

SIMULATING CRYPTOCURRENCY PORTFOLIO RISK

A Monte Carlo Comparison of Bitcoin, Ethereum, and Mixed Crypto Portfolios

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Abstract:

Cryptocurrency investing is often discussed in terms of high returns, but the risk side is just as important. This study uses Monte Carlo simulation to examine how a \$10,000 investment could behave over one year when it is placed in Bitcoin, Ethereum, or a portfolio combining both assets. The simulation uses 10,000 one-year paths with 252 daily observations per path. Daily return and volatility assumptions are based on recent academic evidence, while a 0.79 Bitcoin–Ethereum return correlation is used to preserve the fact that the two assets often move together. Five allocations are compared: 100% Bitcoin, 80% Bitcoin/20% Ethereum, 60% Bitcoin/40% Ethereum, 50% Bitcoin/50% Ethereum, and 100% Ethereum. The results show that Bitcoin produced the lowest simulated volatility and downside risk in this specific model. Adding Ethereum gradually increased expected upside but also increased annualized volatility, the probability of finishing below the initial investment, Value at Risk, and Conditional Value at Risk. The main lesson is therefore not that diversification is useless, but that diversification depends on what is being combined. When two assets are strongly correlated and one is materially more volatile, simply splitting money between them may not reduce risk. The study demonstrates how simulation can turn uncertain crypto outcomes into a range of measurable scenarios and can support more informed risk analysis without pretending to predict the exact future price of either cryptocurrency.

Keywords:

Cryptocurrency, Bitcoin, Ethereum, Monte Carlo simulation, portfolio risk, diversification, Value at Risk

Introduction:

Cryptocurrency has moved from a niche technology topic to an asset class followed by individual investors, institutions, exchanges, and researchers. Bitcoin and Ethereum are the two names that usually receive the most attention. Their appeal is easy to understand: prices can move quickly, markets trade continuously, and investors can gain exposure without the same structure used for traditional securities. The same features that make crypto attractive, however, also make it difficult to manage. Large daily price changes are normal, extreme losses are possible, and past performance can change dramatically from one market period to another.

This creates a useful problem for a simulation course. An investor can look at the historical average return of Bitcoin or Ethereum, but an average does not show the many different paths that an investment might take. Two investments can have a similar expected return and still have very different probabilities of loss. Simulation is valuable because it does not give one single forecast. Instead, it creates thousands of possible outcomes under clearly stated assumptions and lets us study the full distribution of risk.

The research problem in this paper is simple: investors often assume that holding both Bitcoin and Ethereum is safer than holding only one cryptocurrency because the portfolio contains two assets instead of one. That assumption is not guaranteed. Recent evidence shows that Ethereum has historically displayed higher daily volatility than Bitcoin, while the returns of the two cryptocurrencies can also be strongly correlated (Liashenko et al., 2026; Eshaghinasrabadi, 2024). If the assets move together most of the time, adding the more volatile asset may provide less protection than the word “diversification” suggests.

Research gap. Many crypto studies examine volatility, diversification, portfolio optimization, or Value at Risk. Other studies use advanced econometric models that are useful academically but difficult for a normal investor to translate into an intuitive decision. This project focuses on a narrower simulation question: using transparent assumptions, what happens to a one-year \$10,000 portfolio as the allocation gradually shifts from Bitcoin toward Ethereum? The purpose is not to find a guaranteed winning allocation. It is to show how the risk distribution changes and to connect a finance question directly to simulation methods.

The study answers three research questions: (1) How do the simulated ending values of Bitcoin-only, Ethereum-only, and mixed BTC–ETH portfolios differ over one year? (2) Does adding Ethereum reduce or increase portfolio risk under the selected historical parameters and correlation? (3) How do downside measures such as probability of loss, 95% Value at Risk (VaR), and 95% Conditional Value at Risk (CVaR) change across allocations?

The objectives are to build a reproducible Monte Carlo model, compare five portfolio allocations using the same random market scenarios, measure both upside and downside outcomes, and explain the results in a way that is understandable without removing the statistical logic behind the model.

Literature Review:

The academic literature agrees on one point: cryptocurrency returns cannot be treated as calm or normally behaved financial data. Liashenko et al. (2026) report a mean daily log return of 0.1328% for Bitcoin and 0.0608% for Ethereum, with daily standard deviations of 3.5487% and 4.5490%, respectively. They also report negative skewness and high excess kurtosis for both assets. In simple terms, the return distributions contain more extreme observations than a normal bell-shaped distribution would suggest. This matters because a model that focuses only on the average can hide the size of the downside tail.

Earlier volatility research reaches a similar conclusion. Dudek et al. (2024), using cryptocurrency return and realized-variance data, document high daily volatility and substantial excess kurtosis for Bitcoin and Ethereum. Wu and Yueh (2026) also emphasize that cryptocurrency risk management needs models capable of handling time-varying volatility and non-standard return behavior. Together, these studies justify treating crypto risk as a distribution of possible outcomes rather than as one fixed forecast.

A second stream of research asks whether cryptocurrencies improve diversification. Youssef (2023) finds that adding crypto-assets can improve the efficiency of broader portfolios under several investor preferences. Han et al. (2024) extend this idea by examining more than 2,000 cryptocurrencies through factor portfolios and report that selected crypto factors can provide out-of-sample diversification benefits when combined with stocks and bonds. These findings are important, but they involve diversification across crypto and traditional asset classes, not simply splitting a crypto allocation between Bitcoin and Ethereum.

Within cryptocurrency portfolios, the picture is more complicated. Eshaghinasrabadi (2024) report a statistically significant positive correlation of 0.79 between Bitcoin and Ethereum daily log returns in their sample. Saka Ilgin (2024) concludes that Bitcoin and Ethereum can act as portfolio diversifiers relative to selected global financial assets, but also notes that their diversification effects weakened toward the end of the study period. More recent work by Li and Liu (2026) uses a Bayesian mixture-copula framework and shows that Ethereum can contribute to diversification and hedging, although the benefit depends on the risk measure and allocation method. The key point is that diversification is conditional: correlation, volatility, investor preferences, and the chosen period all matter.

Monte Carlo simulation has already been used in portfolio research because it can convert uncertain returns into a large number of possible portfolio outcomes. Platanakis and Urquhart (2021) use 10,000 Monte Carlo iterations alongside portfolio optimization and VaR/CVaR measures to study Bitcoin's diversification role. Their approach supports the use of simulation as a practical bridge between historical statistics and forward-looking risk scenarios. In the present

study, the same broad idea is simplified and focused on a BTC–ETH allocation question suitable for a simulation course.

Macroeconomic Vulnerabilities and Advanced Simulation in Finance

Understanding the volatile risk profiles of Bitcoin and Ethereum requires contextualizing them within broader macroeconomic dynamics and behavioral finance. During periods of severe financial distress, cryptocurrencies frequently act as alternative financial resilience strategies, driven heavily by behavioral determinants, demographic predictors, and the influence of digital platforms (Aoun et al., 2026; El-Chaarani et al., 2025; Mawad & Freiha, 2024). However, quantitative comparative analyses show that while Bitcoin is often touted as a safe haven, its risk-return and volatility profiles differ fundamentally from traditional hedges like physical gold during economic shocks (Beainy & Kamel, 2026). The volatility of these digital assets is deeply intertwined with shifting macroeconomic variables—which demand high technology analytic adeptness to evaluate (Bejjani et al., 2024)—and the persistent dominance of fiat currencies like the US Dollar in global market pricing (Beainy et al., 2025). Consequently, the purported diversification benefits of crypto portfolios are highly sensitive to these overarching macroeconomic vulnerabilities.

To properly capture the non-linear dynamics and extreme tail risks of such volatile assets, modern financial risk management increasingly relies on advanced predictive analytics and simulation techniques. Fostering a data-driven culture and deploying big data analytics have become essential for evaluating complex asset performance and organizational success in volatile markets (Azoury et al., 2024; Subrahmanyam et al., 2024). In quantitative finance, ensemble machine learning and deep learning models are now widely used to analyze how investor sentiment impacts broad market benchmarks and to predict broader economic cycles through asset return behaviors (Khalife et al., 2025; Nasser et al., 2025). Crucially, the application of Monte Carlo simulations—often combined with advanced stochastic frameworks like the Heston model—has proven highly effective in pricing complex financial derivatives and assessing downside risk under extreme market uncertainty (Khalife et al., 2023). By utilizing these smart decision support systems, investors can better navigate market disruptions and construct more resilient portfolios without relying on single-point forecasts (Subrahmanyam & Beainy, 2027).

The literature therefore creates the basis for this project. Crypto returns are volatile and heavy-tailed; Bitcoin and Ethereum can move together strongly; and simulation is a useful way to study risk under uncertainty. The specific contribution here is to show, step by step, whether gradually adding Ethereum to a Bitcoin position improves the simulated risk profile when both assets are modeled together using the same market shocks.

Methodology:

3.1 Research Design

This study uses a quantitative Monte Carlo simulation. The unit of analysis is a hypothetical \$10,000 cryptocurrency portfolio held for 252 days, representing approximately one financial year for comparability with common annualized finance measures. Although crypto trades seven days a week, 252 observations are used as a standardized one-year simulation horizon and this choice is treated as a modeling convention rather than a statement about crypto market opening days.

Five long-only portfolios are tested: 100% Bitcoin; 80% Bitcoin and 20% Ethereum; 60% Bitcoin and 40% Ethereum; 50% Bitcoin and 50% Ethereum; and 100% Ethereum. No leverage, short selling, transaction fees, taxes, staking income, or rebalancing costs are included. Each portfolio is exposed to the exact same set of simulated daily BTC and ETH returns, which makes the comparison fair: only the portfolio weights change.

3.2 Model Inputs and Variables

The baseline return parameters are taken from Liashenko et al. (2026), who report daily log-return means of 0.1328% for Bitcoin and 0.0608% for Ethereum and daily standard deviations of 3.5487% and 4.5490%, respectively. The BTC–ETH correlation is set to 0.79, consistent with the positive daily log-return correlation reported by Eshaghinasrabadi (2024). These are historical estimates, not promises about future performance.

Input	Bitcoin	Ethereum / Joint Assumption
Daily mean return	0.1328%	0.0608%
Daily standard deviation	3.5487%	4.5490%
BTC–ETH correlation	—	0.79
Initial portfolio value	\$10,000	\$10,000
Simulation horizon	252 days	252 days
Number of simulated paths	10,000	10,000

Table 1. Main simulation inputs. Historical return and volatility parameters are based on Liashenko et al. (2026); correlation is based on Eshaghinasrabadi (2024).

3.3 Simulation Equations

For each simulated day t , the model generates a pair of correlated Bitcoin and Ethereum returns. In matrix form, the two daily returns are drawn jointly using the mean vector $\mu = [0.001328, 0.000608]$ and a covariance matrix built from the two standard deviations and the 0.79 correlation. The portfolio daily return is then calculated as:

$$R_{p,t} = w_{BTC} \times R_{BTC,t} + w_{ETH} \times R_{ETH,t}$$

where the two weights sum to 1. The portfolio value evolves through compounding:

$$V_t = V_{t-1} \times (1 + R_{p,t})$$

This process is repeated for 252 days and then repeated across 10,000 independent simulation paths. A fixed random seed of 42 is used so that the reported results can be reproduced exactly with the same code and inputs.

3.4 Risk Measures

The model reports the mean and median ending portfolio value, annualized volatility, probability of ending below the original \$10,000, 95% VaR, 95% CVaR, and a zero-risk-free-rate Sharpe ratio for comparison. In this paper, 95% VaR is expressed as the loss percentage at the fifth percentile of simulated one-year returns. CVaR goes one step further and reports the average loss among the worst 5% of simulated outcomes. This is useful for crypto because the size of bad outcomes matters, not only how frequently they occur.

3.5 Role of Artificial Intelligence and Reproducibility

Artificial intelligence was used as a complementary research tool, mainly to brainstorm the research question, organize the paper, support coding, and improve wording. It was not treated as a source of market data. Academic sources were used for the model parameters, and the simulation calculations were executed programmatically. This separation is important because it keeps the numerical results tied to stated assumptions rather than to unsupported AI-generated figures.

The simulation can be replicated by using the parameters in Table 1, generating 10,000 sets of 252 correlated daily returns, applying the portfolio weights, and compounding each path from \$10,000. Because a fixed seed is stated, another researcher using the same random-number generator and implementation should obtain materially identical results.

Results:

The simulation produced a clear pattern. As the portfolio weight moved from Bitcoin toward Ethereum, the average ending value decreased in this specific parameter set, while downside risk increased. This is not a general rule about the future of either cryptocurrency. It is the direct outcome of the selected historical inputs: Bitcoin has the higher mean return, Ethereum has the higher volatility, and the two returns have a strong positive correlation.

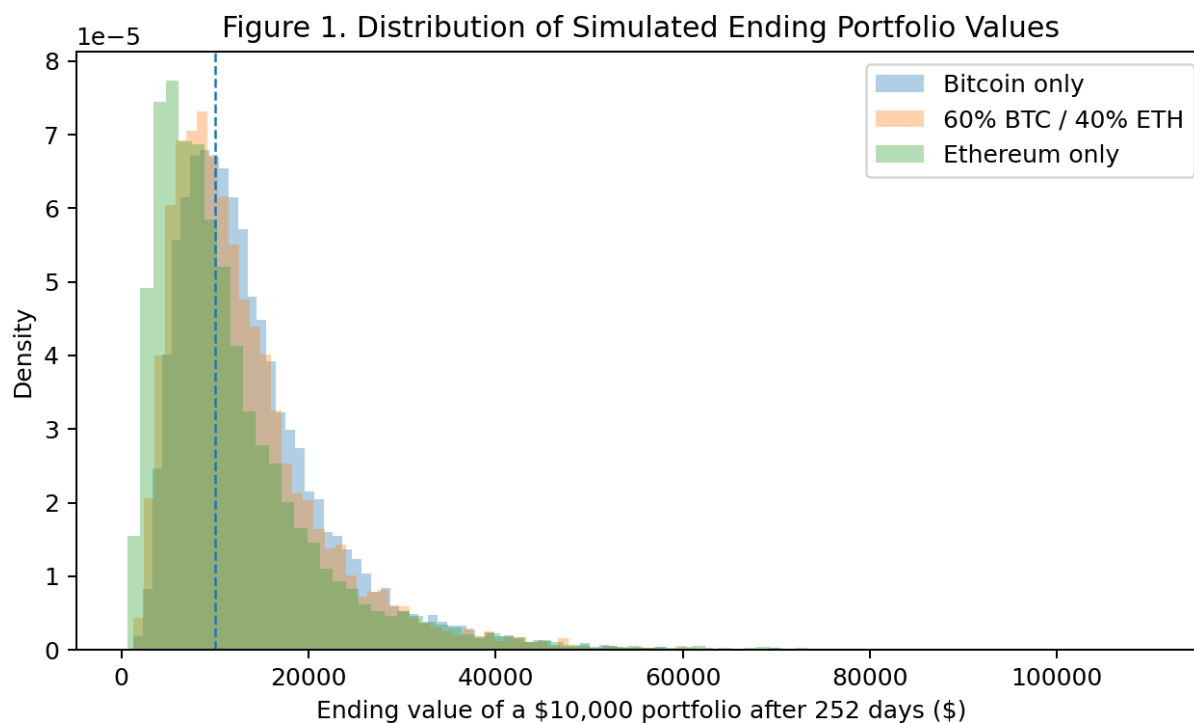
Portfolio	Mean End	Median End	Ann. Vol.	P(Loss)	95% VaR	95% CVaR	Sharpe
Bitcoin only	\$14,037	\$12,022	56.3%	37.1%	52.5%	61.3%	0.60
80% BTC / 20% ETH	\$13,561	\$11,533	57.1%	40.3%	54.9%	63.6%	0.53
60% BTC / 40% ETH	\$13,100	\$11,002	59.3%	43.9%	58.6%	67.0%	0.45
50% BTC / 50% ETH	\$12,876	\$10,709	60.9%	45.7%	60.9%	69.0%	0.41
Ethereum only	\$11,810	\$9,102	72.2%	55.0%	72.6%	79.2%	0.23

Table 2. Monte Carlo results from 10,000 simulated one-year paths. VaR and CVaR are shown as positive loss percentages for readability.

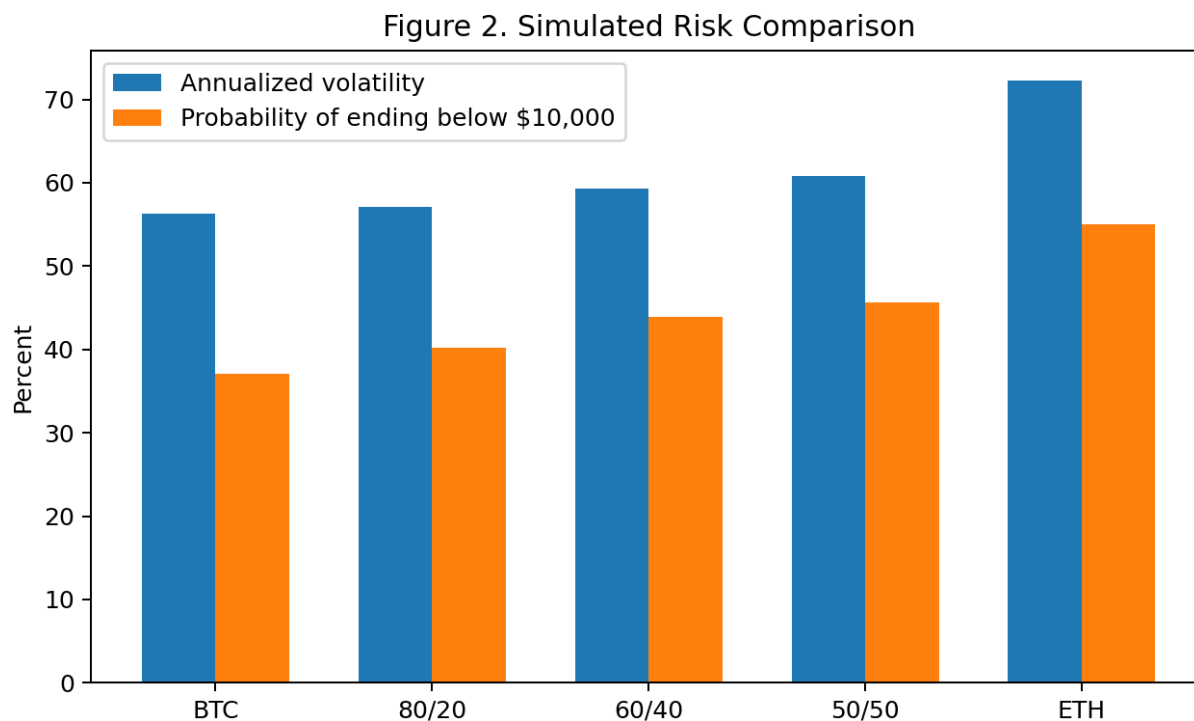
The Bitcoin-only portfolio ended with a mean simulated value of \$14,037 and a median of \$12,022. Its annualized simulated volatility was 56.3%, and 37.1% of the paths finished below the original \$10,000. The 95% VaR was 52.5%, meaning that approximately 5% of simulated one-year outcomes lost more than that amount. The average loss in that worst 5% tail, measured by CVaR, was 61.3%.

Adding a 20% Ethereum allocation did not reduce risk in the model. The 80/20 portfolio had annualized volatility of 57.1% and a 40.3% probability of finishing below \$10,000. With a 40% Ethereum weight, volatility rose further to 59.3% and the probability of loss increased to 43.9%. The 50/50 portfolio followed the same direction, showing that the extra asset did not create enough independent movement to offset Ethereum's higher volatility.

Ethereum-only produced the widest distribution of outcomes. Its mean ending value was \$11,810, but its median was only \$9,102. This gap between the mean and median reflects a distribution in which a smaller number of very strong simulated outcomes pull the average upward. At the same time, 55.0% of Ethereum-only paths ended below the initial investment, and its 95% CVaR reached 79.2%.



Note. The dashed vertical line marks the initial \$10,000 investment. The chart is generated from the simulation outputs reported in Table 2.



Note. Risk rises as more weight is placed in Ethereum under the selected return, volatility, and correlation assumptions.

The results answer the three research questions directly. First, the ending-value distributions are materially different across allocations, with Ethereum creating a wider range of outcomes. Second, adding Ethereum did not reduce volatility in this model; instead, risk rose progressively with the Ethereum weight. Third, the downside measures moved in the same direction: probability of loss, VaR, and CVaR all became less favorable as Ethereum exposure increased. The result is internally consistent with the methodology because the model combines high ETH volatility with a strong positive BTC–ETH correlation.

Discussion and Conclusion:

This study used Monte Carlo simulation to turn a common crypto question into a measurable experiment. Instead of asking which cryptocurrency will “win,” the research asked what can happen to a \$10,000 portfolio across thousands of possible one-year paths and how the risk changes when the allocation shifts between Bitcoin and Ethereum.

Under the assumptions used in the model, Bitcoin-only had the lowest simulated volatility and downside risk. Adding Ethereum increased the spread of possible outcomes and increased the probability of finishing below the initial investment. The 50/50 portfolio therefore did not behave like a lower-risk portfolio simply because it held two assets. This is the most important practical finding of the paper: the number of assets in a portfolio is not the same thing as effective diversification. Correlation and individual asset volatility determine how much risk reduction is actually achieved.

The practical implication is that investors and portfolio managers should test diversification rather than assume it. Simulation is useful here because it makes uncertainty visible. A single expected return can look attractive, while the simulated distribution may reveal a large probability of loss or severe tail outcomes. VaR and CVaR add another layer by showing not only the typical result but also what the bad end of the distribution looks like.

The study also has theoretical value for a simulation course. It shows how random variables, correlation, covariance, repeated trials, compounding, and output distributions can be combined in one finance application. The model is simple enough to reproduce, but still rich enough to show that changing one portfolio weight affects several risk measures at the same time.

There are important limitations. First, the return means, volatilities, and correlation are historical estimates and can change sharply. Second, the baseline simulation uses a multivariate normal return generator even though crypto returns are known to be skewed and heavy-tailed. This can understate the frequency of extreme market moves. Third, volatility is held constant rather than changing through calm and crisis regimes. Fourth, the study includes only Bitcoin and Ethereum and ignores transaction costs, taxes, liquidity differences, staking, and active rebalancing. Finally, the 252-day horizon is used for standardized annualization even though cryptocurrency markets trade every day.

Future research could improve the model by using a Student-t or GARCH-based simulation, adding regime switching, estimating parameters over rolling windows, and comparing crypto with gold, equities, or stable assets. Another useful extension would be to test thousands of portfolio weights and search for an efficient frontier rather than comparing only five allocations. These extensions would make the simulation more realistic while preserving the main lesson of this paper: in a highly uncertain market, a range of possible outcomes is often more informative than one forecast.

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