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Health Capital and a Sustainable Economic-Growth Nexus: A High-Frequency-Data Analysis during COVID-19

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Abstract: The recent COVID-19 pandemic effectively concretized the vitality of health expenditure and the economic-growth nexus, and the threat of new pandemics make re-examining this relationship a necessity. Consequently, this paper focuses on this nexus for developed OECD countries, paying particular attention to the effects of the COVID-19 pandemic. The use of stock indices as proxy variables for health expenditure and economic growth enabled the examination of this nexus by using high-frequency data and financial econometric techniques, specifically via rolling correlation and bivariate GARCH analyses. The data span 1170 observations between 15 May 2018 and 11 November 2022. Since the research period overlaps with the outbreak of Ukraine–Russia war, additional insights are obtained regarding the effects of the war as well. It was found that an increase in health expenditure leads to a delayed increase in economic growth even in the short term, and this relationship mainly develops during crises such as epidemics, wars, supply chain breakdowns, etc., for developed OECD countries. Given the aging population of developed countries, which will probably deteriorate the health status of those countries in the near future, the increasing political tensions around the globe and the considerations of a global recession highlight the importance and the inevitability of investments in health capital for developed countries as well.

Keywords: COVID-19; health expenditure; economic growth; OECD countries; stock indices; proxy variables

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1. Introduction

It was first reported in the late 1950s [1,2] that production increase in developed economies is much faster than that attributable to increases in physical inputs and the labor force in these economies. An early 1960s pioneering study [3] examined the role of education and healthcare in stimulating economic growth regarding health as a capital. The health-led growth hypothesis proposed rests on the notion that investments in healthcare services improve human capital productivity, and healthcare spending provides a continuous stream of return in the future. In the meantime, in another pioneering study, the authors of [4] introduced the term human capital, implying a combination of investments in a human being that improves his/her working capacity. In 1970s, in accordance with the argument of the authors of [5], who underlined that through investing in education and health, a person aims to increase his/her future income, the authors of [6] redefined the term human capital as 'a combination of innate capabilities as well as acquired skills, knowledge and motivation that are used for producing goods and services and represent a source of human and social income', which consequently improves productivity and thus economic growth [7]. Later, with the rise of the Endogenous Growth Theory during 1980s, which differs from neoclassical growth through emphasizing that economic growth is not a result of forces that impinge from the outside, but an endogenous outcome of an economic system [8] generated as a direct result of internal processes such as human capital, innovation and technical progress, the importance of human capital on economic growth and development started to receive accelerating attention theoretically and empirically, leading to a strong consensus on the significance of human capital accumulation for economic growth (among many others, see [9–26]), especially for developing countries, although ongoing internationalization efforts in the healthcare sector have posed problems in terms of data security and, therefore, studies conducted on developing countries present limitations in terms of data reliability [27]. Further, human capital is demonstrated to have both external and internal spillover effects on growth [28] and is argued to have an indispensable role in achieving high levels of sustainable economic growth which, according to Organization for Economic Co-operation and Development (OECD), means growth that balances economic, social, and environmental considerations [29].

Sustainable economic growth refers to the development and expansion of economic activities in a manner that promotes long-term prosperity without compromising the ability of future generations to meet their own needs. This involves achieving a balance between economic growth, social progress, and environmental stewardship. It encompasses strategies that prioritize efficient resource use, environmental conservation, social equity, and resilience to external shocks. As is also noted in [30], unless countries improve their human capital, they can neither achieve sustained economic growth nor will they have a capable workforce to handle the more highly skilled jobs of the future and eventually will be unable to compete effectively in the global economy. Despite how initially the attention was focused on education as the main factor in human capital formation [31], and how the contribution of the health status to growth is less emphasized in the extant literature [32], among the aspects of human capital such as education, training, skills, competencies, intelligence, experience, etc., health deserves special attention, since past empirical research shows that it is much more important for economic growth than even the education level (among others, see [33–36]). Health capital, which implies investments in a human being that are necessary for maintaining his/her health and capacity [31,37], significantly affects the efficiency and the effectiveness of the work force. In this sense, healthcare spending is argued to increase life expectancy and reduce morbidity and infant mortality [31,38–41] on the one hand, and will improve labor productivity, quality of life, and general welfare [42–44] on the other. Health expenditure, as an investment in human capital, will not only support labor supply but will also promote a higher incentive for the worker to improve their skills and knowledge to enjoy the long-term benefits [45], as health enables people to work harder and longer, and to think more clearly [46]. Health provides an environment for people to learn and develop in mentally, physically, and emotionally [47,48]. In turn, an increase in individual human capital will improve the individual's efficiency, supporting the productivity of all production factors [28]. Additionally, improved healthcare services will also help people to recover from health problems and return to work more quickly [42]. Further, due to increased longevity and a decreased number of lost working days attributable to ill-heath, a healthier workforce contributes to an increased output [49]. Moreover, a better health condition leads to higher cognitive skills with positive effects on creative and innovative activities, leading to a more responsive workforce to technological changes as well as innovative processes [31]. Thus, through increasing productivity, health capital fosters sustainable economic growth. In return, the increase in economic growth will positively affect health expenditures and health statuses with a feedback effect [50].

The arguments above highlight the importance of healthcare policies on sustainable economic growth. Hence, it is unsurprising that the relationship between health expenditure and economic growth has been empirically investigated extensively in recent decades (among many others, see [51–66]). However, these studies mainly focus on underdeveloped and developing countries [52,53,55,56,59,61–65], while research on developed countries is relatively rare [46,51,54,57,58]. Nevertheless, the sources of growth for developed and developing economies are not exactly the same. While for developed countries, improved total factor productivity is the major factor fostering growth, for developing countries, poor capital accumulation, especially the problems in the growth of savings and investments, is the major bottleneck [67–69]. Additionally, mortality reductions can support growth in developing countries, whereas they can lead to an aging population in developed ones [70]. Still, a poor health-labor force will adversely affect productivity while the aging populations of developed countries constitute a substantial threat to their health statuses and human capital. Therefore, to reduce these adverse effects, they should invest in health expenditures to improve their health status [71]. Meanwhile, the recent COVID-19 pandemic highlighted considerations of health capital and underlined the vitality of the healthcare expenditure to support economic growth. As argued by the authors of [72], as COVID-19 continues to evolve, new variants will pose a significant risk of overriding the immunity conferred by natural infection and vaccination, which can cause an upswing in reinfections, pandemic activity, and localized outbreaks. Given the threat of new pandemics, it reveals that such pandemics will increase health expenditures in the coming years. Thus, it is clear that long-term health investments should be made, and more efficient health policies should be formulated. All in all, the health capital and economic-growth nexus should be re-examined in detail in many aspects.

Considering the arguments mentioned above, in an attempt to fill a gap in the literature, this paper is designed to examine the health capital and economic-growth nexus during the COVID-19 pandemic, focusing mainly on developed countries. Additionally, since the research period overlaps with the outbreak of the Ukraine–Russia war, which started in February 2021, it will provide additional insights regarding the effects of the war as well. Consequently, this paper aims to contribute to the existing literature in many aspects. First, since most of the major stock exchange markets are based in developed countries, our sample mainly consists of OECD countries for which the relationship between health expenditures and economic growth is relatively under-investigated. In fact, the only exception is China, a non-OECD country, where the Shanghai Stock Exchange is based. More importantly, in the analyses, special attention is devoted to the effects of COVID-19 on this nexus which, to the best of our knowledge, has not been investigated yet due to the fact that our data, methodology, and group is differing from one existing study [63]. Another distinguishing feature of this study lies in the methodological approach it follows. Since no quarterly or monthly frequency data are available on health expenditures by country, the previous research in the literature that examines the relationship between health expenditure and economic growth is conducted by using annual (i.e., low-frequency) data (among others, see [73–78]). However, using proxy variables enables us to examine the health capital and economic-growth nexus with very high-frequency data. In this respect, we use the stock market health index as a proxy for health expenditures and investments in healthcare, i.e., health capital. Since health companies listed on the stock exchanges of developed countries are important health companies around the world, they not only have high trading volumes but are also high-performing companies in research and development. Therefore, the increases in health expenditures and investments in healthcare in these countries lead to an increase in the share prices of companies which will then translate into increases in the value of the health index. Thus, a country's daily health-expenditure data can be followed from the health sector's index movements. Especially during the COVID-19 period, investment news posted on social media probably tends to drive up demand for shares in health companies, thereby causing their stock prices and hence the healthcare index to increase. As can be followed from [79], among the group of seven (G7) countries, the returns on the healthcare indices of the United States, the United Kingdom, France, Italy, and Germany were all positive during the COVID-19 period. The news on social media during the COVID-19 period mainly revolved around vaccines and similar short-term investments, such as that described in [80]. The returns on these investments were realized swiftly during the extraordinary circumstances (for a multi-country and multi-industry analysis on the absorptive intensity and duration of stock-price indices, including healthcare indices, during the shock of the COVID-19 pandemic, see [81]). If these vaccines had failed to achieve their intended purpose, it is likely the pandemic would not have ended as quickly. The investment expenditures made by these companies were promptly reflected in the price series. Consequently, stock market share prices moved upward in response to investment news and served as effective proxies for healthcare consumption or investments during this period.

Similarly to proxy economic growth, we focus on the industrial index, which, as the largest and the fastest-moving sector of the economy, represents a crucial component of economic growth and is the most convenient option for this research. For example, if instead we focus on sectors such as tourism, transportation, and agriculture, seasonal effects and similar behaviors would be encountered, and it would not have allowed us a chance to perform an accurate analysis. Alternatively, if the indices of software, investment, and technology companies were chosen, since we are dealing with sectors that act with too many expectations, companies that price their growth with respect to the future rather than to today would be included in the analysis [50]. The general index, on the other hand, would be more problematic, since it comprises many firms from all sectors, including health companies and others, mentioned above. Thus, within the content of our study, the industrial index is the best representative variable, not only because it plays a locomotive role in growth but displays economic growth in real-time and has little seasonal effect. Correspondingly, the industrial indices of the stock exchange markets under consideration are used in the daily movements of economic growth. Consequently, with the use of health and industrial indices as proxy variables for health capital and economic growth, respectively, we reached a higher frequency of data, which enabled us to examine the relationship between health capital and economic growth in the short term. Additionally, due to the different natures of high-frequency and low-frequency data, different econometric techniques should be used. In this regard, this is the first study that uses financial data and applies financial econometric techniques to examine the health capital and economic-growth nexus. Therefore, we enriched the extant literature by extracting insightful observations from these ephemeral datasets through the application of rolling correlation and bivariate GARCH analyses.

2. Materials and Methods

2.1. Research Data

The daily health sector index data were extracted from the investing.com website, which spans 1170 observations between 15 May 2018 and 11 November 2022. The health-sector and industry-sector indices used as a proxy for health capital and economic growth, respectively, are provided along with their respective sources in Table 1. The developing countries' data have limitations in terms of data reliability, which we have considered extensively in the Introduction Section, so we will not continue to discuss the issue throughout this study, as we have focused on developed OECD.

Table 1. Data sources.

Series	Healthcare Index	Industrial Index	Country
SPC	S&P/TSX Canadian Healthcare (GSPTTHC)	S&P/TSX Canadian Industrials (GSPTTIN)	Canada
DAX	DAX Pharmaceuticals & Healthcare (CXPPX)	DAX Dax Industrial (CXPNX)	Germany
DJH	Dow Jones Healthcare (DJUSHC)	Dow Jones Industrial Average (DJI)	USA
FTSE	FTSE Italia All Share Healthcare (FTITLMS20)	FTSE Italia All Share Industrials (FTITLMS50)	Italy
BEL	BEL Healthcare Net Return (BEHC)	BEL Industrial Engineering (BEIE)	Belgium
AEX	AEX Healthcare (NLHC)	AEX Industrials (NLIN)	Netherlands
CAC	CAC Healthcare (FRHC)	CAC Industrials (FRIN)	France
SSE	SSE Healthcare (SSEHC)	SSE Industrials (SSEIN)	China
SP500	S&P 500 Healthcare (SPXHC)	S&P 500 Industrials (SPLRCI)	USA
NASDAQ	NASDAQ Healthcare (IXC)	NASDAQ Industrial (IXID)	USA

The basic statistics of the price series are provided in Table 2, and the graphical plots of the series under consideration are presented in Figure 1 below.

Table 2. Basic statistics.

Series	Obs	Mean	Std Error	Minimum	Maximum
SPCHLT	1170	72.08	31.11	20.78	145.79
DAXHLT	1170	4561.58	416.73	3346.56	5363.87
DJHLT	1170	1180.94	196.44	809.48	1540.53
FTSEHLT	1170	226.97	54.05	133.03	340.02
BELHLT	1170	3316.75	410.47	2496.01	4448.73
AEXHLT	1170	2249.56	472.56	901.61	3141.06
CACHLT	1170	1807.42	243.72	1419.77	2338.72
SSEHLT	1170	7781.33	1653.93	4841.94	11,615.66
SP500HLT	1170	1263.42	208.83	870.99	1664.58
NASDAQHLT	1170	966.31	172.06	671.20	1356.39
SPCIND	1170	310.45	49.48	209.65	402.24
DAXIND	1170	7068.57	1073.48	3643.08	9279.19
DJIND	1170	29,240.39	3991.94	18,591.93	36,799.65
FTSEIND	1170	34,667.17	4576.91	20,610.94	43,492.60
BELIND	1170	1333.98	292.63	684.88	1983.12
AEXIND	1170	1838.58	521.54	1027.86	3015.40
CACIND	1170	2188.21	250.05	1301.90	2635.57
SSEIND	1170	2351.38	386.72	1724.04	3192.85
SP500IND	1170	712.52	110.48	412.06	905.63
NASDAQIND	1170	8216.23	1965.99	5040.90	12,147.21

As can be seen, Figure 1 contains ten graphs where each refers to a stock market under investigation. For each market, the price series of both the health and the industrial indices are shown. It can be observed that the correlation changes over time. It can also also seen that similar movements in each stock market are realized for the sample period. Although each stock index has its own behaviors, they exhibit similar patterns in some periods.

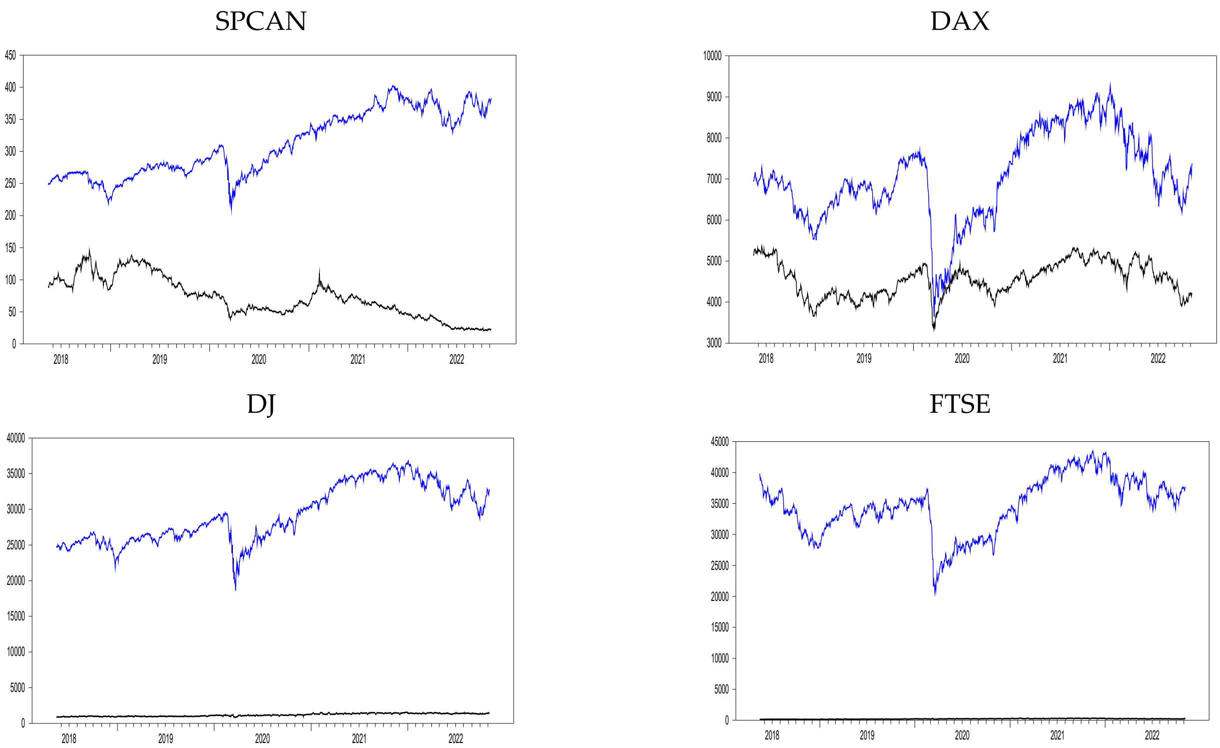

Figure 1. *Cont.*

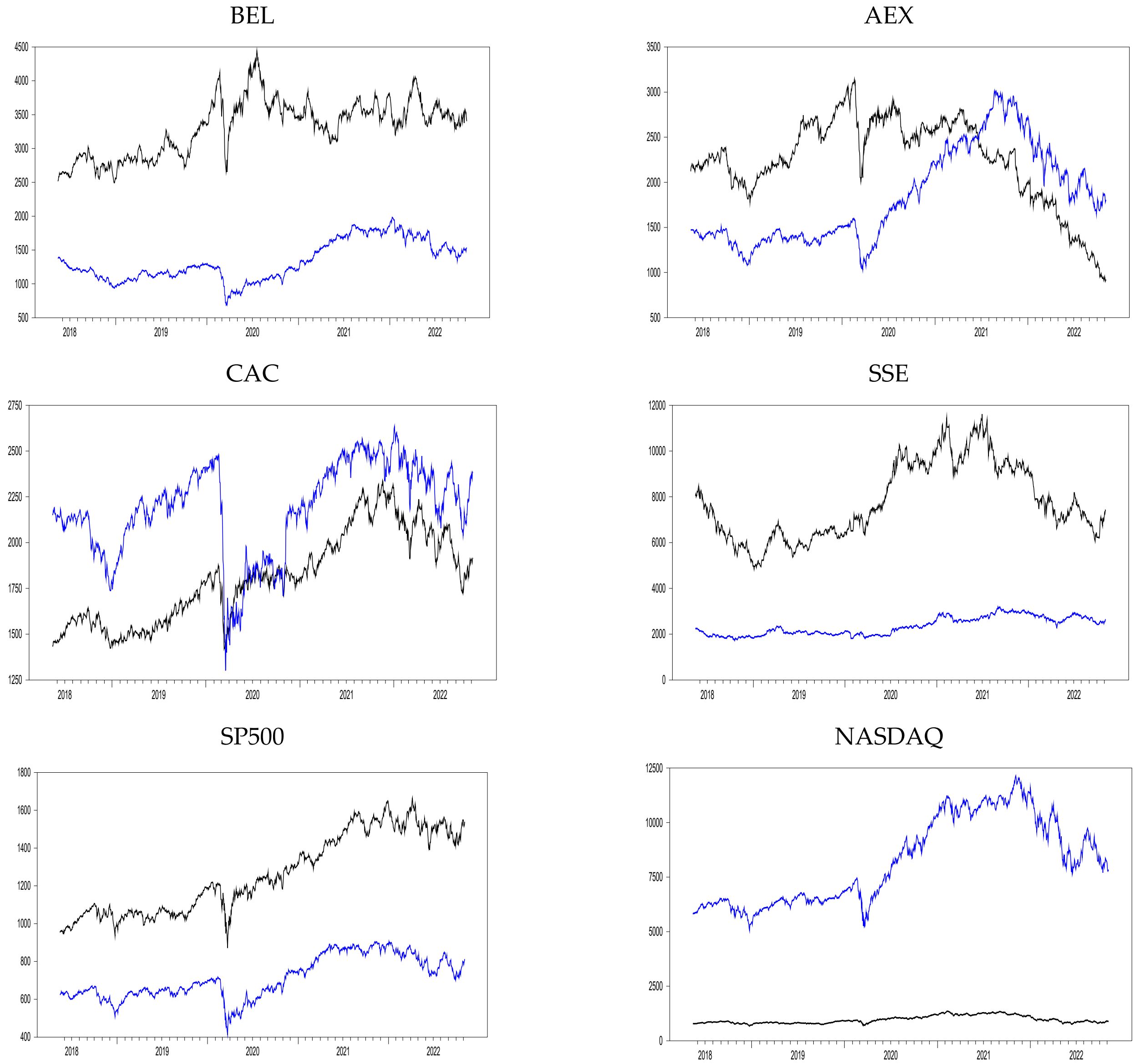

Figure 1. Series under investigation: the blue lines show the industrial-production index, and the black ones show the healthcare index.

2.2. Preliminary Analyses

We started our analyses by examining correlations between the prices of the health and the industrial stock indices. For this purpose, health and industry stock indices were examined with simple correlation analyses, which were performed by considering only the lag numbers in the date range of 15 May 2018–11 November 2022, covering the sampling period. Since simple correlation analysis provides a simple average of the sampling period, rolling window correlation analysis is used for time-varying correlation analysis. We kept the first ten observations constant for the initial correlation in the rolling window and repeated the correlation analysis by adding each day on top. As a result, 1160 correlation calculations were made.

Unit root tests were then applied to proceed with the regression analysis as a next step. An augmented Dickey–Fuller (ADF) test [82] was conducted to determine the integration order for the level series, which enabled us to determine the type of regression analysis. If the series of both the industrial and the health stock indices are stationary for the same market, spurious regression is not a problem; thus, we could obtain statistical inferences with the regression analysis made to the level of the series. If a unit root result characterizes the level in both series, then there is a long-term relationship, and a cointegration analysis can be performed. For this, a long-term regression analysis of the series can be performed, and the existence of a long-term relationship can be examined by performing an [83] Engel Granger (EG) cointegration test analysis on the residuals of the series. Otherwise, a regression analysis can be run by equalizing the integration levels, but in this case, an analysis of how a stock's price affects its return can be made. However, since the sampling period is too short and the prices of the indices are too volatile for a cointegration test to be performed properly, we proceeded with the analyses using the return series.

The health and industrial sectors' stock returns were computed by the equations $HIR_t = \log(HIR_t/HIR_{t-1})$ and $IIR_t = \log(IIR_t/IIR_{t-1})$, respectively. Continuing through the return series provided us with two advantages: evaluating meaningful relationships between prices, which we see in the correlation and regression analyses. First, all returns will be stationary, and we will avoid integration problems. Second, the mean equation, the returns themselves, and the volatility of these returns can be examined with the GARCH or variance equation. In order to capture an advantageous situation, the first difference of the series is taken and converted into a return series. The logarithmic difference is used for this following operation: $R_t = \log(P_t/P_{t-1})$. And to see how the return series' mean and variance effects move cumulatively, similar to the price series, the sliding window correlation analysis is performed in the return series. In order to calculate the correlation, we first keep the first ten series in the analysis and then increase the window one day at a time so that we can see in which direction the cumulative effects change the correlation coefficient every time a new period is added. We find this analysis appropriate in that it shows the accumulation in the cumulative effect more clearly than the one that is performed by adding big blocks or increments.

Then, again, the ADF test is applied to ensure all the return series are stationary and to determine the integration order for the return series. However, since data with volatility are handled with GARCH modeling in time series analysis, and due to the feedback effect between the health index and the industrial index, which requires the analyses to be performed within the VAR equation system, the bivariate GARCH method is preferred to eliminate the endogeneity bias, that is, the feedback effect. This modeling style started in [84] and was later expanded with an equations system. This modeling style enables us to decompose the series as the mean and variance and to examine how the health index affects the industrial index in the period under investigation or how the reverse movement develops. Within the aim of this research, we will focus on examining the causality effects of the variance equation, that is, volatility. Before performing the analysis, a brief technical explanation of the method will be given. When the simple correlation formula is used in the correlation analysis, cov(x,y)/var(x)var(y) does not need a detailed explanation, but the summary of the mathematical structure of this model is provided in the next section.

2.3. Bivariate GARCH Model: Bivariate GARCH Model

We denote both the health index return and industrial-index return, respectively. Then, a VAR model (see [85] for the nonlinear bivariate version of the above modeling strategy) can be written as follows:

$$x_t = \phi_1 + \sum_{i=1}^{p-1} \varphi_{1i} x_{t-i} + \varepsilon_t, \tag{1}$$

where x_t is a (2 × 1) column vector given by $x_t = (HIR_t, IIR_t)'$, ϕ_j j = 1,2 is a (2 × 1) vector of constants, $\varphi_{j,i}$, $j = 1, 2$, and $i = 1, \ldots, p$ are (2 × 2p) matrices of parameters, and $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})$ is a (2 × 1) vector of residuals.

We assume that the vector of residuals ε_t is conditionally normal, with a mean vector 0 and covariance matrix H_t, that is, $(\varepsilon_t|\Omega_{t-1}) \sim \mathrm{N}(0, H_t)$ where Ω_{t-1} is the information set available at time t − 1. We assume that the conditional covariance matrix H_t has the GARCH (1,1) structure proposed by the authors of [80]. (In addition to the diagonal CCC GARCH (1,1) model of [80], we estimated other types of multivariate GARCH models and found similar results. The Akaike Information Criteria (AIC) criteria suggest that the suitable model is CCC GARCH (1,1). The estimation results with other specifications are available upon request.) In particular, we assume that the following:

$$h_{s,t} = \alpha_s + \beta_s h_{s,t-1} + \gamma_s \varepsilon^2_{s,t-1}$$

$$h_{b,t} = \alpha_b + \beta_b h_{b,t-1} + \gamma_b \varepsilon^2_{b,t-1},$$

$$h_{sb,t} = \rho_{s,b} \sqrt{h_{s,t} h_{b,t}} \quad \text{constant correlation}$$

$$h_{sb,t} = \alpha_{s,b} + \beta_{s,b} h_{s,t-1} h_{b,t-1} + \gamma_{s,b} \varepsilon^2_{s,t-1} \varepsilon^2_{b,t-1} \quad \text{BEKK GARCH (1,1)} \tag{2}$$

where $h_{s,t}$ and $h_{b,t}$ are the conditional variances of HIR_t IIR_t, respectively, and are the conditional covariance between HIR_t residuals $\varepsilon_{s,t}$ and IIR_t residuals $\varepsilon_{b,t}$. We used this estimated variance $h_{s,t}$ and $h_{b,t}$ as a proxy for HIR_t uncertainty and IIR_t uncertainty, respectively. It is assumed that $\alpha_i, \gamma_i > 0$, and $\alpha_i \geq 0$ for $i = s, b$ and $-1 \leq \rho \leq 1$ in (2).

3. Results

3.1. Results of the Preliminary Analyses

The results of the time-varying correlation analysis conducted using rolling window correlation analysis are given in Table 3, following [86], and to observe how the results are progressing visually, we present them graphically in Figure 2 below.

Table 3. Simple correlation.

Lag	SPC	DAX	DJ	FTSE	BEL	AEX	CAC	SSE	SP500	NASDAQ
−8	−0.639	0.646	0.889	0.478	0.313	−0.077	0.604	0.676	0.870	0.883
−7	−0.640	0.653	0.891	0.476	0.313	−0.079	0.607	0.675	0.872	0.883
−6	−0.641	0.659	0.894	0.476	0.313	−0.082	0.609	0.674	0.875	0.883
−5	−0.641	0.665	0.897	0.473	0.314	−0.084	0.612	0.672	0.877	0.884
−4	−0.642	0.671	0.900	0.472	0.314	−0.086	0.615	0.671	0.880	0.884
−3	−0.643	0.677	0.903	0.471	0.314	−0.088	0.617	0.670	0.882	0.884
−2	−0.644	0.682	0.905	0.470	0.314	−0.090	0.619	0.670	0.885	0.885
−1	−0.645	0.688	0.908	0.472	0.314	−0.092	0.620	0.669	0.887	0.885
0	−0.646	0.693	0.910	0.471	0.314	−0.095	0.622	0.668	0.890	0.885
1	−0.646	0.689	0.908	0.471	0.312	−0.100	0.616	0.664	0.887	0.880
2	−0.646	0.686	0.905	0.467	0.308	−0.105	0.611	0.660	0.884	0.875
3	−0.647	0.681	0.901	0.464	0.305	−0.110	0.606	0.655	0.880	0.870
4	−0.647	0.677	0.897	0.458	0.302	−0.114	0.601	0.651	0.877	0.865
5	−0.647	0.672	0.893	0.451	0.298	−0.119	0.595	0.647	0.874	0.860
6	−0.647	0.667	0.889	0.444	0.294	−0.124	0.590	0.643	0.871	0.855
7	−0.647	0.663	0.884	0.438	0.291	−0.129	0.585	0.639	0.868	0.850
8	−0.648	0.658	0.880	0.434	0.288	−0.134	0.581	0.676	0.865	0.845
Ljung–Box										
1 to 8	3939.997	4278.685 0.000	7534.31	1935.782	845.855	129.652	3367.882	3968.196	7219.5	6998.2
−8 to −1	3877.698	4197.512 0.000	7596.527	2109.199	925.759	67.638	3535.874	4253.386	7263.9	7353.8
−8 to 8	8307.213	9039.246 0.000	16,102.19	4305.501	1887.391	207.851	7356.547	8744.668	15,412.3	15,270.2

Note: Ljung–Box Serial Correlation test.

Table 3 shows that during this period, there was a strong negative relationship between SPC and AEX stock markets, a strong positive for DJ, SP500, and NASDAQ, a moderate positive for DAX, CAC, and SSE, and finally, a weak positive related to the health and industrial index relationship for FTSE and BEL.

The results of the rolling window correlation analysis show that the correlations between the health and industrial indices have increased in all the stock markets under investigation from 2019:10 to 2020:03. From 2020:03 to 2020:07, the health index increased rapidly, but the industrial index continued to be negatively affected by COVID-19. It can be seen that the reverse movement of both indices decreases the correlation in all stock markets during 2020:03–2020:07. However, the correlation between both sectors again started to increase rapidly during the 2020:07–2022:03 period.

Then, to determine the type of regression analysis, integration orders were obtained using the unit root test applied to the levels of the stock indices data, which are summarized in Tables 4 and 5.

As shown in Table 5, there is no health-and-industrial-index couple that is stationary at this level. It can be observed that only five of the health-and-industrial-index couples (those with the letter S in the last column of Table 5), specifically DAX, AEX, CAC, SSE, and NASDAQ, are both stationary at first-difference, for which cointegration analysis can be applied. While, for the remaining five couples (those with the letter NS in the last column of Table 5), namely SPC, DJ, FTSE, BEL, and SP500, we needed to work with the differences. So, taking both the limitations of the length of the sampling period and the high volatility experienced during that period into account, we proceeded with our analyses with the return series. The logarithmic difference of the return series results is given in Figure 3, and the sliding window correlation analysis is provided in Figure 4 below.

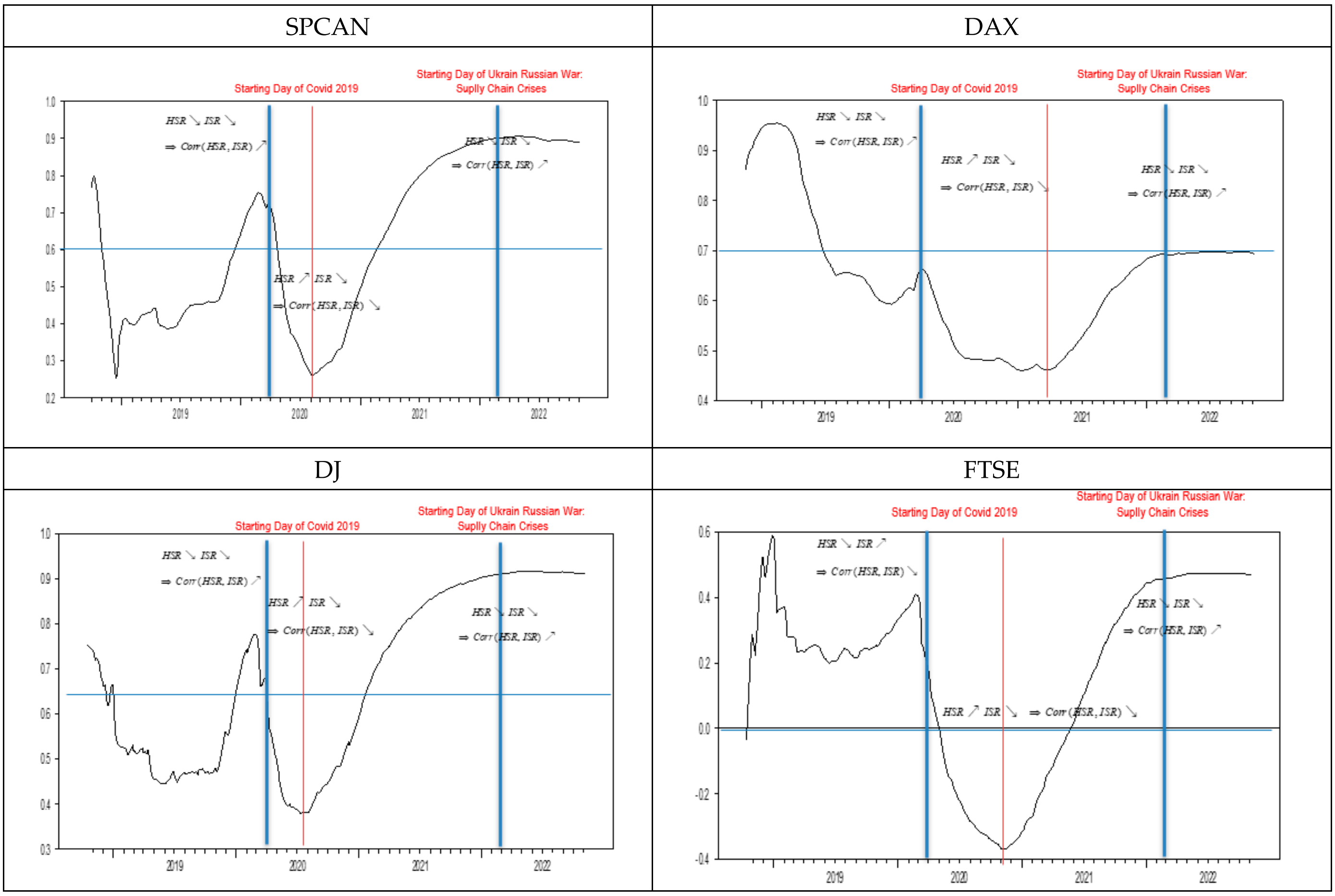

Figure 2. *Cont.*

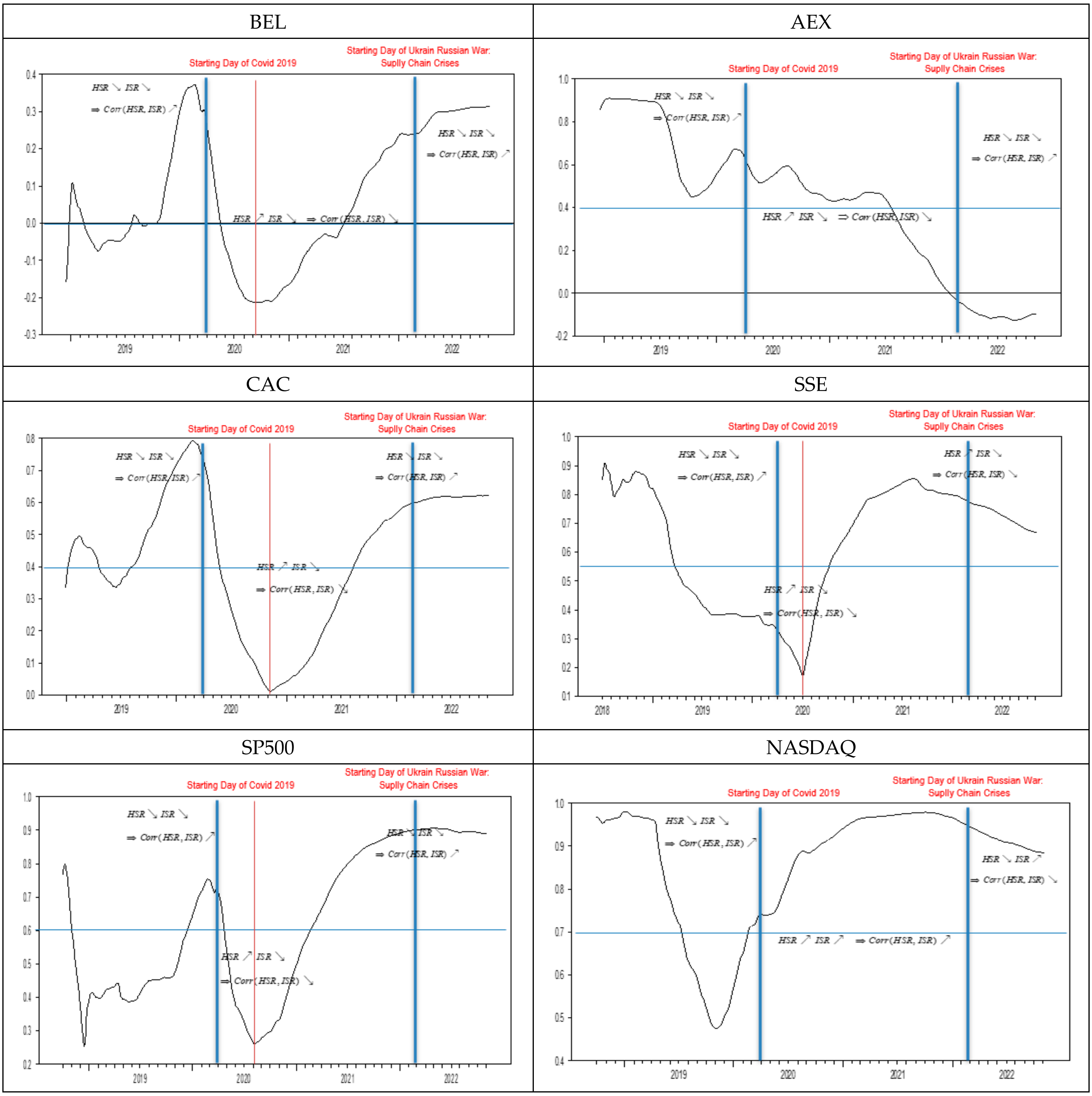

Figure 2. Correlation analysis.

Table 4. ADF test for the integration order for the level series.

Series	Int	Lag	Int and Trend	Lag	Result
SPCHLT	−0.728	8	−2.522	8	Unit Root
DAXHLT	−2.600 *	1	−2.788	1	Stationary
DJHLT	−1.476	12	−3.578 **	12	Stationary
FTSEHLT	−2.224	12	−3.238 *	11	Stationary
BELHLT	−2.772 *	4	−3.331 *	4	Stationary
AEXHLT	0.218	1	−0.741	1	Unit Root
CACHLT	−1.812	1	−2.462	1	Unit Root
SSEHLT	−1.404	1	−1.611	1	Unit Root

Table 4. *Cont.*

Series	Int	Lag	Int and Trend	Lag	Result
SP500HLT	−1.236	10	−3.204 *	10	Stationary
NASDAQHLT	−1.665	2	−1.442	2	Unit Root
SPCIND	−1.132	9	−3.183 *	9	Stationary
DAXIND	−1.768	1	−2.072	1	Unit Root
DJIND	−1.687	9	−2.722	9	Unit Root
FTSEIND	−1.917	1	−2.613	1	Unit Root
BELIND	−1.339	4	−2.464	4	Unit Root
AEXIND	−1.158	6	−1.037	6	Unit Root
CACIND	−2.336	7	−2.725	7	Unit Root
SSEIND	−1.238	5	−2.674	5	Unit Root
SP500IND	−1.634	9	−2.589	9	Unit Root
NASDAQIND	−1.445	10	−0.977	10	Unit Root

Note: For the ADF test, for only the intercept case number of observation T = 1170 **** 1–3.44%, *** 25–3.12%, ** 5–2.86%, and * 10–2.57%. For the intercept and trend case number of observation T = 1170 **** 1–3.96%, *** 25–3.66%, ** 5–3.41%, and * 10–3.12.

Table 5. Type of regression analysis.

Series	Health	Industrial	Result
SPC	I(1)	I(0)	NS
DAX	I(1)	I(1)	S
DJH	I(0)	I(1)	NS
FTSE	I(0)	I(1)	NS
BEL	I(0)	I(1)	NS
AEX	I(1)	I(1)	S
CAC	I(1)	I(1)	S
SSE	I(1)	I(1)	S
SP500	I(0)	I(1)	NS
NASDAQ	I(1)	I(1)	S

Note: %. S: Stationary, NS: Non Stationary.

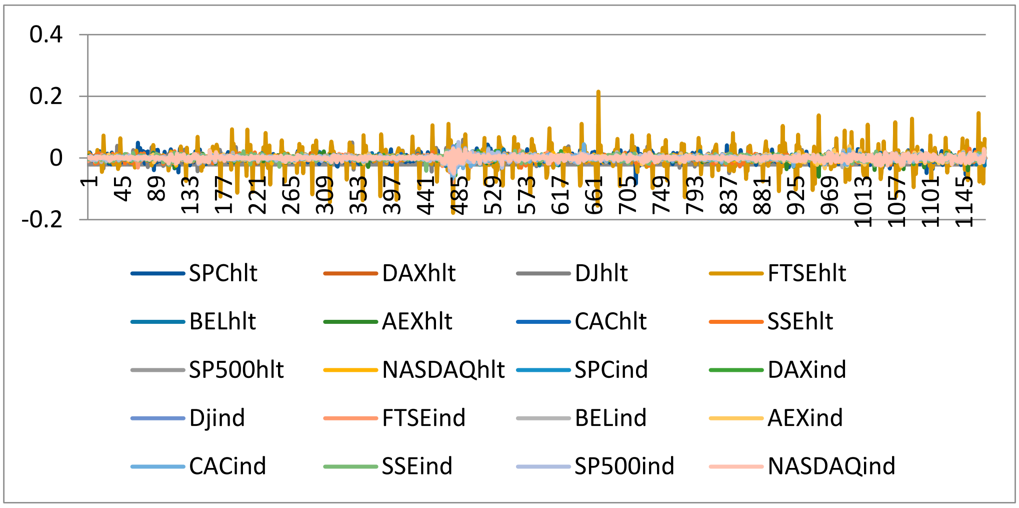

Figure 3. Return series.

If we comparatively examine the rolling window correlation results obtained for the price series shown in Figure 2 and for the return series presented in Figure 4, it can be observed that almost the same results are achieved. As can be observed from Figure 4, for all the health-and-industrial-stock-index couples under consideration, the correlations in the return series increased with the news of the COVID-19 pandemic, with its peak in 2020:03, which finally resulted in the closure of the countries. It can be seen that between 2019:10 and 2020:03, the news of COVID-19 negatively affected both the health and the industrial sectors together, which caused a positive correlation. However, from 2020:03 to 2020:07, the health index increased rapidly, whereas the industrial index continued to be negatively affected by COVID-19. It can be seen that the reverse movement of both indices during that period decreases the correlation in all ten stock-index couples. However, the correlation between both sectors increased rapidly between 2020:07 and 2022:03 again.

Then, the ADF test was applied, and the obtained results for the return series are provided in Table 6 below.

The unit root test results of the return series given in Table 6 confirmed that the return series is stationary, and thus we proceeded with the regression (Bivariate GARCH) analysis.

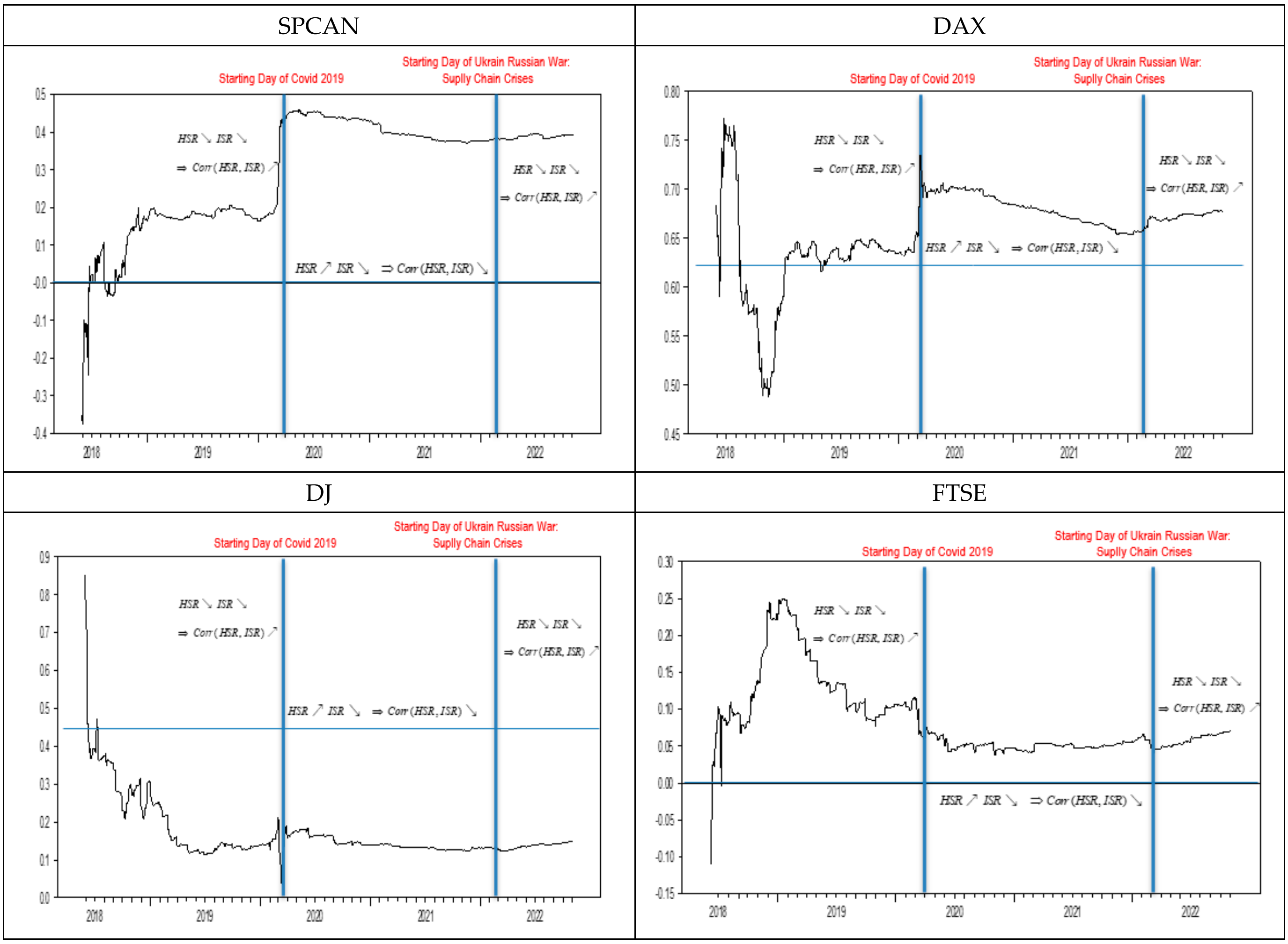

Figure 4. *Cont.*

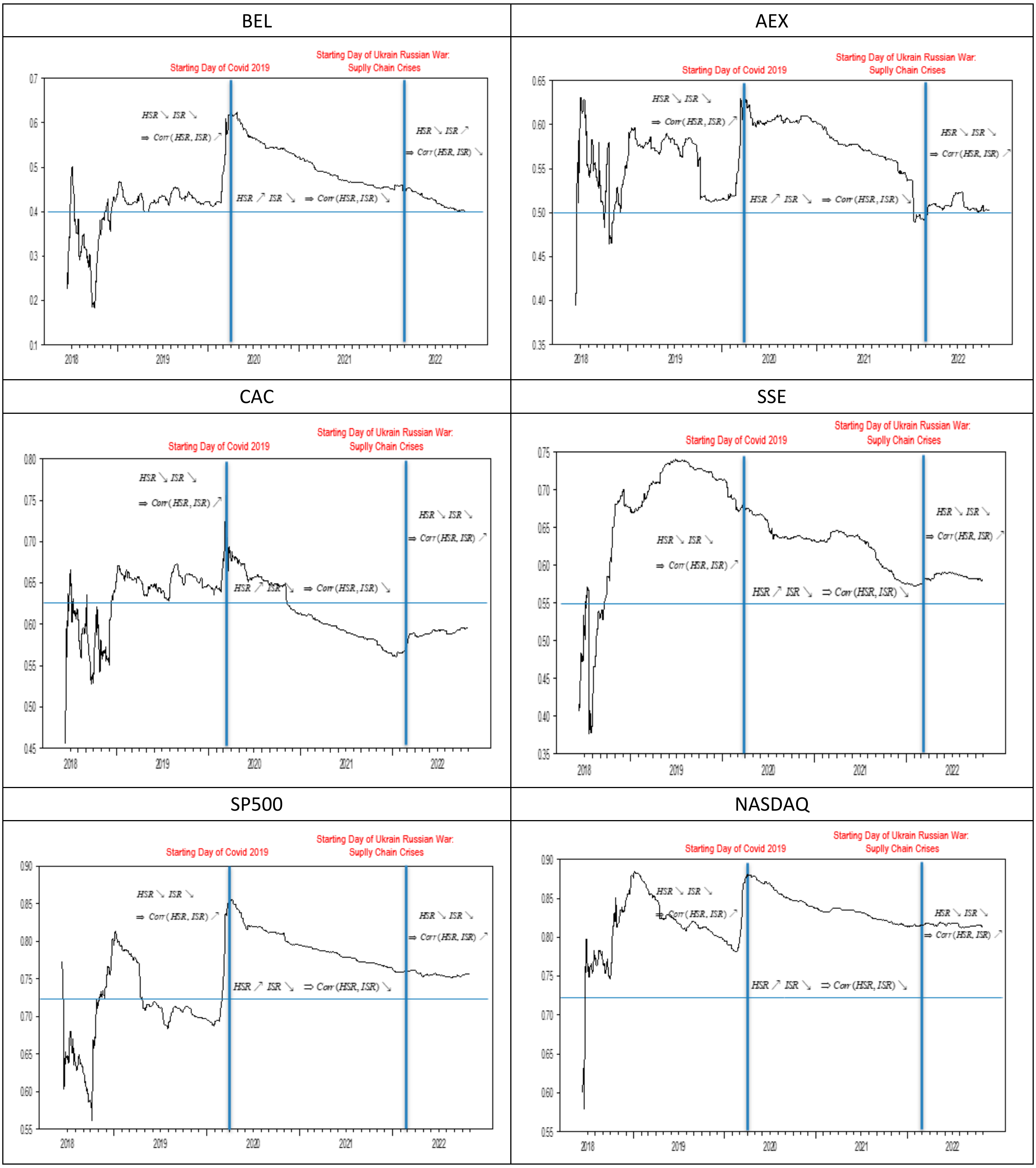

Figure 4. Correlation analysis of return series.

Table 6. ADF test for integration order for the return series.

Series	Int	Lag	Int and Trend	Lag	Result
SPCHLT	−24.414 *	1	−24.414 *	1	Stationary
DAXHLT	−10.887 *	8	−10.887 *	8	Stationary
DJHLT	−14.575 *	12	−14.575 *	12	Stationary
FTSEHLT	−14.036 *	12	−14.036 *	12	Stationary
BELHLT	−15.217 *	3	−15.217 *	3	Stationary
AEXHLT	−12.371 *	6	−12.371 *	6	Stationary
CACHLT	−23.653 *	1	−23.653 *	1	Stationary
SSEHLT	−8.072 *	12	−8.072 *	12	Stationary
SP500HLT	−10.599 *	12	−10.599 *	12	Stationary
NASDAQHLT	−11.033 *	9	−11.033 *	9	Stationary
SPCIND	−9.697 *	12	−9.697 *	12	Stationary
DAXIND	−12.179 *	6	−12.179 *	6	Stationary
DJIND	−10.207 *	8	−10.207 *	8	Stationary
FTSEIND	−11.609 *	6	−11.609 *	6	Stationary
BELIND	−13.490 *	5	−13.490 *	5	Stationary
AEXIND	−14.370 *	5	−14.370 *	5	Stationary
CACIND	−12.592 *	6	−12.592 *	6	Stationary
SSEIND	−16.094 *	4	−16.094 *	4	Stationary
SP500IND	−9.844 *	8	−9.844 *	8	Stationary
NASDAQIND	−10.147 *	8	−10.147 *	8	Stationary

Note: For the ADF test, for only the intercept case number of observation T = 1170 **** 1–3.44%, *** 25–3.12%, ** 5–2.86%, and * 10–2.57%. For the intercept and trend case number of observation T = 1170 **** 1–3.96%, *** 25–3.66%, ** 5–3.41%, and * 10–3.12%. S: suitable, SPCANNS: not suitable.

3.2. Results of the Bivariate GARCH Model

The bivariate GARCH (1,1) model results are given graphically below through Figures 5–14. The contribution of volatility to the mean equation was compared by adding the rolling window correlation analysis to the graphs. Starting with SP Canada, the covariances of the health and industrial return series are given in the first panel. Next, the rolling window correlation of the data containing the mean information of the return is given. Finally, the variance of the health and industrial indices' volatility is given.

As can be seen from Figure 5, the most significant increase in the variance and covariance of the increase in volatility for the SP Canada health index return and industrial index return series was observed on 10 March 2020. Except for this date, the volatility increase of 1 March 2022 did not contribute to these two stock correlations as much as that of 10 March 2020. However, the volatility variance of the relative health index return series remained high. It is observed that the war between Ukraine and Russia did not affect the Canadian supply chains much, but both sectors got seriously affected and separated by the COVID-19 outbreak.

In Figure 6, as can be seen from the DAX health index and industrial index return series, the most significant increase in the variance and covariance of the increase in volatility is observed for 10 March 2020. Except for this date, although the volatility increase dated 1 March 2022 is not as high as that of 10 March 2020, it is still far above the average volatility. Thus, it impacted the two German stock indices' correlations. Germany's dependency on Russian supply chains, especially its reliance on Russia as an energy supplier, has led to high volatility, almost as high as the COVID-19 period. Contrary to the COVID-19 period, it can be observed that the health and industrial indices decreased together, and the positive correlation increased. It can be expected that this positive correlation will be reversed with the investments made in the health sector when the war reaches a greater area of influence and creates a social health problem.

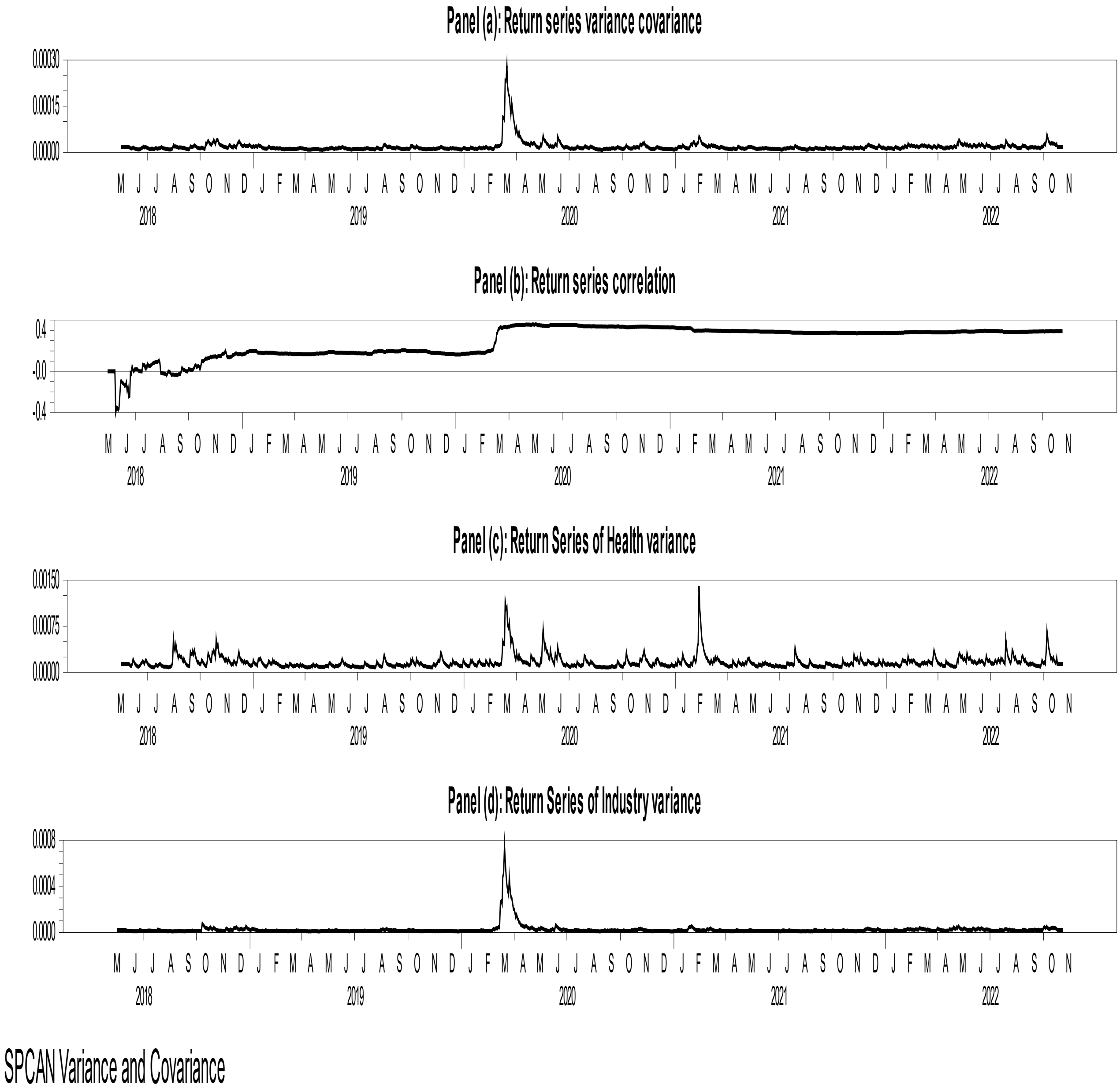

Figure 5. SP CAN variance and covariance.

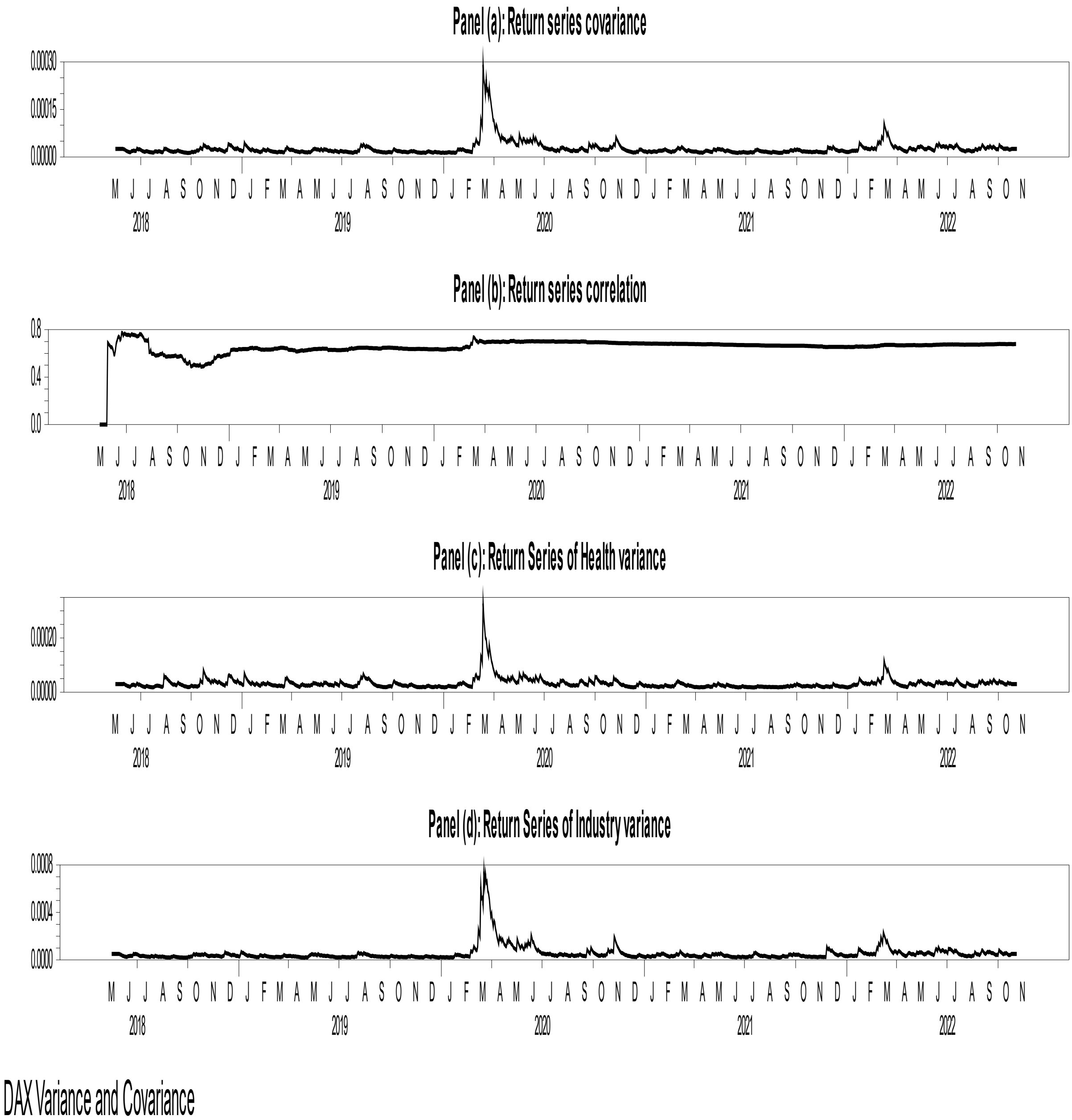

Figure 6. DAX variance and covariance.

As can be followed from Figure 7, the volatility increase had the most significant variance and covariance for the DJ health index and industrial index return series on 10 March 2022. The volatility increase observed on 1 March 2022 did not contribute as much to these two stock correlations as on 10 March 2020. However, the volatility variance of the health index return series remained relatively high. It can be observed that the war between Ukraine and Russia did not affect the supply chains of the DJ index much, but both sectors got severely affected by the COVID-19 outbreak.

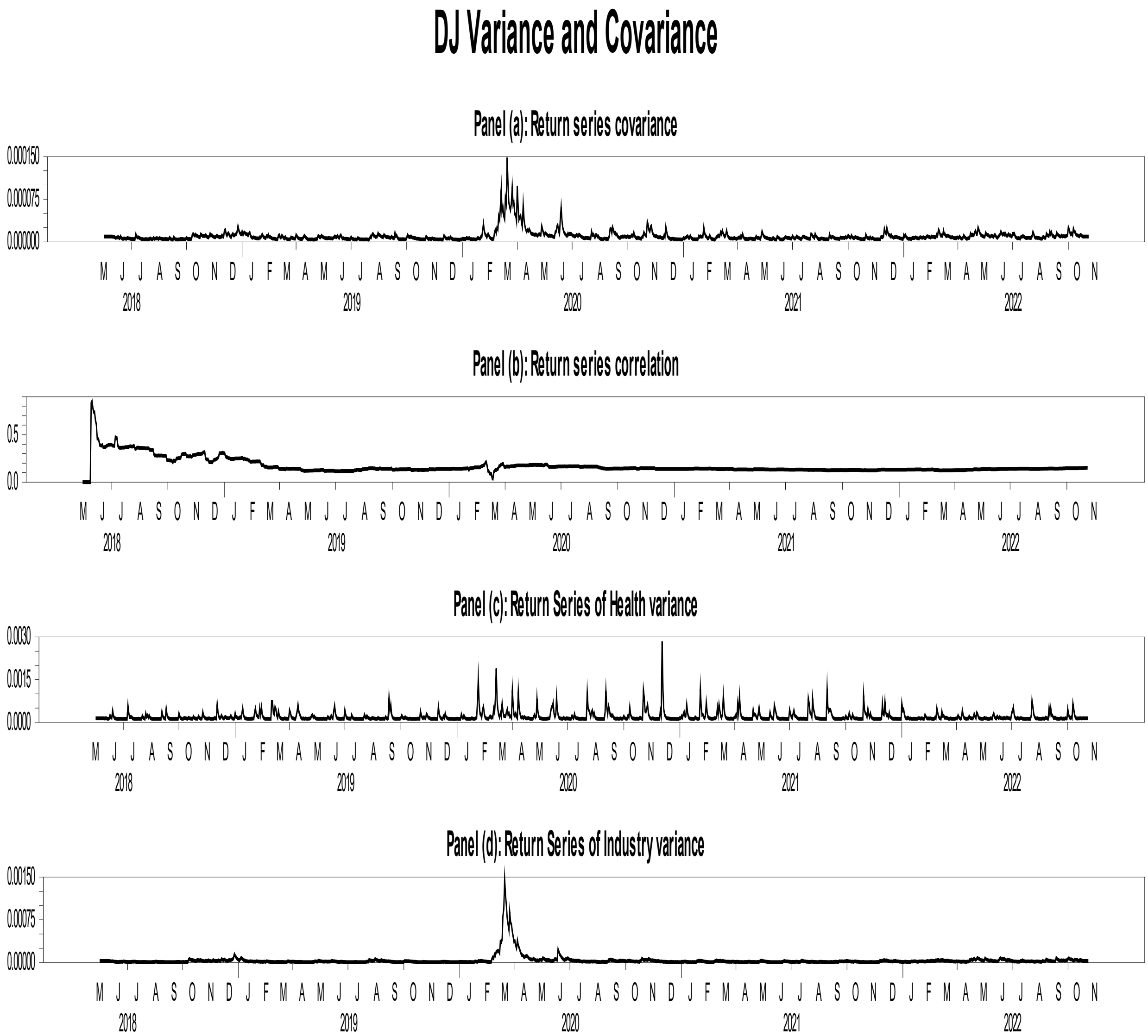

Figure 7. DJ variance and covariance.

In Figure 8, as seen from the FTSE health index and industrial index return series, the volatility increase had the most significant variance and covariance on 10 March 2020. Although the volatility variance of the health index return series remained relatively high, the volatility increase observed on 1 March 2022 falls short of the 10 March 2020 date's. Hence, both sectors got seriously affected by the COVID-19 outbreak and separated, while the war between Ukraine and Russia seems to affect the supply chains of Italy less.

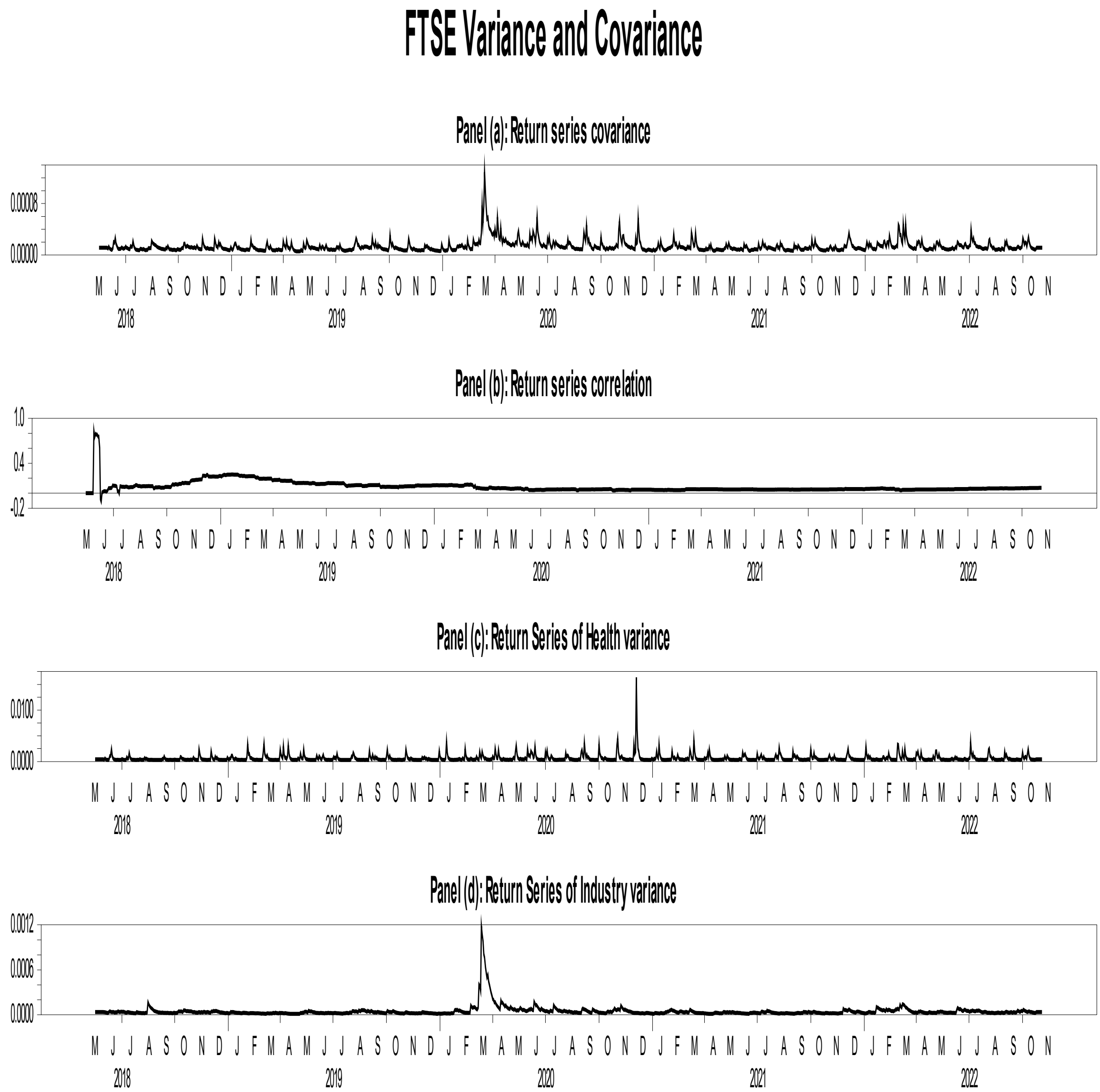

Figure 8. FTSE variance and covariance.

In Figure 9, as can be seen from the BEL health index and industrial index return series, a tremendous increase in the variance and covariance of the increase in volatility was detected on 10 March 2020. Though the volatility increase dated 1 March 2020is not as much as the increase on 10 March 2020, it is still far above the average volatility, indicating the high impact of the Ukraine–Russia war on the two Belgian stock indices. Belgium's dependence on Russian supply chains has caused it to experience volatility almost as high as in the COVID-19 period.

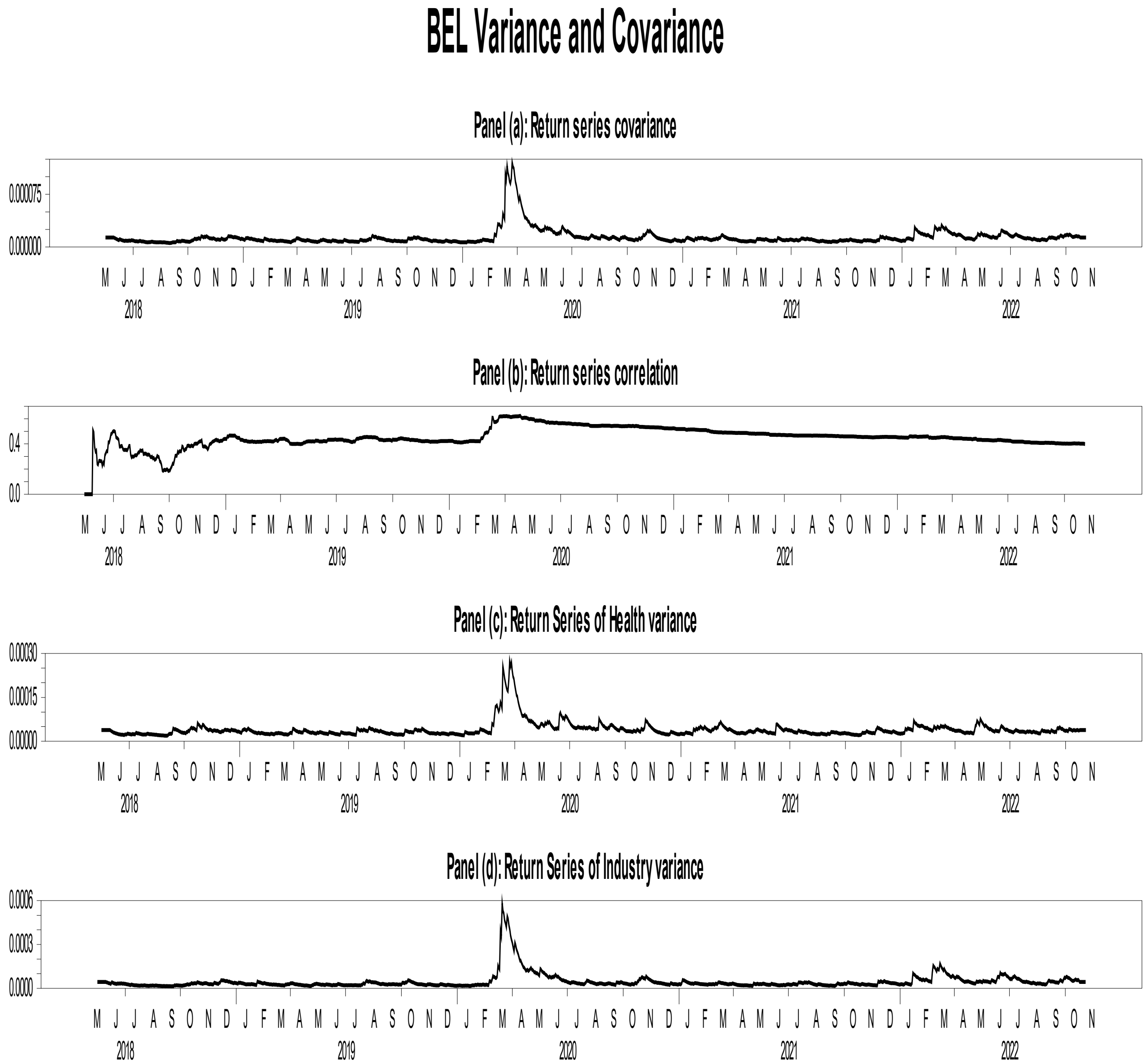

Figure 9. BEL variance and covariance.

As can be seen from the AEX health index and industrial index return series presented in Figure 10, the most significant increase in the variance and covariance of the increase in volatility was witnessed on 10 March 2020. Although the volatility increase dated 1 March 2020 is not as much as the 10 March 2020 date's, it is still far above the average volatility. Hence, the war significantly affected the correlation of the two AEX stock indices. Due to the Netherlands' reliance on Russian supply chains, it experienced almost as high a volatility as in the COVID-19 period.

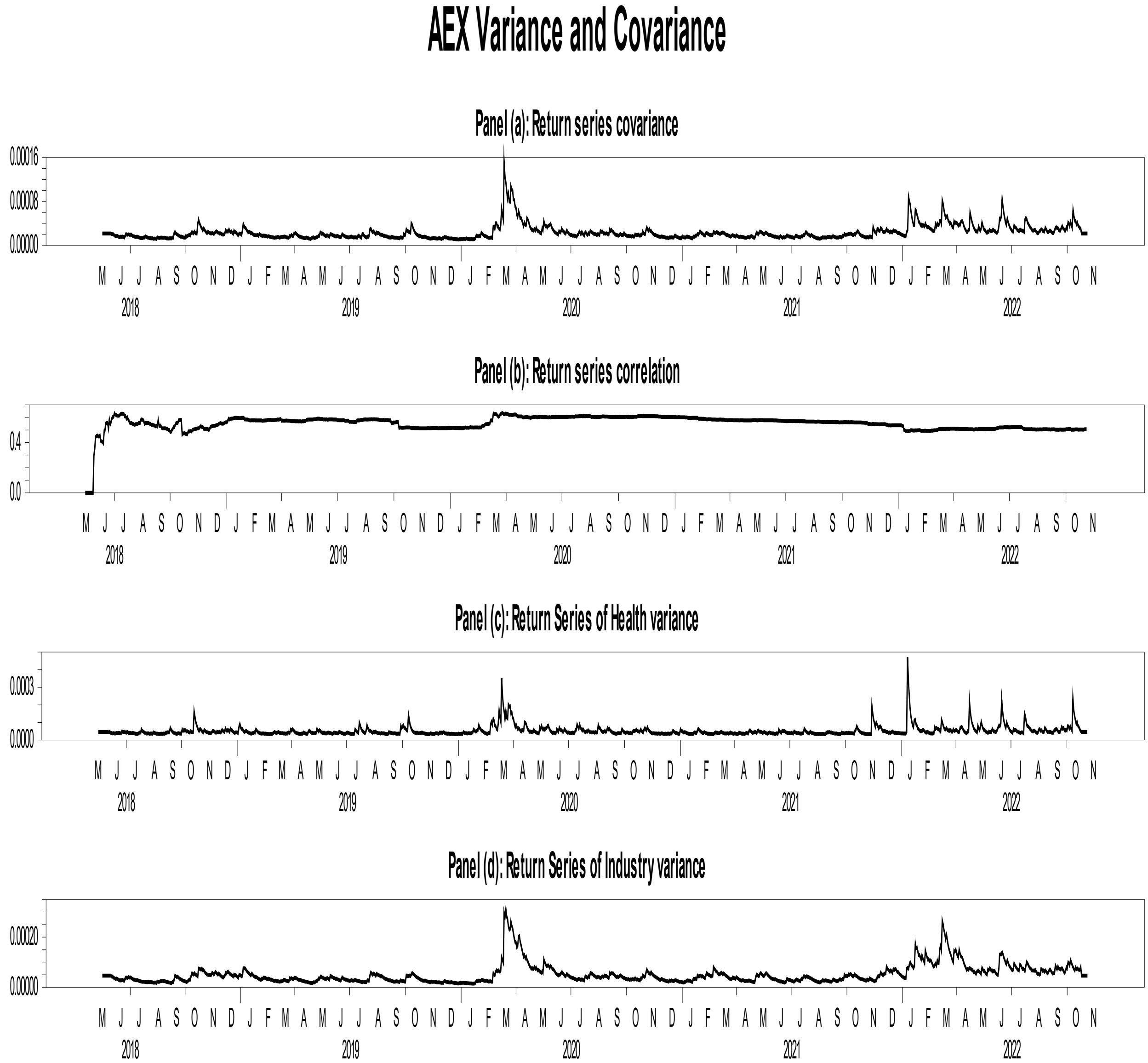

Figure 10. AEX variance and covariance.

As depicted in Figure 11, the most significant increase in the variance and covariance of the return series for the CAC health index and industrial return index was reported on 10 March 2020. Although the volatility increase observed on 1 March 2020is not as much as that of 10 March 2020, it is still far above the average volatility. Thus, France's dependency on Russian supply chains has caused the CAC stock index correlations to experience a high volatility, almost as high as that of the COVID-19 period.

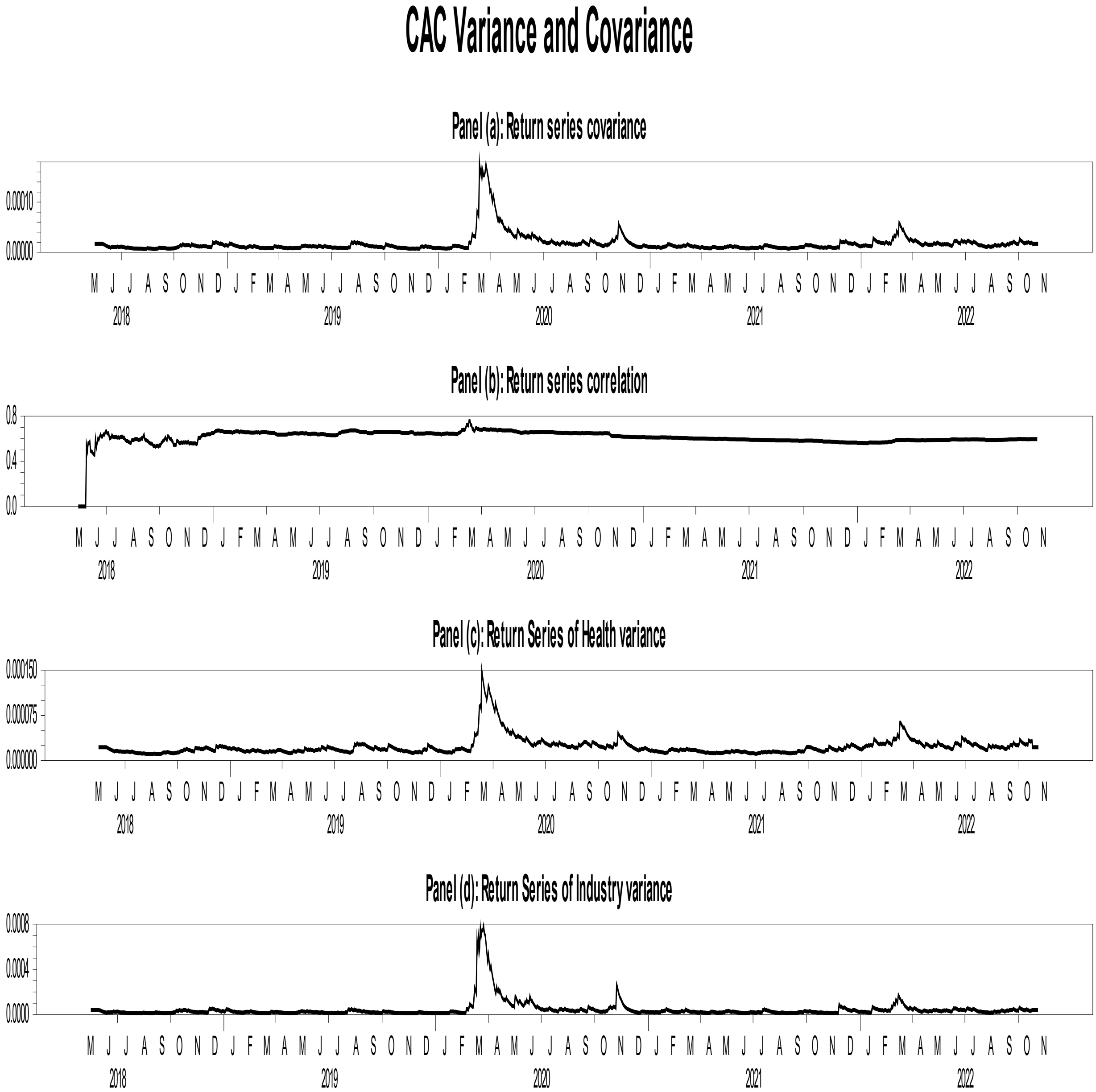

Figure 11. CAC variance and covariance.

As Figure 12 shows, each sector's volatility for the SSE stock indices seems to be high during the COVID-19 pandemic and the Russia–Ukraine war, and all the time. However, the volatility increases in these two periods are observed to be slightly above the usual course. This result may arise from the fact that China is the leading manufacturer in the world, and its dependence on imports, except of energy, is considerably low, while, for energy, it acquired beneficial purchasing terms from Russia, especially following the outbreak of the war and the imposed sanctions on Russia. On the other hand, despite the recent ongoing debates on whether China is still a developing country or a developed one, the incompatible results obtained for SSE stock indices may also reflect this distinction.

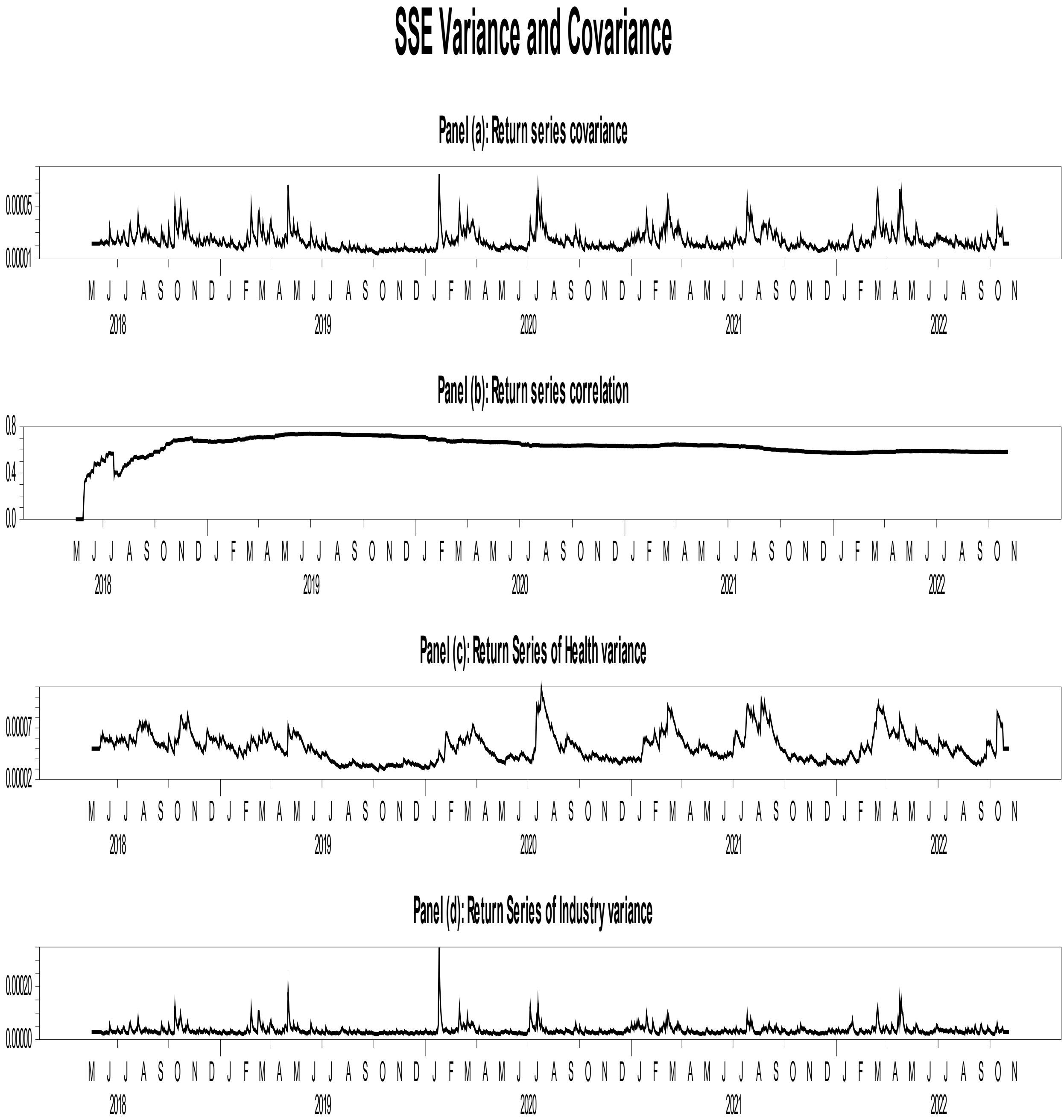

Figure 12. SSE variance and covariance.

In Figure 13, as seen from the SP500 health index and industrial index return series, the most significant increase in the variance and covariance of the increase in volatility is reported on 10 March 2020. Except for this date, the volatility increases of 1 March 2020 do not seem to contribute to these two indices' correlations as much as those of 10 March 2020. Though the volatility variance of the health index return series remained high, it can be observed that the war between Ukraine and Russia did not affect the US supply chains much, but both sectors got seriously affected and separated by the COVID-19 outbreaks.

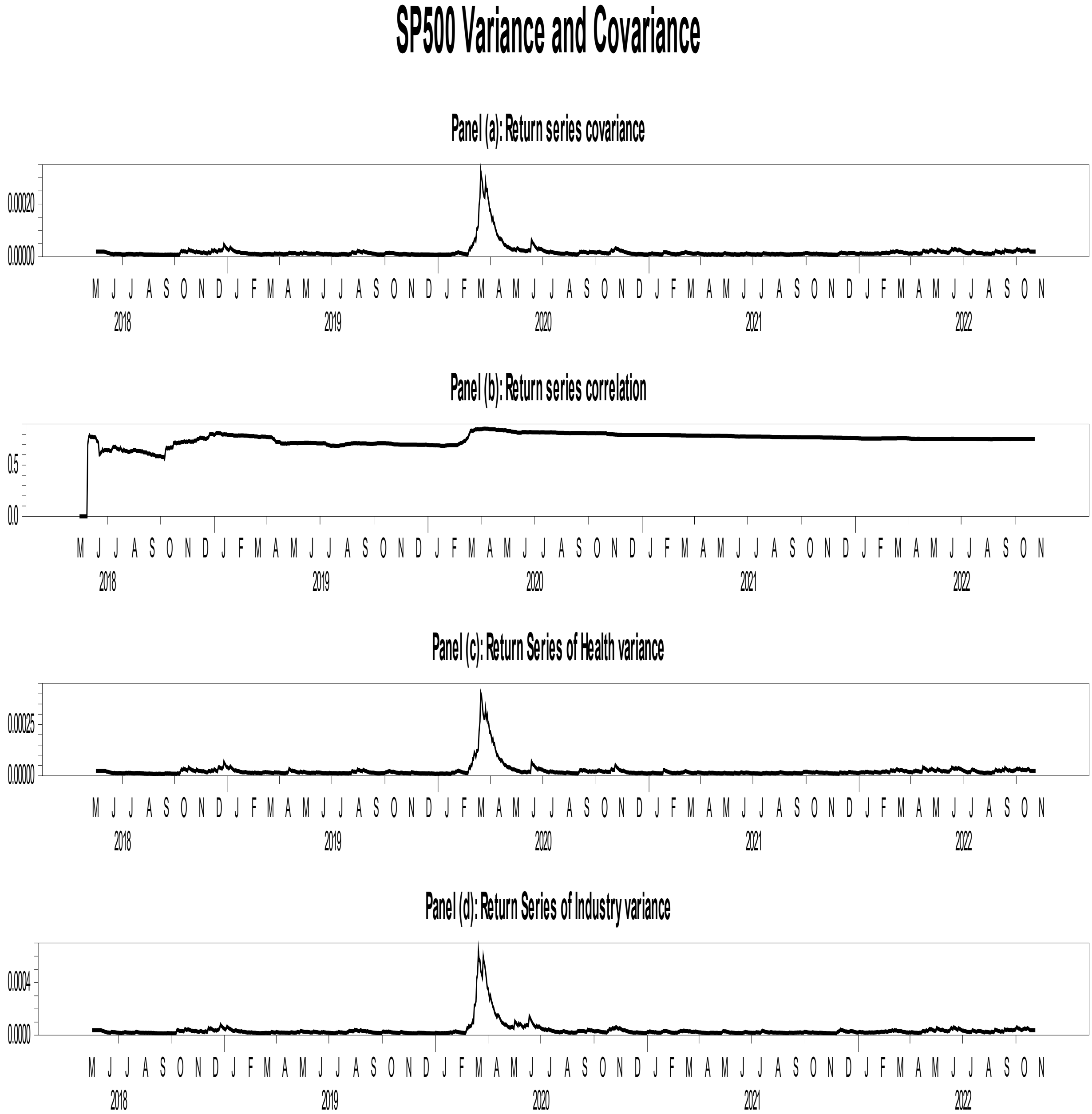

Figure 13. SP500 variance and covariance.

As Figure 14 depicts, the most significant increase in the variance and covariance of the increase in volatility for the NASDAQ health index and industrial index return series can be observed on 10 March 2020. Although the volatility increase dated 1 March 2020 is not as high as the 10 March 2020 date's, it is still far above the average volatility. However, it seems more probable that this high volatility is a consequence of the lockdown the Shanghai Port experienced during the same period. Still, the volatility during that period is still below that of the 2020 March period.

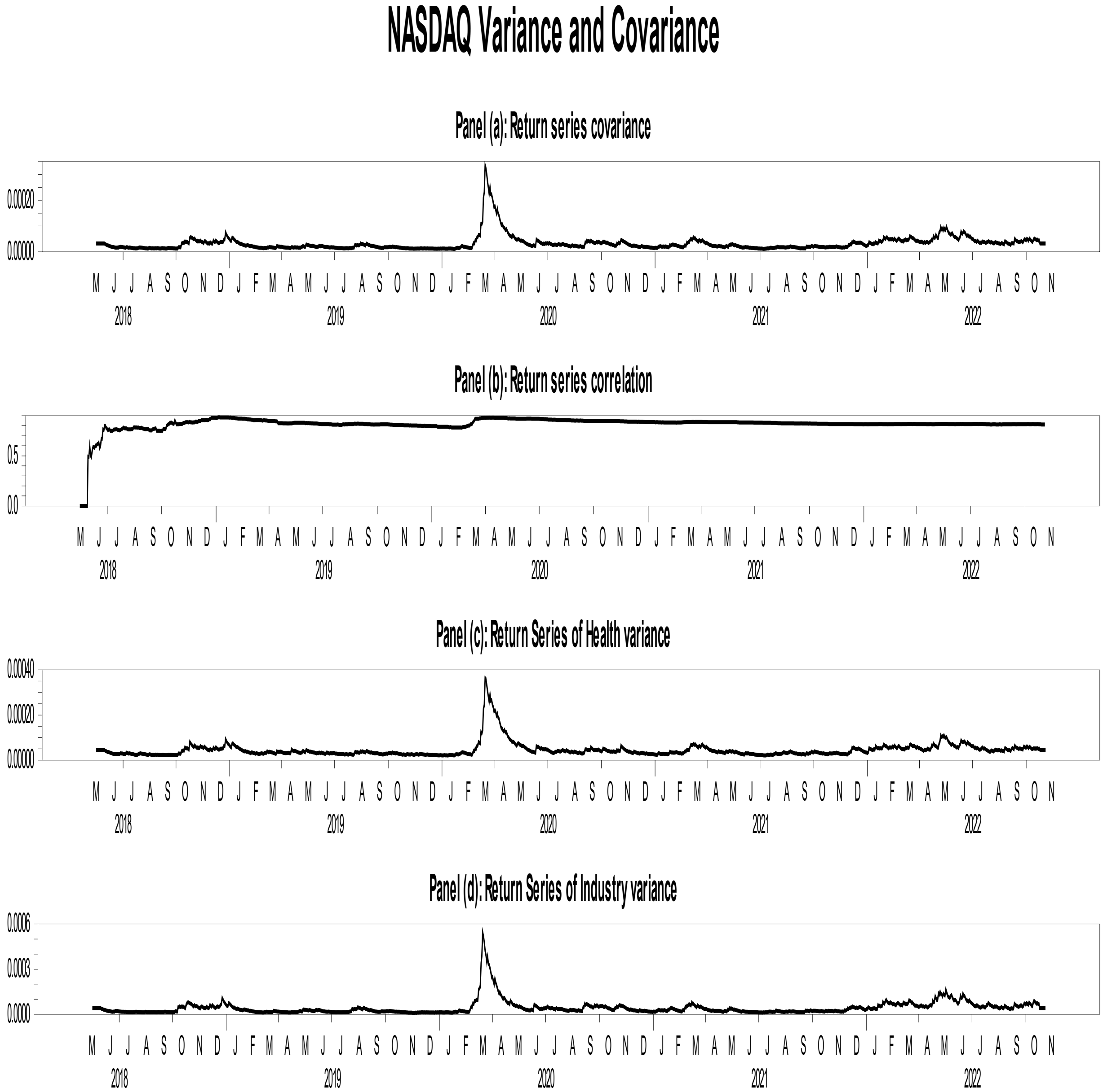

Figure 14. NASDAQ variance and covariance.

4. Discussion

As a result of these analyses, many hypotheses were tested. The first study, dealing with the price and the return series primarily, performed a rolling window correlation analysis. If we comparatively examine the rolling window correlation results obtained for the price series shown in Figure 2 and for the return series presented in Figure 4, it can be observed that almost the same results are attained. As a result of these analyses, it is observed that for all the health and industrial stock index couples under consideration, the correlations in both the price and the return series increased with the news of the COVID-19 pandemic, with its peak in 10 March 2020, which finally ceased with the lockdown of countries worldwide. Between 2019:10 and 2020:03, the news of COVID-19 negatively affected both the health and the industrial sectors, leading to a positive correlation. However, from 2020:03 to 2020:07, the health index increased rapidly, whereas the industrial index continued to be negatively affected by COVID-19. It can be seen that the reverse movement of both indices during that period decreased the correlation in all ten stock-index couples. As of 2020:07, the industrial sector also turned positive with the weakening of the first wave of COVID-19, which raised the expectation that the pandemic would end in a year. The significant investments in the health sector and the rapid production of COVID-19 vaccines not only translated into high price increases for vaccine companies but also demonstrated how health expenditures and investments created an environment where economic growth quickly turned positive, even in the short term. However, the deterioration in the supply chains and difficulties in accessing energy resources due to the Russia–Ukraine war, coupled with the concerns of a recession, caused the direction of the relationship to change in many stock markets from 2020:07 to 2022:03, during which the correlation between both sectors increased rapidly again.

The results of the bivariate GARCH study for the return series enabled us to examine how the series' volatility contributed to this correlation structure, and 10 March 2020 is the most effective day for all markets. Additionally, it is found that the European-based stock index couples, except for Italy, experienced volatility almost as high as the COVID-19 period on 1 March 2020. However, the dissimilar finding obtained for Italy is probably due to its distinct position during the outbreak of the COVID-19 pandemic: Italy was not only among the first countries that experienced the pandemic but also among the most severely affected ones. On the other hand, China also seems to have incompatible results with the rest. The volatility for the Chinese stock indices is high throughout the research period, with only a slight increase during the COVID-19 and the Ukraine-Russia War periods. However, this finding is probably due to the fact that China is the leading manufacturer in the world, and its dependence on imports, except energy, is considerably low while for energy, it acquired beneficial purchasing terms from Russia, especially following the outbreak of the war and the imposed sanctions on Russia. This incompatibility may also be a reflection of the distinction between developed and developing countries as well. Concerning the US-based stock index couples, they all reflect the effects of COVID-19 but do not seem to be affected by the war.

In short, it can be concluded that the European and American continent indices made similar movements during the COVID-19 pandemic, but unlike American ones, European indices were seriously affected by the Russia-Ukraine war. On the other hand, the volatility for the Chinese stock indices is high throughout the research period, with only a slight increase during the war and the outbreak of COVID-19.

As elucidated in the literature survey section, the empirical investigation into the relationship between health expenditures and economic growth has garnered significant attention in recent years (e.g., [51–53,55,56,59–66]). However, the bulk of these studies primarily focus on underdeveloped and developing countries (e.g., [52,53,55,56,59,61–65]), with relatively scant attention paid to developed nations [51]. However, it is noteworthy that the growth dynamics of developed and developing economies diverge significantly. Moreover, these studies are not directly applicable to our discussion herein, and their results cannot be readily compared. This discrepancy arises from two principal factors. Firstly, the studies conducted on developed countries typically utilize annual data. Secondly, the period under examination herein is characterized by extraordinary circumstances, thus necessitating a nuanced examination of the impact of health expenditures on growth dynamics. Nonetheless, a common thread linking our discussion to the aforementioned articles is the assertion that health expenditures bolster economic growth during such extraordinary periods. To offer clarity regarding the distinctions, we will delineate these variances in the subsequent paragraph of this discussion.

Given the inherently short-term nature of the period under investigation, particularly in the context of the COVID-19 pandemic, our examination necessitated the utilization of distinct methodological approaches and informational considerations compared to studies typically centered on annual healthcare expenditure data and its implications for economic growth and sustainability. Moreover, the methodological approach which is used in this study can also cover the dynamics of the Russia–Ukraine war.

Though the underlying hypotheses of these annual studies may appear analogous, the information yielded diverges from the framework proposed in our study for two principal reasons. Firstly, conventional studies predominantly encompass normal periods, thereby precluding insights into the dynamics of the healthcare-economic growth relationship during extraordinary periods. Consequently, our study was deliberately crafted to furnish insights specifically tailored to such exceptional circumstances. Secondly, high-frequency data encapsulates a distinct spectrum of informational nuances. Our study accounts for this by subjecting hypotheses to rigorous testing within an ARCH-GARCH framework, which elucidates the volatility dynamics inherent in high-frequency data. Consequently, studies reliant solely on annual data may not offer comprehensive insights into the multifaceted relationship under scrutiny. In light of these methodological disparities, it is imperative to approach references from studies employing annual data cautiously, as their applicability to our study's context may be limited to technical elucidation.

Limitations

In this study, a rolling correlation analysis was employed to conduct a time-varying correlation examination. Furthermore, in the bivariate GARCH section, heteroskedasticity was assessed by assuming a nonlinear mean equation. Thus, a nonlinear model was utilized for the mean equation, suggesting its potential utility for future investigations. It is noteworthy that the bivariate GARCH model utilized in our study provides dynamic insights into the covariance relationship, thereby constituting a substantial contribution.

Yet, the criticism regarding the absence of causality examination through correlation is indeed warranted. However, it is arguable that, through the implementation of bivariate GARCH analysis, a causal relationship can be inferred, particularly in scenarios where other variables are absent. Notably, variables such as dose/exposure, reversibility, plausibility, and previous experience are inaccessible within high-frequency data. Consequently, the health index represents the final aggregation of these data. Despite the inherent challenge in accessing more granular data at the micro-scale level, the healthcare stock index derived from such data maintains its quality as a high-level aggregation. Nonetheless, within these aggregated high-frequency data, limited basic analysis can be performed. However, the newly developed techniques in time series analysis such as nonlinearities proposed in other [87–91] studies may also be used. On the other hand, there is a growing trend in the literature which considers cross-section dependency and the nonlinearities in panel time series techniques, such as in [92–96]. Conducting these new techniques may also alter the information content of the study. As such, we believe we have used necessary techniques for the initiation of the high-frequency-data techniques for investigating health expenditure and the growth nexus for this early stage.

5. Conclusions

The relationship between health expenditure and economic growth has been studied extensively in the literature, especially with the rise of the Endogenous Growth Theory. However, most of these studies focus on groups of underdeveloped and developing countries, while developed countries are relatively neglected. Nevertheless, given the aging population of developed countries, which leads to a deterioration in their health status and workforce participation, this nexus proves to keep increasing importance for those countries. In addition, we have recently seen the necessity of keeping precautionary reserves in health capital to effectively cope with pandemics such as that of COVID-19, which seems to force an increase in health expenditure and long-term health investment that will affect health capital in the coming years. With this motivation, this research paper concentrates on the health capital and economic-growth nexus for seven OECD countries, namely Canada, Germany, USA, Italy, Belgium, the Netherlands, and France, plus China, during the COVID-19 period, which enabled us to investigate the impact of the COVID-19 pandemic on this nexus. Further, the previous studies, probably due to the lack of monthly and quarterly data on health expenditure by country, examine this nexus using low-frequency (i.e., annual) data. In contrast, working with the proxy variables of the health stock index for health expenditure and the industrial stock index for economic growth allowed us to use daily data, which enabled us to comment on this relationship for the short term.

The use of high-frequency financial data also led us to use financial econometrics. Thus, this study is also unique concerning the used dataset, applied methodology, and selected sampling period. Our findings indicate that an increase in health capital causes delayed economic growth. This effect can also be observed even in the short term. However, it is also found that this relationship mainly comes into effect during crises such as pandemics, wars, supply chain breakdowns, and other factors for developed countries. However, given the aging populations of developed countries, which will probably deteriorate the health statuses of those countries in the near future, and the increasing political tensions around the globe, coupled with the considerations of a global recession, the investments in health capital will become much more vital for developed countries as well. Thus, it is crucial to re-examine the health capital and economic-growth nexus in detail in many aspects. Correspondingly, we highly suggest future research to examine the health expenditure and economic-growth nexus to concentrate on developed countries as well.

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