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Volatility spillovers and hedging effectiveness between health and tourism stocks: Empirical evidence from the US

Afees A. Salisu [a,b], Lateef O. Akanni [a], Xuan Vinh Vo [b,c,*]

[a] Centre for Econometric & Allied Research, University of Ibadan, Ibadan, Nigeria
[b] Institute of Business Research, University of Economics Ho Chi Minh City, Viet Nam
[c] Institute of Business Research and CFVG Ho Chi Minh City, University of Economics Ho Chi Minh City, Viet Nam

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The study evaluates the return and volatility transmission between the health and tourism stocks. The outbreak of covid-19 pandemic brought about an unprecedented crisis in the global health and financial market with the tourism sector being among the largest casualty as it experienced an almost total collapse as a result of economic lockdowns and movement restrictions, while the health sector witnessed considerable boom. We employ the VARMA–CCC-AGARCH model, based on the preliminary tests, on daily data collected for health and tourism stocks between January 02, 2018 and July 09, 2020. The empirical estimation is also partitioned into full, pre-covid-19 and covid-19 periods to elicit the impact of the pandemic outbreak. We further examine the optimal weights of holding health and tourism stocks and compute the hedging ratios in the presence of health risks. Our empirical findings show evidence of significant negative bidirectional return spillover between the health and tourism sectors particularly during the covid-19 period. In addition, the hedge ratios further confirm the hedging effectiveness of health stocks for risks associated with tourism stocks particularly during the pandemic period. Essentially, our results show that a diversified asset portfolio that includes health together with tourism stocks may improve risk-adjusted return performance for investors especially during pandemics.

1. Introduction

The tourism industry is fast becoming a major source of employment contributing vastly to the GDPs of many countries of the world. In recent years, many developing countries focus their economic policies on the promotion of tourism as a potential source of economic growth. In recent times, the tourism industry has witnessed a prominent increase all over the world. For instance, the tourism receipts in 2018 reached 1451 billion US dollars vis-a-vis 2 billion US dollars in 1950, and international tourist arrivals increased to 1,401million in 2018 vis-a-vis 25 million in 1950 (UNWTO, 2019). The total number of medical tourists has also increased, from 19 million travelers in 2005 to 378.27 million in 2018. In 2013, U.S. cross-border exports of health-related personal travel services were $3.3 billion, up from $1.6 billion in 2003, for a 7.7% compound annual growth rate (CAGR). Imports rose from $168 million in 2003 to $1.4 billion in 2013, implying a CAGR of 24%, albeit from a low base. Though health travel services represent only a small share of total trade in personal travel, they have consistently produced a trade surplus for the United States ($1.8 billion in 2013). Health travel exports grew faster than growth in spending on healthcare, with total U.S. personal healthcare expenditures rising at an average rate of 5.6% from 2002 to 2012 before slowing in 2013.

* Corresponding author. Institute of Business Research, University of Economics Ho Chi Minh City, Viet Nam.
E-mail addresses: aa.salisu@cear.org.ng (A.A. Salisu), vinhvx@ueh.edu.vn (X.V. Vo).

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The growth trend of these exports more resembles that of total U.S. travel exports, which rose 7.9% annually from 2003 to 2013. (USITC, 2015). About 0.5% of all air travelers entering the United States annually—between 100,000 and 200,000 people list health treatment as a reason for visiting (this data excludes travelers from Canada and Mexico, the majority of whom travel to the United States overland). Foreign patients most often cite access to advanced medical care as their reason for traveling to this country for treatment.

The outbreak of coronavirus disease Covid 19 triggered crisis in global financial economy, increased business uncertainty and caused a surge in market volatility. Efforts made at containing the spread of the pandemic such as social distancing and travel restrictions have further exacerbated an already bad economic situation (Salisu & Vo, 2020). With commodity prices collapsing and the stock market crashing, investors are now looking to minimize risks and cut losses. Travel and leisure (tourism) stocks have suffered most. According to Statista (2020), businesses in travel and tourism has seen the highest loss in revenue (70%) since the outbreak of Covid 19. However, it is not unexpected that investment in travel and leisure (T & L) stocks would nosedive during a pandemic. Pandemics are usually a bane to tourist arrivals and receipts, often leading to a withdrawal of investment from the sector (Wilder-Smith, 2006; McAleer, Huang, Kuo, Chen, & Chang, 2010). T & L stocks are known to perform well during economic boom and deteriorate during shocks and recession, this is because they are part of a consumer discretionary sector that acts as a cyclical sector (Jalkh et al., 2020). Therefore, it is imperative for investors in T & L stocks, especially in times of high volatility, to seek out appropriate means (a risk-minimizing instrument) of hedging the downside risk in their investment. Doing this may require investment in other performing sectors of the economy and perhaps, at this time, the health care sector may be a veritable option.

The health care sector represents one section of the economy that has witnessed considerable boom in the last 12 months. The sector consists of a large range of companies selling drugs, medical devices, insurance as well as hospitals and health care providers. Health care stocks like XLV have outperformed broader market stocks such as S & P 500 by margin of about 1.3% over the last year (Investopedia, 2020). It will therefore not be out of place if investors begin to consider this sector a safe haven for the diversification and security of their investment. In the past, extant studies have found commodities like gold largely responsible for the stability of capital market, most of these studies crediting gold as a commodity which passes the criteria qualifying it as an hedging instrument (see Capie, Mills, & Wood, 2005; Gencer & Musoglu, 2014; Hillier, Draper, & Faff, 2006; Kumar, 2014; Lu, Wang, & Lai, 2014; Salisu, Ndako, & Oloko, 2019). Moreover, there has been a number of studies that have evaluated the hedging potential of one commodity against the other. For instance, Salisu and Adediran (2019) assessed the inflation hedging potential of coal and Iron ore in Australia. Similarly, Salisu, Raheem, and Ndako (2020) examined the heterogenous behaviour of the inflation hedging property of cocoa. With these and many more, it is obvious that in periods of great market instability, the importance of risk-mitigating hedging instrument cannot be overemphasized.

It is against this background that we motivate our study by seeking to evaluate the effectiveness of health stock as a hedging instrument against fluctuation in global T & L stocks. We find this plausible for a number of reasons, first, to the best of our knowledge we are the first to explore the role of health stocks in hedging the risk of T and L market. Second, the peculiarity of this paper on travel and leisure stocks is premised on the introduction of the new datasets for infectious diseases, and the need to include COVID-19 given its peculiarity. The inclusion of data on COVID-19 makes the analyses on the hedging relationship between health and tourism stocks, and in particular, travel and leisure stocks, more recent and engaging.

Following this background, we offer a brief review of the literature In Section 2, some preliminary analyses are rendered in Section 3 to determine the appropriate model for analyses; we consider both methodology and results on volatility transmission between health and tourism in Section 4; thereafter, we evaluate their hedging effectiveness in Section 5 while Section 6 concludes the paper.

2. A brief review of the literature on the effectiveness of hedging

Hedging which is seen in the work of Rutledge (1972) as a means of reducing the risk associated with a particular financial commitment, particularly when uncertainty reigns supreme, has its theories rooted in the early works by Working (1953, 1962), Johnson (1960), Stein (1961), Rutledge (1972), Ederington (1979), and Franckle (1980). Prominent among these is the Markowitz theory of portfolio selection developed in (1959), and has since adopted by various scholars (see Telser, 1955; Johnson, 1960; Stein, 1961; 1976, pp. 124–130).The portfolio theory approach to hedging measures the ratio and the hedging effectiveness which correspond to the regression coefficient, say β, and the coefficient of determination, say R^2, obtained from regressing the spot price changes on futures price changes (Malliaris and Urrutia, 1991). More recent studies such as Arouri, Jouini, and Nguyen (2011), Salisu and Oloko (2015), Khalfaoui, Boutahar, & Boubaker, 2015 have also contributed to the subject.

Empirically, researchers have also beamed their searchlight on hedging between stocks, especially during crisis (see Basher & Sadorsky, 2016; Chkili, Aloui, & Nguyen, 2014; Jin et al., 2020; Kenourgios, Samitas, & Drosos, 2008; Khalfaoui et al., 2015; Salisu et al., 2020; Salisu & Oloko, 2015) albeit with limited focus on pandemics. In fact, to the best of our knowledge, this study, if not the first, will be among the very first few to consider the hedging effectiveness between two major stocks – health and tourism, that directly feel the heat of COVID-19 the most. The contribution of this study therefore lies in its interest to consider these two stocks, particularly in this period clouded by the COVID-19 uncertainty. Furthermore, the choice of stock to hedge in this study as stated above is informed by the present pandemic, caused by COVID-19, where the risk associated with tourism stock is on the high, hence the need for investors to hedge their fund in the less risky asset, health stock.

3. Data and pre-tests

Following this study objectives as earlier discussed, we collected data for the two main variables of interest namely the health stocks and tourism stock. The two series are respectively proxied using the Dow Jones (DJ) health and tourism sector indices. While the DJ health sector index measures the performance of US firms' stocks in the health care sector, the tourism index measures the stock performance of U.S. companies in the tourism sector. Daily data on these two series were collected from the www.investing.comonline database over the period spanning between January 02, 2018 and July 09, 2020. As discussed in the introduction, the emergence of COVID-19 epidemic and its later declaration by the World Health Organisation as a pandemic has brought about global health and economic crisis at an unprecedented scale (Salisu and Akanni, 2020). In responding to the crisis by countries with border closures to visitors and tourists, the impact on the tourism sector has brought about an almost total halt to international and domestic tourism (UNWTO,[1] 2020). These devastating effects threatens the 29 percent contribution of the tourism sector to the global services exports, about 7 percent contributions to world trade in goods and services and about 300 million jobs contributed to the global economy (UNWTO, 2019).

To account for the pandemic impact, we partitioned the data sample into three sub-samples: (i) before COVID-19, which covers the period before the emergence of COVID-19 (January 02, 2018 to December 31, 2019); (ii) during the COVID-19 pandemic period (January 02, 2020 to July 09, 2020); and, full sample which comprises periods before and during the pandemic.The descriptive analysis of the two returns series, i.e. for health and tourism sectors are presented in Table 1. The statistics considered include mean, maximum, minimum, standard deviation, skewness and kurtosis (see Table 1). The mean of the summary statistics indicates positive average health stock returns negative across the three sub-periods considered, that is, full sample, before and during COVID-19. On the other hand, the average tourism stock return is positive before the emergence of COVID-19 but negative during COVID-19 pandemic period and for the full data sample. By implication, the average returns in the health sector suggests improved performance before and after COVID-19, while the tourism sector witnessed declined stock performance after the coronavirus induced economic turmoil. In fact, the impact of the crisis on the tourism sector seems to more evident with the average stock return showing negative for the full sample, despite the positive average return before COVID-19.

Furthermore, the standard deviation which depicts how volatile are the stock return series shows that tourism sector stocks returns are more volatile that the health sector stock returns across the three sub-sample considered. However, the volatility is higher for both sectors during the COVID-19 pandemic period that the previous period. In addition, the two returns series are negatively skewed and leptokurtic, evident from the negative values of skewness and values of the kurtosis. We also rendered some graphical illustration of the two returns series to evaluate the possible co-movements between them. The graphs depicted in Fig. 1 show evidence of co-movements between the health and tourism stock returns, most especially during the COVID-19 period.

Given the high frequency used in this study and to also determine the appropriate model for analyses, we also consider formal pre-tests such as serial correlation test using the Ljung-Box Q-statistics and the conditional heteroscedasticity test using the ARCH LM test. In addition, we conduct the asymmetry test using the Engle and Ng sign and bias tests as well as the constant conditional correlation (CCC) tests using the Engle-Sheppard test. The results are summarised in Table 2 for the three sub-samples and both sectors. The ARCH-LM tests indicate that the two sectors exhibit ARCH effects, for the full-sample, before and during the pandemic. By implication, both the health and tourism sectors stock returns exhibit conditional heteroscedasticity. Hence, such effects have to be captured when modelling their returns. In a similar vein, the Ljung-Box tests also reveal the existence of serial correlation in the two returns series.

The statistical significance of the Engle-Ng sign and joint size bias tests shows evidence of significant asymmetric effects in the health sector for both the full and during-COVID sample, while both the health and tourism sectors exhibit asymmetric effects in the pre-COVID sample. In addition, the non-significance of Engle-Sheppard tests across the three sub-samples provide statistical support for the assumption of constant conditional correlations between the two stock sectors over the dynamic conditional correlation version. On the basis of foregoing pre-tests and discussions as well as considering the interest of this study to capture the performance spillovers between the health and tourism sectors stocks, the VARMA-AGARCH is preferred over the other variant models including CCC-MGARCH and DCC-MGARCH models among others.

4. The model and empirical analyses

4.1. The model

As earlier discussed, this study employs the VARMA–AGARCH model proposed by Markowitz (1959). The model augments the VARMA–GARCH model by Ling and McAleer (2003) by accounting for asymmetry where such matters relying on the outcome of the formal pre-tests as reported in Table 2.The VARMA–AGARCH model has gained prominence as an instrument for modelling interdependencies among financial time series variables in the presence of asymmetric shock effects (see Salisu & Mobolaji, 2013; Salisu & Oloko, 2015; Caporale, Spagnolo, & Spagnolo, 2016). The proposed variant asymmetry model specifies conditional mean equation with vector autoregressive moving average (VARMA) and conditional variance equation within a multivariate GARCH process framework, in addition to recognizing the asymmetric impacts of shocks on the conditional variance rather than assuming identical asymmetric effect for equal magnitude of positive and negative shocks as suggested by VARMA–GARCH model. However, to measure the cross market asymmetric effect between health and tourism sectors, which is structurally not revealed by the CCC and DCC models (Markowitz (1959)), we specify and estimate a VARMA(1,1)–CCC–AGARCH(1,1) model. The bivariate VARMA(1,1)–CCC–AGARCH(1,1) model is specified for the conditional mean equation and conditional variance equation as follows:

The conditional mean which captures the return spillover effects from the health sector to tourism sector and vice versa is specified as:

[1] UNWTO is an acronym for the United Nations World Tourism Organisation.

Table 1
Descriptive statistics for Health and Tourism Stock Returns (Summary Statistics).

	Health	Tourism
Pane 1a: Full Sample		
Mean	0.0348	−0.0219
Maximum	7.3307	11.4937
Minimum	−10.8202	−13.4000
Standard deviation	1.4414	2.2164
Skewness	−0.5865	−0.8333
Kurtosis	13.0544	12.6616
Number of Observation	634	634
Pane 1b: Before COVID-19		
Mean	0.0416	0.0154
Maximum	4.5254	5.5881
Minimum	−4.6115	−10.8158
Standard deviation	0.9961	1.5010
Skewness	−0.6012	−1.2660
Kurtosis	5.6114	11.9688
Number of Observations	503	503
Pane 1c: During COVID-19		
Mean	0.0075	−0.1767
Maximum	7.3307	11.4937
Minimum	−10.8202	−13.4000
Standard deviation	2.5148	3.9080
Skewness	−0.3694	−0.3651
Kurtosis	6.3899	5.3828
Number of Observations	131	131

Note: The returns series of health and tourism stocks are used for the descriptive analyses.

$$R_t = \Phi + \Psi R_{t-1} + \Omega \varepsilon_t \quad [1]$$

$$\varepsilon_t = D_t \nu_t \quad [2]$$

where $R_t = (r_t^{hlt}, r_t^{tsm})'$ with r_t^{hlt} and r_t^{tsm}respectively denoting health and tourism sectors stock returns in period t;Φ is a (2×1) vector of constant terms of the form $(\varphi^{hlt}, \varphi^{tsm})'$; $\Psi$is a (2×2) matrix of coefficients of the form $\Psi = \begin{pmatrix} \psi_{11} & \psi_{12} \\ \psi_{21} & \psi_{22} \end{pmatrix}$;$\Omega$ is a (2×2) matrix of the coefficients of lagged terms of residuals in the form $\Omega = \begin{pmatrix} \eta_{11} & \eta_{12} \\ \eta_{21} & \eta_{22} \end{pmatrix}$ and it explains the shock spillovers between health and tourism stock returns; $\nu_t = (\upsilon_t^{hlt}, \upsilon_t^{tsm})'$ is a (2×1)independently and identically distributed errors; and $D_t = diag(\sqrt{h_t^{hlt}}, \sqrt{h_t^{tsm}})$ with h_t^{hlt} and h_t^{tsm} being the conditional variances of health and tourism sectors respectively.

The conditional variance equation provides the computation of the volatility spillover effects across the two sectors under consideration and it is specified in Eqs. (3) and (4) for health and tourism sectors returns respectively as:

$$h_t^{hlt} = c^{hlt} + \alpha^{hlt}\left(\varepsilon_{t-1}^{hlt}\right)^2 + \alpha^{hlt}\left(\varepsilon_{t-1}^{tsm}\right)^2 + \beta^{hlt}\left(h_{t-1}^{hlt}\right) + \beta^{hlt}\left(h_{t-1}^{tsm}\right) + \gamma^{hlt}\left(\varepsilon_{t-1}^{hlt}\right)^2\left(I_{t-1}^{hlt}\right) \quad [3]$$

$$h_t^{tsm} = c^{tsm} + \alpha^{tsm}\left(\varepsilon_{t-1}^{tsm}\right)^2 + \alpha^{tsm}\left(\varepsilon_{t-1}^{hlt}\right)^2 + \beta^{tsm}\left(h_{t-1}^{tsm}\right) + \beta^{tsm}\left(h_{t-1}^{hlt}\right) + \gamma^{tsm}\left(\varepsilon_{t-1}^{tsm}\right)^2\left(I_{t-1}^{tsm}\right) \quad [4]$$

The conditional variance equations show that conditional variance for each sector is dependent on its immediate past values and innovations, past values and innovations from the other sector as well as the asymmetric effects for own market. The conditional covariance is expressed as:

$$h_t^{hlt_{tsm}} = \rho^{hlt_{tsm}} \times \sqrt{h_t^{hlt}} \times \sqrt{h_t^{tsm}} \quad [5]$$

where $\rho^{hlt_{tsm}}$ is the conditional constant correlations. Ling and McAleer (2003) provides the estimation procedure, including the structural and statistical properties of the model which covers both the necessary and sufficient conditions (see also Salisu & Oloko, 2015).

The relevant statistics which establishes the goodness of fit of the models is determined with the minimum values of Akaike Information Criterion (AIC) and Schwartz Bayesian Criterion (SBC). In addition, the Ljung–Box statistic is used to test for autocorrelation and the null hypothesis is that there is no autocorrelation, while the McLeod–Li statistics is employed to test for ARCH effects with the underlying null hypothesis is that there are no ARCH effects in the model. The estimated model is robust when the null hypothesis of both the Ljung–Box and McLeod–Li statistics are not rejected. We present and discuss the estimation results in the next section.

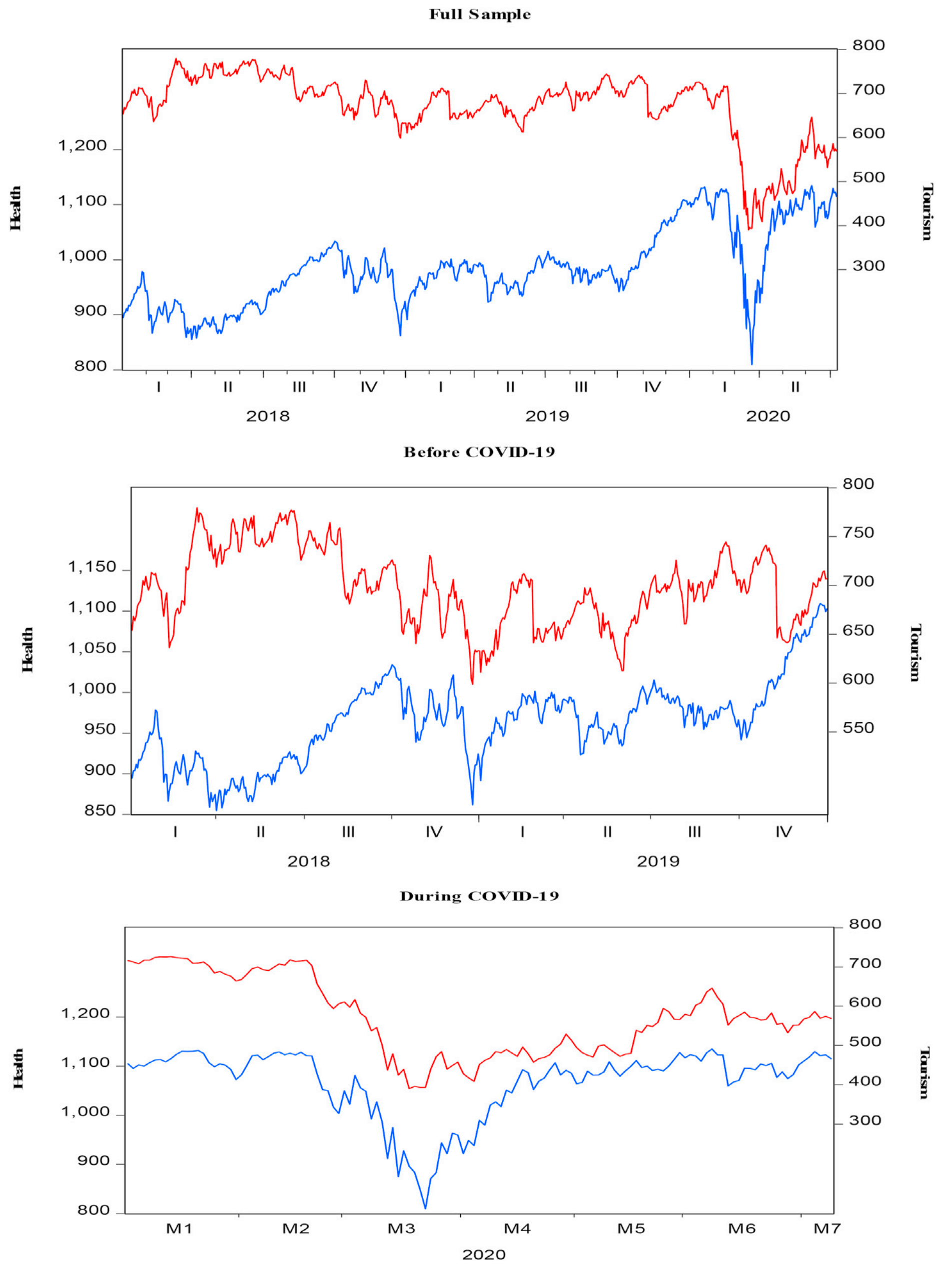

Fig. 1. Co-movements between health and tourism stock indices.

4.2. Discussion of results

Table 3 summarises the results of the bivariate VARMA-AGARCH model. As discussed in the model section, we partitioned the results into two segments based on the parameters of interest. The first pane of Table 3 summarises the mean equation which analyses the return and shock spillovers between the health and tourism sector stock returns. On the other hand, the second pane presents the variance equation estimates which captures the volatility, shock and asymmetric spillovers between the two sectors under consideration. A cursory look at the mean equation results shows that there are no statistically significant return and shock spillovers between the health and tourism sectors for the full data and before-COVID estimations. However, the results show significant returns and shock spillovers between the health and tourism sector stock returns is significant only in the COVID-19 data sample. By implication, for the full sample and pre-COVID era, the results show that health stock returns in current period does not depend on the immediate past returns in the tourism sector. Conversely, the immediate past returns on health stocks do not statistically affect the health stock returns in the current period. However, during the pandemic, returns spillover relationship between the two sectors shows that bi-directional return spillover transmissions between the two sectors, that is there is a significant negative return spillover from the health (tourism)

Table 2
Conditional heteroscedasticity, autocorrelation and asymmetry tests).

Pane 2a: Conditional Heteroscedasticity and Autocorrelation Tests						
	Full sample		Before COVID-19		During COVID-19	
	Health	Tourism	Health	Tourism	Health	Tourism
ARCH LM (5)	55.069 (0.00)	25.532 (0.00)	6.009 (0.00)	0.046 (0.99)	7.787 (0.00)	3.286 (0.01)
ARCH LM (10)	37.411 (0.00)	15.887 (0.00)	6.881 (0.00)	0.102 (0.99)	5.612 (0.00)	2.172 (0.03)
LB(5)	18.351 (0.00)	8.132 (0.15)	3.555 (0.62)	1.666 (0.89)	8.545 (0.13)	5.219 (0.39)
LB(10)	91.345 (0.00)	34.249 (0.00)	13.154 (0.22)	5.392 (0.86)	31.088 (0.00)	18.084 (0.05)
$LB^2(5)$	401.31 (0.00)	215.37 (0.00)	37.91 (0.00)	0.234 (0.99)	52.352 (0.00)	28.315 (0.00)
$LB^2(10)$	792.33 (0.00)	357.92 (0.00)	95.16 (0.00)	1.035 (1.00)	113.44 (0.00)	45.437 (0.00)
Pane 2b: Asymmetry test and CCC test						
Sign bias	1.764* (0.078)	1.592 (0.112)	0.428 (0.669)	2.257** (0.024)	1.765* (0.080)	0.409 (0.683)
Negative bias	0.408 (0.683)	0.066 (0.947)	0.330 (0.742)	0.636 (0.525)	0.569 (0.570)	0.242 (0.809)
Positive bias	0.770 (0.442)	0.355 (0.723)	2.223** (0.027)	0.566 (0.572)	0.027 (0.978)	0.755 (0.452)
Joint bias	6.950* (0.074)	3.413 (0.332)	7.059* (0.070)	6.299* (0.098)	4.547 (0.208)	0.640 (0.87)
ES test	0.104 (0.949)		0.729 (0.695)		0.230 (0.891)	

Note: The ARCH LM tests refer to the Engle (1982) test for conditional heteroscedasticity while the LB and LB2 imply the Ljung-Box tests for autocorrelations involving the standardized residuals in levels and squared standardized residuals respectively. The null hypothesis for the ARCH LM test is that the series has no ARCH effects (that is, it is not volatile) while LB test for null hypothesis is that the series is not serially correlated; ES test imply the Engle-Sheppard CCC χ^2_2 test; the values in parentheses – ( ) denote the computed probability values.

Table 3
Estimation results for VARMA-AGARCH model

Variables	Full sample	Before COVID-19	During COVID-19
Mean Equation			
μ_1	0.0518* (0.069)	0.0433 (0.194)	0.0966*** (0.000)
μ_2	0.0116 (0.837)	0.0394 (0.469)	0.0590*** (0.000)
ϕ_1	0.0279 (0.486)	0.0667 (0.160)	-0.0806*** (0.000)
ϕ_2	0.0095 (0.818)	-0.0333 (0.385)	-0.0732*** (0.000)
θ_1	-0.0311 (0.198)	-0.0394 (0.469)	-0.0643*** (0.000)
θ_2	-0.0208 (0.772)	0.0692 (0.328)	-0.1357*** (0.000)
Variance Equation			
c_1	0.0179*** (0.003)	-0.0049 (0.654)	0.5177*** (0.000)
c_2	0.0428*** (0.000)	0.0578*** (0.000)	0.8748*** (0.000)
α_{11}	-0.0354*** (0.000)	-0.0334 (0.196)	0.0391*** (0.000)
α_{22}	-0.0099*** (0.000)	-0.0435*** (0.000)	-0.0597*** (0.000)
α_{12}	0.0106*** (0.000)	0.0113*** (0.001)	0.0559*** (0.000)
α_{21}	0.1614*** (0.000)	1.1076*** (0.000)	-0.0374*** (0.000)
β_{11}	0.8323*** (0.000)	0.8568*** (0.000)	0.9750*** (0.000)
β_{22}	1.0099*** (0.000)	1.0043*** (0.000)	0.6735*** (0.000)
β_{12}	0.0202*** (0.000)	0.0326*** (0.000)	-0.1112*** (0.000)
β_{21}	-0.2004*** (0.000)	-0.1157*** (0.000)	0.6209*** (0.000)
γ_1	0.1965*** (0.000)	1.1448*** (0.000)	0.0391*** (0.000)
γ_2	0.0002 (0.969)	0.0267*** (0.000)	0.1024*** (0.000)
ρ_{12}	0.5583*** (0.000)	0.5127*** (0.000)	0.6903*** (0.000)
Model diagnostics			
AIC	6.549	5.948	8.996
SBC	6.682	6.108	9.417
Hannan-Quinn	6.601	6.011	9.167

Note: Parameters in mean and variance equations are as defined in the model given in equations [1] to [4[; the subscripts 1 and 2 respectively indicate health and tourism sectors returns respectively; the asterisks ***, ** and *denote statistical significance at 1%, 5% and 10% level. The values in parentheses – ( ) denote the computed probability values. Best model is selected based on minimum values ofAkaike Information Criterion (AIC) and Schwartz Bayesian Criterion (SBC). Note that AIC and SBC are not comparable for the different partitions.

sector stock returns to tourism (health) sector stock returns. This is explained by the negative and significant values of $\theta_1$and $\theta_2$for the two sectors respectively during the COVID period. Although, the magnitude of the negative effect of health stock returns on the tourism sector returns (0.1357) is higher than when compared to the other way around (0.0643). That is, a one percent increase in health stock returns will lead to a decline in tourism stocks returns in the succeeding period by about 0.14 percent, on the other hand, one percent increase in tourism stock returns in preceding period will only lead to a decrease in health stock returns by approximately 0.06 percent. The implication of these findings is not farfetched given the unprecedented magnitude of health and economic risks of the ongoing global pandemic and while it is extremely difficult to quantify its exact magnitude, the health sector has witnessed increased attention and investments across both public and private sectors in a bid to finding solutions to the pandemic, the tourism sector on the other hand has been brought to almost a total halt as a result of economic lockdowns and travel restrictions. This finding is consistent with the findings of (Kim, Kim, & O'Neill, 2013; Lee & Jang, 2011; Li, Feng, Li, & Sun, 2020; Paraskevas & Quek, 2019; Park, Song, & Lee, 2017) which established that tourism firms are exposed to event related risks such as the 9/11 attacks and the financial crisis of 2008.

Next, we discuss the results of the volatility spillover effects captured in the variance equation of the estimated model and as presented in pane B of Table 3. The parameters of interest include the ARCH terms (that is, α_{11}, α_{12}, α_{21} and α_{22}) and the GARCH terms (that is β_{11}, β_{12}, β_{21} and β_{22}). The results show that all the parameters are statistically significant across the three data partitioning. Specifically, the lagged own shocks for the health sector stock returns (α_{11}) negatively and significantly influence its volatilities both in the full sample and before COVID-19 estimation, but positive and significant during the COVID-19 period. Essentially, while the health sector returns have negatively responded to previous own shocks before the occurrence of COVID-19, the response is positive during the pandemic period. For the tourism sector, the lagged own shock response (α_{22}) is negative and significant across the three period subsamples. For the lagged own conditional variance, it is positive and it significantly influence the volatilities of the two markets across the data partitions. By implication, previous return volatilities in each of these markets have potentials of leading to a higher volatility in the succeeding periods.

In addition, the cross-sector volatility spillover effects between the health and tourism sector show that the current conditional volatility of each market does not only depends on immediate past values and innovations but also on those of the other markets. However, the signs and magnitude of bi-directional volatility transmissions differ for each market across the three period sub-samples considered. The full sample and pre-COVID results show that conditional volatility of the health sector returns responds positively to past shocks of tourism returns, while the response of tourism stock returns to immediate past conditional volatility of health stock returns is positive. On the contrary, the signs changed during the COVID estimation with health sector returns responding negatively to the immediate past conditional volatility of tourism sector returns while the response is positive contrariwise.

In terms of asymmetric shock effects, the results show evidence of positive and significant own asymmetric shock effects for both the health and tourism sector returns given the values of γ_1 and γ_2 for the two sectors respectively. However, the magnitude of the asymmetric shocks for the health stock returns is larger in the pre-COVID period than that of the pandemic period. On the other hand, the magnitude of the asymmetric shocks for the tourism stocks is larger after the occurrence of COVID-119. Essentially, the high volatility and asymmetric information shocks of the tourism sector (0.10) heightened during the pandemic more than the health sector (0.04). Furthermore, we rendered several post-estimation diagnostics such as the Ljung–Box statistic to test for autocorrelation and McLeod–Li statistics is employed to test for remaining ARCH effects. The diagnostic tests summarised in Table 4 show robustness of our results based on the Ljung-Box and Mcleod-Li tests. The results of the Ljung-Box test indicate that the null hypothesis of no serial correlation cannot be rejected, similarly the adequacy of the ARCH and GARCH terms are supported by the McLeod test which shows that there are no remaining ARCH effects.

5. Portfolio management between health and tourism stocks in the presence of health risks

We extend the estimation results from the VARMA-CCC-MGARCH model discussed above to evaluate the optimal weights of a health-tourism stocks portfolio as well as their hedge ratios. The significance of volatility spillovers between the two sectors indicate that investors' assets n both sectors are volatile and susceptible to risk and uncertainty. To avoid the associated risks in volatile assets, investors can engage in hedging by engaging in futures contract without jeopardising expected returns. To implement this, we construct an optimal portfolio weight (OPW) which establishes the optimal proportion of health and tourism stocks to be included in the investment portfolio. Following Kroner and Ng (1998) and Arouri et al. (2011), the optimal portfolio weight of holding the two stock assets – health (*hlt*) and tourism (*tsm*), is constructed using the conditional variance and covariances and it is given as (see also Salisu & Mobolaji, 2013; Salisu & Oloko, 2015):

$$\varpi_{hlt\_tsm,t} = \frac{h_t^{hlt} - h_t^{hlt_{tsm}}}{h_t^{tsm} - 2h_t^{hlt_{tsm}} + h_t^{hlt}} \quad [6]$$

and,

$$\varpi_{hlt\_tsm,t} = \begin{cases} 0, & \text{if} \quad \varpi_{hlt\_tsm,t} < 0 \\ \varpi_{hlt\_tsm,t}, & \text{if} \quad 0 < \varpi_{hlt\_tsm,t} \le 1 \\ 1, & \text{if} \quad \varpi_{hlt\_tsm,t} > 1 \end{cases} \quad [7]$$

Table 4

Post estimation diagnostics.

	Full Sample		Before COVID-19		During COVID-19	
	Health	Tourism	Health	Tourism	Health	Tourism
Ljung-Box Q(2)	0.8708 (0.6470)	2.8715 (0.2379)	0.3201 (0.8521)	0.4372 (0.8036)	2.6248 (0.2692)	6.4569** (0.0396)
Ljung-Box Q(5)	1.0409 (0.9592)	3.9033 (0.5634)	1.7730 (0.8796)	2.2638 (0.8116)	3.5656 (0.6135)	7.7522 (0.1704)
McLeod-Li(2)	0.2241 (0.8940)	0.4466 (0.7999)	0.0687 (0.9662)	0.5992 (0.7411)	0.1589 (0.9236)	1.3993 (0.4968)
McLeod-Li(5)	7.3892 (0.1933)	1.5341 (0.9091)	11.448** (0.0432)	2.5580 (0.7677)	3.6010 (0.6082)	1.9916 (0.8503)

Note: The Ljung-Box and McLeod tests provide the empirical statistics respectively for the serial correlation and remaining conditional heteroscedasticity of orders 2 and 5 for robustness purposes.

where $\varpi_{hlt_tsm,t}$denotes the weight of health stocks in a one-dollar health/tourism stock portfolio at time $t.h_t^{hlt_{tsm}}$ is the conditional covariance between the health and tourism stock returns at time t. Consequently, the optimal weight of the health stocks in the two asset classes considered can be evaluated as $1 - \varpi_{hlt\_tsm,t}$. The optimal weight is computed for the full-sample, pre-COVID and during the COVID periods. The results as summarised in Table 5 show that the optimal weight of health stocks in one-dollar health–tourism stock portfolio is −1.80% before the outbreak of COVID-19 and -14.00% after the outbreak. Clearly, the optimal weight ratio during the pandemic is negatively higher than the ratio obtained before the outbreak of COVID-19.

In addition, we construct the optimal hedge ratio (OHR) following Kroner and Sultan (1993), which accordingly considered a portfolio of two assets and conclude that the risk of the investment portfolio is minimised if a long position of one dollar in health stocks can be hedged by a short position of $\alpha_t$dollars in the tourism stocks. The formulation of the OHR between health and tourism stock returns is defined as: (see also Arouri et al., 2011; Salisu and Mobolaji (2013); Salisu and Oloko (2015))

$$\alpha_{hlt\_tsm,t} = \frac{h_t^{hlt_{tsm}}}{h_t^{hlt}} \quad [8]$$

The OHM results are summarised in the lower pane of Table 5. The high values of the values of the hedge ratios suggest that risks associated with tourism stocks can be hedged by taking a short position in health sector stocks. In a similar fashion to the optimal weight ratio, the optimal hedge ratio is not different as the value during the pandemic shows that hedge effectiveness of health stocks is more noticeable during the pandemic. Besides, the results established that considering the impacts of the emergence COVID-19 on the hedging effectiveness between the two sectors is important. This is evident in the values of the hedging ratio for the full sample period (0.71), as compared to the pre-COVID value (1.06) and during COVID (1.25).

6. The role of exchange and interest rates in hedging effectiveness of health-tourism stocks

We extend the empirical estimation by investigating the role of exchange rate and interest rates in the effectiveness of hedging between health and tourism stocks. It is clear that changes in certain macroeconomic fundamentals could affect both health and tourism sectors. One of such fundamentals is the possible impact that the foreign exchange rate and changes in the value of various currencies exerts on tourism (including medical tourism) and tourists demands (Samirkaş & Samirkaş, 2016). On the other hand, prevailing interest rates are found to affect health sector stock performance. Health-care stocks exhibit consistent revenues and with relatively bigger dividends pay-outs. Hence, this makes stocks more attractive when rates fall among other reasons, especially in uneasy economic environments (Imbert, 2019). We account for both interest and exchange rates by including them as exogenous regressors in the mean equation specified in eqn. [1].

The results of the extended bivariate VARMA-AGARCH model is summarised in the appendix for both the mean and variance equations which respectively analyses the return and shock spillovers between the health and tourism sector stock returns as well as the volatility, shock and asymmetric spillovers between the health and tourism sectors after accounting for interest and exchange rates. The estimated results across the three sub-periods, that is full sample, before and during COVID-19, show similar spillover relationship between the two sectors as established in the main results. In a similar vein, the post-estimation diagnostics summarised in Table A2 in the Appendix further show robustness of the obtained results particularly for the before and after pandemic estimation. Essentially, the results of the Ljung-Box test indicate that the null hypothesis of no serial correlation cannot be rejected, while McLeod test which shows that there are no remaining ARCH effects. Finally, the estimated optimal weight ratio during the pandemic period estimation shows a negatively higher value than the ratio obtained in the pre-COVID estimation, while the optimal hedge ratio further shows that health stocks hedging effectiveness is more pronounced during the COVID period estimation than pre-COVID (see Table A3).

7. Conclusion

This paper empirically evaluates the possible hedging interaction between health and tourism stocks using the VARMA–CCC–AGARCH model by allowing for spillover analysis as well as own and cross-sector asymmetric effects. In order to account for the role of the unprecedented COVID-19 global pandemic, we portioned the empirical analysis into pre- and during-pandemic as well as the full sample estimation which covers both periods. The results show significant bidirectional return spillovers between the health and tourism sectors during the pandemic with a negative return spillover from the health sector to tourism sector and vice versa. The computed optimal weight and hedge ratios further confirmed that the hedge effectiveness of health stocks for risks associated with tourism stocks particularly after the pandemic with the optimal hedge ratio further confirming that the hedge effectiveness of health stocks for tourism stocks is more noticeable during the pandemic. Essentially, our estimated results show that with the outbreak of COVID-19, a diversified asset portfolio that includes health stocks alongside tourism stocks may improve the risk-adjusted return

Table 5
Optimal portfolio weights and hedge ratios.

	Full sample	Before COVID-19	During COVID-19
$\varpi_{sz,t}$	0.2454	−0.0180	−0.1400
$\alpha_{sz,t}$	0.7079	1.0564	1.2481

Notes: The table reports average optimal weights and hedge ratios in a health-tourism asset portfolio.

performance. These findings further exhibit robustness as it does not differ even after accounting for both interest and exchange rates in the returns and volatility spillover analysis.

Author statement

Afees A. Salisu: Conceptualization, Validation, Formal analysis, Data Curation, Writing - Original Draft, Writing - Review & Editing. **Lateef O. Akanni:** Validation, Formal analysis, Data Curation, Writing - Original Draft. **Xuan Vinh Vo:** Conceptualization, Methodology, Writing - Review & Editing, Supervision, Project administration.

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Appendix

Additional results.

Table A1
Estimation results for VARMA-AGARCH model

Variables	Full sample	Before COVID-19	During COVID-19
Mean Equation			
μ_1	2.3223*** (0.000)	−2.229*** (0.000)	12.523*** (0.001)
μ_2	0.5233*** (0.000)	−1.720*** (0.000)	37.711*** (0.000)
φ_1	0.0295 (0.000)	0.057 (0.213)	−0.105*** (0.000)
φ_2	−0.081*** (0.000)	−0.020 (0.562)	−0.156*** (0.000)
θ_1	−0.086*** (0.000)	0.016 (0.000)	−0.079*** (0.000)
θ_2	0.014*** (0.000)	0.039 (0.000)	−0.009*** (0.000)
Variance Equation			
c_1	0.019*** (0.000)	−0.003*** (0.000)	0.298*** (0.000)
c_2	0.492*** (0.000)	0.033*** (0.000)	0.280*** (0.000)
α_{11}	−0.036*** (0.000)	−0.128*** (0.000)	−0.003*** (0.000)
α_{22}	−0.074*** (0.000)	−0.031*** (0.000)	−0.077*** (0.000)
α_{12}	−0.003*** (0.000)	0.006*** (0.000)	0.054*** (0.000)
α_{21}	−0.077*** (0.000)	0.039*** (0.000)	−0.196*** (0.000)
β_{11}	0.962*** (0.000)	0.944*** (0.000)	0.974*** (0.000)
β_{22}	−0.063*** (0.000)	1.040*** (0.000)	0.671*** (0.000)
β_{12}	−0.003*** (0.000)	0.032*** (0.000)	−0.082*** (0.000)
β_{21}	2.229*** (0.000)	−0.066*** (0.000)	0.901*** (0.000)
γ_1	0.131*** (0.000)	0.185*** (0.000)	0.103*** (0.000)
γ_2	0.185*** (0.000)	−0.005*** (0.000)	0.187*** (0.000)
ρ_{12}	0.554*** (0.000)	0.534*** (0.000)	0.709*** (0.000)
AIC	6.661	5.885	9.000
SBC	6.824	6.081	9.510
Hannan-Quinn	6.724	5.962	9.207

Note: Parameters in mean and variance equations are as defined in the model given in equations [1] to [4[; the subscripts 1 and 2 respectively indicate health and tourism sectors returns respectively; the asterisks ***, ** and *denote statistical significance at 1%, 5% and 10% level. The values in parentheses – ( ) denote the computed probability values. Best model is selected based on minimum values ofAkaike Information Criterion (AIC) and Schwartz Bayesian Criterion (SBC). Note that AIC and SBC are not comparable for the different partitions.

Table A2
Post Estimation Diagnostics

	Full Sample		Before COVID-19		During COVID-19	
	Health	Tourism	Health	Tourism	Health	Tourism
Ljung-Box Q(2)	5.7193* (0.0573)	12.309*** (0.0021)	0.0687 (0.9663)	0.2346 (0.8893)	2.5928 (0.2735)	6.6671** (0.0357)
Ljung-Box Q(5)	6.3046 (0.2777)	12.621** (0.0272)	1.0640 (0.9572)	1.0999 (0.9541)	3.6389 (0.6025)	8.2597 (0.1425)
McLeod-Li(2)	6.0171* (0.0494)	0.2077 (0.9013)	1.8132 (0.4039)	0.1533 (0.9262)	0.1981 (0.9057)	1.6607 (0.4359)
McLeod-Li(5)	26.827*** (0.0001)	0.5081 (0.9918)	15.4355*** (0.0087)	0.7438 (0.9805)	4.9897 (0.4171)	2.2951 (0.8070)

Note: The Ljung-Box and McLeod tests provide the empirical statistics respectively for the serial correlation and remaining conditional heteroscedasticity of orders 2 and 5 for robustness purposes.

Table A3
Optimal portfolio weights and hedge ratios

	Full sample	**Before COVID-19**	**During COVID-19**
$\varpi_{sz,t}$	0.0982	−0.0522	−0.1429
$\alpha_{sz,t}$	0.8407	1.1858	1.2152

Notes: The table reports average optimal weights and hedge ratios in a health-tourism asset portfolio.

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