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EFFECT OF HEALTH SYSTEM PERFORMANCE ON VOLATILITY DURING THE COVID-19 PANDEMIC: A NEURAL NETWORK APPROACH

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Abstract. The study proposes an assessment of the link between the performance of national health systems and volatility during the COVID-19 pandemic. Data from the World Health Organization was accessed regarding the Global Health Security Index of the states considered in the analysis as well as the categories based on which it is determined. To characterise volatility, a representative stock market index was considered for each of the 60 states analysed. Data processing was carried out using an artificial neural network. The main results show that: i) before the pandemic, the link between market volatility and the performance of national health systems was weak; ii) during the pandemic, the connection between the two variables is much stronger; iii) between the six categories that define the Global Health Security Index, norms, health, and prevention had the greatest influence on volatility.

Keywords: volatility, neural network, Global Health Security Index, pandemic, World Health Organization.

JEL Classification: M41, C83, L20, G32, M10, O16.

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1. Introduction

Volatility constitutes a fundamental aspect of financial market operations, serving as a metric for risk and uncertainty pertaining to financial assets, and impacting all participants within the stock market. Volatility forecasting is essential to allow the improvement of the decision-making process, especially during periods of financial turbulence. Accurately estimating volatility during major events, such as the COVID-19 pandemic, poses difficulty due to the complex nature, dynamics, and non-stationary behaviour of such a phenomenon.

Research conducted over the past three years addresses a significant gap in economic literature regarding the virus's impact on economies. Various approaches have been employed by researchers to measure volatility amidst the COVID-19 outbreak, including breakpoint investigation (Chahuán-Jiménez et al., 2021; Thangamuthu et al., 2022), assessments of stock market information efficiency levels (Chipunza et al., 2020; Arashi & Rounaghi, 2022), and evaluations of contagion effects (Joseph et al., 2020; Samitas et al., 2022), among others. While notable progress has been achieved, precise determinations regarding the direction, magnitude, and transmission pathways remain elusive.

The adverse repercussions of heightened volatility on the stock market are well-documented (Dzieliński et al., 2018). Faced with substantial losses, the imperative to seek safe-haven investments emerged from an investment standpoint. Consequently, a portion of capital shifted towards assets such as gold, bitcoin, and foreign currencies, traditionally considered a 'safe haven' during periods of financial tumult (Corbet et al., 2020; Ji et al., 2020).

The COVID-19 pandemic has represented an unprecedented threat to health systems since the beginning of 2020. Medical services have been severely impacted due to the high number of illnesses, inadequate resources for health facilities, social restrictions, shortage of medicines and medical equipment, and insufficient health personnel.

The primary drivers behind the surge in volatility included panic, fear, and uncertainty induced by the virus's effects, as well as the quest for a viable vaccine (Lyócsa et al., 2020). According to Arenas et al. (2020), the virus's reproductive capacity, coupled with its asymptomatic behaviour, facilitated the onset of a major crisis within national health systems. The necessity of limiting the spread of COVID-19 and upholding effective medical infrastructure prompted restrictions on movement. As the COVID-19 pandemic intensified, states responded by curbing economic activity, limiting population mobility, and implementing stimulus plans to mitigate economic contraction and layoffs (Gunay & Can, 2022; Zheng et al., 2021).

Numerous studies have delved into stock market volatility, both during and after the pandemic. Some of these studies have explored the connection between the health system and volatility (Lal et al., 2022; Rouf et al., 2022). Various authors have examined products (Chu et al., 2020), medical services (Feng et al., 2020; Greenhalgh et al., 2020; Rouf et al., 2022), vaccines (Lyócsa et al., 2020; Wang et al., 2022), infrastructure (Hunjra et al., 2021), treatment capabilities (Hu et al., 2022; Xu et al., 2021), and medical personnel (Pei et al., 2022). However, we observed that health systems were generally considered as a whole and their impact on volatility was viewed as unidirectional.

In addition, some researchers have studied the extent to which the impact of individual measures of a medical nature has influenced the volatility of equity markets (Karanasos et al., 2021; Rouf et al., 2022; Zaremba et al., 2020), currencies (Corbet et al., 2020), commodities (Corbet et al., 2020; Parmaksiz et al., 2023). Evidence has been identified of the influence of some medical measures adopted during the pandemic on the volatility of the stock market, such as: health policy (Arfaoui & Yousaf, 2022; Hunjra et al., 2021), vaccination (Baek & Lee, 2022; Wang et al., 2022), personal protective equipment (Garcia-Santaolalla & de Klerk, 2022), telehealth (Bettencourt et al., 2023), investment in healthcare (Arfaoui & Yousaf, 2022), stringency policies (Kotcharin et al., 2023). Our findings indicate a notable absence of research considering the components of a health system and their individual and aggregate influence on national market volatility.

We have not identified any comprehensive work that investigates the link between the GSHI, or another representative index for a medical system, and the volatility of shares at a national level that includes countries from all continents.

The paper is structured into the following sections. The initial section provides an introduction and a concise overview of the topic in the existing literature, followed by subsequent sections covering data, methodology, results, conclusions, limitations, and avenues for future research.

2. Literature review

The rapid spread of COVID-19 led to an increasing number of people falling ill, consequently elevating pressure on medical systems worldwide. Within a short period, the disease rate surpassed the capacity for hospital treatment. The emergence of initial fatalities, coupled with the absence of an antidote, shifted the focus towards national medical systems. Even states holding top positions in the WHO rankings were soon overtaken by the pandemic.

Various factors, particularly daily reports of deaths and illnesses, adversely influenced investor psychology. Jin et al. (2022) proposed the notion that various economic and medical standards between states could lead to varying effects on stock markets. The news effect emerged as a valuable tool capable of influencing investors. Furthermore, online social media granted public access to an immense pool of information (Engelberg & Parsons, 2011; Zhang & Hamori, 2021). The occurrence of an unexpected event generated an immediate and disproportionate response in asset prices. However, as new information became available and people acquired a better understanding of the situation, the markets corrected (Zheng et al., 2021). The effects of pandemic measures and new cases on stock market volatility diminished after 2021.

According to several studies, the health system played a pivotal role in managing the pandemic (Hu et al., 2022; Lal et al., 2022). Measures to prevent and contain the virus were implemented by all analysed states, providing a common foundation to estimate the impact on volatility. Infectious disease messages conveyed by public health officials tend to affect investor sentiment and stock markets alike (Smith, 2006). Hunjra et al. (2021) demonstrated that the impact of government health policies influenced investors' behaviour and caused volatility of various strengths in East Asian capital markets.

The methods recently used in the study of the volatility of financial assets identified by the authors included logistic regression (Chang et al., 2022), stochastic dominance of the second order (Ozdemir & Tokmakcioglu, 2022), multivariate regression based on a deep neural network with backpropagation algorithm and Bayesian network (Naveed et al., 2023), traditional econometric models Neuro Fuzzy, ANFIS and CANFIS, EGARCH and VaR (Sahiner et al., 2021), Analytic Hierarchy Process (AHP) method, ANN based on FF5F model factors (Jan & Ayub, 2019), and ANN based on the multilayer perceptron model as a machine learning algorithm (Khansari et al., 2022).

Machine learning (ML) models have impressively demonstrated their efficacy in developing accurate and efficient prediction systems (Rouf et al., 2022). One such method that contributed to volatility estimation included the neural network (NN; Ge et al., 2022). This approach has acquired significant popularity due to successful applications in other domains (Fatima & Uddin, 2022).

The use of variables in ANN processing by various researchers includes historical values (Chang et al., 2022), stock returns (Jan & Ayub, 2019), stock selection methods and portfolio optimisation (Ozdemir & Tokmakcioglu, 2022), traded derivative contracts (TFDCs), exchange rate, daily COVID-19 cases and deaths (Naveed et al., 2023), bond markets of BRICS countries (Castello & Resta, 2022), and capital markets indices (Sahiner et al., 2021). ANN modelling is preferred over GARCH and EGARCH models as neural network prediction models demonstrate improved forecast accuracy (Sahiner et al., 2021). ANN can serve as an alternative compared to traditional methods, especially in the presence of major turbulence (Castello & Resta, 2022).

The NN algorithm consists of a layered structure, similar to the biological neural organization that includes three categories of layers: input, hidden, and output layer (Rosenblatt, 1958). The first layer plays the role of receiving and processing data. The generated information is then directed to the hidden layer, which allows the interaction between the input and output neurons. The output layer generates the response calculated by the NN (Chang et al., 2022). Recurrent ANNs and their memory characteristics contribute to accuracy prediction. In addition, the number of hidden layers can be increased as more frequencies can be added, and alternative activation functions and input variables can be studied.

The GHSI is a tool designed to assess a state's overall health security. Based on open-source information, the index establishes the degree to which the 195 signatory countries of the International Health Regulations meet a number of 85 indicators grouped into six categories (GHS Index, 2021). Regardless of the presence of a few doubts regarding the content of some indicators, the weightage of the indicators, the priorities of high-income countries and the scoring system represent a global benchmark for any national health system. By way of elaboration, the GHSI complements existing tools and provides a broad picture of the state of global health security (World Health Organization [WHO], 2018). The advantages presented by the GHSI, the informational content, and the fact that it is the first comprehensive assessment and benchmarking of health security, determined its choice as a variable in the present research. We propose the following hypothesis:

H_0. There is a relationship between the GHSI and the volatility of the stock market during the analyzed period.

H_1. There is no relationship between the GHSI and the volatility of the stock market during the analyzed period.

The objective of this research was to establish a connection between the volatility of stock indices during the COVID-19 pandemic and the performance of health systems for each state included in the analysis. Studying the link between the GHSI index and stock volatility is still a missing link. In order to address this research gap, 60 states situated on different continents were selected for the study. Indicators and the Global Health Security Index were taken into account for each state analysed in the years 2019 and 2021. Given the dynamic and non-linear nature of the data, predicting stock market behaviour is a challenging task.

Our search on reputable research portals revealed a dearth of articles exploring the relationship between the GHSI and volatility, which further highlights the significance of delving into this topic.

3. Data and research methodology

3.1. Data

The paper investigates the relationship between the performance of health systems and the volatility of the capital markets in the analysed states. A total of 60 states were selected to provide a comprehensive global perspective on the phenomena under study.

To gauge volatility, the most representative index for each state in the analysis was considered. Daily data for each index was downloaded from the Investing platform (Investing, n.d.). Data regarding the performance of national health systems were also retrieved (GHS Index, 2021). According to the WHO (2018), each country has an annual Global Health Security Index that reflects the performance of its medical system. The scoring methodology involves categorising medical data into six groups: prevention, detection, response, health, norms, and risk (See Appendix for "Global Health Security Index structure").

The GHSI for 2021 classifies the states into six categories, 87 indicators, and 171 questions (GHS Index, 2021). Table 1 demonstrates the states included in the analysis, along with their associated index and the global score of their health system. The score for each analysed state was further detailed according to the WHO's defined categories in Appendix, Table A2. Data were processed using IBM SPSS Statistics 26 software.

Table 1. Stock market and health system index

No.	Country	Stock market index	Health index	
			2019	2021
1.	Australia	ASX200	72.60	71.10
2.	Belgium	BEL20	60.80	59.30
3.	Bosnia and Herzegovina	BIRS	35.80	35.40
4.	Brazil	BOVESPA	51.10	51.20
5.	Bulgaria	SOFIX	60.80	59.90
6.	Canada	TSX	68.30	69.80
7.	Chile	IPSA	54.40	56.20
8.	China	SHC	48.20	47.50
9.	Colombia	COLCAP	51.50	53.20
10.	Croatia	CROBEX	49.30	48.80
11.	Cyprus	CYMAIN	42.10	41.90
12.	Egypt	EGX30	28.60	28.00
13.	Estonia	OMX TALLINN	55.00	55.50
14.	Finland	HEX	71.70	70.90
15.	France	CAC40	62.30	61.90
16.	Germany	DAX40	65.60	65.50
17.	UK	FTSE250	67.90	67.20
18	Greece	ATHEX	51.00	51.50
19.	Netherlands	AEX	66.60	64.70
20.	Hungary	BUX	54.70	54.50
21.	Iceland	ICEX	48.10	48.50
22.	India	SENSEX30	43.10	42.80
23.	Indonesia	JCI	49.80	50.40
24.	Israel	TA100	48.90	47.20
25.	Ireland	ISEQ	55.20	55.30
26.	Italy	FTSEMIB	51.90	51.90
27.	Japan	NIKKEI	59.50	60.50
28.	Latvia	OMX RIGA	60.60	61.90
29.	Lithuania	OMX VILNIUS	56.80	59.50
30.	Malaysia	FBM KLCI	55.70	56.40
31.	Malta	MSE	39.80	40.20
32.	Mexico	IPC	55.90	57.00
33.	Mongolia	MNE	41.00	41.00
34.	New Zealand	NZX50	58.30	62.50
35.	Nigeria	NSE30	37.60	38.00
36.	Norway	OSEAX	60.90	60.20
37.	Pakistan	KSE	30.70	30.40
38.	Peru	SPBLPGPT	54.30	54.90
39.	Philippines	PSEI	44.70	45.70
40.	Poland	WIG20	54.90	55.70

End of Table 1

No.	Country	Stock market index	Health index	
			2019	2021
41.	Portugal	PSI20	56.90	54.70
42.	Qatar	QSI	46.90	48.70
43.	Czech Republic	PX	54.00	52.80
44.	Romania	BET	45.60	45.70
45.	Russia	RTS	48.10	49.10
46.	Saudi Arabia	TASI	44.90	44.90
47.	Singapore	STI	56.50	57.40
48.	Serbia	BELEX15	45.00	45.00
49.	Slovenia	SBITOP	68.30	67.80
50.	Slovak Republic	SAX	53.10	54.40
51.	South Africa	JTOPI	54.80	45.80
52.	South Korea	KOSPI50	65.70	65.40
53.	Spain	IBEX	60.60	60.90
54.	Sweden	OMX STOCKHOLM	65.90	64.90
55.	Switzerland	SMI	59.70	58.80
56.	Thailand	SET	68.70	68.20
57.	Turkey	XU100	49.90	50.00
58.	Ukraine	PFTS	38.10	38.90
59.	Argentina	MERVAL	55.30	54.40
60.	US	S&P500	76.10	69.80

Note: source of data: https://www.investing.com; https://www.ghsindex.org.

3.2. Methodology

The pandemic introduced an additional challenge in selecting the most suitable analysis models, given the recent advancements in ML methods. The collected data underwent processing with the assistance of NNs, specifically the multilayer perceptron (MLP). The MLPs were utilised to study volatility during the COVID-19 pandemic (Fatima & Uddin, 2022; Ibrahim et al., 2022; Khansari et al., 2022; Naveed et al., 2023) and post-pandemic period (Sahiner et al., 2021). These models describe the intricate relationships between independent predictor variables (Lu et al., 2016).

The choice of the method was based on the advantages it confers compared to other procedures. Thus, it was observed that NNs contribute to an increase in the predictability of stock prices compared to conventional methods (Sahiner et al., 2021), capture information in a more comprehensive manner (Chang et al., 2022), have a high error tolerance (Mijwel, 2018), accurately process sets of homogeneous data (Castello & Resta, 2022; Tripathi et al., 2022), demonstrate a better long-term predictive power compared to statistical methods (Jan & Ayub, 2019), and are superior to regression models or those based on the approach technique (Ozdemir & Tokmakcioglu, 2022). Compared to linear models, NNs can provide solutions to complex relationships without being reprogrammed (Caliskan Cavdar & Aydin, 2020; Talwar et al., 2022). The use of NNs allows the management of non-linear, univariate and multivariate relationships, the dynamics of which are difficult to follow with other methods.

Although NNs have several advantages, they are characterised by certain limitations. Determining the optimal combination is difficult, and the volume of data is often large to obtain an accurate result (Caliskan Cavdar & Aydin, 2020). In addition, there are limitations in handling qualitative information (Li & Xiong, 2005), and the perceptron cannot identify linearly inseparable data (Chang et al., 2022). NNs assume the tuning of a few hyperparameters (Roshandel-Arbatani et al., 2019) and are sensitive to scaling (Khansari et al., 2022). Lastly, they cannot forecast the financial situation of markets without information classification (Naveed et al., 2023).

Volatility for each index was determined based on the daily closing prices using the relationship:

$$R_{i,t} = \frac{P_{i,t}}{P_{i,t\text{-}1}} \times 100, \tag{1}$$

where $R_{i,t}$ represents the value of index i in period t, $P_{i,t}$ is the index value in period t, and $P_{i,t-1}$ is the index value in period $t-1$.

A neural network model consists of a multilayer perceptron and a group of interconnected nodes. Multilayer perceptrons belong to the traditional category of NNs and possess broad applicability. They are capable of estimating a nonlinear volatility function $y = f(X)$, where X represents the input data (Lu et al., 2016). The perceptron model of the layers involves a weighted linear function of the input values, $X = (x_1, x_2, \ldots, x_n)$, expressed by the following relation:

$$a_j = \sum_{i=1}^{n} \omega_{ji}^{(1)} \times x_i, \tag{2}$$

where n represents input nodes.

The activation of a hidden unit j is obtained with a function f defined as follows:

$$f(a_j) = \frac{1}{1 + \frac{1}{e^{a_j}}}; \tag{3}$$

$$f(a_j) = f\left(\sum_{i=1}^{n} \omega_{ji}^{(1)} \times x_i\right). \tag{4}$$

A node on the output layer is defined as follows:

$$y_k = \tilde{f}\left(\sum_{j=1}^{m} \omega_{jk}^{(2)} \times \left(\sum_{i=1}^{n} \omega_{ji}^{(1)} \times x_i\right)\right). \tag{5}$$

As MLPs are interconnected, any node on a layer is connected with a certain weight ω_{ij} to every node on the next layer. Estimating volatility involves defining the function:

$$\hat{y}_{t+1} = f(X_t), \tag{6}$$

where $\hat{y}_{t+1}$ represents the estimated volatility, and X_t is the observation matrix composed of previous return.

A neural network involves a training process to acquire the correct results. Training is initiated by providing input and output known values. The neural network-specific algorithm adjusts the weights of hidden nodes and output nodes until the obtained result aligns with the actual value in the training sample. After the training process is complete, the model can be used to generate new output data drawn from the remaining initial sets. If the fit is accepted, the relationships between the input and output data can be generalized to generate predictions on other samples.

4. Results

This section presents the results related to stock index variations for all 60 states considered in the analysis. Appendix (Tables A3 and A4) contains the descriptive statistics of the series of logarithmic returns over the entire considered period. The average, median, minimum and maximum values provide us with information about the value range of the stock market indices during the analyzed period. It can be seen that the skewness indicator has values different from 0 for all the series considered to have the meaning of an asymmetry. For most of the series, the value of the indicator is negative, which indicates a negative impact of the health index on the analyzed stock market indicators.

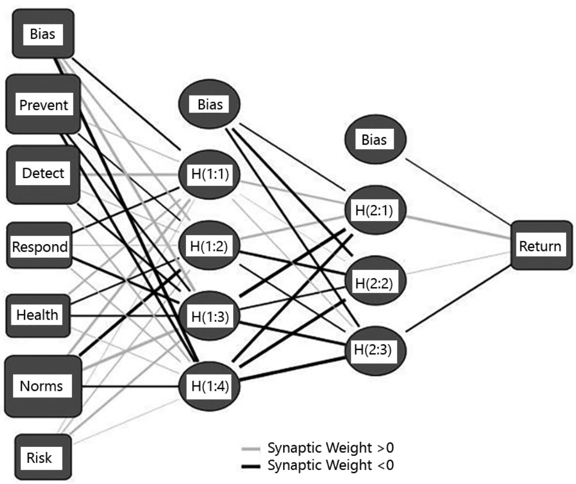

Figure 1. Multilayer perceptron model (2019)

During our research, we employed a neural model with two hidden layers. The input layer comprised the six criteria outlined by the WHO with a bias unit. The hidden layers consisted of five and four nodes, respectively, including one bias unit. At the outset of the output layer, a single node represented volatility.

Figure 1 depicts the results obtained for the year 2019, with a relative error of 0.963 in training and 1.536 in testing. The parameter estimations are presented in Table 2.

Figure 2 illustrates the results for the year 2021, indicating a relative error of 0.931 in training and 1.02 in testing. Parameter estimations for 2021 can be found in Table 3.

The importance of independent variables was as follows: norms (0.283), health (0.273), prevent (0.244), risk (0.089), respond (0.079), and detect (0.033). Although surprising, these results align with the perspective of government actions. The rapid spread of the COVID-19 pandemic prompted rapid responses from governments (Dinh & Paresh, 2020).

Table 2. Predicted Parameters for 2019

Predictor		Predicted							
		Hidden Layer 1				Hidden Layer 2			Output Layer
		H(1:1)	H(1:2)	H(1:3)	H(1:4)	H(2:1)	H(2:2)	H(2:3)	Return
Input Layer	(Bias)	–0.203	0.262	0.425	–0.463				
	Prevent	0.055	–0.065	–0.221	–0.327				
	Detect	0.401	0.056	–0.223	0.214				
	Respond	–0.181	0.043	–0.319	0.147				
	Health	0.228	–0.137	–0.165	0.053				
	Norms	0.370	–0.420	0.492	–0.198				
	Risk	0.041	0.109	0.289	0.031				
Hidden Layer 1	(Bias)					–0.061	–0.336	–0.240	
	H(1:1)					0.259	0.020	0.057	
	H(1:2)					0.340	–0.327	–0.132	
	H(1:3)					–0.501	–0.167	–0.350	
	H(1:4)					–0.401	–0.459	–0.493	
Hidden Layer 2	(Bias)								–0.047
	H(2:1)								0.414
	H(2:2)								0.043
	H(2:3)								–0.175

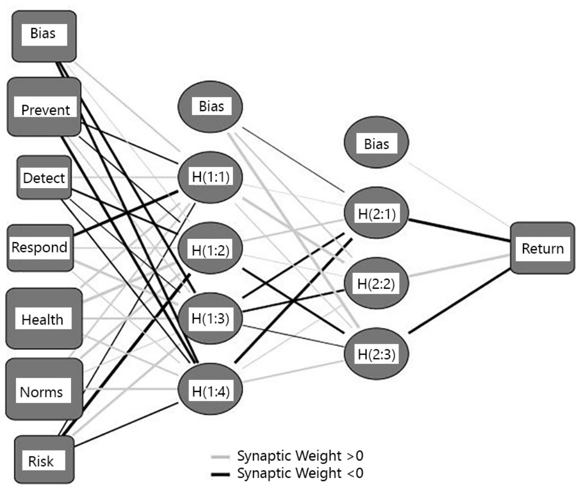

Figure 2. Multilayer perceptron model (2021)

5. Discussion

The measures taken by governments included investments in health systems, which rationalise the influence of this category. Other measures included in this category were related to testing policy, public information campaign, facial coverings, investment in COVID-19 vaccines and health care, contact tracing, and vaccination policy (Hale et al., 2022).

Another explanation for these results may lie in the set of public health norms established by the WHO, which were framed as nonpharmaceutical interventions aimed at mitigating and containing the virus (WHO, 2020a, 2020b). The recommended measures included the isolation and home quarantine of suspected cases, as well as social distancing for the elderly and those suffering from comorbidities.

Furthermore, government interventions in health and protective policies, as well as fiscal measures, included business closures, social distancing (Chu et al., 2020), investments in protective equipment, quarantine, testing, and treatment of positive cases (Hunjra et al., 2021), contact tracing, travel restrictions, border closures, workplace closing, school closures, restrictions on internal movement, closed public transport, restrictions on gathering size, and preventive measures at ports and airports.

Table 3. Predicted parameters for 2021

Predictor		Predicted							
		Hidden Layer 1				Hidden Layer 2			Output Layer
		H(1:1)	H(1:2)	H(1:3)	H(1:4)	H(2:1)	H(2:2)	H(2:3)	Return
Input Layer	(Bias)	0.229	0.058	–0.363	–0.370				
	Prevent	–0.179	–0.128	0.169	–0.392				
	Detect	0.222	–0.262	–0.086	–0.193				
	Respond	–0.473	0.168	0.380	0.114				
	Health	0.303	0.490	0.284	0.239				
	Norms	0.225	0.346	0.100	0.325				
	Risk	–0.132	–0.492	0.350	–0.220				
Hidden Layer 1	(Bias)					–0.029	0.222	0.487	
	H(1:1)					0.009	0.441	0.108	
	H(1:2)					0.274	0.020	–0.328	
	H(1:3)					–0.325	–0.291	–0.059	
	H(1:4)					–0.415	0.102	0.242	
Hidden Layer 2	(Bias)								0.043
	H(2:1)								–0.486
	H(2:2)								0.414
	H(2:3)								–0.378

According to Hunjra et al. (2021), a correlation between price volatility and government health measures was observed in four Asian states (China, Japan, Singapore, and Thailand). The authors studied the link between volatility and individual health policies. Provided that these four states were included in the selected sample of our current research, we corroborate the findings of the authors regarding the varying impact of protective measures adopted.

Health emerged as the second most influential category impacting volatility in 2021. Such a result may have occurred due to actions taken to ensure the well-being of medical personnel, optimising available hospital capacity, establishing new patient treatment units, maximising medical resources, implementing medical countermeasures, and the exponential increase in medical supply chain deliveries (Hale et al., 2021). The pandemic facilitated the rise of Internet hospitals offering outpatient services to the public through specialised technologies (Xu et al., 2021).

The "prevent" category encompassed several actions, among which, in the authors' view, the testing and immunisation campaign played a decisive role. Additionally, potential explanations include public campaigns (Hale et al., 2021), facial coverings (Feng et al., 2020; Greenhalgh et al., 2020), and biosecurity and biosafety measures (Vennis et al., 2022).

Among the recommendations for preparedness and prevention against the impacts of future pandemics formulated by Lal et al. (2022), financial measures should be observed for their significant influence on capital markets. Ensuring the financing of investments from global health security, financial mechanisms for a pandemic response, and domestic and regional financing for the pandemic can lead to a reduction in the capital market assets volatility.

According to Vo et al. (2022), the volatility of stock markets in the Asia-Pacific region can no longer be solely attributed to the COVID-19 virus from 2021. Our results support the conclusions of these studies. Although countermeasures had waned in 2021, there is an increase in the correlation between diminishing volatility and the performance of national health systems. Prevention and surveillance remain crucial activities that have helped curb the spread of COVID-19. Another recommendation would be to anticipate outbreaks using a free internet tool Google Health Trends, as demonstrated by Fulk et al. (2022).

Our study illustrates that when markets operate normally without being affected by turbulence, there is no significant relationship between health system performance and financial market volatility. If turbulences of the nature of pandemics occur, decisions and actions in the medical field significantly impact the dynamics of financial markets. Among the working hypotheses proposed in the study, based on the existing gap in the literature, H_0 is accepted. Stock volatility occurs when various regulations or health measures are implemented. Although states implemented common public health measures, their effect on stock prices varied across countries, which is in line with evidence provided by Zaremba et al. (2020).

6. Conclusions

The results demonstrate that the COVID-19 virus has shifted investors' focus towards health systems. To validate the increasing strength of the connection between health system performance and stock market volatility, an NN model was employed.

The findings affirm the connection between the categories comprising the global health system index and the volatility of market values in the states studied in this analysis. While such a link was found to be insignificant in 2019, an amplified connection was observed during the pandemic. Among the six categories constituting the GHSI, three exerted a more pronounced influence in 2021: norms, health, and prevention. The remaining categories and associated stocks aligned with medical principles; however, they showed a minor impact on volatility in both 2019 and 2021. In addition to these aspects, it is imperative to underscore the pivotal role of research, particularly in the medical field.

Medical countermeasures have the potential to somewhat stabilise the stock market during pandemics. Thus, during a pandemic, investors and portfolio managers can turn to states that adopt consistent prevention rules and measures.

The results have implications for financial market participants. Medical and government authorities and regulators should consider the impact of health measures on stock price volatility and capital market balance. During pandemics, investors and portfolio managers should consider the decisions made in states characterised by a higher GHSI index to inform their own decisions about stocks, options, risk management, and hedging policy in the stock market. With such results, investors can implement appropriate diversification and hedging strategies during turbulent times to protect themselves.

The study's limitation arises from the absence of values for the year 2020 concerning the health index. As this data is anticipated to be released by the WHO, it is crucial to acquire complete results. The connection between health and volatility may have been more robust during the first wave of the pandemic in 2020. To substantiate this, further studies exploring the existence of a link between volatility and health systems could be conducted during other pandemics induced by Zika, SARS, FTM, and similar pathogens. Future research endeavours may delve into the 87 indicators defining the Global Health Security Index and their relationship with volatility.

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Author contributions

The authors state that they contributed equally to the article.

Disclosure statement

The authors declare no conflict of interest.

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APPENDIX

Table A1. Health Index by Category

Country	Prevent		Detect		Respond		Health		Norms		Risk	
	2019	2021	2019	2021	2019	2021	2019	2021	2019	2021	2019	2021
Australia	67.4	65.2	80.1	82.2	65.9	61.6	67.6	69.2	75.2	72.2	78.7	76.0
Belgium	56.0	54.2	52.9	52.9	51.6	46.4	64.3	64.2	60.8	61.1	78.1	77.2
Bosnia and Herzegovina	31.7	30.4	13.8	13.9	36.4	36.7	40.7	41.7	41.4	38.9	50.3	50.7
Brazil	49.7	49.7	52.5	53.6	61.1	56.3	50.3	50.3	39.7	41.7	54.2	55.9
Bulgaria	66.7	66.8	61.7	61.7	42.8	38.9	59.3	60.8	69.4	69.4	62.8	61.7
Canada	70.0	70.4	66.4	70.8	49.3	49.2	65.8	67.3	75.9	79.2	81.4	81.8
Chile	46.9	47.2	49.6	58.1	60.3	59.5	50.4	52.9	52.8	53.1	66.3	66.2
China	43.9	43.9	48.5	48.5	42.5	38.5	50.6	51.8	38.9	38.9	64.2	63.4
Colombia	49.0	50.9	49.4	57.9	52.7	49.8	46.2	48.5	61.5	61.5	49.8	51.0
Croatia	49.4	47.7	37.8	37.8	32.9	31.0	51.4	51.4	56.9	59.7	65.8	65.0
Cyprus	44.2	44.1	24.1	25.0	35.4	34.0	32.0	32.3	52.5	52.8	65.0	62.9
Egypt	16.2	15.7	18.8	18.9	23.4	20.9	18.4	18.8	33.6	33.3	60.7	60.3
Estonia	42.0	42.5	41.3	41.3	60.0	56.2	47.9	49.4	66.3	66.7	74.8	76.9
Finland	60.2	58.2	66.1	67.5	78.3	70.7	65.5	68.7	77.8	77.8	81.6	82.6
France	61.4	59.4	45.4	45.7	51.8	47.7	68.8	70.4	62.6	65.3	82.7	82.9
Germany	49.1	49.1	70.9	72.4	62.9	56.3	54.7	56.0	71.9	75.0	82.7	83.9
UK	63.4	63.5	64.9	70.8	66.9	64.8	66.7	68.3	70.3	62.5	74.5	73.0
Greece	48.2	44.8	48.9	48.9	49.0	46.7	44.4	46.2	57.3	63.9	56.4	58.0
Netherlands	59.1	57.8	59.5	57.1	65.5	58.2	66.9	66.7	67.7	68.1	79.7	80.2
Hungary	51.0	49.4	38.1	38.1	53.2	50.1	55.9	54.6	59.6	62.5	69.2	71.7
Iceland	37.3	40.0	34.9	36.4	46.4	47.9	49.7	52.2	38.7	34.4	80.5	79.9
India	29.7	29.7	40.8	43.5	33.9	30.3	46.1	46.1	47.2	47.2	59.5	60.2
Indonesia	32.9	31.8	49.9	55.4	55.3	50.2	40.3	41.2	63.9	68.9	54.3	55.0
Israel	41.6	52.9	45.1	50.4	48.0	41.4	53.9	51.7	34.8	55.6	68.2	79.9
Ireland	52.9	52.9	50.1	50.4	42.4	41.4	50.5	51.7	55.6	55.6	79.1	79.9
Italy	47.2	47.2	49.7	49.7	45.7	43.2	40.2	40.2	61.6	65.3	65.5	65.9
Japan	44.9	43.1	60.4	71.1	61.6	59.5	50.4	51.6	66.7	66.7	70.5	70.9

Table A1

Country	Prevent		Detect		Respond		Health		Norms		Risk	
	2019	2021	2019	2021	2019	2021	2019	2021	2019	2021	2019	2021
Latvia	50.4	51.6	73.9	77.1	54.9	51.2	57.8	60.6	56.9	59.7	68.4	71.3
Lithuania	37.7	38.2	62.9	64.3	53.0	58.7	55.0	59.9	62.5	62.5	68.5	73.30
Malaysia	40.5	37.7	61.6	72.5	63.6	61.4	37.5	36.6	53.0	56.4	73.5	73.9
Malta	34.7	36.2	21.3	21.8	28.5	27.4	25.8	26.4	55.3	55.6	73.4	73.8
Mexico	41.8	41.9	52.0	54.3	62.7	64.8	53.5	54.7	68.1	68.1	57.3	57.9
Mongolia	31.2	30.2	37.9	37.9	42.5	41.1	24.3	24.3	44.4	46.2	64.2	66.3
New Zealand	46.5	45.0	54.4	75.3	52.8	50.3	47.8	48.9	63.7	77.8	77.1	77.7
Nigeria	20.8	20.1	37.1	37.9	42.6	43.2	23.4	23.4	57.7	62.8	41.5	40.7
Norway	51.5	53.8	49.2	46.3	63.6	57.5	45.0	45.0	66.2	69.4	88.3	89.0
Pakistan	17.1	17.1	28.0	29.2	20.7	18.8	26.1	26.8	46.5	45.8	45.2	44.8
Peru	37.7	37.7	52.7	57.8	47.8	45.8	67.4	71.7	63.7	61.5	55.2	55.0
Philippines	27.7	37.7	43.0	57.8	41.9	45.8	46.4	71.7	54.6	61.5	52.6	55.0
Poland	44.9	43.5	37.6	42.5	56.8	53.3	54.0	52.7	65.8	72.2	69.9	70.1
Portugal	52.8	52.8	43.5	42.6	50.7	41.5	52.2	53.9	61.9	59.7	77.3	77.5
Qatar	34.8	36.4	37.2	39.7	54.6	55.2	41.4	42.4	45.3	46.7	68.3	71.7
Czech Republic	46.4	46.1	37.8	37.8	52.7	50.1	55.8	55.8	55.4	51.4	75.1	75.6
Romania	40.3	39.0	39.4	44.0	26.7	24.7	46.7	47.9	55.3	55.6	63.6	63.3
Russia	44.0	45.5	40.0	43.6	49.2	44.7	53.4	58.9	51.4	51.4	50.0	50.5
Saudi Arabi	33.4	33.4	51.0	52.1	34.9	32.7	39.8	40.7	49.4	49.5	60.3	61.2
Singapore	48.4	46.8	53.7	61.1	63.3	61.3	46.2	47.3	47.7	48.6	79.6	79.5
Serbia	44.0	44.0	28.6	28.6	38.1	36.3	48.5	50.9	51.1	51.4	58.7	58.5
Slovenia	66.0	65.7	67.9	70.8	62.5	59.9	67.6	72.8	71.9	63.9	72.9	73.4
Slovak Republic	51.6	51.3	35.9	37.1	40.7	43.7	60.7	62.7	58.9	59.7	71.8	72.2
South Africa	44.8	32.1	81.5	50.0	57.7	62.0	33.3	29.2	46.3	43.1	61.8	58.5
South Korea	50.9	48.8	69.2	73.8	71.4	65.0	60.2	62.5	67.5	69.4	73.8	73.1
Spain	47.6	47.5	66.4	70.8	58.5	54.6	51.2	52.9	63.6	63.9	75.4	75.6
Sweden	79.9	77.3	63.8	62.5	42.3	39.8	53.6	53.5	70.5	73.6	83.6	82.7
Switzerland	50.2	50.2	40.7	42.5	69.1	64.9	50.9	50.9	64.7	59.7	84.0	84.6
Thailand	62.2	59.7	83.9	91.5	74.9	67.3	63.1	64.7	67.2	68.9	58.2	57.2
Turkey	50.7	51.1	38.8	41.4	40.2	36.6	51.3	53.9	59.7	59.7	57.5	57.2
Ukraine	31.8	31.4	29.7	32.8	29.1	26.1	41.0	49.1	48.9	47.2	45.4	46.7
Argentina	41.5	41.5	55.5	56.7	47.3	43.6	64.4	64.4	62.7	59.7	59.8	60.6
US	78.8	79.4	76.3	80.1	70.4	65.7	75.2	75.2	81.9	81.9	73.6	73.3

Note: source of data: https://www.ghsindex.org.

Table A2. Global Health Security Index structure

Category	Aspects included
1) Prevention of the emergence or release of pathogens	1.1) Antimicrobial resistance 1.2) Zoonotic disease 1.3) Biosecurity 1.4) Biosafety 1.5) Dual-use research and culture of responsible science 1.6) Immunisation
2) Early detection & reporting epidemics of potential international concern	2.1) Laboratory systems strength and quality 2.2) Laboratory supply chains 2.3) Real time surveillance and reporting 2.4) Surveillance data accessibility and transparency 2.5) Case-based investigation 2.6) Epidemiology workforce
3) Rapid response to and mitigation of the spread of an epidemic	3.1) Emergency preparedness and response planning 3.2) Exercising response plans 3.3) Emergency response operation 3.4) Linking public health and security authorities 3.5) Risk communication 3.6) Access to communications infrastructure 3.7) Trade and travel restrictions
4) Sufficient & robust health sector to treat the sick & protect health workers	4.1) Health capacity in clinics, hospitals and community care centres 4.2) Supply chain for health system and healthcare workers 4.3) Medical countermeasures and personnel deployment 4.4) Healthcare access 4.5) Communications with healthcare workers during a health emergency 4.6) Infection control practices and availability of equipment 4.7) Capacity to test and approve new medical countermeasures
5) Commitments to improving national capacity, financing and adherence to norms	5.1) IHR reporting compliance and disaster risk reduction 5.2) Cross-border agreements on public health and animal health emergency 5.3) International commitments 5.4) JEE and PVS 5.5) Financing 5.6) Commitment to sharing of genetic & biological data & specimens
6) Overall risk environment and country vulnerability to biological threats	6.1) Political and security risk 6.2) Socio-economic resilience 6.3) Infrastructure adequacy 6.4) Environmental risks 6.5) Public health vulnerabilities

Note: source of data: https://www.ghsindex.org.

Table A3. Descriptive statistics (2019)

Index	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
ASX200	0.000732	0.001577	0.019283	–0.028885	0.006875	–0.871139	5.397891	92.24688	0.000000
BEL20	0.000806	0.001031	0.029229	–0.031862	0.008412	–0.576504	4.386462	34.41387	0.000000
BIRS	0.000356	0.000000	0.051466	–0.064661	0.009953	–0.731111	16.50308	1921.575	0.000000
BOVESPA	0.000970	0.001801	0.027529	–0.038105	0.011161	–0.548834	3.872440	20.23370	0.000040
SOFIX	–0.000127	–0.000439	0.026495	–0.019374	0.005955	0.997742	6.126859	140.4585	0.000000
TSX	0.000694	0.000750	0.014936	–0.018823	0.004630	–0.459890	4.219186	24.29594	0.000005
IPSA	–0.000378	–0.000684	0.077586	–0.047160	0.010510	1.240539	16.23039	1857.289	0.000000
SHC	0.000876	0.000504	0.054493	–0.057455	0.011391	–0.184922	7.992468	253.7479	0.000000
COLCAP	0.000906	0.000977	0.021327	–0.026512	0.007639	–0.559329	4.085838	24.70945	0.000004
CROBEX	0.000626	0.00067	0.020734	–0.015957	0.004402	0.259208	5.276415	55.87092	0.000000
CYMAIN	5.37E–05	–0.000790	0.043380	–0.045693	0.012268	0.357016	4.294847	22.04691	0.000016
EGX30	0.000230	9.22E–05	0.032564	–0.054645	0.010187	–0.616678	7.520074	221.3517	0.000000
OMXTALLINN	0.000362	0.000409	0.014526	–0.011581	0.003415	0.433452	5.611095	78.53186	0.000000
HEX	0.000463	0.001085	0.030819	–0.023280	0.008232	–0.036903	3.611953	3.941817	0.139330
CAC40	0.000956	0.001626	0.026878	–0.036355	0.008363	–0.738271	5.568519	92.89480	0.000000
DAX40	0.000900	0.001537	0.033144	–0.031563	0.008838	–0.355115	4.909725	43.24455	0.000000
FTSE250	0.000867	0.001227	0.041047	–0.020123	0.007457	0.653987	7.229493	205.7938	0.000000
ATHEX	0.001687	0.002023	0.059118	–0.043748	0.011930	0.208587	6.304091	113.6833	0.000000
AEX	0.000855	0.001131	0.023859	–0.032201	0.007442	–0.687612	5.368673	79.39462	0.000000
BUX	0.000605	0.000706	0.023640	–0.017494	0.007747	0.085546	2.680231	1.342653	0.511030

Continued Table A3

Index	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
ICEX	0.000892	8.15E–05	0.027539	–0.030287	0.007959	0.077135	4.058362	11.72528	0.002844
SENSEX30	0.000532	0.000344	0.051859	–0.020838	0.008677	1.164056	8.431873	353.6192	0.000000
JCI	7.77E–05	0.000670	0.019475	–0.026285	0.007129	–0.191370	3.393871	3.066523	0.215831
TA100	0.000745	0.001153	0.020082	–0.031285	0.007075	–0.694844	5.138632	65.86293	0.000000
ISEQ	0.001058	0.001072	0.036658	–0.028608	0.009717	0.078464	3.488475	2.785896	0.248342
FTSEMIB	0.000991	0.001095	0.033114	–0.029120	0.009336	–0.386973	4.246428	22.51235	0.000013
NIKKEY	0.000792	0.000940	0.025782	–0.030526	0.008600	–0.064365	4.205348	14.69436	0.000644
OMXRIGA	0.000434	0.000399	0.054531	–0.040916	0.008308	0.709258	12.33046	916.6746	0.000000
OMXVILNIUS	0.000570	0.000458	0.012944	–0.011354	0.003148	0.471170	4.942385	47.96804	0.000000
FBMKLCI	–0.000201	–0.000254	0.013955	–0.016796	0.004798	–0.244870	3.605294	6.138030	0.046467
MSE	0.000176	0.000406	0.021835	–0.022197	0.005002	0.182734	6.142340	102.9976	0.000000
IPC	0.000118	–0.000431	0.024226	–0.022423	0.008155	0.227199	3.506798	4.826261	0.089535
MNE	–0.000397	–0.000769	0.025058	–0.023855	0.007122	–0.096866	4.122551	13.51721	0.001161
NZX50	0.001077	0.001268	0.018630	–0.021565	0.006074	–0.421346	4.044651	18.83991	0.000081
NSE30	–0.000701	–0.001307	0.042572	–0.021630	0.008629	0.772372	5.986931	115.9069	0.000000
OSEAX	0.000522	0.000687	0.025282	–0.025696	0.008388	–0.168812	3.659101	5.666852	0.058811
KSE	0.000283	0.000149	0.035111	–0.026813	0.011649	0.131784	3.091089	0.797098	0.671293
SPBLPGPT	0.000231	0.000407	0.014635	–0.024099	0.006248	–0.510663	3.822164	17.97850	0.000125
PSEI	0.000175	8.94E–05	0.027854	–0.029954	0.009280	0.030666	3.547151	3.069247	0.215537
WIG20	–0.000224	–0.000763	0.029674	–0.028280	0.009039	0.105639	3.961464	9.973156	0.006829

End of Table A3

Index	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
PSI20	0.000375	0.000382	0.027832	–0.022148	0.007642	–0.153321	3.582254	4.583092	0.101110
QSI	5.63E–05	–0.000179	0.033764	–0.042529	0.008018	–0.230226	7.189337	184.2866	0.000000
PX	0.000482	0.000890	0.016183	–0.020792	0.005910	–0.550751	4.074593	24.56858	0.000005
BET	0.001166	0.000979	0.036825	–0.043235	0.008634	–0.128661	7.299683	191.7194	0.000000
RTS	0.001412	0.001399	0.028331	–0.040322	0.009463	–0.379598	4.665920	35.05287	0.000000
TASI	0.000293	0.001155	0.024149	–0.036154	0.008951	–0.392065	3.705199	11.53871	0.003122
STI	0.000236	0.000278	0.015349	–0.030429	0.006210	–0.446073	5.245263	60.56021	0.000000
BELEX15	0.000363	0.000120	0.033794	–0.032935	0.006541	–0.501185	10.09028	536.2701	0.000000
SBITOP	0.000571	0.000336	0.014360	–0.016527	0.004531	0.076950	4.259636	16.43916	0.000269
SAX	0.000222	0.000000	0.027012	–0.042232	0.007635	–0.941682	9.456902	467.4660	0.000000
JTOPI	0.000462	0.000185	0.021976	–0.028303	0.008492	–0.355422	3.310612	6.218382	0.044637
KOSPI50	0.000610	0.000549	0.024720	–0.033229	0.008777	–0.274340	3.700578	8.347514	0.015394
IBEX	0.000435	0.000427	0.024855	–0.028069	0.007834	–0.348039	3.955222	14.78463	0.000616
OMXSTOCKHOLM	0.000929	0.001351	0.029534	–0.027793	0.008827	–0.421317	3.809256	14.16111	0.000841
SMI	0.000913	0.001439	0.022564	–0.021055	0.006673	–0.329339	3.846843	11.89368	0.002614
SET	3.64E–05	–0.000116	0.018496	–0.018595	0.005942	–0.048604	3.386395	1.607347	0.447681
XU100	0.001019	0.001436	0.040425	–0.058399	0.012943	–0.428490	5.647245	80.00398	0.000000
PFTS	–0.000413	–0.000348	0.049418	–0.021445	0.007478	2.068399	16.30987	1732.202	0.000000
MERVAL	0.001205	0.004924	0.097312	–0.476922	0.041645	–6.311638	73.24865	51578.98	0.000000
S&P500	0.001006	0.001012	0.033759	–0.030230	0.007878	–0.637566	6.234040	126.3887	0.000000

Table A4. Descriptive statistics (2021)

Index	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
ASX200	0.000482	0.000813	0.018653	–0.023796	0.007178	–0.484152	3.754443	15.94693	0.000344
BEL20	0.000675	0.000771	0.023727	–0.026498	0.007952	–0.249906	3.498621	5.358164	0.068626
BIRS	0.000572	0.000000	0.044944	–0.054433	0.007646	–0.215747	20.85178	3401.304	0.000000
BOVESPA	–0.000514	0.000584	0.035977	–0.049884	0.013272	–0.540639	3.735916	17.60629	0.000150
SOFIX	0.001427	0.001148	0.024419	–0.019857	0.007419	0.206646	3.452384	3.848478	0.145987
TSX	0.000784	0.001264	0.020293	–0.023394	0.006613	–0.420138	4.306914	25.24733	0.000003
IPSA	0.000124	–0.000334	0.092508	–0.097946	0.016332	–0.456168	11.75069	806.3220	0.000000
SHC	0.000193	0.000334	0.023751	–0.025191	0.008821	–0.286429	3.370467	4.712305	0.094784
COLCAP	–7.71E–05	–0.000447	0.031807	–0.029500	0.010076	0.138181	3.858575	8.304748	0.015727
CROBEX	0.000714	0.000896	0.015107	–0.014887	0.004577	–0.142526	4.094100	13.31573	0.001284
CYMAIN	0.000716	0.000473	0.036658	–0.033435	0.010869	0.118706	3.943505	9.741751	0.007667
EGX30	0.000397	0.000606	0.026555	–0.024844	0.009030	–0.032400	2.892184	0.160871	0.922714
OMXTALLINN	0.001587	0.001765	0.051975	–0.043524	0.010389	–0.275199	7.458514	211.0626	0.000000
HEX	0.000667	0.001235	0.035817	–0.035734	0.008851	–0.275041	4.694867	33.33923	0.000000
CAC40	0.000982	0.001620	0.028659	–0.048671	0.008803	–0.880237	7.046028	209.2983	0.000000
DAX40	0.000575	0.001052	0.032525	–0.042408	0.009065	–0.458974	5.570978	79.18343	0.000000
FTSE250	0.000539	0.000637	0.018920	–0.032395	0.007717	–0.523664	4.166051	25.89634	0.000002
ATHEX	0.000398	0.001153	0.025808	–0.045562	0.010093	–0.94533	5.333738	93.59208	0.000000
AEX	0.000949	0.001307	0.034532	–0.032623	0.008970	–0.193225	4.195617	16.97255	0.000206
BUX	0.000739	0.000968	0.028350	–0.029855	0.009985	–0.084607	2.987132	0.302387	0.859681
ICEX	0.001350	0.001908	0.035367	–0.029663	0.008230	0.091955	4.803697	34.24112	0.000000

Continued Table A4

Index	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
SENSEX30	0.000805	0.000709	0.048802	–0.038737	0.009998	–0.144142	5.938969	89.74999	0.000000
JCI	0.000389	0.000771	0.034403	–0.021473	0.008604	0.179318	3.783921	7.648263	0.021837
TA100	0.001111	0.000947	0.018501	–0.030113	0.007911	–0.409581	3.795877	13.26187	0.001319
ISEQ	0.000524	0.000157	0.043643	–0.045873	0.010870	0.019424	5.252052	54.53743	0.000000
FTSEMIB	0.000809	0.001533	0.030698	–0.047064	0.009828	–0.639590	5.522944	85.34988	0.000000
NIKKEY	0.000196	0.000297	0.030698	–0.040668	0.011732	–0.220761	3.311097	2.977997	0.225598
OMXRIGA	0.000462	0.000112	0.038138	–0.035760	0.007532	0.326557	7.483300	212.1075	0.000000
OMXVILNIUS	0.000675	0.000446	0.017878	–0.024746	0.005689	0.015176	5.291382	54.48277	0.000000
FBMKLCI	–0.000153	–0.000161	0.020119	–0.022422	0.006803	0.058240	3.485536	2.545061	0.280122
MSE	–0.000189	–0.000261	0.033925	–0.018437	0.007149	0.663321	5.575852	85.69884	0.000000
IPC	0.000750	0.000816	0.020936	–0.029681	0.008859	–0.329470	3.268981	5.339920	0.069255
MNE	0.003377	0.001170	0.065249	–0.051449	0.017037	0.873854	5.818765	113.2075	0.000000
NZX50	–1.77E-05	0.000102	0.020864	–0.021734	0.006824	0.146440	3.349525	2.174775	0.337096
NSE30	0.000197	–1.84E-07	0.028799	–0.024048	0.006640	0.130122	7.351352	196.3539	0.000000
OSEAX	0.000880	0.000926	0.026545	–0.032642	0.008857	–0.303015	3.758753	9.901266	0.007079
KSE	7.70E-05	–0.000461	0.027189	–0.048201	0.009350	–0.313760	5.737277	81.16491	0.000000
SPBLPGPT	4.96E-05	5.19E-06	0.054061	–0.080608	0.015262	–0.274364	8.035910	268.3764	0.000000
PSEI	–9.58E-06	0.000462	0.049817	–0.036718	0.011771	0.063628	4.910370	38.18446	0.000000
WIG20	0.000712	0.000660	0.033144	–0.037316	0.010969	0.011797	3.527305	2.913770	0.232961
PSI20	0.000498	0.001084	0.031405	–0.027326	0.009716	–0.209377	3.322229	3.001253	0.222990

End of Table A4

Index	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
QSI	0.000434	0.000355	0.027315	–0.028131	0.005819	–0.054935	6.901249	158.0301	0.000000
PX	0.001307	0.001100	0.032351	–0.019116	0.006964	0.270697	4.666090	32.09623	0.000000
BET	0.001138	0.001040	0.017080	–0.034709	0.007143	–0.938577	6.245990	147.6317	0.000000
RTS	0.000549	0.001568	0.040505	–0.057083	0.013804	–0.612628	4.467977	38.84722	0.000000
TASI	0.001044	0.001423	0.027887	–0.046339	0.007394	–0.991338	10.53741	632.7455	0.000000
STI	0.000371	0.000627	0.029228	–0.025737	0.007233	–0.012677	4.413843	21.07907	0.000026
BELEX15	0.000401	5.06E-05	0.021596	–0.025910	0.005525	–0.069169	6.172096	105.0138	0.000000
SBITOP	0.001317	0.001221	0.020465	–0.026703	0.005979	0.065708	5.203977	51.18524	0.000000
SAX	0.000566	0.000000	0.068036	–0.016407	0.007052	3.512718	35.68526	11595.96	0.000000
JTOPI	0.000838	0.000823	0.032617	–0.028886	0.010629	–0.236291	3.240070	2.926737	0.231455
KOSPI50	4.48E-05	0.000327	0.051186	–0.032191	0.011359	0.416613	4.625338	34.47186	0.000000
IBEX	0.000298	0.000787	0.031483	–0.050836	0.010238	–0.562805	5.148091	62.73377	0.000000
OMXSTOCKHOLM	0.001009	0.001524	0.027377	–0.040816	0.009473	–0.430893	4.769328	40.82995	0.000000
SMI	0.000727	0.001591	0.020767	–0.024138	0.006683	–0.314001	3.999394	14.74444	0.000628
SET	0.000557	0.000647	0.026285	–0.023229	0.007577	–0.040901	4.139766	13.11200	0.001422
XU100	0.000922	0.001980	0.052385	–0.103068	0.016483	–2.078919	14.79874	1623.665	0.000000
PFTS	0.000183	0.000000	0.034320	–0.014654	0.003171	6.392419	70.84339	48853.32	0.000000
MERVAL	0.002002	0.001598	0.071151	–0.064130	0.019626	0.008949	3.529315	2.851693	0.240305
S&P500	0.000945	0.001364	0.023512	–0.026013	0.008256	–0.369155	3.699471	10.86079	0.004381