The Effectiveness of Multivariate Garch Models in Portfolio Selection in the Context of the Covid-19 Pandemic

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ABSTRACT
Uncertainty modeling is a critical aspect of quantitative finance, utilized in the three primary domains: portfolio allocation, risk management, and valuation of financial instruments. This modeling offers statistical characteristics of price fluctuations, therefore identifying methods to enhance predictions in the context of the COVID-19 Pandemic.This paper examines the efficacy of optimal portfolios through experiments utilizing two representatives multivariate GARCH models, CCC-GARCH and DCC-GARCH, within the framework of the COVID-19 epidemic in Vietnam. The methodology ofthe study was conducted based on data from the financial market in Vietnam from 2019 to 2023. The application of multivariate GARCH methods in portfolio selection continues to be a subject of considerable debate.The research findings indicate that multivariate GARCH models substantially exceed the broader market (VN-Index) across six portfolio performance criteria during the evaluation period. Only the CCC-GARCH model demonstrates more extraordinary performance than conventional estimate models, whereas the DCC-GARCH model exhibits inferior results. This may stem from constraints associated with portfolio turnover rates, which significantly influence transaction costs, and the comparatively prolonged computing time, hindering the actual execution of strategies. The unique contribution ofthe research contributions is anticipated to enhance investors' comprehension of the efficacy of multivariate GARCH models in portfolio selection within the Vietnamese financial market.

Keywords: Effectiveness of multivariate; GARCH models; portfolio;COVID-19 Pandemic

INTRODUCTION

The covariance matrix is a crucial element in assessing risk and the correlation among assets in portfolio management. It offers profound insights into the portfolio's risk level, assisting investors in making logical and empirically based decisions. Investors can utilize the covariance matrix to change asset combinations and design a portfolio that meets their return goals while maintaining risk (Ledoit & Wolf, 2022). This matrix helps investors diversify their holdings, according to Khan et al. (2023). It reduces risk and strengthens stability during market turmoil. The ever-changing and complicated market requires covariance matrix estimates to optimize portfolio selection and risk management.

Estimating the covariance matrix is difficult, especially for large numbers of assets, which increases estimation errors and instability. Crisis or large occurrences like the COVID-19 pandemic produce extreme market volatility, making it harder to foresee. A sample covariance matrix based on previous data would not reliably reflect future correlations. In response to these issues, academics have introduced the Shrinkage method, the Random Matrix Theory (RMT) approach, and the multi-factor model-based method to estimate covariance matrix parameters. (2012); Fama & French (2015).

In addition to the above-described research areas, multivariate GARCH models for covariance matrix estimation have interested investors, according to Aziz et al. (2019). There is controversy regarding whether multivariate GARCH models can determine the optimum portfolio strategy. Scholars like Pojarliev & Polasek (2003) and Engle et al. (2019) recommend multivariate GARCH models because they can swiftly detect and respond to market changes. Some research challenges this notion, suggesting that multivariate GARCH models may perform poorly with huge datasets or high transaction costs.

This study examines how multivariate GARCH models, specifically CCC-GARCH and DCC-GARCH, can help Vietnam's COVID-19 pandemic portfolio selection tactics. With 400 portfolio stocks, the input data is large. COVID-19 emerged in Vietnam between January 1, 2019, and October 31, 2023, the research period. The findings should help investors understand multivariate GARCH models' portfolio selection efficacy, especially in certain financial market circumstances. The author will present the study's structure in the following sequence: Literature review, methodology, research results, and conclusion.

Theoretical Framework

Classical approaches to effective portfolio selection are typically static, as they focus solely on a given period or moment without considering a continuum of time intervals. Consequently, these methodologies neglect the fluctuations in conditional variances and covariances of asset returns within the portfolio (Fiszeder, 2011). The utilization of multivariate GARCH models enables investors to implement a dynamic strategy in portfolio selection. The multivariate GARCH process facilitates the modeling of time-varying conditional variances and covariances of returns. If the variances and covariances of returns are not stable, forecasts derived from multivariate GARCH models will offer enhanced advantages in the selection of an optimal portfolio.

Numerous recent research endorses the application of multivariate GARCH models in portfolio selection. The research performed a survey on the efficacy of the DCC-GARCH model with errors adhering to Gaussian, Student's t, and SkewedStudent's t distributions (Rai & Garg, 2022). The findings indicated that the DCC-GARCH model, used to stock portfolios from European, U.S., and Japanese markets, exhibited optimal performance with the skew Student's t error model; nevertheless, superior models are required to comprehensively account for the asymmetry in asset series. Fiszeder (2011) assessed the efficacy of various techniques in least volatility portfolio selection for seventy equities from the Warsaw Stock Exchange, employing eight attributes of multivariate GARCH models alongside six additional methods. Multivariate GARCH models, including the DCC and CCC models with parameters computed in two steps, shown superior performance in stock allocation relative to alternative methods.

Skrinjaric and Sego (2016) employed MGARCH, encompassing CCC-GARCH and DCC-GARCH, inside Croatia's financial market to enhance daily portfolio selection, utilizing the CROBEX stock market index, CROBIS bond market index, and the kuna/euro exchange rate to model the co-movement of daily returns and risk. According to the results, using the MGARCH method to build and rebalance a portfolio reduced volatility and increased cumulative returns compared to strategies without this method. MGARCH improves selection efficiency in these processes. Using weekly pricing data from 2009 to 2012 for funds including the Equity Trust Fund, Future Plan Fund, and Unit Trust Fund, Siaw et al. (2017) optimized the Mean-VaR of HFC Investment Limited funds using two models, ARMA-GARCH and ARMA-DCC GARCH. Multivariate GARCH to model maximal value-at-risk (VaR) produced the best portfolio.

In their 2019 study, Aziz et al. compared symmetric GARCH models to GJR-GARCH. In the study, they employed risk-adjusted metrics for short-sold and non-short portfolios with eight stock and four bond indexes from different nations. These countries were the US, UK, Germany, Japan, the Netherlands, Canada, and Hong Kong. The out-of-sample results demonstrated that dynamic models decreased portfolio risk and enhanced realized returns more than static models. In their simulation-based portfolio optimization study to reduce left-tail risk, Peng et al. (2022) presented a Markov regime-switching GARCH model with multivariate innovations (MRS-MNTS-GARCH) to address fat tails and volatility cluster The research found that tail risk indicators like CVaR and CDaR outperformed standard deviation-based portfolios (Wang et al., 2018).

Many studies have questioned the efficacy of multivariate GARCH models in portfolio selection. This study evaluated the dynamic conditional correlation (DCC-GARCH) model of Khalfaoui et al. (2022) to conventional methods. In the short term, the dynamic conditional correlation model outperforms historical data-based covariance matrices, but in the long term, the opposite is true. Santos & Ferreira (2017) examined key GARCH model portfolio selection factors. Using a sample of 69 stocks from the S&P100 index, this study developed 16 portfolio selection procedures over a 25-year period by applying a set of criteria to the covariance matrix. The results indicated that in scenarios without transaction costs, dynamic covariance models like GARCH produced risk-adjusted performance similar to that of static covariance characteristics. However, in more realistic scenarios with varying transaction costs, portfolios based on static covariance models outperformed because they required a lower level of portfolio turnover. Particularly in high transaction cost situations, portfolio policies aimed at reducing estimation error by ignoring the off-diagonal elements of the covariance matrix proved to be more efficient (Liu& Shehzad, 2023).

Through the review above, it is evident that more specific research is needed on the effectiveness of multivariate GARCH models in optimal portfolio selection, particularly in new contexts. In this study, the author will analyze the effectiveness of the multivariate GARCH process using two representative models, CCC-GARCH and DCC-GARCH, in the context of the COVID-19 pandemic.

Research Data and Methodology

Estimating the Covariance Matrix Based on Multivariate GARCH Models

Constant Conditional Correlation GARCH (CCC-GARCH): The CCC-GARCH model, developed by Ghorbel& Jeribi(2021), is a multivariate time series model with time-varying conditional variances and covariances but constant correlation coefficients. Since the conditional correlation matrix does not depend on time, the conditional covariance matrix H_t is calculated as follows:

$$H_t = D_t R D_t \quad (1)$$

Where R is the constant correlation matrix with elements$R = \rho_{ij}$, and$\rho_{ii} = 1$ for i = 1,…,n, where n is the number of stocks in the portfolio.$D_t = \mathrm{diag}(\sqrt{h_{1t}},\ldots,\sqrt{h_{nt}})$ is the diagonal matrix that only includes the standard deviations of the assets and is typically modeled using a univariate GARCH model. The off-diagonal elements of H_t become:

$$[H_t]_{ij} = h_{it}^{1/2} h_{jt}^{1/2} \rho_{ij}\ , i \neq j \quad (2)$$

For i ≥ 1, j ≥ 1, the processes $r_{it}$are modeled as univariate GARCH(p, q) models, and therefore, the conditional variances can be written in vector form as follows:

$$h_t = \omega_t + \sum_{j=1}^{q} A_j\, r_{t-j}^{*} + \sum_{j=1}^{p} \beta_j\, h_{t-j} \quad (3)$$

Where$\omega_t$is an n x 1 vector; A_i and$B_j$are n x n diagonal matrices; $r_{t-j}^{*} = r_t \ \Theta\ r_t$ and Θ is the Hadamard product. For$H_t$to be positive definite, R must be positive definite, and the diagonal elements of matrices A_i and$B_j$must be positive (except when p = q = 1).

Dynamic Conditional Correlation GARCH (DCC – GARCH)

The Dynamic Conditional Correlation (DCC-GARCH) model was introduced by Engle et al. (2019) as an extension of the CCC-GARCH model. The DCC model uses the same formula as equation (1), but instead of modeling R as a constant matrix, it is modeled dynamically with R_t depending on time t, specifically as follows:

$$H_t = D_t R_t D_t \quad (4)$$

Equation (2) will now become:

$$[H_t]_{ij} = h_{it}^{1/2} h_{jt}^{1/2} \rho_{ij,t} \quad (5)$$

$D_t$in equation (4) will take the following form:

$$D_t = \begin{bmatrix} \sqrt{h_{1,t}} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sqrt{h_{n,t}} \end{bmatrix} (6)$$

Với $h_{it} = \omega_{it} + \sum_{j=1}^{q_i} \alpha_{ij}\, r_{it-j}^{2} + \sum_{j=1}^{p_i} \beta_{ij}\, r_{i,t-j}$

In this case, H_t is guaranteed to be positive definite if and only if the conditional variances h_{it}, where i =1,…,n are clearly defined, and the matrix R_t must also be positive definite for every t. This results in the DCC-GARCH model requiring more computation in practice compared to the CCC-GARCH model, as the conditional correlation matrix needs to be inverted at each t during every iteration.

The DCC model, introduced by Engle et al. (2019), has a dynamic conditional correlation structure as follows:

$$Q_t = (1 - \alpha - \beta)S + \alpha \varepsilon_{t-1} \varepsilon_{t-1}^{'} + \beta Q_{t-1} \quad (7)$$

Where Q_t is the covariance matrix; αis a positive parameter, while βis a non-negative parameter, with the condition that the sum of α and β is less than 1. S represents the underlying correlation matrix of the standardized residualsε_t. Although this process ensures the positive definiteness of the matrix, it does not always guarantee the validity of the generated correlation matrices. The correlation matrix$R_t$will be determined based onQ_t as follows:

$$R_t = (I\ \Theta\ Q_t^{1/2})\ Q_t\ (I\ \Theta\ Q_t^{1/2}) \quad (8)$$

Portfolio Optimization Function

The minimum variance portfolio (GMVP) optimization function was chosen to construct the optimal portfolio. There are two reasons why the author chose this optimization function: (i) This optimization function only requires a single input parameter, which is the portfolio's covariance matrix (Clarke et al., 2011), making it convenient for evaluating the effectiveness of multivariate GARCH models in the portfolio optimization process. (ii) The GMVP optimization function tends to generate portfolios with superior performance compared to those selected using the mean-variance method (Bednarek & Patel, 2018).

The objective function of GMVP is to minimize the portfolio's variance and is estimated by the following formula (Clarke et al., 2011): **Minimize**$w^T \hat{\Sigma} w$(9)

Where w is the weight vector of the portfolio; $w^T$is the transpose of the weight vector w; $\hat{\Sigma}$ is the covariance matrix estimated from the multivariate GARCH model.

Let w_i be the weight of the investment in stock i. Assuming that the entire capital in the portfolio is always fully allocated and the optimization process does not account for short selling, the weights of the stocks in the portfolio in equation (1) must satisfy the following condition: $\sum_{i=1}^{n} w_i = 1$ and $w_i \geq 0$ (10)
From the optimal objective function in equation (9) and the constraints in equation (10), the optimal weights (w^*) of the stocks in the portfolio will be determined as follows:

$$w^* = \frac{\Sigma^{-1}\mathbf{1}}{\mathbf{1}^T \Sigma^{-1}\mathbf{1}} \quad (11)$$

Where $\sum^{-1}$: is the inverse matrix of the estimated covariance matrix $\widehat{\Sigma}$, and 1 is a vector of ones.

Criteria for evaluating the effectiveness of a portfolio
To evaluate the effectiveness of multivariate GARCH models in portfolio selection, the author used six different evaluation criteria to measure various aspects of the portfolio. The aspects measured include the portfolio's profitability (CR criterion), the portfolio's risk level (AV and VaR criteria), the correlation between return and risk (SR criterion), transaction cost efficiency (PTR criterion), and the computation time for portfolio optimization (CT criterion). These evaluation criteria are detailed in Table 1.

Table 1. Description of the criteria for evaluating the effectiveness of a portfolio

No	Portfolio evaluation criteria	Formula	Meaning
01	Cumulative return (CR)	$\left(\frac{\text{Ending value} - \text{Beginning value}}{\text{Beginning value}}\right) \times 100\%$	The cumulative return of a portfolio is significant to investors because it reflects the ability to generate profits from an investment over a specific period, including both dividend income and the increase in the value of the stocks in that portfolio.
02	Average annual volatility (AV)	Standard deviation of the portfolio $\sigma_p = \sqrt{(\sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j \mathrm{Cov}(i,j)}$ Where w, σ, and Cov are the weights, standard deviation, and covariance of the stocks in the portfolio, respectively.	Standard deviation is an important metric for determining the level of risk in a portfolio. This metric reflects the volatility of the portfolio's returns compared to its average value. A high standard deviation indicates that returns fluctuate significantly, suggesting higher risk; conversely, a low standard deviation indicates more stable returns, implying lower risk.
03	Sharpe ratio (SR)	$SR_p = \frac{R_p - r_f}{\sigma_p}$ Where R_p, r_f and σ_p are the portfolio's average return, the risk-free rate, and the portfolio's standard deviation, respectively.	The Sharpe ratio allows investors to assess the effectiveness of a portfolio by comparing the returns obtained with the level of risk taken. A higher Sharpe ratio indicates that the investor is receiving higher returns for each unit of risk.
04	Portfolio turnover rate (PTR)	$\text{Turnover}_P = \frac{1}{M-T-1}\sum_{i=1}^{M-1}\sum_{j=1}^{N}(\lvert w_{k,j,t+1} - w_{k,j,t+}\rvert)$ Where M is the total number of observations and T is the number of in-sample observations, $w_{k,j,t+1}$ is the weight of the stocks at time t+1, and $w_{k,j,t+}$ is the weight of those stocks at the time before portfolio rebalancing.	Portfolio turnover rate is an important indicator that reflects the level of trading activity within a portfolio. A high turnover rate may indicate that the trading strategy involves frequent buying and selling, which can lead to high transaction costs and potential

			tax liabilities from short-term capital gains. Maintaining a low turnover rate can help optimize long-term investment performance.
05	Value at Risk (VaR)	$VaR_\alpha = Z_\alpha \times \sigma_p \times \sqrt{T}$ Where: ▪ α is the 99% confidence level ▪ Z_α is the z-score corresponding to the confidence level from the normal distribution ▪ σ_p is the standard deviation of the portfolio ▪ T is the time period for measuring VaR, calculated in years. For daily VaR, T is set to 1/252 (assuming 252 trading days in a year)	VaR measures the maximum potential loss that a portfolio may incur over a specified time period, based on a predetermined confidence level. VaR shows investors the potential loss in tough market situations. This knowledge allows them to make informed investment decisions and adjust portfolio structure.
06	Computation time (CT)	CT = n × t Hardware affects the average computation time, t, and the number of calculations, n. In this study, the author will examine trading techniques on one computer with these requirements: Equipped with 32 GB RAM and a 2.90 GHz Intel (R) Core (TM) i5-10400 CPU with 12 cores.	Computation time affects estimating model evaluation and daily investment strategies. Reduced computation time allows investors to make investment decisions rapidly using the latest data and information, improving operational efficiency and decision quality.

Source: Compiled by the author

The author will also compare the optimization results of the two multivariate GARCH models to the conventional Sample-based estimate model and the whole market index to better understand their influence on portfolio selection. The portfolio's sample covariance matrix will be based on Nguyen et al. (2020):

$$\begin{cases} Cov(r_i, r_j) = \frac{1}{T-1}\sum_{t=1}^{T}(r_{i,t} - \overline{r_i})(r_{j,t} - \overline{r_j}) = \hat{\sigma}_{i,j} \ (i \neq j) \\ Var(r_i) = \frac{1}{T-1}\sum_{t=1}^{T}(r_{i,t} - \overline{r_i})2 = \hat{\sigma}_i^2 \ (i = j) \end{cases} \quad (12)$$

Where $r_{i,t}$, $\overline{r_i}$, $r_{j,t}$, $\overline{r_j}$ are the t-time returns and average returns of stock i or j. Meanwhile, the study portfolio's equities are from HOSE-listed businesses, therefore the VN-Index is the market representative index.

Study Results

The data collected consists of daily price series of stocks listed on the Ho Chi Minh City Stock Exchange (HOSE). The number of stocks on the market changes annually due to the participation of new companies and the delisting of previously listed companies, but the number of stocks on HOSE consistently ranged from 369 to 407 during the research period from 2019 to 2023 (Table 2). Additionally, the statistics show that the highest and lowest stock prices were 292,000 VND and 950 VND, respectively. The standard deviation, or the average daily volatility of a stock, ranged from a high of 6.8% to a low of 0.56%. The average daily market volatility also saw some variation during the research period, with the highest market volatility occurring in 2022 (1.57%) and the lowest in 2019 (0.68%). The average daily trading volume of the market also experienced significant growth, rising from 139.2 million shares per day in 2019 to 705.82 million shares per day in 2023 (a fivefold increase compared to 2019).

Table 2. Statistical description of the research data

Descriptive information		**2019**	**2020**	**2021**	**2022**	**2023**
Number of stocks	Min	369	376	386	400	391
	Max	377	386	401	407	402

Stock price(VND)	Low	980	950	1470	1390	1550
	High	289000	258900	292000	280000	262900
Standard deviation	Low	0.73%	0.64%	0.85%	0.84%	0.56%
	High	6.8%	6.3%	4.90%	4.93%	4.11%
The average daily standard deviation of the market		0.68%	1.44%	1.33%	1.57%	1.07%
The average daily trading volume of the market (million shares)		139,2	296,55	699,34	617,59	705,82

Source: Compiled by the author

The data was collected from January 1, 2019, to October 31, 2023, and divided into two specific periods: (i) Period 1 (from January 1, 2019, to December 31, 2019): this is considered the in-sample period, used to initialize the first covariance matrix. This also means that the author only considers stocks that have been listed on the market for at least one year to ensure stability in the portfolio optimization process; (ii) Period 2 (from January 1, 2020, to October 31, 2023): this is considered the out-of-sample period or the testing period. According to information from the Ministry of Health (2023), Vietnam's first COVID-19 case occurred in January 2020, and the disease was officially reclassified as an infectious disease on October 20, 2023. Therefore, this period is appropriate for testing the effectiveness of estimation methods.

Table 3. Comparison of the effectiveness of estimation methods during the testing period from January 1, 2020, to October 31, 2023

Portfolio evaluation criteria	**Market index**	**Sample**	**CCC – GARCH**	**DCC – GARCH**
Cumulative return (CR)	6.22%	36.59%	**44.5%**	16.96%
Average annual volatility (AV)	21.88%	8.68%	**7.62%**	9.04%
Sharpe ratio (SR)	0.18	0.99	**1.3**	0.5
Portfolio turnover rate (PTR)	-	**4.02%**	6.11%	6.91%
Value at Risk (VaR)	-2.74%	-1.06%	**-0.92%**	-1.12%
Computation time (CT)	-	**537 seconds**	1163 seconds	117423 seconds

Source: Compiled by the author

The research findings demonstrate that the application of multivariate GARCH models, specifically CCC-GARCH and DCC-GARCH, for optimizing portfolio selection throughout the COVID-19 period from January 1, 2020, to October 31, 2023, yielded significant outcomes as follows:

The author used the Python programming language for data analysis, utilizing packages from open libraries including Scikit-learn, Pandas, TensorFlow, and pyOpt. The code pertaining to multivariate GARCH estimation functions was also cited from the research conducted (Engle et al., 2019).

Initially, both multivariate GARCH models surpassed the market index in all assessment metrics throughout the study duration. The cumulative returns of CCC-GARCH and DCC-GARCH were 44.5% and 16.96%, respectively, equating to 7.15 times and 2.72 times the market's cumulative return of 6.22% during the same period. In Figure 1, we observe that the two multivariate GARCH models generated better portfolio returns in two phases, namely from January 2020 to January 2021 and from June 2022 to October 2023. However, during the phase from January 2021 to June 2022, the overall market showed better returns, experiencing strong growth in that period. Overall, the volatility of returns from the two multivariate GARCH models was not significant compared to the volatility of the broader market. This is further reflected in Figure 2, where we observe the average annual volatility (AV) of the portfolios. This volatility was 7.62% for CCC-GARCH and 9.04% for DCC-GARCH, while the average annual volatility of the market was 21.88%. This also demonstrates that the risk level of the portfolios constructed based on multivariate GARCH models was relatively lower compared to the overall market risk.

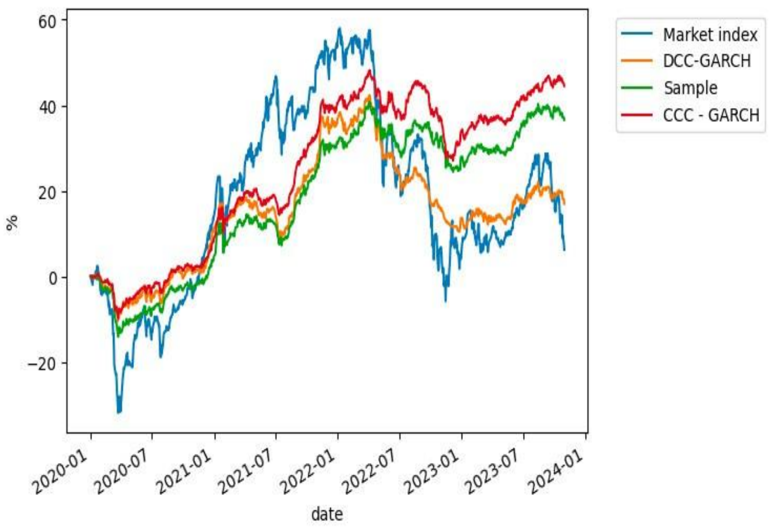

Figure 1. Comparison of cumulative returns (CR) of the methods during the period from January 1, 2020, to October 31, 2023
Source: Author's calculations

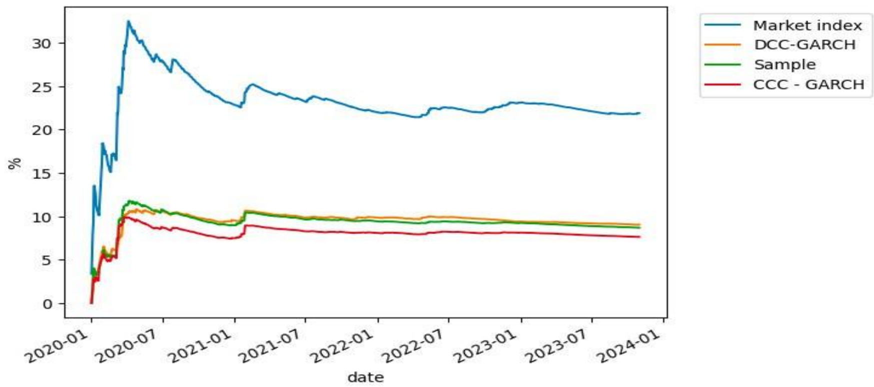

Figure 2. Comparison of average annual volatility (AV) of the methods during the period from January 1, 2020, to October 31, 2023
Source: Author's calculations

Figures 1 & 2 showed that the Sharpe ratio (SR) of the two multivariate GARCH models is significantly higher than the overall market index (Figure 3). This can be easily explained, as both multivariate GARCH models are able to create portfolios with higher returns compared to the market, while the risk level of the portfolios is lower than that of the overall market, thus driving the Sharpe ratio higher.

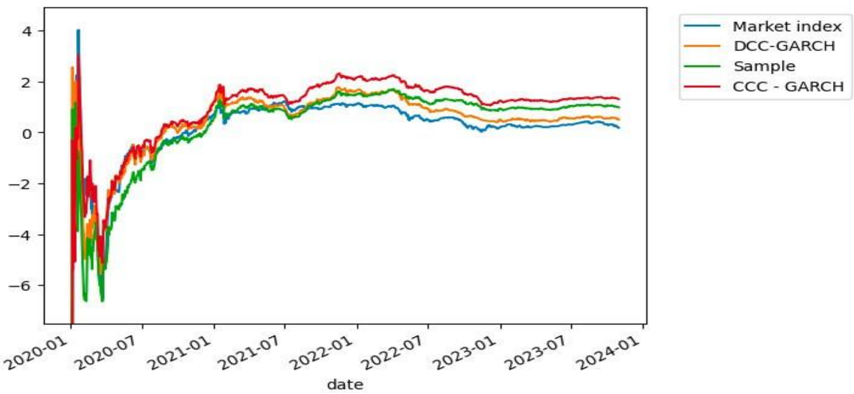

Figure 3. Comparison of Sharpe ratios of the methods during the period from January 1, 2020, to October 31, 2023
Source: Author's calculations

DISCUSSION OF FINDINGS

First of all, the Valueat Risk (VaR) also indicates that the risk levels of the two multivariate GARCH models are lower than the overall market risk. The VaR at the 99% significance level for the CCC-GARCH and DCC-GARCH models were (-0.92%) and (-1.12%), respectively, which are significantly lower than the VaR measured for the overall market at (-2.74%).

Secondly, between the two multivariate GARCH models, the CCC-GARCH model performed significantly better in portfolio selection compared to the DCC-GARCH model and the traditional Sample method across most evaluation criteria during the study period. The CCC-GARCH model not only excelled in creating portfolios with high returns but also had the lowest risk levels, which led to the model having the highest Sharpe ratio (1.3 times) and being the only model with a Sharpe ratio exceeding 1 among those studied (Figure 3). The superiority of the CCC-GARCH model was further demonstrated through the VaR metric, with the model having the lowest measured risk at a VaR value of (-0.92%). While the CCC-GARCH model outperformed, the DCC-GARCH model did not deliver satisfactory results compared to the traditional Sample estimation method. Throughout the COVID-19 period, the conventional sample method performed better than the DCC-GARCH model across all six evaluation criteria applied in this study.

Thirdly,the multivariate GARCH models also have certain limitations. (i) The research results show that the PTR (Portfolio Turnover Rate) of multivariate GARCH models is significantly higher compared to the traditional method (6.91% and 6.11% compared to 4.02% for the traditional model). This leads to risks for investors when rebalancing the portfolio, as a higher turnover rate will significantly impact transaction costs in practice. (ii) Computation time is also an important issue for multivariate GARCH models. We can see that the CCC-GARCH model requires double the computation time, and the DCC-GARCH model requires 219 times the computation time compared to the traditional model under the same conditions, with around 400 stocks in the portfolio.

This empirical analysis supports earlier research on multivariate GARCH models' portfolio selection effectiveness, including Fiszeder (2011), Engle et al. (2019), and Aziz et al. Their capacity to promptly recognize and adapt to market changes makes these models popular. The findings suggests that multivariate GARCH models may not work effectively in other instances like the COVID-19 pandemic. Due to its sensitivity, multivariate GARCH models may not be feasible and increase transaction costs (De Nard et al., 2022).

CONCLUSION AND RECOMMENDATIONS

Multivariate GARCH approaches may not be beneficial in portfolio selection in several cases. This study tests two standard models, CCC-GARCH and DCC-GARCH, to determine how the COVID-19 pandemic affected the Vietnamese financial market from 2019 to 2023. Both multivariate GARCH models outperformed the VN-Index across all six portfolio evaluation criteria. The CCC-GARCH model beat the standard estimate approach, but the DCC-GARCH did not. Possible explanation: portfolio turnover rate (PTR) requirement and expanded computing time limits. The former significantly affects transaction costs, whereas the latter hinders the practical implementation of ideas. In order to aid market players and prospective investors in making more informed investment decisions, this study aims to provide a better understanding of the performance of multivariate GARCH models.

The author plans to compare and contrast the results from the Vietnamese market with those from other financial markets in order to assess the effectiveness of multivariate GARCH models in portfolio selection. To enhance the precision and foresight of these models, the project will incorporate state-of-the-art machine learning techniques simultaneously. When complex financial data is analyzed using machine learning, model efficacy is improved and new techniques are made possible. These works aim to offer a more thorough understanding of the efficacy of multivariate GARCH models and encourage their utilization in global portfolio management.According to the research findings, the author provided recommendations for management agencies, including the Stock Exchange, State Securities Commission, and investors.

The derivatives market in Vietnam has recently been established, resulting in regulatory loopholes and inconsistencies, as well as inadequate consequences for violations of market information disclosure. Consequently, market managers must evaluate and enhance the information disclosure mechanism and market monitoring system for futures trading platforms; they should establish a reliable system of information disclosure indices that accurately represent market supply and demand, refine the legal framework, and advance the futures market in a secure and sustainable manner. Furthermore, market management authorities must adapt to international practices and standards while closely regulating the futures market in conjunction with the financial sector.

Secondly, it is essential to diversify the portfolio composition of investors engaged in the futures market. Contemplate establishing the room to facilitate foreign investors' participation in the market. This reduces capital accumulation for the market, enhances reputation, and fosters worldwide economic integration.

Finally, diversifying investment goods mitigates market risks and facilitates the management of shocks. The futures market in Vietnam is presently nascent, and the offerings available to investors remain singular. To mitigate risks and enhance market appeal, management agencies must investigate and provide a broader range of derivative products with varied maturity dates and underlying assets.

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