Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Gold price and exchange rate in pre and during Covid-19 period in India: Modelling dependence using copulas

Pritish Kumar Sahu a, Debi Prasad Bal b, Pradip Kundu c,∗

a International Management Institute, Bhubaneswar, 751003, India
b Department of Economics and Finance, Birla Institute of Technology and Science, Pilani, Rajasthan, 333031, India
c School of Computer Science and Engineering, XIM University, Bhubaneswar, 752050, India

A B S T R A C T

This study examines the dynamic relationship between the gold price and the exchange rate in pre- and during Covid-19 pandemic in India. We consider the periods of about equal length for both the pre- and during Covid-19 by considering the data from January 1, 2019 till February 28, 2021. The descriptive analysis shows a significant increase in the dynamics of gold price and exchange rate after mid-March 2020. The results derived from the ARDL approach show a positive and significant relationship between the gold price and exchange rate both in the long and short run. We have selected the best fitted bivariate copula to study the joint distribution of the gold price and the exchange rate. Using the copula model, we examine the relationship between the gold price and exchange rate in a bivariate framework. We have studied the dependence between them including the tail dependencies using the fitted copula. Our findings reveal that the gold price and exchange rate are significantly correlated for the entire study period, and it also reveals that there is no tail dependence. However, the mutual association between the variables is not confirmed in the considered Covid-19 period.

1. Introduction

India is the fourth largest importers of gold (Mukherjee and Mukherjee, 2020; Reserve Bank of India Handbook, 2019) and a key exporter of gold Jewellery (Department of Commerce, Ministry of Commerce and Industry, Govt. of India) in the World. The volatility in gold prices happens to be a major concern for the policymakers and government in maintaining the Balance of Payments (BOP) and the foreign exchange reserve. Statistics reveal India’s import of gold increased to US$ 34.6 billion during the financial year 2020–21, up by 22.6% over the last year (Ministry of Commerce and Industry, Govt. of India). An increase in the price of gold will have a bearing on India’s current account deficit (CAD) and rupee depreciation. Reserve Bank of India handbook of statistics (2021) attributes the increased import of Gold as one of the major reasons for the rupee depreciation in the year 2020. Given this, the volatility of gold price has both direct and indirect impact on the macroeconomic fundamentals of the economy. A rising gold prices depreciates the domestic currency causing disequilibrium in the balance of trade and thereby the economic growth (Khani et al., 2021; Singhal et al., 2019; Jain and Ghosh, 2013; Sjaastad, 2008; Tully and Lucey, 2007; Sjaastad and Scacciavillani, 1996). Conversely, an increasing price of gold transfers the wealth from importing country to exporting country (Bal and Rath, 2015).

Similarly, the volatility in the exchange rate leads to influences the gold prices for importing countries like India. More specifically, when Indian rupees depreciate over other currencies, the investors may prefer gold in order to avoid the risks (Verma and Dhiman, 2020; Jain and Biswal, 2016; Joy, 2011; Capie et al., 2005) which causes increase in the gold prices (Reboredo, 2012). At the same time, gold is also used as a hedge against risk during economic and financial crisis (Salisu et al., 2021; Arouiri et al., 2015; Qadan and Yagil, 2012; Hood and Malik, 2013). Stated differently, gold is considered a safe haven at the time of significant macroeconomic fluctuations and is preferred as a store of value by the investors leading to the increase in the prices of gold (Panagiotou, 2021; Baur and Lucey, 2016; Baur and McDermott, 2010; Kaul and Sapp, 2006). Many existing studies have found a strong relationship between gold prices and exchange rate (Joy, 2011; Reboredo and Rivera-Castro, 2014; Fresoli and Ruiz, 2016; Dong et al., 2019). It is usually seen that the weakening of a country’s currency leads to high volatility in gold prices (Capie et al., 2005; Joy, 2011; Dong et al., 2019; Khani et al., 2021). Particularly, in the developing and emerging markets the volatility is significant between the gold, exchange rate and...
therefore the increases in gold prices could have deteriorated the balance of payments during the Covid-19 pandemic can capture the short run and long run during the Covid-19 pandemic period. Finally, we have analysed the relationship among them by using best-fit copula, with the view to understand the dependence between the variables interacting simultaneously, not in isolation of one another.

Our entire dataset is split into two sub-samples i.e. pre-Covid period and during the Covid period in order to capture our analysis for the Covid-19 pandemic effects. Our first period covers January 1, 2019 to 31st December 2019, i.e. before the official reporting of first Covid-19 case in India (it is reported that, India had officially recorded the first case of Covid-19 on January 27, 2020). The second period covers roughly the same duration of post first reported case of Covid-19 (i.e. January 1, 2020 to February 28, 2021). In other words, both the pre-Covid and the during Covid period consider the data for about equal period each for a rational and reasonable analysis. Though a dearth of literature is now being widely used in economics and finance (Aloui and Aïssa, 2016; Bouyé et al., 2000; Elie et al., 2019; Canela and Collazo, 2012; Genest et al., 2009; Hung, 2020; Malevergne and Sornette, 2003; Mokni and Mansouri, 2017; Zhang and Singh, 2007; Yu et al., 2020) because of its advantages in studying dependence. In this study, we have used the copula concept to study the dependence structure between exchange rate (USD/INR) and gold price by choosing appropriate copula to model the joint (bivariate) distribution. As the fitted copula contains complete information about the joint distribution of the variables, using this fitted copula, we have studied some important concepts of dependencies including the tail dependencies.

3. Data description and analysis

We collected daily data for the variables of interest, namely the global gold price (USD/ounce) and exchange rate (INR/USD) for the period January 1, 2019–February 28, 2021. Fig. 1 depicts the dynamics of Gold Price (USD/Ounce) and Exchange Rate (INR/USD) for the considered total period. It is observed that both experienced a significant increase after Mid-March 2020, i.e. right at the time of spread of Covid-19 in India and the subsequent lockdown thereafter.

To extend the analyses to account for the Covid-19 pandemic effects we split the whole data sample to two additional sub-samples: (i) before Covid-19 (January 1, 2019–December 31, 2019) which covers the period before the emergence of Covid-19 and (ii) Covid-19 period that
is, January 1, 2020 to last date of our considered sample (February 28, 2021). For the analysis, we consider natural logarithm of the original values of both the data, i.e. we consider the transformation $y = \ln(x)$, and we denote log-transformed data as LGP and LEX for gold price and exchange rate respectively.

In Table 1, it is observed that the distribution during the Covid-19 period is highly negatively skewed as compared to before Covid-19 period. This indicates that the probability distribution of the LGP is about to its mean is highly negatively distributed. In the next steps we have conducted the unit root test and concluded that both the gold price and exchange rate are stationary at first order difference form. Once we confirm the stationary property of the variable we conducted the autoregressive distributed lag model (ARDL) and the results are presented in Table 2. Here, C represents the intercept (constant) of the ARDL model.

It shows that there exist a long run and significant relationship between exchange rate and gold price during the Covid-19 period. It implies that one per cent change in exchange rate leads to about 1.73 percentage increase in gold price. More specifically, when the exchange rate is depreciating, at that time the value of gold prices rises. The possible reason could be-as the onset of a crisis increases the panic, the investors invest in gold market leading to increased demand for gold and hence gold prices in the long-run. A similar pattern is also observed in case of the total sample. Whereas, our findings show that there is no significant relationship between exchange rate and gold price before Covid-19 period. Once the existence of long-run relationship between the two variables is confirmed, the next step performs the short-run elasticity as presented in Table 3.

The results of the short-run elasticity follow a similar pattern like in the long-run. However, the magnitude of the effect of exchange rate on gold price is less as compared to long run. The speed of adjustment coefficient is observed in error correction term i.e. here in ECM coefficients. It implies that the exchange rate takes almost 4 days to move towards the long run equilibrium during Covid-19 period and almost 19.

---

### Table 1

Descriptive statistics.

| Variable | During Covid-19 | Before Covid-19 | Total Period |
|----------|-----------------|-----------------|--------------|
|          | Mean            | S.D             | Sk.          | Mean            | S.D             | Sk.          | Mean            | S.D             | Sk.          |
| LGP      | 7.49            | 0.06            | -0.64        | 7.28            | 0.06            | -0.05        | 7.38            | 0.13            | 0.13          |
| LEX      | 4.31            | 0.02            | -0.27        | 4.26            | 0.01            | -0.44        | 4.28            | 0.03            | 0.14          |

Note: LGP = Logarithm of Gold Price; LEX = Logarithm of Exchange Rate.

---

### Table 2

Long run elasticity. Dependent variable- LGP.

| Variable | Model-I: During Covid-19 | Model-II: Before Covid-19 | Model-III: Total Period |
|----------|--------------------------|---------------------------|-------------------------|
|          | Coefficient              | Coefficient               | Coefficient             |
| LEX      | 1.73***                  | 0.92                      | 3.63***                 |
| C        | 0.002***                 | 3.30                      | -8.23**                 |

Note: *** and ** indicates significance at 1% and 5% level respectively.

---

### Table 3

Short run elasticity dependent variable- LGP.

| Variable | Model-I: During Covid-19 | Model-II: Before Covid-19 | Model-III: Total period |
|----------|--------------------------|---------------------------|-------------------------|
|          | Coefficient              | Coefficient               | Coefficient             |
| $\Delta$LEX | 0.07***                 | 0.06                      | 0.72***                 |
| $\Delta$C  | 0.10                     | 0.02                      | -0.16*                  |
| ECM(-1)   | -0.04***                 | -0.07***                  | -0.19***               |
| R- squared | 0.96                    | 0.97                      | 0.99                    |
| Adjusted R- squared | 0.96 | 0.96 | 0.99 |
| $\Delta t$ (2) | 0.06                    | 0.49                      | 5.02***                 |
| $\Delta t$ (1) | 74.36***                | 32.29***                  | 4.42*                   |
| ECM(1)    | 1.10                     | 0.72                      | 0.32                    |

Note: *** and ** indicates significance at 1% and 5% level respectively.

---
days whenever we have taken the total samples. We also find a significant and negative sign in case of before Covid-19 period. It shows that it takes almost 7 days to establish a long-run relationship between exchange rate and gold price before Covid-19. Our result also satisfies all the residual diagnostic criterion. Therefore, our results are robust in nature. Further we have tested the stability of the model by using CUSUM and CUSUM SQ test. It suggests that all of our models are stable.

Further we have tested the stability of the model by using τ. Measures of dependence and copula selection include Spearman and Kendall rank-based correlation coefficients. Therefore, our results are robust in nature. cant and negative sign in case of before Covid-19 period. It shows that it takes approximately every 4 days whenever we have taken the total samples. We also find a significant correlation with p-value less than 0.01 which confirms that distribution of both X and Y are significantly different from normal distribution. So we will use the non-parametric correlation, namely, Spearman and Kendall rank-based correlation tests.

Spearman rank correlation coefficient (ρ) is obtained as 0.786297 with the corresponding p-value is less than 0.01.

Next we assess the association between X and Y by means of Kendall’s tau rank correlation. Kendall’s tau is a non-parametric (rank-based correlation) measure of dependence (measure of monotone association) between random variables commonly associated to copulas. It provides a distribution free test of independence and a measure of concordance between two observed variables X1 and X2 and is defined as

\[ \tau(X_1, X_2) = \frac{\text{E}[\text{sign}(X_1 - \bar{X}_1)(X_2 - \bar{X}_2)]}{\text{Var}(X_1) \text{Var}(X_2)} \]

where (\bar{X}_1, \bar{X}_2) is independent of (X_1, X_2) but has the same joint distribution as (X_1, X_2).

For our considered X and Y, we obtained \( \tau(X, Y) = 0.542028 \) and the corresponding p-value is less than 0.01. The correlation results are shown in Table 4. From these results it follows that X and Y are significantly correlated.

It is to be noted that Kendall’s tau depends only on the unique copula C to the joint distribution of X1 and X2, and is given by

\[ \tau(X_1, X_2) = 4 \int_0^1 \int_0^1 C(u_1, u_2) dC(u_1, u_2) - 1. \]

Rank correlations can be very useful for calibrating copulas to data. After fitting appropriate copula model for (X, Y), we can match the value of Kendall’s tau to the already obtained empirical \( \tau(X, Y) = 0.542028 \).

Copula selection:

Here we select appropriate bivariate copula \( C \) for \((X, Y)\) that captures the complete information about the joint distribution between X and Y. Usually, the selection of the most appropriate copula family is based on the Akaike Information Criterion (AIC) (Akaike, 1974), the Bayesian Information Criterion (BIC) (Schwarz, 1978), and on the log-likelihood (loglik) values. We have selected appropriate copula based on AIC, BIC and log-likelihood values using the Vine Copula (Schepsmeier et al., 2015) package of the statistical software R. The best fitted copula is survival BB8 (rotated BB8 copula, 180°) which is given by

\[ C(u_1, u_2) = u_1 + u_2 - 1 + C_{BB8}^{BB}(1 - u_1, 1 - u_2), \]

where with parameters as \( \theta \) (parameter 1) = 6 and \( \delta \) (parameter 2) = 0.72. Table 5 shows all the relevant information.

We obtain the Kendall’s tau for our selected copula as 0.54 with p-value less than 0.01 which is exactly equal to the empirical \( \tau \).

Identification of appropriate copula has two major implications. According to the theorem of Sklar (1959) it provides a way to analyse the dependence structure of multivariate distributions without studying marginal distributions in the sense that the copula \( C \) contains complete information about the joint distribution of X and Y apart from the marginal distributions. Precisely, \( C \) is the joint distribution function of X and Y after transformation to variables \( U_1 \) and \( U_2 \) both having Uniform \([0, 1]\) distribution, via \((U_1, U_2) = (F_X(X), F_Y(Y))\). Again if the marginal distributions are identified then explicitly provides the multivariate distribution function of the dependent variables. If we denote the distribution (marginal) functions of X and Y as \( F_X(x) \) and \( F_Y(y) \) respectively, then the joint distribution function of X and Y is given by

\[ F(x, y) = C(F_X(x), F_Y(y)), \]

and the joint density \( f \) is given by

\[ f(x, y) = c(u_1, u_2)f_X(x)f_Y(y), \]

where \( c(u_1, u_2) = \frac{\partial^2 C(u_1, u_2)}{\partial u_1 \partial u_2} \) is the density to the associated copula where \( u_1 = F_X(x) \) and \( u_2 = F_Y(y) \), and \( f_X(x) \) and \( f_Y(y) \) are the marginal densities of X and Y.

Let us now double check the parameters of fitted survival BB8 copula. For that purpose we have estimated the parameters of bivariate survival BB8 copula for the pseudo-observations of the actual data using the method of maximum likelihood estimation. We have obtained the parameters of the fitted copula as \( \theta = 6 \) and \( \delta = 0.72 \).

We now test some other Copula families (Clayton, Gumbel, Student, Frank, Joe, BB1, BB6, BB7 and BB8) in order to explore the possibilities of other copula families. First, pseudo-observations of the studied data sets were computed and then different copula families were fitted using the Maximum Likelihood Method, and the values of the AIC, BIC, and log-likelihood (loglik) criteria were estimated. Form Table 6 it is

| Copula family | Par 1 \( (\theta) \) | Par 2 \( (\delta) \) | AIC | BIC | loglik | Kendall’s tau |
|---------------|-------------------|-------------------|-----|-----|--------|--------------|
| Survival BB8  | 6                 | 0.72              | –   | –   | 232.88 | 0.54         |
|               | BB8               | 461.76            | 453.11 |     |        |              |

### Table 4

| Methods                  | Correlation coefficient |
|--------------------------|------------------------|
| Spearman rank correlation| 0.786***               |
| Kendall’s tau rank correlation| 0.542***               |

*** indicates significance at 1% level.
selected copula:\\\[\text{criteria.}\\\]

observed that based on AIC, BIC, and loglik values, Frank copula could selected survival BB8 copula.\\\[\text{Fig. 3. Fitted Copula families with their parameters and the AIC, BIC, log-likelihood}\\\]

Table 6

| Copula family | Par 1 | Par 2 | AIC     | BIC     | loglik |
|---------------|-------|-------|---------|---------|--------|
| Clayton       | 1.243 | -     | -279.748| -275.422| 140.874|
| Gumbel        | 1.651 | -     | -204.292| -199.966| 103.146|
| Student t     | 0.668 | 30    | -312.1  | -303.45 | 158.05 |
| Frank         | 6.677 | -     | -439.608| -435.282| 220.804|
| Joe           | 1.672 | -     | -95.6193| -91.2931| 48.8096|
| BB1           | 1.13  | 1.05  | -278.03 | -269.37 | 141.01 |
| BB6           | 1     | 1.65  | -202.14 | -193.49 | 103.07 |
| BB7           | 1     | 1.24  | -277.67 | -269.02 | 140.84 |
| BB8           | 6     | 0.61  | -354.55 | -345.9  | 179.28 |

Fig. 2. Pseudo-observations of the data set \((X, Y)\).\\\[\text{Fig. 3. Pseudo-observations of the real data set vs. simulated data from the}\\\]

observed that based on AIC, BIC, and loglik values, Frank copula could be the next best fitted copula among these copula families besides the survival BB8 copula.

Visualization of pseudo-observations and simulated data from the selected copula:

We consider pseudo-observations \((u_1, u_2)\) of the real data set \((X, Y)\) which is shown in Fig. 2, and also simulated data from the selected survival BB8 copula with parameters \(\theta = 6\) and \(\delta = 0.72\). Kendall’s tau rank correlation coefficient for the simulated data is obtained as 0.546 as compared to the empirical tau = 0.542. Fig. 3 depicts the pseudo observations of the real data set and simulated observations with the selected copula.

Tail dependencies: After the best Copula (survival BB8 copula) is selected, in the next step we have studied tail dependence. The concept of bivariate tail dependence relates to the amount of dependence in the upper-right quadrant tail or lower-left quadrant tail of a bivariate distribution. Thus it is a concept that is relevant to dependence on extreme values. If \(X\) and \(Y\) are two continuous random variables having distribution functions \(F_X\) and \(F_Y\) respectively, then an upper tail dependence coefficient (upper TDC) \(\lambda_U\) (Nelsen, 2007) is defined as

\[
\lambda_U = \lim_{u \to 0} P\{Y > F_Y^{-1}(u)|X > F_X^{-1}(u)\}
\]

and a lower tail dependence coefficient \(\lambda_L\) is defined as

\[
\lambda_L = \lim_{u \to 1} P\{Y < F_Y^{-1}(u)|X < F_X^{-1}(u)\}
\]

when the limit exists. So \(\lambda_U, \lambda_L \in [0, 1]\) and \(\lambda_U = 0 (\lambda_L = 0)\) means there is no upper (lower) tail dependence. The TDC roughly refers to the probability that one margin exceeds a high/low threshold given that the other margin already exceeds a high/low threshold. These coefficients are nonparametric and depend only on the copula of \(X\) and \(Y\). For bivariate copula \(C\), these coefficients are defined as (Frahm et al., 2005)

\[
\lambda_U = \lim_{u \to 0} \frac{\overline{C}(u, u)}{1 - u} \quad \text{and} \quad \lambda_L = \lim_{u \to 1} \frac{\overline{C}(u, u)}{u}.
\]

Where \(\overline{C}\) is the joint survival function defined as

\[
\overline{C}(u_1, u_2) = P\{U_1 > u_1, U_2 > u_2\} = 1 - u_1 - u_2 + \overline{C}(u_1, u_2).
\]

In the case \(\lambda(u) = P\{U_2 > u|U_1 > u\} = \frac{\overline{C}(u, u)}{\overline{C}(u_1, u_2)}\), then \(\lambda(u)\) defines the quantile-dependent measure of dependence. Fig. 4 shows the values of \(\lambda(u)\) for the selected survival BB8 copula.

4.2. Analysis for the data set before Covid-19 (January 1, 2019–December 31, 2019)

The correlation results for this period are shown in Table 7. From these results it follows that the variables are also significantly correlated in this period but the strength of the association is less as compared to the considered whole period.

For this period, the best-fitted selected copula based on AIC, BIC and log-likelihood values using the VineCopula (Schepsmeier et al., 2015) package is the Survival Clayton copula which is given by

\[
C(u_1, u_2) = u_1 + u_2 - 1 + C_{\text{Clayton}}^{\text{Surv}}(1 - u_1, 1 - u_2),
\]

Where,

\[
C_{\text{Clayton}}^{\text{Surv}}(u_1, u_2) = \max\left\{\left[\left(1 - \theta\right)u_1 - u_2\right]^{\frac{1}{\theta}} - 1, 0\right\},
\]

with parameters as \(\theta = 0.86\). Here the upper tail dependence coefficient is given by \(\lambda_U = 2^{-\frac{1}{\theta}} = 0.45\), which indicates (asymptotic) dependence in the upper tail in this period.

Fig. 4. Quantile-dependent measure for the selected survival BB8 copula.
It is observed that both the exchange rate and the gold prices experienced a significant increase after Mid-March 2020. This increase is observed at a time when Covid-19 started to spread widely in India and right after the declaration of Covid-19 as a pandemic. 2021 shows the result in line with the expectations. First, using the descriptive data analysis, it is observed that both the exchange rate and the gold prices experienced a significant increase after Mid-March 2020. We obtain Kendall’s tau rank correlation coefficient as 0.0215 with corresponding p-value as 0.587, and Spearman rank correlation coefficient as 0.054 with corresponding p-value as 0.348. So from both the results the association (dependence) between the variables is not confirmed in this period.

5. Conclusion and policy implications

At the time when the Covid-19 uncertainties have significantly affected the economic decision of people around the globe, our study investigated and captured the relationship between the gold prices and the exchange rate during the pre-Covid and the Covid-19 period. An equitably distributed period between January 1, 2019 and February 28, 2021 shows the result in line with the expectations. First, using the descriptive data analysis, it is observed that both the exchange rate and the gold prices experienced a significant increase after Mid-March 2020. This increase is observed at a time when Covid-19 started to spread widely in India and right after the declaration of Covid-19 as a pandemic by the World Health Organization (WHO). 1 The subsequent lockdown in India brought economic uncertainties which in turn increased the demand and investment in the gold market. Second, our analysis shows a highly skewed descriptive statistics during the Covid-19 as compared to the pre-Covid-19 period indicating that the probability distribution of the LGP is about to its mean is highly negatively distributed. Using the LGP as dependent variable, both the short-run and the long-run elasticity result shows a significant relationship between exchange rate and gold price during the Covid-19 period and the entire study period. However, the magnitude and the intensity of the effect of exchange rate on gold price in the short-run is observed less as compared to long-run. We have selected the appropriate bivariate copula and studied the joint distribution of the gold prices and the exchange rate. As the copula capture complete information about the joint distribution of the variables, it permits the modeling of complex dependency patterns including the tail dependencies. It is important to understand the dependence between the variables interacting simultaneously, not in isolation of one another. Based on our findings, these two variables are significantly correlated for the considered total period but the extremes are asymptotically independent. However, interrelation (dependence) between these two variables is not found in the considered Covid-19 period.

Our findings have certain important implications for the policy makers and investors. Using the LGP as dependent variable, our study confirms a long run significant relationship between exchange rate and gold price during the Covid-19 period. As the economy during the pandemic experiences a slowdown, the investment in gold increases because of the uncertainty. At the same time, the pandemic hit both the liquidity and the capital flows and hence the policy measures should be directed for both the domestic and external sectors to minimise the impact. Domestic measures such as expansionary monetary and fiscal policy is required to increase the liquidity which can be diverted to other sectors of the economy for investment away from the gold and money market. Similarly, during the pandemic, the export earnings reduces drastically as compared to import bills putting a downward pressure on the domestic currency for a country like India. This is because, imports such as petroleum products cannot be avoided even after the reduced export earnings during the pandemic. Hence, in external front the government should undertake the appropriate policy measures to facilitate the export, reduce import and implement favorable policy for capital inflow. This will not only strengthen the balance of payment situations but also reduces the downward pressure on the domestic exchange rate. As our findings shows a strong positive correlation between the gold and exchange rate, the implication for the investors is that either of the market (i.e. gold or currency market) is considered as a hedge for the other market.

Declaration of competing interest

No potential conflict of interest.

Authors’ contributions

Conceptualization, Methodology, Formal analysis and investigation: [Debi Prasad Bal, Pradip Kundu, Pritish Kumar Sahu]; Data curation: [Pritish Kumar Sahu]; Writing - original draft preparation, review & editing: [Debi Prasad Bal, Pradip Kundu, Pritish Kumar Sahu].

Acknowledgments

The authors are thankful to the Editors and the anonymous Reviewers for their valuable suggestions which lead to an improved version of the manuscript.

References

Abed, R.E., Zardoub, A., 2019. On the co-movements among gold and other financial markets: a multivariate time-varying asymmetric approach. Int. Econ. Econ. Pol. 16, 701-719.
Aloui, R., Aïna, M.S.B., 2016. Relationship between oil, stock prices and exchange rates: a vine copula based GARCH method. N. Am. J. Econ. Finance 37, 458-471.
Arouri, M.E.H., Lahiani, A., Nguyen, D.K., 2015. World gold prices and stock returns in China: insights for hedging and diversification strategies. Econ. Model. 44, 273-282.
Boyeé, E., Durrieu, V., Nikeghbali, A., Riboulet, G., Roncalli, T., 2000. Copulas for Finance-A Reading Guide and Some Applications. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1152535. (Accessed 25 June 2021).
Capie, F., Mills, T.C., Wood, G., 2005. Gold as a hedge against the dollar. Jour of Intl Fin Mkt. Institution and Money 15, 343–352.
Coles, S., Heffernan, J., Tawn, J., 1999. Dependence measures for extreme value analyses. Extremes 2 (4), 339-365.
Dong, M.C., Chen, C.W.S., Lee, S., Sriboonchitta, S., 2019. How strong is the relationship among Gold and USD Exchange Rates? Analytics based on structural change models. Comput. Econ. 53, 343–366.
Ellie, B., Najj, J., Dutta, A., Uddin, G.S., 2019. Gold and crude oil as safe-haven assets for clean energy stock indices: blended copulas approach. Energy 178, 544-553.
Frahm, G., Junker, M., Schmidt, R., 2005. Estimating the tail-dependence coefficient: properties and pitfalls. Instr. Math. Econ. 37 (1), 80–100.
Fresoli, D.E., Ruiz, E., 2016. The uncertainty of conditional returns, volatilities and correlations in DCC models. Comput. Stat. Data Anal. 100, 170–185.
Hood, M., Malik, F., 2013. Is gold the best hedge and a safe haven under changing stock market volatility? Rev. Financ. Econ. 22, 47–52.
Hung, N.T., 2020. Conditional dependence between oil prices and CEE stock markets: a copula-GARCH approach. East. Eur. Countrys. 11 (1), 62
Jain, A., Biswal, P.C., 2016. Dynamic linkages among oil price, gold price, exchange rate, and stock market in India. Resour. Pol. 49, 179–185.
Jain, A., Ghosh, S., 2013. Dynamics of global oil prices, exchange rate and precious metal prices in India. Resour. Pol. 38 (1), 88–93.
Joe, H., 1997. Multivariate Models and Dependence Concepts. Chapman and Hall, London.
Joy, Mark, 2011. Gold and the US dollar: hedge or haven? Finance Res. Lett. 8 (3), 120–131.
Khani, M., Vahidinia, S., Abbasi, A., 2021. A deep learning-based method for forecasting gold price with respect to pandemics. SN Computer Science 2, 335.
Long, S., Zhang, M., Li, K., et al., 2021. Do the RMB exchange rate and global commodity prices have asymmetric or symmetric effects on China’s stock prices? Financial innovation 7, 48.
Mokni, K., Mansouri, F., 2017. Conditional dependence between international stock markets: a long memory GARCH-copula model approach. J. Multinat. Financ. Manag. 42, 116–131.
Mokni, K., Youssef, M., 2019. Measuring persistence of dependence between crude oil prices and GCC stock markets: a copula approach. Q. Rev. Econ. Finance 72, 14–33.

1 The WHO declared the Covid-19 as a pandemic on 11 March 2020.
Nelsen, R.B., 2007. An Introduction to Copulas. Springer Science & Business Media.

Panagiotou, D., 2021. Re-examining the leverage effect and gold’s safe haven properties with the utilization of the implied volatility of gold: a non-parametric quantile regression approach. SN Bus Econ 1, 93.

Qudan, M., Yagil, J., 2012. Fear sentiments and gold Price: testing causality in-mean and in-variance. Appl. Econ. 19 (4), 363-366.

Raza, N., Shahzad, S.J.H., Tiwari, A.K., Shahbaz, M., 2016. Asymmetric impact of gold, oil prices and their volatilities on stock prices of emerging markets. Res. Pol. 49, 290–301.

Reboredo, J.C., Rivera-Castro, M.A., 2014. Can gold hedge and preserve value when the US dollar depreciates? Econ. Modell. 39, 168–173.

Reserve Bank of India, 2019. Handbook of statistics on Indian economy 2018-19. September. https://www.rbi.org.in/scripts/AnnualPublications.aspx?head=Han dbook+of+Statistics+on+Indian+Economy.

Salisu, A.A., Vo, X.V., Lawal, A., 2021. Hedging oil price risk with gold during COVID-19 pandemic. Resour. Pol. 70, 101897.

Schepsmeier, U., Stoeber, J., Brechmann, E.C., Graeber, B., Nagler, T., Erhardt, T., et al., 2015. Package ‘VineCopula’. R package version 2 (5).

Singhal, S., Choudhary, S., Biswal, P.C., 2019. Return and volatility linkages among International crude oil price, gold price, exchange rate and stock markets: evidence from Mexico. Res. Pol. 60 (1), 255-261.

Sjaastad, L.A., 2008. The price of gold and the exchange rates: once again. Resour. Pol. 33 (2), 118–124.

Sjaastad, L.A., Scacciavillani, F., 1996. The price of gold and the exchange rate. J. Int. Money Finance 15 (6), 879–897.

Tully, E., Lucey, B.M., 2007. A power GARCH examination of the gold market. Res. Int. Bus. Finance 21 (2), 316–325.

Verma, R., Dhiman, D., 2020. A causal study on gold, SENSEX, and gold exchange traded funds. Gold Bull. 53, 121–128.

World Gold Council, 2021. Gold outlook 2021, 25th April. https://www.gold.org/goldhub/research/outlook-2021.

Yu, L., Zha, R., Stafylas, D., He, K., Liu, J., 2020. Dependences and volatility spillovers between the oil and stock markets: new evidence from the copula and VAR-BEK-GARCH models. Int. Rev. Financ. Anal. 68, 101280.