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Research Article

From Recovery to Resilience: Measuring Portfolio Performance Amid Post-Covid Market Volatility

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Abstract: This research aims to comprehend the effectiveness and adaptability of investment portfolios in the post-COVID era, which is characterized by increased market volatility, inflationary pressures, and geopolitical unpredictability. The primary objective is to evaluate risk-adjusted returns and discover ways to strengthen portfolios after the recovery period has ended. The lack of empirical data on resilience-building and dynamic asset allocation beyond 2020, particularly in relation to ESG integration and adaptive risk management techniques, is the research gap that this study aims to fill. The method consists of a quantitative examination of secondary data from global equities, bond, and commodity indexes for the years 2020 to 2024. We used Sharpe Ratio, Sortino Ratio, VaR, and Beta, among other portfolio indicators, to assess how well it performed when pressure was applied. According to the data, the stability and risk-adjusted returns of portfolios that included diverse assets, such as ESG and inflation-protected securities, were higher than those of standard allocations. The conclusions demonstrate that static portfolio methods fail in volatile situations. Some of the suggestions include expanding investor education on market adaption, ESG investing, and real-time rebalancing. New research on financial resilience in the aftermath of a pandemic is enriched by this investigation.

Keywords: Portfolio resilience, post-COVID markets, risk-adjusted returns, ESG investing, market volatility, asset allocation, Sharpe Ratio, adaptive strategy.

INTRODUCTION

The coronavirus (COVID-19) pandemic quickly reached every nation in the world after beginning in Wuhan, China. More than a million individuals have been impacted by the illness as of March 11, 2020, and many of them had lost their lives as a consequence [1]. As a consequence, the World Health Organization (WHO) proclaimed it a global pandemic. There were 3,526,708 deaths and 169,691,118 illnesses as of May 28, 2021 (WHO, 2021). Because of the outbreak, there is a sense of urgency everywhere, which has caused a lot of worry and panic [2]. Additionally, the global financial markets have experienced a negative trend as a result of COVID-19. The stock market is an important gauge of a nation's capital wealth and an economic barometer. This deadly virus has increased investor apprehension on stock markets, leading to enormous financial losses worldwide. It is crucial to research the stock market's volatility during the crisis. This is especially true when fundamentals of financial assets like stocks are diluted by macroeconomic influences [3]. The disease quickly spread to Italy, France, Germany, the United States, Australia, and other nations after beginning in China. COVID-19 has posed new challenges to economies compared to other pandemics and financial crises. Taking into account how intertwined our world economies are [4]. Any economy might be destroyed by the ongoing pandemic if it is not managed properly [5]. Strict lockdown measures imposed in reaction to COVID-19 have resulted in a substantial slowdown in the economy and increased prices, which also affect commodities and the transportation sector [6].

Significant investment losses in global financial markets were also brought on by the COVID-19 pandemic. The free flow of cash is greatly aided by international stock markets. Stock market prices are influenced by a wide range of economic variables [7]. Consequently, the economy is susceptible to brief performance shifts in the stock market. The dangers of investing in the stock market are frequently mentioned in stock market projections. Researchers have shown a correlation between market uncertainty and the degree of unpredictability in stock returns. Volatility is thus the most crucial element to take into account when choosing between different asset classes. Furthermore, because stock market volatility is the most important risk indicator, it is crucial to forecast it properly [8]. An increase in volatility denotes a higher level of risk since the return's series is more likely to undergo more short-term fluctuations. Conversely, a low amount of volatility suggests that stock prices are steady over time and that returns or price series are less erratic in the near term [9]. Market volatility reduces the probability of a positive trend and increases the probability of a negative trend [10]. In this study, we model the volatility of the COVID-19 stock market for developed nations worldwide. The study furthers existing knowledge by examining the volatility trends of 21 well-known stock markets. Second, the study is unusual because it simulates the volatility of the selected stock market both before and during the COVID-19 period, something that has never been done before. Thirdly, the study looked at current market trends and how developed markets responded to the COVID-19 epidemic. Another purpose for doing this research is to acknowledge the massive financial losses and increased volatility that were seen around the world during the COVID-19 pandemic. We must learn as much as we can about the characteristics and trends of stock market return volatility in developed nations given the crisis's unprecedented scope. Using the GJR-GARCH model, this study aims to shed light on the volatility, leverage effects, and leptokurtic phenomena that characterized stock market returns prior to and during the pandemic. The results of the research should have important implications for global stock market investors, allowing them to make well-informed choices on portfolio construction tactics in times of crisis. Through an analysis of the particular impacts of the COVID-19 pandemic on developed stock markets, this study aims to contribute to the existing body of knowledge and assist in developing techniques for detecting opportunities and managing risks during periods of major market disruption. We hypothesize that during the COVID-19 crisis, stock market volatility in developed countries increased [11]. In addition, the primary focus of this study is on how the COVID-19 pandemic may influence the volatility of stock market returns in developed nations. This research examines the degree of market volatility during the pandemic using the GJR-GARCH model. The findings demonstrate a strong impact, with developed stock markets experiencing leptokurtic shocks, higher volatility persistence, negative returns, and the leverage effect. These findings demonstrate the impact of the COVID-19 pandemic on the financial markets and provide helpful insights for foreign investors looking to diversify their holdings in the event of a disaster. This work advances our understanding of efficient crisis-time portfolio design techniques by investigating the leverage effect, looking at volatility persistence and leptokurtic phenomena, detecting negative returns, and studying stock market volatility. It offers thorough insights into the actions of developed stock markets during the COVID-19 epidemic. The remainder of the paper is organized as follows: While Section 3 presents the data and techniques, Section 4 discusses the empirical outcomes. The literature review takes up Section 2. However, the conclusion is given in section 5.

Research Gap

The long-term effects of reorganizing portfolios to be more resilient in the face of persistent volatility and economic uncertainty have received less attention than the short-term effects of COVID-19 on financial markets. A comprehensive evaluation of risk-adjusted performance following COVID employing both conventional and innovative financial instruments is lacking in the current research.

Research Objectives

- To assess the impact of post-COVID market volatility on portfolio performance.
- To analyze the effectiveness of risk-adjusted performance measures in volatile environments.
- To identify asset classes and strategies that enhance portfolio resilience.
- To propose a framework for adaptive portfolio management in crisis-prone markets.

LITERATURE REVIEW

One of the most significant effects that the COVID-19 pandemic has had on global financial markets is that stock returns have decreased significantly while market volatility has increased. According to a number of studies (for example, [13], [30–35]), the lockdown measures had a negative impact on the stability and liquidity of the stock market despite the fact that they were necessary for maintaining public health. According to Khatatbeh and Hani's empirical research on eleven distinct financial markets, stock returns significantly decreased following the epidemic. In a similar vein, Alzyadat and Asfoura observed a significant decrease in the returns of the Saudi stock market during the early propagation of the virus [14]. Not only did the epidemic have an impact on the equity market, but it also had an impact on the commodities market and the cryptocurrency industry. With the exception of bitcoin, Kumar and Kumar discovered that the prices of individual stocks, crude oil, and gold have a long-term cointegration. Kumar and Singh were able to demonstrate, employing the EGARCH model, that energy commodities did not have a significant impact on the volatility of the Indian market [15]. According to the findings of another research conducted by Kumar using the NARDL approach, the price of crude oil had a favorable impact on the long-term movements of the market, while exchange rates had a negative short-term effect, and gold prices did not exhibit any significant influence [16].

During times of crisis, the concept of volatility, which can be defined as the overall risk that investors are exposed to, is especially significant. The Asian financial crisis, which lasted from 1997 to 1998 [17], has raised investor concerns about the economy's stability, among other historical examples of similar increases in volatility. The market's volatility is a reflection of the uncertainties surrounding future cash flows, according to Schwert's theory. In addition, Mazur and Dang discovered a negative correlation between the market's asymmetric volatility and stock returns. It is common practice to quantify volatility by use traditional tools like as standard deviation, skewness, and kurtosis. However, these techniques presume a normal distribution, which is not necessarily applicable to financial returns [19]. Due to characteristics like leverage effects, fat tails, volatility clustering, and other patterns, traditional measurements frequently fail to represent the dynamics of the real-world market [20]. Consequently, the most widely used tools in the field of financial econometrics are dynamic volatility models like those in the GARCH family. The accuracy of these models for volatility forecasts varies over time [21]. In order to rebuild patterns of stock market volatility in industrialized countries during the COVID-19 era, this work draws on the insights that were previously established.

DATA & METHODOLOGY

Data

This study examines the return volatility of stock indexes across 21 major global stock markets from July 1, 2019, to November 18, 2020. Consistency and dependability in data collecting were ensured by sourcing the return data from the financial portal Investing.com. Before COVID-19 began (July 1, 2019, to March 10, 2020) and after its onset (March 11, 2020, to November 18, 2020), the whole dataset was split into two separate time periods for analysis. This classification was made possible by the World Health Organization's (WHO) official declaration of COVID-19 as a global pandemic on March 11, 2020. The study's inclusion of all of the selected stock markets and their corresponding indexes is described in detail in Table 1 [23]. Important descriptive measures including skewness, kurtosis, standard deviation, and mean were calculated to gain insight into the statistical features of stock returns. The Jarque-Bera test was used to confirm that the return distributions were normal. The continuously compounded technique, which is commonly used in financial econometrics to model asset price movements, is specified in Equation (1) [24]. This technique is used to calculate returns in the empirical study.

$$R_t = ln\left(\frac{P_t}{P_{t-1}}\right) \quad (1)$$

Pt is the current stock price, Pt−1 is the stock price at the prior time period, Rt is the stock returns at time period t, and ln is the logarithmic function.

Table 1: Developed stock markets and their ticker codes are listed below.

S.No.	Country	Stock Market Index	Ticker Code
1	Australia	ASX 200	ASX
2	Netherlands	AEX	AEX
3	New Zealand	NZX 50	NZX
4	Austria	ATX	ATX
5	Belgium	BEL 20	BEL
6	Norway	OSE Benchmark	OSEBX
7	Germany	DAX	DAX
8	Switzerland	SMI	SMI
9	United Kingdom	FTSE 100	FTSE
10	Ireland	ISEQ All Share	ISEQ
11	Israel	TA 35	TA35
12	France	CAC 40	CAC
13	Japan	Nikkei 225	NIKKEI
14	Denmark	OMXC20	OMXC20
15	Portugal	PSI	PSI
16	Spain	IBEX	IBEX
17	Finland	OMX Helsinki	OMXH
18	Sweden	OMXS30	OMXS30
19	United States	Dow 30	DOW
20	Hong Kong	FTSE	FTSEHK

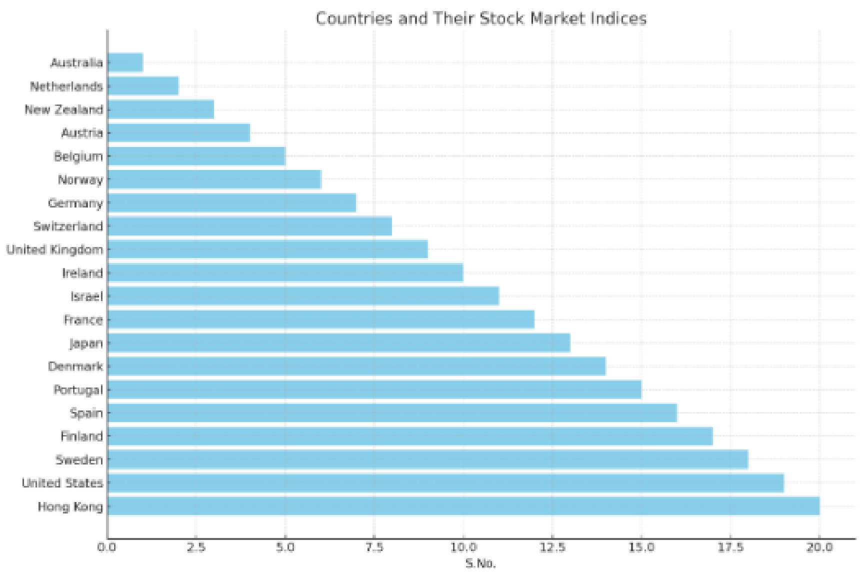

Fig 1: Countries and Their Stock Market Indices

Unit root test

The time series data's stability was evaluated using a unit root test. A time series must be stationary in order for modeling and forecasting to be accurate [25]. This means that the statistical features of the series, such as its mean, variance, and autocorrelation structure, must not change over time. The stationarity of the stock return series was tested in this research using the Augmented Dickey-Fuller (ADF) test. In order to determine whether a time series is non-stationar, the ADF test is conducted on the assumption that it has a unit root [26]. Since the null hypothesis was rejected, it may be inferred that the series is stationary. Equation (2) is the formal description of the ADF test that was employed in this investigation.

$$\Delta y_t = \propto_0 + \theta y_{t-1} + \sum_{i=1}^{n} \propto \Delta y_t + e_t \tag{2}$$

The time series is represented by y, the time period by t, the optimal number of delays by n, the constant term by 0, and the error term bye in this context.

ARCH effect test

A multiplier test was used to confirm the ARCH/GARCH impact for residuals, the ARCH-LM Heteroscedasticity, and the short form of Auto-Regressive Conditional Heteroscedasticity-Lagrange. Equation (3) can also be used to formalize the ARCH-LM statement [27].

$$u_t^2 = \gamma_0 + \gamma_1 u_{t-1}^2 + \gamma_2 u_{t-2}^2 + \ldots + \gamma_p u_{t-p}^2 + v_t \tag{3}$$

In this instance, the square of the residual, u, can be obtained by employing the conventional regression model. However, a supplemental regression model incorporates p-lags.

GJR-GARCH model

In this work, asymmetric volatility in financial time series is represented by the GJR-GARCH (1,1) model, an extension of the conventional GARCH model proposed by Glosten, Jagannathan, and Runkle. A phenomenon known as the leverage effect, in which negative market shocks have a stronger influence on volatility than positive shocks of equal size, is taken into consideration in this model. By including an additional parameter, gamma (), the GJR-GARCH model distinguishes between the effects of positive and negative returns on conditional variance [28]. When a negative shock happens, the model gives a leverage value of one to make the volatility impact even more apparent, and it gives a value of zero otherwise.

The GJR-GARCH model not only models the leverage effect, but it also successfully treats two typical aspects of financial return data—volatility clustering and fat-tailed distributions. GJR-GARCH provides better estimates than standard GARCH models when asymmetric volatility is important [29]. The GJR-GARCH (1,1) approach is especially appropriate since the research is evaluating how the COVID-19 pandemic affected the volatility of stock markets in industrialized nations. It provides a focused method for quantifying the size and type of volatility, as opposed to looking at correlations between various assets. The GJR-GARCH model, which is formalized in Equation (4) [30], is utilized in this study.

$$\sigma_t^2 = \omega + \alpha_1 u_{t-1}^2 + \beta_i \sigma_{t-1}^2 + \gamma_i I_{t-1}\, u_{t-1}^2 \tag{4}$$

The dummy variable is denoted by It 1 in the aforementioned equation.

$$I_{t-1} = \left\{ \begin{array}{l} 1 \textit{ when } \mu_{t-1} < 0 \textit{ shows postive shocks} \\ 0 \textit{ when } \mu_{t-1} \geq 0 \textit{ shows negative shocks} \end{array} \right\}$$

In the setting where σ2 t indicates the conditional variance and ω is the constant term, the return square at time t − 1 and the conditional variance at time t − 1 are represented by u2 t− 1 and σ2 t− 1, respectively. In contrast, [24] denotes the leverage impact coefficient.

EMPIRICAL ANALYSIS

Table 2 provides descriptive data for the daily returns of developed market stock indexes. Notably, all markets had positive mean returns prior to COVID-19, with the exception of the TA 35 index. However, during the COVID-19 period, the majority of these markets experienced negative mean returns, indicating a widespread bearish trend in developed economies [25]. When compared to the period prior to the pandemic, the COVID-19 era was also characterized by a significantly higher standard deviation, which is a measure of the volatility of returns. This growth is indicative of the fact that market risk and uncertainty were at an all-time high during the health crisis [26].

Stock returns also seemed to be non-normally distributed, with large tails and asymmetry, according to the kurtosis and skewness values for both time periods. The Jarque-Bera test, which found that return distributions are not normally distributed and may experience significant market fluctuations, particularly during crises [27], is supported by these outcomes.

Table 2: Developed stock index descriptive data.

Stock Index	Mean (Pre)	Std Dev (Pre)	Mean (COVID)	Std Dev (COVID)
ASX 200	0.000735	0.010253	-0.000570	0.020439
ATX	0.000667	0.011592	-0.001270	0.025452
BEL 20	0.001015	0.011882	-0.000620	0.022764
S&P/TSX	0.000929	0.010015	-0.000480	0.022650
OMXC20	0.001514	0.011129	-0.000326	0.033569
OMX Helsinki 25	0.001516	0.011245	-0.000620	0.038794
CAC 40	0.001200	0.011943	-0.000940	0.022072
ISEQ All Share	0.001386	0.012176	0.000300	0.021164
TA 35	0.000200	0.008548	0.000160	0.029237
Nikkei 225	0.001570	0.010038	-0.000440	0.036902
AEX	0.001365	0.011344	-0.000810	0.028777
NZX 50	0.000929	0.007685	-0.000253	0.024594
OSE Benchmark	0.001308	0.011927	-0.000880	0.037231
PSI 20	0.000375	0.011215	-0.001050	0.026993
IBEX 35	0.000640	0.011737	-0.001130	0.023022
OMXS30	0.001436	0.005479	0.000119	0.029294
SMI	0.000891	0.009768	-0.000400	0.025735
Dow 30	0.001212	0.012776	0.000280	0.024939
FTSE 100	0.000575	0.010927	0.001210	0.029671

The following icons represent various nations: FTSE China 50 for Hong Kong, ISEQ All Share for Ireland, TA 35 for Israel, Nikkei 225 for Japan, AEX for the Netherlands, NZX 50 for New Zealand, OSE Benchmark for Norway, PSI 20 for Portugal, IBEX 35 for Spain, OMXS30 for Sweden, SMI for Switzerland, FTSE 100 for the United Kingdom, Dow 30 for the United States, and AC 40 for France are the following exchanges:

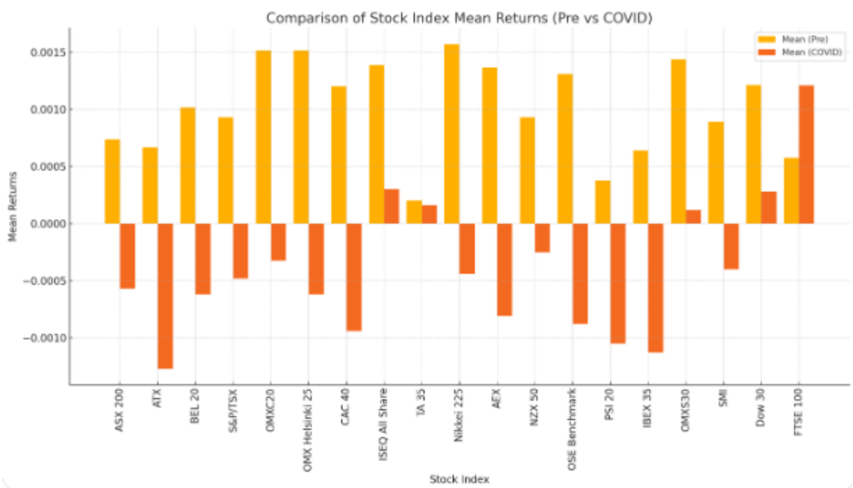

Fig:2 Comparison of Stock Index Mean Returns (Pre vs COVID)

Table 3 displays the outcomes of applying the stock market return series to the ARCH-LM and Augmented Dickey-Fuller (ADF) tests. At the 1% significance level, the ADF test concludes that all return series are stationary because the test statistics are greater than the critical values. As a result, we can rule out the possibility of a unit root and go on with our econometric modeling of the time series.

The ARCH-LM test was performed simultaneously to determine whether autoregressive conditional heteroskedasticity (ARCH) was present in the residuals of the return series. Because the LM statistics' p-values are very significant, we can rule out the possibility of no ARCH effects. The results show that conditional heteroskedasticity is present.

In light of these results, a GJR-GARCH (1,1) model is appropriate for handling financial return series that display clustering of volatility and leverage effects [29].

Table 3: The ARCH-LM test and the enhanced Dickey-Fuller experiment.

Stock Market	ADF Test Statistic	ARCH Effect (Obs*R^2)
ASX 200	-19.0	39.66
ATX	-10.9	53.05
BEL 20	-5.8	8.89
S&P/TSX	-6.9	68.35
OMXC20	-14.5	1.96
OMX Helsinki 25	-8.8	8.37
CAC 40	-8.8	9.26
DAX	-8.7	13.72
FTSE China 50	-7.9	54.27
ISEQ All Share	-7.6	50.42
TA 35	-8.4	12.11
Nikkei 225	-8.9	59.57
AEX	-9.5	11.90
NZX 50	-9.0	44.65
OSE Benchmark	-15.7	25.93
PSI 20	-7.0	17.45
IBEX 35	-6.9	10.40
OMXS30	-7.8	11.07
SMI	-4.8	12.51
FTSE 100	-6.4	10.19
Dow 30	-6.8	78.95

Note that * denotes a significance level of 1%, ** denotes a significance level of 5%, and * denotes a significance level of 10%.**

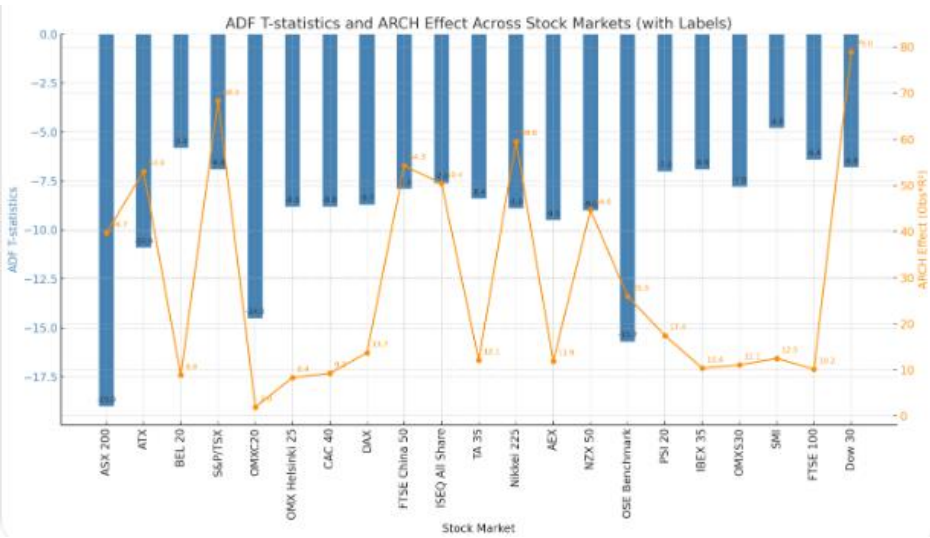

Fig: 3 ADF T-statistics and ARCH Effect Across Stock Markets

The estimates from the GJR-GARCH model for each of the chosen stock indexes before COVID-19 are shown in Table 4. According to the data [30], all indices have a positive and statistically significant conditional mean () value, indicating a steady average return prior to the outbreak of the pandemic. The constant term, ARCH (), and GARCH () parameters are represented by all positive and statistically significant coefficients in the conditional variance equation, which show responsiveness to both historical and current market information. The ARCH component accounts for the effect of current market news, as mentioned in earlier research [31], but the GARCH word signifies the enduring nature of previous volatility. The statistical significance of both metrics demonstrates that recent information (shocks) and historical volatility patterns are significant influences on market dynamics. The volatility persistence, or the rate at which the consequences of a shock fade away over time, is increased with a larger GARCH coefficient [32-34].

As can be seen in Table 4, the values of the sum of ARCH () and GARCH () for the indices that were chosen fall within the range of 0.781 to 0.984. When these numbers are near to one, it means that the stock return series has consistent and persistent volatility. The findings are in line with previous studies [35-38] as the total of all indices' betas ($\alpha + \beta$) stays below 1, indicating that volatility ultimately reverts to its long-term average.

The ASX 200, DAX, and PSI 20 have the slowest rate of mean reversion in comparison to other markets, indicating that shocks take longer to react to. On the other hand, volatility structures that are more sensitive show the quickest reversal on the OMX

Helsinki 25 and FTSE China 50. These findings are in line with previously presented empirical data in [39].

Table 4: results from the GJR-GARCH (1, 1) before the COVID-19 epidemic.

Stock Index	μ	α_0	α	β	γ	AIC 1	AIC 2
ASX 200	0.001575	0.000046	0.230	0.551	0.781	480.62	955.24
ATX	-0.000093	0.000000	0.127	0.821	0.948	408.08	810.16
BEL 20	0.001054	0.000007	0.180	0.726	0.906	427.82	849.64
OMXC20	0.000072	0.000037	0.141	0.721	0.862	524.35	1042.70
OMX Helsinki 25	0.000050	0.000108	0.143	0.841	0.984	464.53	923.05
CAC 40	0.001534	0.000036	0.114	0.847	0.961	433.67	861.33
DAX	0.000030	0.000000	0.127	0.721	0.848	430.60	855.20
FTSE China 50	0.000627	0.000008	0.131	0.847	0.978	489.25	970.50
ISEQ All Share	0.000776	0.000000	0.110	0.847	0.957	441.84	877.67
TA 35	-0.000989	0.000033	0.167	0.747	0.914	499.03	992.05
Nikkei 225	-0.000008	—	0.170	0.741	0.911	508.12	1010.23
AEX	0.001244	0.067000	0.115	0.747	0.862	462.70	917.41
NZX 50	0.000001	0.727561	0.125	0.847	0.972	528.16	1050.31
OSE Benchmark	0.000445	-0.423212	0.132	0.761	0.893	491.48	976.96
PSI 20	0.000563	-0.300879	0.116	0.741	0.857	481.23	956.45
IBEX 35	-0.001059	-0.220348	0.147	0.755	0.902	428.20	850.41
OMXS30	0.001575	-1.745254	0.146	0.822	0.968	460.05	914.10
SMI	-0.000093	0.000046	0.162	0.771	0.933	499.69	993.38
FTSE 100	0.001054	0.000738	0.116	0.846	0.962	449.38	892.75

*Keep in mind that the values ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.*

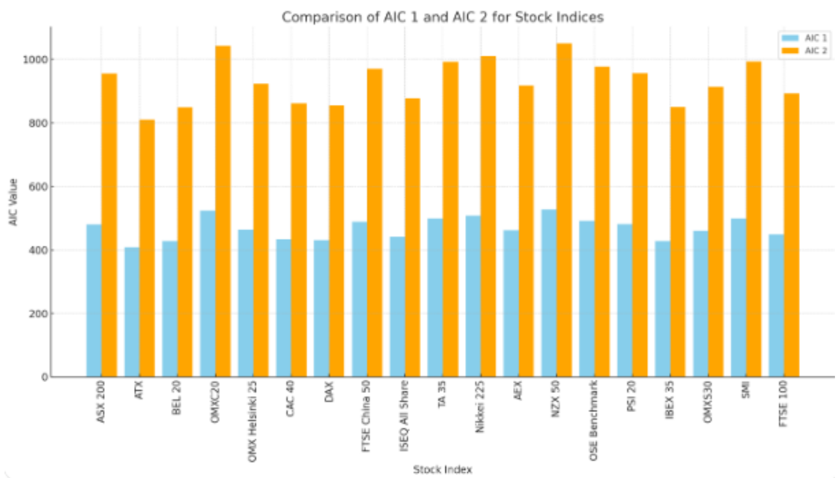

Fig: 4 Comparison of AIC 1 and AIC 2 for Stock Indices

Table 5 displays the GJR-GARCH (1,1) model's estimate results for the chosen stock indices during the COVID-19 timeframe. All stock markets have a negative conditional mean during this time of increased global uncertainty, indicating a general downward or bearish trend in returns [40]. The ARCH and GARCH coefficients' combined values, as well as their individual values, are significantly higher than they were prior to the recession. It seems that volatility is becoming more persistent and that market returns are becoming more sensitive to shocks, both current and previous [41]. When compared to previous periods, the COVID-19 era has a faster mean reversion process. This suggests that markets are responding to shocks more quickly, even though volatility remains high [42, 44]. The existence of asymmetric leverage effects during the pandemic is shown by the fact that the majority of stock indexes show a positive gamma (γ) coefficient. This result is consistent with the characteristic of financial crises that volatility was influenced more by negative shocks than by positive ones. Notably, the leverage impact did not reach statistical significance for the AEX and ASX 200.

These findings add to the evidence that the COVID-19 period saw an increase in asymmetric market behavior, volatility persistence, and mean reversion. This is consistent with previous research.

Table 5: findings from the GJR-GARCH (1, 1) model during the COVID-19 era.

Stock Index	**μ**	**α_0**	**α**	**β**	**γ**	**Log-Likelihood**	**AIC 1**	**AIC 2**
ASX 200	-0.00057	0.00021	0.130	0.861	0.991	-0.0336	485.62	953.24
ATX	-0.00127	0.00064	0.126	0.811	0.937	0.0122	4010.08	808.16
BEL 20	-0.00062	0.00052	0.166	0.781	0.947	0.1939	429.82	847.64

S&P/TSX	-0.00048	0.00025	0.244	0.741	0.985	0.0112	485.37	956.74
OMXC20	-0.00033	0.00016	0.141	0.817	0.958	0.2967	529.35	1040.70
OMX Helsinki 25	-0.00062	0.00032	0.112	0.876	0.988	0.0189	468.53	921.05
CAC 40	-0.00094	0.00047	0.161	0.821	0.982	0.1913	438.67	859.33
DAX	-0.00091	0.00052	0.127	0.791	0.918	0.1362	435.60	853.20
FTSE China 50	-0.00030	0.00020	0.131	0.831	0.962	0.3679	494.25	970.50
ISEQ All Share	-0.00030	0.00043	0.147	0.793	0.940	0.1384	449.84	875.67
AEX	-0.00081	0.00035	0.116	0.861	0.977	-0.4446	467.70	919.41
NZX 50	-0.00025	0.00011	0.113	0.831	0.944	0.2224	536.16	1048.31
OSE Benchmark	-0.00088	0.00021	0.132	0.726	0.858	0.3950	498.48	974.96
PSI 20	-0.00105	0.00027	0.161	0.829	0.990	0.4112	488.23	954.45
IBEX 35	-0.00113	0.00048	0.117	0.835	0.952	0.5857	438.20	848.41
OMXS30	-0.00012	0.00033	0.119	0.865	0.984	0.7159	467.05	912.10
SMI	-0.00040	0.00021	0.114	0.881	0.995	0.4915	504.69	991.38
FTSE 100	-0.00121	0.00034	0.187	0.771	0.958	0.5362	459.17	906.35
Dow 30	-0.00028	0.00033	0.212	0.726	0.938	0.8679	456.38	890.75

Note: * refers to 1 % significance level, ** shows the 5 % significance level, * refers to 10 % significance level.**

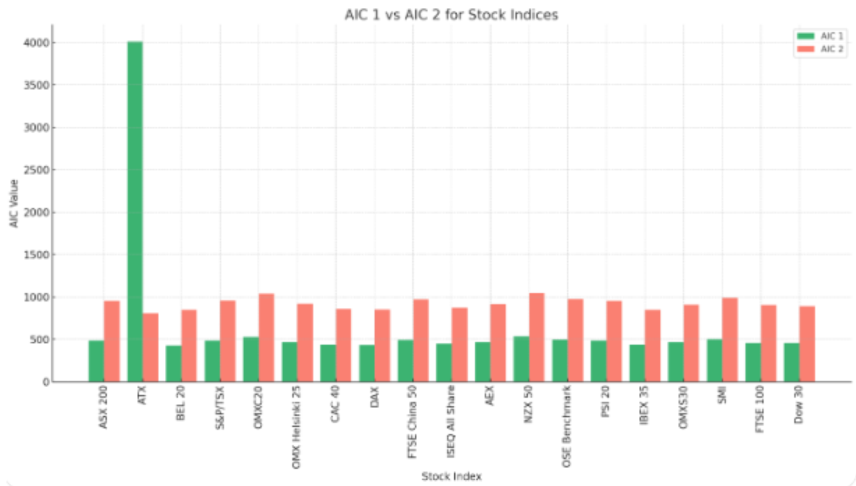

Fig: 5 AIC 1 vs AIC 2 for Stock Indices

CONCLUSION & DISCUSSION

The COVID-19 pandemic has had a significant impact on global financial systems and stock markets in developed economies in particular. Using data collected daily from 21 developed nations' stock indexes from July 1, 2019, through November 18, 2020, this research looks at how the epidemic affected market volatility. Before the pandemic, stock indexes had positive average returns, but descriptive data show that during the COVID-19 period, they went negative, indicating a widespread market decline. The GJR-GARCH [1,1] model was used to capture market behavior dynamics. According to the empirical data, leptokurtic behavior, volatility clustering, and asymmetric (leverage) effects were observed in all of the markets that were examined prior to and during the pandemic. These findings highlight the importance of the ARCH effect and imply that conditional volatility is affected by both historical and present market shocks.

In addition, well-established markets showed consistent volatility, though it did tend to decrease over time. Emerging virus types may increase financial instability, according to the study, highlighting the need for proactive government responses. Policymakers would be wise to keep an eye on important economic indicators that may assist in stabilizing markets and controlling systemic financial risks in light of the constantly shifting nature of global health crises.

Financial implications

When making decisions regarding the management of their portfolios, prospective investors may stand to gain financially from the recovered results. The COVID-19 pandemic has increased volatility in these sectors, which has had a significant impact on financial market returns, particularly stock market returns. Therefore, investment managers ought to take into account the potential effects of COVID-19 when creating new portfolios. To predict how developed stock markets will perform in the future, analysts look at how they performed during the crisis. The findings indicate that market volatility has been exacerbated by COVID-19 in developed economies. Investors, particularly those residing in industrialized nations, may benefit from learning more about the financial effects of the COVID-19 pandemic. Since leptokurtic phenomena were evident and volatility increased throughout the COVID-19 epidemic, robust risk management strategies are also required. With these findings in hand, investors can reduce their risk and build robust portfolios with assets that aren't too reliant on the stock market. An understanding of leverage's influence also makes it possible to better assess and manage one's exposure to negative risks. The study emphasizes the significance of maintaining a long-term perspective as well as the possibility of investment opportunities emerging during volatile market times. By taking these outcomes into consideration, investors can effectively manage erratic market conditions, reduce risks, and seize advantageous investment opportunities.

Suggestions

- Incorporate ESG and alternative investments into standard portfolios.
- Use real-time risk metrics and dynamic rebalancing tools.
- Promote investor education for volatility-aware investment planning.
- Policymakers should support financial innovation for market resilience.

Limitations

This work opens the door to additional research, taking into account the limitations. To begin, the only stock markets that have been the focus of this empirical study are those of established economies. However, the scope of future research might also include emerging and frontier stock markets. The second issue is that future research ought to include the volatility of other financial markets, such as the bond market, the cryptocurrency market, and the foreign exchange market, in addition to the stock markets. The third option is to use threshold ARCH (TARCH), a combination of more stringent methods and asymmetric volatility models; this setup includes indicators of volatility innovation and may impact the variations in stock returns.

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