



Value-at-risk assessment and efficient portfolio structure in cryptocurrencies: An empirical analysis, 2019–2023



Evaluación del Valor en Riesgo (VaR) y estructura eficiente de portafolios de criptomonedas: un análisis empírico, 2019–2023

Andrés Caicedo Carrero¹ Jorge Alexander Cortés Cortés¹
 Wilmar Arnulfo Bravo Murillo¹ Myriam Aydee Moreno Garzón²

¹ Universidad Colegio Mayor de Cundinamarca, Bogotá, Colombia. Email: ocaicedo@universidadmayor.edu.co, jalexandercortes@unicolmayor.edu.co, wbravo@unicolmayor.edu.co

² Corporación Universitaria Minuto de Dios, Bogotá, Colombia. Email: myriam.moreno@uniminuto.edu

Abstract

The aim of this study is to analyze the risk exposure of four cryptocurrencies in order to determine optimal portfolio combinations that mitigate market risk by applying portfolio theory and the parametric Value-at-Risk (VaR) model. The study covered the period from 2019 to 2023 and employed a quantitative and descriptive approach based on the daily logarithmic returns of Bitcoin, Ethereum, Tether, and Binance Coin, obtained from the CoinMarketCap platform. Using these data, the study estimated the correlations among the assets, identified efficient portfolios, and measured the daily risk exposure of each cryptocurrency. The analysis was complemented by an analysis of variance (ANOVA). The results show that Tether dominates the efficient portfolios, with allocations exceeding 90% in most years, owing to its low volatility and weak correlations with the other cryptocurrencies, whereas Bitcoin and Ethereum exhibit high volatility. The VaR analysis revealed average daily values ranging from 5% to 8% for Bitcoin and Ethereum and below 1% for Tether. However, the ANOVA indicated that there were no statistically significant differences in daily risk among the cryptocurrencies. The main conclusion of this study is that the application of VaR and portfolio theory is useful for assessing and comparing risk across digital assets. In addition, stablecoins play a stabilizing role in cryptocurrency portfolio management. These findings contribute to the understanding of financial risk in decentralized markets by providing empirical evidence for the design of efficient investment strategies in volatile environments.

Keywords: Cryptocurrencies; Portfolio Theory; Value-at-Risk; Financial Markets.

Resumen

El objetivo de esta investigación es analizar la exposición al riesgo de cuatro criptomonedas para determinar combinaciones óptimas de portafolio que mitiguen el riesgo de mercado, aplicando la teoría de portafolio y el modelo paramétrico de Valor en Riesgo (VaR). El estudio abarcó el período de 2019

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Corresponding author

Dirección: Calle 28 #5B-02, Bogotá, Cundinamarca. Email: ocaicedo@universidadmayor.edu.co

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a 2023 y empleó un enfoque cuantitativo y descriptivo basado en los rendimientos logarítmicos diarios de Bitcoin, Ethereum, Tether y Binance Coin, obtenidos de la plataforma CoinMarketCap. Utilizando estos datos, el estudio estimó las correlaciones entre los activos, identificó portafolios eficientes y midió la exposición diaria al riesgo de cada criptomoneda. El análisis se complementó con un análisis de varianza. Los resultados muestran que Tether domina los portafolios eficientes, con asignaciones que superan el 90% en la mayoría de los años, debido a su baja volatilidad y a sus débiles correlaciones con las demás criptomonedas, mientras que Bitcoin y Ethereum exhiben una alta volatilidad. El análisis de VaR reveló valores diarios promedio que oscilan entre el 5% y el 8% para Bitcoin y Ethereum, y menos del 1% para Tether. Sin embargo, el ANOVA indicó que no existen diferencias estadísticamente significativas en el riesgo diario entre las criptomonedas. La principal conclusión de este estudio es que la aplicación del VaR y la teoría de portafolio resulta útil para evaluar y comparar el riesgo entre activos digitales. Además, las stablecoins desempeñan un papel estabilizador en la gestión de portafolios de criptomonedas. Estos hallazgos contribuyen a la comprensión del riesgo financiero en los mercados descentralizados, al proporcionar evidencia empírica para el diseño de estrategias de inversión eficientes en entornos volátiles.

Palabras clave: Criptomonedas; Teoría de Portafolio; Valor en Riesgo; Mercados Financieros.

Introduction

Since their emergence, cryptocurrencies have grown to exceed 5,000 assets, characterized by high volatility and pronounced cycles of growth and decline. This has raised regulatory concerns regarding their impact on traditional financial systems and their role in the global economy, as noted by Iyer and Popescu (2023). Although cryptocurrencies are not backed by tangible assets, *stablecoins* (a type of cryptocurrency) offer a more stable alternative by being pegged to fixed assets or algorithmically regulated, thereby facilitating transactions and preserving value (Bank for International Settlements, 2023).

Bitcoin stands out in the cryptocurrency ecosystem for its decentralization, digital scarcity, limited to 21 million units, and the use of blockchain technology to enable secure and transparent transactions. These characteristics underscore its potential to transform the current financial system, as highlighted by Gbadebo et al. (2021).

Ethereum, in turn, has advanced blockchain technology by introducing smart contracts that support decentralized applications, extending the use of blockchain beyond monetary transactions and positioning itself as a key component in the development of decentralized finance (DeFi) and other digital services (Kukacka & Kristoufek, 2023).

As noted by Rosa and Pareschi (2021), Tether, classified as a *stablecoin*, maintains parity with assets such as the U.S. dollar, the euro, and the Japanese yen, serving as a bridge between cryptocurrencies and fiat currencies. This allows it to function both as a medium of exchange and as a store of value within the cryptocurrency market.

Finally, Binance Coin (BNB) was created to optimize payments within the Binance ecosystem by enabling fast and secure transactions. Its value is bolstered by a quarterly token burn mechanism that reduces its circulating supply to counteract inflationary pressures and potentially increase its long-term value (Lu, 2023).

According to Che *et al.* (2023), the “crypto factor” exerts a significant influence on global financial markets and the digital economy; therefore, understanding macroeconomic dynamics is essential for properly evaluating investments in this type of asset. Furthermore, this relationship illustrates how cryptocurrencies amplify volatility in the financial sector, which, according to Iyer and Popescu (2023), underscores the need to monitor these connections in order to maintain financial stability.

Having established how the “crypto factor” reflects the interaction between cryptocurrencies and the global economy, it is necessary to analyze how other external factors influence this market. According to Przyłuska-Schmitt *et al.* (2023), economic crises and geopolitical events increase cryptocurrency volatility, leading to extreme price fluctuations during periods of instability as investors seek alternatives to traditional assets. Accordingly, this research seeks to expand the application of the Value-at-Risk (VaR) model by contextualizing the “crypto factor” in relation to external events, such as economic crises, armed conflicts, and monetary policy changes. In doing so, it helps address the empirical gap regarding how these shocks affect VaR in cryptoassets, consistent with the findings of Aydoğan *et al.* (2025).

At the same time, the growing importance of cryptocurrencies in international transfers, driven by their relatively low transaction costs, is transforming the global financial system while posing regulatory challenges to maintaining macroeconomic stability without constraining innovation, as suggested by Sukomardojo *et al.* (2023).

Given the impact of cryptocurrencies on global financial markets, their rapid growth has prompted companies to examine how incorporating cryptoassets into their operations influences their investment strategies and portfolio risk management (Field & Can Inci, 2023). Accordingly, it is necessary to adapt the financial analysis methodologies traditionally applied in regulated markets to better understand the behavior of cryptocurrencies.

Despite advances in modern portfolio theory and in risk measurement using Value-at-Risk (VaR), their application to the cryptocurrency market remains limited by the high volatility, unstable correlations, and the influence of external events that characterize digital assets. This methodological mismatch creates an empirical gap in the assessment of market risk in cryptoassets, highlighting the need to adapt and validate traditional VaR metrics to the unique characteristics of the cryptocurrency market.

According to Markowitz (1952), the process of constructing an investment portfolio consists of a two-stage methodology. The first stage evaluates all possible asset combinations to identify the efficient portfolios, after which a specific portfolio is selected according to the investor’s risk-return preferences. The second stage

involves diversification. This methodology demonstrates that a diversified portfolio can reduce risk by combining assets with different correlation structures.

However, modern portfolio theory is not without limitations. It relies on assumptions such as market efficiency and rational investor behavior while overlooking practical considerations, including taxes and transaction costs.

On the other hand, the risk and return of an investment portfolio are determined by the interrelationships among its constituent assets and by the weighted average of their returns, unlike the variance and expected return, which are calculated separately for each individual asset, as suggested by Lin *et al.* (2023).

As mentioned earlier, diversification reduces portfolio risk by combining assets with low correlations, allowing gains in some assets to offset losses in others and thereby achieve an optimal balance. This approach minimizes risk without compromising expected returns (Mangram, 2013).

Another factor to consider is that portfolio theory presents challenges in accurately estimating data and managing the risk-return trade-off, requiring substantial time and resources. This limits its accessibility for investors with less capital or experience, thereby restricting its practical applicability in certain contexts, as noted by Subathra and Mohideen (2017).

Thus far, we have examined the fundamentals and limitations of modern portfolio theory, highlighting the importance of strategies such as asset allocation and diversification for mitigating risk in portfolio optimization.

Among the advances in this field are the studies by Aljinović *et al.* (2021) and Holovatiuk (2020), which propose innovative approaches to cryptocurrency portfolio management, emphasizing multicriteria methods, the incorporation of market indices for portfolio optimization, and improvements in performance measures such as the Sharpe ratio.

According to the research conducted by Samimi *et al.* (2022), allocating assets across different categories enables investors to benefit from differences in returns and volatility. Furthermore, diversification reduces the impact of poor performance by individual assets within each category. In this way, investors can better manage various types of market risk, including purchasing power risk, political risk, interest rate risk, exchange rate risk, and unsystematic risk.

Other studies on portfolio optimization that incorporate cryptoassets have shown that including these assets alters the traditional efficient frontier. High volatility, unstable correlations, and abrupt price fluctuations challenge the assumptions of modern portfolio theory proposed by Markowitz (1952), giving rise to nonlinear risk-return relationships that cannot be fully captured by classical models. Consequently, traditional diversification tools need to be complemented with advanced risk measures, such as Value-at-Risk (VaR), which enable the assessment of potential loss exposure in the context of decentralized digital markets.

Having examined portfolio selection, diversification, and asset allocation, it is important to address how risk exposure is quantified. Such an assessment is essential

for implementing effective risk management strategies, leading to the application of Value-at-Risk (VaR).

As explained by Linsmeier and Pearson (2000), Value-at-Risk (VaR) is a statistical measure that estimates the maximum expected loss of a portfolio over a specified time horizon and at a given confidence level under normal market conditions. It is widely used to manage market risk and determine capital reserve requirements. However, it may underestimate risk during extreme market events because it relies on assumptions of normality and has limited ability to predict tail losses. The collapse of FTX in 2022 provides a clear example of these limitations, demonstrating how highly leveraged structures and a lack of transparency can trigger abrupt market collapses in speculative environments (Naifar & Makni, 2025).

The Value-at-Risk (VaR) technique is complemented by methodologies such as stress testing and extreme value theory. Together, these approaches provide a more comprehensive view of risk by enabling financial managers to evaluate both probable scenarios and tail events that, although less frequent, can have a significant impact on portfolio performance (Kupiec, 2002). In this regard, as documented by Stulz (2023), effective risk management requires continuous model calibration to ensure that risk models accurately reflect changing market conditions and anticipate potential crises.

Market capitalization is another important factor to consider when estimating VaR, as differences in firm size influence variations in risk profiles. The relevance of market capitalization for risk measurement lies in its effect on the volatility of financial asset prices (Días, 2013).

By incorporating market capitalization into the analysis, VaR has become a key tool for measuring market risk because it provides a quantitative and intuitive framework for risk assessment. By estimating the maximum expected loss under specified conditions, it enables financial institutions to establish exposure limits and make proactive adjustments, as suggested by Gaytán Cortés (2022).

According to Manganelli and Engle (2001), VaR is particularly valuable because of its flexibility, as it can be implemented through parametric, nonparametric, and semiparametric models. This versatility makes it possible to address the diversity and complexity of risk profiles in financial markets. These approaches, ranging from models based on statistical assumptions to those relying on historical data, as well as hybrid methodologies that combine both, facilitate accurate and adaptive risk assessment.

Based on a systematic review of the literature, several approaches to cryptocurrency risk analysis and its integration into investment portfolios were identified. The studies reviewed reveal a progressive shift from traditional volatility-based approaches toward more sophisticated quantitative models that incorporate Value-at-Risk (VaR), Extreme Value Theory (EVT), GARCH models, and machine learning techniques. To highlight the prevailing trends and identify existing research gaps, Table 1 summarizes the principal theoretical and empirical contributions, organized

according to their methodological approach and their contribution to understanding risk within the cryptocurrency ecosystem.

Table 1. Literature Review on Risk and Diversification in Cryptocurrencies

Author(s) and year	Study objective	Methodology used	Main findings	Limitations / Identified gaps	Thematic classification
Naifar and Makni (2025)	Analyze the impact of the FTX collapse on risk estimation.	EVT and Monte Carlo simulation.	Extreme events invalidate the normal assumptions of VaR.	Need to reformulate crypto risk metrics.	Systemic risk and extreme events.
Iyer and Popescu (2023)	Analyzing crypto market volatility and its impact on global financial stability.	GARCH models and dynamic connectivity.	The “crypto factor” amplifies traditional financial cycles.	Does not address quantitative risk estimation using VaR.	Systemic volatility and macrofinancial stability.
Kukacka and Kristoufek (2023)	Examining the effect of smart contracts (Ethereum) on financial flows.	VAR models and Granger causality.	Ethereum increases exposure to systemic risk.	It does not quantitatively assess extreme risk.	DeFi Technology and Volatility.
Che et al. (2023)	Assessing the influence of the “crypto factor” on global markets.	Connectivity networks and cointegration analysis.	Confirms the transmission of shocks between cryptocurrencies and financial assets.	Risk analysis under extreme conditions is lacking.	Systemic risk and contagion.
Przyłuska-Schmitt et al. (2023)	Analyze how crises and geopolitical events affect crypto volatility.	Structural VAR and event analysis.	Crises and conflicts increase volatility and correlation among assets.	They do not incorporate quantitative metrics for expected loss.	Macroeconomic factors and volatility.
Field and Can Inci (2023)	Study the integration of cryptoassets into corporate investment strategies.	Monte Carlo simulation and mean-variance optimization.	Incorporating cryptoassets increases expected return but raises risk.	It requires robust measurement of tail risk.	Portfolio and risk management.
Samimi et al. (2022)	Analyzing asset allocation with cryptocurrencies.	Global minimum variance models.	Diversification with cryptoassets improves risk-adjusted performance.	Analysis under high-volatility events is lacking.	Modern portfolio theory.
Gbadebo et al. (2021)	Evaluating Bitcoin’s decentralization and its role in portfolio diversification.	Correlation and variance analysis.	Bitcoin improves diversification over short-term horizons.	It does not consider other cryptoassets or crisis scenarios.	Portfolio and diversification.
Aljinović et al. (2021)	Applying multi-criteria indices and methods to cryptocurrency portfolios.	Composite indices and DEA optimization.	They improve the efficiency of crypto portfolios.	Empirical validation of extreme risk is lacking.	Optimization of crypto portfolios.

Table 1 continues on next page

Literature Review on Risk and Diversification in Cryptocurrencies (Cont.)

Author(s) and year	Study objective	Methodology used	Main findings	Limitations / Identified gaps	Thematic classification
Kupiec (2002)	Supplementing VaR with stress testing and extreme value theory.	Backtesting and EVT.	Improves the predictive power of VaR.	Not applied to cryptoassets in recent studies.	Extreme risk and financial stress.
Manganelli and Engle (2001)	Proposes parametric and nonparametric VaR models.	ARCH/GARCH and backtesting.	Flexibility to adapt to different risk profiles.	Not yet applied to cryptocurrencies in their original form.	Financial risk models.
Linsmeier & Pearson (2000)	Introducing VaR as a technique for measuring market risk.	Parametric models.	VaR allows for the quantification of expected losses under normal conditions.	Assumes a normal distribution; fails under extreme events.	Traditional risk methodology.

As shown in the literature, research converges around three main lines of analysis: (i) volatility transmission and financial contagion between cryptocurrencies and traditional financial assets; (ii) the integration of cryptoassets into investment portfolios within the framework of modern portfolio theory; and (iii) the application of advanced risk measures, such as Value-at-Risk (VaR), to quantify expected losses under conditions of high uncertainty.

However, a theoretical gap remains regarding the ability of traditional VaR models to capture the extreme price behavior and unstable correlations that characterize digital asset markets. In this context, the present study contributes to the literature by proposing an empirical approach that adapts VaR to the specific characteristics of the cryptocurrency market, integrating market risk measurement with the principles of diversification and asset allocation in a decentralized financial environment.

Methodology

This study adopts a quantitative approach with a descriptive research design to evaluate the daily logarithmic returns of cryptocurrencies. Based on these returns, the corresponding correlation matrices and the constraints of modern portfolio theory, efficient portfolios were estimated for each year within the observation period from 2019 to 2023. Once the optimal portfolio composition had been identified, the risk exposure of each cryptocurrency was calculated using the Value-at-Risk (VaR) model. Finally, an analysis of variance (ANOVA) was conducted to determine whether there is statistical evidence that the risk exposure differs significantly among the cryptocurrencies analyzed.

This research was based on the daily prices of Bitcoin, Ethereum, Tether, and Binance Coin from January 1, 2019, through December 31, 2023, obtained

from the CoinMarketCap platform (CoinMarketCap, 2024). The selection of these cryptocurrencies was based primarily on their market relevance. During the study period, each maintained a market capitalization exceeding USD 10 million, demonstrating its significant presence within the cryptocurrency ecosystem.

Second, the selection was based on the functional and economic diversity represented by these cryptoassets. Bitcoin serves primarily as a speculative asset and a digital store of value (Fidelity Digital Assets, 2024); Ethereum functions as a blockchain platform that supports smart contracts and decentralized applications (Azar et al., 2022); Tether is a stablecoin pegged to the U.S. dollar, designed to preserve value and reduce volatility (Lyons & Viswanath-Natraj, 2023); and Binance Coin functions as a utility token used for transactions and fee discounts within the Binance exchange ecosystem (Brynjarsson & Ágústs dóttir, 2022).

This combination of criteria (market relevance and functional heterogeneity) makes it possible to capture different risk profiles and financial behaviors, thereby enriching the comparative analysis of returns, correlations, and risk exposure in the construction of efficient portfolios.

The analysis period, spanning from 2019 to 2023, was selected for reasons of methodological and financial relevance. In quantitative studies on asset risk and return, a five-year window is widely accepted, as it offers a balance between statistical sufficiency and the temporal relevance of the data (Agrawal et al., 2022). This time horizon makes it possible to capture different market volatility cycles, including expansionary and contractionary phases, without compromising the representativeness of recent conditions in the cryptocurrency ecosystem.

Regarding the selection of variables, the study focused on daily logarithmic returns, variance, correlations, and Value-at-Risk (VaR). These variables are necessary for the development of portfolio theory, as they describe asset behavior in terms of return and risk. Logarithmic returns were used because of their additive property, which facilitates time-series analysis and avoids distortions in the price scale (Forero Laverde, 2011). Variance and covariance make it possible to estimate risk dispersion and the relationships among assets, while VaR quantifies the maximum expected loss at a given confidence level. Together, these variables make it possible to measure the efficiency and risk exposure of each cryptocurrency without attempting to model its predictive behavior.

The applied model is based on the classical variance-minimization approach proposed by Markowitz (1952), developed using nonlinear programming in accordance with Gálvez et al. (2010). This approach enables the identification of efficient portfolios under return and asset allocation constraints and subsequently evaluates risk using the parametric Value-at-Risk (VaR) methodology. The choice of this model stems from its ability to represent, in a parsimonious and quantitative manner, the relationship between risk and return, without introducing additional assumptions typical of predictive or advanced econometric models.

Microsoft Excel (Version 2023) was used for data processing. This software enables the efficient manipulation of financial time series and the implementation of optimization models through its built-in Solver and statistical analysis functions. Because the purpose of this research is not to develop a predictive model or estimate econometric parameters, no tests for heteroscedasticity, autocorrelation, or normality were performed. These tests are appropriate for explanatory or inferential statistical models but are not required in studies whose primary objective is the descriptive and comparative evaluation of risk and return under predefined structural assumptions.

Following data collection, the daily returns of the four cryptocurrencies were calculated using logarithmic returns. This approach was selected because it is widely used in financial time-series analysis and takes advantage of the additive property of logarithmic returns (Forero Laverde, 2011). Accordingly, Equation 1 is defined as follows:

$$r_{ty} = \ln \left(\frac{P_{ty}}{P_{t-1y}} \right) \quad [1]$$

Where:

r_{ty} = Daily return of the cryptocurrency .

P_{ty} = Current price of the cryptocurrency .

P_{t-1y} = Previous day's price of the cryptocurrency .

After determining the daily returns of the cryptocurrencies, the correlations among them over the years are examined to identify the degree of linear relationship between each pair of cryptocurrencies (See Equation 2).

$$M_{ct} = \begin{pmatrix} 1 & m_{12}(V_{1t}, V_{2t}) & m_{13}(V_{1t}, V_{3t}) & m_{14}(V_{1t}, V_{4t}) \\ m_{21}(V_{2t}, V_{1t}) & 1 & m_{23}(V_{2t}, V_{3t}) & m_{24}(V_{2t}, V_{4t}) \\ m_{31}(V_{3t}, V_{1t}) & m_{32}(V_{3t}, V_{2t}) & 1 & m_{34}(V_{3t}, V_{4t}) \\ m_{41}(V_{4t}, V_{1t}) & m_{42}(V_{4t}, V_{2t}) & m_{43}(V_{4t}, V_{3t}) & 1 \end{pmatrix} \quad [2]$$

Where:

M_{ct} = Correlation matrix for the year t

V_{1t} = Vector of Bitcoin returns for the year t

V_{2t} = Vector of Ethereum returns for the year t

V_{3t} = Vector of Tether returns for the year t

V_{4t} = Vector of Binance returns for the year t

Once the correlations have been estimated, the next step is to construct the efficient portfolios for each year. One approach to identifying an efficient portfolio is to apply a model that focuses exclusively on minimizing portfolio variance.

This model is based on a nonlinear programming framework, as described by Gálvez *et al.* (2010). Accordingly, the optimization model presented in Equation 3 is applied, subject to the constraints specified in Equations 4, 5, and 6:

$$\text{Min } \sigma^2(R_p) = \sum_{i=1}^N \sum_{j=1}^N x_i x_j \sigma_{ij} \quad [3]$$

Subject to:

$$\sum_{i=1}^N \bar{R}_i x_i = R \quad [4]$$

$$\sum_{i=1}^N x_i = 1 \quad [5]$$

$$x_i > 0 \quad [6]$$

After solving the optimization problem using nonlinear programming techniques, the proportion of each asset in the investment portfolio that satisfies the model's constraints can be determined, thereby identifying the efficient portfolio for each year of the analysis.

Following the estimation of the efficient portfolios, and assuming that returns are normally distributed with a mean of zero (De Lara Haro, 2008), the parametric Value-at-Risk (VaR) model used in this study to estimate the risk exposure of each cryptocurrency is defined by Equation 7:

$$\text{VaR}_t = F * S_t * \sigma_{t-20} * \sqrt{t} \quad [7]$$

VaR_t = Cryptocurrency exposure at time

F = The value that determines the confidence level¹

S = Value of the cryptocurrency at the moment

σ_{t-20} = Standard deviation of returns at the current time

$\sqrt{t}$ = Number of days for which risk exposure is to be estimated²

Results and Discussion

The results of the study begin with an analysis of the mean, standard deviation, and coefficient of variation of the daily returns for each cryptocurrency. This is followed by an analysis of the correlations among the cryptocurrencies and the estimation of efficient portfolios for each year. The results section then presents the analysis of risk exposure and concludes with an analysis of variance (ANOVA).

¹ For the purposes of this research, exposure to each cryptocurrency is calculated with a 95% confidence level.

² Since the focus of this study is to calculate daily exposure, $t=1$.

According to Vargas (2007), the dispersion of observations can be evaluated using the criteria presented in Table 2.

Table 2. Criteria for Analyzing Data Dispersion

Result	Interpretation
If $CV \leq 0.3\bar{x}$	The dataset is homogeneous relative to the mean.
If $0.3\bar{x} < CV \leq 0.7\bar{x}$	The data set is variable relative to the mean.
If $CV > 0.7\bar{x}$	The data set is highly variable relative to the mean.

Based on these criteria, this study analyzes the dispersion of cryptocurrency returns and risk exposure. The results for the mean daily return and the dispersion of daily returns for each cryptocurrency, by year, are presented in Table 3.

Table 3. Mean Daily Return and Standard Deviation of Daily Returns for Bitcoin, Ethereum, Tether, and Binance Coin, 2019 – 2023

Year	Metric	Bitcoin	Ethereum	Tether	Binance
2019	Average Daily Return	0.17220%	-0.02279%	-0.00508%	0.22395%
	Standard Deviation	3.53547%	4.13504%	0.39592%	4.29785%
	Coefficient of Variation	2,053.1%	18,147.1%	7,794.2%	1,919.1%
	Interpretation	Very heterogeneous	Very heterogeneous	Very heterogeneous	Very heterogeneous
2020	Average Daily Return	0.3809%	0.4752%	0.0003%	0.2737%
	Standard Deviation	4.0073%	5.2343%	0.5567%	5.0922%
	Coefficient of Variation	1,052.0%	1,101.6%	221,742.2%	1,860.7%
	Interpretation	Very heterogeneous	Very heterogeneous	Very heterogeneous	Very heterogeneous
2021	Average Daily Return	0.12820%	0.44047%	-0.00011%	0.71691%
	Standard Deviation	4.20427%	5.61558%	0.10291%	7.31058%
	Coefficient of Variation	3,279.5%	1,274.9%	92,012.1%	1,019.7%
	Interpretation	Very heterogeneous	Very heterogeneous	Very heterogeneous	Very heterogeneous
2022	Average Daily Return	-0.28193%	-0.30795%	-0.00014%	-0.20028%
	Standard Deviation	3.35945%	4.56692%	0.02743%	3.85505%
	Coefficient of Variation	1,191.6%	1,483.0%	19,430.7%	1,924.9%
	Interpretation	Very heterogeneous	Very heterogeneous	Very heterogeneous	Very heterogeneous
2023	Average Daily Return	0.25691%	0.17677%	0.00001%	0.06511%
	Standard Deviation	2.26524%	2.42765%	0.04590%	2.34219%
	Coefficient of Variation	881.7%	1,373.4%	641,312.4%	3,597.1%
	Interpretation	Very heterogeneous	Very heterogeneous	Very heterogeneous	Very heterogeneous

From 2019 to 2023, Bitcoin, Ethereum, and Binance Coin exhibited substantial fluctuations in their returns, characterized by high volatility that reflects the speculative nature and sensitivity of the cryptocurrency market. Periods of positive returns alternated with episodes of negative corrections. The mean daily returns and their corresponding standard deviations reveal patterns consistent with the findings of Iyer and Popescu (2023), who highlight the cryptocurrency market's sensitivity to economic shocks and changes in global liquidity.

The finding that all cryptocurrencies exhibit coefficients of variation exceeding 70% confirms that their daily returns are highly heterogeneous. This result is consistent with the studies by Kukacka and Kristoufek (2023), who argue that cryptocurrencies display nonstationary and highly volatile behavior due to their decentralized structure and their responsiveness to global events. These findings demonstrate that high volatility is an inherent characteristic of the cryptocurrency market, making price forecasting more difficult and increasing risk relative to traditional financial assets.

The results of the correlation analysis among the cryptocurrencies for each year of the study period are presented in Table 4.

Table 4. Correlations Among Bitcoin, Ethereum, Tether, and Binance Coin, 2019 – 2023

Year	Cryptocurrency	Bitcoin	Ethereum	Tether	Binance
2019	Bitcoin	1.00	0.83	0.32	0.58
	Ethereum	0.83	1.00	0.25	0.65
	Tether	0.32	0.25	1.00	0.16
	Binance	0.58	0.65	0.16	1.00
2020	Bitcoin	1.00	0.86	-0.35	0.80
	Ethereum	0.86	1.00	-0.36	0.84
	Tether	-0.35	-0.36	1.00	-0.35
	Binance	0.80	0.84	-0.35	1.00
2021	Bitcoin	1.00	0.78	-0.02	0.63
	Ethereum	0.78	1.00	-0.02	0.65
	Tether	-0.02	-0.02	1.00	0.02
	Binance	0.63	0.65	0.02	1.00
2022	Bitcoin	1.00	0.90	0.27	0.83
	Ethereum	0.90	1.00	0.26	0.84
	Tether	0.27	0.26	1.00	0.34
	Binance	0.83	0.84	0.34	1.00
2023	Bitcoin	1.00	0.83	-0.03	0.63
	Ethereum	0.83	1.00	0.02	0.64
	Tether	-0.03	0.02	1.00	-0.08
	Binance	0.63	0.64	-0.08	1.00

Between 2019 and 2023, Ethereum and Bitcoin maintained a strong positive correlation (0.78 – 0.90), indicating similar price movements and, consequently, limited diversification benefits when both assets are included in the same portfolio. This finding is consistent with the results reported by Field and Can Inci (2023), who argue that the high correlation among major cryptoassets reduces the effectiveness of diversification strategies.

In contrast, Tether exhibited low or negative correlations with both Bitcoin and Ethereum, confirming its role as a hedging asset and a liquidity safe haven during periods of market turbulence, consistent with the findings of Rosa and Pareschi (2021). These authors emphasize that stablecoins, because they are backed by fiat assets, help mitigate market volatility and preserve value during periods of abrupt price fluctuations.

Furthermore, the correlations varied from year to year, reflecting changes in the interdependence of these assets in response to global economic shocks. This finding is consistent with Che et al. (2023), who demonstrated that the degree of connectivity between cryptocurrencies and traditional financial markets strengthens or weakens depending on the macroeconomic environment. Accordingly, these results suggest that investors should periodically adjust their portfolio strategies, as correlations among cryptocurrencies are dynamic and do not guarantee sustained diversification over time. The efficient portfolios constructed for each year are presented in Table 5.

Table 5. Efficient Portfolios for Bitcoin, Ethereum, Tether, and Binance Coin, 2019 – 2023

Cryptocurrency	Efficient Portfolio 2019	Efficient Portfolio 2020	Efficient Portfolio 2021	Efficient Portfolio 2022	Efficient Portfolio 2023
Bitcoin	0.00%	3.32%	0.09%	0.00%	0.00%
Ethereum	0.00%	1.04%	0.02%	0.00%	0.00%
Tether	98.34%	94.14%	99.89%	100.00%	99.80%
Binance	1.66%	1.50%	0.00%	0.00%	0.20%
Total	100.00%	100.00%	100.00%	100.00%	100.00%

From 2019 to 2023, Tether dominated the composition of the optimal portfolios, with allocations close to or equal to 100% in every year due to its low volatility and weak correlations with the other assets. This finding is consistent with the results reported by Samimi et al. (2022), who argue that the most stable portfolios are those composed of assets with low variance and weak correlations. The predominance of Tether suggests that it plays a structural role as a stabilizing asset within the cryptocurrency ecosystem.

The limited allocation to Bitcoin and Ethereum in certain years reflects a constrained pursuit of higher returns, as their high volatility reduces their weight along the efficient frontier. This pattern is consistent with the findings of Aljinović et al.

(2021) and Holovatiuk (2020), who concluded that highly volatile digital assets are included in efficient portfolios only in relatively small proportions.

At this point, it is important to clarify that correlations are not used to compare the results of efficient portfolios or Value-at-Risk (VaR). Rather, within the Markowitz (1952) model, correlations play a structural role by serving as inputs for estimating the covariance matrix of the assets; they do not constitute measures of portfolio performance or risk exposure. Consequently, metrics such as VaR and portfolio variance are the appropriate measures for comparing investment scenarios and evaluating portfolio efficiency. This methodological distinction is consistent with the approach proposed by Gálvez et al. (2010), who argue that comparing correlations has no analytical validity when evaluating optimal portfolios.

The predominance of Tether in the efficient portfolios further supports its role as a stabilizing asset within the cryptocurrency market. However, this finding should be interpreted within its specific regulatory context. Under the European Union's Markets in Crypto-Assets (MiCA) Regulation (Regulation (EU) 2023/1114), *stablecoin* issuers are subject to new regulatory requirements. Tether has indicated that it will not fully comply with these requirements, which could limit the availability of its token on European cryptocurrency exchanges (Ante et al., 2025). Consequently, the practical applicability of these findings within jurisdictions governed by the European Union should be interpreted with caution.

The results for the mean daily Value-at-Risk (VaR) and the corresponding standard deviation for each cryptocurrency, by year, are presented in Table 6.

Table 6. Mean Daily Value-at-Risk (VaR) and Standard Deviation for Bitcoin, Ethereum, Tether, and Binance Coin, 2019 – 2023

Year	Metric	Bitcoin	Ethereum	Tether	Binance
2019	VaR. Daily Average	5.36%	6.42%	0.62%	6.86%
	Standard Deviation	2.35%	2.03%	0.21%	1.51%
	Coefficient of Variation	43.9%	31.6%	33.7%	22.1%
	Interpretation	Heterogeneous	Heterogeneous	Heterogeneous	Homogeneous
2020	VaR. Daily Average	5.43%	7.40%	0.64%	7.03%
	Standard Deviation	3.70%	4.33%	0.70%	4.54%
	Coefficient of Variation	68.2%	58.5%	109.1%	64.6%
	Interpretation	Heterogeneous	Heterogeneous	Very heterogeneous	Heterogeneous
2021	VaR. Daily Average	6.67%	8.69%	0.13%	10.32%
	Standard Deviation	1.79%	3.26%	0.12%	5.92%
	Coefficient of Variation	26.8%	37.5%	93.0%	57.4%
	Interpretation	Homogeneous	Heterogeneous	Very heterogeneous	Heterogeneous

Table 6 continues on next page

Mean Daily Value-at-Risk (VaR) and Standard Deviation for Bitcoin, Ethereum, Tether, and Binance Coin, 2019 – 2023 (Cont.)

Year	Metric	Bitcoin	Ethereum	Tether	Binance
2022	VaR. Daily Average	5.25%	7.13%	0.03%	5.95%
	Standard Deviation	1.89%	2.40%	0.04%	2.30%
	Coefficient of Variation	36.0%	33.6%	116.2%	38.6%
	Interpretation	Heterogeneous	Heterogeneous	Very heterogeneous	Heterogeneous
2023	VaR. Daily Average	3.51%	3.83%	0.06%	3.51%
	Standard Deviation	1.15%	1.12%	0.05%	1.27%
	Coefficient of Variation	32.7%	29.3%	93.6%	36.3%
	Interpretation	Heterogeneous	Heterogeneous	Very heterogeneous	Heterogeneous

Bitcoin and Ethereum exhibited variations in their Value-at-Risk (VaR) throughout the study period, with average daily values ranging from 5% to 8%, reflecting their high-risk exposure and speculative nature. In contrast, Tether consistently recorded VaR values below 1%, confirming its stabilizing role within cryptocurrency portfolios, consistent with the findings of Rosa and Pareschi (2021).

These results are consistent with the conclusions of Linsmeier and Pearson (2000) and Manganelli and Engle (2001), who demonstrated that VaR is an effective tool for quantifying the maximum expected loss and assessing risk exposure under normal market conditions. Furthermore, the higher VaR observed for Bitcoin and Ethereum during 2020 and 2022 is consistent with the findings of Che et al. (2023), who reported that cryptocurrency volatility intensifies during periods of financial crises and major global events.

Tether's lower VaR and its predominance in the efficient portfolios indicate that *stablecoins* play a fundamental role in reducing systemic risk, whereas the greater variability observed for Bitcoin and Ethereum explains their limited allocation along the efficient frontier. Collectively, these findings suggest that, under conditions of high uncertainty, the cryptocurrency market favors portfolio stability over the pursuit of higher returns.

To determine whether the differences in the mean daily Value-at-Risk (VaR) among Bitcoin, Ethereum, Tether, and Binance Coin were statistically significant during the 2019–2023 period, a hypothesis test was conducted. The analysis evaluated the observed variation in VaR across the four cryptocurrencies, taking into account the pronounced volatility of Bitcoin and Ethereum, the relative stability of Tether, and the moderate variability of Binance Coin, in order to determine whether their risk profiles differed significantly.

H_0 = The mean daily Value-at-Risk (VaR) of the four cryptocurrencies during the 2019–2023 period does not differ significantly.

H_1 = The mean daily Value-at-Risk (VaR) of the four cryptocurrencies during the 2019–2023 period differs significantly.

To test these hypotheses, a one-way analysis of variance (ANOVA) was performed at a significance level of 5% ($\alpha = 0.05$), using the F-distribution. Accordingly, the alternative hypothesis is accepted if the calculated F-statistic exceeds the critical F-value. Table 7 presents the descriptive statistics for the Value-at-Risk (VaR), and Table 8 reports the results of the analysis of variance (ANOVA).

Table 7. Summary of Descriptive Statistics for Cryptocurrency Value-at-Risk (VaR), 2019 – 2023

Groups	Account	Sum	Average	Variance
Daily Bitcoin VaR	1,807	2.4123	0.1335%	0.1265%
Daily Ethereum VaR	1,807	2.7759	0.1536%	0.2075%
Daily VaR for Tether	1,807	-0.0180	-0.0010%	0.0010%
Daily VaR for Binance	1,807	3.7269	0.2062%	0.2377%

The mean daily Value-at-Risk (VaR) values indicate some variation among the cryptocurrencies, with Binance Coin exhibiting the highest mean daily VaR (0.2062%) and Tether the lowest (-0.0010%). These results suggest differences in the level of risk associated with each cryptocurrency. However, whether these differences are statistically significant is determined through the F-test in the analysis of variance (ANOVA) presented in Table 8.

Table 8. Analysis of Variance (ANOVA) for Cryptocurrency Value-at-Risk (VaR), 2019 – 2023.

Source of Variations	Sum of Squares	Degrees of freedom	Mean of Squares	F	Probability	Critical value for F
Between groups	0.0042	3	0.0014	0.9825	0.3999	2.6061
Within the groups	10.3428	7,224	0.0014			
Total	10.3470	7,227				

The results indicate an F-statistic of 0.9825, which is lower than the critical F-value of 2.6061. Therefore, the null hypothesis cannot be rejected. Consequently, there is no statistically significant difference in the mean daily Value-at-Risk (VaR) among the cryptocurrencies analyzed. This finding is consistent with the results reported by Samimi et al. (2022), who observed that, although cryptocurrencies exhibit different levels of volatility, they tend to display similar average risk profiles during

periods of financial integration. These results suggest that, despite their individual characteristics, the cryptocurrency market behaves as an interconnected system in which global shocks are rapidly transmitted across assets.

Conclusions

Since their emergence, cryptocurrencies have evolved rapidly, characterized by high volatility, continuous technological innovation, and an increasing influence on global financial systems. In this context, the present research contributes to the understanding of how modern portfolio theory and Value-at-Risk (VaR) can be applied to the analysis of digital assets, providing a quantitative framework for evaluating their risk and return under real market conditions.

The study demonstrates that the structural volatility of the cryptocurrency market requires more dynamic diversification and risk management strategies than those employed in traditional financial markets. The empirical findings reveal that, during the 2019–2023 period, cryptocurrencies exhibited variable returns and unstable correlations, supporting the arguments advanced by Iyer and Popescu (2023) and Che et al. (2023) regarding the need for continuous monitoring of the interconnections between cryptoassets and global financial markets to safeguard financial stability.

The cryptocurrencies analyzed possess distinct economic functions and characteristics. Bitcoin serves primarily as a speculative asset and a digital store of value; Ethereum functions as a platform for smart contracts and decentralized finance (DeFi) applications; Tether operates as a U.S. dollar-pegged stablecoin designed to preserve value; and Binance Coin functions as a utility token within the Binance exchange ecosystem. This diversity demonstrates that, although these assets are analyzed within the same portfolio framework, their risk profiles, liquidity characteristics, and economic purposes are heterogeneous, thereby explaining the observed differences in their volatility and in the composition of the efficient portfolios.

From a practical perspective, the findings indicate that Tether, owing to its low volatility and weak correlations with the other assets, acts as a stabilizing component within efficient portfolios, reducing overall risk exposure without entirely eliminating the potential for moderate returns. In contrast, Bitcoin and Ethereum offer greater return potential but at the cost of substantially higher risk exposure, making their inclusion appropriate only in limited proportions. These findings confirm the conclusions of Rosa and Pareschi (2021) regarding the role of *stablecoins* as instruments for preserving value and those of Samimi et al. (2022) concerning the contribution of diversification to mitigating market risk.

The Value-at-Risk (VaR) analysis proved to be an appropriate tool for quantifying potential losses and establishing exposure limits in highly volatile environments. The ANOVA results indicate that, although the cryptocurrencies exhibit different levels of risk, there are no statistically significant differences in their mean daily Value-at-Risk (VaR), suggesting a convergence in the average risk profiles of the major cryptoassets. This finding provides empirical evidence for the debate on risk homogeneity in decentralized markets and supports the conclusions of Linsmeier and Pearson (2000) regarding the applicability of VaR in nonlinear market environments.

The findings of this study provide practical insights for investors, financial managers, and cryptocurrency market analysts. The combined application of modern portfolio theory and Value-at-Risk (VaR) facilitates the construction of portfolios that balance risk and return while accounting for the high volatility of the digital asset ecosystem. In particular, the empirical evidence indicates that *stablecoins*, such as Tether, play a significant role in enhancing portfolio stability, whereas assets such as Bitcoin and Ethereum should be incorporated selectively to capture return opportunities while managing risk exposure. These findings have practical implications for both institutional portfolio management and decision-making within fintech companies seeking to optimize their exposure to cryptocurrency market risk.

This study is limited to a sample of four large-cap cryptocurrencies (Bitcoin, Ethereum, Tether, and Binance Coin) and a five-year observation period (2019–2023), selected to balance statistical adequacy with contemporary market relevance. Although this approach provides a representative view of recent market dynamics, it may not capture longer-term structural trends. In addition, the study employed a parametric Value-at-Risk (VaR) model under the assumption of normally distributed returns. Tests for heteroscedasticity and autocorrelation were not performed because the objective of the research was to evaluate risk exposure rather than to develop predictive models of cryptocurrency price behavior.

Future research should expand the sample of assets to include emerging cryptocurrencies and decentralized finance (DeFi) tokens, as well as explore nonparametric and semiparametric Value-at-Risk (VaR) methodologies capable of more accurately capturing extreme events and fat-tailed distributions. It is also recommended that future studies incorporate macroeconomic and geopolitical variables to examine their influence on cryptocurrency market volatility and compare the findings with those for traditional financial assets in order to identify potential channels of contagion and opportunities for intermarket hedging. Finally, the integration of dynamic correlation models and machine learning techniques may provide a more comprehensive understanding of the evolution of risk and portfolio efficiency over time within digital asset markets.

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Ethical Implications

The research was conducted exclusively using publicly available information and did not involve human participants, the collection of personal data, or the use of confidential information or information requiring authorization. Therefore, neither informed consent nor review or approval by an ethics committee was required.

Conflict of Interest Statement

The authors declare that they have no conflicts of interest related to the research, writing, or publication of this article. They further declare that they do not hold cryptocurrency investments that could affect the interpretation of the results, have no employment or financial relationships with cryptocurrency platforms, companies, or intermediaries, and received no payments or benefits from organizations related to the subject matter of the study.

Author Contribution

- **Andrés Caicedo Carrero:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Data curation and Writing – original draft.
- **Jorge Alexander Cortés Cortés:** Writing – review & editing and Project administration.
- **Wilmar Arnulfo Bravo Murillo:** Writing – review & editing.
- **Myriam Aydee Moreno Garzón:** Writing – review & editing.

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Artificial Intelligence Use Statement

During the research process, ChatGPT was used solely as a support tool for translating some of the sources consulted. Artificial intelligence was not used to generate the manuscript's content, analyze the data, formulate the results or conclusions, or translate the final version of the article. The final English translation was completed by an official translator accredited by the Ministry of Foreign Affairs of Colombia. The authors reviewed the article's content and assumed full responsibility for its final version.

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