

Crypto currencies: A Profitable Potential for International Portfolio Diversification in Times of Geopolitical Crisis?

Rifa Atrous¹, Ezzeddine Abaoub²

¹Univ. Manouba, ESCT, LARIMRAF LR21ES29, Tunisia,

²Faculty of Economic Sciences and Management of Nabeul, Tunisia,

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Abstract

In this study, we explore the impact of incorporating crypto currencies, including Bitcoin, Ethereum, Dogecoin, Ripple and Litecoin, into five traditional financial portfolios, consisting of equities, tech stocks, commodities, oil and currencies. Using data covering the period from August 2015 to December 2024, with a daily frequency, we evaluate the performance of these portfolios by applying three performance measures, including the Naïve equal-weight portfolio, the portfolio based on the Markowitz Mean-Variance approach, and the optimized Sharpe ratio. Our results highlight that integrating cryptocurrencies into traditional portfolios improves risk-adjusted returns. Ethereum stands out as offering promising advantages over Bitcoin in terms of diversification. In fact, this study contributes to the financial literature by exploring the diversification of existing portfolios with multiple cryptocurrencies and extending the analysis to the post period including the COVID-19 crisis, the Russia-Ukraine conflict and the Israel-Palestine conflict. Our results have significant implications for investors and financial analysts seeking to improve their portfolio's risk/return profile in a financial environment characterized by geopolitical and economic turbulence.

Keywords: Cryptocurrencies, Financial innovation, Portfolio diversification, Investment, Financial market, Technological innovation

1. Introduction and literature review

Recent years have been marked by exponential growth in technological advances, which have forced a major transformation of the traditional global economy. Schwab (2017) defines this era as the “fourth industrial revolution”, characterized by the massive integration of digital technologies. The meteoric emergence of cryptocurrencies is at the heart of this technological revolution, which has profoundly transformed the way individuals and financial institutions perceive and manage their assets. Interest in digital assets has continued to grow, and investment in cryptocurrencies has attracted the attention of investors worldwide. Notably, Bitcoin has experienced considerable growth and, as of December 31, 2024, the total market capitalization of the cryptocurrency market reached 3.39 trillion USD according to CoinGecko.com. Indeed, this capitalization highlights the potential influence of cryptocurrencies on financial markets. Investing in cryptocurrencies provides several advantages for investors, such as diminished

expenses and delays related to financial transactions (Perez et al., 2020). Bitcoin presents characteristics intermediate between those of gold and the dollar, offering hedging capabilities particularly in times of financial crises and advantages as a medium of exchange (Dyhrberg, 2016).

In recent years, cryptocurrencies have attracted the interest of several researchers. In addition, Baur et al (2018) analyzed Bitcoin's performance by comparing it with other asset classes including the S&P500, over the period from July 2010 to June 2015. Their findings indicate that Bitcoin is mainly used as a speculative investment rather than an exchange currency. The authors suggest that Bitcoin, thanks to its low correlation with other asset classes, could offer significant diversification benefits. The incorporation of cryptocurrencies into conventional portfolios poses both obstacles and opportunities, underscoring the necessity of considering the unique characteristics of each cryptocurrency (Borri, 2019; Hu et al., 2019; Ardia et al., 2019). Previous research has laid the groundwork for further analysis of the implications of investing in cryptocurrencies, particularly in terms of portfolio management and diversification. Brière et al. (2015) use the mean-variance efficiency test of Huberman and Kandel (1987) and Ferson and Harvey (1993) to test whether the incorporation of Bitcoin improves investment opportunities over the period from July 23, 2010, to December 27, 2013. Their results show that including even a small proportion of Bitcoins in a well-diversified portfolio can significantly improve the risk-return trade-off. Similar findings were reported by Okechukwu (2024), who showed that cryptocurrencies exhibit low correlation with traditional assets, helping to improve the Sharpe ratio of portfolios. Corbet et al (2018) examined returns and volatility transmission between Bitcoin, Ripple, Litecoin as well as other assets such as gold, bonds, equities and the Global Volatility Index (VIX) over the period from early 2013 to July 2017. In fact, their findings reveal that cryptocurrencies are relatively insulated from external economic and financial shocks, offering diversification benefits for short-term investors. However, the main cryptocurrencies are interconnected, with positive contagion effects, particularly during rapid increases in Bitcoin prices. Corbet et al. (2018) also point out that cryptocurrencies are sensitive to internal structural changes, such as regulation and cyberattacks, affecting their volatility and liquidity. Other studies focus on cryptocurrencies as hedging instruments, Selmi et al. (2018) found that Bitcoin serves as a more effective hedge and safe haven against oil price declines than gold. Guesmi et al (2019), using multivariate GARCH models, showed that short positions in Bitcoin hedge risks linked to other financial assets. Similarly, Su et al. (2020) and Ma et al. (2020) found that a short position in the Bitcoin market may also serve as a useful hedge to reduce the risks connected to different financial asset investments. In addition, Liu (2019) used empirical data from ten major cryptocurrencies, covering the period from August 7, 2015 to April 9, 2018, and showed that diversification between different cryptocurrencies significantly improves portfolio performance. Using the CoVar model, the authors evaluated conditional risk exposure over the period from January 17, 2017, to April 15, 2018. Borri et al. (2019) demonstrate that cryptocurrencies are highly correlated with each other, while being weakly correlated with other global financial assets, including gold. As a result, they find that cryptocurrencies could offer attractive returns and attractive hedging properties. In a more recent contribution, Gambarelli et al. (2023) have investigated the hedging ability of cryptocurrencies in bearish and bullish European market

conditions and compare them to gold as a safe-haven asset. The authors highlight asymmetric effects in the relationship between cryptocurrencies and stock market returns, exploring the benefits of diversification through cryptocurrencies. [Wang et al \(2025\)](#) demonstrate that in times of crisis, gold strengthens its role as a safe-haven, particularly in the Chinese and South African markets, while cryptocurrencies tend to exhibit more volatile behavior. Among digital assets, Bitcoin emerges as the most optimal investment, whereas the global crypto index reveals a lower hedging efficiency compared to gold. Recent years have been marked by a series of geopolitical crises that have raised concerns about the stability of financial markets. In addition, several studies that have been conducted on the impact of the COVID-19 pandemic on the optimization of financial portfolios, have revealed that COVID-19 cases anticipate financial market returns, and that Bitcoin improves portfolio performance by reducing risk, confirming its safe haven status before and during the pandemic ([Trichilli & Boujelbène Abbes,2022](#); [Abdelmalek, 2023](#); [Veliu and Aranitasi, 2024](#)). In a similar context, [Goodell and Goutte \(2021\)](#) investigated the role of cryptocurrencies as diversification assets, hedges and safe havens in the face of financial market fluctuations during the COVID-19 pandemic. In fact, their results show a significant increase in co-movements between cryptocurrencies and stock market indices as the COVID-19 pandemic progressed. However, Bitcoin and Tether futures stood out by displaying negative co-movements with stock market indices, indicating their role as safe havens. More recent research has focused on the effect of geopolitical crises. [Adekoya et al \(2022\)](#) suggest that the Russian-Ukrainian war highlighted the role of geopolitical upheavals in market dynamics. Indeed, the conflict prompted investors to turn to safe-haven assets, anticipating higher oil and gold prices. In the same context, [Raza Rabbani et al \(2021\)](#) show that commodity markets reacted quickly and sharply to geopolitical tensions. [Attarzadeh et al \(2024\)](#), using TVP-VAR and QVAR models, examined dynamic spillovers among cryptocurrencies, gold, energy markets (WTI oil and renewables), and equities (S&P 500). Their results reveal heterogeneous return and volatility transmissions. During stable periods, Bitcoin maintains a low correlation with traditional assets, reinforcing its diversification benefits; however, during crises such as the COVID-19 pandemic and the Russia-Ukraine conflict, its volatility rises sharply, weakening its hedging properties. In a related study, [Naeem et al \(2024\)](#), using an innovative methodology combining network analysis and implied volatility measures, highlighted the central role of precious metals such as gold in transmitting shocks during crises (COVID-19, Russia-Ukraine war). Furthermore, [Olaniran et al \(2025\)](#) studied the impact of the Russia-Ukraine conflict (2022-2023) on major cryptocurrencies (Bitcoin, Ethereum, Binance Coin, Ripple) and found that these assets exhibited resilience as diversification tools amid geopolitical uncertainty. [Khan et al \(2024\)](#) applied the QVAR (Quantile VAR) model to assess the impact of geopolitical risks on commodity returns (precious metals, energy, agriculture) during the Russia-Ukraine and Palestine-Israel conflicts. Their findings indicate a resilience of commodities to extreme geopolitical shocks, with low interconnectivity and heterogeneity of reactions across assets. However, [Gunay et al \(2024\)](#) report significant risk spillovers among traditional commodities during geopolitical events such as COVID-19, the Russia-Ukraine war, and the Israeli-Palestinian conflict. Similarly, [Prayoga et al \(2024\)](#), analyzing the impact of the Israeli-Palestinian conflict on financial markets, showed significant abnormal returns for stock market indices (Dow Jones, Nikkei, etc.) and commodities (gold, oil), confirming their sensitivity to geopolitical shocks.

In this study, we examine the impact of incorporating several cryptocurrencies into existing financial portfolios. However, given the rapidly changing financial landscape, it is imperative to consider more diversified strategies to improve the risk-return trade-off. Indeed, this study presents multifaceted contributions. Firstly, the sample period covers the Russo-Ukrainian and Israeli-Palestinian conflicts, as well as COVID-19. We therefore use data from August 31, 2015, to December 31, 2024, encompassing information crucial to understanding recent trends, particularly those that emerged after the outbreak of the latest geopolitical crises. Secondly, our study is distinguished by the inclusion of several cryptocurrencies in the diversification of existing portfolios, drawing on recent data. Previous research has often focused on a single cryptocurrency portfolio or the exclusive integration of Bitcoin. While there have been studies in this area, such as the work of [Ma et al. \(2020\)](#) and [Petukhina et al. \(2021\)](#), which examined the period from 2014 to 2019, our study extends this analysis to the last five years, a period marked by significant growth in cryptocurrencies, notably following the COVID-19 pandemic and more recently the Russo-Ukrainian and Israeli-Palestinian conflicts. Third, our study provides an innovative perspective by analyzing in depth the risk-return profiles of traditional portfolios both with and without cryptocurrency incorporation. We also propose an efficient frontier comparison using mean-variance analysis. It is worth noting that such an analysis has never been undertaken for portfolios including assets such as oil, commodities, and even the price of wheat, while incorporating several cryptocurrencies. Our study positions itself as a pioneer in this field. Furthermore, we used a variety of portfolio optimization techniques, such as the mean-variance method, the naive portfolio, and optimization based on the Sharpe ratio, all of which were influenced by the research conducted by [Ma et al. \(2020\)](#). Our findings demonstrate that, for a given degree of risk, diversified portfolios incorporating cryptocurrencies yield higher returns than traditional portfolios made up entirely of traditional assets, except for currency portfolios. Furthermore, it is interesting to note that when asset short sales are allowed, the benefits of diversification are even more pronounced. Thirdly, our study highlights that Ethereum offers more promising advantages compared to the results obtained with Bitcoin and Dogecoin. In fact, most previous research has mostly explored diversification using Bitcoin as a starting point. Our results so urge financial and investors analysts to explore cryptocurrencies other than Bitcoin for their investments and diversification strategies. The rest of the paper is organized as follows. Section 2 provides the data and methodologies used in the study. In Section 3, we will synthesize the results obtained from the integration of cryptocurrencies into the various traditional portfolios. Section 4 is dedicated to discussing the results and presenting other relevant findings. Section 5 concluded the paper.

2. Data and methodology

This section describes the dataset that was used and outlines our methodology for data analysis. It should be mentioned that we employed traditional techniques for portfolio optimization. Furthermore, our research explores the introduction of cryptocurrencies into five distinct portfolios, with a particular focus on their impact on the risk-return trade-off. Portfolio performance is assessed using three distinct performance measures. The first measure is the Naïve portfolio, with equal weightings. The second measure employed is the Markowitz Mean-Variance portfolio, which aims to maximize the portfolio's expected return under the constraint

of expected return and risk, thus enabling us to plot the efficient frontier for each asset class, while incorporating various cryptocurrencies. Finally, we also use the optimized Sharpe ratio to assess portfolio performance. In fact, this study looks at the impacts of cryptocurrencies on portfolios comprising various asset classes.

2.1. Data

The five main cryptocurrency names by market capitalization—Bitcoin, Ethereum, Dogecoin, Ripple, and Litecoin—are used in this study. Cryptocurrency data was extracted from coinmarketcap.com, covering the period from August 31, 2015 to December 31, 2024, with daily observations for a total of 74944 data entries. We also explore various portfolios and optimization techniques that incorporate cryptocurrencies into existing portfolios, encompassing equities, tech stocks, oil, currencies and commodities among others for a total of 32 financial assets. Data for each asset was extracted for the same period, from sources including MSCI, OECD, World Bank and Yahoo Finance. In addition, we used the risk-free rate recorded on December 31, 2024, based on 1-year US Treasury bonds. Table 1 provides an overview of the exhaustive list of assets and currencies included in this study. It should also be noted that we have analyzed financial asset returns based on the dates of the latest geopolitical crises, namely covid-19 (December 2019), the Russian-Ukrainian conflict (February 2022) and the Israeli-Palestinian conflict (October 2023).

2.2. Optimization techniques

In this research on international portfolio diversification, the focus is on the effect of incorporating cryptocurrencies into traditional financial asset portfolios on the risk-return trade-off. The optimization methods applied are inspired by the approach of Ma et al. (2020). The first step involves the daily collection of data on cryptocurrencies and traditional financial assets. To calculate logarithmic returns, we apply the following classical formula:

$$r_{i,t} = \log \left[\frac{P_{i,t}}{P_{i,t-1}} \right] \tag{1}$$

Where $P_{i,t}$ is the price of asset i at time t , and $P_{i,t-1}$ is the price of asset i at time $t-1$, and $r_{i,t}$ is the return on asset i at time t .

We calculate the average expected risk/return ratio μ_i and the standard deviation σ_i for asset i , using the following formulas respectively:

$$\mu_i = E(r_i) = \frac{\sum_{t=1}^n r_{i,t}}{n} \tag{2}$$

$$\sigma_i = \sqrt{\frac{\sum_{t=1}^n (r_{i,t} - \mu_i)^2}{n-1}}$$

(3)

Where n represents the number of observations for asset i .

Once the returns and standard deviations have been calculated, we annualize both values. Markowitz recommends calculating mean returns and standard deviations for individual assets, which provide the return and risk characteristics of these assets. We use the following version of Markowitz's mean-variance analysis:

$$(4) \quad \begin{aligned} & \text{Max} && E(R) \\ & \text{S/C : } w^T \Sigma w = \alpha \\ & \sum_{i=1}^m w_i = 1 ; w_i \geq 0, \forall i, \end{aligned}$$

Where $w = (w_1, w_2, \dots, w_n)$ is the vector of weights; Σ denotes the variance-covariance matrix and α is the given level of risk, as measured by the variance.

The main objective of this approach is to find the optimal portfolio that maximizes returns, while respecting certain constraints. Markowitz (1952) also provided a conceptual framework for determining the optimal weights of assets in an investment portfolio, maximizing expected returns for a given level of risk. Our objective was to find an optimal portfolio that maximizes returns, while respecting certain constraints, notably the sum of weights equal to 1 and long positions on all assets. We solved this problem for different risk levels, traced the efficient frontier of the portfolios considered in our study, and optimized the Sharpe ratio to observe the effects of diversification through cryptocurrencies.

2.3. Sharpe ratio

The Sharpe ratio measures the relative performance of a portfolio compared with a risk-free asset, such as a 10-year US Treasury bond. It is calculated as follows:

$$\text{Sharpe Ratio} = \frac{E(R) - R_f}{\sigma_p} \tag{5}$$

Where R_f is the annualized risk-free rate and σ_p is the square root of the variance. To maximize the Sharpe ratio while maintaining the portfolio's asset weights, we have solved the following optimization problem:

$$\begin{aligned} & \text{Max} \frac{E(R) - R_f}{\sigma_p} \\ & \text{S/C } w^T \Sigma w = \alpha \\ & \sum_{i=1}^m w_i = 1 \end{aligned} \tag{6}$$

Where w_i are the asset weights of a given portfolio.

The second condition in the above formula suggests that the sum of all asset weights must equal 1. The above problem is solved, first, by allowing long asset positions, indicating that the weights of each asset that makes up the portfolio is, either positive or zero, is that $w_i \geq 0 \forall i$. The optimization problem is also solved by allowing sales of the cryptocurrencies to arrive at an optimized solution and is later obtained by removing the condition $w_i \geq 0 \forall i$, on the weights. The problem is solved using the solver in Excel.

2.4. Sharpe Ratio limits

Although the Sharpe ratio remains one of the most widely used indicators in financial performance evaluation, its application presents several theoretical and empirical limitations. The measure assumes that asset returns are normally distributed or that investors exhibit quadratic preferences—assumptions that are rarely met in real-world financial markets. This is especially true in the case of hedge funds, whose return distributions often display pronounced skewness and high kurtosis (Brooks & Kat, 2002; Agarwal & Naik, 2004; Malkiel & Saha, 2005). In such contexts, the standard deviation used by the Sharpe ratio as a risk proxy proves inadequate, as it fails to differentiate between favorable and unfavorable volatility and does not effectively capture tail risks. Furthermore, as emphasized by Zakamouline (2010), applying the Sharpe ratio over longer investment horizons tends to favor low-volatility assets at the expense of those with higher return potential but positively skewed distributions, due to its inability to account for higher-order moments such as skewness and kurtosis. To address these shortcomings, various alternative performance measures have been developed, most notably the Sortino and Rachev ratios—which offer a more refined assessment of the risk-return trade-off by incorporating distributional asymmetries (Biglova, Ortobelli, Rachev, & Stoyanov, 2004; Farinelli et al., 2008). Moreover, while some studies have reported strong correlations between rankings derived from the Sharpe ratio and those based on alternative measures (Eling & Schuhmacher, 2007; Eling, 2008), such statistical convergence may be misleading. Zakamouline (2010) demonstrates that these correlations can conceal substantial discrepancies in fund rankings, particularly when return distributions are highly non-normal or when Sharpe ratios are elevated.

In this study we examine the diversification of existing asset portfolios by incorporating cryptocurrencies. We consider five asset classes: technology stocks, performance stocks, exchange rates for five currencies, oil and four commodities, including the price of wheat. The results, along with a comparative analysis between naive and diversified portfolios, are presented in the following section.

Table 1 Assets used in the study

Cryptocurrencies	Technological firms	Stocks		Currency	Commodities	Oil/Energy
Bitcoin	Microsoft	Berkshire Inc (BRKa)	Hathaway	USD/Euros	Copper	Brent Crude Oil
Ethereum	Apple	JPMorgan Co (JPM)	Chase &	USD/Japanese Yen	Coffee	Natural Gas
Ripple	Google	Johnson & Johnson (JNJ)		USD/Canadian Dollar	Gold	Crude Oil
Litecoin	Amazon	Procter & Gamble (PG)		USD/British Pound	Wheat	Uranium
Dogecoin	Meta	Visa (V)		USD/Australian Dollar	Silver	
	NVIDIA			USD/Swiss Franc		
	Tesla					

3. Results

In this section we present the results of the analysis of different asset portfolios, highlighting the impact of incorporating cryptocurrencies in terms of diversification and risk-return trade-off while also highlighting the impact of geopolitical crises.

3.1. Descriptive statistics

Descriptive statistics on daily returns ([Appendix1](#)) indicate that cryptocurrencies such as Dogecoin (0.45%), Ethereum (0.34%) and XRP (0.41%) delivered the highest returns over the study period. Their average performance reflects a high speculative potential, which is counterbalanced by considerable volatility, with standard deviations of 9.98%, 5.63% and 6.89% respectively. Among technology stocks, Nvidia (0.275%) and Tesla (0.205%) posted notable average returns, confirming their classification as high-growth equities. In contrast, Gold (0.0415%), recorded modest but stable returns, consistent with its reputation as a safe-haven asset. As expected, volatility measured by standard deviation, is highest among cryptocurrencies, followed by technology stocks. Precious metals (e.g., gold, silver) and major currencies exhibit much lower volatility, indicating relatively stable returns. The skewness and kurtosis coefficients highlight the generalized non-normality of returns. The majority of assets show a leptokurtic distribution, with kurtosis values well above 3. For example, Dogecoin (kurtosis = 690.95), Crude Oil (-1253.63), or certain stocks such as Amazon and Google, illustrate this marked presence of extreme events in returns time series. Similarly, the positive skewness of several cryptocurrencies and commodities reveals a propensity to generate extreme gains, while some

stocks exhibit negative skewness, reflecting significant bearish shocks. An analysis of return histograms (Fig.1), further supports these observations. Across most currencies examined, no abnormal return variations were detected during major geopolitical crises namely, the COVID-19 pandemic, the Russia-Ukraine war, and the Israel-Palestine conflict except for the USD/EUR pair. This exception is likely due to its status as the most actively traded currency pair globally.



Fig. 1 Histogram of financial asset returns



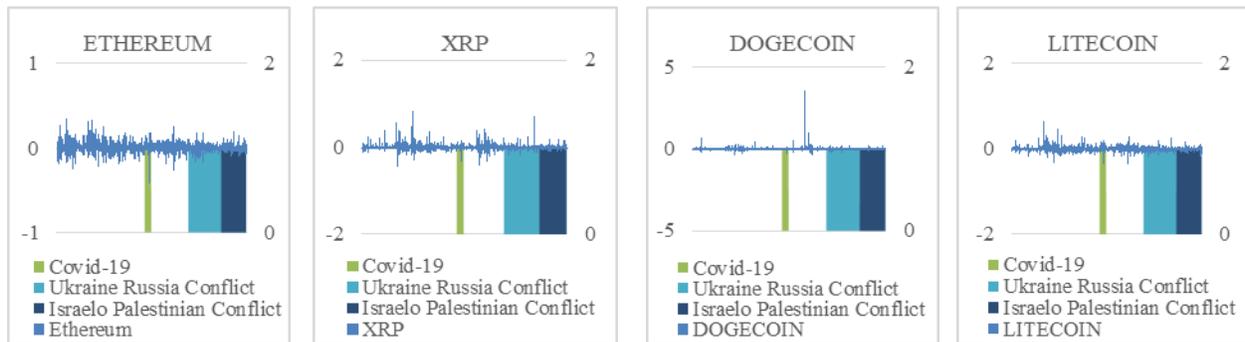


Fig. 1 Histogram of financial asset returns (continued)

As for large-cap stocks such as Berkshire Hathaway Inc (BRKa), Johnson & Johnson, Visa (V) etc., the data indicate a relative insensitivity to the Russian-Ukrainian conflict and Israeli-Palestinian conflicts. In contrast, during the COVID-19 pandemic, these assets experienced a significant increase in volatility, reflecting the overall trend in the financial market. Technology companies, however, were heavily affected by the covid-19 pandemic, as can be seen from the histograms for Microsoft, Apple, Meta, Nvidia and Tesla. This volatility can also be observed in the commodities and energy markets, notably crude oil (WTI), Brent, and uranium. Cryptocurrencies, meanwhile, experienced a significant upward trend during the same period, with notable gains observed in Bitcoin, Ethereum and Litecoin. These findings align with [Olaniran et al. \(2025\)](#), who emphasize the resilience of cryptocurrencies as diversification assets in times of crisis, even if their volatility increases considerably. The Russian-Ukrainian conflict also triggered turbulence in the financial markets, particularly in commodities returns on copper, wheat, natural gas and uranium experienced excessive volatility. In fact, these results reinforce the findings of [Gunay et al \(2024\)](#), [Khan et al \(2024\)](#) and [Adekoya et al \(2022\)](#), that commodities react strongly to geopolitical shocks, with significant risk transmissions. Finally, we observed a notable increase in Meta's performance during this period, which could be explained by the increased role of social networks in times of war. Moreover, this dynamic was confirmed during the Israeli-Palestinian conflict, with similar variations observed in the returns of Meta and Tesla.

3.2. Analysis of different investment portfolios

In this study, we examined each asset class from three perspectives: the naive portfolio, the efficient frontier using the Markowitz mean-variance approach for different risk levels, and the optimized Sharpe ratio. In addition, we repeated these analyses by incorporating cryptocurrencies into each of these portfolios and then compared performance in terms of return and risk profile. [Fig.2](#) revealed the risk/return profile of the efficient frontier of a portfolio composed exclusively of cryptocurrencies. We observe that returns on the cryptocurrency portfolio tend to increase as the level of risk increases. In fact, this trend corroborates the findings of [Brière et al. \(2015\)](#) regarding the relationship between Bitcoin returns and volatility, suggesting that integrating this digital currency into an asset portfolio can benefit investors in terms of diversification. Distinguishing returns between periods of high and low volatility, [Koutmos \(2019\)](#) finds that returns are generally higher during phases of increased volatility.

However, this increase does not systematically compensate for higher levels of volatility, exposing investors to extreme risks.

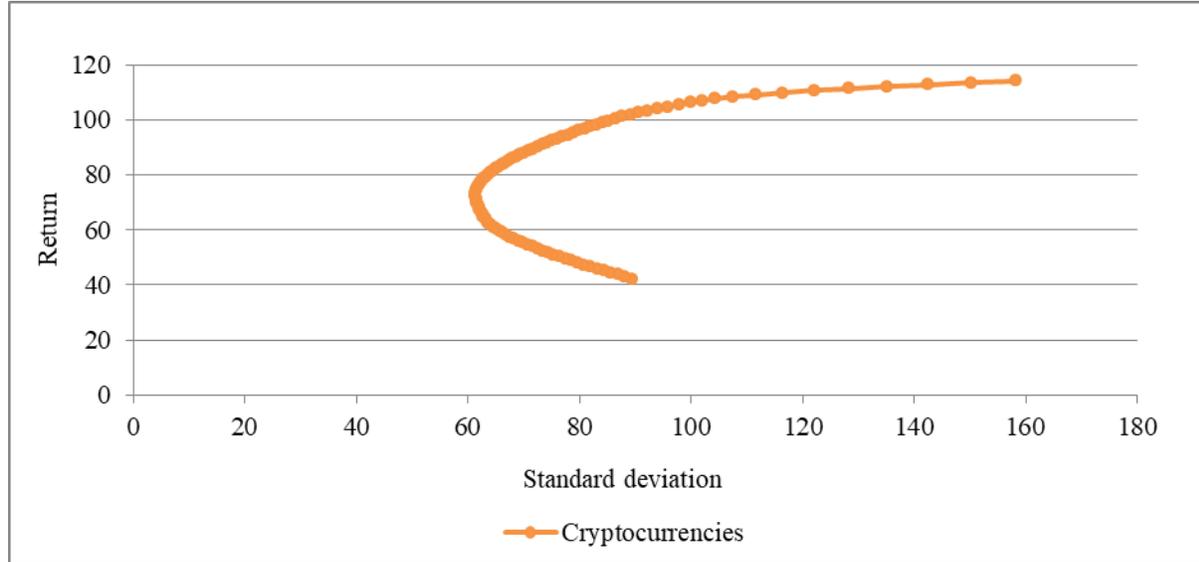


Fig. 2 Efficient cryptocurrencies portfolio

Table 2 Descriptive statistics for cryptocurrency portfolio returns

	Naïve Portfolio	Optimized Sharpe ratio
Mean	120,095%	121,544%
Standard deviation	90,403%	79,734%
Sharpe ratio	1,282	1,472

Consequently, we have extended our analysis by evaluating the potential for portfolio diversification through the inclusion of various cryptocurrencies. Table 2 presents the results for two portfolios composed exclusively of the 5 cryptocurrencies studied : Bitcoin, Ethereum, Litecoin, Dogecoin and Ripple (XRP). The first is a naive portfolio, where investments are evenly distributed across all cryptocurrencies. Optimized Sharpe ratio statistics are also provided, using an annual rate of 4.16% for US Treasury bonds to December 31, 2024, as the risk-free rate. The optimized strategy achieves an average outperformance of 121.54% versus 120.095% for naive diversification. However, this performance is accompanied by increased volatility, with standard deviation falling from 90.403% to 79.734%. The optimized Sharpe ratio reaches 1.472, underlining the portfolio's improved efficiency, albeit with a high level of associated risk. We then studied the various asset portfolios included in our analysis. For this purpose, we initially assembled a portfolio of five stocks from leading technology companies, namely Microsoft, Google, Apple Inc, Amazon, Meta, Tesla and Nvidia. Fig.3 reveals the efficient frontier of the equity portfolio. We have also constructed a diversified portfolio

including equities as well as cryptocurrencies, as shown in the same figure. It is notable that, for a given level of risk, the diversified portfolio outperforms. Table 3 indicates the performance of the different portfolios, based on measures such as mean, standard deviation and Sharpe ratio. The results confirm a modest improvement in returns for the Sharpe-optimized diversified portfolio.

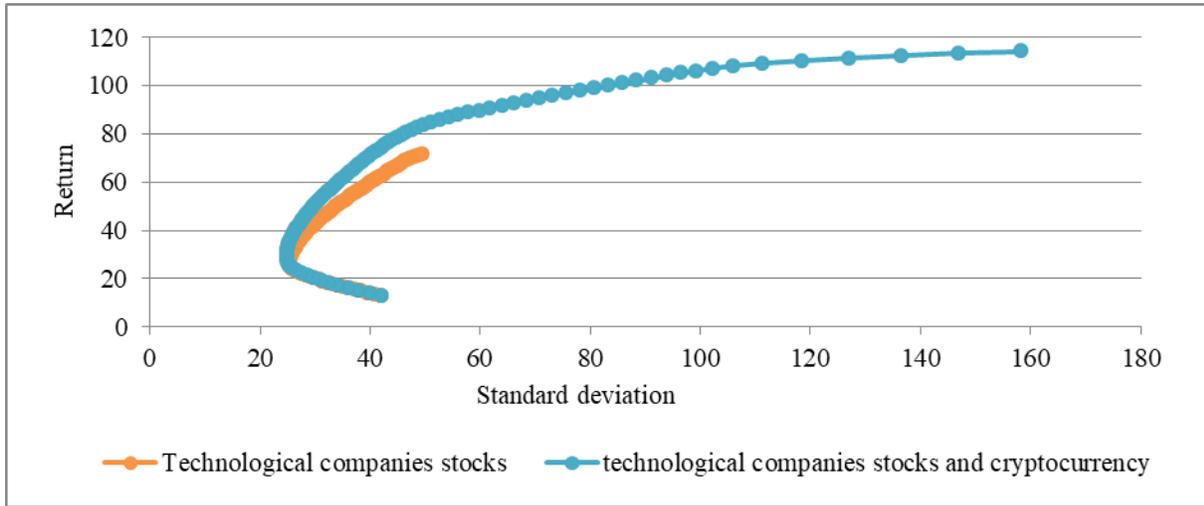


Fig. 3 Efficient frontier of a portfolio of technological stocks

Table 3 Descriptive statistics for technology stocks and cryptocurrency portfolios

	Technology firms' stocks		Technology firm's stocks +cryptocurrencies			
	Naïve Portfolio	Optimized Sharpe Ratio	Naïve Portfolio	Optimized Sharpe Ratio	Optimized Ratio Short allowed	Sharpe selling
Mean	49,117%	93,380%	78,691%	107,989%	137,967%	
Standard deviation	35,737%	52,212%	46,869%	50,714%	59,353%	
Sharpe ratio	1,258	1,709	1,590	2,047	2,254	

Interestingly, the ability to sell portfolio assets led to better results. The integration of cryptocurrencies into the technology company equity portfolio significantly improved returns, from 93.380% to 137.967%. The Sharpe ratio also increased, from 1.709 to 2.254, indicating even more effective risk management for higher returns. However, portfolio risk increased slightly, from 52.212% to 59.353%. The authorization of short-term cryptocurrency sales proved to be a key factor in this portfolio's improved performance. In fact, these results highlight the value of incorporating cryptocurrencies into a technology equity portfolio to improve risk-adjusted performance, particularly when active management and complex strategies such as short

selling are permitted. We then examined the diversification of a portfolio composed of the best-performing assets, namely Berkshire Hathaway Inc (BRK), JPMorgan Chase & Co, Johnson & Johnson (JNJ), Procter & Gamble Company (PG) and Visa Inc Class A. Fig.4 illustrates the efficient frontiers of a portfolio composed exclusively of equities, as well as that of the portfolio diversified by cryptocurrencies. We observed that, for a given level of risk, a diversified portfolio offers better returns, which translates into a higher Sharpe ratio. Table 4 details the results of the different portfolios, in terms of mean, standard deviation and Sharpe ratio. The results of the naive portfolio show that the integration of cryptocurrencies leads to a decrease in the Sharpe ratio, due to the equal distribution of investments across all assets. In fact, this also applies to a portfolio composed of technology company shares. Integrating cryptocurrencies into a portfolio composed of large-cap stocks generated an average return of 79.485%, with a standard deviation of 41.120%. However, it is essential to note that this investment strategy also increased the overall risk of the portfolio. Indeed, these results show that incorporating cryptocurrencies, especially in strategies optimized and complex by allowing short sales, can significantly improve the risk-adjusted performance of a traditional portfolio composed solely of equities.

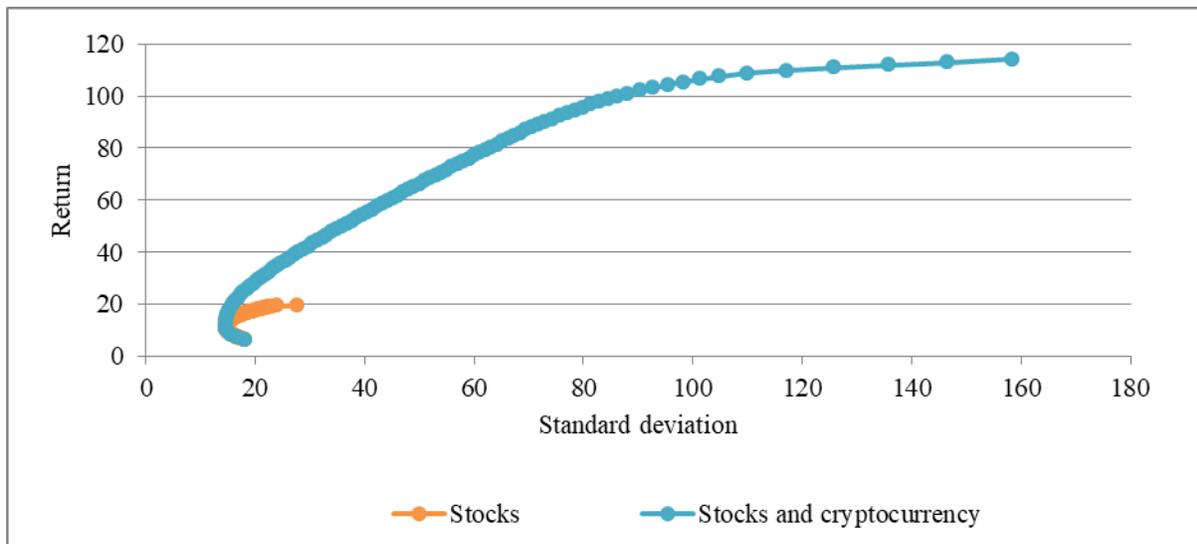


Fig. 4 Efficient frontier for a diversified portfolio of stocks

Table 4 Descriptive statistics for stocks and cryptocurrencies portfolios

	Stocks		Stocks + cryptocurrencies			
	Naïve Portfolio	Optimized Sharpe Ratio	Naïve Portfolio	Optimized Sharpe Ratio	Optimized Ratio Short selling allowed*	Sharpe
Mean	20,204%	23,190%	70,150%	56,095%	79,485%	
Standard deviation	19,851%	21,247%	47,915%	32,317%	41,120%	
Sharpe ratio	0,808	0,896	1,377	1,607	1,832	

* additional condition applied on weights to be ≤ 1

The results of the naïve portfolio show that the integration of cryptocurrencies leads to a decrease in the Sharpe ratio, due to the equal distribution of investments across all assets. In fact, this also applies to a portfolio composed of technology company shares. Integrating cryptocurrencies into a portfolio composed of large-cap stocks generated an average return of 79.485%, with a standard deviation of 41.120%. However, it is essential to note that this investment strategy also increased the overall risk of the portfolio. Indeed, these results show that incorporating cryptocurrencies, especially in strategies optimized and complex by allowing short sales, can significantly improve the risk-adjusted performance of a traditional portfolio composed solely of equities. We then apply this methodology to a portfolio of five foreign currencies, namely the euro, Japanese yen, Canadian dollar, British pound and Australian dollar. We observed that the performance of the diversified portfolio including cryptocurrencies outperformed that of the portfolio composed of all five currencies, for the same level of risk. The results are illustrated in Fig.5, and Table 5 details the quantitative aspects. The optimized portfolios show a substantial improvement in risk-adjusted return. The Sharpe ratio for an optimized all-currency portfolio is 0.041, which is considerably low. The incorporation of cryptocurrencies into the currency portfolio resulted in a significantly higher average return of 95.478%. However, this return is accompanied by substantial risk, characterized by a high standard deviation of 61.982%. Nevertheless, the optimized Sharpe ratio remains high, at 1.473. We examine the impact of incorporating cryptocurrencies on the commodity portfolio, namely wheat, gold, coffee, copper and silver. We observed that the return on the diversified portfolio including cryptocurrencies outperformed that of the portfolio composed of the five currencies, for the same level of risk.

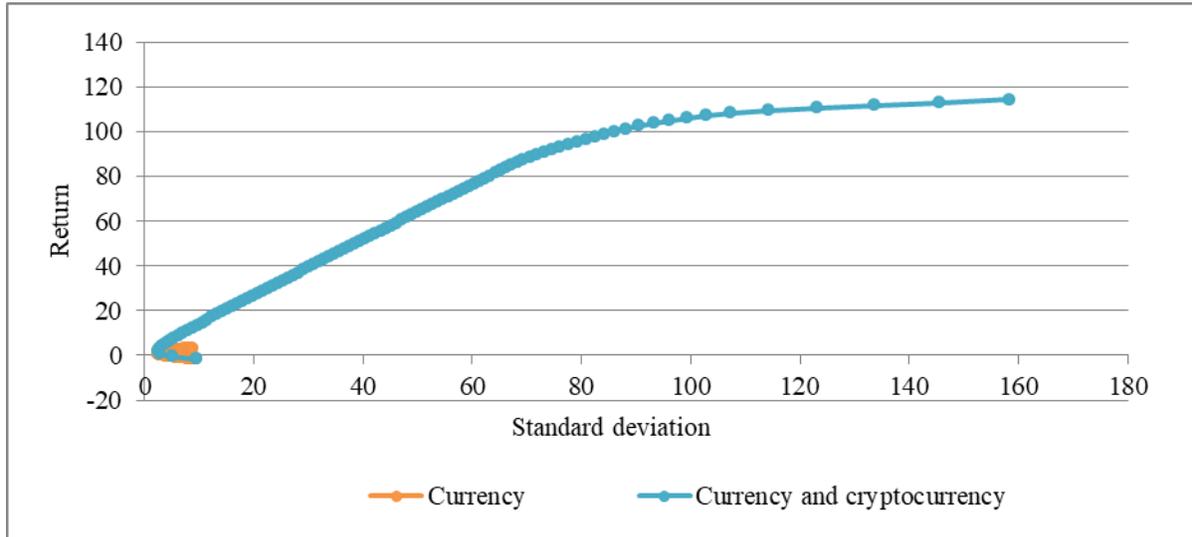


Fig. 5 Efficient frontier of a currency exchange portfolio

Table 5 Descriptive statistics for currencies portfolios

	Currencies		Currencies + cryptocurrencies	
	Naïve Portfolio	Optimized Sharpe Ratio	Naïve Portfolio	Optimized Sharpe Ratio
Mean	0,539%	4,595%	54,883%	95,478%
Standard deviation	4,633%	10,701%	41,119%	61,982%
Sharpe ratio	-0,781	0,041	1,234	1,473

The efficiency frontiers are illustrated in Fig.6, and the quantitative aspects are presented in Table 6. We have observed that incorporating cryptocurrencies into the commodities portfolio improves the risk-return trade-off with a high-risk ratio and a Sharpe ratio above 1. In fact, strategies optimized to maximize the Sharpe ratio demonstrate a significant improvement in risk-adjusted return. The Sharpe ratio rises from 0.751 for a commodity-only portfolio to 1.594 with the incorporation of cryptocurrencies in an optimized approach. When short selling is allowed, the Sharpe ratio rises to 1.794, indicating even more effective risk management and returns of 57.202%.

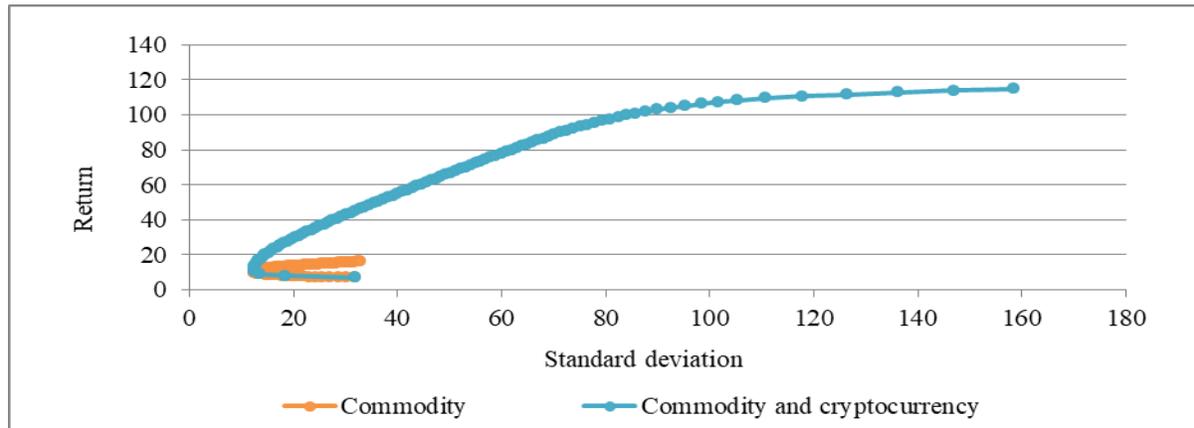


Fig. 6 Efficient frontier of commodities portfolio

Table 6 Descriptive statistics for commodities portfolios

	Commodities		Commodities + cryptocurrencies			Sharpe Ratio Short selling allowed*
	Naïve Portfolio	Optimized Sharpe Ratio	Naïve Portfolio	Optimized Sharpe Ratio	Optimized Ratio	
Mean	15,272%	16,418%	67,684%	51,676%	57,202%	
Standard deviation	18,759%	16,317%	47,151%	29,806%	29,558%	
Sharpe ratio	0,592	0,751	1,347	1,594	1,794	

* additional condition applied on weights to be ≤ 1

Finally, we study the impact of incorporating cryptocurrencies into an oil portfolio that comprises three assets, namely the price of Brent crude oil, crude oil, uranium and natural gas. We combined this portfolio due to the volatility of the oil barrel mainly in times of crisis as evidenced by the period of covid-19 and that of the Ukraine-Russia war. The results are illustrated in Fig.7, while Table 7 presents the quantitative aspects. The naive portfolio combining oil and cryptocurrencies shows a higher average return of 71.393% compared to an oil-only portfolio of 10.51%, although volatility has also increased from 49.840% to 56.608%. Optimization strategies led to a clear improvement in risk-adjusted returns. For example, the optimized Sharpe ratio of an oil-only portfolio is 0.611, while incorporating cryptocurrencies yields a Sharpe ratio of 1.536. When short sales are allowed, the Sharpe ratio rises to 1.799, with an average return of 110.777%, indicating more effective risk management and maximized returns, despite an above-average risk of 59.250%.

4. Discussion and results

We were able to observe, in all the cases previously outlined, except for the currency portfolio, that the inclusion of cryptocurrencies in a diversified portfolio offers superior returns compared to a portfolio made up solely of traditional assets, while maintaining an equivalent level of risk as measured by the standard deviation of the portfolios. Diversified cryptocurrency portfolios outperformed traditional portfolios not only of technology companies, but also of other types of stocks, in both long and short portfolios. Furthermore, diversification across cryptocurrencies delivered higher returns for the same level of risk. Better results were observed when short selling of assets was allowed. It is notable that the improved results were seen without the application of additional conditions to the commodities portfolio. Thus, it is possible to conclude that incorporating cryptocurrencies into existing portfolios can significantly boost returns while offering better diversification, thereby reducing portfolio risk. In addition, our empirical analysis also confirmed that Ethereum offers better diversification capacity than Bitcoin, closely followed by Dogecoin. Previous studies have mainly focused on the diversification of traditional portfolios using Bitcoin exclusively ([Kajtazi and Moro, 2019](#); [Guesmi et al., 2019](#); [Symitsi and Chalvatzis, 2019](#)).

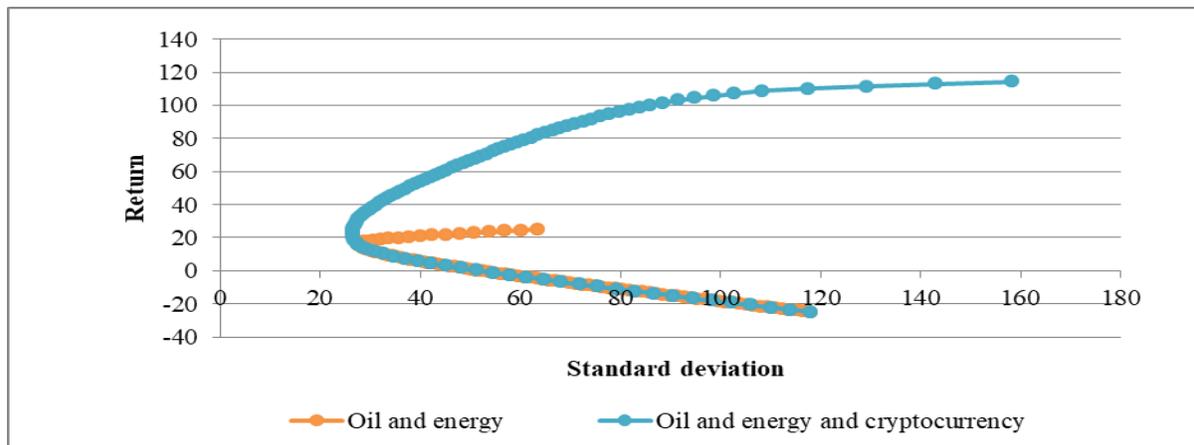


Fig. 7 Efficient frontier of oil and energies portfolio

Table 7 Descriptive statistics for oil and energies portfolios

	Oil and Energies		Oil and Energies + cryptocurrencies			
	Naïve Portfolio	Optimized Sharpe Ratio	Naïve Portfolio	Optimized Sharpe Ratio	Optimized Ratio Short selling allowed*	Sharpe
Mean	10,510%	25,20%	71,393%	87,117%	110,777%	
Standard deviation	49,840%	34,40%	56,608%	53,992%	59,250%	
Sharpe ratio	0,127	0,611	1,188	1,536	1,799	

The five portfolios analyzed in this research all performed better in terms of risk/return trade-offs when cryptocurrencies were included, particularly when short selling was allowed and except for the currency portfolio, which is characterized by high volatility. For example, (Table 8) for the technology equities portfolio, diversification by Ethereum shows a return of 117.86% with a risk of 58.70% and a Sharpe ratio greater than 1 and amounting to 1.937, and its results are almost similar to those of the same portfolio diversified by Bitcoin and Dogecoin. For the commodities portfolio, the incorporation of cryptocurrencies improves the average return and Sharpe ratio, although the impact is not as marked. Indeed, Bitcoin provides the best return of 37.16% and a Sharpe ratio above 1 of 1.455, although Ethereum and Dogecoin also improve overall performance. Similarly, for the oil portfolio, Ethereum outperforms the other cryptocurrencies in terms of return at 77.75% and Sharpe ratio at 1.317. In sum, the incorporation of cryptocurrencies, and Ethereum in particular, tends to improve the risk-adjusted performance of portfolios across sectors, albeit with variability depending on asset types and specific cryptocurrencies. Fig. 8 reveals that Ethereum exhibits a narrower interquartile range (IQR), and higher median returns compared to Bitcoin, suggesting more stable performance, while Dogecoin shows higher volatility with outliers. However, the ANOVA results (Table 9) indicate no statistically significant differences between cryptocurrency groups (C(Crypto): $F = 0.40$, $*p* = 0.67$), implying that the observed visual trends in the boxplot may not generalize to broader populations.

In the scientific literature, several studies have examined the performance of portfolios including cryptocurrencies (Platanakis et al., 2018; Platanakis and Urquhart, 2019; Borri, 2019; Liu, 2019 ; Ma et al., 2020). Most of these studies discussed portfolio diversification by focusing exclusively on Bitcoin. In fact, we identified only three papers in which Petukhina et al. (2021) and Ma et al. (2020) highlighted diversified portfolios comprising several cryptocurrencies. Petukhina et al. (2021) presented results regarding liquidity-related risk and return optimization of S&P100 stocks, the bond index and the commodity index, using data observed over the period from April 2014 to October 2017. Interestingly, our results corroborate those obtained by Petukhina et al. (2021) suggesting that cryptocurrencies offer better diversification opportunities for investors. Examining data from January 2015 to December 2017, Petukhina et al. (2021) concluded that cryptocurrencies can improve a portfolio's risk/return profile, particularly as part of a strategy targeting high returns. Finally, the study by Ma et al. (2020) investigated the incorporation of Bitcoin and Ethereum, demonstrating that Ethereum has a better diversification capacity than Bitcoin in most of the portfolios studied. Our contribution to this literature lies in carrying out an empirical analysis on a recent dataset, covering the period from August 2015 to December 2024, while including cryptocurrencies, and incorporating the period of the COVID-19 pandemic and that of the Ukrainian-Russian conflict and the Israeli-Palestinian conflict.

Table 8 Portfolio diversification with optimized Sharpe ratio using Bitcoin (only), Ethereum (only) and Dogecoin (only)

Portfolios	Without cryptocurrencies	Bitcoin	Ethereum	Dogecoin
Technological companies' stock	Mean : 93,38%	Mean : 111,14%	Mean : 117,86%	Mean : 114,49%
	Standard deviation :52,21%	Standard deviation : 53,77%	Standard deviation : 58,70%	Standard deviation : 58,38%
	Sharpe Ratio :1,709	Sharpe Ratio : 1,989	Sharpe Ratio : 1,937	Sharpe Ratio : 1,890
Stocks	Mean : 23,19%	Mean : 54,60%	Mean : 53,84%	Mean : 44,81%
	Standard deviation : 21,25%	Standard deviation : 33,67%	Standard deviation : 35,79%	Standard deviation : 33,29%
	Sharpe Ratio : 0,895	Sharpe Ratio : 1,497	Sharpe Ratio : 1,388	Sharpe Ratio : 1,221
Currencies	Mean : 4,59%	Mean : 81,81%	Mean : 83,58%	Mean : 96,75%
	Standard deviation : 10,70%	Standard deviation : 61,19%	Standard deviation : 70,17%	Standard deviation :109,28%
	Sharpe Ratio : 0,041	Sharpe Ratio : 1,269	Sharpe Ratio : 1,132	Sharpe Ratio : 0,847
Commodities	Mean : 16,42%	Mean : 37,16%	Mean : 36,79%	Mean : 27,04%
	Standard deviation : 16,32%	Standard deviation : 22,68%	Standard deviation : 24,85%	Standard deviation : 19,72%
	Sharpe Ratio : 0,751	Sharpe Ratio : 1,455	Sharpe Ratio : 1,313	Sharpe Ratio : 1,160
Oil & energies	Mean : 25,2%	Mean : 74,76%	Mean : 77,75%	Mean : 63,79%
	Standard deviation :34,4%	Standard deviation : 49,18%	Standard deviation : 55,84%	Standard deviation : 53,22%
	Sharpe Ratio : 0,611	Sharpe Ratio : 1,435	Sharpe Ratio : 1,317	Sharpe Ratio : 1,120

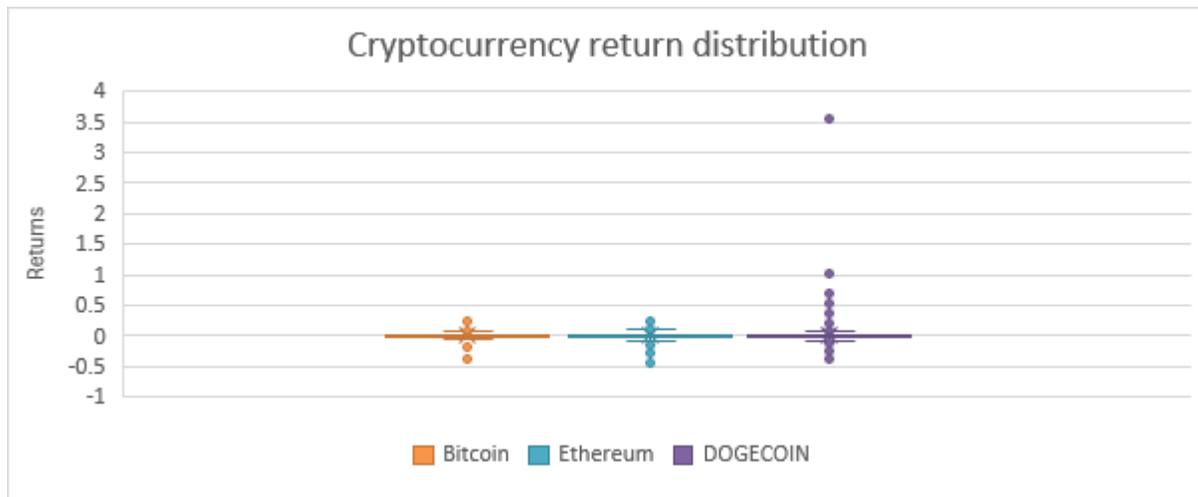


Fig.8 Cross-Cryptocurrency Return Analysis

Table 9 Anova Test

	sum_sq	df	F	PR(>F)
C(Crypto)	0,003903	2,0	0,399652	0,670569
Residual	34,380885	7041,0	NaN	NaN

Our results are consistent with the findings of previous studies. In addition, we have provided an in-depth analysis of the diversification of technology stocks, currency portfolios, oil portfolios, as well as other stocks and commodity portfolios, while including wheat prices. We also compared naive portfolios with efficient portfolio frontiers, in terms of diversification “with” and “without” cryptocurrencies.

5. Conclusion

Technological advances linked to the fourth industrial revolution have brought cryptocurrencies and blockchain technology to the fore, within an increasingly competitive financial environment. This revolution is affecting not only the foundations of traditional financial systems, but also investors' portfolio management strategies. This article provides empirical evidence that confirms the validity of the hypothesis that integrating cryptocurrencies into a diversified portfolio made up of various asset classes increases the portfolio's return potential. The rapid growth of cryptocurrencies makes these assets attractive, boosting portfolio returns and contributing to risk diversification. In addition, a comparison is made between diversified portfolios incorporating cryptocurrencies and portfolios without these assets, using the classic Markowitz model based on mean-variance analysis. The results demonstrate superior returns for an equivalent level of risk, in favor of diversified portfolios incorporating cryptocurrencies. This study also looked at diversification using three cryptocurrencies: Bitcoin, Dogecoin and Ethereum. At the end of this empirical validation, we found that Ethereum outperformed Bitcoin. However, the validity of these results under different metrics and optimization techniques remains subject to future investigation. Our findings suggest that cryptocurrencies offer investment opportunities for further exploration, and this study can be extended in the context of the Russia-Ukraine war and in crisis situations.

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Appendix 1

Descriptive statistics on returns on assets used

	BITCOIN	DOGECOIN	ETHEREUM	LITECOIN	XRP	BRENT CRUDE OIL	CRUDE OIL	NATURAL GAS	URANIUM	AMAZON
Mean	0.002710	0.004557	0.003484	0.001698	0.004086	0.000503	-0.001010	0.000939	0.000650	0.000726
Median	0.001632	-0.000940	-0.000262	0.000000	-0.001290	0.000829	0.001992	0.000000	0.000000	0.001183
Maximum	0.252472	3.554932	0.353604	0.665871	0.834642	0.315466	0.376623	0.464812	0.124825	0.135326
Minimum	-0.371695	-0.389199	-0.423462	-0.361742	-0.460105	-0.244036	-3.059661	-0.259537	-0.105673	-0.948895
Std. Dev.	0.039308	0.099837	0.056287	0.056419	0.068927	0.025491	0.074452	0.039991	0.021984	0.028378
Skewness	-0.068263	20.06547	0.450657	1.433576	2.712078	0.183995	-31.63340	0.855499	0.320075	-15.93274
Kurtosis	10.20083	690.9545	8.573154	19.94713	29.40885	23.14380	1253.631	14.01157	6.308659	538.0424
Jarque-Bera	5061.701	46341534	3110.216	28828.63	70928.32	39609.86	1.53E+08	12118.12	1108.255	28034302
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	6.347490	10.67295	8.158966	3.975978	9.568306	1.177061	-2.365974	2.198620	1.523066	1.701129
Sum Sq. Dev.	3.617198	23.33369	7.416709	7.451677	11.12188	1.521102	12.97650	3.743883	1.131388	1.885251
Observations	2342	2342	2342	2342	2342	2342	2342	2342	2342	2342

	APPLE	GOOGLE	META	MICROSOFT	NVIDIA	TESLA	WHEAT	COFFEE	COPPER	GOLD	SILVER
Mean	0.001100	0.000520	0.001113	0.001130	0.002750	0.002049	0.000239	0.000626	0.000331	0.000415	0.000443
Median	0.000994	0.001415	0.001054	0.001059	0.002791	0.001307	-0.000540	0.000000	0.000187	0.000440	0.000302
Maximum	0.119808	0.099652	0.232824	0.142169	0.243696	0.219190	0.217761	0.100284	0.074642	0.059477	0.092862
Minimum	-0.128647	-0.949925	-0.263901	-0.147390	-0.187559	-0.210628	-0.106823	-0.086260	-0.066940	-0.049787	-0.116491
Std. Dev.	0.018030	0.026511	0.024078	0.017057	0.030558	0.036737	0.020069	0.020703	0.013853	0.009264	0.018064
Skewness	0.003630	-19.69428	-0.342550	0.060141	0.271470	0.279989	0.779087	0.258930	0.008253	-0.069593	-0.265124
Kurtosis	8.454622	707.4753	24.63279	10.54640	8.312268	7.256902	10.44612	4.109012	4.605333	6.976611	8.124874
Jarque-Bera	2903.392	48580581	45712.63	5558.609	2782.586	1798.928	5647.405	146.1883	251.5081	1545.019	2590.398
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	2.575556	1.218161	2.606187	2.646941	6.440629	4.797927	0.559547	1.466782	0.776253	0.972923	1.037104
Sum Sq. Dev.	0.760975	1.645371	1.357179	0.681063	2.185954	3.159370	0.942877	1.003431	0.449254	0.200904	0.763845
Observations	2342	2342	2342	2342	2342	2342	2342	2342	2342	2342	2342

	USD/AUD	USD/CAD	USD/CHF	USD/EUR	USD/GBP	USD/JPY	BRKA	JNJ	JPM	PG	V
Mean	-2.42E-05	5.94E-05	6.54E-05	7.78E-06	-6.96E-05	0.000116	0.000553	0.000264	0.000772	0.000454	0.000762
Median	0.000144	0.000112	-0.000157	0.000000	-5.21E-05	0.000265	0.000226	0.000194	0.000390	0.000588	0.001351
Maximum	0.028943	0.030138	0.028839	0.028545	0.030731	0.027049	0.112875	0.079977	0.180125	0.120090	0.138426
Minimum	-0.031682	-0.018905	-0.022342	-0.027752	-0.076039	-0.037250	-0.107979	-0.100379	-0.149649	-0.087373	-0.135472
Std. Dev.	0.006325	0.004450	0.004598	0.004655	0.005926	0.005588	0.012086	0.011431	0.017449	0.011781	0.015501
Skewness	-0.068441	0.084874	0.361853	-0.034850	-0.981064	-0.320986	-0.384868	-0.165273	0.420274	0.230140	0.169183
Kurtosis	4.356404	5.025169	5.148823	5.551475	17.88628	6.559696	14.20331	12.75615	17.11712	15.54845	13.22342
Jarque-Bera	181.3652	403.0314	501.6946	635.7441	22000.29	1276.738	12305.91	9298.887	19516.64	15386.51	10210.41
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	-0.056763	0.139078	0.153257	0.018219	-0.162996	0.270757	1.295216	0.617609	1.807566	1.062696	1.784266
Sum Sq. Dev.	0.093642	0.046352	0.049497	0.050716	0.082200	0.073112	0.341948	0.305878	0.712776	0.324904	0.562509
Observations	2342	2342	2342	2342	2342	2342	2342	2342	2342	2342	2342