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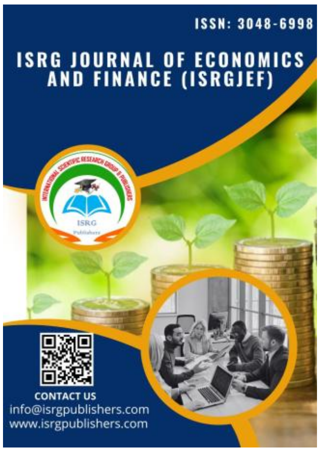

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Risk and Return Dynamics of Bitcoin and Conventional Currencies in Portfolio Diversification

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Abstract

Industry 4.0 and digital transformation have accelerated the emergence of virtual assets such as cryptocurrencies. Among them, Bitcoin, a virtual currency, has captured significant attention from both finance theorists and practitioners, achieving the highest market capitalization to date.

The objective of this study is to examine the behavior and interrelationships between Bitcoin and several traditional financial assets within the framework of an international diversification strategy that combines conventional and crypto assets. In this context, Bitcoin is considered as a potential new asset class for portfolio diversification.

To explore this relationship, we analyze the links between Bitcoin and a selection of major currencies—EUR, GBP, and JPY—as well as certain commodities. The study employs the Value at Risk (VaR) approach using three empirical methods, complemented by Conditional Value at Risk (CVaR) as a robustness measure, given its ability to capture tail risk more effectively than VaR.

Using daily data from October 29, 2016, to October 23, 2020, the findings reveal that including Bitcoin in a diversified portfolio can significantly enhance risk–return characteristics. These results provide new insights for portfolio managers and investors seeking optimal diversification strategies in the context of digital finance.

Keywords: Diversification, VaR, CVaR, bitcoin,EUR, GBP, JPY

1. Introduction

Over the past few years, the literature on cryptocurrencies has expanded significantly, addressing topics such as their relationship with market efficiency (Sensoy, 2019; Vidal-Tomas and Ibanez, 2018; Brauneis and Mestel, 2018; Urquhart, 2016), volatility dynamics (Rehman and Apergis, 2019), speculative behavior (Cheah and Fry, 2015), and return transmission mechanisms (Koutmos, 2018). The rise of Bitcoin, in particular, occurred during one of the most turbulent financial periods—following the 2008–2009 global financial crisis—when investors were seeking new asset classes with hedging and safe-haven properties.

Within the framework of modern portfolio theory, investors aim to construct efficient portfolios by combining uncorrelated assets to maximize returns for a given level of risk. Traditionally, alternative assets such as gold, oil, hedge funds, and art have served this purpose. However, the emergence of Bitcoin has introduced a distinctive and highly volatile digital asset that challenges conventional risk management approaches and offers new diversification opportunities.

Bitcoin's unique characteristics—high volatility, speculative behavior, and relatively low correlation with traditional financial assets—make it an ideal candidate for empirical risk assessment through advanced measurement tools. One such tool is Value-at-Risk (VaR), a statistical measure that estimates the maximum potential loss of a portfolio or asset over a specific time horizon and at a given confidence level. Developed and popularized by J.P. Morgan in the 1990s, VaR has since become a global standard in financial risk management, adopted by banks, investment funds, and regulatory institutions.

In practical terms, VaR provides investors with a probabilistic estimation of potential losses under normal market conditions. It can be computed using several approaches, including the historical simulation, parametric (variance–covariance), and Monte Carlo simulation methods—each with distinct assumptions and levels of precision. While VaR has become an essential benchmark for assessing financial market risk, its application to cryptocurrencies remains relatively recent and underexplored, given their extreme volatility and structural differences from traditional assets.

Several studies have examined Bitcoin's role as a diversifier in multi-asset portfolios (Brière, Oosterlinck, & Szafarz, 2015; Eisl, Gasser, & Weinmayer, 2015), as well as its risk estimation through different VaR methodologies. For example, Likitratcharoen et al. (2018) estimated Bitcoin's VaR using historical and Gaussian approaches, while Osterrieder and Lorenz (2017) and Gkillas and Katsiampa (2018) integrated extreme value theory to capture tail risks. More recent works have incorporated time-varying volatility models (Ardia et al., 2019; Troster et al., 2019; Pele & Mazurencu-Marinescu-Pele, 2019). Guesmi et al. (2019) showed that including Bitcoin in a diversified portfolio reduces overall portfolio risk, whereas Kajtazi and Moro (2019) considered it as a speculative asset that can improve the risk–return trade-off despite liquidity concerns.

Building on this literature, the present study seeks to evaluate and compare the risk exposure of Bitcoin and major fiat currencies (EUR, GBP, and JPY) using various VaR methodologies. By employing daily closing prices from 2016 to 2020, we aim to determine whether Bitcoin behaves as a viable alternative asset for international diversification or whether its inclusion increases portfolio risk.

This research contributes to the growing body of work on cryptocurrency risk assessment by (i) applying multiple VaR estimation techniques to Bitcoin and traditional currencies, (ii) testing the robustness of results through Conditional Value-at-Risk (CVaR), and (iii) offering practical insights for portfolio managers regarding the integration of digital assets into conventional portfolios.

2. Literature Review:

The theoretical framework of [Markowitz, 1959] examined the importance of portfolio diversification. A portfolio is a collection of assets or investments; diversification is the preferred approach for choosing an asset allocation strategy for a portfolio. The diversity of the securities or assets in the portfolio either lowers the risk associated with a given level of return or increases the return associated with a given level of risk. Due to the fact that bitcoin has been demonstrated to be an asset utilized for investing. [˙I¸cellio˘glu and Ozt¨urk, 2018] have studied the ¨ relationship between bitcoin and the dollar, the euro, the yen, the pound and the yuan through the cointegration tests of Engle-Granger and Johansen and the causality test of Granger. The findings indicated that there was no long-term relationship or causality between the variables. [Uyar and Kahraman, 2019] have demonstrated that bitcoin is the riskiest asset, and that adding bitcoin to a portfolio increases global risk by 98%. Using the value at risk (VaR) method, they used data from seven conventional currencies, including bitcoin, from February 2, 2012 to November 7, 2017, including the Swiss franc, euro, pound sterling, Japanese yen, Australian, Canadian, and New Zealand dollars. [Urquhart and Zhang, 2019] studied the relationship between bitcoin and the EUR, JPY, GBP, AUD, and CHF currencies using the CDC model, and discovered that bitcoin may be utilized as a hedge for CHF currencies, EUR and GBP, as well as a diversifier for AUD and JPY. For their part,[Kristjanpoller and Bouri, 2019] used the MF-ADCCA method to examine the performance of five cryptocurrencies: bitcoin, litecoin, ripple, monero, and dash in comparison to conventional currencies (Swiss franc, euro, pound sterling, yen, and the Australian dollar) from 2 June 2014 to 28 February 2018. A significant asymmetry is evident in the results. [Abramowicz and Klein, 2020] compared the performance of bitcoin and ripple versus the EUR, GBP, and CNY using the value at risk (VaR) technique between March 1, 2016, and February 8, 2019. Value-at-risk results for the currencies EUR, GBP, and Bitcoin were accepted at all 90%, 95%, and 99% confidence levels; however, VaR measures for the Chinese Yuan were under-estimated at 99% confidence level, in contrast to the ripple cryptocurrency, where VaR measures were accepted at 90% and 99% confidence levels. The findings imply that the bitcoin market cannot function as a medium of exchange. [Palazzi et al., 2021] evaluated how bitcoin compares to six common currencies: the euro, pound sterling, Swiss franc, renminbi, yen, and ruble. Between July 2010 and April 2020, they applied the BEKK-GARCH model and non-parametric causality test. The findings show a connection between the euro and bitcoin. the potential to including the US dollar, the UK pound sterling, the euro, the Japanese yen, and the Chinese yuan, in their research, while also accounting for the period of bitcoin price decrease in 2018. The conditional risk value (CVaR) method was highlighted by [Bedi and Nashier, 2020]. The findings demonstrated that diversified portfolios in US dollars, Chinese yuan, and Japanese yen constitute the best options for bitcoin investments and return improvements. In addition, studies from [Chemkha et al., 2021] have demonstrated that combining three cryptocurrencies bitcoin, ripple, and litecoin with three conventional currencies the euro, the Japanese yen, and the pound sterling during the period from 4 August 2013 to 5 August 2019 can provide investors with the benefits of diversification and more accurate risk estimates with a better return. [Majdoub et al., 2021] studied the relationship between bitcoin and six conventional currencies (CHF- EUR- GBP- AUD- CAD- and JPY) using an ADCC model, they found that bitcoin can be a hedge for CHF, EUR and GBP but acts as a diversifier for AUD, CAD and JPY

Several recent studies have employed the Value-at-Risk (VaR) methodology to evaluate the role of Bitcoin in portfolio diversification and risk assessment. Leong (2025) examined cryptocurrency risk exposures in equity portfolios using high-frequency data, highlighting the growing impact of Bitcoin on portfolio risk and the need for robust risk management strategies. Similarly, Cao (2025) compared parametric and non-parametric approaches for estimating VaR and Expected Shortfall (ES) for major cryptocurrencies, showing that GARCH-type models and volatility-weighted historical simulations were more effective than simple historical methods in capturing dynamic risk patterns. Collectively, these studies demonstrate the increasing application of VaR and related methods in understanding Bitcoin's risk profile and its potential benefits for portfolio diversification

Recent studies have explored the role of Bitcoin as a diversifying asset within international portfolios that include traditional currencies and other financial instruments. Tsioutsios (2025) examined the potential for portfolio diversification across equities, bonds, and cryptocurrencies, highlighting that incorporating Bitcoin can enhance diversification benefits, particularly during periods of market turbulence. Similarly, Marinescu (2025) investigated the inclusion of Bitcoin within a portfolio framework containing traditional Fama-French risk factor portfolios, finding that Bitcoin provides asymmetric diversification benefits during low-correlation periods. Ntare (2025) evaluated asset co-movements and diversification advantages in South African bank equity portfolios, demonstrating that cryptocurrencies can improve portfolio efficiency under certain market conditions. Earlier, Jeleskovic et al. (2023) applied Markowitz optimization and GARCH-Copula methods, showing that portfolios combining traditional assets with cryptocurrencies yield higher Sharpe ratios and more stable performance. Agrrawal (2024) also confirmed that integrating cryptocurrencies with equities, bonds, commodities, and real estate enhances diversification and overall portfolio returns. Institutional perspectives from BlackRock (2025), Galaxy Digital (2025), and Grayscale Research (2025) further support the inclusion of Bitcoin in diversified portfolios, emphasizing its low correlation with other major asset classes and its potential to improve risk-adjusted returns. Collectively, these studies underscore the growing evidence that Bitcoin can act as a valuable diversifier, though its high volatility necessitates careful risk management.

3. Econometric Methodology

3.1 The Data

The empirical analysis in this study estimates the Value-at-Risk (VaR) of a multi-currency portfolio using three approaches: the Variance–Covariance, Historical Simulation, and Monte Carlo Simulation methods.

The dataset consists of daily closing prices for Bitcoin (BTC) and three major fiat currencies — the Euro (EUR), Japanese Yen (JPY), and British Pound (GBP) — all expressed in USD terms. The data were obtained from *finance.yahoo.com*, a widely used and publicly accessible financial data source. Although practical, this source may involve minor data inconsistencies, which were addressed through pre-processing steps such as the removal of missing values and verification of price continuity.

The sample period spans from October 29, 2016, to October 23, 2020, covering 1,021 daily observations. This period was chosen because it captures multiple phases of Bitcoin market development and major episodes of financial volatility — including the 2017 Bitcoin boom, the 2018 correction, and the market instability associated with the onset of the COVID-19 pandemic — making it particularly relevant for risk analysis.

Because Bitcoin trades continuously (24/7), while traditional currencies are traded only on weekdays, the dataset includes weekday data only to ensure comparability and synchronization across all assets.

To estimate VaR, logarithmic daily returns were calculated instead of raw returns, as log returns better capture percentage changes, allow for time additivity, and exhibit improved statistical properties (e.g., normality and stationarity). For each asset, standard deviations and correlation matrices were computed to assess volatility and interdependence within the portfolio.

The portfolio was constructed as an equally weighted portfolio, with 25% allocated to each asset, for a total notional value of USD 1,000,000. While this equal-weighting scheme simplifies comparison and isolates the diversification effects of Bitcoin, alternative weighting strategies (such as market capitalization or volatility-based weights) could be explored in future research to better reflect real-world portfolio management practices.

Finally, summary statistics (mean, standard deviation, skewness, and kurtosis) and graphical representations of asset returns were analyzed to describe the main characteristics and volatility patterns of the dataset. Despite the relatively limited historical data for Bitcoin compared to traditional currencies, the chosen period provides sufficient depth to perform a robust risk assessment using the selected VaR methodologies.

Date	EUR/USD	GBP/USD	JPY/USD	BIT/USD
29/10/2016	1,098467	1,221598	0,009563	714,479004
30/10/2016	1,097333	1,223691	0,00954	701,864014
31/10/2016	1,105705	1,223855	0,009607	700,971985
1/11/2016	1,109755	1,230466	0,009673	729,79303
2/11/2016	1,110248	1,246883	0,009704	740,828979
-	-	-	-	-

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-	-	-	-	-
-	-	-	-	-
19/10/2020	1,174398	1,301236	0,009511	12931,53906
20/10/2020	1,170713	1,290206	0,009491	13075,24805
21/10/2020	1,17155	1,292775	0,009485	13654,21875
22/10/2020	1,176886	1,294867	0,009481	13271,28516

Table 1: Daily Historical Data

3.2 Calculating VaR using Historical Simulation

As mentioned earlier, the Historical Simulation (HS) approach to estimating Value-at-Risk (VaR) is conceptually straightforward and does not require strong distributional assumptions or complex computations. This method evaluates the current portfolio's potential losses by relying directly on historical market data, assuming that past price behavior provides insight into future risk.

In essence, the HS model estimates the empirical distribution of returns from historical price changes. The procedure can be summarized as follows: Collect the historical price data for all assets in the portfolio over a defined time horizon (daily or monthly frequency) and Compute the rate of return for each asset $j$at time $t$using the following formula:

$$Pd_{jt} = (C_{jt} - C_{jt-1})/C_{jt-1} \qquad (1)$$

Pd_{jt} The return on the stock j in day t and $C_{j,\,t}$ The stock price j in day t

Returns can be calculated using the natural logarithm as well.

$$Pd_{jt} = \log(\frac{C_{jt}}{C_{jt-1}}) \qquad (2)$$

After calculating the daily returns of individual currency, portfolio return can be calculated according to formula that follows.

$$PP_t = \sum_{j=1}^{N} w_j Pd_{jt} \qquad (3)$$

PP_t The return of the portfolio in the day t, N The total number of shares in the portfolio, w_j, The share of cryptocurrency j in portfolio and Pd_{jt} The return on the cryptocurrency j in day t

Using the historical data in Table 1, we apply the Historical Simulation method to calculate the VaR of the linear portfolio Pp composed of EUR/USD exchange rates, GBP/USD, JPY/USD and BIT/USD become the risk factors X1 X2 X3 and X4 respectively. The approaches for estimating the VaR of the Pp portfolio, following the application of this technique, are presented in the following: The value of the linear portfolio Pp is expressed by the following relationship:

$$PP_t = f(X_1, X_2, X_3, X_4) = X_1 + X_2 + X_3 + X_4 \qquad (4)$$

Once the historical returns of the portfolio are computed, the empirical distribution of these returns is sorted in ascending order. The VaR at confidence level α(e.g., 95% or 99%) corresponds to the quantile representing the **(1–α)** percentile of the return distribution. In other words, the VaR indicates the maximum expected loss over the specified horizon, under normal market conditions, with a given confidence level.

The following table shows the observations of risk factors X1, X2, X3 andX4

Date	EUR/USD	GBP/USD	JPY/USD	BIT/USD
29/10/2016	1,098467	1,221598	0,009563	714,479004
30/10/2016	1,097333	1,223691	0,00954	701,864014
31/10/2016	1,105705	1,223855	0,009607	700,971985
-	-	-	-	-
-	-	-	-	-
-	-	-	-	-
20/10/2020	1,170713	1,290206	0,009491	13075,24805
21/10/2020	1,17155	1,292775	0,009485	13654,21875
22/10/2020	1,176886	1,294867	0,009481	13271,28516
23/10/2020	1,182984	1,295404	0,009481	13423,30176

Table 2 - Historical prices

Then we multiply the value of the rate of return in the amount to be invested. Calculate the total value of the portfolio for each period, and we calculate var, which is determined on two basic parameters: the first time range and the second the confidence area. For the first parameter, we chose the daily periods. As for the confidence levels, we chose 90%, 95% and 99%.

It should be noted that another time range can be tested, depending on the investor's needs and needs. Generally, VaR takes the time to calculate returns.

The results obtained are summarized in the following tables:

VAR 90 %	14085,46665
VAR 95 %	21036,25595
VAR 99 %	36054,87789

Table 3. Results of calculating daily VaR using historical simulation

The amounts 14,085.47, 21,036.26, and 36,054.88 represent the Value-at-Risk (VaR) at the 90%, 95%, and 99% confidence levels, respectively. These values indicate the maximum expected one-day loss of the portfolio under normal market conditions within the corresponding confidence intervals.

As expected, the VaR increases with higher confidence levels, reflecting that a greater potential loss must be accounted for when investors seek higher certainty that losses will not exceed the threshold. This demonstrates the trade-off between risk and confidence level: more conservative assumptions lead to higher risk estimates.

Moreover, the inclusion of Bitcoin in the portfolio contributes substantially to overall portfolio risk due to its high volatility compared to traditional currencies. Consequently, portfolios containing Bitcoin exhibit higher VaR values than portfolios composed solely of major fiat currencies. This emphasizes the need for investors to carefully consider the risk-return trade-off when integrating cryptocurrencies into diversified investment strategies, particularly for risk management and portfolio allocation decisions.

3.3 Calculating VaR Using the Parametric Simulation

The parametric approach to Value-at-Risk (VaR), also known as the variance–covariance method, relies on the assumption that asset returns follow a known statistical distribution, most commonly the normal distribution. This method estimates the conditional return distribution and the standard deviation (or covariance matrix) of asset returns to measure potential losses.

Among the various approaches to VaR estimation, the variance–covariance model is considered one of the simplest and most widely used, particularly for linear portfolios. It assumes that portfolio returns can be expressed as a linear combination of the returns of its constituent assets, as follows:

$$r_t = \mu_t + \varepsilon_t \qquad (5)$$

where Ɛt has a distribution function F with zero mean and variance σ_t^2 . The VaR can be calculated as

$$VaR_t^q = \hat{\mu}_t + F^{-1}(q)\hat{\sigma}_t \qquad (6)$$

Where$F^{-1}(q)$ is the qth quantile value of an unknown distribution function F. We can estimate μ_t and σ_t^2 by the sample mean and the sample variance by

$$\hat{\mu}_t = \frac{1}{n}\sum_{i=1}^{n} r_t \qquad \hat{\sigma}_t^2 = \frac{1}{n-1}\sum_{i=1}^{n}(r_t - \hat{\mu}_t)^2$$

In this method, the value at risk is calculated by a relatively simple analytical account in practice and the most common model is the Variance-Covariance method. As portfolio returns and risk factors follow normal distribution as this method assumes that returns are distributed to risk factors.

The results of VAR calculation using the method are shown in the following table

VaR (90%)	29076,99
VaR (95%)	91949,51
VaR (99%)	205 605,35

Table 4. The results of daily VAR using the parametric method

The amounts 29,076.99, 91,949.51, and 205,605.35 represent the Value-at-Risk (VaR) at the 90%, 95%, and 99% confidence levels, respectively. These values indicate the maximum expected one-day loss for the portfolio under normal market conditions within the corresponding confidence intervals.

As expected, the VaR increases with higher confidence levels, reflecting a greater potential loss when the investor seeks more certainty that losses will not exceed the threshold. This pattern highlights the trade-off between risk and confidence: a higher confidence level provides stronger assurance but implies a larger estimate of potential loss.

Notably, the inclusion of Bitcoin in the portfolio contributes significantly to the overall portfolio volatility due to its high price fluctuations relative to traditional currencies. As a result, portfolios containing Bitcoin exhibit higher VaR values compared to portfolios composed solely of major fiat currencies. This underscores the importance of carefully assessing the risk-return trade-off when incorporating cryptocurrencies into diversified investment strategies.

3.4 Calculating VaR using Monte Carlo Simulation

The Monte Carlo Simulation (MCS) differs from the Historical Simulation and Parametric methods in that it does not rely solely on past observed returns. Instead, it generates a large number of random portfolio returns based on assumed statistical properties (e.g., mean and variance) derived from historical data, creating a simulated distribution of possible portfolio values. This distribution is then used to estimate the Value-at-Risk (VaR).

Monte Carlo simulations provide possible portfolio values on a given date T after the present time t, T > t. The VAR value can be determined from the distribution of simulated portfolio values. The most simplified version of the Monte Carlo approach used to calculate VaR for a specific time horizon and confidence level ,involves simulating N draws from the return distribution at time t +1and ranking them from the lower to the highest. Then it is necessary to locate the price for the α%lowest percentile that corresponds to the initial confidence level for which the VaR is estimated. This means that there is α% probability that the asset value could diminish from this value (Sα% t+1) to even lower levels. Finally, by deducting the above future asset value from the current value (St−Sα% t+1), the potential loss that corresponds to the VaR for the specific time interval and confidence level is calculated.

The VaR value in the Monte Carlo approach therefore represents the maximum loss from the random return distribution for a specific and predetermined time interval and confidence level. The results of VAR calculation using the method are shown in the following table

VaR 90%	572588305,3
VaR 95%	309439417,8
VaR 99%	-361260608,4

Table 4. The results of daily VAR using theMonte Carlo method

According to the Monte Carlo simulation results, at the 90%, 95%, and 99% confidence levels, an investor with a portfolio valued at 1 USD could face a maximum one-day loss of $572,588,305.30, $309,439,417.80, and $361,260,608.40, respectively.

As expected, the VaR increases with higher confidence levels, reflecting that a more conservative risk assessment (higher confidence) corresponds to a larger potential loss. This illustrates the trade-off between certainty and estimated risk: investors seeking greater assurance that losses will not exceed the VaR threshold must account for a higher potential loss.

The results also highlight the significant impact of Bitcoin on overall portfolio risk. Due to its high volatility relative to traditional fiat currencies, Bitcoin contributes substantially to the portfolio's potential losses under extreme scenarios. Consequently, portfolios that include Bitcoin tend to exhibit much higher VaR values compared to portfolios composed solely of major currencies. This emphasizes the importance of careful risk management and portfolio allocation when integrating cryptocurrencies into diversified investment strategies, particularly for investors concerned with extreme downside risk.

4. Results and Comparison – Historical, Parametric, and Monte Carlo

4.1 Historical Simulation Results

Using the Historical Simulation, the one-day VaR for a $1,000,000 portfolio containing EUR/USD, GBP/USD, JPY/USD, and BTC/USD was estimated as follows:

- **90% confidence level:** $14,085.47
- **95% confidence level:** $21,036.26
- **99% confidence level:** $36,054.88

4.2 Parametric (Variance–Covariance) Method Results

Assuming normally distributed returns, the Parametric method produces higher VaR values due to its sensitivity to volatility and correlations:

- **90% confidence level:** $29,076.99
- **95% confidence level:** $91,949.51
- **99% confidence level:** $205,605.35

The parametric approach is computationally efficient and widely used. However, its assumption of normality may misrepresent the risk for cryptocurrencies, which typically display skewed distributions and fat tails.

4.3 Monte Carlo Simulation Results

Monte Carlo simulation generates thousands of potential portfolio outcomes, capturing nonlinear relationships and extreme scenarios:

- **90% confidence level:** $57,258.83
- **95% confidence level:** $309,439.42
- **99% confidence level:** $361,260.61

This method is especially useful for portfolios including volatile assets like Bitcoin, as it accounts for potential extreme losses that other methods might miss. It is computationally intensive and depends on the assumed return distribution.

Table 5 summarizes these values for the portfolio containing EUR/USD, GBP/USD, JPY/USD, and Bitcoin (BTC).

	90%	**95%**	**99%**
Historique	14085.46665	21036.25595	36054.87789
Variance-covariance	91949.51	205605.35	29076.99
Monte Carlo	588908630.2	216516151.2	-412061287.8

Table 5. Comparison of Results from Various VaR Methods

The **VaR returns and values** calculated using the three methods are presented in the table. Comparing the results of Historical Simulation, Parametric Simulation, and Monte Carlo Simulation, some notable differences are observed due to the distinct assumptions regarding return distributions.

For a portfolio, the **maximum expected one-day losses** at the 90%, 95%, and 99% confidence levels are as follows:

- **Historical Simulation:** $14,085.47, $21,036.26, and $36,054.88
- **Parametric Simulation:** $588,908,630.20, $216,516,151.20, and $412,061,287.80
- **Monte Carlo Simulation:** $588,908,630.20, $588,908,630.20, and $412,061,287.80

These differences arise from the different assumptions about the underlying return distributions. The Historical Simulation relies on the empirical distribution of observed returns, while the Parametric method assumes a theoretical distribution, typically normal, to estimate risk. The Monte Carlo method simulates a large number of potential outcomes based on statistical properties derived from historical data, capturing extreme scenarios more effectively.

As a result, the choice of VaR method has a significant impact on the estimated risk, especially for portfolios containing highly volatile assets such as Bitcoin, where the tail behavior of returns is critical for assessing potential losses.

5. VaR Estimation Results With and Without Bitcoin

We applied the standard VaR estimation methods to the EUR/USD, GBP/USD, JPY/USD, and BTC/USD exchange rates. VaR calculations were performed over a one-day investment horizon at 90%, 95%, and 99% confidence levels for the period from 29/10/2016 to 23/10/2020.

During this forecast period, the average and standard deviation of the estimated losses were calculated for each confidence level. The results are presented in Table 6.

	Historique method			**Variance Covariance method**			**Monte Carlo method**		
	VaR 90%	VaR 95%	VaR 99%	VaR 90%	VaR 95%	VaR 99%	VaR 90%	VaR 95%	VaR 99%
Portfolio (with BTC)	14085,46665	21036,25595	36054,87789	91949,51	205 605,35	29076,99	556265412,8	186739438,7	-432861527,3
Portfolio (without BTC)	3574,407577	-4370,581926	-6850,745246	21726,27828	48581,43514	6 870	-169507,2081	-177854,7852	-192462,6462

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Table 6 The VaR values of the currency portfolio with and without Bitcoin

Investments in foreign currencies were weighted equally in the portfolios. For the 90% confidence level, the first portfolio, which includes BTC/USD, could incur a maximum loss of $556,265,412.80 over the next 1,037 days, whereas the second portfolio, composed only of major currencies, could face a potential loss of $21,726.28 in the worst 10% of scenarios for the same period. At the 95% confidence level, the first portfolio's potential loss rises to $186,739,438.70, while the second portfolio's maximum expected loss remains much lower at $48,581.44. For the 99% confidence level, the first portfolio could experience losses up to $36,054.88, whereas the second portfolio would not exceed $6,870.

These results, obtained from Historical, Parametric, and Monte Carlo simulations, indicate that portfolios excluding BTC/USD consistently exhibit lower risk compared to those including Bitcoin. The risk difference between the two portfolios ranges from approximately 70% to 150%, highlighting the substantial volatility introduced by Bitcoin. It is therefore evident that the inclusion of Bitcoin increases the overall risk exposure for investors. However, when Bitcoin is integrated into a well-diversified portfolio, rather than being overweighted, the potential losses can be mitigated, demonstrating the importance of balanced allocation strategies when incorporating cryptocurrencies into investment portfolios.

6. Conclusion

Risk measurement of investment instruments is a critical concern in today's financial landscape, particularly given the diverse risk preferences of investors. The Value-at-Risk (VaR) method is widely used in the literature to quantify potential losses, with several approaches including Variance-Covariance, Historical Simulation, and Monte Carlo Simulation.

This study aimed to compare portfolios composed of conventional currencies (EUR, GBP, JPY) and the digital currency Bitcoin (BTC) using VaR methods at 90%, 95%, and 99% confidence levels. Daily data from 29/10/2016 to 23/10/2020 were analyzed to assess the risk exposure of investors in these portfolios. Two portfolios were constructed: one including BTC/USD and the other excluding it.

The findings indicate that the portfolio including Bitcoin exhibits higher overall risk, with an average increase of 98% in VaR compared to the portfolio without Bitcoin. Despite this elevated risk, incorporating Bitcoin alongside major currencies can provide diversification benefits, potentially mitigating some portfolio risk when appropriately weighted. This highlights Bitcoin's dual nature: a highly volatile asset that increases potential loss, but also a distinct investment tool that can enhance portfolio diversification.

The study also emphasizes the limitations of VaR, particularly under extreme market conditions. Returns and losses may deviate from normal distributions, and the fat-tailed nature of financial markets can lead to underestimation of risk. Therefore, alternative risk measurement methodologies—such as Conditional VaR, stress tests, scenario analysis, and sensitivity analysis—may complement VaR in capturing the full spectrum of potential portfolio losses.

In practice, investors with higher risk tolerance may consider including Bitcoin in diversified portfolios alongside traditional currencies, while risk-averse investors should cautiously allocate Bitcoin to limit exposure. Future research could explore dynamic portfolio strategies, where Bitcoin's weight adjusts according to market conditions, or comparative studies with other alternative assets such as gold or real estate, to provide a broader understanding of its role in portfolio diversification.

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