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GOVERNMENT RESPONSE STRINGENCY INDEX: AN ALTERNATIVE FOR THE VOLATILITY DETERMINING DURING PANDEMICS

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Abstract. The spread of the Covid-19 virus on all continents has caused a rapid evolution of the volatility of stock indices. To prevent and counteract the effects of this global event, researchers have tried to identify the causes, amplitude, and persistence of volatility. To measure volatility using statistical models, most authors chose the number of illnesses or deaths caused by the Covid-19 virus. However, the method of recording and reporting the number of illnesses and deaths by each state, assumed certain shortcomings reported in the literature. As an alternative, Hale et al. (2021, p. 8) proposed the Government Response Stringency Index (SI). The research proposes the determination of volatility with GARCH and VAR methods using the SI index as a variable. For this purpose, 28 countries from all continents were considered. The analysis period was March 19, 2020 to December 31, 2021. The main findings are: 1) the determination of volatility for 28 analysed countries; 2) some countries show better adaptability to the pandemic; 3) the differences between the volatility calculated with the SI index and the number of illnesses or deaths are small; 4) the links between the markets are stronger in the postcrisis period. Based on these results, comparative analyzes can be carried out between states, geographical areas and continents. Furthermore, the results allow us to appreciate other major events that affected the world capital market.

Keywords: GRSI, volatility, Covid-19 pandemic, index, casualties, number of casualties.

JEL Classification: G32, M10, O16.

Introduction

The COVID-19 pandemic was a global event that generated a social, economic and financial crisis on all continents. The effects of the pandemic on capital markets have been difficult to estimate, even if researchers have developed such a topic.

The rapid spread of the Covid-19 virus has affected stock markets around the world. Thus, the markets reacted in terms of increased volatility and risk, reduced stock market activity, lower market rates for financial securities, massive withdrawal of capital, losses for listed companies and others. The main causes that determined these effects were uncertainty about the evolution of the virus and the duration of the pandemic.

In the last three years, numerous studies have been published that have helped fill this gap in the literature. Even if remarkable progress has been made, it is difficult to establish a strategy to protect against such a phenomenon. In the studies carried out, most authors demonstrated that the main variables that determined volatility in the stock markets were the number of infections and deaths generated by the Covid-19 pandemic (Aslam et al., 2021; Czech et al., 2020; Lahmiri & Bekiros, 2020; Liu et al., 2021). However, more recent studies have shown that there have been difficulties in establishing the two variables in many countries around the world. These difficulties were related to the collection, record, and reporting of cases to national and international health organisations (Aslam et al., 2021; Wu et al., 2021; Souza de Souza & Silva, 2020). Considering that the study of daily volatility was carried out taking into account the daily cases of illnesses and deaths, any late reporting led to the deterioration of the results.

Therefore, the Government Response Stringency Index (SI) of Hale et al. (2021, p. 8) was established as an alternative to the number of injuries and deaths. Having such a starting point, the article proposes the determination of volatility on all continents according to the dynamics of

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the SI index. To carry out the investigation, stock market indices, the number of disease cases, and SI for a number of 28 countries were considered. This study is also motivated by the need for more comprehensive information on the response of financial markets to unexpected or unpredictable events. The SI provides a global and comprehensive view of the government's response to the COVID-19 pandemic (Hale et al., 2021, p. 8).

The objective of the investigation is to estimate the volatility determined by the Covid-19 virus in the capital markets of the countries considered in the analysis using SI indices as the independent variable. The numerical values obtained for volatility will be compared with the results obtained by other researchers who used as a variable the number of dead or injured from the Covid-19 virus. The comparative analysis of the results allows us to evaluate whether SI is more accurate in determining volatility.

The work is structured into sections. The following section contains a summary of the relevant literature on capital market volatility during the COVID-19 pandemic. The third section includes data and time series. The fourth section describes the methodology followed in the investigation. The last sections present results, robustness tests, conclusions and future research directions.

1. Literature review

Through the consequences it generates, volatility of the value markets is a central topic in the stock markets. Investors, financial asset managers, investment funds, capital markets authorities, governments and individuals are categories interested in the dynamics of such a phenomenon. The asymmetric impact of volatility has been demonstrated in the literature and was also confirmed during the Covid-19 pandemic by Nippani and Washer (2004, p. 1105), Zhang and Mao (2022, p. 10). It consists in the appearance and manifestation of negative effects, more pronounced compared to the positive ones.

In the framework of the research carried out in the last 3 years regarding the volatility of stock indices, the data collected by the authors were processed statistically, or other methods such as: Martingale difference spectral testing techniques (Okorie & Lin, 2021, p. 3), wavelets (Valls Martinez & Cervantes, 2021; Lahmiri & Bekiros, 2020), entropy (Lahmiri & Bekiros, 2020, p. 3), Markov chains (Atkeson, 2020, p. 5), machine learning (Baek et al., 2020, p. 5) and others. Most studies used statistical models such as regression analysis (Chahuan-Jiménez et al., 2021, p. 3), multiple linear regression (Souza de Souza & Silva, 2020, p. 164), OLS (Mohsin et al., 2020, p. 614), ADRL (Jin, 2022, p. 3), VAR (Aslam et al., 2021; Corbet et al., 2020; Youssef et al., 2021; Yu et al., 2021; Muhammad et al., 2021).

The literature analysis shows that the most used statistical model was GARCH (Lahmiri & Bekiros, 2020; Liu et al., 2021; Chundakkadan & Nedumparambil, 2021; Nguyen et al., 2022; Harjoto & Rossi, 2023) or its variants TGARCH (Czech et al., 2020, p. 7), GARCH-in-Mean (Hongsakulvasu & Liammukda, 2020, p. 64), EGARCH (Mohsin et al., 2020, p. 616); DCC-GARCH (Nguyen et al., 2022, p. 5).

To measure volatility during the Covid-19 pandemic, researchers analysed different periods, from a few hours after the first cases of illness to 2–3 years. Most authors have established volatility during the first pandemic wave. If we follow the geographical area, the analysis of the literature shows that a large number of authors have followed the dynamics of volatility at the level of developed stock markets (Baek et al., 2020; Corbet et al., 2020; Jin, 2022; Lahmiri & Bekiros, 2020; Liu et al., 2021; Nguyen et al., 2022; Okorie & Lin, 2021; Youssef et al., 2021; Zhang & Mao, 2022). We propose a global volatility analysis for a problem that affected stock markets in all countries, over a period of time that includes all pandemic waves.

From searches on representative research portals, we identified two papers that analysed volatility across a large number of markets located on different continents (Chahuan-Jiménez et al., 2021; Souza de Souza & Silva, 2020). There are comprehensive studies, but they had a different research orientation, such as breakpoint analysis, level of markets' information efficiency, and contagion effect (Chahuan-Jiménez et al., 2021; Nippani & Washer, 2004).

The variables pursued by researchers in the study of volatility are different. Among them are the health index (Chahuan-Jiménez et al., 2021, p. 3), cultural and macroeconomic aspects (Souza de Souza & Silva, 2020, p. 164), Google Search Volume Index (Chundakkadan & Nedumparambil, 2021, p. 4), microblogging sentiment investors (Fariska et al., 2021, p. 62), number of tests to detect the virus (Czech et al., 2020, p. 4), variation in mortality rates (Karlinsky & Kobak, 2021, p. 2) and others. The most common independent variables are: the number of infected people (Lee et al., 2020, Czech et al., 2020; Vo et al., 2022; Valls Martínez & Cervantes, 2021; Wu, 2021; Baek et al., 2020; Ashraf, 2020) and the number of deaths caused by the Covid-19 virus (Ashraf, 2020; Lee et al., 2020; Czech et al., 2020).

Several articles reported certain problems related to the measures adopted by public health authorities in each country during the pandemic period (Chu et al., 2020; Petherick et al., 2021, Gros et al., 2021). Chisadza et al. (2021, p. 3042) identified a nonlinear relationship between government response indices and the number of deaths. In response to these problems, the Government Response Stringency Index developed by Hale et al., (2021, p. 8) was proposed. The authors evaluated the impact of government decisions on deaths caused by the COVID-19 pandemic worldwide. For the development of the index, 186 countries were taken into account, and the analysed period was between March 19, 2020 and December 31, 2021.

2. Data and time series

The countries analyzed were chosen based on objective criteria such as: heavily affected by the Covid-19 virus,

Table 1. Indices analysed (source: authors calculations using EVIEWS)

Index	Country
AEX	Netherland
AOR	Australia
ATHEX	Greece
BEL20	Belgium
BOVESPA	Brazil
CAC 40	France
DAX 40	Germany
FMIB	Italy
FTSE 100	United Kingdom
IBEX	Spain
IPC	Mexico
JCI	Indonesia
KOSPI 50	Korea
NIKKEY	Japan
NZX 50	New Zealand
OMX Riga	Latvia
OMX Tallinn	Estonia
OMX Vilnius	Lithuania
PSI20	Portugal
RTS	Russia
SENSEX 30	India
SHC	China
SMI	Switzerland
SP 500	United States
TA 100	Israel
TSX	Canada
WIG 30	Poland
XU 100	Turkey

all continents covered in order to have a global image of volatility, being among the 186 countries taken into account at establishing the SI index. A single representative index (benchmark) was chosen for each state.

Table 1 shows the selected countries and the associated index. For each index, daily closing prices were downloaded using (https://www.investing.com) platform. The same step was done with the daily values of the SI index, using the (https://ourworldindata.org/) platform. The time series were completed over the same period of equal length.

3. Methodology

The daily return of the indices was calculated as the difference of the logarithms of the daily closing prices, a procedure frequently found in volatility analysis (Wu et al., 2021; Czech et al., 2020; Valls Martínez & Cervantes, 2021; Mohsin et al., 2020; Harjoto & Rossi, 2023).

$$R_{i,t} = \ln\left(P_{i,t}\right) - \ln\left(P_{i,t-1}\right) = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right), \tag{1}$$

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

In Appendix "Descriptive statistics" the null hypothesis of a unit root is rejected as the test value is less than the critical value for any of the significance levels. Daily logarithmic returns series are significant at 1%, 5%, and 10% levels. It follows that the series are stationary and do not follow a stochastic process. The quantile-quantile (Q–Q) plot allowed for comparison of distributions. All eigenvalues are placed inside a unit circle (data available on request).

Based on simulations, the GARCH model was chosen for processing time series. Such models are widely applied for time series analysis (Czech et al., 2020; Hongsakulvasu & Liammukda, 2021; Mohsin et al., 2020). These models simultaneously test and evaluate return and volatility. The relation describing the Garch (p, q) model is as follows:

$$h_t = \varphi + \sum_{k=1}^{p} \theta_k \cdot h_{t-k} + \sum_{i=1}^{q} b_i \cdot u_{t-i}^2, \tag{2}$$

where p is the lagged terms of the conditional variance (h), q are the lagged terms of the squared error (u^2) (Engle, 1982; Bollerslev, 1986). To ensure the stationarity condition $b_0 > 0$, $0 \le b_1 < 1$, $b_1 + \theta_1 < 1$. If $p = q = 1$, then the Garch (1, 1) model becomes:

$$h_t = \varphi + \theta_1 \cdot h_{t-1} + b_1 \cdot u_{t-1}^2 . \tag{3}$$

Research continued to establish the causes of volatility. For this purpose, the vector autoregression (VAR) model developed by (Sims, 1980, p. 33) was applied to demonstrate that there is a dependence between SI and volatility. Each variable in the VAR application appears as a linear combination of its past eigenvalues. Historical values of each variable are considered together with a serially uncorrelated error term.

$$INDEX_t = \delta_1 + \sum_{j=1}^{k} \beta_j \cdot INDEX_{t-j} + \sum_{j=1}^{k} \gamma_j \cdot SI_{t-j} + u_{1t}; \tag{4}$$

$$SI_t = \delta_2 + \sum_{j=1}^{k} \psi_j \cdot SI_{t-j} + \sum_{j=1}^{k} \varphi_j \cdot INDEX_{t-j} + u_{2t}, \tag{5}$$

where δ_1, δ_2 are free terms; β, ψ, γ, φ are the coefficients of the variables; u_{1t}, u_{2t} are white noise.

The following research hypotheses were formulated:

H1. There is a strong dependence between SI and volatility during the analysed period;

H2. There is no relationship between SI and volatility during the analysis period.

The VAR order of the series is determined by the p-value in Equation (5). It was identified with Akaike (AIC) and Schwarz (SC) information criteria (Mauricio, 2006, p. 3653):

$$AIC = -\frac{2 \cdot N^*}{n} + \frac{2 \cdot r}{n}; \tag{6}$$

$$SC = -\frac{2 \cdot N^*}{n} + \frac{r \cdot \ln(n)}{n}, \quad (7)$$

where N^* is the Napierian logarithm of the likelihood relation, r is the number of estimated parameters, and n is the number of observations.

The Johansen test allows the INDEX and SI variables to be evaluated as vectors (MacKinnon et al., 1999, p. 567):

$$INDEX = |p,u|, SI = |q,u|, \quad (8)$$

where p and q are the components of the series vector, and u is the number of cointegration vectors.

For each VAR model, the Granger causality test was used (Corbet et al., 2020; Fariska et al., 2021; Kumeka et al., 2022; Moslehpour et al., 2022). The Granger test identifies if the variable X brings additional information (besides the past values of Y) that can be useful in the prediction of X. To test whether X is Granger-caused by Y, the regression equation is estimated as follows:

$$Y_t = \mu + \sum_{i=1}^{k} \beta_i Y_{t-i} + \sum_{j=1}^{k} \alpha_j X_{t-j} + \epsilon_t. \quad (9)$$

Similarly, whether Y is the cause of the X regression equation becomes:

$$X_t = \mu + \sum_{i=1}^{k} \xi_i X_{t-i} + \sum_{j=1}^{k} \delta_j Y_{t-j} + \epsilon_t, \quad (10)$$

where X and Y are the variables μ is free term β_i, α_j, ξ_i and δ_j are the coefficients of the variables, and ϵ_t is white noise (error).

Statistical data was processed with the EViews 13 software (Quantitative Micro Software, USA).

4. Results. Robustness tests

Appendix "Descriptive statistic" presents the results for all series over the entire considered period. From the results, it can be stated that the time series do not follow a normal distribution. It can be seen that the skewness indicator has values different from 0 for all the series having the meaning of an asymmetry. The mean of the skewness is located to the right of the peak distribution. Therefore, the mean value is less than the median and shifts to the right. Negative skewness is found in the AOR, BEL 20, IPC, NZX 50, SENSEX 30 and XU 100 indices, which are skewed to the left.

Kurtosis shows the amplitude of extreme results. All measured values are greater than 3. Such a result shows that the data series have thicker tails compared to the normal distribution and the stock index returns are leptokurtic. All the series have excess kurtosis, which shows a high probability of recording extreme results. The highest results were recorded for TSX (+25.98), SENSEX 30 (+24.44) and BEL 20 (+23.48). In the same period, the lowest results were measured at WIG 30 (+4.70) and IPC (+4.99).

The null hypothesis of series normality is rejected at the critical level of 1% and by means of the Jarque-Bera test, the associated probabilities of this test is zero. Therefore, the standard deviation does not adequately describe the volatility of the return series due to the fact that it does not correctly capture the characteristics of the data series. As can be seen in Table 2 the probability is 0%. The risk level of these indices is high, which means that the stock markets are unstable.

From Appendix "Daily index returns", it can be observed that the indices show the characteristics of volatility clustering. Some indices, such as ATHEX, DAX 40, NIKKEY, and SENSEX 30 show high volatility throughout the period. Other stock indices such as AOR, IPC, OMX Riga, OMX, Tallinn, and OMX Vilnius show lower volatility. We find that most of the indices have a similar trend, accelerated volatility followed by stabilisation. Volatility fluctuations remain in the BOVESPA, NIKKEY, PSI 20, RTS, SHC, and WIG 30 indices.

Some preliminary tests were performed to detect ARCH effects to establish heteroskedasticity. For this purpose, the Q test, partial autocorrelation (PAC), and autocorrelation (AC) were established (Greene, 2002, p. 268). The number of lags used for all series was 20. The numerical values obtained are presented in Table 2.

Table 2. Heteroskedasticity results (source: authors calculations using EVIEWS)

Indices	Lag	AC	PAC	Q-Stat	Prob.
AEX	20	–0.014	–0.019	176.130	0.00
AOR	20	–0.005	–0.128	203.270	0.00
ATHEX	20	–0.029	–0.016	151.330	0.00
BEL 20	20	0.031	0.041	255.380	0.00
BOVESPA	20	–0.049	–0.079	146.510	0.00
CAC 40	20	–0.006	–0.070	193.760	0.00
DAX 40	20	0.031	–0.016	191.320	0.00
FMIB	20	0.031	–0.079	190.550	0.00
FTSE 100	20	0.024	–0.097	217.410	0.00
IBEX	20	–0.061	–0.037	199.590	0.00
IPC	20	0.043	–0.048	127.700	0.00
JCI	20	–0.108	–0.019	161.250	0.00
KOSPI 50	20	–0.008	0.014	195.570	0.00
NIKKEY	20	–0.088	–0.107	201.610	0.00
NZX 50	20	0.066	0.028	186.270	0.00
OMX Riga	20	0.110	–0.014	173.350	0.00
OMX Tallinn	20	–0.040	–0.039	118.990	0.00
OMX Vilnius	20	–0.040	–0.046	138.520	0.00
PSI 20	20	0.041	–0.014	145.580	0.00
RTS	20	–0.032	–0.065	149.450	0.00
SENSEX 30	20	0.021	–0.100	191.930	0.00
SHC	20	0.031	–0.006	136.470	0.00
SMI	20	0.040	0.000	151.550	0.00
SP 500	20	0.093	–0.147	293.100	0.00
TA 100	20	–0.043	0.025	177.740	0.00
TSX	20	0.169	–0.013	217.050	0.00
WIG 30	20	0.079	0.058	144.840	0.00
XU 100	20	–0.054	–0.090	165.120	0.00

Note: * denotes rejection of the hypothesis at the 0.05 level; ** MacKinnon-Haug-Michelis (1999) p-values.

After performing these tests, the GARCH (1.1) model was applied. Parameters b_1 and θ_1 reproduce the short-term dynamics of conditional variance. Thus, b_1 captures the speed of volatility adjustment. and θ_1 indicates the persistence of volatility. A value close to 1 show that indices are slowly returning to their mean value and shocks are diminishing over time. We checked conditions $b_0 > 0$, $0 \leq b_1 < 1$, $b_1 + \theta_1 < 1$. Also, the model is not relevant from a statistical point of view for the BOVESPA index since the value of $p > 0.05$ (Appendix "Daily index returns").

The results obtained with the DW test (Durbin & Watson, 1950, p. 409) exclude autocorrelation between data series. Numeric values are in the range (0–4). A value close to the mean of the range excludes autocorrelation of the data series. The results are close to 2 for all data series. The highest results are found in the AEX (2.2) and RTS (2.14) indices, and the lowest at OMX Riga (1.82), 1.88 (NIKKEY) (data available on request).

The results for the log-likelihood function show the extent to which the model fits all data series. Estimation of the logarithmic likelihood function under a skewed distribution having the significance of an excess of kurtosis. The results converge to small negative values due to the small number of parameters and high values for the log-likelihood indicator (data available on request).

In general, the results for the probability p are less than 0.05 and show the statistical significance of the results. Null values of the probability are determined by a strong relation between the predictive models and the time series.

The stationarity of the time series was checked for the subsequent choice of a suitable analysis model. For this purpose, the Augmented Dickey-Fuller (ADF) test, frequently used in time series processing, was applied in the Appendix "ADF results" (Corbet et al., 2020; Youssef et al., 2021; Fariska et al., 2021; Zhang & Mao, 2022).

To establish the causality between SI and stock indices, the Granger test was applied. In the period analysed, was identified no causal dependence between indices and SI. The results were checked with the Johansen cointegration test. Two statistical tests were used, eigenvalue and trace statistics. The eigenvalue tests the hypothesis of a co-integration relationship. Therefore, the results clearly suggest that the variables are not cointegrated. For AEX, BEL20, BOVESPA, IBEX, NICKEY, OMX Riga, OMX Vilnius, PSI 20, SP 500 and WIG 30 cases, the probability is greater than 5%. However, the correlation cannot be rejected up to lag 20. Therefore, the GARCH model can also be used for these data series (data available on request).

The use of SI allowed for the measurement of volatility in the analysed period. Small differences are found between the volatility calculated using disease cases (Lee et al., 2020; Czech et al., 2020; Vo et al., 2022; Valls Martínez & Cervantes, 2021; Wu, 2021; Muhammad et al., 2021) or deaths (Lee et al., 2020, p. 612).

We confirm the results obtained in another large-scale analysis that included 28 countries around the world (Souza de Souza & Silva, 2020, p. 170). Similarly, we find that some value markets showed greater adaptability to the pandemic. Before confirmation of the first cases of the disease, there is an increase in volatility in the countries under analysis, according to the articles (Souza de Souza & Silva, 2020; Youssef et al., 2021; Lee & McKibbin, 2004; Atkeson, 2020; Chahuan-Jiménez et al., 2021; Mohsin et al., 2020).

Conclusions, limitations, and research directions

The results show that the COVID-19 pandemic generated major shocks that had a negative effect on the stock market indices. Moreover, the distribution of daily return series does not follow a normal distribution, but is leptokurtic for each index.

Synthesis of literature in the area of pandemics shows that no previous virus has caused such increases in volatility. Compared to the crises generated by other viruses in the past, there were a higher volatility. We can see that the volatility generated by other viral infections had a regional effect compared to the Covid-19 pandemic. From this point on, comparative analyses can be made between the effects generated by Covid-19 and Zika, SARS, foot and mouth disease, H1N1, and others.

Our results allow comparisons between the volatility recorded during the pandemic and other negative events, with the exception of viral infections, which affected the world economy or only certain geographical areas (military or political conflicts, the eurozone debt crisis, OPEC oil shocks, the 2008 crisis and others).

An advantage of the paper is the consideration of a long period of analysis that caught the pandemic waves. Our results do not confirm the fact that countries that had greater economic and political stability during the pandemic had lower volatility.

An increase in volatility is found before the confirmation of the first cases of disease in the analyzed countries. Volatility also increased dramatically as first cases of illness were confirmed in the countries analyzed. The volatility growth curve is similar to the volatility dynamics in each of the countries analysed in the first months of 2020. The results are consistent with hypotheses H1. Such analyzes can be divided by state, pandemic cycles or shorter periods of time. A major shortcoming is determined by the start date of the index, which does not allow for comparisons with previous major events.

The use of the index to determine volatility may be limited because it is not developed by an international institution. But can be used as an alternative in studying volatility during pandemics. It is interesting to do a comparative analysis of the results that can be obtained with the help of the SI index through specific machine learning procedures. For the BOVESPA indices, it is recommended to use a different GARCH model.

In our opinion, the moments that decisively contributed to the growth and spread of volatility were: the declaration by the WHO of the pandemic on 11 March 2020, the moment of the appearance of the first case of illness and the appearance of the first death caused by Covid-19 in each state, the declaration of emergency, and the imposition of lockdown on the national territory.

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Author contributions

The authors state that they contributed equally to the article.

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Appendix

Table A1. Descriptive statistic (source: authors calculations using EVIEWS)

Variable	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Prob.
AEX	0.0015	0.0013	0.0859	–0.0381	0.0123	0.5908	8.4671	599.631	0.00
AOR	0.0010	0.0011	0.0635	–0.0616	0.0117	–0.1096	9.0910	704.273	0.00
ATHEX	0.0014	0.0014	0.1085	–0.0788	0.0160	0.9190	11.964	1552.56	0.00
BEL 20	0.0005	0.0007	0.0736	–0.1533	0.0162	–2.1014	23.481	8524.33	0.00
BOVESPA	0.0010	0.0009	0.0925	–0.0567	0.0166	0.2776	6.2470	200.293	0.00
CAC 40	0.0014	0.0014	0.0806	–0.0487	0.0136	0.4654	8.7086	641.204	0.00
DAX 40	0.0014	0.0010	0.1041	–0.0457	0.0141	0.7450	10.811	1196.11	0.00
FMIB	0.0013	0.0016	0.0855	–0.0493	0.0135	0.1307	7.6442	411.105	0.00
FTSE 100	0.0008	0.0007	0.0867	–0.0539	0.0125	0.3979	9.5263	814.075	0.00
IBEX	0.0007	0.0009	0.0823	–0.0517	0.0142	0.5021	7.3810	385.511	0.00
IPC	0.0009	0.0005	0.0474	–0.0549	0.0118	–0.1479	4.9956	76.6466	0.00
JCI	0.0010	0.0008	0.0970	–0.0534	0.0125	0.7395	12.694	1738.77	0.00
KOSPI 50	0.0014	0.0017	0.0898	–0.0754	0.0145	0.3615	9.4245	771.511	0.00
NIKKEY	0.0012	0.0006	0.0773	–0.0462	0.0134	0.5573	7.1049	330.192	0.00
NZX 50	0.0007	0.0006	0.0694	–0.0789	0.0100	–0.1793	16.887	3626.59	0.00
OMX RIGA	0.0009	0.0003	0.0509	–0.0358	0.0079	0.8146	8.2869	563.657	0.00
OMX TALLINN	0.0016	0.0012	0.0520	–0.0435	0.0098	0.0620	7.9299	452.954	0.00
OMX VILNIUS	0.0011	0.0008	0.0459	–0.0381	0.0063	0.4041	12.743	1772.14	0.00
PSI 20	0.0009	0.0010	0.0753	–0.0295	0.0117	0.6185	6.5912	276.518	0.00
RTS	0.0014	0.0019	0.0883	–0.0793	0.0177	0.0585	6.6263	249.021	0.00
SENSEX 30	0.0016	0.0023	0.0859	–0.1410	0.0151	–1.5231	24.450	8663.71	0.00
SHC	0.0007	0.0008	0.0555	–0.0460	0.0101	0.0039	6.1517	180.866	0.00
SMI	0.0010	0.0012	0.0678	–0.0552	0.0101	0.4053	10.596	1099.05	0.00
SP 500	0.0015	0.0017	0.0897	–0.0608	0.0127	0.5532	11.809	1484.55	0.00
TA 100	0.0014	0.0008	0.0723	–0.0468	0.0119	0.5371	7.8275	446.374	0.00
TSX	0.0013	0.0016	0.1129	–0.0540	0.0115	1.5909	25.984	10072.2	0.00
WIG 30	0.0012	0.0007	0.0506	–0.0549	0.0138	0.1370	4.7069	55.9097	0.00
XU 100	0.0017	0.0027	0.0581	–0.1031	0.0156	–1.5484	12.352	1803.59	0.00

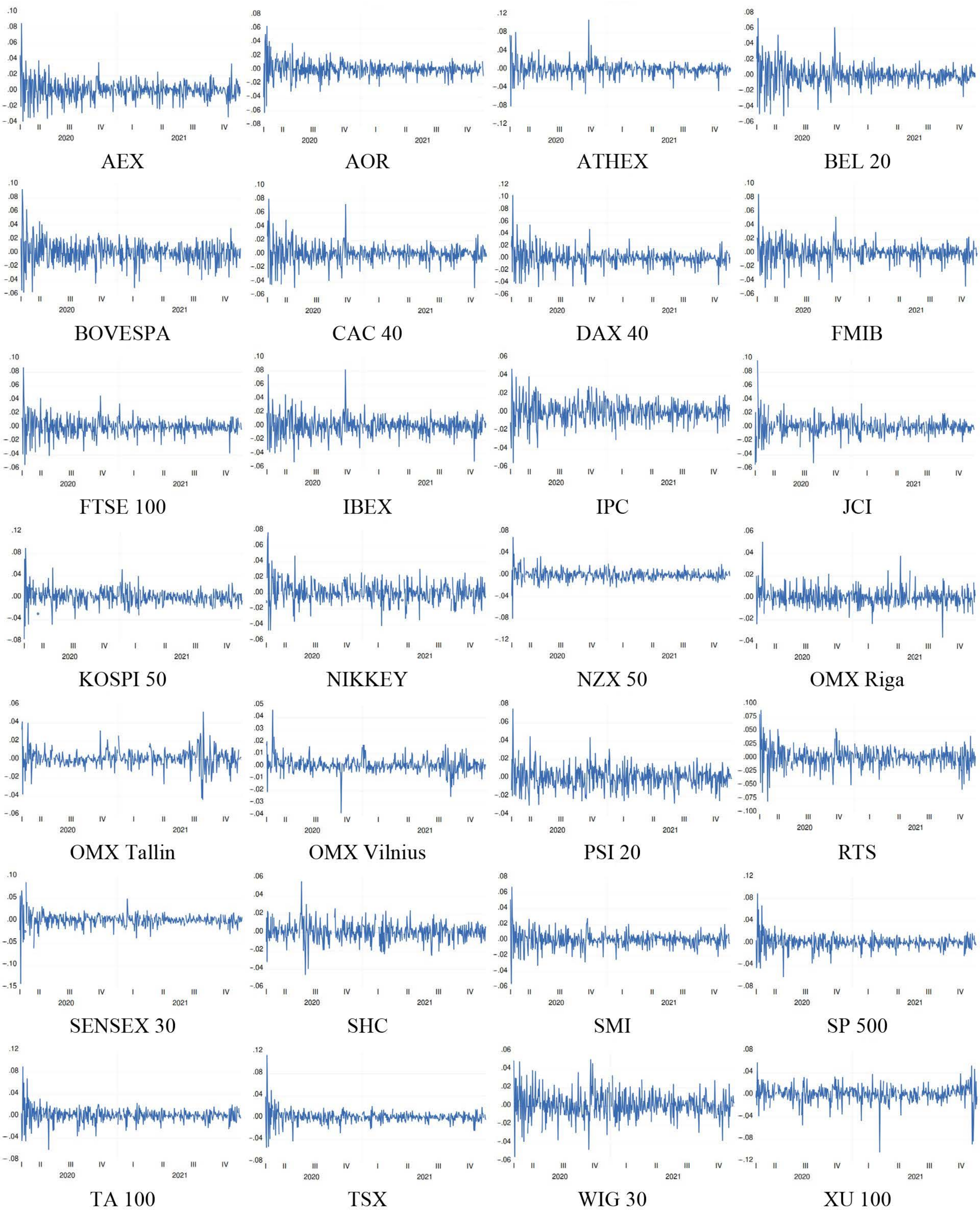

Figure A1. Daily index returns (source: authors calculations using EVIEWS)

Table A2. ADF results (source: authors calculations using EVIEWS)

ADF	t-Statistic	Prob.	ADF	t-Statistic	Prob.
AEX	−16.29224	0.000	SI Netherland	−20.84484	0.000
1%	−3.444562		1%	−3.444404	
5%	−2.867700		5%	−2.867631	
10%	−2.570115		10%	−2.570077	
AOR	−13.96154	0.000	SI Australia	−21.38625	0.000
1%	−3.444823		1%	−3.444562	
5%	−2.867815		5%	−2.867700	
10%	−2.570176		10%	−2.570115	
ATHEX	−14.16844	0.000	SI Greece	−20.86858	0.000
1%	−3.445127		1%	−3.444890	
5%	−2.867949		5%	−2.867845	
10%	−2.570248		10%	−2.570192	
BEL20	−15.88936	0.000	SI Belgium	−21.204220	0.000
1%	−3.444311		1%	−3.444404	
5%	−2.867590		5%	−2.867631	
10%	−2.570055		10%	−2.570077	
BOVESPA	−14.96502	0.000	SI Brazil	−20.65829	0.000
1%	−3.445162		1%	−3.444957	
5%	−2.867965		5%	−2.867874	
10%	−2.570256		10%	−2.570208	
CAC 40	−16.47897	0.000	SI France	−21.40570	0.000
1%	−3.444562		1%	−3.444404	
5%	−2.867700		5%	−2.867631	
10%	−2.570115		10%	−2.570077	
DAX 40	−16.04250	0.000	SI Germany	−19.36152	0.000
1%	−3.444757		1%	−3.444594	
5%	−2.867786		5%	−2.867715	
10%	−2.570161		10%	−2.570122	
FMIB	−15.04310	0.000	GSI Italy	−8.81429	0.00
1%	−3.444691		1%	−3.444890	
5%	−2.867757		5%	−2.867845	
10%	−2.570145		10%	−2.570192	
FTSE 100	−16.96620	0.0000	SI United Kingdom	−18.01586	0.000
1%	−3.444823		1%	−3.444659	
5%	−2.867815		5%	−2.867743	
10%	−2.570176		10%	−2.570138	
IBEX	−15.69366	0.000	SI Spain	−21.307100	0.000
1%	−3.444627		1%	−3.444467	
5%	−2.867729		5%	−2.867658	
10%	−2.570130		10%	−2.570092	
IPC	−14.77042	0.000	SI Mexico	−14.608180	0.000
1%	−3.444856		1%	−3.444659	
5%	−2.867830		5%	−2.867743	
10%	−2.570184		10%	−2.570138	
JCI	−14.20648	0.000	SI Indonesia	−20.75361	0.000
1%	−3.445481		1%	−3.445267	
5%	−2.868105		5%	−2.868011	
10%	−2.570332		10%	−2.570281	
KOSPI 50	−15.19690	0.000	SI South Korea	−20.88969	0.000

Continue of Table A2

ADF	t-Statistic	Prob.	ADF	t-Statistic	Prob.
1%	−3.445197		1%	−3.444957	
5%	−2.867980		5%	−2.867874	
10%	−2.570265		10%	−2.570208	
NIKKEY	−16.40677	0.000	SI Japan	−20.703710	0.000
1%	−3.445267		1%	−3.445127	
5%	−2.868011		5%	−2.867949	
10%	−2.570281		10%	−2.570248	
NZX 50	−13.40504	0.000	SI New Zealand	−20.84034	0.000
1%	−3.444991		1%	−3.444691	
5%	−2.867889		5%	−2.867757	
10%	−2.570216		10%	−2.570145	
OMX RIGA	−14.53261	0.000	SI Latvia	−21.57306	0.0000
1%	−3.445232		1%	−3.444991	
5%	−2.867995		5%	−2.867889	
10%	−2.570273		10%	−2.570216	
OMX TALLIN	−11.36677	0.000	SI Estonia	−20.31562	0.000
1%	−3.445232		1%	−3.444823	
5%	−2.867995		5%	−2.867815	
10%	−2.570273		10%	−2.570176	
OMX VILNIUS	−14.73850	0.000	SI Lithuania	−20.99064	0.000
1%	−3.445025		1%	−3.444890	
5%	−2.867904		5%	−2.867845	
10%	−2.570224		10%	−2.570192	
PSI 20	−14.62123	0.000	SI Portugal	−8.952623	0.000
1%	−3.444594		1%	−3.444531	
5%	−2.867715		5%	−2.867686	
10%	−2.570122		10%	−2.570107	
RTS	−13.08827	0.000	SI Russia	−21.59962	0.000
1%	−3.444856		1%	−3.444594	
5%	−2.867830		5%	−2.867715	
10%	−2.570184		10%	−2.570122	
SENSEX 30	−21.66252	0.000	SI India	−20.62805	0.000
1%	−3.445059		1%	−3.444957	
5%	−2.867919		5%	−2.867874	
10%	−2.570232		10%	−2.570208	
SHC	−12.13193	0.000	SI China	−20.30509	0.000
1%	−3.445481		1%	−3.445162	
5%	−2.868105		5%	−2.867965	
10%	−2.570332		10%	−2.570256	
SMI	−15.65984	0.000	SI Switzerland	−20.78468	0.000
1%	−3.444856		1%	−3.444659	
5%	−2.867830		5%	−2.867743	
10%	−2.570184		10%	−2.570138	
SP 500	−16.67513	0.000	SI U.S.A.	−21.86790	0.000
1%	−3.444890		1%	−3.444659	
5%	−2.867845		5%	−2.867743	
10%	−2.570192		10%	−2.570138	
TA 100	−14.91083	0.000	SI Israel	−20.55094	0.000
1%	−3.445409		1%	−3.445127	

End of Table A2

ADF	t-Statistic	Prob.	ADF	t-Statistic	Prob.
5%	−2.868073		5%	−2.867949	
10%	−2.570315		10%	−2.570248	
TSX	−15.82084	0.000	SI Canada	−23.46873	0.000
1%	−3.444991		1%	−3.444757	
5%	−2.867889		5%	−2.867786	
10%	−2.570216		10%	−2.570161	
WIG 30	−15.76828	0.000	SI Poland	−20.33036	0.000
1%	−3.444923		1%	−3.444757	
5%	−2.867859		5%	−2.867786	
10%	−2.570200		10%	−2.570161	
XU 100	−15.38168	0.000	SI Turkey	−20.24842	0.000
1%	−3.445025		1%	−3.444856	
5%	−2.867904		5%	−2.867830	
10%	−2.570224		10%	−2.570184	

Table A3. GARCH estimates (source: authors calculations using EVIEWS)

Dependent variable	Coefficient	Std. Error	z-Statistic	Prob.
AEX	0.001539	0.00049	3.136755	0.0017
AOR	0.000301	0.001593	0.189077	0.8500
ATHEX	5.77E-03	0.003887	1.485387	0.1374
BEL 20	0.001610	0.000326	4.941297	0.0000
BOVESPA	0.006991	0.003537	1.976779	0.0481
CAC 40	0.002601	0.000415	6.264686	0.0000
DAX 40	0.001197	0.001912	0.626190	0.5312
FMIB	0.003042	0.00303	1.004146	0.3153
FTSE 100	0.001257	0.000328	3.835370	0.0001
IBEX	0.003122	0.002549	1.224595	0.2207
IPC	0.001092	0.001135	0.962236	0.3359
JCI	−0.006912	0.003565	−1.938808	0.0525
KOSPI 50	0.009229	0.003690	2.500688	0.0124
NIKKEY	−0.001553	0.002611	−0.594874	0.5519
NZX 50	0.000163	0.000607	0.268146	0.7886
OMX RIGA	0.000955	0.001349	0.708078	0.4789
OMX TALLINN	0.000956	0.001142	0.837497	0.4023
OMX VILNIUS	0.000927	0.000876	1.057639	0.2902
PSI 20	0.001243	0.001858	0.669144	0.5034
RTS	0.000914	0.002771	0.329761	0.7416
SENSEX 30	0.002618	0.003081	0.849578	0.3956
SHC	0.000946	0.003545	0.266998	0.7895
SMI	0.002223	0.001562	1.423192	0.1547
SP 500	0.000816	0.002822	0.289159	0.7725
TA 100	0.002638	0.001423	1.853515	0.0638
TSX	0.002990	0.004681	0.638848	0.5229
WIG 30	0.003341	0.001486	2.248535	0.0245
XU 100	−0.000207	0.002645	−0.078085	0.9378

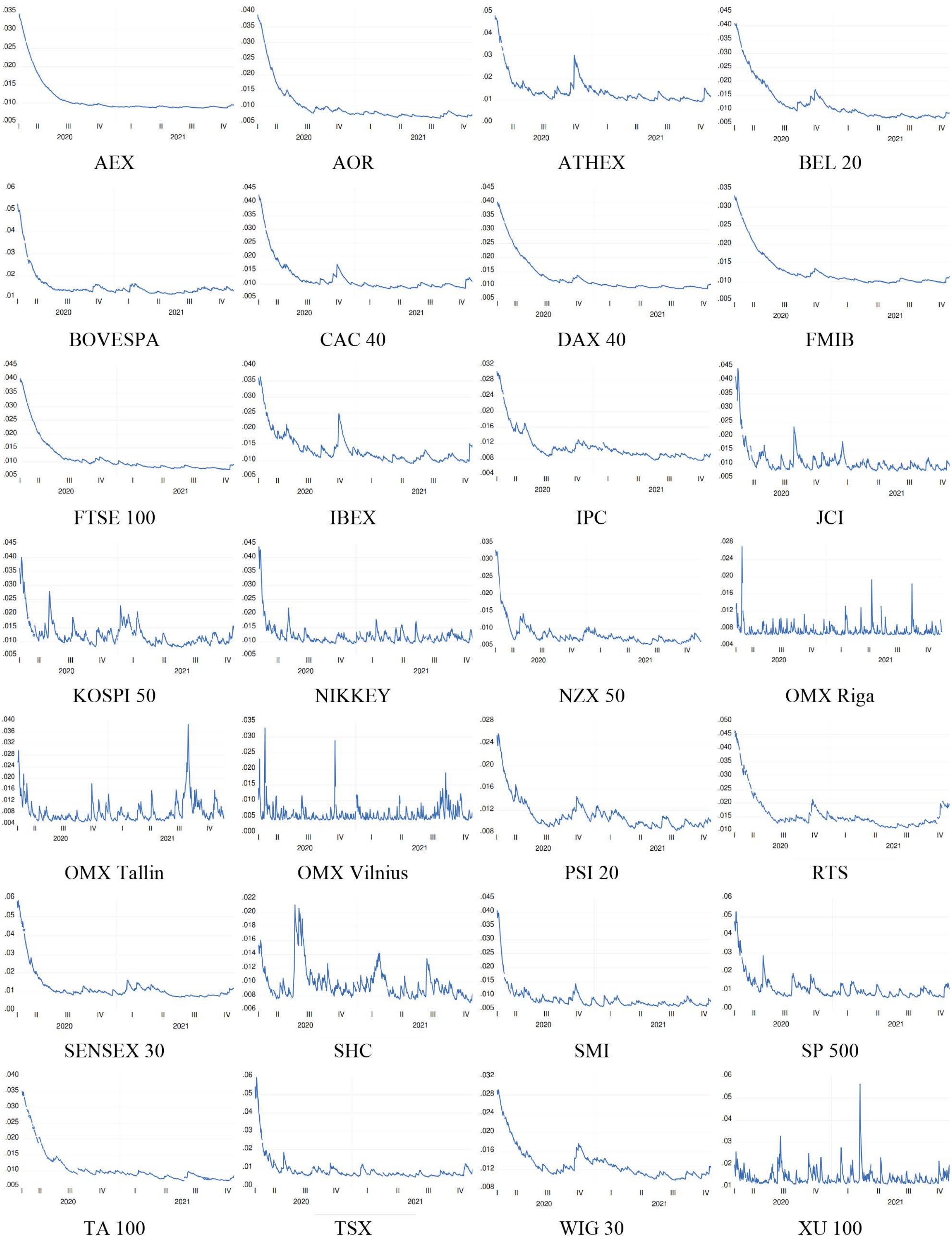

Figure A2. Conditional standard deviation (source: authors calculations using EVIEWS)