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OPTIMAL CRYPTOCURRENCY PORTFOLIO CONSTRUCTION USING GARCH-BASED MONTE CARLO SIMULATION

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ABSTRACT

This study investigates the construction of an optimal cryptocurrency portfolio comprising Ethereum and Solana using a GARCH-based Monte Carlo simulation framework. Asset volatilities were modelled individually through GARCH (1,1) processes, while asset correlations were captured using standardized residuals and Cholesky decomposition. Simulation results over 180- and 360-day horizons showed that the optimized portfolio achieved slightly higher cumulative growth factors and better upside capture compared to an equal-weighted benchmark, particularly during volatile market phases. In out-of-sample testing, the return-to-risk optimized portfolio delivered a total return of 34% over six months, compared to 33% for the equal-weighted strategy, while maintaining a higher return-to-risk ratio (0.06 versus 0.05) and lower volatility (3% versus 4%). Over a one-year period, both portfolios converged closely, with the equal-weighted strategy achieving a slightly higher total return of 45% compared to 43% for the optimized portfolio. These findings suggest that GARCH-based optimization can enhance portfolio resilience and risk-adjusted returns, although its realized return advantage may diminish in synchronized market conditions.

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1. INTRODUCTION

The global investing landscape has been significantly impacted by the emergence of digital assets known as cryptocurrencies, introducing unique opportunities accompanied by considerable risks. These digital currencies, led by Bitcoin (BTC), Ethereum (ETH), and Solana (SOL), represent different sectors within the blockchain ecosystem, including store-of-value assets, smart contract platforms, and scalable decentralized financial solutions. Although cryptocurrencies are characterized by unstable price dynamics, driven by market sentiment, regulatory developments, macroeconomic uncertainty, and technological innovation, they have increasingly gained a role in diversified investment portfolios [1], [2].

Traditional portfolio optimization frameworks, such as Markowitz mean-variance theory, typically rely on assumptions of continuous volatility, normally distributed returns, and time-invariant covariance structures [3], [4], [5]. In cryptocurrency markets, where sudden regime shifts, volatility clustering, and heavy-tailed return distributions frequently occur, these assumptions are often violated [6], [7], [8]. Empirical studies such as [9], [10], [11], [12] demonstrate that Bitcoin returns deviate significantly from Gaussian assumptions, while [13], [14] report notable volatility persistence across crypto assets. These findings imply that risk modelling methods for crypto portfolios must extend beyond traditional frameworks.

Addressing these limitations, researchers have increasingly adopted models capable of capturing time-varying volatility, such as the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model introduced by Bollerslev (1986) [15], [16]. This model effectively captures volatility clustering and persistence, phenomena particularly evident in cryptocurrency returns. Katsiampa [10] successfully applied GARCH-family models to Bitcoin, demonstrating superior out-of-sample volatility forecasting compared to static models. Moreover, multivariate extensions like the DCC-GARCH model have been developed to model dynamic correlations across assets, though their practical application in larger portfolios often faces computational challenges [17], [18]. Consequently, semi-parametric approaches such as combining univariate GARCH specifications with a static correlation matrix have gained traction for high-dimensional simulations and risk stress-testing [19].

Concurrently, Monte Carlo simulation has proven to be an effective tool for generating forward-looking scenarios of future returns within a probabilistic framework. Unlike historical simulations that rely solely on past return sequences, Monte Carlo methods incorporate empirical volatility dynamics and random uncertainty, making them well-suited for portfolio optimization under uncertainty and nonlinear market conditions [20]. Previous studies by [21], [22], [23] illustrate the strength of Monte Carlo simulation frameworks in portfolio construction contexts. When combined with volatility models like GARCH and a well-estimated correlation structure, Monte Carlo simulations can generate thousands of plausible market outcomes, providing a robust and flexible foundation for designing volatility-aware portfolios [24], [25].

Building upon these advances, this study integrates GARCH (1,1) modeling, Cholesky decomposition-based correlation estimation, and Monte Carlo simulation to construct an optimal cryptocurrency portfolio consisting of ETH and SOL [26]. The decision to exclude Bitcoin (BTC) from the portfolio was based on its relatively lower volatility and established role as a store-of-value asset, which differs markedly from the more platform-oriented and utility-driven nature of Ethereum and Solana. Including BTC could introduce concentration bias and dampen the portfolio's responsiveness to volatility-based optimization. By focusing on two higher-beta assets, the simulation framework is better positioned to capture meaningful co-movement and volatility interaction — key components in a forward-looking risk optimization context.

Following GARCH (1,1) model estimation for each asset's return series, standardized residuals were calculated and used to derive a static correlation matrix. This matrix served as the basis for Cholesky decomposition, allowing for the generation of correlated standard normal innovations. These innovations were embedded into Monte Carlo simulations to project return paths over medium- and long-term horizons. By incorporating both asset-specific volatility dynamics and cross-asset correlations, the simulated returns represent plausible future market outcomes under uncertainty. Portfolio weights were optimized for each simulation based on a return-to-risk objective, excluding the risk-free rate to reflect the crypto environment's speculative nature. The resulting optimized portfolio was then evaluated against a benchmark equal-weighted strategy using out-of-sample data from January 2024 to January 2025 This methodology delivers a volatility-aware, simulation-driven portfolio framework that aligns with the unique risk-return structure of cryptocurrency markets, offering practical value for investors seeking to navigate high-uncertainty asset classes.

2. RESEARCH METHODS

This study employs a GARCH-based Monte Carlo simulation framework to construct an optimal cryptocurrency portfolio composed of ETH and SOL. The methodology consists of five main stages: data preparation, volatility modelling, return path simulation, portfolio optimization, and performance evaluation. The approach is designed to incorporate both the time-varying nature of volatility and the interdependencies between assets in a forward-looking, simulation-driven portfolio construction process.

Daily closing prices for ETH and SOL were collected from Yahoo Finance for the period ranging from January 1, 2023, to December 31, 2024. The full sample was divided into an in-sample training period, from January 1, 2023, to December 31, 2023, and two out-of-sample testing periods: January 1, 2024, to June 30, 2024, and January 1, 2024, to December 31, 2024. This structure allowed for both medium-term and full-year horizon performance evaluations. Logarithmic returns were computed from price relatives between time t and $t-1$, where P_t denotes the closing price at time t.

$$r_t = \log \frac{P_t}{P_{t-1}}. \tag{1}$$

Log returns were used in the modeling stage, such as for GARCH estimation, due to their advantageous statistical properties, including time-additivity, variance stabilization, reduced sensitivity to outliers, and improved distributional normality. However, portfolio returns in this study were calculated using simple arithmetic returns, as the standard method for aggregating asset returns in a portfolio applies only to simple returns.

To model the time-varying volatility of each asset, univariate GARCH (1,1) models were estimated for the log return series of both ETH and SOL. The GARCH model specification allows the conditional variance at time t to depend on both the squared residual from the previous time and the conditional variance at $t-1$, thus capturing volatility clustering behavior observed in financial time series. The model was expressed as:

$$r_{i,t} = \mu_i + \epsilon_{i,t}, \tag{2}$$

$$\epsilon_{i,t} = \sigma_{i,t} z_{i,t}, \quad z_{i,t} \sim \mathcal{N}(0,1), \tag{3}$$

$$\sigma_{i,t}^2 = \omega_i + \alpha_i \epsilon_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2. \tag{4}$$

Maximum Likelihood Estimation (MLE) was used to fit the model parameters $(\omega, \alpha_i, \beta_i)$ for each asset. The choice of GARCH (1,1) was motivated by its parsimony and empirical success in capturing conditional heteroskedasticity in asset returns, particularly in highly volatile markets such as cryptocurrencies [10].

After estimation, standardized residuals were obtained by dividing each residual by its time-varying conditional standard deviation, i.e., $z_t = \frac{\epsilon_{i,t}}{\sigma_{i,t}}$. This transformation normalizes the residuals, ensuring unit variance and rendering them suitable for estimating cross-asset dependence via correlation analysis. These standardized innovations preserve the temporal structure of the original series while filtering out the influence of conditional volatility, allowing for a cleaner estimation of asset interaction in the next simulation stage.

To capture cross-asset dependencies, a static correlation matrix was computed from the standardized residuals of the three GARCH models. This correlation matrix was then factorized using the lower-triangular Cholesky decomposition, which expresses the correlation matrix as the product of a lower-triangular matrix and its transpose. The resulting lower-triangular matrix was multiplied by independent standard normal innovations to produce correlated standard normal shocks across assets. These shocks were subsequently scaled by the modeled conditional volatilities and used to simulate 1,000 return paths over 180- and 360-day horizons for each asset using the following formula:

$$r_{i,t+h} = \mu_i + \sigma_{i,t+h} z_{i,t+h}. \tag{5}$$

where the volatility is recursively generated using the GARCH model, and are correlated shocks introduced via Cholesky transformation.

Simulated return paths were used to optimize portfolio weights based on a return-to-risk ratio objective, analogous to the Sharpe ratio but without a risk-free rate. For each simulation, the expected return and standard deviation were computed, and the weight vector was chosen to maximize the following:

$$\max \frac{E[R_p]}{\text{Std}[R_p]} \quad \text{subject to} \quad \sum w_i = 1, \quad w_i \geq 0. \tag{6}$$

Optimization was conducted in Python using the SLSQP algorithm from the scipy.optimize library, a gradient-based method for nonlinear problems with constraints. It iteratively approximates the objective with a quadratic model and the constraints with linear models, solving the subproblem until convergence. While an analytic solution exists for the mean–variance optimization problem without the non-negativity constraint, SLSQP was used here to incorporate both full-investment and no–short-selling constraints, ensuring practical applicability in the crypto asset management context.

The optimized weights derived from the simulation process were subsequently applied to real daily return data for two distinct out-of-sample periods: from January 1, 2024, to June 30, 2024 (180 days), and from January 1, 2024, to December 31, 2024 (360 days). These two horizons were selected to evaluate the portfolio's performance under both medium-term and long-term conditions, allowing for an assessment of the model's sensitivity to different holding periods and market regimes. During each period, the optimized portfolio's performance was directly compared to that of a naïve equal-weighted benchmark, which serves as a commonly accepted passive allocation strategy in both academic research and industry practice.

Performance comparison was conducted across three key metrics: cumulative return, portfolio volatility, and return-to-risk ratio (analogous to the Sharpe ratio, excluding the risk-free rate). Cumulative return measures absolute growth, volatility captures overall risk exposure, and the return-to-risk ratio quantifies performance efficiency — all of which are essential for evaluating the robustness and practical viability of the optimization framework. This dual-horizon back testing approach provided a grounded assessment of the model's predictive effectiveness in real-world conditions, particularly in the highly volatile and nonlinear environment of cryptocurrency markets. It further enabled the identification of potential trade-offs between short-term risk-adjusted gains and longer-term return convergence in periods of synchronized asset movement.

3. RESULTS AND DISCUSSION

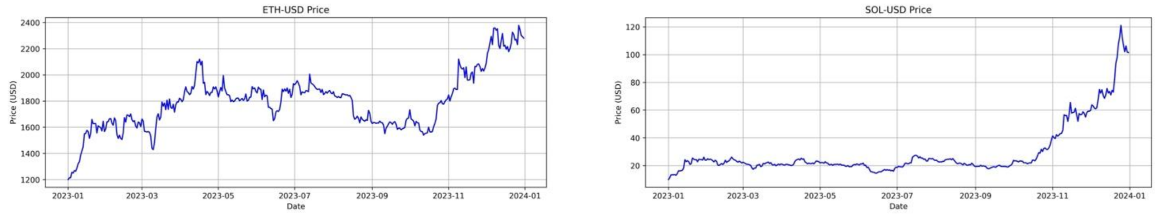
The results of this study are presented in several stages, beginning with an exploration of each assets nature from its historical price. Continuing with the volatility dynamics captured by the GARCH (1,1) models, followed by the portfolio optimization using simulation. The final part discusses the comparative performance between the optimized and equal-weighted portfolios, with emphasis on return distributions and risk-adjusted outcomes from its out-of-sample performance.

Fig. 1 presents the price evolution of Ethereum (ETH) and Solana (SOL) over the in-sample period from January 1, 2023, to December 31, 2023, offering a foundational overview of the underlying assets analyzed in this study. The visual trajectories reveal notable price swings in both assets, characterized by alternating periods of sharp appreciation and subsequent correction. These waving patterns underscore the inherently volatile nature of cryptocurrency markets, where prices often respond rapidly to shifts in investor sentiment, macroeconomic news, or changes in market liquidity.

ETH and SOL both exhibit significant fluctuations, but with differing magnitudes and frequencies. Ethereum, as a more established asset, displays relatively smoother price trends with occasional spikes, while Solana experiences more abrupt rises and drops, likely due to its smaller market capitalization and higher speculative activity. This pronounced cyclicality highlights the presence of momentum phases followed by reversals, which are not easily captured through static models. As such, the observed dynamics further motivate the use of GARCH-based models to better represent the conditional variance over time. In short, the patterns in Figure 1 serve as both a descriptive and diagnostic tool, confirming the necessity of time-varying risk modeling in simulation-based portfolio construction.

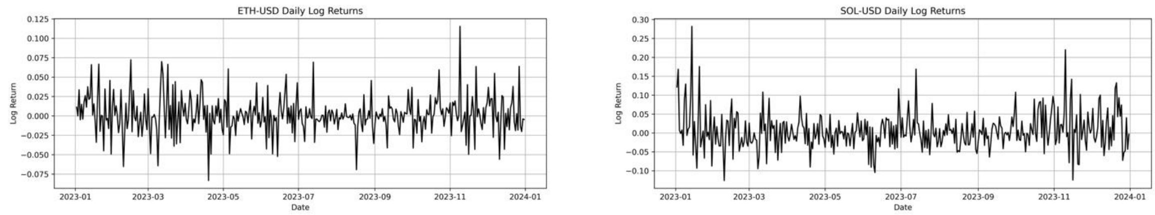
Fig. 2 displays the daily log return series for ETH and SOL during the same in-sample period, offering a more detailed view of the underlying price dynamics by isolating the relative changes from day to day. The return patterns clearly demonstrate alternating periods of high and low volatility, highlighting the unstable and non-linear nature of cryptocurrency returns. Unlike prices, which tend to trend, log returns fluctuate around a mean of zero and are more suitable for modeling stochastic behavior.

A detailed view reveals distinct volatility clustering, where large movements including both positive and negative tend to group together, followed by periods of relative calm. This phenomenon is particularly prominent in both ETH and SOL, suggesting that the magnitude of returns is dependent on past volatility, a key feature of financial time series that violates the assumption of constant variance in classical models. The absence of a clear linear trend and the presence of clustering justify the application of a GARCH (1,1) model, which is specifically designed to capture such time-varying volatility structures. By modeling the conditional variance based on past squared returns and lagged variance terms, GARCH allows for dynamic risk estimation that evolves with market conditions, thereby enhancing the accuracy of forward-looking simulations in a highly volatile asset class like cryptocurrency.



(a) (b)

Figure 1. Assets' Closing Price
(a) ETH-USD Closing Price, (b) SOL-USD Closing Price
(Source: Python, Jupyter Notebook)



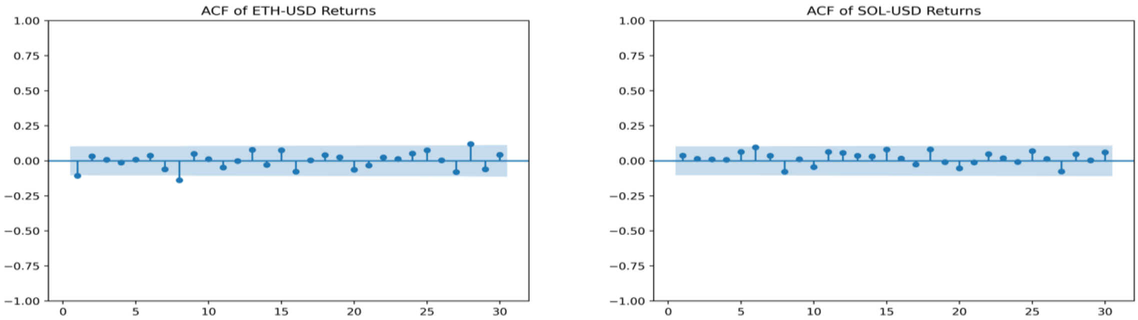
(a) (b)

Figure 2. Assets' Daily Log Return
(a) ETH-USD Daily Log Return, (b) SOL-USD Daily Log Return
(Source: Python, Jupyter Notebook)

Figs. 3 and 4 present the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots for the log returns of ETH and SOL, calculated over 30 lags. These diagnostic tools are essential for identifying linear dependencies in time series data. Both ACF and PACF plots reveal that the vast majority of autocorrelation coefficients lie well within the 95% confidence intervals, indicating an absence of statistically significant autocorrelation in the return series. This suggests that past returns have minimal predictive power over future returns, consistent with the weak-form efficiency hypothesis, which posits that current asset prices fully reflect all available historical price information.

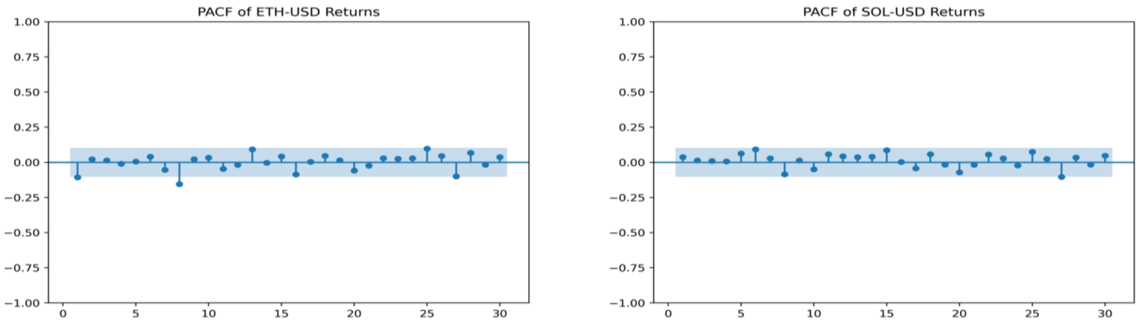
This statistical independence in mean return behavior does not, however, extend to the return variance. Despite the lack of linear serial correlation, the presence of volatility clustering observed in the raw return plots suggests a more complex underlying variance structure. In other words, large shocks, whether positive or negative, tend to be followed by other large shocks, and small changes by small changes, even though the direction of movement is random. This conditional heteroskedasticity phenomenon violates the assumptions of constant variance models and supports the application of GARCH-based models. By explicitly modeling the time-varying conditional variance, the GARCH (1,1) specification captures these volatility dynamics effectively, making it a suitable choice for forecasting risk and simulating realistic return paths in cryptocurrency portfolios. Thus, the results from the ACF and PACF analysis, combined with visual inspection of the return series, provide robust empirical justification for employing GARCH models in this context.

While the returns themselves exhibit insignificant serial dependence, the volatility clustering observed visually in the return series indicates that the variance process may be time-varying rather than constant. Although the ACF and PACF of the returns do not signal autocorrelation, this does not hinder the existence of conditional heteroskedasticity, which is a common feature in financial return data. Therefore, these results support the application of GARCH models to model the dynamic volatility behavior of ETH and SOL returns more appropriately.



(a) (b)

Figure 3. Assets' Daily Log Return
(a)ETH-USD Daily Log Return, (b) SOL-USD Daily Log Return
(Source: Python, Jupyter Notebook)



(a) (b)

Figure 4. Assets' Daily Log Return
(a) ETH-USD Daily Log Return, (b) SOL-USD Daily Log Return
(Source: Python, Jupyter Notebook)

The standardized residuals from the GARCH (1,1) models were used to generate a static correlation matrix to include interaction between assets in the simulation process. By standardizing the residuals, time-varying volatility do not distort the correlation calculation, enabling a more accurate evaluation of the pure linear dependency between asset shocks.

Table 1. Correlation Matrix

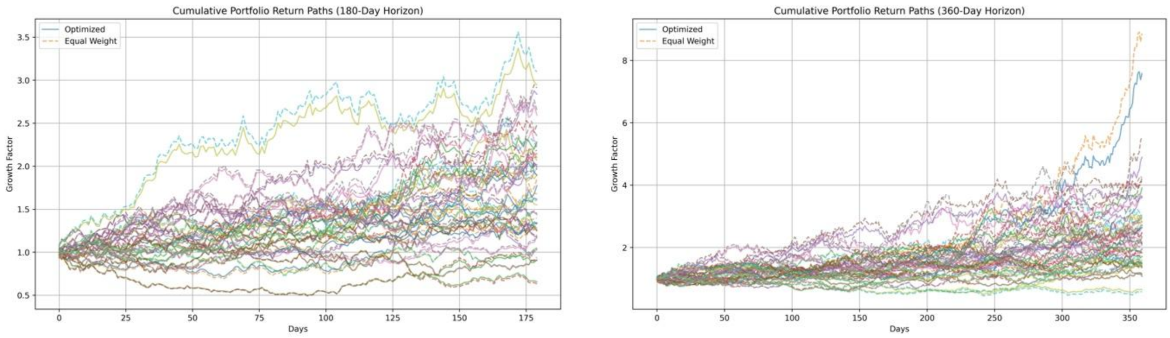
	ETH-USD	**SOL-USD**
ETH-USD	1	0.627122
SOL-USD	0.627122	1

Table 1 presents the static correlation matrix calculated from the standardized residuals of the GARCH (1,1) models for ETH and SOL. The correlation value of approximately 0.627 between the two assets indicates a moderate to strong positive linear relationship in their standardized innovations. This result is in line with empirical patterns observed in the broader cryptocurrency market, where assets frequently exhibit joint responses to systemic market drivers, including macroeconomic announcements, global risk sentiment, and platform-level technological developments.

Such a correlation magnitude has important implications for portfolio construction and simulation. A correlation coefficient above 0.6 implies that diversification benefits may be partially constrained, particularly during synchronized upswings or downturns. Nevertheless, capturing and accounting for this relationship remains essential for any realistic forward-looking simulation. By using standardized residuals, the correlation matrix reflects pure co-movements between asset-specific shocks, filtered from time-varying volatility — making it a more accurate input for Monte Carlo simulation than raw return correlations, which are often distorted by heteroskedasticity.

This static correlation matrix serves as a foundational component for the Cholesky decomposition step, enabling the generation of correlated shocks in the simulation phase. Although more sophisticated alternatives such as DCC-GARCH or copula-based dependence structures exist, the use of a static matrix derived from filtered residuals offers a robust and computationally efficient approach, particularly in low-dimensional portfolio contexts like the ETH-SOL pair. The correlation structure embedded in Table 1, therefore, not only captures meaningful asset interdependence but also supports the methodological integrity of the simulation framework used to generate optimized portfolio allocations.

In order to create correlated random shocks in the Monte Carlo simulation, these correlation estimates were subsequently split using the Cholesky method. The simulation methodology may generate return paths that represent both asset-specific volatility and joint dynamics by combining GARCH-derived volatility with this static correlation structure.



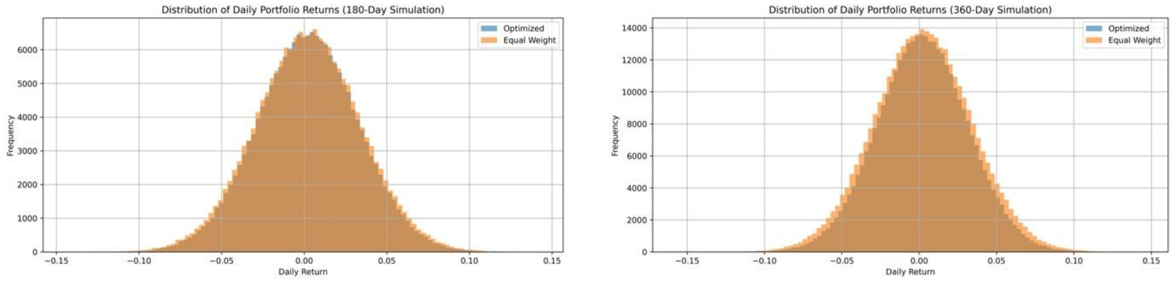
(a) (b)

Figure 5. Portfolio Simulated Paths Comparison
(a) 180-Days Simulated Paths, (b) 360-Days Simulated Paths
(Source: Python, Jupyter Notebook)

Figs. 5 (a) and (b) depict Monte Carlo–generated cumulative return paths for the optimized and equal-weighted strategies over 180-day and 360-day horizons. Each thin line corresponds to a single simulated trajectory, illustrating path-by-path variability, while the thicker lines summarize the central tendency (average/median) for each strategy. The visible spread of the thin lines indicates the range of plausible outcomes under the simulated conditions, which widens over the longer horizon. This dispersion reflects the stochastic nature of returns and the time-varying volatility captured by the GARCH-based framework, highlighting both the uncertainty inherent to crypto markets and the comparative behavior of the two strategies across scenarios.

In the 180-day simulations, the optimized portfolio consistently outperforms the equal-weighted benchmark in terms of upper-tail outcomes. While most return paths cluster between a growth factor (cumulative growth of the portfolio) of 1.0 and 2.0, the optimized portfolio more frequently exceeds the 2.0 mark. This suggests that the allocation strategy, which leverages forward-looking volatility estimates, is better positioned to exploit favorable short- to medium-term return opportunities. The improved performance reflects the benefit of weighting assets based on their expected return-to-risk profiles, as captured in the simulation process. In this study, growth factors are computed from simulated daily portfolio returns produced by the GARCH(1,1)–Cholesky Monte Carlo paths, aggregated multiplicatively over the 180-day horizon.

Extending to the 360-day horizon, the spread of simulated outcomes becomes significantly wider, consistent with the compounding effects of volatility and return uncertainty over longer periods. Both strategies exhibit scenarios where cumulative returns exceed a factor of 4.0; however, the optimized portfolio continues to generate a higher concentration of favorable trajectories in the upper percentiles. This indicates that even under long-term compounding risk, volatility-aware optimization retains some degree of performance edge. Nevertheless, the increasingly wide range of final values also illustrates a critical insight: while GARCH-based simulations improve the expected risk-return balance, they do not eliminate the probabilistic nature of market behavior. Thus, the results reinforce the dual role of optimization under volatility — to pursue higher returns when conditions are favorable, while remaining structurally attuned to uncertainty and downside risks that cannot be fully diversified away in high-volatility markets like crypto.



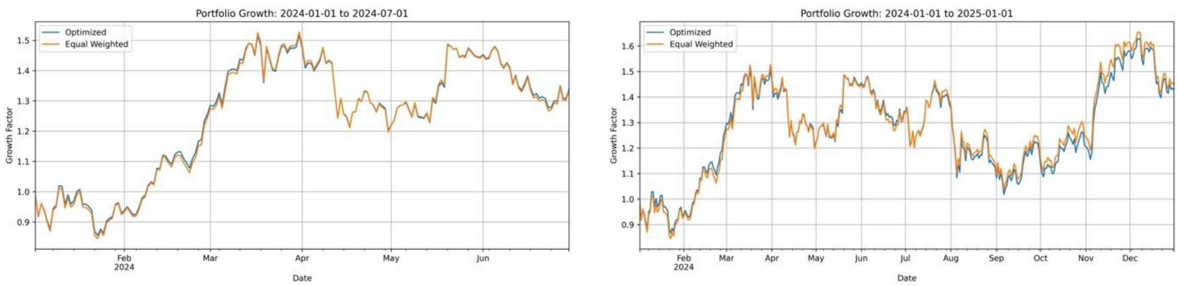
(a) (b)

Figure 6. Histogram of Simulated Portfolio Daily Return
(a) 180-Days Simulated Histogram, (b) 360-Days Simulated Histogram
(Source: Python, Jupyter Notebook)

Figs. 6 (a) and (b) further reinforce the simulation findings by presenting histograms of the simulated daily return distributions for both portfolio strategies over 180-day and 360-day horizons. These distributions reveal that both the optimized and equal-weighted portfolios exhibit near-normal, bell-shaped curves, suggesting a relatively symmetrical return profile under the assumptions embedded in the Monte Carlo process. The use of GARCH-generated volatility in combination with correlated return innovations produces a probabilistically consistent structure, which translates into realistic daily return dynamics over the simulated paths.

However, a key distinction emerges in the form of a slight rightward skew in the optimized portfolio's return distribution, especially over the longer 360-day horizon. This skewness, although not extreme, reflects a subtle tilt in favor of more frequent positive deviations from the mean, an indication of enhanced upside potential. Such asymmetry is particularly appealing for investors seeking convex payoff structures, where the likelihood of extreme positive returns is marginally greater than that of large losses. Importantly, this feature is achieved without a noticeable increase in volatility or tail risk, as the overall shape and width of the return distribution remain comparable across both strategies.

This alignment between marginal improvements in daily return characteristics and the previously observed cumulative growth advantage provides further validation for the simulation-driven optimization approach. It suggests that performance gains are not only visible at the aggregate level but are also embedded in the daily behavior of the optimized portfolio. From a risk management perspective, maintaining a similar day-to-day volatility structure while improving return asymmetry supports the case for adopting GARCH-based optimization in environments characterized by high-frequency market uncertainty, such as cryptocurrency markets.



(a) (b)

Figure 7. Portfolio Growth Comparison
(a) 6-Month Out-of-Sample Performance, (b) 1-Year Out-of-Sample Performance
(Source: Python, Jupyter Notebook)

Fig. 7 illustrates the out-of-sample growth trajectories for the optimized and equal-weighted portfolios across two distinct investment horizons: a six-month period from January to July 2024, and a full-year horizon from January 2024 to January 2025. These plots serve as real-market validations of the simulation-based optimization approach. During the initial six-month period, both strategies demonstrate a strong upward trend, driven by favorable market momentum, with values peaking around a growth factor of 1.45 in early April. Although the equal-weighted strategy briefly outperforms the optimized portfolio during the most rapid growth phase between March and April, the difference is minimal and short-lived. By the end of June 2024, the optimized portfolio achieves a final growth factor of approximately 1.34, marginally outperforming the equal-weighted portfolio at 1.33.

This narrow gap highlights that during relatively bullish, stable environments, the added value of volatility-sensitive optimization may be subtle, especially when the constituent assets are moving in close tandem. Nevertheless, the optimized portfolio manages to maintain performance parity while also offering structural advantages in volatility control, as reflected in earlier results.

Over the extended 360-day horizon, the return paths for both strategies continue to exhibit high co-movement, reaffirming the influence of strong cross-asset correlation in the ETH-SOL pair. Temporary deviations are observed during market rallies in March and November, where the optimized strategy briefly achieves stronger gains due to its reactivity to conditional volatility shifts. However, by the end of the evaluation period, both strategies converge, posting final growth factors of 1.43 for the optimized portfolio and 1.45 for the equal-weighted portfolio. This convergence indicates that in prolonged, trend-following markets with synchronized asset behavior, the return advantage of GARCH-based optimization becomes less pronounced.

Table 2. Portfolio Out-of-Sample Performance

	180-Days		**360-Days**	
	Optimal	**Equal-Weighted**	**Optimal**	**Equal-Weighted**
Total Return	0.34	0.33	0.43	0.45
Volatility	0.03	0.04	0.03	0.04
Return-to-Risk	0.06	0.05	0.03	0.03

Still, the ability of the optimized portfolio to maintain comparable returns while managing volatility more effectively—shown earlier through lower variance and higher return-to-risk ratios—confirms its role as a robust, risk-sensitive alternative. Particularly for investors prioritizing risk containment over pure return maximization, the optimized strategy offers meaningful practical value, especially during uncertain or rapidly changing market conditions.

Table 2 summarizes the out-of-sample performance metrics of the optimized and equal-weighted portfolios over two evaluation periods: a medium-term 180-day horizon and a long-term 360-day horizon. Key performance indicators reported include total return, volatility, and return-to-risk ratio, each offering a distinct lens through which to assess the comparative strength of the portfolio strategies. Over the 180-day period, the optimized portfolio outperformed the equal-weighted benchmark by a small margin, achieving a total return of 34% versus 33%. More notably, the optimized portfolio maintained a superior return-to-risk ratio of 6% compared to 5%, which indicates that the strategy was able to deliver better returns per unit of risk. This suggests that the simulation-driven optimization approach effectively leveraged short-term volatility conditions, tilting asset weights toward those with more favorable risk-adjusted profiles.

Importantly, the volatility observed in the optimized portfolio was lower (3%) compared to that of the equal-weighted portfolio (4%), confirming that the allocation method was not only performance-driven but also risk-sensitive. This reinforces the idea that the GARCH-based simulation framework enhances the quality of portfolio construction by aligning capital allocation with forward-looking volatility expectations.

In contrast, over the 360-day horizon, the performance differential narrows further. Both portfolios delivered the same return-to-risk ratio of 3%, while the equal-weighted strategy achieved a slightly higher total return of 45% compared to 43% for the optimized portfolio. Despite this marginal return advantage, the optimized portfolio again demonstrated consistently lower volatility. This outcome is especially meaningful in the context of long-term portfolio resilience, where downside protection and drawdown control can be as valuable as incremental return enhancements.

Overall, Table 2 highlights a central insight: while the realized return advantage of GARCH-based optimization may diminish in extended bull or synchronized markets, its strength lies in superior volatility management and maintaining a stable return profile. This is particularly relevant for institutional or risk-averse investors who seek portfolio strategies that perform well not only in absolute terms, but also under probabilistic and stress-tested frameworks.

The overall findings demonstrate that GARCH-based Monte Carlo optimization can provide improvements in cryptocurrency portfolio performance, particularly in terms of volatility management and risk-adjusted returns. The simulation results over horizons show that while the optimized portfolio paths exhibit slightly higher cumulative growth factors and better upside capture during volatile periods, the realized advantages over simple equal-weighted strategies remain relatively limited when assets are highly correlated, and market trends are synchronized.

Out-of-sample evaluation further support these observations. Over a six-month period, the optimized strategy achieved a slightly higher return-to-risk ratio, while over a full year, both strategies delivered similar risk-adjusted outcomes, with the equal-weighted portfolio posting higher total returns. The important thing is that the optimized portfolio consistently maintained lower volatility across both periods, highlighting its ability to stabilize portfolio performance even when excess returns were not significantly superior. These results suggest that volatility-sensitive optimization techniques can enhance portfolio resilience, but their realized return advantage may depend heavily on occurring market dynamics and asset behavior.

4. CONCLUSION

This study examined the construction of an optimal cryptocurrency portfolio by integrating GARCH-based volatility modeling with Monte Carlo simulation, focusing on two actively traded digital assets ETH and SOL. By modeling asset-specific volatility using GARCH (1,1) and capturing asset dependencies through a static correlation matrix derived from standardized residuals, the research constructed forward-looking return paths to simulate realistic market behavior. These simulated scenarios were then used to optimize portfolio weights under a return-to-risk objective, enabling the comparison of the optimized strategy against a traditional equal-weighted benchmark.

Simulation results indicated that the optimized portfolio achieved modestly higher cumulative growth and superior upside capture during volatile market phases, particularly over short- to medium-term horizons. These improvements were achieved while maintaining lower overall volatility, suggesting that GARCH-informed optimization offers enhanced control over portfolio risk without materially sacrificing returns. In out-of-sample testing over a six-month horizon, the optimized portfolio achieved a slightly higher return-to-risk ratio of 6% compared to 5% for the equal-weighted portfolio, with a lower volatility profile. Over the longer one-year horizon, performance convergence was observed, with the equal-weighted strategy marginally outperforming in total return. However, the optimized portfolio continued to exhibit lower risk, validating its strength as a volatility-stabilizing allocation mechanism.

The findings underscore the practical value of incorporating volatility-aware optimization techniques in cryptocurrency investment strategies. While the marginal return advantage of the optimized portfolio may diminish under long-term trend-following market conditions or during periods of high asset synchronization, its consistent reduction in volatility offers meaningful utility to risk-sensitive investors, particularly those with capital preservation objectives or institutional constraints.

Future research can build upon this framework in several directions. First, expanding the portfolio to include a broader set of cryptocurrencies, including Layer-2 tokens, or stablecoins, may enhance diversification and allow deeper insight into cross-sector dynamics within the crypto ecosystem. Second, replacing the static correlation matrix with a time-varying approach, such as Dynamic Conditional Correlation (DCC-GARCH) or copula-based dependence structures, could improve accuracy in capturing evolving inter-asset relationships. Third, incorporating higher-order moment optimization such as skewness-aware or tail-risk-sensitive objectives. This would offer a more comprehensive risk profile for investors concerned with asymmetric or extreme return outcomes.

Lastly, this methodology could be extended beyond crypto into hybrid portfolios that combine traditional financial assets with digital currencies, allowing analysis of how volatility-aware optimization performs in mixed-market conditions. As cryptocurrencies continue to gain institutional adoption, frameworks like the one proposed in this study can play an increasingly vital role in bridging quantitative finance techniques with the unique challenges of digital asset allocation.

Author Contributions

Staenly: Conceptualization, Methodology, Software, Formal Analysis, Investigation, Visualization, Writing Original Draft, Project Administration. Josep Ginting: Supervision, Methodology, Validation, Writing – Review and Editing, Resources. Maria Yus Trinity Irsan: Data Curation, Resources, Validation, Writing – Review and Editing, Visualization. All authors contributed to manuscript refinement, approved the final version, and agreed to be accountable for all aspects of the work.

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Declarations

Competing interest. The authors declare no competing interest.

Declaration of Generative AI and AI-assisted Technologies

Generative AI tools were used solely for language refinement (grammar, spelling, and clarity). The scientific content, analysis, interpretation, and conclusions were developed entirely by the authors. The authors reviewed and approved all final text.

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