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Dynamic spillovers between precious metals and travel & tourism stocks in South-East Asia: do infectious disease outbreaks matter?

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ABSTRACT

The interconnection between travel and leisure industry and precious metals markets has attracted a lot of interest among investors, policy makers, practitioners and market participants. We investigate the role of infectious diseases-based uncertainty on the dynamic connectedness between Southeast Asia travel and tourism stocks indices and four major precious metals namely; gold, silver, palladium, and platinum over the period 31 March 2015 to 5 February 2021. We adopt the time-varying parameter vector autoregressions (TVP-VAR) and the nonparametric causality-in-quantiles approach for its methodological superiority over linear approaches in capturing the presence of causality at different quantiles of the commodity distribution. The following is discernible from our analyses. First, we find strong spillovers between the two markets, implying there are diversification options. Second, silver and platinum are best effective portfolio diversification tools among precious metals. Third, strong evidence of nonlinearity makes it crucial for consideration when examining the role of diseases-based uncertainty in affecting the interactions between travel and tourism stocks and metals markets. Lastly, connectedness between uncertainty due to infectious diseases and the markets is stronger mostly around the lower and normal quantiles. These results have important policy implications for policymakers and market participants.

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1. Introduction

The analysis of risk transmissions across markets has gained prominence among market participants and researchers in recent times. This is due to its several critical practical implications in terms of market efficiency, asset allocation, hedging, and portfolio risk management. According to Mensi et al. (2017), cross-market linkages increase significantly following periods of crisis, indicating the likely presence of

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contagion effects, which limit international portfolio diversification benefits. Some of such crisis include the 1998 Asian Financial Crisis, 2008 Global Financial Crisis, 2012 European Sovereign Debt Crisis, and the ongoing COVID-19 pandemic. Investors and portfolio managers now look to the precious metals for alternative ways of effectively managing their portfolios in the face of crisis situations.

Many studies have examined the relationship between precious metals and various asset classes, ranging from oil prices to commodity prices, financial assets, real estates, cryptocurrencies, among others (see for example, Adekoya et al., 2020; Arouri et al., 2015; Baur & Lucey, 2010; Baur & McDermott, 2010; Fasanya et al., 2021c; Fasanya & Awodimila, 2020; Sikiru & Salisu, 2021). In the same vein, studies on the use of precious metals as a hedging tool continues to gain prominence in the finance literature. Examples include: Baur and Lucey (2010), Hood and Malik (2013), Arouri et al. (2015), Lucey and Li (2015), Aye et al. (2016), Bhatia et al. (2020) and Sikiru and Salisu (2021). This keen interest in precious metals is due to investors' readiness to diversify away from the rising risk in the stock markets by investing in other asset groups (Arouri et al., 2015). This is not surprising as precious metals possess intrinsic attributes which make them stores of value as they help hedge against inflation. In addition, precious metals act as financial arbitrage and serve as safe havens during times of financial turbulence and crises because they have smaller correlations with equities and provide distinct volatilities and returns at the sector and market levels (see Arouri & Nguyen, 2010; Baur & Lucey, 2010).

From a theoretical perspective, there is compelling evidence to assume a connection between/among financial assets based on the Modern portfolio theory by Markowitz (1959) which adopts the mean-variance (return-risk) framework to analyse portfolio choice and diversification decisions. This is important as there is need for risk minimization in the face of unfavourable economic conditions and volatile business cycles. As an improvement on the modern portfolio theory, the Capital asset pricing model (CAPM) was developed, postulating a linear relationship between an asset's risk and its expected rate of return. This theory was expanded to account for international market concerns, culminating in the formulation of the international capital asset pricing model (ICAPM), which allows investors to shift their investments from domestic assets like stocks to financial instruments like gold amid market unrest (Sikiru & Salisu, 2021).

In the empirical safe haven literature, a number of studies have examined the relationship between precious metals and stock returns while gold in particular, is commonly regarded in financial markets as an excellent hedge and a safe haven asset (see for example, Adekoya et al., 2020; Arouri et al., 2015; Baur & Lucey, 2010; Baur & McDermott, 2010; Sikiru & Salisu, 2021). For instance, Baur and Lucey (2010) demonstrate that gold acts as a safe haven for equities in the United States, the United Kingdom, and Germany, particularly after severe negative shocks to stock markets. Sikiru and Salisu (2021) also find that gold serves as a very strong hedge and safe haven for travel & tourism stocks, most especially in the pandemic period. However, Lucey and Li (2015) demonstrate that when gold fails, silver, palladium, and platinum function as a safe haven.

Motivated by the aforementioned explanations, and considering the present epidemic and the necessity for diversification among investors, this study investigates whether investors in South-East Asian travel and tourism stocks may benefit from the potential of precious metals as a viable investment option and for risk management purposes. For a number of reasons, the emphasis on South-East Asia travel and tourist stocks is purposeful and justifiable. One, in 2019, the travel and tourism industry contributed more than 393 billion US dollars to South-East Asia's GDP, up from 197.3 billion dollars in 2010 (Statista, 2021). Two, the coronavirus outbreak that has caused an economic crisis has had its worst effect on the travel & tourism sector with about 70% loss in revenue (Sikiru & Salisu, 2021). This is due to the severe demand shock for services such as mass transportation, hospitality, tourism, and logistics which affects the competitiveness of affected nations and, as a result, may result in significant losses in tourist revenues (Sikiru & Salisu, 2021).

Based on the above insights, this paper adds to the body of knowledge on infectious diseases by focusing on the causal influence of uncertainties due to infectious disease outbreaks (EMV_ID) on the volatility connectedness between the South-East Asia travel & tourism stocks and the precious metals market. First, we examine the connectedness between the markets, because market integration may suggest a lack of viable diversification alternatives, which may expose one to risk, as these integration makes the market more susceptible to greater loss due to financial contagion in a crisis situation. In addition, in the wake of the ongoing pandemic, we assess the attendant strength of precious metals in serving as a hedge against risk exposure. To do this, we adopt the Antonakakis et al. (2020) time-varying parameter vector autoregressions (TVP-VAR) technique. Unlike the Diebold and Yilmaz (2012) approach, TVP-VAR avoids the problem of choosing an optimal rolling window size and prevents loss of observations during estimation (Fasanya et al., 2021a).

Second, motivated by the paucity of research on how volatility connectedness between the South-East Asia travel & tourism stocks and the precious metals market is driven by notable exogenous factors, we examine the causal effect of EMV_ID on the volatility transmissions within the markets by utilizing the Balcilar et al. (2018) non-parametric causality-in-quantiles approach which is efficient in testing the nonlinear causality of the kth order across all quantiles of the whole distribution of commodity returns and is sturdy to the occurrence of misspecification errors, structural breaks, and outliers, mostly common to financial time series. Unlike the majority of research in the literature that relate, uncertainties due to infectious disease outbreaks, stocks and precious metals in separate settings, this study explores how uncertainties due to infectious disease outbreaks affects the interaction between the South-East Asia travel & tourism stocks and precious metals market. Since it is common practice in the literature (see, e.g., Adekoya et al., 2020; Fasanya et al., 2021a), we validate our choice by utilizing the Brock et al. (1996) BDS test for non-linearity. Our findings support the use of the nonlinear causality-in-quantiles technique.

The rest of the paper is structured as follows. Following this background, a brief literature review of the effect of COVID 19 on tourism stocks and metals markets in Section 2. We provide a description of the methodology to characterise the behaviour of our preliminary texts in Section 3. Section 4 presents the interconnection analyses between uncertainty due to infectious diseases and the dynamic spillovers between the travel and tourism industry and the precious metals market, while Section 5 concludes.

2. Brief review of the effects of COVID-19 pandemic on tourism stocks and precious metals markets

There are plethora of studies that have examined the role of health uncertainty on stocks and metals in recent times especially with the 2020 COVID-19 global pandemic which triggered acute declines in stock and metals prices, mainly due to a collapse in metals demand and unexpected shock to the financial market. Sikiru and Salisu (2021) empirically assess the returns and volatility spillover interactions between gold and US travel and tourism equities, as well as the former's hedging efficacy against the latter. The VARMA-CCC-GARCH model and its asymmetric variation were used in the study to assess spillover analysis, as well as own and cross-market shock and volatility spillover effects. Their findings show that there are strong bidirectional return spillovers between gold asset returns and travel and tourism stock returns. The calculated optimal weight and hedge ratios suggest that gold's hedging performance against risks related with travel and tourism equities is particularly visible during the COVID period. Fasanya et al. (2022) analyze the influence of uncertainty due to infectious diseases in forecasting twenty international airline stocks using a nonparametric causality-in-quantiles approach and find that airline stock prediction is strongest around the lower quantiles, with little evidence in the middle and higher quantiles. Škare et al. (2021) evaluate the COVID-19 pandemic's implications and address the pandemic's long-term detrimental impact on the travel and leisure industry. Crespí-Cladera et al. (2021) evaluated the financial distress of Spanish and Portuguese service companies during the COVID-19 pandemic using accounting data. According to the survey, financial distress primarily harms small businesses. Likewise, Kaczmarek et al. (2021) demonstrate that global travel and leisure companies with low valuations, limited leverage, and substantial investments were less vulnerable to the pandemic-induced slump. Further, a recent study by Zargar and Kumar (2021) confirmed the spillover of shocks related to investor mood, fear, sentiment, and policy uncertainty to the tourism sector in the United States during the COVID-19 era. However, Shahzad et al. (2021) found that the results reveal that with the onset of the COVID-19 pandemic, bad contagion among tourism companies considerably increased in the United States, and spillover across firms is still significant.

During a crisis, precious metals are said to serve as a safe haven (Baur & Lucey, 2010; Fasanya et al., 2021c). Recent studies, such as Conlon & McGee, 2020, Ji et al., 2020, and Umar & Gubareva, 2021 have attempted to examine whether gold has this safe-haven property in comparison to other asset classes during the COVID-19 pandemic and provide supporting evidence, whereas other studies, such as Kumar (2020), find this property to be compromised. Umar et al. (2021) examine the relationship between the COVID-19 triggered global panic index (GPI) and precious metals return and volatility using the TVP-VAR technique. They discovered a positive relationship between the GPI and precious metals, with the GPI acting as a shock transmitter and precious metals, particularly gold, acting as net receivers. While silver has the highest shock resistance, platinum and palladium have a time-varying transmission pattern. With the exception of silver, their findings dispute precious metals' safe-haven status during the COVID-19 pandemic. On the same note, Bouri et al. (2021) using the TVP-VAR connectedness technique, we can see an increase in the connection between five assets during the pandemic: gold, crude oil, equities, currencies, and bonds. On the contrary, using the Diebold and Yilmaz (2014) connectedness measure, Bahloul and Khemakhem (2021) analyze the dynamic connectedness between commodity returns and volatilities and Islamic developed and developing market indexes. They find significant spillover transmission, particularly during the COVID-19 pandemic. Furthermore, numerous publications concentrate specifically on metals. For example, Farid et al. (2021) examined intraday volatility transmission across precious metals, energy, and stocks and discovered that gold is the second most important volatility transmitter to other markets after US equities. Umar and Gubareva (2021) investigate the dynamic return and volatility vulnerability of some major industrial (Aluminium, Copper, Lead, Nickel, Tin, and Zinc) and precious metals (Gold, Palladium, Platinum, and Silver) metals to risk, demand, and supply crude oil shocks. They report that total return and volatility connectedness change with time, and that the net directional volatility connectedness increases significantly during the COVID-19 pandemic.

Prior research proposes that we evaluate the relationship between travel and tourism stocks and precious metals under uncertainty due to infectious diseases considering pre-COVID and during COVID-19 periods. The present study is anticipated to provide light on the linkages between popular financial investments before as well as during pandemic phase. As a result of the pandemic, there may be inexplicable economic relationships between tourism stocks and precious metals, we shall analyse the effect of pandemic uncertainty on the connection between the stock and precious metals markets. Specifically, we shall examine the dynamic spillovers between travel and tourism stocks and precious metals to characterize the degree of connectedness and subsequently relate to uncertainty due to infectious diseases under a non-parametric framework. To this end, our paper is intended to provide further perspectives on the linkages between financial markets and metal markets under various COVID-19 pandemic scenarios.

3. Methodology

In this section, we partition the empirical strategy of our paper into two stages. In the first part, we use the time varying parameter VAR (TVP-VAR) technique to model the connection between travel & tourism stocks and precious metals markets. The next phase of our empirical strategy considers the linear and non-linear causal relationship between uncertainty due pandemic and the estimated connectedness dynamics in stage one.

3.1. Time varying parameter VAR (TVP-VAR)

Extending the dynamic spillovers approach of Diebold and Yilmaz (2009, 2012), we follow the TVP-VAR connectedness framework of Antonakakis and Gabauer (2017) specified through a Kalman filter process as:

$$y_t = V_t r_{t-1} + \omega_t \omega_t | \rho_{t-1} \sim N(0, \sigma_t) \tag{1}$$

$$vec(V_t) = vec(V_{t-1}) + \tau_t \tau_t | \rho_{t-1} \sim N(0, \varepsilon_t) \tag{2}$$

with

$$r_{t-1} = \begin{pmatrix} y_{t-1} \\ y_{t-2} \\ \vdots \\ y_{t-q} \end{pmatrix} \; and \; V_t = \begin{pmatrix} V_{1t} \\ V_{2t} \\ \vdots \\ V_{qt} \end{pmatrix}$$

where, y_t and r_{t-1} are $\mathrm{m} \times 1$, *and* $\mathrm{mq} \times 1$ vectors, respectively, $\rho_{\mathrm{t}-1}$ shows all the available sets of information until $\mathrm{t}-1$, V_t and V_{it} are $\mathrm{m} \times \mathrm{mq}$ and $\mathrm{m} \times \mathrm{m}$ dimensional matrices, respectively. Also, the error term ω_t is an $\mathrm{m} \times 1$ vector while τ_t is an $m\mathrm{q} \times 1$ dimensional vector. In the model set-up, σ_t *and* ε_t are $\mathrm{m} \times \mathrm{m}$ and $\mathrm{m}^2\mathrm{q} \times \mathrm{m}^2 q$ dimensional matrices which depict the time varying variance-covariance matrices. The vectorization of V_t however is characterized by $vec(V_t)$ is an $\mathrm{m}^2\mathrm{q} \times 1$ dimensional vector.

In evaluating the dynamic spillovers using this framework, it is crucial to estimate both the generalized impulse response functions (GIRF) and generalized forecast error variance decompositions (GFEVD). In doing this, we use the Wold theorem as specified in Eq. (3) to transform the TVP-VAR to its vector moving average (VMA) representation.

$$y_t = T'(M_t(r_{t-2} + \pi_{t-1}) + \pi_t) \tag{3}$$

$$= T'\left(M_t(M(r_{t-3} + \pi_{t-2}) + \pi_{t-1})\pi_t\right) \tag{4}$$

$$\vdots \tag{5}$$

$$= T'\left(M_t^{k-1} r_{t-k-1} + \sum_{j=0}^{k} M_t^j \pi_{t-j}\right) \tag{6}$$

with

$$M_t = \begin{pmatrix} & V_t & \\ I_{m(q-1)} & & 0_{m(q-1)\times \mathrm{m}} \end{pmatrix} \pi_t = \begin{pmatrix} \omega_t \\ 0 \\ \vdots \\ 0 \end{pmatrix} = T\omega_t \;\; T = \begin{pmatrix} I \\ 0 \\ \vdots \\ 0 \end{pmatrix}$$

where M_t, π_t and T are $\mathrm{mq} \times \mathrm{mq}$, $\mathrm{mq} \times 1$ and $\mathrm{mq} \times \mathrm{m}$ dimensional matrices.

As Eq. (6) approaches ∞, we consider its limit form as defined as;

$$y_t = \lim_{k\to\infty} T'\left(M_t^{k-1} r_{t-k-1} + \sum_{j=0}^{k} M_t^j \pi_{t-j}\right) = \sum_{j=0}^{\infty} T' M_t^j \pi_{t-j} \tag{7}$$

$$y_t = \sum_{j=0}^{\infty} T' M_t^j T \omega_{t-j} A_{jt} = T' M_t^j T,\ \ j = 0, 1, \ldots \tag{8}$$

$$y_t = \sum_{j=0}^{\infty} A_{jt} \omega_{t-j} \tag{9}$$

where A_{jt} represents a $\mathrm{m} \times \mathrm{m}$ matrix.

Any shock in variable i characterized by responses of all variables j is defined by the GIRFs $(\vartheta_{\mathrm{ij,t}}(H))$. In the event of a structural model, the H-step-ahead forecast is estimated in two different scenarios of shock and no-shock to variable I, but the difference in these two cases can be taken to be shock in variable i, which is computed by

$$GIRF_t\left(H, \alpha_{j,t}, \beta_{t-1}\right) = E\left(y_{t+H} \middle| \mathrm{d_j} = \alpha_{j,t}, \beta_{\mathrm{t}-1}\right) - E\left(y_{t+\mathrm{T}} \middle| \beta_{\mathrm{t}-1}\right) \tag{10}$$

$$\vartheta_{\mathrm{ij,t}}(H) = \frac{A_{H.t}\sum_t d_j \quad \alpha_{j,t}}{\sqrt{\sum_{jj,t}}\ \sqrt{\sum_{jj,t}}} \alpha_{j,t} = \sqrt{\sum_{jj,t}} \tag{11}$$

$$\delta_{\mathrm{ij,t}}(H) = \sum\nolimits_{jj,t}^{-\frac{1}{2}} A_{H,t} \sum\nolimits_t b_j, \tag{12}$$

where b_j is an $\mathrm{m} \times 1$ selection vector with unity in the jth position, and zero otherwise. Also, the pairwise directional spillovers from j to i are computed through the $GFEVD(\tilde{\rho}_{ij,t}\ (H))$ by normalizing the variance shares and adding them to one. The GFEVD is calculated as follows:

$$\tilde{\rho}_{ij,t}\ (H) = \frac{\sum_{t=1}^{H-1} \alpha_{\mathrm{ij,t}}^2}{\sum_{j=1}^{m} \sum_{t=1}^{H-1} \alpha_{\mathrm{ij,t}}^2} \tag{13}$$

with
$\sum_{j=1}^{n} \tilde{\rho}_{ij,t}\ (H) = 1$ and $\sum_{i,j=1}^{n} \tilde{\rho}_{ij,t}\ (H) = m$

In Eq. (13), the numerator is the cumulative effect of a shock in variable i, while the denominator is the cumulative effect of all the shocks. Thereafter, we deduce the total connectedness index through the use of the GFEVD.

$$C_t(H) = \frac{\sum_{i,j=1,i\neq j}^{m} \tilde{\rho}_{ij,t}\ (H)}{\sum_{i,j=1}^{m} \tilde{\rho}_{ij,t}\ (H)} * 100 = \frac{\sum_{i,j=1,i\neq j}^{m} \tilde{\rho}_{ij,t}\ (H)}{m} * 100 \tag{14}$$

The effect of a shock in any of the variable to the other variables is explained by Eq. (14) and this entails other parts of the model in characterizing the direction of connection across the variables. This direction is of three form, which include, total directional connectedness to others; total directional connectedness from others; and net total directional connectedness. These directions are key in explaining the dynamic of the spillovers across the variables in the framework and they are defined by Eqs. (15)–(17) below.

Directional connectedness to others:

$$C_{i\rightarrow j,t}(H) = \frac{\sum_{i,j=1,i\neq j}^{m} \tilde{\rho}_{ji,t}\ (H)}{\sum_{i,j=1}^{m} \tilde{\rho}_{ji,t}\ (H)} * 100 \tag{15}$$

Directional connectedness from others:

$$C_{i\leftarrow j,t}(H) = \frac{\sum_{i,j=1,i\neq j}^{m} \tilde{\rho}_{ij,t}\ (H)}{\sum_{i,j=1}^{m} \tilde{\rho}_{ij,t}\ (H)} * 100 \tag{16}$$

Net total directional connectedness – we subtract Eq. (15) from (16):

$$C_{i,t} = C_{i\rightarrow j,t}(H) - C_{i\leftarrow j,t}(H) \tag{17}$$

From Eq. (17), a positive $C_{i,t}$ means that variable i influences the network more than itself being influenced while a negative $T_{i,t}$ means that variable i is driven by the network.

The last part of the connectedness framework is to further enunciate the pattern of the net total directional connectedness by calculating to the net pairwise directional connectedness as defined below:

$$NPDC_{ij}(H) = \left(\tilde{\rho}_{jit}\ (H) - \tilde{\rho}_{ijt}\ (H)\right) * 100 \tag{18}$$

The decision of who becomes the net receiver or giver is determined by the signs of Eq. (18). If it is positive, then, variable i *dominates* variable *j, or otherwise.*

3.2. Nonparametric causality-in-quantile test

The second phase of the paper focuses on the causal relationship between the estimated spillovers in stage one and the disease-based uncertainty. We follow the approach of Balcilar et al. (2018) which rests on the causality methods of Nishiayama et al. (2011) and Jeong et al. (2012). To this end, the variable x_t (infectious diseases uncertainty- EMV-ID) does not cause y_t (stocks-precious metals spillovers) in the $\sigma - quantile$ with respect to the lag-vector of $\{y_{t-1}, \ldots, y_{t-q}, x_{t-1}, x_{t-q}\}$ if

$$Q_{\sigma}\left(y_t | y_{t-1}, \ \ldots, y_{t-q}, \ x_{t-1}, \ldots, x_{t-q}\right) = Q_{\sigma}\left(y_t | y_{t-1}, \ \ldots, y_{t-q}\right) \tag{19}$$

while x_t causes y_t in the σth quantile with respect to $\{y_{t-1}, \ldots, y_{t-q}, x_{t-1}, x_{t-q}\}$ if

$$Q_\sigma\left(y_t|y_{t-1}, \ldots, y_{t-q}, x_{t-1}, x_{t-q}\right) \neq Q_\sigma\left(y_t|y_{t-1}, \ldots, y_{t-q}\right) \tag{20}$$

Therefore, $Q_\sigma\left(y_t|\cdot\right) = \sigma th$ quantile of y_t depending on t and $0 < \sigma < 1$. We denote $V_{t-1} \equiv (y_{t-1}, \ldots, y_{t-q})$, $U_{t-1} \equiv (x_{t-1}, \ldots, x_{t-q})$, and $W_t = (U_t, V_t)$; and $F_{y_t|W_{t-1}}(y_t|W_{t-1})$ and $F_{y_t|V_{t-1}}(y_t|V_{t-1})$ represents the conditional distribution of y_t given W_{t-1} *and* V_{t-1} respectively. Also, $F_{y_t|V_{t-1}}(y_t|V_{t-1})$ is assumed to be absolutely continuous in y_t for almost all W_{t-1}. If we proceed by denoting $Q_\sigma(W_{t-1}) \equiv Q_\sigma\left(y_t|W_{t-1}\right)$ and $Q_\sigma(V_{t-1}) \equiv Q_\sigma\left(y_t|V_{t-1}\right)$, then we have $F_{y_t|W_{t-1}}\left\{Q_\sigma\left(y_t|W_{t-1}\right)\right\} = \sigma$ with a probability of one. Following the causal representations of (19) and (20), the hypotheses statements are;

$$H_0 = P\left\{F_{y_t|W_{t-1}}\left\{Q_\sigma\left(y_t|W_{t-1}\right)\right\} = \sigma\right\} = 1, \tag{21}$$

$$H_1 = P\left\{F_{y_t|W_{t-1}}\left\{Q_\sigma\left(y_t|W_{t-1}\right)\right\} = \sigma\right\} < 1, \tag{22}$$

Within the framework of Jeong et al. (2012), the distance measure $J = \left\{\tau_t E(\tau_t|W_{t-1}) f_W(W_{t-1})\right\}$, where τ_t and $f_z(W_{t-1})$ are the regression error and marginal density function of Z_{t-1}, respectively. The regression error emanates through its basis in the null hypothesis as specified in Eq. (21), which can only be true if and only if $E[1\left\{y_t \leq Q_\sigma(V_{t-1})|W_{t-1})\right\} = \sigma$ or, equivalently, $1\left\{y_t \leq Q_\sigma(V_{t-1})\right\} = \sigma + \tau_t$, where $1\{\cdot\}$ is the indicator function. Thus, Jeong et al. (2012) specifies the distance measure, $G \geq 0$, as follows:

$$G = E\left[\left\{F_{y_t|W_{t-1}}\left\{Q_\sigma\left(y_t|W_{t-1}\right)\right\} - \sigma\right\}^2 f_W(W_{t-1})\right] \tag{23}$$

It is crucial to note that the null hypothesis stated in (21) can only be true if and only if $G = 0$, while we will have $G > 0$ under the alternative hypothesis in Eq. (22). Also, Jeong et al. (2012) introduces a feasible kernel-based test statistic for J which has the following form:

$$\hat{G}_T = \frac{1}{\mathrm{T}(T-1)s^{2q}} \sum\nolimits_{t=q+1}^{T} \sum\nolimits_{r=q+1, r\neq t}^{T} K\left(\frac{W_{t-1} - Z_{s-1}}{s}\right) \hat{\tau}_t \hat{\tau}_s, \tag{24}$$

where $K(\cdot)$ denotes the kernel function with bandwidt*hs*. T, q, $\hat{\tau}_t$ is the sample size, lag-order and estimate of the regression error, respectively. The estimate of the regression error is computed as thus:

$$\hat{\tau}_t = 1\left\{y_t \leq \hat{Q}_\sigma(Y_{t-1})\right\} - \sigma \tag{25}$$

Also, we further use the nonparametric kernel method to estimate the σth conditional quantile of y_t given V_{t-1} as $\hat{Q}_\sigma(V_{t-1}) = \hat{F}^{-1}_{y_t|V_{t-1}}(\sigma|V_{t-1})$, where the Nadarya-Watson Kernel estimator is specified as follows

$$\hat{F}_{y_t|V_{t-1}}\left(y_t|V_{t-1}\right) = \frac{\sum_{r=q+1,r\neq t}^{T} N\left(\frac{V_{t-1}-V_{r-1}}{s}\right) 1(y_r \leq y_t)}{\sum_{r=q+1,r\neq t}^{T} N\left(\frac{V_{t-1}-V_{r-1}}{s}\right)} \tag{26}$$

where $N(\cdot)$ is the kernel function and s is the bandwidth.

To illustrate the causality in higher order moment, we adopt the approach of Balcilar et al. (2018) and then assume

$$y_t = h(V_{t-1}) + \vartheta(U_{t-1})\tau_t, \tag{27}$$

where τ_t is the white noise process and $h(\cdot)$ and $\vartheta(\cdot)$ equals the unknow functions that satisfy pertinent conditions for stationarity. Although, this specification allows not granger-type causality testing from U_{t-1} *to* y_t, however, it could detect the "predictive power" from U_{t-1} *to* y_t^2 when $\vartheta(\cdot)$ is a general nonlinear function. Thus, we re-formulate Eq. (27) to account for the null and alternative hypotheses for causality in variance in Eqs. (28) and (29), respectively.

$$H_0 = P\left\{F_{y_t^2|W_{t-1}}\left\{Q_\sigma\left(y_t|W_{t-1}\right)\right\} = \sigma\right\} = 1, \tag{28}$$

$$H_1 = P\left\{F_{y_t^2\ |W_{t-1}}\left\{Q_\sigma\left(y_t|W_{t-1}\right)\right\} = \sigma\right\} < 1, \tag{29}$$

We obtain the feasible test statistic for the testing of the null hypothesis in Eq. (28), and then replace y_t in Eqs. (24)–(26) with y_t^2 (that is, volatility). With the inclusion of Jeong et al. (2012) approach, we overcome the issue that causality in mean implies causality in variance. Specifically, we interpret the causality in higher-order moments through the use of the following model:

$$y_t = h(U_{t-1}, V_{t-1}) + \tau_t, \tag{29}$$

Thus, we specify the higher order quantile causality as

$$H_0 = P\left\{F_{y_t^k|W_{t-1}}\left\{Q_\sigma\left(y_t|W_{t-1}\right)\right\} = \sigma\right\} = 1,\ for\ k = 1, 2, \ldots, k, \tag{30}$$

$$H_1 = P\left\{F_{y_t^k\ |W_{t-1}}\left\{Q_\sigma\left(y_t|W_{t-1}\right)\right\} = \sigma\right\} < 1,\ for\ k = 1, 2, \ldots, k. \tag{31}$$

Overall, we test that x_t Granger causes y_t in σth quantile up to the K-th moment through the use of Eq. (30) to construct the test statistic of Eq. (24) for each k. Although, Nishiyama et al. (2011) note that it is not easy to combine different statistics for each $k = 1, 2, \ldots, k$ into one statistic for the joint null in Eq. (30) which is mutually correlated. However, to circumvent this issue, we adopt a sequential-testing method as described by Nishiyama et al. (2011) with some modifications. To begin with, we test for the nonparametric granger causality in mean (k = 1). Failure to reject the null of k = 1 does not translate into non causality in variance, thus, we construct the tests for k = 2. Finally, we test for the existence of causality-in-mean and variance successively. We determine the lag order using SIC. The bandwidth is selected through the use of least squares cross-validation method. For $K(\cdot)$ and $L(\cdot)$, we utilize the Gaussian kernels.

4. Discussion of results

4.1. Data and preliminary analyses

This study examines the potential of regularly traded precious metals such as palladium, platinum, gold, and silver to provide appropriate hedges and act as possible assets for investment portfolio diversification in the face of market risks. arising from infectious diseases in South-east Asia. Therefore, we adopt daily data from 31 March 2015 to 5 February 2021 based on data availability and the need to have the same start and end dates for the series. The analyses are conducted using both the full sample and the sample covering the COVID-19 pandemic period. Data on travel and tourism stocks and precious metals are sourced from the Thomson Reuters DataStream, and the Infectious Disease Equity Market Volatility (EMV-ID), which is a proxy for uncertainties due to pandemics and epidemics, was developed by Baker et al. (2020) and are available for download from http://www.policyuncertainty.com. The returns of the series (r_t) are computed as the first difference of the natural logarithm of the level series (Pt); this is expressed in the equation:

$$r_t = (\Delta \log(p_t)) \times 100$$

where (r_t) represents the calculated returns of South-east Asian travel & tourism stocks and precious metals under study. (P_t) represents their respective price levels.

We provide preliminary results showing the statistical features of the underlying series, as is typical procedure in empirical literature. Table 1 summarizes the descriptive statistics based on the return series of the underlying variables. Mean, maximum, minimum, standard deviation, Jarque-Berra, kurtosis, and skewness statistics comprise the statistics evaluated (see Table 1). The mean of the summary statistics indicates positive average values across board except for travel & tourism stock returns and platinum which record negative average values which are likely attributable to the adverse effect of the COVID-19 pandemic. Furthermore, the standard deviation,

Table 1. Summary statistics.

	Tourism	Palladium	Platinum	Gold	Silver	EMV_ID
Mean	−0.0197	0.0763	−0.0005	0.0274	0.0313	3.9793
Median	0	0	0	0	0	0.33
Maximum	11.4664	16.9615	9.3411	5.1334	8.4809	68.3700
Minimum	−10.9793	−15.6769	−14.4184	−5.2646	−13.5273	0
Std. Dev.	1.2169	2.0156	1.5252	0.8838	1.5632	9.3655
Skewness	−0.4646	−0.6314	−0.6473	−0.0861	−0.6831	3.0833
Kurtosis	17.6793	14.7174	11.5613	7.4545	10.6915	13.6318
JB stat.	13774	8842.715	4773.184	1265.189	3885.279	9611.284
Prob.	0	0	0	0	0	0
Obs.	1528	1528	1528	1528	1527	1528

Source: Compiled by the authors.

Table 2. Unit root test results.

	ADF			PP		
Series	*Level*	*First Diff.*	*I(d)*	*Level*	*First Diff.*	*I(d)*
Tourism	−15.2473c***	==	I(0)	−40.9320c***	==	I(0)
Palladium	−35.2450c***	==	I(0)	−35.1574c***	==	I(0)
Platinum	−24.6938c***	==	I(0)	−37.9727c***	==	I(0)
Gold	−39.8648c***	==	I(0)	−39.9170c***	==	I(0)
Silver	−24.2300c***	==	I(0)	−36.7178c***	==	I(0)
EMV_ID	−3.4410c**	==	I(0)	−13.0767c***	==	I(0)

Note: ADF represents Augmented Dickey-Fuller unit root test while PP represents Phillips-Perron unit root test. c indicates a model with constant and deterministic trend as exogenous lags are selected based on Schwarz info criteria.***, **, * imply that the series is stationary at 1%, 5% and 10% respectively.
Source: authors computation.

which is a measure of some level of volatility in time series, shows evidence of high volatilities across the series considered with EMV_ID and gold exhibiting the highest and lowest volatilities (9.3655 and 0.8838 respectively). Unsurprisingly, for the Jarque-Bera test, we reject the null hypothesis of normal distribution for all the series following the reports of the skewness and kurtosis statistics. Kurtosis estimates exceed the standard threshold while the skewness values are negative for all the returns series. This shows there are extreme fluctuations in these financial and commodity markets. Sikiru and Salisu (2021) also find similar evidences in a slightly related study.

Results from the brief descriptive analysis have the following implications. First, the non-normality of the series shows a relative indication of a heavy right or left tail and excess kurtosis, signifying the existence of nonlinearity and/or structural shifts along the series' time paths, implying that employing linear or constant parameter models would provide misleading findings. This validates the use of a quantile-based causality test. Second, due to the presence of heavy tails and significant levels of volatility, the relationship must be examined in both the conditional-mean and conditional-variance models (see Fasanya et al., 2021a).

It is usual practice in the literature to test the series for non-stationarity as a requirement for dealing with time series data with large T. As a result, we subject each series in our model to unit root testing. We employ the Augmented Dickey-Fuller (ADF) and Philips-Perron (PP) tests. The stationarity test findings in Table 2 show that all variables are integrated of order I(0) at the 5% significance level.

4.2. Spillover results

With the objective of examining the volatility interactions between both markets in view, first, we examine the dynamic volatility spillover among the markets. Table 3 presents the averaged connectedness measures. The results indicate increased market connectedness, since the TCI value of 46.9% implies that on average, 46.9% of the forecast error variation in one asset may be traced to innovations in all others. Second, we calculate the net directional spillover by subtracting a country's overall contributions FROM others from its total contributions TO others. Positive (negative) values imply that the asset under consideration is a net shock giver (receiver). Our findings indicate a significant spillover effect across markets, with all of them considerably contributing and receiving.

Table 3. Dynamic connectedness results.

TO	Tourism	Palladium	Platinum	Gold	Silver	FROM
Tourism	61.5	10.2	11.8	6.8	9.7	38.5
Palladium	10.8	51.5	16.9	9.6	11.2	48.5
Platinum	10.4	12	49.5	11.7	16.4	50.5
Gold	7.8	6.4	12.9	51.7	21.2	48.3
Silver	7.7	7.7	16.1	17.2	51.3	48.7
Contribution TO others	36.6	36.4	57.7	45.3	58.5	234.5
NET directional connectedness	−1.9	−12.1	7.2	−3	9.8	**TCI = 46.9**

Source: Compiled by the authors.

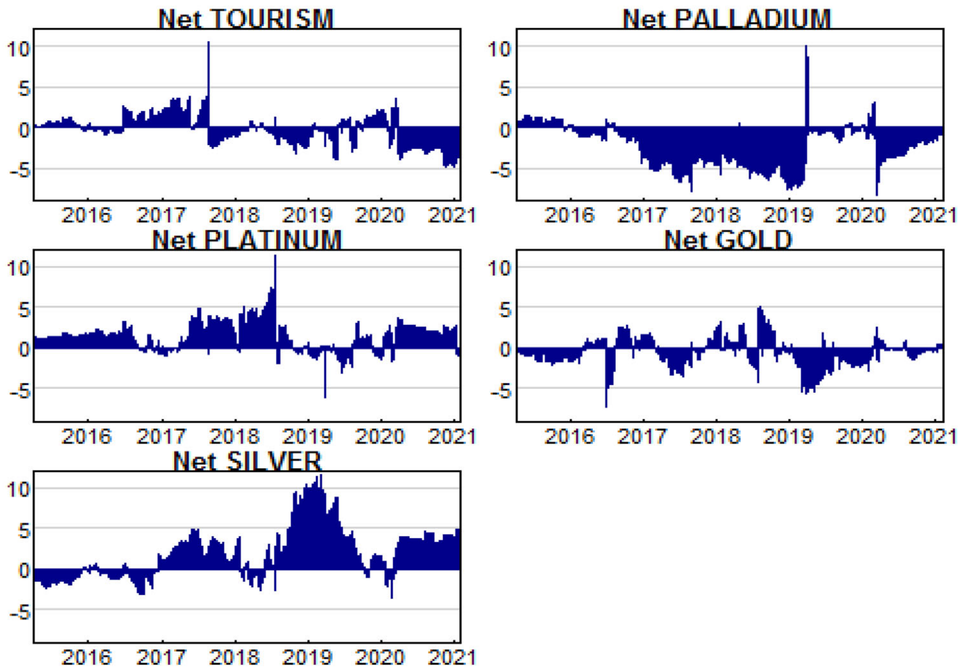

Figure 1. Net total directional connectedness.
Source: authors computation.

Silver and Platinum, on average, are the largest net shock givers, with values of 9.8% and 7.2%, respectively, whereas Palladium (−12.1%), Gold (−3%), and Tourism (−1.9%) are the highest net shock receivers, suggesting that they receive more than they transmit. The net spillover results in Table 3 match the net spillover graphs in Figure 1. These results are in line with predictions, and they back up the descriptive results in Table 1, which demonstrate that Palladium and Gold have positive returns. However, in terms of diversification options, results show that silver and platinum are the most effective portfolio diversification tools among precious metals for investors in Southeast Asian Travel and Tourism stocks, with the lowest vulnerability to idiosyncratic shocks (7.7% and 7.8%, respectively). As a result, investors in Southeast Asian Travel & Tourism companies may employ silver and platinum to achieve their desired returns while assuming low risk. The study's findings are comparable to those of Lucey and Li (2015) and Sikiru and Salisu (2021).

When these spillover transmissions are linked to uncertainties caused by pandemics and epidemics, it is clear that the global financial and commodities markets have been empirically demonstrated to be severely influenced by SARS, EBOLA, and COVID-19 pandemics due to increasing financialisation (see Chen et al., 2009; Fasanya et al., 2021b; Ji et al., 2020; Salisu et al., 2020). Particularly, the COVID-19 pandemic has led to global economic slowdown, and has had a significant adverse impact on the travel and tourism industry, resulting in a 70% revenue loss (Salisu & Vo, 2020; Statista, 2020). Thus, the connectedness across the markets may be driven uncertainties due to pandemics and epidemics. This implies that uncertainties due to pandemics and epidemics may induce volatility shocks to the other markets. The likelihood of uncertainties caused by pandemics and epidemics affecting volatility spillovers between financial and commodities markets is therefore the major focus of this study, which is covered in the next section

4.3. Causality results

Having observed strong volatility transmissions across financial and commodity markets, we examine the role of uncertainties due to pandemics and epidemics on the connectedness between these markets. We achieve this by investigating the causal effect of uncertainties due to pandemics and epidemics (EMV_ID) on the total spillover and net spillover for each asset from a linear perspective. Our findings (see Table 4, Panel A) show that EMV ID has a significant influence in the vast majority of cases at the 10% level of significance. This is most likely due to the existence of nonlinearity in the series.

Furthermore, to confirm our suspicion, we determine the presence of nonlinearity in the series, by adopting the BDS test proposed by Brock et al. (1996). The findings (see Table 4, Panel B) reveal significant evidence of a nonlinear connection between

Table 4. Causality results.

Panel A: Linear causality test results					
EMV_ID does not granger cause:				**F-stats**	**Prob.**
Total Spillovers				2.0042	0.1351
Net Tourism				10.1998***	0
Net Palladium				1.1058	0.3312
Net Platinum				1.8167	0.1629
Net Gold				0.2965	0.7434
Net Silver				3.3844**	0.0342
Panel B: BDS Test Result					
EMV_ID is the causal variable	**2**	**3**	**4**	**5**	6
Total Spillovers	0.1241***	0.2266***	0.2979***	0.3445***	0.3712***
Net Tourism	0.1187***	0.2189***	0.2876***	0.3318***	0.3565***
Net Palladium	0.1247***	0.2281***	0.3004***	0.3480***	0.3752***
Net Platinum	0.1240***	0.2269***	0.2986***	0.3457***	0.3726***
Net Gold	0.1237***	0.2260***	0.2971***	0.3435***	0.3701***
Net Silver	0.1245***	0.2276***	0.2992***	0.3460***	0.3730***

Note Panel A: This table reports the causality test results for the linear Granger-causality test. The symbols ***, **, * represent a rejection of the underlying null hypothesis that EMV_ID does not Granger-cause each of the variables considered at the 1%, 5%, and 10% levels of significance, respectively.
Note Panel B: Values in the cell represent the BDS test statistic. The symbols ***, **, * represent the rejection of the underlying null hypothesis of linearity at the 1%, 5%, and 10% levels of significance, respectively.
Source: authors computation.

EMV ID and total and net spillovers for each asset, with the null hypothesis of serial dependency rejected at the highest significance levels. As a result, relying on the linear Granger-causality test may result in erroneous inferences due to misspecification errors.

Given the substantial evidence of nonlinearity, we resort to the quantiles-based causality tests due to its inherent ability to accommodate nonlinearity. Figures 2 and 3 present the results of the causality-in-quantiles test for conditional-mean and variance, respectively. We show findings for both the full sample and the COVID-19 phase. Across the board, we find substantial evidence to reject the null hypothesis of no Granger-causality for both the full sample and the COVID-19 periods. This contradicts the results of the linear granger causality test even though the effect of uncertainties due to pandemics and epidemics on the connectedness between the markets seems more pronounced for the COVID-19 pandemic period when considering the causality-in-conditional mean. Furthermore, for the lower and middle quantiles, the causal evidence is mostly significant. However, the causality becomes weak at the extreme quantiles, suggesting that the effect of uncertainties due to pandemics and epidemics on the connectedness between the markets is sensitive to the degree of the performance of both markets. When the markets are performing at their peak, uncertainties due to pandemics and epidemics seems to be weak in affecting their interactions. This finding also supports the empirical findings of prior research, which show that the travel and tourism business is highly vulnerable to a variety of event-related risk, such as the Asian crisis, the 9/11 attacks in the U.S., and the 2008 global financial crisis. and some other geopolitical risks and pandemic/epidemic based crisis (see also Fasanya et al., 2021a; Kim et al., 2013; Lee & Jang, 2011; Li et al., 2020; Paraskevas & Quek, 2019; Park et al., 2017; Shrydeh et al., 2019; Sikiru & Salisu, 2021).

Some implications could be drawn from our research. First, there is significant connection between Southeast Asia Travel & Tourism stocks and the precious metals market. Second, in terms of diversification options, findings suggest that silver and

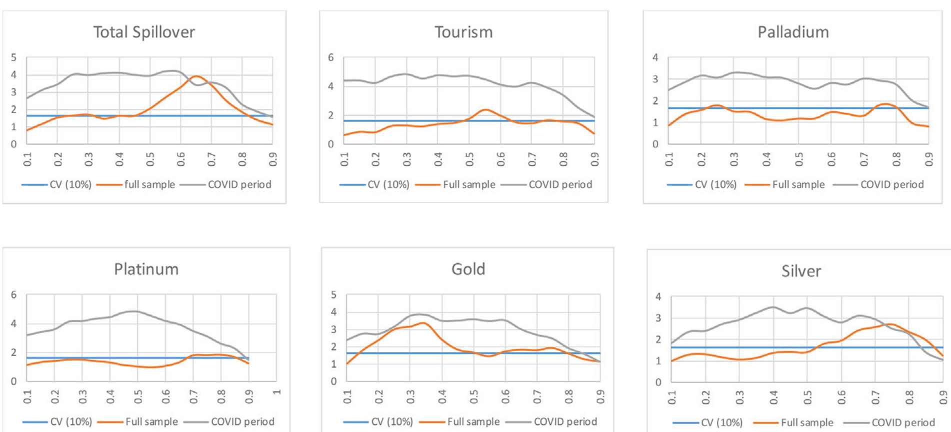

Figure 2. Results of causality in conditional-mean. *Note:* The above figures are graphical representations of the Causality-in-quantiles in conditional mean. CV represents critical value at the 10% level.
Source: authors computation.

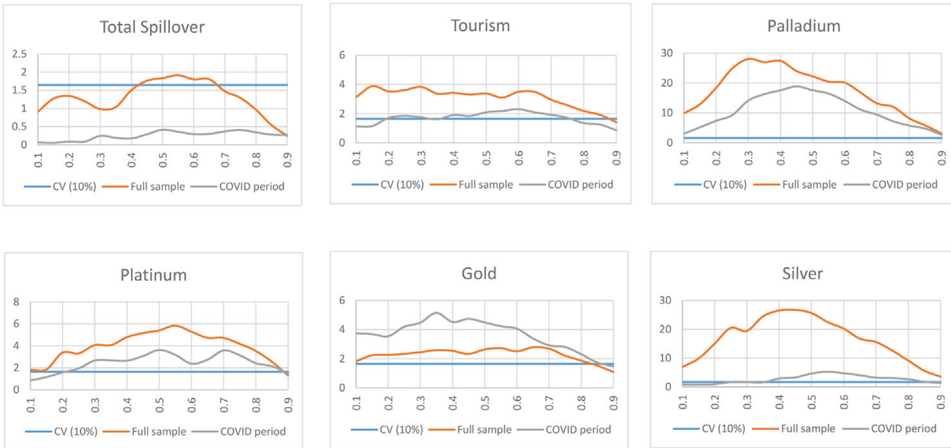

Figure 3. Results of causality in conditional-variance. *Note:* The above figures are graphical representations of the Causality-in-quantiles in conditional variance. CV represents critical value at the 10% level.
Source: authors computation.

platinum are the most effective portfolio diversification tools among precious metals for investors in Southeast Asian Travel and Tourism stocks as they show the least vulnerability to idiosyncratic shocks from the travel and tourism stocks. Third, the connectedness between both markets are primarily influenced by uncertainties due to pandemics and epidemics, although the causal effect appears to be stronger around the lower and middle quantiles in most circumstances. Fourth, the consideration of nonlinearity is crucial when examining the role of uncertainties due to pandemics and epidemics in affecting the interactions between both markets.

5. Conclusion and implications for policy

We examine volatility transmissions between Southeast Asia Travel & Tourism Stocks and precious metals market and investigate the causal effect of uncertainties due to pandemics and epidemics (EMV_ID) on this relationship. We discover considerable market connectivity, and our findings strongly suggest a nonlinear causative link between uncertainties due to pandemics and epidemics and the connectedness between both markets predominantly at lower and median quantiles. This underscores the disturbing effects of uncertainties due to pandemics and epidemics, which important in the formulations of policies aimed at achieving stability.

To begin, we evaluate volatility spillovers between the tourism and precious metal markets by adopting the time-varying parameter vector autoregressions (TVP-VAR) approach proposed by Antonakakis et al. (2020) to investigate the connectedness between the markets. We utilize daily data on South-East Asia tourism market and four precious metals (gold, palladium, platinum, and silver) from 31 March 2015 to 5 February 2021. The nonparametric quantile-in-causality test is then applied to investigate how EMV ID influences the relationship between both markets. The following findings are revealed from our results: i) There is compelling evidence of a link between the tourism and precious metals markets; ii) following moments of crisis, the connection between the two markets intensifies, especially triggered to uncertainties due to pandemics and epidemics. iii) non-linearity is very crucial to examine the role of uncertainties due to pandemics and epidemics (EMV_ID) in affecting the interactions between the tourism and precious metal markets iv) the causal effect of uncertainties due to pandemics and epidemics on the connectedness between the two markets is stronger during the COVID-19 pandemic period. Our results are consistent with Sikiru and Salisu (2021), which indicates strong bidirectional return spillovers between gold asset returns and stock returns in travel and tourism. However, the study employs a different methodological approach to test for volatility connectedness between both markets, and does not explore how uncertainties due to pandemics and epidemics affects this interaction.

The implications of these discoveries are significant for scholars, investors, and politicians. For academics, our study demonstrates that non-linearity must be integrated into modelling frameworks in order to arrive at valid inferences when investigating interactions between the tourism and precious metal markets, since its absence can easily generate spurious results. For investors, understanding how these markets interact can help enhance both short and long-term portfolio strategies. Our findings reveal that the connectedness between these markets is driven by uncertainty induced by infectious diseases, and volatility transmission results demonstrate that tourism investors with portfolios incorporating precious metals have limited options for diversification. Investors must closely monitor changes in the global business cycle, particularly during precarious periods that affect global capital flow and credit activity, which may alter business cycles and thus induce risk transmissions, and adjust their investment portfolios accordingly to mitigate losses. Furthermore, investors must incorporate assets with relative stability (such as silver and platinum) in their investment portfolios in order to improve the performance of their cumulative adjusted risks.

Finally, the negative consequences of a shock to either market are likely to be protracted due to the bi-directional feedback effect, which might have long-term economic consequences. As a result, authorities must fortify financial markets against risk exposures, as markets serve as a barometer for measuring macroeconomic success. As a result, negative shocks to the financial markets have an impact on the whole economy. As part of future studies, it would be interesting to extend the diversification properties of precious metals to risk associated with other financial assets such as the equity market, cryptocurrencies, and property investment, specifically looking into the impact of pandemic induced uncertainties.

Data availability statement

The dataset used in this study will be made available on request.

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