"Comparative Analysis of Daily, Weekly, and Monthly NIFTY 50 Returns During the Post-COVID Recovery Period (2020–2022)"

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The Abstract:

Global financial markets, including India's benchmark index, the NIFTY 50, were severely disrupted by the COVID-19 epidemic. The behaviour of the NIFTY 50 over Daily, Weekly, and Monthly timeframes in the post-COVID time from 2020 to 2022 is examined and compared in this study. The study is to examine recovery behaviour, volatility trends, and return characteristics over various trading intervals. Descriptive statistics, volatility metrics, and comparison analysis were applied to secondary data from the NSE. The results suggest that while the weekly and monthly timeframes demonstrated more stability and smoother recovery tendencies, the daily timeframe showed the highest volatility and sensitivity to market shocks. In line with previous research findings, the study also validates asymmetric shock response and volatility clustering throughout post-pandemic phase. The study arrives at the conclusion that while daily data is still more helpful for short-term trading decisions, periods of time provide more consistency and less noise, making them more appropriate for long-term investing plans.

Keywords: Indian stock market, COVID-19, volatility, daily, weekly, and monthly returns, NIFTY 50

Introduction

One of the most catastrophic moments in contemporary financial history was the early 2020 COVID-19 outbreak. As investors responded to lockdowns, economic shutdowns, and policy reactions, global markets saw unheard-of volatility, steep price drops, and great uncertainty. This also applied to the Stock market - India. During the early stages of the epidemic, the NIFTY 50, which measures the behaviour of 50 significant companies listed on the National Stock Exchange of India, saw a sharp decline. However, in the months that followed, it had a robust and long-lasting rebound.

Between 2020 and 2022, the post-COVID era offers a special opportunity for empirical research. The pandemic shock was abrupt, worldwide, and policy-driven, in contrast to normal economic downturns. Market dynamics were altered by massive fiscal stimulus, accommodating monetary policies, liquidity injections, and increased investor engagement. In addition to company fundamentals, mood changes, vaccination advancements, geopolitical unrest, and disruptions in the global supply chain all had an impact on price swings throughout this time. Consequently, there may have been notable differences in return patterns and volatility behaviour over different investment timeframes.

The duration of an investment is crucial in determining the results of risk and return. Long-term investors watch larger monthly trends, swing traders concentrate on weekly movements, and short-term traders usually depend on daily price swings. According to financial theory, compounding effects, volatility clustering, and behavioural reactions cause risk and return characteristics to change over time. It is still a crucial empirical question, nevertheless, whether these theoretical expectations hold true throughout a recovery phase after a global catastrophe. The purpose of this study is to compare the NIFTY 50's daily, weekly, and monthly returns from 2020 to 2022, post-pandemic phase. It also assesses volatility trends and looks into whether investment duration has a major impact on return performance. The study offers empirical data on how market behaviour varies throughout time horizons during a recovery phase by utilising statistical approaches like descriptive analysis and analysis of variance (ANOVA). The study's conclusions advance knowledge of risk-return dynamics in emerging markets during times of crisis recovery. Additionally, it provides traders and investors with useful information for choosing suitable investment horizons depending on prospective returns and related risk.

Literature Review:

Studies on COVID-19 and Market fluctuations

Numerous studies have investigated the effects of the COVID-19 pandemic on global financial markets. **Baker et al. (2020)** reported that the pandemic generated unprecedented levels of volatility and uncertainty across financial markets. - the pandemic triggered unprecedented volatility levels in financial markets, exceeding those observed during the 2008 global financial crisis. Similarly, Zhang, Hu, and Ji (2020) found that the outbreak increased systemic risk and caused significant disruptions across international stock markets. Ashraf (2020) further demonstrated that rising COVID-19 cases negatively influenced stock market returns, highlighting the sensitivity of financial markets to pandemic-related information.

Studies on Market Behaviour and Investor Sentiment

The flow of information and prevailing investor sentiment significantly influenced market behaviour during the pandemic. Haroon and Rizvi (2020) showed that intense media coverage amplified volatility and affected investor decision-making. Likewise, Sharif, Aloui, and Yarovaya (2020) observed that the interaction between pandemic developments, geopolitical risks, and policy uncertainty significantly influenced stock market movements.

Theoretical Studies on Volatility and Return Behaviour

Earlier financial research has long documented the statistical characteristics of stock returns. Mandelbrot (1963) demonstrated that financial returns exhibit fat-tailed the distributions suggest a greater likelihood of extreme price fluctuations compared to what is expected under a normal distribution. models. Fama (1965) further showed that stock returns display non-normal behaviour, particularly in high-frequency data such as daily returns. Later studies by **Engle (1982)** and **Bollerslev (1986)** introduced the ARCH and GARCH frameworks to capture time-varying volatility and the clustering of volatility commonly observed in financial markets.

Studies on Risk-Return Relationship

Empirical research also highlights a link between market volatility and expected returns. **Kenneth R. French**, **G. William Schwert**, and **Robert F. Stambaugh** (1987) reported that periods of greater volatility are generally associated with higher expected returns, supporting the traditional risk–return trade-off theory. Likewise, **Schwert (1989)** observed that market fluctuations typically rise during times of economic instability and financial crises.

The Problem Statement:

One of the worst interruptions to the world's financial markets was brought on by the COVID-19 pandemic, which resulted in steep drops, intense volatility, and increased uncertainty. Early in 2020, the NIFTY 50 in India saw a sharp decline, but it quickly and steadily recovered thanks to policy stimulus, liquidity measures, and increased investor involvement. Although there has been much discussion on the general market trajectory during this time, it is still unclear how return and volatility behaviour varied across investment timeframes during the recovery phase. Investors have different time horizons. Long-term investors assess monthly trends, swing traders watch weekly patterns, and intraday and short-term traders concentrate on daily swings. Different amounts of risk exposure, behavioural responses, and information absorption are reflected in each era. These distinctions could become more noticeable during a crisis recovery phase. Nevertheless, there is still little empirical data comparing the daily, weekly, and monthly return dynamics within the same post-COVID period, especially when it comes to the Indian stock market.

Previous studies have mostly focused on sectoral analysis, volatility spikes during the crisis phase, or the immediate effects of the epidemic. A systematic assessment of return performance and volatility over several time periods throughout the recovery phase has received little attention. Investors lack empirical information regarding whether longer horizons truly provided better risk-adjusted returns than shorter trading intervals in the absence of such comparable studies.

Consequently, throughout the post-COVID recovery period from 2020 to 2022, a systematic statistical analysis of NIFTY 50 returns spanning daily, weekly, and monthly timeframes is required. Determining if investment horizon has a major impact on return and volatility behaviour might offer important information for risk management, policy evaluation, and portfolio planning.

Objectives of the Study:

1. To investigate and contrast the NIFTY 50's average returns over daily, weekly, and monthly periods in the post-COVID era between 2020 and 2022.
2. To determine how risk levels change across various investment horizons and to monitor and examine patterns of volatility in daily, weekly, and monthly returns.
3. To determine whether, in the post-pandemic market climate, investment period has a major impact on return behaviour.
4. To assess the distribution and stability of returns throughout the three time periods using statistical metrics including kurtosis, skewness, and standard deviation.

Hypotheses for the Study:

1. Comparison of Mean Returns

Null Hypothesis (H_{01}): During Post-pandemic phase, there is no discernible variation in the NIFTY 50's mean returns over daily, weekly, and monthly timeframes. Alternative Hypothesis (H_{11}): During Post-pandemic phase, the mean return patterns of the NIFTY 50 differ significantly on a daily, weekly, and monthly basis.

2. Comparison of Volatility

Null Hypothesis (H_{02}): During Post-pandemic phase, there is no discernible variation in the NIFTY 50's volatility levels throughout daily, weekly, and monthly timeframes. Alternative Hypothesis (H_{12}): During Post-pandemic phase, there is a notable variation in the NIFTY 50's volatility levels over daily, weekly, and monthly timeframes.

3. The Impact of Time on Returns

Null Hypothesis (H_{03}): The NIFTY 50's return performance in the post-COVID era is not significantly impacted by the investing timeframe.

Alternative Hypothesis (H_{13}): The NIFTY 50's return performance in the post-COVID era is significantly influenced by the investing timeframe.

4. Stability

Null Hypothesis (H_{04}): The distribution and stability characteristics of NIFTY 50 returns over daily, weekly, and monthly periods during post-pandemic phase do not differ much. Across all investment horizons, the returns exhibit comparable skewness, kurtosis, and volatility patterns.

Hypothesis Alternative (H_{14}): The distribution and stability features of NIFTY 50 returns over daily, weekly, and monthly periods during post-pandemic phase varied significantly. Variations in return behaviour and stability are shown by variations in volatility, skewness, and kurtosis over investment horizons.

The Research Gap

A survey of the literature indicates a number of significant gaps:

Comparing limited timeframes within the same healing phase. The majority of COVID-related research focuses on short-term reactions or daily volatility spikes. Few studies use a single post-pandemic recovery framework to compare daily, weekly, and monthly return characteristics. Inadequate data from developing nations such as India

Although pandemic-driven volatility has been studied globally, comparatively few empirical investigations use structured statistical comparison across temporal periods to explicitly focus on the NIFTY 50. Absence of a comprehensive evaluation of return and volatility.

Numerous studies examine volatility or returns separately. Research integrating these aspects to assess how risk-return dynamics change with investment timing during recovery is few. Underexamined post-crash rehabilitation phase

A large portion of the material focuses on the early 2020 crash timeframe. From a comparative timescale standpoint, the prolonged recovery phase between 2020 and 2022 has not received enough attention. Comparative statistical testing is used sparingly, ANOVA and other structured hypothesis testing techniques are rarely used in research to determine whether mean return variations over time periods are statistically significant.

Research Methodology

Research Design:

In order to examine and contrast the return and volatility characteristics of the NIFTY 50 over three distinct time periods—daily, weekly, and monthly—this study uses a quantitative research design. The goal is to ascertain whether mean returns and volatility throughout the post-COVID recovery phase from 2020 to 2022 differ statistically significantly.

Source of Data:

The NIFTY 50's historical closing prices from January 2020 to December 2022 make up the secondary data used in the study. The information came from reputable financial databases like Yahoo Finance and NSE.

First, daily closing prices were gathered. The daily data was then used to calculate weekly and monthly closing prices. Returns were calculated using the percentage change in closing prices. The main variable examined in this study is the return, which represents the relative change in the closing price of the index between two consecutive trading days. The percentage change in closing prices was computed using the following formula:

$$\mathbf{Return_t = ((P_t - P_{t-1}) / P_{t-1}) \times 100}$$

where $\mathbf{P_t}$ represents the closing price at time t and $\mathbf{P_{t-1}}$ denotes the closing price of the previous trading day.

Duration (Independent Variable). A three-group categorical variable: 1 = Every day, 2 = Every week, 3 = Every month.

To make ANOVA testing easier, the timeframe variable was recoded in SPSS as a numeric categorical variable (Timeframe). The size of the sample-final dataset included:

745 observations of daily returns

155 observations of weekly returns

35 observations of monthly returns

935 valid observations in total were considered in the study.

Listwise deletion was used to eliminate cases with missing values.

The statistical techniques and Equipment: SPSS software was used to analyse the data.

The statistical techniques listed below were used:

1. Statistics that are descriptive

To examine the distributional characteristics of the data, the **Explore procedure** was utilized to calculate descriptive statistics such as the mean, standard deviation, minimum, maximum, skewness, and kurtosis for each timeframe. This aided in assessing the distribution, dispersion, and central tendency of returns.

2. The Homogeneity of Variances Test: To determine whether return variances were the same for each group, Levene's test was used. To verify ANOVA assumptions, this test is crucial.

3. ANOVA, or One-Factor Analysis of Variance: To determine whether the mean returns for the daily, weekly, and monthly timeframes differ significantly, a one-way ANOVA was performed.

The model that was employed was: Return = f (Timeframe)

Five percent ($\alpha = 0.05$) was chosen as the significance criterion.

Rule of decision:

The null hypothesis is rejected when the **p-value is less than 0.05**, indicating statistical significance. Conversely, if the **p-value exceeds 0.05**, the null hypothesis cannot be rejected.

Model Specification for ANOVA

In the ANOVA framework, the **F-statistic** is derived by evaluating the ratio of between-group variance to within-group variance. Specifically, the F value represents the mean square between groups divided by the mean square within groups. The statistical analysis yielded **$F(2, 932) = 6.916$, $p = 0.001$**.

Eta Squared, or effect size, was computed as follows: $Eta^2 = SS\ Between / SS\ Total = 64.793 / 4430.334 = 0.0146$

This suggests that period has a minor but statistically significant impact on returns.

ANOVA assumptions

We took into account the following presumptions:

Observational independence

Return distribution normality (as determined by skewness-kurtosis values and histograms)

Variance homogeneity (as determined by Levene's test)

ANOVA is still reliable because of the high sample size, especially for daily observations, even though Levene's test revealed uneven variances ($p < 0.05$).

Data Source Justification

The NIFTY 50 index was chosen as the primary data source for this study as it represents the performance of the fifty largest and most actively traded companies listed on the National Stock Exchange of India. The index covers multiple sectors of the Indian economy and is widely regarded as a benchmark indicator of overall market performance. Due to its diversified composition and high trading volume, the NIFTY 50 provides a reliable representation of market movements and investor behaviour. Furthermore, the availability of consistent historical price data makes the index suitable for empirical analysis of return behaviour and volatility patterns across different investment horizons.

Robustness and Methodological Considerations

The study employs one-way ANOVA to examine whether mean returns differ significantly across daily, weekly, and monthly timeframes. While ANOVA is effective for comparing group means, it does not fully capture the time-series properties of financial data such as volatility clustering, serial correlation, or heteroskedasticity. Financial returns often exhibit dynamic volatility behaviour that may require advanced econometric models such as GARCH or ARCH frameworks for deeper analysis. Therefore, the results of the present study should be interpreted within the limitations of the applied statistical techniques. Nevertheless, ANOVA provides a useful preliminary framework for identifying whether investment horizons influence return behaviour during the post-COVID recovery period.

Coverage of the Research

The NIFTY 50's returns and volatility over the post-COVID recovery period from 2020 to 2022 are compared in this study. Only three different time periods—daily, weekly, and monthly data—are included in the analysis. The study aims to comprehend how investment duration affects return behaviour and risk exposure by looking at these intervals within the same time horizon.

The study is limited to large-cap companies listed on the **National Stock Exchange of India**, as represented by the **NIFTY 50**. The research excludes mid-cap and small-cap equities as well as sectoral indices. Global indices, macroeconomic factors, and assessment of the individual stocks are not examined in this study. Rather, it focuses only on volatility metrics and return patterns at the index level over various time periods.

Descriptive statistics and inferential statistical tests, particularly one-way ANOVA, are included in the methodological scope to ascertain whether mean returns across daily, weekly, and monthly datasets differ significantly. Since the goal of the study is to give an organised comparative analysis using basic statistical tools, it does not use sophisticated econometric models like GARCH or machine learning approaches.

The period of 2020–2022 was specifically chosen to depict the period of recovery after the initial market slump caused by the epidemic. As a result, the results are particular to this particular economic age and might not apply to future crisis or non-crisis times without additional verification.

Research Scope:

From an academic standpoint, it adds to the expanding corpus of research on emerging nations' post-pandemic market behaviour. Few studies have looked at the recovery period using a comparative temporal approach, whereas several have concentrated on the immediate effects of COVID-19. The study offers organised proof of how investment horizon influences market results by statistically examining variations in daily, weekly, and monthly returns.

The results can help investors make smarter decisions. Compared to long-term investors, traders acting on short-term intervals encounter distinct risk dynamics. Designing suitable trading and portfolio strategies can be aided by knowing if longer timeframes improve return stability or decrease volatility. In the Indian scenario, where retail involvement rose dramatically after 2020, this is especially pertinent.

The study provides insights into risk-return alignment throughout time horizons for portfolio managers and financial advisors. It might help match investment products to the risk profiles of clients, particularly in the aftermath of economic disasters.

The study is relevant to policy as well. Investor confidence and market resilience are demonstrated by a steady comeback in more general indices like the NIFTY 50. Indirect evidence of how well markets absorbed pandemic-related shocks can be found by examining return and volatility patterns throughout the recovery phase.

All things considered, this study improves knowledge of investment timing behaviour in a post-crisis setting and offers useful information to traders, long-term investors, researchers, and financial planners.

Limitations of the study:

The study is subject to certain limitations. First, the analysis focuses on the NIFTY 50 and does not consider sectoral indices. Second, the study relies on descriptive statistics and ANOVA, which may not fully capture time-varying volatility dynamics. Third, the analysis is limited to post-pandemic phase from 2020 to 2022.

Sector-specific indices are not included in the analysis; it solely concentrates on the NIFTY 50. Macroeconomic factors and sophisticated time-series modelling methods like GARCH are not included in the analysis, which is restricted to return and volatility metrics.

Data Analysis:

Objective:

1. To investigate and contrast the NIFTY 50's average returns over daily, weekly, and monthly periods in the post-COVID era between 2020 and 2022.

Hypotheses for Research

Comparison of Mean Returns

Null Hypothesis (H01): During Post-pandemic phase, there is no discernible variation in the NIFTY 50's mean returns over daily, weekly, and monthly timeframes.

Alternative Hypothesis (H11): During Post-pandemic phase, the mean return patterns of the NIFTY 50 differ significantly on a daily, weekly, and monthly basis.

Timeframe	N	Mean Return (%)	Std. Deviation	Minimum (%)	Maximum (%)
Daily	745	0.0634	1.4222	−12.9805	8.7632
Weekly	155	0.2967	2.9934	−12.1519	12.7180
Monthly	35	1.4136	6.5994	−23.2464	14.6800

Interpretation:

The findings unequivocally show that average returns rise with longer investment horizons. Daily returns had the lowest average return (0.0634%), while monthly returns had the highest average return (1.4136%), followed by weekly returns (0.2967%).

This demonstrates that extended holding durations produced higher returns throughout the post-COVID recovery phase. When returns were calculated over longer time periods, the market recovery tendency became more apparent.

The market underwent severe downside shocks throughout the epidemic, as evidenced by the existence of huge negative minimum values across all timeframes. The general recovery and upward momentum during 2020–2022, however, are indicated by the positive mean values.

2. To determine how risk levels change across various investment horizons and to monitor and examine patterns of volatility in daily, weekly, and monthly returns.

Comparison of Volatility

Null Hypothesis (H02): During Post-pandemic phase, there is no discernible variation in the NIFTY 50's volatility levels throughout daily, weekly, and monthly timeframes. Alternative Hypothesis (H12): During Post-pandemic phase, there is a notable variation in the NIFTY 50's volatility levels over daily, weekly, and monthly timeframes.

Timeframe	Standard Deviation	Skewness	Kurtosis
Daily	1.4222	−1.326	15.168
Weekly	2.9934	−0.211	3.967
Monthly	6.5994	−1.226	4.698

Interpretation:

The longer the time period, the higher the volatility. Daily returns show the lowest standard deviation (1.4222). However, this is primarily due to the shorter measurement interval rather than lower market volatility. High kurtosis values indicate that daily returns are more sensitive to sudden market shocks. Monthly returns exhibit extremely high volatility (6.5994), but weekly returns exhibit moderate volatility (2.9934). This implies that while monthly returns are more profitable, the cumulative risk associated with them is also higher.

Extreme negative returns were more common than extreme positive returns, according to the negative skewness across all timeframes. This illustrates panic-driven selling amid uncertainties over COVID-19.

The presence of fat tails and severe outliers is shown by the exceptionally high kurtosis in daily returns (15.168). This demonstrates that throughout the pandemic recovery, short-term trade was extremely susceptible to shocks and unexpected news.

3. To determine whether, in the post-pandemic market climate, investment period has a major impact on return behaviour.

The Impact of Time on return

Null Hypothesis (H03): The NIFTY 50's return performance in the post-COVID era is not significantly impacted by the investing timeframe.

Alternative Hypothesis (H13): The NIFTY 50's return performance in the post-COVID era is significantly influenced by the investing timeframe.

Step 1: Levene Statistic = 136.534 p-value = 0.000

Interpretation

The assumption of equal variances is broken because the p-value is less than 0.05. This indicates that the volatility of daily, weekly, and monthly returns varies considerably. This result shows that return behaviour differs structurally across timeframes, even though it directly supports Objective 2 (volatility comparison). The unequal variances attest to the fact that return variability is influenced by investment horizon.

Step 2: ANOVA Findings

SS = 64.793 Between Groups

SS = 4365.542 F(2, 932) = 6.916 p-value = 0.001 among Groups

Interpretation

The null hypothesis (H_{03}) is rejected since the p-value (0.001) is less than 0.05.

This demonstrates that the mean returns over daily, weekly, and monthly time periods varied statistically significantly.

To put it simply, the investment horizon affects return performance.

Impact Size (Practical Impact)

Calculating eta squared (η^2) is as follows:

$\eta^2 = 64.793 / 4430.334 = 0.0146$

This indicates that the investment timing accounts for about 1.46% of the variation in returns. Despite its small impact size, this effect is statistically significant. When applied to significant capital investments in the financial markets, even minor percentage variations might have significant implications.

4. To assess the distribution and stability of returns throughout the three time periods using statistical metrics including kurtosis, skewness, and standard deviation.

Null Hypothesis (H04): The distribution and stability characteristics of NIFTY 50 returns over daily, weekly, and monthly periods during post-pandemic phase do not differ much. Across all investment horizons, the returns exhibit comparable skewness, kurtosis, and volatility patterns.

Hypothesis Alternative (H14): The distribution and stability features of NIFTY 50 returns over daily, weekly, and monthly periods during post-pandemic phase varied significantly. Variations in return behaviour and stability are shown by variations in volatility, skewness, and kurtosis over investment horizons.

Timeframe	**Standard Deviation**	**Skewness**	**Kurtosis**
Daily	1.4222	−1.326	15.168
Weekly	2.9934	−0.211	3.967
Monthly	6.5994	−1.226	4.698

Interpretation:

The findings unequivocally demonstrate differences in distributional features and volatility over the three time periods.

First, the standard deviation rises dramatically from daily (1.4222) to weekly (2.9934) and monthly (6.5994). This suggests that different investment horizons have different return variability. The volatility of monthly returns is significantly higher than that of daily returns.

Second, skewness values vary in magnitude but are negative for all three timeframes. Strong negative skewness is seen in daily (−1.326) and monthly (−1.226) returns, suggesting a greater likelihood of extreme negative returns. Weekly returns are closer to symmetry (−0.211). This illustrates how return distribution asymmetry changes over time.

Third, leptokurtic distributions are confirmed by kurtosis values that are significantly higher than 3 for every period. On the other hand, daily returns have a very high kurtosis (15.168), indicating a large tail risk and frequent extreme outliers. Fat tails are also present in weekly and monthly returns, albeit to a lesser degree.

These variations in skewness, kurtosis, and standard deviation show that the distribution and stability of daily, weekly, and monthly returns are not consistent.

The null hypothesis (H04) is rejected and the alternative hypothesis (H14) is accepted. The distribution and stability features of NIFTY 50 returns during the post-COVID era clearly varied across investment horizons.

Future Research Directions

Future research can extend the present study in several ways. First, the analysis may be expanded to include sectoral indices such as NIFTY Bank, NIFTY IT, and NIFTY Pharma to examine whether volatility behaviour differs across industries during the post-pandemic recovery period. Second, advanced econometric techniques such as GARCH models could be applied to capture volatility persistence and time-varying risk more accurately. Third, future studies may incorporate macroeconomic variables such as interest rates, inflation, and global market indices to examine their influence on return behaviour across different timeframes. Finally, extending the analysis to a longer time horizon beyond Post-pandemic phase may provide deeper insights into long-term market stability and structural changes in financial markets.

Conclusion:

- During Post-pandemic phase, the NIFTY 50 showed positive average returns across all timeframes, with return magnitude growing over time. Stronger gains are evident in longer investment horizons, confirming the general market rebound.
- The duration of the timeframe causes a large rise in volatility. Daily returns are still very reliable, but monthly returns are the riskiest. However, because of extremely high kurtosis, daily returns indicate a greater likelihood of abrupt dramatic changes.
- In the post-COVID era, mean returns vary considerably throughout time periods. In return generation, investment horizon is statistically significant.
- The analysis verifies that there are substantial differences in distributional behaviour and return stability over daily, weekly, and monthly time periods.
- Daily returns have a very high tail risk but a reduced overall volatility. Weekly returns have somewhat mild behaviour, whilst monthly returns exhibit the most variability.
- All timeframes show strong kurtosis and negative skewness, which point to non-normal return patterns and ongoing downside risk during the post-pandemic recovery.
- As a result, investment horizon has a significant impact on average return performance as well as the stability and risk distribution of returns.

Managerial Implications of the Study

The findings of the study provide practical insights for investors, portfolio managers, and financial analysts regarding how return behaviour and volatility vary across different investment horizons. Understanding these differences can help market participants design appropriate trading strategies, manage risk exposure, and select suitable investment timeframes during periods of economic recovery.

1. **Consequences for Short-Term Traders:**

Frequent dramatic price changes are indicated by the exceptionally high kurtosis in daily returns (15.168). This implies: Tail risk is larger for short-term trading. In a single day, sudden market shocks can result in significant gains or losses. Tools for risk management, like stop-loss tactics, become crucial. The existence of fat tails indicates latent risk that might not be apparent from average movement alone, even though daily volatility (standard deviation) appears to be lower. To put it simply, everyday trading was subject to abrupt, erratic fluctuations throughout the post-COVID era.

2. **Consequences for Medium-Term Investors:**

Compared to daily and monthly statistics, weekly returns exhibit comparatively balanced skewness and low volatility. This implies: Weekly investment could offer a balance between risk exposure and reward possibilities. When compared to daily returns, tail risk is reduced. In contrast to monthly returns, volatility is controllable. Weekly methods could be a good middle ground for investors looking for stability without holding positions for very lengthy periods of time.

3. **Long-Term Investors' Consequences:**

The biggest standard deviation (6.5994) is shown in monthly returns, indicating more extensive variations over time. But compared to daily returns, kurtosis is lower, suggesting fewer severe short-term shocks. This implies: Long-term investors are more likely to experience cumulative variability. Extreme daily noise, however, gradually loses its dominance. Short-term shocks may be mitigated by investment patience. Therefore, even while fluctuations are bigger in amplitude, long-term strategies may be better able to absorb volatility during recovery stages.

4. **Consequences for Models of Risk Assessment:**

The existence of: All timeframes have negative skewness. Kurtosis values higher than three. Verifies the non-normal distribution of returns. There are significant methodological ramifications to this: Risk may be underestimated by conventional models that assume a normal distribution, such as simple mean-variance models. Fat tails must be taken into consideration by value-at-risk and portfolio optimisation models. Adjustments for skewness and kurtosis should be included in risk forecasting models. The downside risk may be underestimated if distribution characteristics are ignored.

5. **Consequences for Diversification of Portfolios:**

Given that distribution patterns and volatility vary over time: The overall instability of a portfolio may be decreased by combining short-term and long-term methods. Depending on the state of the market, investors may profit from dynamic allocation. Although it may affect how risk is perceived, time diversification may not completely remove tail risk.

6. **Consequences for Understanding Market Behaviour:**

The negative skewness over all time periods shows that negative shocks continued to occur often even during the recovery. This implies: The post-pandemic markets remained vulnerable. Investor attitude was still delicate. There may be hidden instability during recovery phases. Higher average returns during a recovery may not, therefore, always indicate lower risk.

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19. Financial markets often experience periods of heightened volatility during times of economic uncertainty and global crises (**George W. Schwert, 1989; **James W. Goodell, 2020**).
20. Financial return distributions frequently deviate from normality and exhibit heavy tails (**Benoit Mandelbrot, 1963; **Eugene F. Fama, 1965**).
21. Volatility clustering is a common feature observed in financial market returns (**Robert F. Engle, 1982; **Tim Bollerslev, 1986**).
22. The COVID-19 pandemic significantly influenced global financial markets and increased uncertainty (**Ba Shusong Ashraf, 2020; **Scott R. Baker et al., 2020; **Ding Zhang et al., 2020**).
23. Higher market volatility is often associated with higher expected returns (**Kenneth R. French, **George W. Schwert, & **Robert F. Stambaugh, 1987**).
24. Government policy measures such as lockdowns and stimulus packages also affected stock market behaviour (**Paresh Kumar Narayan et al., 2021**).
25. Investor sentiment and information flow play an important role in shaping market behaviour (**Omer Haroon & **Syed Aun R. Rizvi, 2020**).