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Effect of Structural Breaks on Stock Market Performance during COVID-19 Period in Sri Lanka

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ABSTRACT

This study investigates the effects of structural breaks on the Colombo Stock Exchange (CSE) performance over the COVID-19 period. Stock market returns and volatility are used to proxy the stock market performance. Structural breaks were identified by using the Bai-Perron (2003) test. An ARMA (p,q) model fitted for stock returns was augmented using dummy variables for the structural breaks to measure the effect of structural breaks on stock market returns. The model was further extended as a volatility regression model (GARCH, EGARCH, or TGARCH) to measure the effect of structural breaks on stock market volatility. The results confirmed the presence of structural breaks following COVID-19-related news in CSE. Seventeen such breaks were identified. However, only three significantly influenced the stock market returns and the volatility. As a result, the study's consequences affect stockbrokers, multinational organizations, portfolio managers, and investors, allowing them to foresee market patterns and take preventative action in the event of structural breaks.

Keywords: All Share Price Index, structural breaks, stock market return, stock market volatility

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INTRODUCTION

An unparalleled global crisis began when the COVID-19 epidemic first appeared in Wuhan, China, in December 2019. According to the G lobal Uncertainty Index and the World Pandemic Uncertainty Index, the level of uncertainty in the globe was higher than it had ever been between pandemics (Central Bank of Sri Lanka, 2020). For nations like Sri Lanka, the effects of COVID-19 were particularly severe, leading to an economic downturn of 4.5% and a stunning loss of around $3.94 billion (Department of Economic and Social Affairs, United Nations, 2020). As a result, unemployment rates significantly increased, rising to over 6% in the second quarter and continuing, it is predicted, throughout the year (Center for International Private Enterprise [CIPE], 2020). As a result, Sri Lanka's economy shrank by 3.6% in 2020, and on April 6, 2020, its currency, the Sri Lankan Rupee, lost about 9% of its value versus the US dollar.

Vinothanantharaj (2020) underlined that because Sri Lanka is a tiny open economy with limited fiscal capacity, the pandemic presented special issues for the country . This situation brought about financial market instability, capital withdrawals, and a sharp drop in foreign investments. Foreign-owned T-bills and T-bonds witnessed a 70% outflow in a short period of time, totaling US$ 372 million or 0.42% of GDP. As a result of supply chain interruptions brought on by the pandemic, food prices increased, which increased inflationary pressures (CSE, 2020). The Colombo Stock Exchange (CSE) saw a severe collapse, with its March 2020 decline being the sharpest in eight years.

Share prices at CSE decreased as a result of the pandemic's uncertainty, falling precipitously in March 2020. As a result, foreign investors sold shares for US$ 273 million (about Rs. 56 billion) in 2020 and US$ 25 million (roughly Rs. 5.1 billion) in January 2021. Notably, within two months, there was a 70% outflow of foreign T-bills and T-bonds, which led to 5.3% depreciation in the value of the Sri Lankan Rupee (Huettemann, 2020). The government temporarily suspended trade to reduce sales after Sri Lanka's main stock market index, the ASPI, reached an eight-year low on May 12, 2020 (Huettemann, 2020). In such economic conditions, a nation's foreign reserves, which include assets like foreign marketable securities and monetary gold, are extremely important. The beneficial effects of foreign portfolio investment (FPI) on economic growth were highlighted by Albulescu (2015).

Surprisingly, despite the economic uncertainty, local investors took the risk of investing in equities during the bear market because they didn't fully understand net asset value and the state of the market. This transition from a bear to a bull market demonstrated the tenacity and capacity of local investors to turn the market around ("Ekwa Jayagamu," 2021). Similarly, during the pandemic, the stock market saw a drop followed by a recovery, including in Sri Lanka (Karavias et al., 2022).

Given this, the study's goal is to carefully examine the structural failures that took place between December 1, 2019, and June 30, 2021. Identifying whether these breaks were a result of COVID-19 is a crucial goal. It is important to research how structural breaks affected Sri Lanka's stock market during the COVID-19 period because it sheds light on how resilient and adaptable the market is to outside shocks, helps to understand the particular dynamics of the country's economy, and educates investors and policymakers about risk management and long-term stability in unpredictable times. The study also aims to evaluate how these structural fractures affect returns and volatility in the stock market. Understanding the origins and extent of these structural breaches is important, especially when they occur in tandem with a significant global event like the COVID-19 pandemic. It is feasible to learn more about the complex relationship between market performance and unprecedented external shocks by looking at these tendencies.

LITERATURE REVIEW

The stock market plays a crucial role in modern economies by easing resource allocation among various investments and providing a venue for trading securities of publicly traded businesses. The history of stock market activity in Sri Lanka begins in the 18th century. However, the Sri Lankan share market experienced significant expansion in the late 1970s, as seen by an increase in the number of listed businesses and a rise in total market value, driven by the adoption of open market economic methods. Following the late 1970s, market-friendly policies were implemented, and succeeding Sri Lankan administrations gave priority to promoting private investment within the country (Attapattu & Gunaratne, 2013).

In a study by Jameel and Teng (2022), the focus of the analysis was on how exchange rate volatility affected stock market return volatility in the context of the Colombo Stock Exchange. The analysis of structural breaks in the exchange rates of the US dollar (USD) and Sri Lankan rupee (LKR) was a major focus. The study identified periods of structural breaks (SBPs) based on their matching dates using the Bai-Perron structural break test.

The All-Share Price Index (ASPI) returns from the Colombo Stock Exchange were treated as dependent variables in the study's framework, while the volatility of the USD exchange rate was treated as an independent variable. Using this information to explore the relationship between exchange rate volatility and stock market return volatility, Jameel calculated the volatility of the USD exchange rate using the Generalized Auto-Regressive Conditional Heteroscedasticity (GARCH) model. According to Jameel's findings, volatility shocks persisted in the USD exchange rate and ASPI over a long period of time, revealing unique structural break points. The analysis found a complex association between currency market volatility and the Sri Lankan stock market, even though the relationship had a non-uniform impact across the large dataset. Instead, this influence highlighted differences over various structural break times, highlighting the complex relationship between these important economic variables.

A thorough investigation of the effects of COVID-19 on stock return volatility in 15 countries, including Sri Lanka, was carried out by Kusumahadi and Permana in 2021. Their research set out to identify significant structural shifts that occurred during this observation window using daily data spanning from January 2019 to June 2020, noting that these transitions occurred earlier in the time period as well as after the initial COVID-19 instance. They used a persuasive analytical strategy based on threshold generalized autoregressive conditional heteroskedasticity regressions. Except for the United Kingdom, their data showed that the introduction of COVID-19 had an impact on stock return volatility in the majority of the countries they studied. Their research also showed a favorable association between return volatility and the existence of COVID-19 in a nation. It's important to remember that this influence was only moderately strong in all countries under consideration.

In light of these findings, the researchers stressed the need for more thorough investigations into additional elements contributing to stock return volatility beyond the simple incidence of the COVID-19 epidemic. This highlights how intricately different elements interact with stock market dynamics, driving a deeper comprehension of the mechanisms influencing market behavior.

Karavias et al. (2022) have revealed a significant connection between structural fractures and the performance of the Australian stock market by examining the global landscape. According to their findings, many economies, including Australia, have shown signs of recovery despite the continued pandemic. This finding suggests a fundamental change in how stock returns and the structurally broken COVID-19 problem are related. The importance of determining when a structural rupture occurs, particularly when attempting to determine its repercussions, is stressed by researchers. Notably, their research was able to identify a structural rupture that occurred between January 3, 2020, and the first week of April. The impact of COVID-19 on stock returns retained a negative sway before the break, but after the break, this influence waned to a neutral position, signaling a clear change in the course of time.

The researchers stress that although markets respond to COVID-19, these responses are transient in nature. The implication is that market reactions are temporary, supporting the idea that, despite initial volatility, market flexibility and resilience typically outweigh long-term negative effects.

METHODOLOGY

For this quantitative research, the researchers have gathered ASPI data from 1st December 2019 to 30th June 2021 as the sampling period. Moreover, the researchers have considered the structural breaks as the independent variable and stock market returns as the dependent variable for this study. The data was analyzed by using the Stata Software.

To identify the structural breaks, the ICSS algorithm of Inclan and Tiao (1994), the modified version of 2004, CUSUM type tests, and Bai-Perron (2003) can be used. Out of those, to examine the multiple structural breaks that occurred in the Colombo stock exchange during the COVID-19 period, Bai-Perron (2003) has been adopted because it will be more appropriate for non-stationary data sets. The Bai-Perron technique is chosen because it can identify structural discontinuities in non-stationary datasets, which is an important feature for stock market data analysis because it considers both abrupt and gradual changes, it is appropriate for capturing subtle changes in financial time series, which are frequently non-stationary. Because of its adaptability and resilience in managing the intricacies of the Sri Lankan stock market, this approach was selected over others.

Moreover, the researchers have adopted the AR (1) model out of ARMA (PQ) models since it minimizes the AIC criteria. Thus, the model with dummy variables for each of the structural breaks has been developed as follows.

Yt = α0 + α1Yt-1 + α2Yt-2 + ...+ αpYt-p - Θ1Ɛt-1 - Θ2Ɛt-2 - ... - ΘqƐt-q + D1+D2+Dn ... + Ɛt... (1)

Where: Yt: The dependent variable at time "t." α0, α1, α2, ..., αp: Autoregressive coefficients for the dependent variable up to "p" lags. Yt-1, Yt-2, ..., Yt-p: Past values of the dependent variable up to "p" lags. Θ1, Θ2, ..., Θq: Moving average coefficients for the error terms up to "q" lags. Ɛt-1, Ɛt-2, ..., Ɛt-q: Past values of the error terms up to "q" lags. D1, D2, ..., Dn: Dummy variables representing structural breaks or discrete changes in the model. Ɛt: The error term at time "t," representing the difference between the observed value and the predicted value by the model at time "t."

To obtain the most fitted model of stock market volatility, well-known econometric models such as ARCH, GARCH, EGARCH, and TGARCH were considered for the investigation. Out of that, GARCH (1) (1) has been adopted by the researchers as it has the minimum criteria of AIC and log-likelihood than the other options which were considered. Thus, the model can be shown as follows.

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 + d_1 D_1 + d_2 D_2 + ... + d_n D_n + \varepsilon_t \text{ ....[2]}$$

Where ω,αi, and βi are the parameters of the GARCH(p, q) model, as before. σ2 is the lagged squared returns and lagged conditional variances, respectively. W is the constant or intercept term, representing the long-term average of the conditional variance. a2 is the coefficient of the lagged squared returns or errors representing the short-term impact of past shocks on the current conditional variance. N is the number of structural breaks or event dummies. D represents the dummy variable for the structural break or event…D is the coefficient associated with the dummy variable.

RESULTS AND DISCUSSION

This section describes the data analysis and discussion of the results of the various tests. Here, data analysis is conducted based on Bai and Perron's (2003) structural break test.

Measuring Structural Breaks

According to Bai and Perron's (2003) test, seventeen structural breaks were identified during the period from 1st December 2019 to 30th June 2021 through structural breaks testing. The first structural break was recognized on 27th December 2019. The second structural break was identified on 24th January 2020. The third break in CSE was identified on 27th February 2020. The fourth break in CSE was identified on 18th May 2020. On 24th June 2020, CSE reported its fifth break. The sixth break in CSE was recognized on 17th July 2020. On 14th August 2020, CSE reported its seventh break. The eighth break in CSE was identified on 9th September 2020. On 5th October 2020, CSE identified its ninth break. The tenth break in CSE was identified on 5th November 2020. On 1st December 2020, CSE has identified its eleventh break. The twelfth break in CSE was identified on 24th December 2020. On 22nd January 2021, CSE reported a thirteenth break. On 22nd January 2021, CSE reported a thirteenth break. The fourteenth break in CSE was identified on 18th February 2021. On 17th March 2021, the fifteenth break in CSE was identified. The sixteenth break of CSE was identified on 12th April 2021. The last break in CSE was identified on 10th May 2021.

Measuring the Effect of Structural Breaks on Stock Returns

Unit root test

The Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test were used in the study to conduct an investigation into the possibility of unit roots in the stock return series.

Table 1: Unit Root Test

Stock return indexes	Augmented Dickey-Fuller test statistic		Phillips-Perron Test Statistics	
	I (0)	I (1)	I (0)	I (1)
ASPI	0.0000	0.0000	0.0000	0.0000
DASPI	0.0000	0.0000	0.0000	0.0000
Market Return	0.0000	0.0000	0.0000	0.0000

Source: Results of the Analysis

Based on the particular information set that each category responds to, the idea of market efficiency was divided into three separate categories in Fama's key work from 1970. The terms *"weak form efficiency," "semi-strong form efficiency,"* and *"strong form efficiency"* are used to describe these groups. According to the weak form efficiency theory, stock market prices include all historical data. This suggests that prices have no memory and price fluctuations over time are statistically unrelated. The ASPI, DASPI, and Market return results from the unit root tests show no autocorrelations. According to this conclusion, the ASPI, DASPI, and market return are signs of low efficiency. The findings also imply that, due to the absence of serial dependence, the raw returns of all analyzed indices can be used for future econometric modeling.

Fitting the models

ARMA (p, q) models were considered, assigning several values for p and q progressively starting from 1 when fitting the time series model to the stock returns in CSE.

Table 2: Parameter Estimates from fitting ARMA (p, q)

	Model		Coefficient	Sig.	Log likelihood estimate	AIC
1	AR (1)	AR(1)	0.21	0.0000	986.9948	-5.743410
2	AR (2)	AR(1)	0.21	0.0000	987.1723	-5.738614
		AR (2)	0.03	0.3998		
3	AR (3)	AR(1)	0.21	0.0000	987.2215	-5.733070
		AR(2)	0.02	0.4681		
		AR(3)	0.01	0.6404		
4	ARMA(1 1)	AR(1)	0.44	0.0025	987.2492	-5.739062
		MA(1)	-0.23	0.1590		
5	ARMA(1 2)	AR(1)	0.78	0.0000	987.9850	-5.737522
		MA(1)	-0.57	0.0000		
		MA (2)	0.09	0.1200		
6	ARMA(1 3)	AR(1)	0.78	0.0000	987.9852	-5.731692
		MA(1)	-0.57	0.0000		
		MA(2)	-0.09	0.1200		
		MA (3)	-0.00	0.9700		
7.	ARMA (2 1)	AR (1)	0.94	0.0000	987.9215	-5.737151
		AR (2)	-0.11	0.1728		
		MA (1)	-0.73	0.0007		

8.	ARMA (2 2)	AR (1)	- 0.66	0.0004	987.7770	-5.730478
		AR (2)	0.16	0.3048		
		MA (1)	0.88	0.0007		
		MA (2)	0.06	0.6767		
9.	ARMA (2 3)	AR (1)	-0.03	0.8979	988.8258	-5.730762
		AR (2)	0.69	0.0000		
		MA (1)	0.25	0.2947		
		MA (2)	-0.59	0.0010		
		MA (3)	-0.13	0.0232		
10	ARMA(3 1)	AR(1)	0.86	0.0015	988.0760	-5.732222
		AR(2)	-0.12	0.1130		
		AR(3)	0.03	0.4924		
		MA (1)	-0.65	0.0139		
11	ARMA(3 2)	AR(1)	0.10	0.7600	988.3849	-5.728192
		AR(2)	0.73	0.0000		
		AR(3)	-0.13	0.1000		
		MA(1)	0.10	0.7700		
		MA (2)	-0.65	0.0000		
12	ARMA (3 3)	AR(1)	-0.46	0.2200	989.3558	-5.728022
		AR(2)	0.56	0.0100		
		AR(3)	0.30	0.2000		
		MA(1)	0.68	0.0700		
		MA(2)	-0.39	0.2100		
		MA(3)	-0.35	0.0200		

Source: Results of the analysis

The model fitting was started with AR (1). Since AR (1) was statistically significant at a 95% confidence level, AR (2) was also considered. Even though AR (2) was not significant, AR (3) was also tested to check the worthiness of progressively increasing and testing the AR component in the model. As both AR (2) and AR (3) models are not significant, the researcher decided to stop increasing the AR components in the model. Then, the researcher introduced an MA (1) component to the AR (1) fitted previously, making it an ARMA (1, 1). Even though the MA component is not significant, the researcher continuously increased the MA components and AR components to see whether the higher order lagged levels were significant or not. However, the introduction of higher- order lagged levels in both AR and MA components failed to fit a significant model. Thus, AR (1) is taken as the best-fitted model for the market returns in CSE during the considered period of study. Then, the dummy variables developed to represent each of the structural breaks identified in the above section were introduced to the AR (1) model as mean regresses.

Table 3: Tested Dummy Variables from Fitting AR (1)

Variable	cCoefficient	Std. Error	z-Statistic	Probability
D1	-0.000919	0.005958	-0.154327	0.8774
D2	-0.002879	0.007910	-0.364022	0.7161
D3	-0.013551	0.002039	-6.645557	**0.0000**
D4	0.005515	0.003339	1.651343	0.0996

D5	-0.001388	0.004891	-0.283692	0.7768
D6	0.002862	0.009251	0.309339	0.7573
D7	0.000930	0.009751	0.095339	0.9241
D8	0.008355	0.006091	1.371691	0.1711
D9	-0.001369	0.001923	-0.712059	0.4769
D10	0.003115	0.007710	0.403983	0.6865
D11	0.003543	0.009139	0.387696	0.6985
D12	0.011948	0.003898	3.065260	**0.0024**
D13	-0.003573	0.001588	-2.250134	**0.0251**
D14	-0.003329	0.002576	-1.292148	0.1972
D15	0.002593	0.004668	0.555536	0.5789
D16	-0.001320	0.003385	-0.389892	0.6969
D17	0.002403	0.005741	0.418645	0.6758
AR(1)	0.115661	0.040475	2.857590	**0.0045**

** Implies that the coefficient is significant at a 0.05 percent probability level*
Source: Results of the analysis

According to the reported results in Table 3, three dummy variables (D3, D12, and D13) are statistically significant at a 95% confidence level. These dummy variables represent structural breaks identified on 27th February 2020, 24th December 2020, and 22nd January 2021.

Measuring the Effect of Structural Breaks on Stock Market Volatility

Results from Table 4 show that market returns had the best fit using an AR (1) model. The Autoregressive Conditional Heteroskedasticity (ARCH) effects are confirmed by the chosen model. Notably, the ARCH LM test showed a strong rejection of the null hypothesis that there are no ARCH effects in the residuals up to the first order. The study investigated different models such as GARCH(1, 1), GARCH(1, 2), and GARCH(2, 2) to discover the most appropriate model for capturing market volatility patterns to delve into the nature of these ARCH effects.

Table 4: Tested GARCH (p q) Models, EGARCH (1, 1) and TGARCH (1, 1)

		Models				
		GARCH(1, 1)	**GARCH(1,2)**	**GARCH(2,2)**	**EGARCH(1,1)**	**TGARCH(1,1)**
AR(1)	Coefficient (P-value)	0.342	0.347	0.336	0.307	0.38
		0.0000	0.0000	0.0000	0.0000	0.0000
C	Coefficient (P-value)	3.82E-06	3.18E-06	6.88E-07	-	4.43E-06
		0.0069	0.0155	0.1605		0.0033

RESID(-1)^2	Coefficient (P-value)	0.346966 0.0000	0.292826 0.004	0.280989 0.0000	-	0.284618 0.0000
RESID(-2)^2	Coefficient (P-value)	-	-	-0.242694 0.0028	-	-
RESID (-1)^2 *(RESID(-1)<0)	Coefficient (P-value)	-	-	-	-	0.1583 0.201
GARCH(-1)	Coefficient (P-value)	0.704023 0.0000	0.898351 0.0005	1.641881 0.0000	-	0.695431 0.0000
GARCH(-2)	Coefficient (P-value)	-	-0.147416 0.4313	-0.67675 0.0000	-	-
C(2)	Coefficient (P-value)	-	-	-	-0.787712 0.0000	-
C(3)	Coefficient (P-value)	-	-	-	0.541725 0.0000	-
C(4)	Coefficient (P-value)	-	-	-	0.957007 0.0000	-
AIC		-6.256778	-6.251454	-6.255124	-6.244638	-6.255491
Log Likelihood		1073.909	1073.999	1075.626	1071.833	1074.689

*Note: * implies that the coefficient is significant at a 0.05 percent probability level*
Source: Results of the analysis

According to Table4, the GARCH (1, 1) and GARCH (2, 2) models are significant. Then, comparing AIC and Log Likelihood values, the researcher selected GARCH (1, 1) because the GARCH (1, 1) model's AIC value is lower than the GARCH (2, 2) model. Furthermore, the researcher tested EGARCH (1, 1) and TGARCH (1, 1) models to select the most fitted model with Log likelihood and AIC values. According to this table, the EGARCH (1, 1) model is also fitted. Then, comparing AIC and Log-Likelihood values, the researcher selected GARCH (1, 1) because the GARCH (1, 1) model's AIC value is lower than the EGARCH (1, 1) model. Thus, other models are insignificant (P-value > 0.05) under the 95% confidence level.

Then, the researcher analyzed using the GARCH (1, 1) model for the interpretation of dummy variables.

Table 5: GARCH (1, 1) Regression Model of Market Volatility

Variable	Coefficient	Std. Error	z-Statistic	Probability
C	1.18E-05	5.31E-06	2.217904	0.0266
RESID (-1) ^2	0.203363	0.087726	2.318163	0.0204
GARCH (-1)	0.266910	0.147037	1.815250	0.0695
D1	1.57E-05	1.07E-05	1.471384	0.1412
D2	7.71E-07	6.72E-06	0.114758	0.9086
D3	0.000406	0.000276	1.469162	0.1418
D4	2.62E-05	1.93E-05	1.353297	0.1760
D5	2.78E-05	1.48E-05	1.873067	0.0611
D6	3.97E-06	1.05E-05	0.379848	0.7041
D7	-2.15E-07	7.80E-06	-0.027574	0.9780
D8	4.74E-05	2.17E-05	2.185996	**0.0288**
D9	0.000433	8.37E-05	5.174729	**0.0000**
D10	1.65E-06	8.99E-06	0.183694	0.8543
D11	-9.66E-08	7.84E-06	-0.012319	0.9902
D12	9.13E-05	5.57E-05	1.637662	0.1015
D13	0.000559	0.000264	2.115184	**0.0344**
D14	0.000153	0.000112	1.367411	0.1715
D15	4.53E-05	2.97E-05	1.525730	0.1271
D16	0.000113	7.24E-05	1.566968	0.1171
D17	1.81E-05	2.17E-05	0.832634	0.4051

Source: Results of the analysis
*Note: * implies that the coefficient is significant at a 0.05 percent probability level*

Table 5 demonstrates that three dummy variables (D8, D9, and D13) have a positive statistically significant effect on stock volatility and are statistically significant at the 95% level of confidence. These dummy variables represent structural breaks identified on 9th September 2020, 5th October 2020, and 22nd January 2021. Further describing this table, only the two dummy variables (D7 and D11) have obtained negative coefficients, whilst all other dummies have taken positive coefficients. A positive coefficient indicates that as the value of the independent variable increases, the mean of the dependent variable also tends to increase. A negative coefficient suggests that the dependent variable tends to decrease as the independent variable increases.

These findings show that the third goal of this investigation has been achieved. D8, D9 and D13 are the dummy variables with the greatest influence on stock market volatility. If the price of a stock fluctuates rapidly in a short period, hitting new highs and lows, it is said to have high volatility. If the stock price moves higher or lowers more slowly or stays relatively stable, it is said to have low volatility.

CONCLUSION

This empirical study looks at the size and type of structural breaks that occurred in Sri Lanka's stock market during the COVID-19 period, which was initially characterized by more intense oscillations. There were major COVID-19 effects on both a local and global scale from late 2019 to mid-2021. The study used Bai and Perron's (2003) technique to identify seventeen structural break periods that span the COVID-19 timeframe from December 1, 2019, to June 30, 2021. ARMA (p q) models were used to analyze the impact of these breaks on stock market returns, with the AR (1) model chosen for dummy variables based on log-likelihood and AIC. Notably, the stock market results were considerably impacted by three dummy variables corresponding to February 27, 2020, December 24, and January 22, 2021. The research then used the GARCH (p, q), EGARCH (p, q), and TGARCH (p, q) models to examine the effects of structural breaks on stock market volatility during the COVID-19 era.

The findings of this study suggest that though seventeen significant structural breaks arose during COVID-19 period in the Sri Lankan stock market, not all the structural breaks affected the stock returns or the stock volatility within the Sri Lankan context due to some reasons. The structural breaks may have had little long-term influence on stock market returns or volatility since investors and market participants may have rapidly acclimated to the new information. Not only that, if markets are effective, structural breaks may be quickly incorporated into stock prices with minimal long-term influence on returns or volatility. Finally, Market adaptations and market efficiencies can be highlighted as the outlying factors for the impactful structural breaks over the stock returns and also for the stock volatility. The findings emphasize the necessity for informed investor decisions and proactive government to prevent market crashes and help comprehend the relationships between structural disruptions and stock market performance.

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