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The changing economic relationship between some of the major COVID-19 impacted countries with prominent wealth: a comparative study from the view point of stock markets

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Abstract In the present work, a study has been made over the prime stock indices of some fiscally prominent countries impacted by COVID-19. The countries are separated in two ways: (1) considering gross total number of infected cases—here seven mostly impacted countries with certain global economic influence are selected; (2) considering the concentration of the infected cases—here six major impacted countries with considerable influence are selected. This sort of categorization is itself a novel strategy which is capable of including some less populated, but severely impacted countries of economic importance. The objective of the present analysis is to comprehend the impact of COVID-19 on these markets and to recognize the effect of COVID-19 on mutual association and dependence between these markets. To add more flavour of reliability, we have taken a new and fresh strategy of fixing the time frames under consideration before and during COVID-19 pandemic as uniform. We have used both linear and nonlinear Granger causality analysis and employed generalized forecast error variance decomposition analysis to review the exogeneity and endogeneity of the individual markets. The present study shows that this pandemic has changed the underlying relationship: some exogenous stock markets have become endogenous and vice versa in the pandemic. Linear relationship has been reduced radically, whereas nonlinear relationship has been improved during the COVID-affected period. TASE, the highest returned and significantly uncorrelated index, emerged as the most exogenous market in the pre-COVID period, though it is nonlinearly endogenous in the long term, in the COVD-affected period. CAC 40 is the most endogenous market for the short term in both pre-COVID and COVID-affected period. B3 and NYSE, exogenous in the pre-COVID period, turned out to be linearly endogenous in the COVID-affected duration, whereas BIST 100 and BSE SENSEX are found to be exogenous markets in the COVID-affected period according to both linear and nonlinear causal analysis. They were also exogenous in the pre-COVID era for the short-term period, with BSE SENSEX exhibiting exogeneity anti-persistently for the COVID-affected period too. Association among the markets is more in long term rather than short term. A possible conclusion is also that the markets may regain long-term association once the effect of COVID would fade away.

1 Introduction

The hasty stretch of COVID-19 pandemic has emerged as a global peril. This has impacted the global stance surprisingly, and this menace is not only a global health emergency issue, but has also resulted in a momentous slump to global economy. A huge number of countries at different periods of time have imposed lockdown with a multitude of strategies as well as quarantine policies and social distancing measures to acquire some sort of control over this catastrophe. Even in the absence of strict imposition of lockdown, there was restriction and limit in intra- and intercountry haulage to put a brake to the brisk proliferation of the virus. To add to this aggravation, sensing an insane uncertainty and being panic stricken, the nature of consumption and stockpile among the consumers transformed drastically. Financially weaker companies are suffering a lot and unorganized sectors have been greatly affected. There are millions of official reports of recently jobless people from different corners of the globe. Newly muted variants of SARS-Cov-2 virus, viz., Alpha, Beta, Gamma, Delta, Omicron etc., in a very short span of time are being generated,worsening the situation. Wang and Han [1] have

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warned that the COVID-19 pandemic may not end with Delta (B.1.617.2) and the latest muted variant Omicron (B 1.1.529). Gowrisankar et al. [2] observed that Omicron did not alter the pattern of the daily positive cases. Wang and Cheng [3] performed a sequence analysis of Omicron in South Africa. Easwaramoorthy et al. [4] compared and estimated the epidemic curve of the first and second wave of COVID-19. In this connection, some models have been proposed to identify the scenario of the spread of COVID-19 and consequent patterns [5–8]. Jamez and Menzies worked with 92 countries and observed that the equity market of a country is not dependent on its success in managing COVID-19 [9]. Kavitha et al. [10] tried to provide an estimated time frame for the ending of the second and third wave of COVID-19 pandemic in India. Baret et al. [11] showed that there is a global decline in the share of oil and equity due to the COVID-19 pandemic. Izzeldin [12] inferred that COVID-19 negatively impacted the stock markets of G7 countries, along all sectors, with healthcare and consumer service facing the hit most and the technology sector being least affected. Heliodoro et al. [13] deduced that integration between G7 markets was significantly lower during the COVID-19 period September, 2019 to June, 2020. Kumeka et al. [14] found that the Nigerian stock market responded negatively to both domestic and global growths in the total confirmed cases of and deaths due toCOVID-19 from February 27, 2020 to September 4, 2020. Igwe [15] raised the concern of a possible increase in volatility in stock markets due to this pandemic. A considerable amount of drop in the US and UK markets was visible during March, 2020 [16]. Bora and Basistha [17] showed that the volatility of in Indian stock markets increased during this pandemic.

Samadder and Bhunia [18] concluded that out of the top 45 stock markets in terms of market capitalization, those of about one-third countries (viz. Greece, Columbia, Mexico, Spain, Bangladesh, Great Britain, Nasdaq-USA, NYSE-USA, New Zealand, Shenzhen-China, Switzerland, Canada, Poland, and Austria) are volatile. Burdekin et al. [19] and Salisu et al. [20] comprehended that volatility increased from January 1, 2020 to September 30, 2020. Oluwasegun et al. [21], using TVP-VAR, evidenced a strong volatility spillover across S&P 500, gold, crude oil, bitcoin and USD, from January 21, 2020 to July 2, 2020. However, Watorek et al. [22] have drawn a rather optimistic conclusion that though enormous, the evil impact of COVID-19 over the global market will be short-time or anti-persistent.

Bal and Mohanty [23] deduced that daily cases of COVID-19 and Indian stock markets linearly Granger cause each other. Samadder [24] investigated that linear Granger causality decrease and nonlinear Granger causality increases in the 2011–2020 decade, in the case of major stock market indices listed in E7 group, with IBOVESPA of Brazil and SSE of China emerging as the most exogenous and endogenous markets in this period. Gherghina et al. [25] employed Granger causality on autoregressive distributive lag (ARDL) model of daily stock market returns of Bucharest stock exchange, in the time frame of December 31, 2019 to April 20, 2020 and emphasized that the daily death cases of Italy have a negative effect on Romanian 10-year bond yield. Romanian 10-year bond yield, compared to Bucharest stock exchange, is more sensitive to the news of COVID-19. Prabheesh [26] using Toda and Yamoto Granger causality test, showed that foreign portfolio (FPI) has unidirectional causality effect on NIFTY 50 in the period from January 1, 2020 to September 30, 2020. Amar [27] carried out Toda–Yamamoto–Dolado–Lütkepohl (TYDL) causality analysis on the global (S&P Global 1200), regional (S&P Asia 50, S&P Europe 350) and country (S&P 500, S7P China 500, S7P Japan 500) scenario during COVID-19 crisis period between December 31, 2019 and June 30, 2020 and observed that the Chinese stock market had no influence on the rest of the indices, whereas the European stock index appeared to influence other market sentiments. Oluwasegun et al. [21] used Granger linear causality test and non-linear causality test of Balcilar et al. [28] and found existence of a fair amount of casualty between COVID-19 pandemic and connectedness among the assets, with mostly established causality at the lower and middle level quartiles. Camba and Camba [29] applied Granger causality test on the Philippines stock exchange index, peso–dollar exchange and retail pump price of diesel in the Philippines and observed that COVID-19 daily infections unidirectionally affected the Philippines stock exchange index and peso–dollar exchange, but has no effect on the retail pump price of diesel in the Philippines.

Variance decomposition method, performed on the same data set in the short run, divulges that COVID-19 daily infections are responsible for explaining only a small part of the fluctuations of Philippines stock exchange index, peso–dollar exchange and retail pump price of diesel in the Philippines [29]. Prabheesh and Kumar [30] induced structural variance decomposition on oil price returns, exchange rates, NIFTY 50 returns, and uncertainty shocks in India and comprehended that the COVID-19-induced uncertainty distorted the dynamics between oil and stock prices in the initial periods from December 31, 2019 to April 28, 2020. Jelilov et al. [31] analyzed that all share index return responded negatively to COVID-19 shock between February 27, 2020 and April 20, 2020. Siriopoulos et al. [32] searched the reasons for the volatility in European stock exchanges in the first 4 months of 2020 and generalized the impulse response function and variance decomposition method and interpreted that the Chinese stock market accounted for about 34% of the volatility of European stock markets, whereas international uncertainty was responsible for 7% of the volatility. Moreover, the impact of COVID-19 daily cases and deaths on European stock markets is negligible, below 1%. Zhang and Mao [33] employed Granger causality to find the relation between Shanghai–Shenzhen 300 and S&P 500 from January 1, 2019 to June 30, 2020, dividing the whole period into three time frames and concluded that Shanghai–Shenzhen 300 Granger caused S7P 300 for all the periods, but not the reverse. Variance decomposition analysis on these two indices strengthens this result.

Though these studies analyzed volatility, causality and variance decomposition either individually for some stock exchange or for a group of indices, none of them considered the choice of the countries according to the severity of impact of COVID-19, either by considering gross total number of infected cases, or by considering the concentration of the infected cases (number of infected cases per million population). Here in the present study, to have a better outlook, we selected and categorized the countries in the above two ways: (1) in the first category, seven most impacted countries with certain global economic influence were selected, viz. USA, India, Brazil, France, Turkey, UK and Italy; (2) in the second category, six major impacted countries with considerable influence were selected, viz., Sweden, Netherlands, Belgium, Israel, Spain and Switzerland. Also, the time frames under consideration before and during the COVID-19 pandemic for most of the available literature were not uniform, but we have taken these to be uniform to have a more balanced comparison and reliable study.

In the present work, we have exercised both linear and nonlinear Granger causality analysis [34–36] to understand how lethal the shock of COVID-19 was on these leading stock markets and how the reciprocated association and dependence between these markets were reordered and restructured by this pandemic. Also, we have employed generalized forecast error variance decomposition analysis [37, 38] to reassess the exogeneity and endogeneity of these markets. In fine, the present analysis is an excursion over the imperative outlook of the pan global interplay between financial independence and cohesiveness as it was just before this pandemic and as it is emerging during the pandemic.

2 Data and methodology

The study is based on the analysis over the prime stock indices of some economically influential countries impacted by COVID-19 categorized into two based on impact: (1) on the basis of gross total number of infected cases and here seven mostly impacted countries with certain global economic influence were selected, viz., USA (34.549,398), India (30,410,577), Brazil (18,559,164), France (5,775,301), Turkey (5,425,652), UK (4,800,048) and Italy (4,259,906); (2) on the basis of the density of the infected cases (number of infected cases per one million population)and here six major impacted countries with considerable fiscal influence were selected, viz., Sweden, Netherlands, Belgium, Israel, Spain and Switzerland [39]. Thefirst case of COVID-19 was reported on December 29, 2019 [40]. Hence, the analysis was performed in two time frames termed: pre-COVID period (from 1 July 2018 to 31 December 2019) and COVID-affected period (1 January 2020 to 30 June 2021). We have taken similar time frames for the pre-COVID and COVID-affected periods to balance the scale to have a more neutral analysis. Daily log return series of the prime stock exchanges of the above-mentioned countries were taken into consideration, viz., AEX Index (Netherlands), BEL 20 (Belgium), BIST 100 (Turkey), Brazil Bolsa Balcao/B3 (Brazil), BSE SENSEX (India), CAC 40 (France), FTSE MIB (Italy), IBEX 35 (Spain), London Stock Exchange/LSE (UK), NYSE composite (USA), OMX Stockholm 30/ OMX 30(Sweden), Swiss Market Index/SMI (Switzerland) and TASE (Israel) [41–45]. If P_t is the daily closing value of the stock index, the series under consideration is $\ln\left(\frac{P_t}{P_{t-1}}\right)$. As the log return series has a higher chance of being stationary, which is the prime condition to fit the vector autoregressive model (VAR), as well as it is expected to be detrended, it is taken into account for our analysis.

As different stock exchanges have different holidays and data over some of the days are not available, data for mismatched dates among all the indices are omitted to make the analysis uniform. The number of data points for the pre-COVID period and COVID-affected period are 227 and 241, respectively.

Econometric analysis for augmented Dickey–Fuller (ADF) unit root test [46] and linear Granger causality [34] was performed using Eviews 11 package software, whereas nonlinear Granger causality [35, 36] test was estimated using GCtest-win software. Forecast error variance decomposition using generalized impulse response function was obtained using MATLAB R2021A software with Econometrics toolbox.

2.1 Augmented Dickey–Fuller unit root test

Augmented Dickey–Fuller unit root test [46] is one of the efficient techniques to check the stationary nature of a time series. If y_t, $t = 1, 2, \dots, N$ represents a time series, an autoregressive model with lag p is given by

$$y_t = \alpha + \beta t + \sum_{i=1}^{p} \phi_i y_{t-i} + e_t, \tag{1}$$

where e_t is the residual series and $\alpha + \beta t$ is the linear deterministic trend. Lag order can be selected based on different information criteria such as Akaike information criterion (AIC), Schwartz information criterion (SIC), and Hannan–Quinn Information criterion (HIC). Dickey–Fuller regression equation corresponding to this AR (p) model is given by

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + e_t, \tag{2}$$

where Δ is the first difference operator. Clearly, $\gamma = \phi_1 - 1$. For non-stationary process, changes of y_t, i.e., Δy_t, should not depend on the current level y_t. So, γ

should be 0, or alternatively $\phi_1 = 1$, indicating unit root is present in the model. H_o: $\gamma = 0$ (series is non-stationary) is tested against H_1:γ ¡ 0. If the absolute value of test statistic $\mathrm{DF}_\gamma = \frac{\hat{\gamma}}{\mathrm{SE}(\hat{\gamma})}$ is greater than critical value at a specified level of significance, the null hypothesis is rejected, i.e., assumption of stationarity of the model is accepted.

2.2 Multivariate vector autoregression and linear Granger causality analysis

A multivariate vector autoregression (VAR) model of lag p corresponding to n number of variables $y_1, y_2, \ldots y_n$, each of size N and error term is given by

$$Y_t = \varphi_0 + \sum_{k=1}^{p} \varphi_k Y_{t-k} + \varepsilon_t, \tag{3}$$

where $Y_t = (y_1, y_2, \ldots y_n)^{\mathrm{T}}$, $\varphi_l = (\varphi_{ij})^{(l)}_{n\times n}$ for $l = 1, 2, \ldots, p$, $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t}, \ldots, \varepsilon_{nt})^{\mathrm{T}}$, in which ε_{mt} is the residual of y_m, $m = 1, 2, \ldots n$.

Lag order can be elected using minimum value of Akaike information criterion (AIC), Schwartz information criterion (SIC), and Hannan–Quinn information criterion (HIC) [47].

Ganger causality analysis, as proposed by Granger [34], is effective to detect if one time series is useful to predict another. y_i is said to Granger cause y_j if y_i makes significant contribution to the prediction of y_j. It can be measured by checking the joint influence of ${\varphi_{ji}}^{(l)}$ on y_j. For non-normal distribution, Wald test can be performed where the statistics $W = \frac{(\mathrm{SSE}_R - \mathrm{SSE}_U)}{\mathrm{SSE}_U/(T-2p-1)} \sim \chi^2_p$ under

$$H_o : \overset{(l)}{\varphi_{ji}} = 0, \quad l = 1, 2, \ldots, p \tag{4}$$

against

$$H_1 : \overset{(l)}{\varphi_{ji}} \neq 0 \text{ for some } l = 1, 2, \ldots, p. \tag{5}$$

If W is greater than the critical value at a specified level of significance, the null hypothesis is rejected, i.e., we can interpret that y_i Granger causes y_j.

2.3 Nonlinear Granger causality analysis: Diks–Panchenko test

Linear Granger causality analysis is ineffective to test nonlinear causality between the variables. For this reason, nonlinear granger causality analysis is to be performed to find any significant nonlinear association between the time series.

Diks–Panchenko test [35, 36, 48] is a modification of the Himestra–Jones test [49] to TEST nonlinear Ganger causality. If x_t does not Ganger cause y_t, then for the corresponding random variables X_t and Y_t,

$$Y_{t+1}|\left(X_t^{l_x}; Y_t^{l_y}\right) \sim Y_{t+1}|Y_t^{l_y}, \tag{6}$$

where $X_t^{l_x} = (X_{t-l_x+1}, \ldots, X_t)$ and $Y_t^{ly} = \left(Y_{t-l_y+1}, \ldots, Y_t\right)$, l_x and l_y being lag of x_t and y_t, respectively.

Remaining $Z_t = Y_{t+1}$ and denoting $W_t = (X_t^{l_x}, Y_t^{l_y}, Z_t)$, (6) can be rewritten as

$$Z|((X, Y) = (x, y) \sim Z|(Y = y), \tag{7}$$

which implies that, under H_0, i.e., assumption of non-Granger causality of y_t by x_t,

$$\frac{f_{X,Y,Z}(x, y, z)}{f_{X,Y}(x, y)} = \frac{f_{Y,Z}(y, z)}{f_Y(y)}, \tag{8}$$

where f s are the corresponding probability density functions.

(8) is equivalent to

$$\frac{f_{X,Y,Z}(x, y, z)}{f_Y(y)} = \frac{f_{X,Y}(x, y)}{f_Y(y)} \frac{f_{Y,Z}(y, z)}{f_Y(y)}. \tag{9}$$

Himnestra and Jones used correlation-integral estimator, of the form $C_{W,n}(\varepsilon) = \frac{2}{n(n-1)} \sum\sum_{i<j} I^W_{ij}$, where $I^W_{ij} = I(\|W_i - W_j\| \leq \varepsilon)$, $\|.\|$ is the maximum norm to each density function, to obtain

$$\frac{C_{X,Y,Z}(\varepsilon)}{C_Y(\varepsilon)} = \frac{C_{X,Y}(\varepsilon)}{C_Y(\varepsilon)} \frac{C_{Y,Z}(\varepsilon)}{C_Y(\varepsilon)}. \tag{10}$$

But this is not true in general. As a result, Himnestra and Jones test result faces severe size distortion problem in many cases. Diks and Panchenko [35, 36, 48] incorporated a conditional dependence measure by introducing a local weighting function $g(x,y,z)$ and modified (9) as

$$H_o : q = E\left[\left(\frac{f_{X,Y,Z}(x, y, z)}{f_Y(y)} - \frac{f_{X,Y}(x, y)}{f_Y(y)} \frac{f_{Y,Z}(y, z)}{f_Y(y)}\right) \times g_{X,Y,Z}(x, y, z)\right] = 0. \tag{11}$$

Under H_o, $\left(\frac{f_{X,Y,Z}(x,y,z)}{f_Y(y)} - \frac{f_{X,Y}(x,y)}{f_Y(y)} \frac{f_{Y,Z}(y,z)}{f_Y(y)}\right)$ vanishes and that is the reason for the expectation of $\left[\left(\frac{f_{X,Y,Z}(x,y,z)}{f_Y(y)} - \frac{f_{X,Y}(x,y)}{f_Y(y)} \frac{f_{Y,Z}(y,z)}{f_Y(y)}\right) g_{X,Y,Z}(x, y, z)\right]$ to be equal to 0. $g(X, Y, Z)$ is not unique. Using $g_{X,Y,Z}(x, y, z) = f^2_Y(y)$ is advantageous, as it follows normal distribution for the corresponding estimator and asymptotic distribution of the test statistics is obtained. For this value,

$$H_o : q = E[f_{X,Y,Z}(x,y,z) f_Y(y) - f_{X,Y}(x,y) f_{Y,Z}(y,z)] = 0 \quad (12)$$

is incurred.

A natural estimator of q based on indicator function is

$$T_n(\varepsilon) = \frac{(2\varepsilon)^{-d_x-2d_y-d_z}}{n(n-1)(n-2)} \times \sum_i \left[\sum_{k,k\neq i} \sum_{j,j\neq i} \left(I_{ik}^{XYZ} I_{ij}^{Y} - I_{ik}^{XY} I_{ij}^{YZ} \right) \right], \quad (13)$$

where $I_{ij}^W = I(\|W_i - W_j\| < \varepsilon)$.

Denoting local density estimators of a d_W-variate random variable W at W_i by $\widehat{f}_W(W_i) = \frac{(2\varepsilon)^{-d_W}}{n-1} \sum_{j,j\neq i} I_{ij}^W$, $T_n(\varepsilon)$ is simplified as

$$T_n(\varepsilon) = \frac{(n-1)}{n(n-2)} \sum_i (\widehat{f}_{X,Y,Z}(X_i,Y_i,Z_i) \widehat{f}_Y(Y_i) - \widehat{f}_{X,Y}(X_i,Y_i) \widehat{f}_{Y,Z}(Y_i,Z_i)). \quad (14)$$

For a sequence of bandwidths ε_n of the form $\varepsilon_n = Cn^{-\beta}, C > 0$ and $\beta \in \left(\frac{1}{4}, \frac{1}{3}\right)$, under suitable mixing conditions [50], if the covariances between the local density estimators are taken into account, we can have

$$\sqrt{n} \frac{T_n(\varepsilon_n) - q}{S_n} \to N(0,1), \quad (15)$$

where S_n^2 is a consistent estimator of asymptotic variance of $T_n(\varepsilon_n)$.

H_o is rejected at a preassigned significance level α if $\sqrt{n}\frac{T_n(\varepsilon_n)-q}{S_n} > z_{1-\alpha}$.

2.4 Generalized forecast error variance decomposition test

Granger causality is useful only to predict the causal relationship between two variables, but quantitative measurement of the degree of exogeneity or endogeneity is not computed by it. One approach to measure the degree of dependency of the variables is generalized forecast error variance decomposition (GFEVD) analysis, suggested by Koop et al. [37] and Pesaran and Shin [38]. Forecast error variance decomposition defined as the contribution to the forecast error variance of each variable is accounted for by shocks to all variables in the system. It explains how much percentage of fluctuation of a variable is accounted for by variance of shocks in other variables. For an exogenous variable in a system in a VAR(p) model, own shocks will explain all of its forecast error variance [51]. In addition, it detects which of the independent variables is more important in explaining the variability in the dependent variables over time.

Generalized variance decomposition is unique and independent of the ordering of the variables. It also measures contemporaneous shock effects which is an advantage over orthogonal variance decomposition.

The moving average representation of a VAR(p) model, $\Phi(L)y_t = \varepsilon_t$, is given by

$$Y_t = \Phi^{-1}(L)\varepsilon_t = \Psi(L)\varepsilon_t, \quad (16)$$

where $\Psi(L) = I_n + \Psi_1 L + \Psi_2 L^2 + \cdots$

Ψ_is can be computed from the identity

$$\Phi(L)\Psi(L) = \left(I_n - \sum_{i=1}^{p} \Phi_i L^i\right)\left(I_n + \sum_{i=1}^{\infty} \Psi_i L^i\right) = I_n. \quad (17)$$

Using (17), (16) can be remodeled as

$$Y_t = \sum_{l=0}^{\infty} \Psi_l \varepsilon_{t-l}.$$

Forecast error of predicting Y_{t+s} conditional on information available at t is

$$e_{t+s} = Y_{t+s} - \mathrm{E}_t(Y_{t+s}) = \sum_{l=o}^{s-1} \Psi_l \varepsilon_{t+s-l}. \quad (18)$$

The total forecast error covariance is

$$\mathrm{Cov}(e_{t+s}) = \sum_{l=o}^{s-1} \Psi_l \sum \Psi_l'. \quad (19)$$

Now, the forecast error of predicting Y_{t+s} conditional on information available at t is given by

$$e_{t+s}^i = \sum_{l=0}^{s-1} \Psi_l \varepsilon_{t+s-l} - E(\varepsilon_{t+s-1} | \varepsilon_{i,t+s-l}), \quad (20)$$

assuming the future shocks to the i-th variable at time t, $t+1, \ldots t+s-1$ are $\varepsilon_{i,t}, \varepsilon_{i,t+1}, \varepsilon_{i,t+2}, \ldots, \varepsilon_{i,t+s-1}$, respectively.

Assumption of ε_t following a multivariate normal distribution derives that [32]

$$E(\varepsilon_t | \varepsilon_{it} = \delta_i) = (\sigma_{1i}, \sigma_{2i}, \ldots, \sigma_{ni})' \sigma_{ii}^{-1} \delta_i = \sum e_i \sigma_{ii}^{-1} \delta_i, \quad (21)$$

e_i being $n \times 1$ matrix with the i-th element unity and other elements zero, where $\delta_j = \sqrt{\sigma_{jj}}$, i.e., one-unit standard deviation shock. So, forecast error covariance of e_{t+s}^i is given by

$$\mathrm{Cov}\left(e^i_{t+s}\right) = \sum_{l=o}^{s-1} \Psi_l \sum \Psi_l' - \sigma_{ii}^{-1}\left(\sum_{l=0}^{s-1} \Psi_l \sum e_i e_i' \sum \Psi_l'\right), \quad (22)$$

Hence, the change in the s-step forecast error variance of Y_{t+s} applying condition on future shocks to the i-th variable is given by

$$\Delta_{is} = \sigma_{ii}^{-1}\left(\sum_{l=0}^{s-1} \Psi_l \sum e_i e_i' \sum \Psi_l'\right), \quad (23)$$

which implies that the s-step ahead forecast error variance decomposition of the i-th variable attributable to shocks for the j-th variable is given by

$$\theta^g_{ij,s} = \frac{\sigma_{ii}^{-1} \sum_{l=0}^{s-1} \left(e_i' \Psi_l \sum e_j\right)^2}{\sum_{l=0}^{s-1} \left(e_i' \Psi_l \sum \Psi_l' e_j\right)}. \quad (24)$$

3 Results

3.1 Analysis of data for the pre-COVID period

3.1.1 Descriptive statistics

Table 1 describes the preliminary statistical attributes of log return data corresponding to the daily closing value of stock indices from July 1, 2018 to December 31, 2020 and from January 1, 2020 to June 30, 2021 respectively. In this pre-COVID period (sample size 227), TASE exhibits highest central return (M 0.002, MD 0.002), but with high uncertainty (SD 0.016) and riskier market to invest. BIST 100 is low-returning index (M − 0.0009) with high fluctuation (SD 0.14), whereas IBEX 35 is low-returning index (MD − 0.00002) with less volatility (SD 0.008). Hence, IBEX is comparatively safer to invest, though the return may be less. NYSE composite is least risky (SD 0.009) and B3 is the highest fluctuating index (SD 0.021). It is also evident from Jarque–Bera test that all the selected series follow non-normal distributions, except higher volatile markets TASE and B3. All exchanges except BSE, LSE and TASE are positively skewed emphasizing faster rate of decrease to the right of the peak for these three exchanges. All stock markets are leptokurtic in nature, having sharper peak than normal distribution, showing that the rate of change of price is higher in all the exchanges.

In the COVID-affected period (sample size 241), TASE preserves its highest value in terms of median (MD 0.001979) with high fluctuation 0.029684. It indicates that, though TASE generates higher return in the middle of the COVID-affected period, it has a volatile tendency. BIST 100 exhibits the highest mean by 0.018219 with more uncertainty (SD 0.297031). So, BIST 100 also follows high-risk–high-return strategy. SMI is the least fluctuated index (SD 0.013891) and more stable market. LSE is possibly the most volatile (SD 0.299213) and low-returning market (M − 0.019628), making it a very risky market to invest. LSE and TASE exhibit negative skewness affirming the tendency of faster declination of these markets from the peak. The nature of BSE changed from negatively skewed to positively skewed in this period. This observation points that BSE is more persistent near its peak during the COVID-affected period. Kurtosis in the COVID-affected period is positive and much more than that in the pre-COVID period, for all the exchanges. This clearly enhances the greater rate of change in price in COVID-affected period, confirming much more volatility in this period. All the markets follow non-normal distribution in the COVID-affected period.

3.1.2 Correlation

Correlation measures the co-movement of stock markets in a time period. It is a crude estimation of linear dependency between them. It is established from Table 2 that all the correlations are positive, which enhances the chance of simultaneous movement of these stock markets in the same direction before the COVID pandemic, emphasizing possible linear relationship among these stock exchanges. There is strong positive correlation between AEX-BEL 20, AEX-FTSE MIB, AEX-IBEX 35, AEX-OMX 30, AEX-SMI, BEL20-CAC40, BEL 20-FTSE MIB, BEL 20-OMX 30, BEL 20-SMI, CAC 40-FTSE MIB, CAC 40-IBEX 35, CAC 40-OMX 30, CAC 40-SMI, FTSE MIB-IBEX 35, FTSE 35-OMX 30, FTSE 35-SMI, IBEX 35-OMX 30, IBEX 35-SMI and OMX 30-SMI. Almost all the correlations were positive in the COVID-affected period too, except for B3 and AEX, B3 and BIST 100, B3 and CAC 40, B3 and IBEX 35, B3 and NYSE composite, B3 and SMI, OMX 30 and AEX, OMX 30 and LSE, and BIST100 and TASE. In this period, most of the strong positive correlations during the pre-COVID period are preserved in the likes of AEX-BEL 20, AEX-FTSE MIB, AEX-IBEX 35, AEX-SMI, BEL20-CAC40, BEL 20- FTSE MIB, BEL 20-SMI, CAC 40-IBEX 35, CAC 40-SMI, FTSE MIB-IBEX 35 and FTSE MIB-SMI. In addition, AEX-NYSE composite, BEL 20-IBEX 35, CAC 40-NYSE composite, FTSE MIB-NYSE composite joined the list. BIST 100, B3, BSE SENSEX, LSE, NYSE composite and TASE do not show significant correlation with any other stock exchanges, indicating possible gain of international diversification.

3.1.3 Stationarity test: ADF unit root test

As stationarity condition is prior assumption for a vector autoregression (VAR) model, ADF unit root test is applied to each individual series to check it during the

Table 1 Descriptive statistics for log return data

Period	Measure	AEX	BEL 20	BIST 100	B3	BSE SENSEX	CAC 40
Pre-COVID	Mean	− 0.000474	− 0.000523	− 0.000900	− 0.003438	− 0.000582	− 0.000510
COVID affected		− 0.001036	− 0.000726	0.018219	0.005599	− 0.000660	− 0.000417
Pre-COVID	Median	− 0.000850	− 0.000958	− 0.002173	− 0.003638	− 0.000899	− 0.000322
COVID-affected		− 0.001035	− 0.000698	− 0.001871	0.000186	− 0.002711	− 0.001280
Pre-COVID	Maximum	0.033738	0.034806	0.058399	0.062898	0.022672	0.033713
COVID-affected		0.113758	0.153275	4.602084	1.442867	0.141017	0.130983
Pre-COVID	Minimum	− 0.017235	− 0.019730	− 0.040425	− 0.070944	− 0.036801	− 0.022819
COVID-affected		− 0.085907	− 0.073606	− 0.058103	− 0.176007	− 0.085947	− 0.08061
Pre-COVID	Std. Dev	0.007723	0.008387	0.013790	0.021256	0.007957	0.008589
COVID-affected		0.016419	0.018296	0.297031	0.098231	0.019954	0.018496
Pre-COVID	Skewness	0.678999	0.690937	0.636170	0.104577	− 0.191909	0.384573
COVID-affected		1.375186	2.480362	15.34495	13.05512	1.959198	1.646980
Pre-COVID	Kurtosis	4.280831	4.313625	4.890213	3.299499	5.168378	3.980370
COVID affected		17.07907	24.97097	237.3096	191.8787	17.10177	17.43605
Pre-COVID	Jarque–Bera (probability)	32.9532	34.38281	49.13133	1.262172 (0.53)	45.86517	14.68605
COVID-affected		2066.423	5094.462	560,755.5	365,084.0	2151.062	2201.634

Period	FTSE MIB	IBEX 35	LSE	NYSE composite	OMX 30	SMI	TASE
Pre-COVID	− 0.000786	− 0.000126	− 0.001364	− 0.000422	− 0.000189	− 0.000674	0.002231
COVID affected	− 0.000481	− 0.000303	− 0.019628	0.000054	− 0.002185	− 0.000775	0.000480
Pre-COVID	− 0.000623	− 0.0000214	− 0.001029	− 0.000519	− 0.000696	− 0.000501	0.001812
COVID-affected	− 0.001570	− 0.000523	− 0.000688	− 0.001408	− 0.002157	− 0.001049	0.001979
Pre-COVID	0.036076	0.027870	0.046039	0.028677	0.029545	0.031813	0.041272
COVID-affected	0.185411	0.151512	0.101641	0.125950	0.047800	0.101399	0.124805
Pre-COVID	− 0.027331	− 0.019718	− 0.142701	− 0.018660	− 0.02505	− 0.022564	− 0.052438
COVID-affected	− 0.085495	− 0.082253	− 4.632814	− 0.095642	− 0.068491	− 0.067805	− 0.158741
Pre-COVID	0.010184	0.007961	0.016030	0.007106	0.009119	0.007801	0.015831
COVID-affected	0.020489	0.019786	0.299213	0.019316	0.014282	0.013891	0.029684
Pre-COVID	0.343943	0.409525	− 2.920908	0.967147	0.471793	0.558508	− 0.260958
COVID-affected	3.702272	1.838455	− 15.30085	1.885351	0.058432	1.492245	− 0.690938
Pre-COVID	3.551357	3.572650	28.92716	5.764996	3.594162	5.107711	3.309686
COVID affected	35.50013	20.3383	236.4158	17.75144	6.146641	18.54076	8.208709
Pre-COVID	7.350852	9.446728 (0.01)	6680.841	107.6992	11.76031		3.483522 (0.18)
COVID-affected	11,157.15	3152.895	55,650.3	2327.89	99.56322	2514.658	291.6123

Table 2 Correlation result for log return data

Period		AEX	BEL 20	BIST 100	B3	BSE SENSEX	CAC 40	FTSE MIB	IBEX 35	LSE	NYSE composite	OMX 30	SMI	TASE
Pre-COVID	AEX	–												
COVID-affected		–												
Pre-COVID	BEL 20	**0.84**	–											
COVID-affected		**0.79**	–											
Pre-COVID	BIST 100	0.23	0.20	–										
COVID-affected		0.03	0.06	–										
Pre-COVID	B3	0.16	0.14	0.12	–									
COVID-affected		– 0.01	0.01	– 0.00	–									
Pre-COVID	BSE SENSEX	0.26	0.26	0.16	0.08	–								
COVID-affected		0.53	0.56	0.04	0.08	–								
Pre-COVID	CAC 40	0.091	**0.85**	0.18	0.16	0.27	–							
COVID-affected		0.09	**0.84**	0.05	– 0.00	0.58	–							
Pre-COVID	FTSE MIB	**0.76**	**0.76**	0.17	0.13	0.15	**0.79**	–						
COVID-affected		**0.89**	**0.85**	0.04	0.00	0.51	0.92	–						
Pre-COVID	IBEX 35	**0.80**	**0.82**	0.23	0.07	0.19	**0.82**	**0.82**	–					
COVID-affected		**0.83**	**0.85**	0.09	– 0.00	0.56	**0.93**	**0.91**	–					
Pre-COVID	LSE	0.39	0.32	0.05	0.05	0.07	0.39	0.25	0.26	–				
COVID-affected		0.08	0.04	0.01	0.01	0.05	0.03	0.04	– 0.00	–				
Pre-COVID	NYSE composite	0.64	0.62	0.26	0.26	0.22	0.66	0.57	0.57	0.26	–			
COVID-affected		**0.73**	0.66	0.00	– 0.03	0.50	**0.79**	**0.74**	**0.76**	0.03	–			
Pre-COVID	OMX 30	**0.79**	**0.78**	0.13	0.12	0.21	**0.81**	**0.71**	**0.72**	0.33	0.57	–		
COVID-affected		– 0.01	0.14	0.09	0.10	0.30	0.06	0.06	0.07	– 0.18	– 0.06	–		
Pre-COVID	SMI	**0.82**	**0.77**	0.13	0.14	0.32	**0.82**	0.68	**0.72**	0.35	0.53	**0.76**	–	
COVID-affected		**0.89**	**0.75**	0.00	– 0.02	0.51	**0.84**	**0.82**	**0.75**	0.10	0.68	0.03	–	
Pre-COVID	TASE	0.23	0.29	0.00	0.05	0.15	0.28	0.26	0.23	0.07	0.15	0.27	0.19	–
COVID-affected		0.37	0.24	– 0.04	0.03	0.21	0.28	0.29	0.23	0.02	0.30	0.01	0.31	–

Bold values signify strong correlation (more than 0.70) between the indices

Table 3 ADF unit root test result for log return data

Stock exchange	Pre-COVID period			COVID-affected period			Conclusion
	Lag	p value	t stat value	Lag	p value	t stat value	
AEX	1	0.00*	− 11.3897	16	0.00*	− 4.69	Stationary
BEL 20	1	0.00*	− 11.801	13	0.00*	− 6.04	Stationary
BIST 100	0	0.00*	− 14.4402	0	0.00*	− 15.37	Stationary
B3	0	0.00*	− 15.5061	2	0.00*	− 9.53	Stationary
BSE SENSEX	2	0.00*	− 9.43279	6	0.00*	− 5.83	Stationary
CAC 40	2	0.00*	− 10.0048	5	0.00*	− 7.49	Stationary
FTSE MIB	0	0.00*	− 15.0449	11	0.00*	− 5.86	Stationary
IBEX 35	2	0.00*	− 10.3987	5	0.00*	− 7.43	Stationary
LSE	2	0.00*	− 9.90058	0	0.00*	− 15.46	Stationary
NYSE composite	3	0.00*	− 8.88172	9	0.00*	− 4.88	Stationary
OMX 30	16	0.00*	− 4.27342	7	0.00*	− 6.45	Stationary
SMI	1	0.00*	− 12.0325	8	0.00*	0.00	Stationary
TASE	2	0.00*	− 9.1552	6	0.00*	− 7.38	Stationary

* denotes rejection of the hypothesis at the 0.01 level

COVID-affected period. The presence of unit root confirms that the series is nonstationary. Table 3 summarizes the result confirming that all the series are stationary at 1% level of significance. Lag length was selected comparing minimum value between Akaine information criterion (AIC) and Schwartz information criterion (SIC). Bartlett kernel and Newey–West bandwidth was used. Linear deterministic trend was assumed. It is to be mentioned that, as the series are different, different lags are obtained. All the lags have increased during COVID-affected period except LSE and OMX 30. This signifies that almost all the stock exchanges became more dependent on the past values of its own return.

3.1.4 Linear Granger causality test

As ADF unit root test result supports the assumption of stationarity of each variable, a vector autoregression (VAR) model, comprising all the 13 stock market indices, in the pre-COVID period, is created to understand movement of all the markets together. Optimal lag length is measured according to minimum among Akaine information criterion (AIC), Schwartz information criterion (SIC) and Hannan–Quinn information criterion (HIC) and was found to be 15. As most of the variables do not satisfy the normality condition (Table 1), Granger causality–Wald test is performed to check the existence of unidirectional or bidirectional causality among the stock markets. Table 4 describes the result. Only those relationships which were found as statistically significant with 5% level of significance are shown. p value of less than equal to 0.05 for a pair implies that the corresponding independent stock market linearly Granger cause the corresponding dependent stock market.

It is evident from Table 4 that there is a sufficient number of linear causal relationships (72 out of possible 156) in the system. It is revealed that B3, NYSE composite and TASE are not granger caused by any stock market, implying that they are exogenous markets. Among these, B3 causes only two markets and hence B3 behaves almost indifferently in this period of study. On the other side, BIST 100 notably influences nine indices and hence plays a key role in this causality analysis. SMI is caused by only BIST 100. CAC 40, being affected by all other markets, is an endogenous stock market. BIST 100, BSE SENSEX, IBEX 35, LSE, NYSE composite, SMI and TASE have impact on AEX; AEX, BIST 100, IBEX 35 and TASE make significant contribution to the prediction of BEL 20; CAC 40, IBEX 35 and SMI Granger cause BIST 100; AEX, BEL 20, BIST 100, CAC 40, IBEX 35, LSE, OMX 30 and TASE has a Granger cause effect on BSE SENSEX; FTSE MIB is affected by all markets except NYSE composite and OMX 30, whereas LSE and OMX 30 are influenced by all indices, but AEX and B3 and B3 and BSE SENSEX respectively. On IBEX 35, AEX, BEL 20, BIST 100, FTSE MIB, LSE, SMI and TASE have significant impact. In brief, bidirectional causality is observed between AEX ↔ BSE SENSEX, AEX ↔ IBEX 35, BEL 20 ↔ IBEX 35, BIST 100↔ CAC 40, BIST 100 ↔ IBEX 35, BIST 100 ↔ SMI, BSE SENSEX ↔ CAC 40, BSE Index ↔ LSE, CAC 40 ↔ FTSE MIB, CAC 40 ↔ LSE, CAC 40 ↔ OMX 30, FTSE MIB ↔ IBEX 35, FTSE MIB ↔ LSE, IBEX 35 ↔ LSE and LSE ↔ OMX 30; unidirectional causality is running from AEX → BEL 20, AEX → CAC 40, AEX → FTSE MIB, AEX → OMX 30, BEL 20→ BSE SENSEX, BEL 20 → CAC 40, BEL 20 → FTSE MIB, BEL 20 → LSE, BEL 20 → OMX 30, BIST 100 → AEX, BIST 100 → BEL 20,

Table 4 Linear Granger causality-Wald test on log return data

Period	Independent stock markets	Dependent stock markets χ^2 statistic (p value)												
		AEX	BEL 20	BIST 100	B3	BSE SENSEX	CAC 40	FTSE MIB	IBEX 35	LSE	NYSE composite	OMX 30	SMI	TASE
Pre-COVID	AEX	–	26.68 (0.03)			27.58 (0.02)	46.96 (0.00)	39.71 (0.00)	40.32 (0.00)			28.50 (0.02)		
COVID-affected		–			40.98 (0.00)									
Pre-COVID	BEL 20		–			30.32 (0.01)	33.99 (0.00)	33.78 (0.00)	32.59 (0.01)	38.36 (0.00)		26.37 (0.03)		
COVID-affected		–			33.42 (0.00)									
Pre-COVID	BIST 100	36.73 (0.00)	35.88 (0.00)	–		26.23 (0.04)	68.33 (0.00)	50.28 (0.00)	50.44 (0.00)	35.22 (0.00)		39.68 (0.00)	25.35 (0.05)	
COVID-affected				–	52.11 (0.00)						28.69 (0.03)			
Pre-COVID	B3				–		32.04 (0.01)	30.78 (0.01)						
COVID-affected					–						27.52 (0.04)			
Pre-COVID	BSE SENSEX	26.68 (0.03)				–	29.94 (0.01)	34.89 (0.00)		41.81 (0.00)				
COVID-affected					28.82 (0.03)	–					32.77 (0.01)			
Pre-COVID	CAC 40			27.30 (0.03)		25.74 (0.04)	–	29.52 (0.01)		36.30 (0.00)		27.43 (0.03)		
COVID-affected					31.43 (0.01)		–							
Pre-COVID	FTSE MIB						26.38 (0.03)	–	28.07 (0.02)	37.71 (0.00)		26.70 (0.03)		
COVID-affected					36.14 (0.00)			–						
Pre-COVID	IBEX 35	29.73 (0.01)	35.52 (0.00)	27.96 (0.02)		29.42 (0.01)	41.13 (0.00)	25.15 (0.05)	–	30.42 (0.01)		34.29 (0.00)		

Table 4 (continued)

Period	Independent stock markets	Dependent stock markets χ^2 statistic (p value)												
		AEX	BEL 20	BIST 100	B3	BSE SENSEX	CAC 40	FTSE MIB	IBEX 35	LSE	NYSE composite	OMX 30	SMI	TASE
COVID-affected									–					
Pre-COVID	LSE	30.78 (0.01)				41.02 (0.00)	50.50 (0.00)	28.08 (0.02)	28.81 (0.02)	–		33.10 (0.00)		
COVID-affected		31.19 (0.0.01)			43.06 (0.00)		27.84 (0.03)			–	36.51 (0.00)	32.56 (0.01)		
Pre-COVID	NYSE composite	27.99 (0.02)					44.72 (0.00)		25.02 (0.05)	33.56 (0.00)	–	34.83 (0.00)		
COVID-affected					27.48 (0.04)						–			
Pre-COVID	OMX 30					44.76 (0.00)	26.68 (0.03)			27.20 (0.03)		–		
COVID-affected			27.12 (0.04)		30.26 (0.02)		31.95 (0.01)		26.78 (0.04)			–		
Pre-COVID	SMI	34.08 (0.00)		31.45 (0.01)			52.10 (0.00)	29.87 (0.01)	37.73 (0.00)	27.29 (0.03)		26.82 (0.03)	–	
COVID-affected					42.78 (0.00)								–	
Pre-COVID	TASE	27.54 (0.02)	32.28 (0.01)			41.82 (0.00)	49.00 (0.00)	41.87 (0.00)		56.48 (0.00)		25.78 (0.04)		–
COVID-affected					43.89 (0.00)									–

BIST 100 → BSE SENSEX, BIST 100 → FTSE MIB, BIST 100→ LSE, BIST 100 → OMX 30, B3 → CAC 40, B3→ FTSE MIB, BSE SENSEX → FTSE MIB, FTSE MIB → NYSE composite, IBEX 35 → BSE SENSEX, IBEX 35→ CAC 40, IBEX 35 → OMX 30, LSE → AEX, NYSE composite → AEX, NYSE composite → CAC 40, NYSE composite → IBEX 35, NYSE composite → LSE, NYSE composite → OMX 30, OMX 30→ BSE SENSEX, SMI → AEX, SMI → CAC 40, SMI → FTSE MIB, SMI → IBEX 35, SMI → LSE, SMI → OMX 30, TASE → AEX, TASE → BEL 20, TASE → BSE SENSEX, TASE → CAC 40, TASE → FTSE MIB,TASE → LSE and TASE → OMX 30.

For the COVID-affected period, computed optimal lag is 16 and a VAR (16) model is created. As no variable satisfies normality condition (Table 1), again Granger causality-Wald test is used to investigate causality among the variables (Table 4). It is clear from Table 4 that the number of linear causal relationships reduced noticeably in the COVID-affected period (21 out of possible 156 linear causal relationships). There are a number of exogenous markets: BIST 100, BSE SENSEX, FTSE MIB, LSE, SMI and TASE. LSE, making impact on five indices plays a key part in this time frame. B3, caused by 11 indices, is most endogenous in this period. On the other part, exogenous indices FTSE MIB and TASE influence only B3. Hence, these two markets are almost indifferent in this system. Bidirectional linear causality is observed only between B3↔ NYSE composite, whereas unidirectional linear causality happens between AEX → B3, BEL 20→ B3, BIST → B3, BIST → NYSE composite, BSE SENSEX → B3, CAC 40→ B3, FTSE MIB → B3, LSE → AEX, LSE → B3, LSE → CAC 40, LSE → NYSE composite, LSE → OMX 30, OMX 30→ BEL 20, OMX 30→ B3, OMX 30→ CAC 40, OMX 30→ IBEX 35, SMI → B3 and TASE → B3.

3.1.5 Nonlinear Granger causality test

As linear granger causality test is unable to capture nonlinear causal relationship among variables, pairwise bivariate nonlinear granger causality test, illustrated by Diks and Panchenko [35, 36], is performed for the pre-COVID period and the result is given in Table 5. Optimal lag length of each pair is assessed according to minimum between Akaike information criterion (AIC) and Schwartz information criterion (SIC). Embedding dimension is set to the lag length increase by 1. The value of β, in the bandwidth $\varepsilon = Cn^{-\beta}$ in Diks–Panchenko test, is taken as $\frac{2}{7}$, as for this choice of β, mean squared error of the estimator is asymptotically least. Covariance between conditional concentrations for a bivariate series arises mainly to volatility and for estimation of the autoregressive heteroskedasticity model (ARCH), C is taken as 8. If the sample size is small, the bandwidth may be high which would produce erroneous calculation. Hence, the upper bound of the bandwidth is fixed as 1.5, i.e., $\varepsilon = \max(8n^{-\frac{2}{7}}, 1.5)$.

It is found that the number of nonlinear Granger causal relationship in the pre-COVID period is much lesser than the number of linear Granger causal relation (20 compared to 72). BIST 100, B3, BSE SENSEX, LSE and TASE are exogeneous stock markets. Also, BIST 100, B3, LSE and TASE do not have any significant impact on any of the indices. Hence, these markets behave neutrally. B3 and TASE are also exogeneous when linear Granger causality is performed. Hence, these two markets exhibit most exogeneity by causality analysis in the pre-COVID time span. NYSE composite shows exogeneity according to linear granger causality, but it is nonlinearly caused by BSE SENSEX, CAC 40, OMX 30 and SMI. AEX and BEL 20 are impacted by CAC 40 and NYSE composite, respectively. CAC 40 is notably nonlinearly affected by NYSE composite and SMI; FTSE MIB is nonlinearly induced by CAC 40 and SMI; IBEX 35 is driven by AEX, CAC 40, NYSE composite and SMI; OMX 30 is influenced by BSE SENSEX, CAC 40, NYSE composite and SMI; SMI is impacted by AEX and NYSE. In brief, bidirectional nonlinear causality exists between CAC 40 ↔ NYSE composite, NYSE composite ↔ OMX 30 and NYSE composite ↔ SMI and unidirectional nonlinear granger causality is established between AEX → IBEX 35, AEX → SMI, BSE SENSEX → NYSE composite, BSE SENSEX → OMX 30, CAC 40 → AEX, CAC 40→ FTSE MIB, CAC 40→ IBEX 35, CAC 40 → OMX 30, NYSE composite → BEL 20, NYSE composite → IBEX 35, SMI → CAC 40, SMI → FTSE MIB, SMI → IBEX 35 and SMI → OMX 30.

Diks–Panchenko test is repeated on stock indices log return data in the COVID-affected period and the result is shown in Table 5. Table 5 suggests that the number of nonlinear Granger causal relationship is in fact raised in the COVID-affected period (32 compared to 21). BIST 100, B3 and BSE SENSEX are exogenous stock markets in the COVID-affected period. BSE behaves indifferently in the COVID-affected period as it does not show sign of any impact on other indices. NYSE composite continues to be an endogenous market as it is influenced by seven markets. Another exogenous exchange in the pre-COVID period, namely, TASE is endogenous in this period. CAC 40 remains to be crucial important stock market influencing six markets. OMX 30 strengthens its importance in the post-COVID period causing six markets nonlinearly. In the COVID-affected period, bidirectional nonlinear causality is observed between AEX ↔ TASE, BEL 20 ↔ TASE, CAC 40 ↔ OMX 30, CAC 40 ↔ TASE, NYSE composite ↔ SMI, NYSE composite ↔ TASE, unidirectional nonlinear causality is found between AEX → SMI, BEL 20 → AEX, BEL 20 → FTSE MIB, BEL 20 → NYSE composite, BEL 20 → SMI, CAC 40 → FTSE MIB, CAC 40 → IBEX 35, CAC 40 → NYSE composite, CAC 40 → SMI, FTSE MIB → NYSE composite, IBEX 35 → FTSE MIB, IBEX 35 → NYSE composite, IBEX 35 → SMI, NYSE composite → AEX, OMX 30 → AEX, OMX 30 → FTSE MIB, OMX 30 → IBEX 35, OMX 30 → NYSE composite, OMX 30 → TASE and SMI → TASE.

Table 5 Pairwise nonlinear Granger causality-Diks–Panchenko test for log return data

Independent stock markets	Dependent stock markets (p value) Lag												
	AEX	BEL 20	BIST 100	B3	BSE SENSEX	CAC 40	FTSE MIB	IBEX 35	LSE	NYSE composite	OMX 30	SMI	TASE
AEX	–							$t = 1.67$ (0.05) Lag = 0				$t = 1.88$ (0.03) Lag = 2	
	–											$t = 1.79$ (0.04) Lag3	$t = 1.69$ (0.04) Lag2
BEL 20		–											
	$t = 1.74$ (0.04) Lag7	–					$t = 1.65$ (0.05) Lag3			$t = 2.32$ (0.01) Lag10		$t = 1.66$ (0.05) Lag9	$t = 1.94$ (0.03) Lag7
BIST 100			–										
			–										
B3				–									
				–									
BSE SENSEX					-					$t = 1.76$ (0.04) Lag = 0	$t = 1.98$ (0.00) Lag = 1		
					–								
CAC 40	$t = 2.60$ (0.00) Lag = 1					–	$t = 173$ (0.04) Lag = 0	$t = 2.23$ (0.00) Lag = 0		$t = 2.33$ (0.00) Lag = 3	$t = 1.97$ (0.02) Lag = 1		
						–	$t = 1.75$ (0.04) Lag5	$t = 1.67$ (0.05) Lag5		$t = 1.91$ (0.03) Lag10	$t = 1.75$ (0.04) Lag6	$t = 1.73$ (0.04) Lag9	$t = 1.78$ (0.04) Lag6
FTSE MIB							–			$t = 2.07$ (0.02) Lag8			
							–			$t = 2.07$ (0.02) Lag8			
IBEX 35								–					

Table 5 (continued)

Independent stock markets	Dependent stock markets (p value) Lag												
	AEX	BEL 20	BIST 100	B3	BSE SENSEX	CAC 40	FTSE MIB	IBEX 35	LSE	NYSE composite	OMX 30	SMI	TASE
							$t = 1.77$ (0.04) Lag3	–		$t = 1.91$ (0.03) Lag12		$t = 1.96$ (0.03) Lag6	
LSE									–				
									–				
NYSE composite		$t = 2.90$ (0.00) Lag = 2				$t = 1.93$ (0.03) Lag = 3		$t = 1.73$ (0.04) Lag = 0		–	$t = 2.49$ (0.00) Lag = 1	$t = 1.92$ (0.03) Lag = 2	
	$t = 1.81$ (0.03) Lag10									–		$t = 2.21$ (0.01) Lag9	$t = 2.08$ (0.02) Lag5
OMX 30										$t = 1.74$ (0.04) Lag = 1	–		
	$t = 2.07$ (0.02) Lag8					$t = 2.70$ (0.03) Lag6	$t = 2.57$ (0.00) Lag8	$t = 2.16$ (0.02) Lag7		$t = 2.31$ (0.01) Lag7	–		$t = 2.49$ (0.00) Lag1
SMI						$t = 1.92$ (0.03) Lag = 1	$t = 2.17$ (0.01) Lag = 2	$t = 2.06$ (0.02) Lag = 0		$t = 2.15$ (0.02) Lag = 2	$t = 1.60$ (0.05) Lag = 1	–	
										$t = 1.72$ (0.02) Lag9		–	$t = 1.71$ (0.04) Lag2
TASE													–
	$t = 2.10$ (0.02) Lag2	$t = 1.90$ (0.03) Lag7				$t = 1.76$ (0.04) Lag6				$t = 1.69$ (0.05) Lag5			–

Table 6 Generalized variance decomposition analysis based on VAR (15) model for log return data (pre-COVID period)

Variance decomposition of dependent stock markets	Percentage of error forecast variance explained by innovation in independent stock markets in 1st period 10th period 50th period 100th period												
	AEX	BEL 20	BIST 100	B3	BSE SENSEX	CAC 40	FTSE MIB	IBEX 35	LSE	NYSE composite	OMX 30	SMI	TASE
AEX	19.72	11.40	0.51	2.94	0.58	15.54	9.51	9.40	2.37	5.69	12.58	9.76	0.00
	14.51	9.55	3.52	5.04	2.91	9.11	6.82	10.01	6.56	8.34	11.81	9.97	1.86
	7.40	11.16	5.08	7.65	10.81	8.26	5.64	9.21	5.76	9.09	6.57	8.88	4.49
	6.92	11.29	7.17	7.60	11.33	6.94	6.76	6.98	6.92	7.07	6.81	7.30	6.91
BEL 20	12.14	21.01	0.24	2.16	1.61	15.21	12.12	14.32	0.20	1.66	12.78	6.24	0.33
	33.56	14.79	2.66	4.62	5.49	10.86	8.44	12.28	2.93	4.31	11.98	9.07	1.85
	7.76	14.39	6.07	10.05	12.12	8.39	3.44	7.32	5.52	9.37	3.87	9.46	4.15
	1.51	**23.58**	5.29	10.23	19.77	4.79	3.71	4.35	4.25	5.83	3.71	6.08	4.40
BIST 100	1.73	0.75	66.92	2.40	2.45	3.41	2.93	6.93	0.07	10.07	0.56	1.59	0.19
	4.19	2.99	27.06	10.69	6.80	4.15	3.43	5.64	5.27	11.82	5.58	4.20	8.18
	4.98	9.31	10.86	12.20	9.25	6.45	4.14	7.32	6.36	10.28	4.96	8.09	5.79
	4.22	18.87	5.83	11.42	20.91	4.88	4.15	4.95	4.25	5.87	4.18	6.04	4.43
B3	6.78	4.67	3.00	45.54	1.16	7.15	3.58	2.26	7.41	0.28	10.06	5.36	2.75
	8.35	5.58	9.51	18.84	1.11	7.29	3.94	10.69	8.44	4.29	7.03	7.48	7.45

Table 6 (continued)

Variance decomposition of dependent stock markets	Percentage of error forecast variance explained by innovation in independent stock markets in 1st period 10th period 50th period 100th period											
	AEX	BEL 20	BIST 100	B3	BSE SENSEX	CAC 40	FTSE MIB	IBEX 35	LSE	NYSE composite	OMX 30	SMI	TASE
	6.49	9.14	11.17	10.87	7.52	5.97	5.51	8.09	7.25	5.85	6.81	7.51	7.82
	5.70	11.09	7.84	12.25	14.80	5.96	5.87	6.22	5.91	6.06	5.78	5.92	6.59
BSE SENSEX	1.96	5.07	2.43	1.69	66.26	3.29	4.80	6.23	0.96	0.86	1.78	3.62	1.07
	5.28	3.38	8.53	12.78	20.68	3.41	11.36	8.16	9.25	6.16	4.18	3.81	3.00
	8.55	5.63	6.76	7.70	8.49	7.40	8.82	7.96	10.19	5.79	8.50	6.75	7.46
	7.77	8.94	7.34	7.73	5.94	8.03	7.75	7.83	7.55	7.72	7.74	8.02	7.64
CAC 40	14.49	13.31	0.94	2.88	0.91	18.38	12.11	10.87	1.48	4.45	13.82	6.27	0.08
	13.04	11.10	1.65	5.89	1.59	11.58	9.50	11.80	4.00	6.83	12.89	8.14	2.00
	6.88	11.25	5.09	9.35	11.24	9.41	4.64	8.50	5.54	8.92	5.60	9.66	3.92
	5.72	15.49	6.60	9.42	14.47	6.21	5.58	5.93	5.79	6.35	5.54	7.02	5.89
FTSE MIB	10.67	12.77	0.97	1.74	1.60	14.58	22.13	11.42	0.07	3.33	15.29	5.15	0.28
	10.25	9.30	2.15	2.59	3.08	9.75	14.15	11.23	7.33	5.99	12.61	6.49	5.08
	7.60	6.73	7.30	9.34	7.82	7.80	7.79	7.86	8.36	7.04	7.20	7.98	7.18

Table 6 (continued)

Variance decomposition of dependent stock markets	Percentage of error forecast variance explained by innovation in independent stock markets in 1st period 10th period 50th period 100th period											
	AEX	BEL 20	BIST 100	B3	BSE SENSEX	CAC 40	FTSE MIB	IBEX 35	LSE	NYSE composite	OMX 30	SMI	TASE
	7.87	7.27	8.15	8.08	6.13	7.86	7.84	7.71	7.98	7.61	7.79	7.86	7.84
IBEX 35	11.31	16.17	2.46	1.18	2.23	14.04	12.24	23.73	0.00	2.45	9.70	4.43	0.05
	9.72	14.63	3.57	3.65	5.09	9.72	9.33	16.36	3.20	5.80	10.80	6.89	1.23
	7.45	10.26	7.41	8.10	8.43	8.55	7.00	8.66	5.98	8.34	6.56	7.55	5.71
	7.82	8.54	7.67	7.02	6.47	7.78	7.72	7.74	7.85	7.83	7.77	8.01	7.80
LSE	6.81	0.55	0.06	9.21	0.82	4.56	0.18	0.01	56.60	0.50	1.86	16.77	2.07
	5.59	3.06	11.35	8.98	6.72	3.24	4.13	8.53	16.85	9.20	6.62	9.58	6.13
	4.89	7.64	12.23	9.79	9.56	5.88	4.90	7.46	8.26	10.74	4.04	8.92	5.67
	4.18	12.70	8.04	12.70	23.98	4.52	4.28	4.83	4.49	5.69	4.14	5.52	4.93
NYSE composite	11.97	3.27	6.25	0.26	0.54	10.04	6.25	4.29	0.37	41.50	10.97	0.29	4.00
	10.17	8.33	4.55	2.51	8.00	7.38	5.97	4.05	2.97	22.22	9.85	7.62	6.38
	8.20	8.17	6.53	6.18	8.57	8.04	7.66	7.22	6.22	10.50	8.06	7.98	6.67
	7.75	7.86	7.41	7.25	7.68	7.75	7.75	7.77	7.64	8.02	7.77	7.80	7.57

Table 6 (continued)

Variance decomposition of dependent stock markets	Percentage of error forecast variance explained by innovation in independent stock markets in 1st period 10th period 50th period 100th period												
	AEX	BEL 20	BIST 100	B3	BSE SENSEX	CAC 40	FTSE MIB	IBEX 35	LSE	NYSE composite	OMX 30	SMI	TASE
OMX 30	12.91	12.31	0.17	4.47	0.54	15.21	13.97	8.27	0.67	5.35	20.23	5.87	0.03
	12.70	9.39	0.85	5.78	1.96	10.56	10.23	10.47	4.05	7.26	15.24	7.24	4.28
	6.71	11.34	5.09	10.10	11.07	8.94	4.16	7.50	5.18	8.80	5.27	10.72	5.12
	3.29	25.31	5.18	12.55	20.97	4.34	2.98	3.92	3.40	4.76	2.98	6.38	3.92
SMI	14.14	8.49	0.68	3.36	1.56	9.75	6.64	5.33	8.46	0.20	8.28	28.57	4.55
	8.12	7.38	5.56	7.18	2.90	6.32	7.08	7.61	9.13	6.27	8.55	17.69	6.23
	9.96	4.79	5.99	3.99	5.26	8.50	10.85	8.16	9.01	6.93	10.12	8.42	8.01
	8.55	5.30	8.16	6.83	3.98	8.40	8.54	8.37	8.44	8.25	8.55	8.23	8.40
TASE	0.00	1.10	0.20	4.29	1.14	0.31	0.91	0.15	2.59	6.78	0.11	11.32	**71.08**
	7.92	10.01	4.69	4.26	6.01	8.94	9.35	5.18	6.09	9.13	4.80	9.28	14.34
	9.15	6.15	7.10	3.31	8.08	7.78	9.54	7.75	9.06	6.74	9.11	7.52	8.73
	8.20	5.91	7.86	6.89	6.17	8.15	8.26	8.12	8.25	7.94	8.24	7.82	8.19

Table 7 Generalized variance decomposition analysis based on VAR (16) model for log return data (COVID-affected period)

Variance decomposition of dependent stock markets	Percentage of error forecast variance explained by independent stock markets in 1st future period 10th future period 50th future period 100th future period											
	AEX	BEL 20	BIST 100	B3	BSE SENSEX	CAC 40	FTSE MIB	IBEX 35	LSE	NYSE composite	OMX 30	SMI	TASE
AEX	23.02	10.81	1.19	3.44	1.57	15.78	15.08	7.82	0.20	7.18	0.16	13.33	0.42
	13.37	9.66	4.03	5.87	8.27	9.61	10.88	7.73	9.15	5.17	4.32	10.66	1.27
	10.70	9.19	5.18	9.10	6.31	8.88	8.03	7.40	7.37	6.95	6.71	10.63	3.55
	14.88	8.55	4.08	9.27	4.01	6.97	7.86	5.72	6.33	5.97	5.35	17.45	3.57
BEL 20	10.08	21.46	1.64	1.16	3.31	13.87	16.09	10.86	0.63	3.54	3.77	13.60	0.00
	29.60	13.29	3.65	6.51	6.78	9.11	10.36	7.81	8.93	5.47	6.75	10.07	2.61
	8.10	8.89	6.06	7.86	7.53	8.14	7.48	7.62	8.57	6.67	8.56	7.08	7.43
	7.52	7.97	7.44	6.99	8.49	8.35	7.90	8.12	7.54	7.91	8.16	6.09	7.51
BIST 100	7.90	4.74	42.83	0.80	1.49	8.01	3.69	18.61	0.20	1.82	12.85	0.00	4.22
	3.84	6.18	26.92	9.20	3.23	5.21	5.26	9.75	5.91	6.64	11.16	2.54	4.15
	15.58	8.50	12.72	6.26	11.33	7.51	7.29	9.59	9.64	8.01	8.62	4.70	2.83
	4.46	6.94	9.76	6.81	9.99	8.49	7.48	8.80	8.08	8.43	8.90	2.78	9.09
B3	6.75	2.44	0.84	45.15	0.01	9.49	7.39	7.35	1.96	5.34	0.00	12.02	1.26
	11.08	4.15	5.69	20.00	4.82	6.44	8.80	4.62	4.71	6.45	4.53	12.19	6.52

Table 7 (continued)

Variance decomposition of dependent stock markets	Percentage of error forecast variance explained by independent stock markets in 1st future period 10th future period 50th future period 100th future period												
	AEX	BEL 20	BIST 100	B3	BSE SENSEX	CAC 40	FTSE MIB	IBEX 35	LSE	NYSE composite	OMX 30	SMI	TASE
	9.17	6.31	7.38	13.37	5.75	6.64	7.34	5.62	7.75	6.23	8.69	10.39	5.37
	11.48	6.88	6.34	11.34	4.40	5.94	7.44	5.36	7.44	5.86	7.25	15.30	4.94
BSE SENSEX	3.68	8.33	1.87	0.01	54.03	2.87	6.58	4.75	8.69	0.36	3.99	4.06	0.78
	6.35	10.15	4.94	3.17	18.64	6.81	6.83	6.76	9.66	7.68	3.50	9.38	6.12
	8.91	9.57	5.91	7.66	8.61	7.30	7.80	6.88	8.69	6.35	4.92	10.56	6.85
	13.60	9.19	4.27	8.06	4.43	6.47	7.91	5.67	7.34	5.60	4.27	18.26	4.93
CAC 40	12.95	12.22	3.53	3.97	1.01	18.90	15.85	14.16	0.39	6.76	1.56	8.67	0.02
	9.98	10.52	5.97	7.72	4.95	10.07	11.21	9.38	9.31	4.85	5.77	8.84	1.44
	8.02	8.39	6.75	7.94	7.11	8.78	7.78	8.42	8.28	6.78	8.44	7.60	5.70
	7.30	7.50	7.87	7.18	8.58	8.42	7.82	8.19	7.41	7.97	8.24	6.29	7.23
FTSE MIB	12.60	14.42	1.66	3.15	2.34	16.13	19.24	10.51	1.72	5.99	0.76	10.94	0.56
	10.84	11.65	3.77	6.37	7.29	10.10	11.99	8.24	8.63	4.92	4.01	9.95	2.22
	9.94	8.82	5.83	8.35	6.41	9.16	8.28	7.61	7.32	6.58	7.78	8.52	5.40

Table 7 (continued)

Variance decomposition of dependent stock markets	Percentage of error forecast variance explained by independent stock markets in 1st future period 10th future period 50th future period 100th future period												
	AEX	BEL 20	BIST 100	B3	BSE SENSEX	CAC 40	FTSE MIB	IBEX 35	LSE	NYSE composite	OMX 30	SMI	TASE
	9.50	7.83	6.71	7.35	7.65	8.25	8.09	7.64	6.99	7.62	7.48	8.62	6.27
IBEX 35	7.73	11.52	9.89	3.71	2.00	17.06	12.44	22.77	0.10	5.58	3.07	3.99	0.16
	6.80	9.93	13.08	9.25	2.79	8.68	9.50	12.78	6.97	5.65	6.68	4.76	3.13
	5.85	7.17	9.06	6.81	9.28	7.72	7.17	9.27	9.10	6.89	8.68	5.05	7.95
	5.31	7.15	9.07	6.83	9.63	8.56	7.60	8.77	7.87	8.26	8.89	3.49	8.57
LSE	0.54	1.76	0.28	2.62	9.68	1.25	5.38	0.26	60.18	0.29	2.01	1.15	14.60
	8.41	7.77	4.38	2.12	9.63	8.17	6.63	7.67	12.47	10.43	4.93	7.88	9.51
	8.27	8.12	5.10	7.79	6.33	8.22	8.01	8.37	8.22	9.69	6.91	8.65	6.31
	8.81	7.60	5.84	8.39	7.15	7.18	7.70	7.39	8.01	8.93	6.30	10.58	6.11
NYSE composite	11.81	6.24	1.61	4.48	0.25	13.55	11.79	9.27	0.18	37.86	0.06	2.88	0.00
	10.62	7.72	8.33	8.02	5.21	6.92	9.66	6.45	9.05	10.97	4.27	9.83	2.95
	7.52	7.87	6.84	8.45	6.85	7.76	8.21	7.75	8.89	8.65	7.22	8.26	5.73
	8.62	7.84	7.22	7.97	6.61	7.39	7.66	7.12	7.99	7.57	7.32	9.85	6.84

Table 7 (continued)

Variance decomposition of dependent stock markets	Percentage of error forecast variance explained by independent stock markets in 1st future period 10th future period 50th future period 100th future period											
	AEX	BEL 20	BIST 100	B3	BSE SENSEX	CAC 40	FTSE MIB	IBEX 35	LSE	NYSE composite	OMX 30	SMI	TASE
OMX 30	0.35	8.84	15.10	0.00	3.71	4.16	1.98	6.78	1.68	0.09	50.32	2.50	4.50
	8.07	7.88	7.50	3.96	2.68	8.57	9.59	8.57	7.13	6.35	18.88	8.70	2.12
	5.78	6.98	9.20	7.17	11.03	7.73	7.64	9.29	8.17	8.07	11.52	5.91	1.52
	4.69	6.93	9.07	7.01	9.94	8.41	7.59	8.75	7.96	8.52	9.09	3.24	8.79
SMI	14.75	16.15	0.00	6.78	1.91	11.68	14.49	4.46	0.49	1.94	1.27	25.48	0.60
	9.57	11.27	1.47	7.06	6.68	8.71	9.72	5.91	9.03	5.32	6.78	14.65	3.84
	9.86	9.43	4.02	8.02	6.27	8.27	8.24	6.43	8.56	7.25	7.43	10.19	6.03
	14.81	9.76	3.29	9.16	3.07	6.26	8.17	4.98	7.09	5.26	5.07	18.13	4.97
TASE	1.17	0.01	6.35	1.80	0.93	0.08	1.88	0.44	15.63	0.01	5.76	1.51	**64.43**
	7.25	4.47	9.83	3.38	4.67	5.11	5.46	4.04	5.92	10.10	8.79	5.24	25.75
	4.52	5.51	9.85	8.29	9.76	6.20	5.84	7.45	8.16	8.89	8.75	5.24	11.53
	5.27	6.82	8.86	7.98	8.42	7.78	7.05	7.98	8.27	7.92	9.01	4.83	9.83

3.1.6 Variance decomposition analysis

Generalized variance decomposition analysis is generated over a span of 100 periods to measure the degree of exogeneity both in short term and long term. Generalized variance decomposition is used to nullify the impact of the ordering of the innovative variables on the explained forecast error variance of the dependent variable. As covariance between original shocks may not be zero, total forecast error variance may not be 100%. Variances are standardized to get a better idea about the impact of different shock on a dependent market. Outcome for only the 1st, 10th, 50th and 100th period is shown in Table 6 for the pre-COVID period and Table 7 for the COVID-affected period. In the present study, the 1st and 10th period is considered as short term and 50th and 100th period is considered as long term. As 13 stock markets are considered, we fix that an innovation of stock market is important to describe another stock market if the forecast error variance is more than $100/13 = 7.69\%$.

It is evident from Table 6 that TASE is the most exogenous stock market in the pre-COVID era for short term as forecast error variance of it is explained most (71.08%) by its own innovation. BIST (66.92%) and BSE SENSEX (66.26%) also shows sign of exogeneity. These findings support nonlinear Granger causality analysis. Error variance of BSE SENSEX is not described significantly by innovation of any other market in the pre-COVID period for the short term. In the long term, BEL 20 (23.58%) is most exogenous. In the pre-COVID period, CAC 40 is most endogenous in the short term as its own innovation explains least percentage of forecast error variance (18.11%). This interpretation coincides with linear Granger causality analysis. In the long term, OMX 30, explaining only 2.98% forecast variance by own innovation, is most endogenous.

It can be inferred from Table 7 that, for the COVID-affected period, in the short term, TASE, 64.43% of whose forecast error variance is attributable to its own innovation, continues to be the most exogenous stock market and CAC 40, explaining only 18.90% of its error variance by self-innovation and maintaining its endogeneity. In the long term, SMI (18.13%) is the most exogenous market. BSE SENSEX, exogenous in pre-COVID era, changes its characteristic to be most endogenous market in as only 4.43% of its variance is attributable to itself.

The accountability of the independent stock exchanges, for the variation of dependent stock markets, is summarized in Table 8, for easy understanding of the reader. It can be comprehended that innovation in independent stock markets is more responsible for explaining variation of dependent markets in the long run, compared to short run, both in the pre-COVID and COVID-affected period.

4 Discussion

The attempt of the present study is to investigate and analyze the change in economic relationship among the prime stock markets of the countries which are heavily affected by coronavirus, either by total number of cases or by number of cases per one million population till June 30, 2021. The present work has certain clear novelty in its strategic analysis and implementation. Firstly, we have selected and categorized fiscally prominent and impacted countries by means of two different perspectives, viz., by the gross total number of infected cases and by the concentration of infected cases. If we only select the countries by means of the first consideration, obviously some less populated but severely impacted countries would have been missed. Secondly, choice of intervals in the pre-COVID period and within the COVID period is very important and sensitive. We have taken a balanced approach by selecting uniform lengths of time intervals in the pre-COVID and COVID period for all the considered indices. This certainly gives parity in the analysis zone and we expect to have a more reliable analysis under these uniform comparative time zones. TASE maintains its high return in terms of highest median in both the periods, but BIST, which had low return before COVID, performs remarkably well in the midst of COVID producing high return. It should be mentioned that fluctuation in COVID-affected period has increased drastically for almost all the markets, which is consistent with the study by Samadder and Bhunia [18]. As there is uncertainty and worry about the time frame of the pandemic to end and many waves of the pandemic has been generated over time one after another amidst a relatively shorter time frame of stability of the daily COVID-infected cases, most markets seem to be volatile. This result also indicates that the higher return rate may not be stable in long term. B3 and TASE, the only markets satisfying normality criteria in the pre-COVID period, shifted to non-normal category in this pandemic, adding complexity to the system.

Descriptive statistics prevails that, in the pre-COVID period, TASE is detected with highest central return, but with high uncertainty. High-risk–high-return strategy should be followed in this exchange. BIST 100 is low-returning high fluctuating and IBEX 35 is low-returning less volatile index. Hence, IBEX is a comparatively safer place to invest, though return may be less. NYSE composite is least risky and B3 is the highest fluctuating index. All the selected series except higher volatile exchanges B3 and TASE follow non-normal distributions. All exchanges except BSE, LSE and TASE are positively skewed, emphasizing faster rate of decrease to the right of the peak for these

Table 8 Significant variation of dependent stock markets explained by innovation of independent stock markets

Dependent stock markets	Forecasting period	Independent stock markets which account for significant variation of dependent stock markets												
		AEX	BEL 20	BIST 100	B3	BSE SENSEX	CAC 40	FTSE MIB	IBEX 35	LSE	NYSE composite	OMX 30	SMI	TASE
AEX (pre-COVID)	Short-term			×	×	×				×				×
	Long-term	×		×	×			×		×		×		×
AEX (COVID-affected)	Short-term			×	×						×	×		×
	Long-term			×		×			×	×	×	×		×
BEL 20 (pre-COVID)	Short-term			×	×	×				×	×			×
	Long-term			×				×	×	×		×		×
BEL 20 (COVID-affected)	Short-term			×	×	×					×	×		×
	Long-term			×									×	×
BIST 100 (pre-COVID)	Short-term	×	×			×	×	×	×	×		×	×	
	Long-term	×					×	×	×	×		×		×
BIST 100 (COVID-affected)	Short-term					×		×		×	×		×	×
	Long-term				×			×					×	×
B3 (pre-COVID)	Short-term		×			×	×	×			×		×	×
	Long-term	×					×	×		×	×	×	×	
B3 (COVID-affected)	Short-term		×	×		×			×	×	×	×		×
	Long-term		×			×	×	×	×		×			×
BSE SENSEX (pre-COVID)	Short-term	×	×				×				×	×	×	×

Table 8 (continued)

Dependent stock markets	Forecasting period	Independent stock markets which account for significant variation of dependent stock markets												
		AEX	BEL 20	BIST 100	B3	BSE SENSEX	CAC 40	FTSE MIB	IBEX 35	LSE	NYSE composite	OMX 30	SMI	TASE
	Long-term			×										×
BSE SENSEX (COVID-affected)	Short-term	×		×	×		×	×	×		×	×		×
	Long-term			×			×		×		×	×		×
CAC 40 (pre-COVID)	Short-term			×	×	×				×	×			×
	Long-term	×		×								×		×
CAC 40 (COVID-affected)	Short-term			×		×					×	×		×
	Long-term												×	×
FTSE MIB (pre-COVID)	Short-term			×	×	×				×	×		×	×
	Long-term		×								×			
FTSE MIB (COVID-affected)	Short-term			×	×	×					×	×		×
	Long-term			×		×			×	×	×			×
IBEX 35 (pre-COVID)	Short-term			×	×	×				×	×		×	×
	Long-term			×										
IBEX 35 (COVID-affected)	Short-term					×				×	×	×	×	×
	Long-term	×	×		×			×					×	
LSE (pre-COVID)	Short-term	×	×			×	×	×			×	×		×
	Long-term	×					×	×	×			×		×
LSE (COVID-affected)	Short-term			×	×			×	×			×		
	Long-term			×		×						×		×
NYSE composite (pre-COVID)	Short-term			×	×	×		×	×	×			×	×

Table 8 (continued)

Dependent stock markets	Forecasting period	Independent stock markets which account for significant variation of dependent stock markets												
		AEX	BEL 20	BIST 100	B3	BSE SENSEX	CAC 40	FTSE MIB	IBEX 35	LSE	NYSE composite	OMX 30	SMI	TASE
	Long-term			×	×									×
NYSE composite (COVID-affected)	Short-term					×						×		×
	Long-term			×		×						×		×
OMX 30 (pre-COVID)	Short-term			×	×	×				×	×		×	×
	Long-term	×		×				×	×			×		×
OMX 30 (COVID-affected)	Short-term				×	×				×	×			×
	Long-term	×	×		×			×						
SMI (pre-COVID)	Short-term			×	×	×		×	×		×			×
	Long-term		×		×	×								
SMI (COVID-affected)	Short-term			×	×	×			×		×	×		×
	Long-term			×		×			×		×	×		×
TASE (pre-COVID)	Short-term			×	×	×	×		×	×		×	×	
	Long-term		×		×									
TASE (COVID-affected)	Short-term	×	×		×	×	×	×	×				×	
	Long-term	×	×					×					×	

Implies accountability of independent stock market variation of dependent stock market
× Implies non-accountability of independent stock market variation of dependent stock market

three exchanges, supporting the claim that the highest central return of TASE is not stable indeed. Kurtosis analysis confirms that all the exchanges are leptokurtic in nature, confirming the rate of change of price is higher in all the exchanges. During the COVID-affected period, TASE maintained its highest central value in the median associated with high fluctuation. It clarifies that, though TASE generates higher return in the middle of the COVID-affected period, it is still a riskier place to invest and high-risk–high-return strategy should be continued. BIST 100 exhibits the highest mean with more uncertainty. BIST follows the same trend like TASE. SMI has the least fluctuated index and low risk is associated with this market. LSE is possibly the most volatile and low-returning market. So, it is advisable for the investor to be very careful to invest. LSE and TASE exhibit negative skewness affirming the tendency of faster declination of these markets from the peak. The nature of BSE has been shifted from negatively skewed to positively skewed in this period. This observation suggests that BSE is more persistent near its peak during the COVID-affected period. Kurtosis in the COVID-affected period is much more positive compared to the pre-COVID period, for all the exchanges. This clearly signifies that change of stock prices deviates at a greater pace in the COVID-affected period, affirming more volatility in this period, compared to the pre-COVID period.

Correlation analysis indicates that, in the pre-COVID period, all the markets were positively correlated hinting at a possible linear relationship among them. In the COVID-affected period, B3, the most fluctuating market, before the pandemic, follows comovement in reverse direction compared to almost all other markets. BIST100, B3, BSE SENSEX, LSE, NYSE composite and TASE do not have any significant correlation with other markets in both the pre-COVID and COVID-affected period. Hence, international diversification is strongly recommended in this COVID pandemic too to take advantage of possible gain.

All the markets are stationary in both the periods, but increase of lag length of individual stock markets in the COVID-affected period indicates a possible mark of more intra-dependency of present market returns with previous returns in pandemic. It is evident from Figs. 1 and 2 that the number of linear causal relationships among stock markets reduced drastically (21 in the COVID-affected period vs. 72 in the pre-COVID period, out of a possible 156 relationships) in the COVID-affected period which is a very important finding in this study. It is also reflected in the analysis that the number of exogenous stock markets in the COVID-affected period (BIST 100, BSE SENSEX, FTSE MIB, LSE, SMI and TASE) doubled from the pre-COVID period (B3, NYSE composite and TASE). In this pandemic, markets are behaving more and more independently in the linear sense, along with increasing intra-dependency with its own lags. Linear interdependency of markets is reduced, as economic exchange among the countries has been shattered for a long period now. TASE, the highest returned and significantly uncorrelated index, is an exogenous market in both periods as far as linear causality is concerned. This market has stopped causing almost all other markets in the pandemics. But, B3, which was exogenous in the pre-COVID period, turned out to be endogenous in the COVID-affected duration which is another interesting outcome from our study. According to the IMF Foreign Trade forecast, the volume of imports of goods and services is expected to increase by 12.5% in Brazil in 2021 [52]. Maybe this makes B3 depend on investment from other countries. NYSE composite, another exogenous market in the pre-COVID period by linear causal analysis, is endogenous in the COVID-affected period as it is influenced by seven markets during this time. LSE, in five countries, plays a key part in linear causal analysis in the COVID-affected period. On the other handt, exogenous indices FTSE MIB do not make any impact on other markets except B3.

It is evident from Fig. 3 that nonlinear causal relationship has been increased (32 in the COVID-affected period compared to 21 in the pre-COVID period) remarkably during the COVID-affected period. COVID has made the underlying dynamics of the economic causal relationship move more toward nonlinearity. BIST 100, B3 and BSE SENSEX, all of which were exogenous in the pre-COVID nonlinear causal analysis, preserved their exogeneity in the COVID-affected period, too. BIST 100 and BSE SENSEX were exogenous in the COVID-affected linear causality analysis also. Hence, BIST 100 and BSE SENSEX are found to be exogenous markets in the COVID-affected period for both linear and nonlinear causal analysis. This explains the much more stable market conditions of these markets without being much bothered about the COVID situation in other countries. On the contrary, TASE, which was exogenous in the pre-COVID period, transforms to the endogenous market while nonlinear causality is concerned. CAC 40 is established to be a vital stock market in the COVID-affected period influencing six markets. OMX 30 raises its importance in the COVID-affected period making impact on six markets compared to only one before the pandemic.

General forecast error variance decomposition analysis confirms that TASE is an exogenous market, both in the pre-COVID period and the COVID-affected period. So, TASE is the most exogenous stock market in the pre-COVID period in the short term combining all analyses. But the notable finding is that TASE is forecasted to depend heavily on other markets in the long term after the pandemic was over, which is supported by its changing pattern in nonlinear causality analysis. TASE, being the only public stock exchange in Israel, is able to cope up with COVID as investors have no other option to diversify their capitals across other exchanges in Israel. That explains its exogeneity and neutral nature in this period. But COVID has forced it to depend on other countries nonlinearly and also in the long term in future.CAC 40 also is the most endogenous market in the short term for both the pre-COVID and COVID-affected period according to its variance

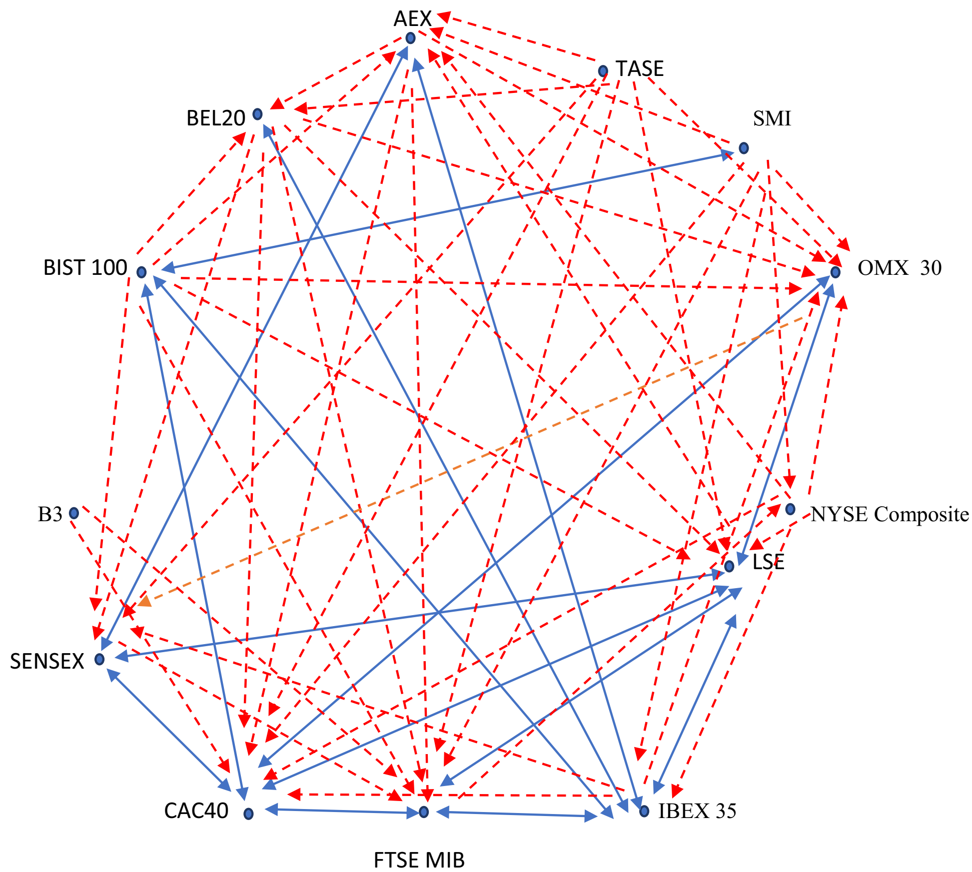

Fig. 1 Pictorial representation of linear Granger causality-Wald test based on VAR (15) model for log return data (pre-COVID period)

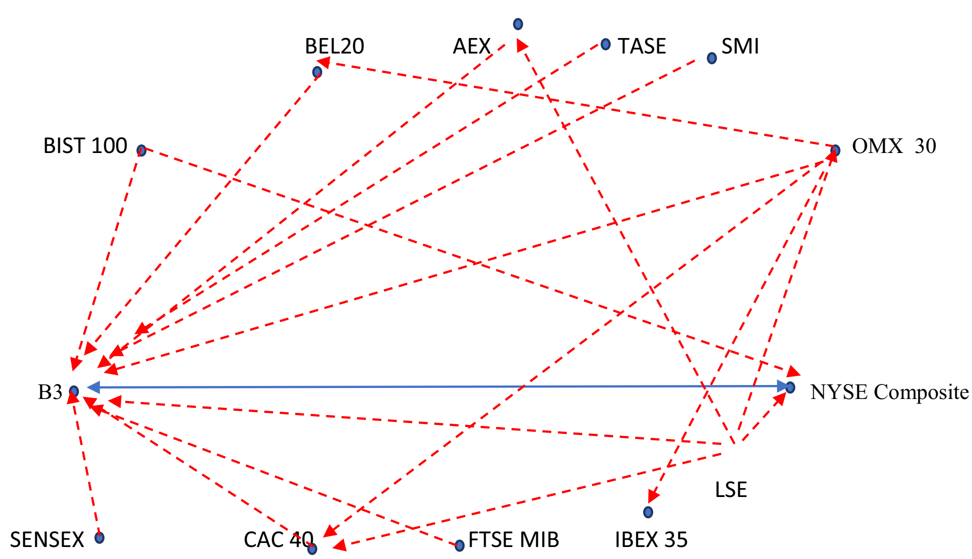

Fig. 2 Pictorial representation of linear Granger causality-Wald test based on VAR (16) model for log return data (COVID-affected period)

decomposition. This study matches with pre-COVID linear causality analysis. BIST 100 and BSE SENSEX is found to be exogenous in the pre-COVID short-term period agreeing with nonlinear causality analysis. BSE SENSEX tends to be exogenous in the short term for the COVID-affected period too, according to the findings from causality analysis. Interest rate in banks and other government-backed investment schemes are declining day by day in India, compelling the potential investors to invest in stock markets making it exogenous for the time being, irrespective of the situation of other foreign stock markets. Hence, it can be interpreted that the exogenous nature of BSE SENSEX may change in the distant future. In fact, variance decomposition analysis shows that association among the markets are more in the long term compared to short term, both in the

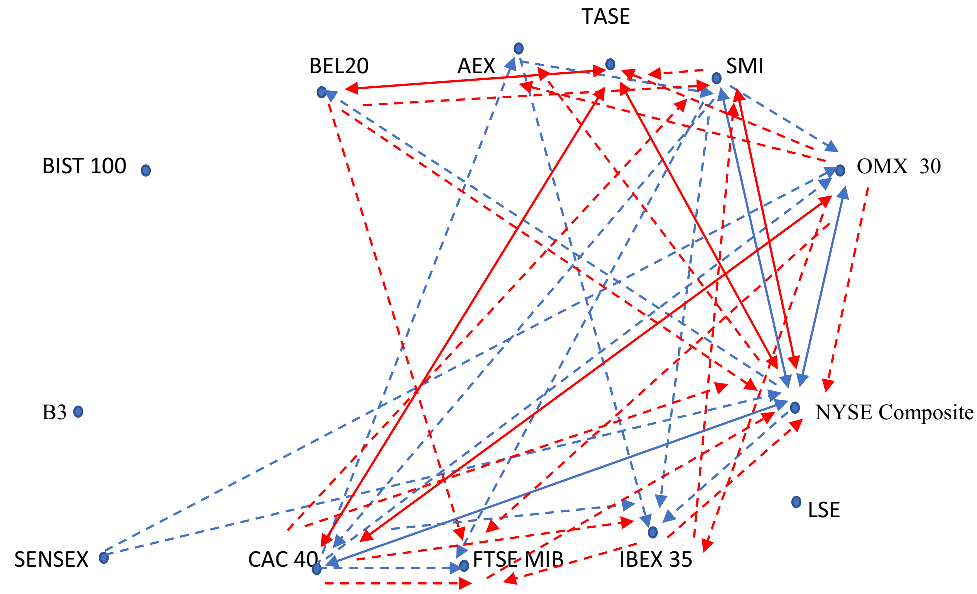

Fig. 3 Pictorial representation of pairwise nonlinear Granger causality-Diks–Panchenko test for log return data (pre-COVID period and COVID-affected period)

pre-COVID and COVID-affected period. Hence, it may be understood that COVID may not hamper the association of the stock exchanges in the long run, and markets are expected to regain long-term association once the effect of COVID fades away.

5 Conclusion

In brief, the COVID pandemic may have changed the underlying relationship among prime stock markets of most affected countries. Some exogenous stock markets may have become endogenous and vice versa in the pandemic. Linear relationship may have been reduced drastically in the COVID-affected period and nonlinear relationship possibly enhanced. Most of the counties may have become independent markets for the time being, though there is prediction of the recovery of the inter-relationship in future. It is advisable to maintain international diversification to enjoy possible gain in this pandemic-affected time. To sum up, the present work indicates an emergence of a new market dynamics in the pan world level. A very important interrogation in this aspect is the sustainability of these newer patterns and trends. Some analyses regarding the persistence have been performed here. A more comprehensive and reliable study can be made upon the availability of more data size.

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