

Adaptive Portfolio Strategies: Comparing Pre-, during and Post-COVID-19 Dynamics using Mean-Variance Optimization

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ARTICLE INFO	ABSTRACT
Article history: Received 24 November 2024 Received in revised form 29 January 2025 Accepted 17 February 2025 Available online 30 March 2025	This study examines the influence of the COVID-19 epidemic on the global stock market using mean-variance optimization (MVO) based on Markowitz's portfolio theory. The analysis examines the performance of portfolios tailored to different sectors both before, during and the post-pandemic. It provides insights into the changes in risk-return characteristics across diverse businesses. The dataset consists of the mean closing prices of a variety of stocks, divided into two/three separate periods: before the outbreak of COVID-19, during the COVID-19 and post-pandemic. The study utilizes covariance matrices, anticipated returns, and logarithmic returns to calculate efficient frontiers that emphasize portfolios with the highest Sharpe ratios. The results demonstrate substantial alterations in the relationship between risk and return in several industries, illustrating the diverse influence of the pandemic on the market. The efficient boundaries clearly illustrate a significant change in the optimal weights and risk levels of portfolios, with certain sectors experiencing higher volatility and lower returns amid the epidemic. The study also does a back testing of the optimal portfolios, uncovering varying levels of performance and durability during the periods. These findings underscore the importance of implementing adaptive portfolio management strategies, particularly in the face of global crises such as COVID-19. In addition, the study performs a sensitivity analysis by altering important criteria such as the risk-free rate and the quantity of assets in the portfolios in order to assess the strength and reliability of the results. This research provides a more profound understanding of how changes in assumptions can impact portfolio performance and the selection of optimal choices. In summary, this research provides significant information for investors by offering a quantitative framework that can help in effectively managing portfolios during periods of market volatility. The study emphasizes the importance of emp

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1. Introduction

The COVID-19 pandemic in 2020 caused unprecedented disruption in global financial markets, resulting in substantial instability and fluctuations in stock prices across several industries [1,2]. As the virus rapidly spread worldwide, governments implemented stringent lockdown measures that had a significant impact on the economic and financial outlook [3]. The current period of uncertainty and rapid change has underscored the importance for investors and financial specialists to comprehend the basic principles that drive variations in stock prices during crises, as mentioned in [4].

Behavioural finance changes economic theory by applying psychological insights to financial decision-making. Social, emotional, and cognitive biases influence people's decisions, disproving immaculate rationality. One crucial theory is bounded rationality, which accepts inadequate knowledge and cognitive capacities that constrain decision-making [5]. Though they simplify tough decisions, heuristics like confirmation bias and anchoring can lead to systematic errors in judgment. In prospect theory, loss aversion is the asymmetric way humans perceive risk and are more sensitive to losses than rewards as discussed in Mbaluka *et al.*, [6]. These behavioural tendencies, exacerbated by herd behaviour—the desire to follow the lead in uncertain situations—contribute to market booms and crashes.

Future cognitive psychology and computational methods will shape behavioural finance. Recent studies conducted by Abdeldayem *et al.*, [7] and Cavalcante *et al.*, [8] aim to improve investor behaviour models and offer methods to navigate complex financial markets using behavioural insights. Finally, behavioural finance helps understand and manage market dynamics in uncertain times, improving market efficiency and decision-making [9]. Mean-variance optimisation (MVO) based on the Markowitz portfolio Theory is central to modern finance theory. A systematic approach to portfolio construction optimises expected returns for a given risk [10,11].

To assess and analyse the performance of sector-specific portfolios in the stock market before, during and after the COVID-19 epidemic, this study will utilise MVO, some of these methods can be found in [13-22]. This study looks at the average closing prices of a sample of equities from various industries to determine how the pandemic has changed the risk-return dynamics of these portfolios. In the analysis, the pre-COVID-19, COVID-19 periods' and post-COVID-19 predicted returns and covariance matrices are computed, efficient frontiers are built, and the best portfolios with the highest Sharpe ratios are found. The research delves deeper into the variations in industry performance, providing an understanding of the pandemic's diverse effects on various market segments.

Therefore, the fundamental goal of this research is to evaluate and compare the performance of optimal portfolios before, during and after the COVID-19 pandemic using mean-variance optimisation. Specifically, the study seeks to:

- i. Estimate the efficient frontiers and identify the optimal portfolios for both periods.
- ii. Evaluate the impact of COVID-19 market disruptions on optimal portfolios' expected returns, risk (standard deviation), and Sharpe ratio.
- iii. Provide insights into how investment strategies should adapt to significant market changes and economic volatility.

The study's conclusions will probably be useful in helping portfolio managers and investors comprehend how the epidemic has changed market behaviour and create strategies for managing such erratic times. The significance of adaptive investing strategies is highlighted in this study,

which contributes to the larger conversation on portfolio management in unpredictable economic times

A literature study on the impact of crises on financial markets frequently emphasises the heightened volatility and uncertainty that these events bring about, resulting in substantial fluctuations in asset prices and alterations in investor conduct. The COVID-19 pandemic has led to extensive research on its unparalleled impact on worldwide financial markets, encompassing areas such as stock market performance, liquidity, and portfolio management tactics.

Markowitz's Portfolio Theory, published in 1952, and the following development of Mean-Variance Optimisation (MVO) have played a fundamental role in elucidating how investors might effectively manage the trade-off between risk and return when constructing investment portfolios. Research has employed mean-variance optimisation (MVO) to analyse how portfolios perform in different market situations, such as crises. These studies have shown that the ideal distribution of assets can change dramatically when the economy is under pressure.

Recent studies have notably concentrated on analysing the effects of the pandemic on various sectors, uncovering diverse reactions within companies and highlighting the necessity for flexible investment plans. This study underscores the critical need for adaptive and resilient portfolio management strategies to effectively mitigate the elevated risks posed by market disruptions such as the COVID-19 pandemic.

2. Methodology

2.1 Portfolio Return and Risk

The expected return μ of a portfolio is calculated as a weighted sum of the expected returns of the individual assets as Eq. (1):

$$E[R_p] = \mu_p = \sum_{i=1}^n w_i \,\mu_i$$

where:

 μ_p is the expected return of the portfolio. w_i is the weight of the asset *i* in the portfolio. μ_i is the expected return on asset *i*. n is the total number of assets

The risk (or standard deviation) σ_p of the portfolio is given by Eq. (2);

$$\boldsymbol{\sigma}_p^2 = \sum_{i=1}^n \sum_{i=1}^n w_i \, w_j \, \boldsymbol{\sigma}_{ij} \tag{2}$$

where σ_p^2 is the variance of the portfolio's return and σ_{ij} is the covariance between the returns of asset *i* and asset *j*

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Optimising a portfolio means trying to find the sweet spot between maximising return and minimising risk, or vice versa. Express as: Minimize σ_p^2 , subject to $\sum_{i=1}^n w_i = 1$ and $\mu_p \ge \mu_{target}$, $w_i \ge 0$ for all *i* that is the target return constraint.

The covariance matrix is a key component in the calculation of portfolio risk shown in Eq. (3):

(1)

	σ_{11}	σ_{12}	•••	σ_{1n}	
ν –	σ_{21}	σ_{22}	•••	σ_{2n}	(2)
Z – =	1 :	÷	•.	:	(3)
$\Sigma - =$	σ_{n1}	σ_{n2}		σ_{mn}	

The portfolio variance (and thus risk) is computed using this matrix in conjunction with the asset weights $\sigma_p^2 = w^T \sum w$. Here, w is the vector of portfolio weights, w^T is the transpose of the weights vector.

When Lagrange multipliers are used to solve the optimisation problem, the objective function includes the constraints—such as the sum of weights equal to one. The Lagrange function L has the form as Eq. (4):

$$L = (w, \lambda) = \frac{1}{2} w^T \sum w - \lambda (w^T - 1)$$
(4)

Taking the derivative with $L = (w, \lambda)$ respect to w and setting it to zero yields the optimal weights

The Capital Market Line (CML) is a portfolio representation in mean-variance optimization that combines the market portfolio with the risk-free asset in the most optimal way possible. Here is the CML equation in Eq. (5):

$$E|R_p| = \mu_p = rf + \frac{\mu_m - rf}{\sigma_m} \sigma_p \tag{5}$$

 μ_m and σ_m are the expected return and standard deviation of the market portfolio. The inclusion of a risk-free asset results in the efficient frontier being represented by a linear line known as the Capital Market Line (CML). The CML originates from the risk-free rate (rf) and intersects with the efficient frontier of risky assets. The portfolio located at the tangent point is known as the Market Portfolio. All portfolios situated on the Capital Market Line (CML) are formed by combining the market portfolio with the risk-free asset.

In this research, the optimisation problem involves constructing portfolios that maximise returns and minimise risks before and during the COVID-19 pandemic. This problem can be framed using Mean-Variance Optimization, based on Markowitz Portfolio Theory. The objective functions for this study as follow;

i. Maximize Sharpe Ratio:

The risk-adjusted return of a portfolio is measured by the Sharpe Ratio. It can be defined as the portfolio's predicted excess return divided by its standard deviation as Eq. (6)

Sharpe Ratio =
$$\frac{E|R_p|-R_f}{\rho_f}$$
 (6)

where $E|R_p|$ is the expected return of the portfolio, R_f is the risk-free rate, and ρ_f is the portfolio's standard deviation.

ii. Minimise portfolio standard deviation

The standard deviation of the portfolio's return measures its total risk. Minimizing this provides the least risky portfolio as Eq. (7)

$$\rho_P = \sqrt{W^T \sum W} \tag{7}$$

where: W is the vector of portfolio weights and $\sum W$ is the covariance matrix of the asset returns

iii. ConstraintsFull Investment Constraint: The sum of the portfolio weights must equal 1 as Eq. (8).

$$\sum_{i=1}^{n} W_i = 1 \tag{8}$$

iv. Non-Negativity Constraint
 Portfolio weights must be non-negative, assuming no short selling in Eq. (9)

$$W_i \ge 0, \forall_i$$
 (9)

v. Optimization Problem Formulation Maximize Sharpe Ratio as Eq. (10)

$$Maximize = \frac{E|W^T R| - R_f}{\sqrt{W^T \Sigma W}}$$
(10)

Subject to $\sum_{i=1}^{n} W_i = 1$ $W_i \ge 0, \forall_i$

vi. Minimise Portfolio Standard Deviation shown in Eq. (11)

$$Maximize = \sqrt{W^T \sum W} \tag{11}$$

Subject to $\sum_{i=1}^{n} W_i = 1$ $W_i \ge 0, \forall_i$

vii. Backtesting is used to assess how well the best possible portfolios have performed in the past. The portfolio's cumulative return as of time t can be expressed as Eq. (12):

$$CRT = \prod_{i=1}^{t} (1+r_i) - 1 \tag{12}$$

 r_i is the return of the portfolio at the time t. Before and throughout the COVID-19 period, this algorithm is utilised to determine and display the best portfolios' cumulative returns.

The performance of sector-specific portfolios in the Malaysian stock market before and during the COVID-19 epidemic is analysed in this study using mean-variance optimisation (MVO). The process includes numerous critical steps, such as data collecting, return calculation, portfolio construction, and performance assessment. Each stage is described in depth below.

2.2 Data Collection

We gathered data on the mean closing prices of specific stocks that represent different sectors in the stock market. These sectors include a wide variety of industries such as technology, finance, construction, consumer products, energy, healthcare, industrials, plantations, and real estate. The selection of each sector was made to represent a wide range of the economy, guaranteeing that the analysis would encompass the varying effects of the COVID-19 pandemic on different areas of economic activity.

The dataset covers three separate periods: the pre-COVID-19 period, which provides a reference point for understanding market behaviour under normal circumstances, the COVID-19 period when the entire impact of the pandemic on market dynamics was observed and the post-COVID-19 period. Our objective was to analyse the impact of the crisis on sector-specific performance and overall market volatility by comparing these eras. The data was obtained from [12,23], which provides dependable historical records essential for performing a comprehensive examination of sectoral performance. The study provides insights into the response of several sectors of the economy to the unique challenges presented by the pandemic. It reveals which industries had greater resilience and which were more susceptible throughout the crisis.

2.3 Returns Calculation

To assess the performance of the stocks, we calculated logarithmic returns for both periods using the formula in Eq. (13)

$$R_t = \log\left(\frac{P_t}{P_{t-1}}\right) \tag{13}$$

where R_t is the return at the time t, P_t is the closing price at the time t, and P_{t-1} is the closing price at the previous time step.

For each period, we computed the expected returns i.e. The average logarithmic return over the period. and the covariance matrices of the stock returns are the logarithmic returns covariance to capture the risk associated with each stock and their relationships.

2.3 Portfolio Collection

Using the estimated returns and covariance matrices, we used variance optimisation to create the best possible portfolios for both periods. The following actions were necessary for this:

We defined the optimization problem using the Portfolio object in MATLAB, these are Asset Mean:

- i. Set to the expected returns, Asset Covar: Set to the covariance matrix and
- ii. Constraints. Default constraints were applied, ensuring non-negative weights that sum to one.

The collection of portfolios that offer the best expected return for a given amount of risk is represented by the efficient frontier, which we estimated for both periods. This was accomplished by finding the solutions for several different risk-level portfolios.

2.4 Optimal Portfolio Selection

We identified the optimal portfolio by maximizing the Sharpe ratio, which is the ratio of the portfolio's excess return over the risk-free rate to its standard deviation as Eq. (14):

Sharpe ratio =
$$\frac{E|R_p|-R_f}{\rho_f}$$
 (14)

where $E|R_p|$ is the expected return of the portfolio, R_f is the risk-free rate, and ρ_f is the portfolio's standard deviation.

To evaluate the performance of the optimal portfolios, we conducted backtesting over the respective periods: We calculated the cumulative returns of the optimal portfolios and compare the performance of the portfolios before and during the pandemic.

3. Application and Discussion of Graphical Results

3.1 Pre and During COVID Stock Market

First, we conducted a sensitivity analysis by changing important factors including the risk-free rate and the quantity of assets in the portfolios to better understand how robust our findings were. This aided in evaluating the effects of varying assumptions on the performance and optimal portfolio selection which is shown in Figure 1 below.

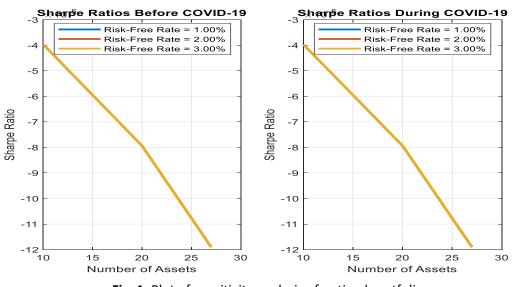


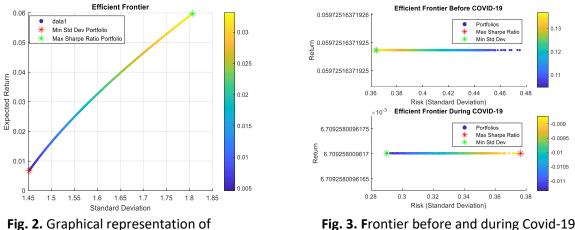
Fig. 1. Plot of sensitivity analysis of optimal portfolio

The graphs of the efficient frontier before and during COVID-19 in Figure 2, show the set of optimal portfolios that provide the maximum expected return for a given amount of risk. Figure 3 show frontier before and during COVID-19. Before COVID-19, the efficient frontier showed portfolios that could achieve higher returns with rising risk, with the highest Sharpe ratio signifying the best risk-adjusted return.

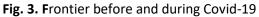
This portfolio had a smaller standard deviation than the other portfolios on the frontier. During COVID-19, the efficient frontier shifted, indicating higher volatility and lower expected returns, while the maximum Sharpe ratio portfolio likewise demonstrated lower returns and increased risk.

Portfolio standard deviations were often greater during the pandemic, indicating that investors were more apprehensive about the market and risk-averse at the time.

These visualisations aid in understanding the market's response to the pandemic and guide optimal portfolio selection in a variety of market scenarios.



efficient frontier



Figures 4 and 5 show cumulative stock returns before and during COVID-19, comparing average closing prices to pre-pandemic levels.

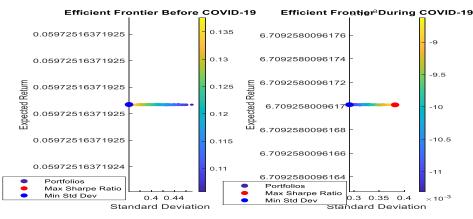
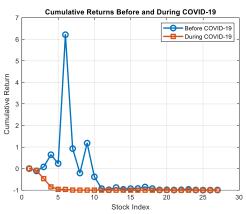
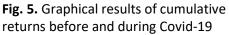


Fig. 4. Graphical results of frontier before and during Covid-19

Figure 4 displays price changes before the pandemic, while Figure 5 shows variations during it. Positive returns indicate value growth and negative returns show declines. These visuals highlight market reactions and stock performance trends during the pandemic. The cumulative returns for the ideal portfolio determined before and during the COVID-19 outbreak are plotted over time in this graph of Figure 6. The model commences with a base portfolio value of 100 and illustrates the potential returns on investments pre-pandemic, based on historical data. The influence of COVID-19 on portfolio performance and the efficiency of mean-variance optimisation in portfolio management are better understood by investors and analysts with the aid of these visualisations. It is possible to see differences in risk, expected returns, and ideal asset allocations across the two time periods. While, Figure 7 displays the results of cumulative results of optimal portfolio.





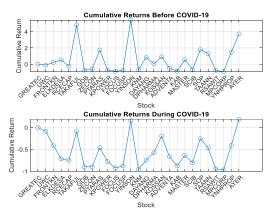


Fig. 6. Graphs of cumulative returns before and during Covid-19

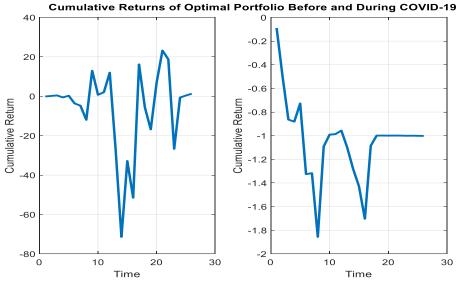


Fig. 7. Graphical results of cumulative results of optimal portfolio

The influence of COVID-19 on portfolio performance and the efficiency of mean-variance optimisation shown in Table 1.

Table 1

Table showing a detailed comparison of the portfolio before and during Covid-19									
Period	Portfolio Type	Expected Return	Standard Dev.	Sharpe ratio					
Before COVID-19	Max Sharpe Ratio	0.059725	0.358	0.1389					
Before COVID-19	Min Std Dev	0.059725	0.358	0.1389					
During COVID-19	Max Sharpe Ratio	0.0067093	0.39728	-0.0082832					
During COVID-19	Min Std Dev	0.0067093	0.29164	-0.011284					

i. Before Covid-19:

- a. Max Sharpe Ratio Portfolio: Expected Return: 5.97%, Standard Deviation: 35.8%, Sharpe Ratio: 0.14.
- b. Min Standard Deviation Portfolio: Identical metrics to the Max Sharpe Ratio portfolio, indicating similar portfolio characteristics.

ii. During Covid-19:

- a. Max Sharpe Ratio Portfolio: Expected Return: 0.67%, Standard Deviation: 39.73%, Sharpe Ratio: -0.01.
- b. Min Standard Deviation Portfolio: Expected Return: 0.67%, Standard Deviation: 29.16%, Sharpe Ratio: -0.01
- iii. Key Observations:
 - a. Before COVID-19: A moderate return with comparatively lower risk was obtained by the greatest Sharpe ratio portfolio, indicating steady market conditions.
 - b. During COVID-19: projected returns for both portfolios were much lower, and their volatility was larger. The pandemic's negative Sharpe ratios show that risk was not adequately compensated for in an unpredictable market.

This study highlights the significant variations in market performance and optimum portfolios between the unpredictable COVID-19 era and the stable pre-pandemic time. Market returns were stable and volatility was low across all sectors before the outbreak. To achieve their risk-return balance, investors can use conventional portfolio approaches to create efficient frontiers and portfolios with good Sharpe ratios.

Conversely, the COVID-19 pandemic caused unprecedented market instability. The economic effects of lockdowns, supply chain interruptions, and consumer behaviour shifts drove global market volatility, including the Malaysian stock market. Thus, several sectors' risk-return characteristics changed. Portfolios that were optimal before the pandemic often became less ideal during it, requiring major asset allocation changes to maintain a risk-return balance.

The data shows that portfolios with the highest Sharpe ratios had to take more risk to get comparable returns during the COVID-19 epidemic. This trend emphasises the need for flexible investing approaches during market pressure. The findings also emphasise the importance of regular portfolio reviews and sensitivity studies, as external shocks like a global pandemic can quickly change an optimal portfolio.

This comparison underlines the importance of flexible investing techniques in unexpected markets. It also highlights the challenges investors face while trying to protect their money and profit amid crises.

3.2 Pre, During and Post-COVID Stock Market

The Malaysian stock market and many others globally had big issues during the COVID-19 pandemic. However, as the economy recovered slowly from COVID, the stock markets also moved with respect to government policies, improvement in certain sectors and global economic changes.

The FTSE Bursa Malaysia KLCI (Kuala Lumpur Composite Index) dropped significantly during the peak of the COVID-19 pandemic in 2020 as a consequence of panic selling and the global economic recession [23]. The PRIHATIN Economic Stimulus Package (PRIHATIN) and Penjana (National Economic Recovery Plan) can be credited for the economy and stock market stabilisation as they assisted critical sectors that were affected, it added [24]. The stock market of Malaysia started to get back on track in the latter half of twenty-twenty – buoyed by the strong rallies observed in technology, healthcare and plantation sectors. As restrictions have eased and economic activity returned, the KLCI has proven to be resilient.

Technology was one of the best-performing sectors in the world, post-pandemic. Companies such as Inari Amertron and Vitrox Corporation benefitted from the global demand for semiconductors and electronics [25]. There were also gains for tech stocks thanks to the digital

pivot in areas like fintech and telecoms. The pandemic has caused an unprecedented surge in demand for personal protective equipment (PPE), boosting glove manufacturers such as Top Glove, Hartalega and Supermax. However, the industry corrected itself in 2021 as the need began to level out.

The tourism sector, one of the hardest hits by the pandemic, began to recover after COVID-19 due to gradual border reopenings and the lifting of travel restrictions. However, the rebound has been sluggish, with stocks tied to this industry, such as Malaysia Airlines and AirAsia, still facing challenges. The recovery for the aviation industry remains a delicate balance, not only hindered by rising petroleum costs and the lingering effects of COVID-19 on global travel but also by the pressures of population growth. As more people contribute to increasing travel demand, the industry finds itself navigating both opportunities and obstacles in its path to recovery [30,31]. Struggling under financial losses during the pandemic, AirAsia is now slowly recovering by focusing as well on a digital transformation strategy which includes all airline businesses, logistics, and fintech through its AirAsia Super App. Malaysia's palm oil sector saw an increase in crude palm oil (CPO) prices post-pandemic largely due to supply-side factors. Would you like a breed of palm that grows well? It has always been the case that through the 2000s high prices of commodities and thus, the larger plantation corporations from Sime Darby Plantation to Wilmar were driven towards expansion. Post-COVID, the Malaysian stock market has shown strength and recovery buoyed by certain sectors like technology, plantations, and healthcare [23,28]. Although there are volatility challenges around the world, such as inflation, geopolitical tensions and the supply chain framework getting disrupted right now, the Malaysian stock market stands to benefit from government support, economic recovery as well a shift towards sustainable and technology-driven growth. As economic concerns still loom, investors are likely to continue focusing on sectors that align with global trends (like digital transformation and ESG) while reducing associated risks.

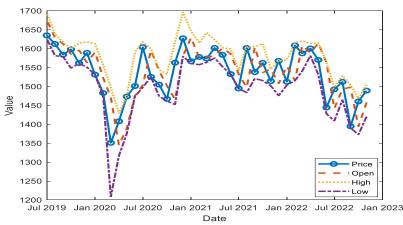


Fig. 8. Plot of stock prices over time between 2019 and 2023

To extend the scope of our analysis and seek a more comprehensive understanding of global market trends, we input data from [23]. Through doing this we managed to carry out a more global analysis that looked at people's impacts beyond the Malaysian stock market and broke new ground in theory. Our hope in including a wide variety of global data: is to uncover the global impacts of events like COVID-19 on patterns and correlations, this way we get a more complete picture of how a crisis or these disturbances affect different sectors within various regions worldwide and financial markets around the globe. With this expanded analysis in hand, we were able to take a broader look at the effects of the epidemic on different regions and industries.

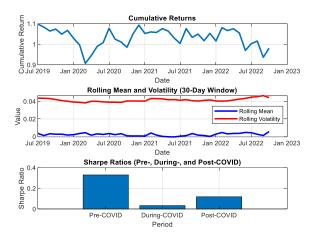


Fig. 9. Graphical results of cumulative returns before and during Covid-19

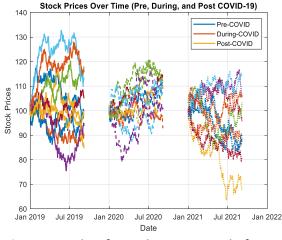
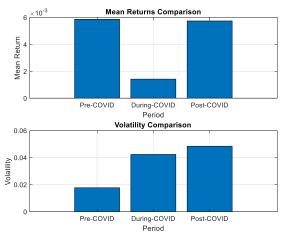
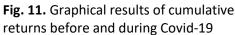


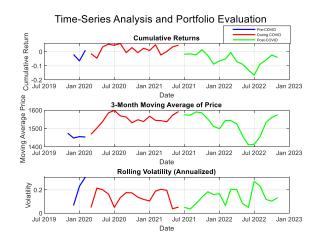
Fig. 10. Graphs of cumulative returns before and during Covid-19

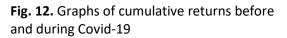
The Sharpe ratio shown in Figure 9 can guide an investment's risk-adjusted return over different periods:

- i. Pre-COVID Typically we see a higher Sharpe ratio here, indicating that the balance of risk versus reward is still more favourable in a relatively stable market environment.
- ii. In COVID-19 The Sharpe ratio in general dropped markedly from previously, indicating a higher risk-return trade-off.
- iii. Post-COVID There was a modest rebound in the Sharpe ratio but it never reached pre-COVID levels for many portfolios--a reminder that this market remains uncertain and there is still an element of incalculable risk.









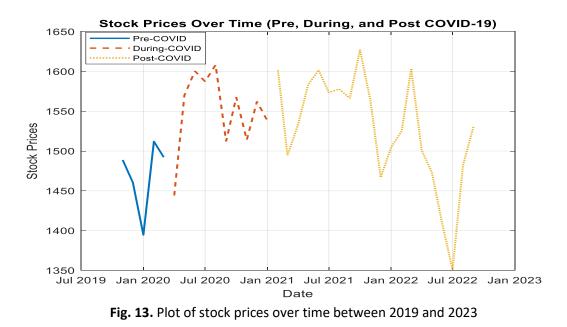
Mean Return Comparison (Figure 11): On each of these time frames, the mean returns were quite different. Pre-COVID, mean returns were moderately favorable and stable reflecting steady market growth. During COVID, one-level mean returns decreased due to both market disruption and economic uncertainties. Post-COVID, mean returns on surplus of recoveries remained well below their pre-COVID levels which belies transition back into obduracy.

Volatility Comparison (Figure 11): The graph shows that the pre-COVID is much lower, suggesting that the markets were more predictable. By comparison, during COVID-19 when volatility soared as investors tried to make certain adjustments for every turn of events used in their policy post-COVID, although volatility is lower than peak pandemic levels, it stands higher than pre-COVID levels, showing ongoing market instability.

Time Series Analysis (Figure 12): Time series analysis of stock prices over the pre-early period, during every CoVid period or post-CoVid era revealed a distinct trend and pattern in market performance. Using metrics such as rolling mean, rolling volatility and logarithmic returns, the analysis tracked stock behaviour over time. Periods in the analysis found That the market framework changed in response to some point outside, as periods of high volatility and changing returns showed how the market responded to global uncertainty.

Portfolio Evaluation: Sharpe ratio, mean returns, and volatility across periods were used for portfolio evaluation. Portfolio performance was consistent before COVID-19, worsened by market disruptions during the epidemic, and improved but remained erratic afterwards. various indicators revealed risk-return trade-offs and assessed how the portfolio handled risk in various market conditions, emphasising the necessity for adaptable solutions to navigate disruptions.

The analysis highlights those external disruptions such as the COVID-19 pandemic can dramatically alter market dynamics, underlining exactly why it is necessary for those trading in volatile conditions not to go without risk management strategies. Investors must be prepared to change their holdings to protect against future uncertainties while capturing opportunities for revival.



Performance measures show how the portfolio or stock performed before, during, and after COVID-19. A breakdown, this is illustrated in Figure 13.

Before COVID, the portfolio had a negative Sharpe ratio (-0.0996), indicating volatility and worse returns than the risk-free rate. This shows pre-pandemic underperformance. The portfolio returned above the risk-free rate during COVID-19, although with moderate volatility. Despite market turmoil, returns were made. Post-COVID (0.0102): The portfolio barely outperformed the risk-free rate, indicating modest returns and volatility.

Sortino Ratio: Pre-COVID (-0.3600): Poor performance with frequent negative returns, highlighting downside risk. It shows that the portfolio lost more before the pandemic. Despite COVID-19, the portfolio generated returns and limited downside risk better than before. post-COVID (0.0206): A near-zero Sortino ratio suggests a stalled recovery due to low returns and limited downside risk mitigation.

Maximum drop: Pre-COVID (-0.0633): The portfolio had a minor drop of 6.33% from peak to trough. The highest drawdown (5.97%) under COVID was slightly lower than pre-COVID, indicating that volatility increased but excessive losses were averted. Post-COVID (-0.1698): The biggest drop (16.98%) suggests delayed or unstable recovery with steeper declines than preceding periods.

The portfolio had positive Sharpe and Sortino ratios during COVID-19, indicating superior risk mitigation. Post-COVID performance was lacklustre and had a greater maximum drawdown, indicating issues in portfolio stability and recovery.

4. Result and Discussion

The findings of our Mean-Variance Optimisation study have shed light on a few important aspects of portfolio building and how risk and return are affected by it, especially about the Malaysian stock market before and during the COVID-19 epidemic. The time series analysis of stock prices before, during, and after the COVID-19 pandemic revealed notable shifts in market behaviour across these periods. The pre-COVID period exhibited relatively stable stock prices with moderate volatility, reflecting more predictable market conditions. However, during the COVID-19 period, there was a sharp increase in volatility and a corresponding decline in mean returns across the majority of stocks, indicating heightened uncertainty and risk. These findings are consistent with market reactions to crises, where investors respond to increased uncertainty by selling off risky assets, which leads to heightened price fluctuations.

Post-COVID analysis showed a partial recovery, with stock prices stabilizing and returning to an upward trend, but volatility remained higher compared to the pre-COVID period. The rolling window analysis, particularly the rolling mean and volatility calculations, provided further insight into the fluctuating performance of individual stocks over time, with a gradual decline in volatility during the recovery phase. The analysis of daily and log returns further emphasized how market disruptions during COVID led to negative returns for many stocks, but post-COVID returns started to show positive signs of recovery. In terms of risk-adjusted returns (Sharpe ratio), the pre-COVID period exhibited relatively higher Sharpe ratios which indicating a favourable risk-return balance. During COVID, the Sharpe ratio significantly declined for most stocks, highlighting the increased risk without commensurate returns. Post-COVID, while some stocks showed improvement in their Sharpe ratios, the risk-return balance had not yet fully recovered to pre-pandemic levels.

- i. Portfolio with Maximum Sharpe Ratio
 - a. Composition: GREATEC makes up the whole portfolio with the highest Sharpe ratio, meaning that this one asset is allocated 100% of the portfolio.
 - b. Expected Return: This portfolio has an annualised anticipated return of 5.97%. Even though this could sound appealing at first, the risk must be considered.
 - c. Risk (Volatility): The portfolio exhibits notable volatility, as evidenced by its remarkably elevated 180.65% standard deviation. Because of the substantial risk involved, there is a significant amount of uncertainty that returns may differ significantly from those anticipated.

- d. Sharpe Ratio: Despite having the highest Sharpe ratio among simulated portfolios, the value of 0.03 is quite low. This indicates that, relative to its volatility, the portfolio does not offer a substantial risk-adjusted return.
- ii. Portfolio with Minimum Standard Deviation
 - a. Composition: UWC makes up the whole portfolio with the lowest standard deviation, as it is allocated 100% to this asset.
 - b. Expected Return: 0.67% annualised projected return is a low figure that indicates little room for growth.
 - c. Risk (Volatility): This portfolio has a standard deviation of 145.15%, which, while lower than the maximum Sharpe ratio portfolio, still indicates high volatility.
 - d. Sharpe Ratio: The Sharpe ratio of 0.00 implies that the expected return does not significantly exceed the risk-free rate, providing no additional return for the risk undertaken.

Based on the analysis of the stock market data before during and post COVID-19, several strategic decisions can be made to optimize portfolio performance while managing risk effectively:

- i. Increase Diversification:
 - a. To avoid pandemic-related risks, diversify assets across sectors and asset classes.
 - b. Consider investing in global markets to reduce exposure to country-specific risks and take advantage of recovery trends in different regions.
- ii. Focus on Defensive and Resilient Sectors:
 - a. Healthcare and Technology: These industries have demonstrated resilience during the pandemic. Investing in healthcare equities like DPHARMA and KOSSAN, or technology stocks like GREATEC and UWC, can provide stability and growth opportunities.
 - b. Consumer Staples: Companies providing essential goods and services tend to perform well during economic downturns, offering a buffer against market volatility.
- iii. Risk Management:
 - a. Reduce High-Volatility Investments: Given the high volatility observed in the portfolios, consider reducing exposure to highly volatile assets. Focus on stocks with lower standard deviation to maintain portfolio stability.
 - b. Hedging Strategies: Implement hedging strategies, such as using options or futures, to protect the portfolio against significant market downturns.
- iv. Monitor Economic Indicators:
 - a. Stay Informed: Closely watch economic indicators, government policies, and pandemic-related developments. Adjust the investment strategy in response to changes in the economic landscape.
 - b. Regular Portfolio Review: Conduct regular portfolio reviews to assess performance and make necessary adjustments to align with changing market conditions.
- v. Consider Fixed-Income and Safe-Haven Assets:
 - Gold and Other Safe-Haven Assets: Invest in gold and other safe-haven assets that tend to retain value during market turbulence.
- vi. Long-Term Perspective:
 - a. Stay Invested: While short-term volatility might be unnerving, keeping a long-term investment perspective can help weather market changes and achieve long-term prosperity.

- b. Value Investing: Look for fundamentally strong companies with good valuation metrics. Market downturns often present opportunities to buy quality stocks at discounted prices.
- vii. Seek Professional Advice:
 - a. Consult with financial advisors or portfolio managers to develop a customised investment strategy based on personal risk tolerance and financial goals.
 - b. Conduct professional research and analysis to uncover investment opportunities and hazards

5. Conclusions

The study underscores the significant influence of the COVID-19 pandemic on portfolio performance throughout pre-pandemic, pandemic, and post-pandemic periods. It illustrates how market volatility and changing economic conditions affected risk-return profiles and necessitated dynamic modifications to investing strategies. The results underscore the importance of implementing adaptable portfolio management strategies, utilising techniques such as mean-variance optimisation, and integrating various performance metrics to adeptly manage market uncertainty. As markets rebound after the pandemic, ongoing surveillance, reallocation, and the incorporation of behavioural insights are essential for enduring portfolio success in a dynamic global financial environment.

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