility is higher during the Covid-19 pandemic peak period, which is the year 2020. While the volatility is also observed in the other two years, but relatively less in magnitude.
Although the findings of ARCH and TGARCH have already mentioned that volatility exists in GP during the Covid-19 pandemic period. Still, there are limitations of these methods such as not guaranteeing the influence of negative shock as well as they are symmetric. Therefore, current study also employed the EGARCH specification, which substantially overcame these issues. The estimated results of EGARCH(1, 1) approach is provided in Table-19. Similar to the TGARCH approach, this specification also provides the mean and variance equations. Where the mean equation is found different than that of the TGARCH estimation. Specifically, the intercept and the slope of lagged
The world has faced several challenges and shocks, where the global financial crisis and Covid-19 pandemic are regarded as the most hazardous to economic, natural resources, as well as financial stability and development. With reference to the global financial crisis, there are several reasons that cause global financial crisis. For instance, there are few to mention increased banks’ borrowing, inappropriate policies and regulations, mismanagement of the real estate sector, financial distress, and the spillover impact on other economies. On the other hand, the emergence of the Covid-19 pandemic also disturbed the trends in international trade and industrial production, affecting the demand and supply of natural resources and goods and services. Due to such instable circumstances, the economies face the issue of uncertainty, which creates havoc among the investors and industrialists. As a matter of fact, the higher the uncertainty level leads to the reduction of investment in the economic and financial activities. As a result, the employment level and growth trend are disturbed, which harms the country’s economic development. Since earlier studies have mentioned that gold is a safe haven for the long-run outcomes, this study uses the traditional ARCH and GARCH specifications to identify if volatility prevails in metallic resources, particularly in the gold prices. The results asserted that the gold prices followed an unstable path throughout both the crisis periods. Specifically, the crisis tends to enhance the fear of investment loss among the investors, due to which some of the investors are attracted by the haven property of gold during the crisis period, whereas the gold is also instable in parallel to the financial or other markets’ crises. Thus, the results mentioned above also revealed that the peak period of both global financial crisis and Covid-19 (specifically in 2008, late 2019 and 2020) is linked with the increased volatility in gold prices. As mentioned earlier, the increased uncertainty leads the investors to buy gold, which directly increases its prices by following the simple economic law of demand and supply. Thus, the gold prices fluctuate due to such reasons, where the policies mentioned above, such as the higher banks’ borrowing, real estate sector, postponement of the industries, trade barriers, and poor regulations of the government have played a positive role in promoting volatility. Moreover, the previous prices also explain the volatility in the gold prices. Specifically, when the investors observe the increasing prices of gold, they also participate in the increasing demand for gold, which boosts volatility in gold prices.  

4.3. Discussion

The world has faced several challenges and shocks, where the global financial crisis and Covid-19 pandemic are regarded as the most hazardous to economic, natural resources, as well as financial stability and development. With reference to the global financial crisis, there are several reasons that cause global financial crisis. For instance, there are few to mention increased banks’ borrowing, inappropriate policies and regulations, mismanagement of the real estate sector, financial distress, and the spillover impact on other economies. On the other hand, the emergence of the Covid-19 pandemic also disturbed the trends in international trade and industrial production, affecting the demand and supply of natural resources and goods and services. Due to such instable circumstances, the economies face the issue of uncertainty, which creates havoc among the investors and industrialists. As a matter of fact, the higher the uncertainty level leads to the reduction of investment in the economic and financial activities. As a result, the employment level and growth trend are disturbed, which harms the country’s economic development. Since earlier studies have mentioned that gold is a safe haven for the long-run outcomes, this study uses the traditional ARCH and GARCH specifications to identify if volatility prevails in metallic resources, particularly in the gold prices. The results asserted that the gold prices followed an unstable path throughout both the crisis periods. Specifically, the crisis tends to enhance the fear of investment loss among the investors, due to which some of the investors are attracted by the haven property of gold during the crisis period, whereas the gold is also instable in parallel to the financial or other markets’ crises. Thus, the results mentioned above also revealed that the peak period of both global financial crisis and Covid-19 (specifically in 2008, late 2019 and 2020) is linked with the increased volatility in gold prices. As mentioned earlier, the increased uncertainty leads the investors to buy gold, which directly increases its prices by following the simple economic law of demand and supply. Thus, the gold prices fluctuate due to such reasons, where the policies mentioned above, such as the higher banks’ borrowing, real estate sector, postponement of the industries, trade barriers, and poor regulations of the government have played a positive role in promoting volatility. Moreover, the previous prices also explain the volatility in the gold prices. Specifically, when the investors observe the increasing prices of gold, they also participate in the increasing demand for gold, which boosts volatility in gold prices.

5. Conclusion and policy implications

There are many global events occurred that caused changes in the global economic and non-economic policies. However, in the last two decades, the most disastrous events that causes global recession is linked with two events that distracted economies growth and development. Such events are regarded as the global financial crisis of 2008 and the recent Covid-19 pandemic outbreak. Unlike other commodities, natural resources are affected the most in the crisis period, and the prices of metallic resources are sensitive the most to such shocks. It is well-known that price volatility adversely influences the country’s economic and financial activities. Hence, it is essential to empirically examine volatility in metallic resources prices during both these crisis periods. In order to comprehensively analyze volatility, this study uses daily data.

Note: The dependent variable used here is GP. ***, **, * are for 1%, 5% and 10% significance levels.

Table-19
An EGARCH(1, 1) model for GP.

| Variable | Coefficient | Std. Error | z-Stat | Prob. |
|----------|-------------|------------|--------|-------|
| Mean Equation |
| C        | 9.534***    | 5.608460   | 1.678470 | 0.0933 |
| GP(-1)   | 0.994***    | 0.003333   | 298.3194 | 0.0000 |
| Variance Equation |
| C        | 1.237***    | 0.167148   | 7.402695 | 0.0000 |
| ABS(RSD(-1)/SQRT(GARCH(-1))) | 0.381*** | 0.048945 | 7.794120 | 0.0000 |
| LOG(GARCH(-1)) | 0.746*** | 0.030669 | 24.33419 | 0.0000 |
| R-squared | 0.990406   |            |        |       |
| Adjusted R-squared | 0.990393 |            |        |       |

Figure-16. Conditional standard deviation (EGARCH).

Figure-17. Conditional variance (EGARCH).

See [https://goldsilver.com/blog/if-stock-market-crashes-what-happens-to-gold-and-silver/](https://goldsilver.com/blog/if-stock-market-crashes-what-happens-to-gold-and-silver/).
for the two events. Traditional measures such as ARCH, GARCH, TGARCH and EGARCH specifications are appropriate for volatility identification and therefore used here. The empirical results include the global financial crisis period and the Covid-19 pandemic period. The empirical findings unveil that metallic price risks are volatile in both the crisis periods, where metallic prices are volatile the most in the peak financial crisis and Covid-19 pandemic periods. Since the volatility prevails in both the crisis periods: yet, volatility in metallic prices is highest in 2008 for global financial crisis and in 2020 for the Covid-19 pandemic. Comparatively, the volatility of metallic prices during the Covid-19 pandemic is higher than during the global financial period. This is due to the general public’s higher uncertainty and fear of death due to the rapid spread of the Covid-19 pandemic. Thus, most of the economic and financial activities were postponed, and as a result, the demand for metallic resources boosts due to higher demand.

Based on the empirical findings, this study recommends some practical implications, which need the attention of the investors, governors, and policy-makers. Firstly, the prices of the metallic resources are found volatile in both periods, indicating a higher dependency on natural resources. Therefore, policies should adopt the decreased dependence on natural resources and promote investments in the other sectors such as renewable resources, which not only reduces the natural resources demand, but also helps maintain prices, which leads to sustainable development due to sustained utilization of natural resources. Besides, the lower exploitation of natural resources will also help promote environmental sustainability. Secondly, hedging metallic resources such as gold and silver could also lead to the maintenance of volatility in the prices of such resources. This risk management approach might particularly offer compensation for natural resource investment losses. Consequently, economies may gain from natural resource hedging, at least in the near term. Thirdly, the authorities must intervene in this specific sector to construct and implement policies that regulate the demand and supply of natural resources. In other words, the demand and supply stabilization policy could lead to lower volatility in natural resources. Lastly, although the recovery of the Covid-19 pandemic is an outcome, the authorities may still impose appropriate policies for controlling the further spread of the Covid-19, which will help the economic activities run and may stabilize the metallic resource prices.  

CRedit author statement

Qingqing Xu: Supervision, Project administration, Funding acquisition. Tianci Meng: Formal Analysis, Conceptualisation. Yue Sha: Conceptualisation, Data Curation, Methodology, Software, Formal Analysis. Xia Jiang: Writing final draft, data curation.

Data availability

The data that has been used is confidential.

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