Optimization of special cryptocurrency portfolios

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Abstract

Purpose – This paper aims to elaborate on the optimization of two particular cryptocurrency portfolios in a mean-variance framework. In general, cryptocurrencies can be classified to as coins and tokens where the first can be thought of as a medium of exchange and the latter accounts for security or utility tokens depending upon its design.

Design/methodology/approach – Against this backdrop, this empirical study distinguishes, in particular, between pure coin and token portfolios. Both portfolios are optimized by maximizing the Sharpe ratio and, subsequently, compared with alternative portfolio strategies.

Findings – The empirical findings demonstrate that the maximum utility portfolio of coins, with a risk aversion of $\lambda = 10$, outweighs alternative frameworks. The portfolios optimized by maximizing the Sharpe ratio for both coins and tokens indicate a rather poor performance. Testing the maximized utility for different levels of risk aversion confirms the findings of this empirical study and confers them more robustness.

Research limitations/implications – Further investigation is strongly recommended as tokens represent a new phenomenon in the cryptocurrency universe, for which only a limited amount of data are available, which restricts the sampling. Furthermore, future study is to include more sophisticated optimization models using different constraints in portfolio creation.

Practical implications – In light of the persistently substantial volatility in cryptocurrency markets, the empirical findings assert that portfolio managers are advised to construct a global minimum variance portfolio. In the absence of sophisticated optimization models, private investors can invest according to the market values of cryptocurrencies. Despite minor differences in the risk and reward ratios of the portfolios tested, tokens tend to be more speculative, especially, if the Tether token is excluded, which may require enhanced supervision and investor protection by regulating authorities.

Originality/value – As the current literature investigates on diversification effects of blended cryptocurrency portfolios rather than making an explicit distinction, this paper reflects one of the first to explore the investability and role of diversifying coins and tokens using a classic Markowitz approach.

Keywords Portfolio diversification, Bitcoin, Sharpe ratio, Portfolio optimization, Cryptocurrencies, Markowitz

Paper type Research paper

1. Introduction

In early 2019, Bitcoin celebrated its 10th anniversary, proving its position as the largest electronic peer-to-peer currency globally. Hence, Bitcoin exhibits one of the pioneers of cryptocurrencies still dominates the market in terms of market value. However, finally,

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alternative coins such as Ethereum, XRP or Litecoin have become increasingly appealing to investors. Currently, over 4,400 cryptocurrencies[1] are traded around the clock, 365 days a year.

The growing interest in cryptocurrencies and its underlying technology – the blockchain – is also reflected in the entry of regular businesses into the crypto-world using the hype of cryptocurrency for their benefit. For instance, the former called Long Island Iced Tea Corp. added the term blockchain to its company name, which led the stock surging to nearly 500% on the same morning the change of the name was announced. Similarly, the market value of the cigar manufacturer Rich Cigars rose by 2,000% in only one trading day after reporting it will focus on new businesses, including blockchain technology (Johnson *et al.*, 2017). Former camera and film manufacturer Kodak has also entered the cryptocurrency universe. The company used an initial coin offering (ICO) to launch the KODAKCoin pushing the stock price up more than 119% within one day (Cornish, 2018).

Notably, the introduction of ICOs, also known as token sales, opened up entirely new opportunities for funding blockchain-related projects and start-ups by the issuance of tokens. Recently, this phenomenon has become an alternative source of venture capital financing as it incurs lower costs and provides greater access to crowd investors compared to traditional forms of financing (Conley, 2017; Catalani and Gans, 2019; Kranz *et al.*, 2019). The funds raised through ICOs in 2017 amounted to over US$6.2bn, while a year later, token sales recorded a new high with revenues of nearly US$9bn[2].

One major reason for the increase in token sales was the introduction of so-called smart contracts on the Ethereum blockchain, which are presented in the white paper of the Ethereum project (Buterin, 2014). Smart contracts automatically execute predefined terms of a contract and play a key role in the progress of digital contracts in both the financial, as well as nonfinancial areas (Crosby *et al.*, 2016; Glaser, 2017). Unlike Bitcoin, the Ethereum blockchain provides an additional layer, on which decentralized applications and democratic autonomous organizations (DAOs) can be built. Another key feature of the Ethereum ecosystem includes the ERC-20 token protocol, which standardizes the coding of smart contracts and, therefore, allows for the tokenization of assets and rights (Buterin, 2014).

Against this backdrop, it is significant to differentiate between tokens issued through an ICO and other cryptocurrencies, also called alternative coins or altcoins. As a matter of fact, all cryptocurrencies can be classified as tokens, however, they differ slightly in their objective and design, entailing different legal and fiscal implications. A major distinction can be made between payment tokens (coins) and tokens with other purposes. A coin, such as Bitcoin, is in principle a digital currency that is primarily used as a medium of exchange to transfer value in a peer-to-peer network (Hahn and Wons, 2018).

Further, other tokens that do not serve as a medium of exchange can be decomposed into utility, equity or asset-backed tokens. As the name already indicates, a utility token provides the investor with specific functionality. Once a utility token is purchased, the user can redeem the token to obtain benefits for products and applications the company will provide in the future. An equity token is similar to securities and common stocks in terms of their properties. Besides, the equity token may include profit sharing or provide voting rights of the company. Finally, the asset-backed token incorporates a claim on an asset of the active side of the balance sheet, i.e. that such a token is backed by a physical asset such as gold or other common assets (Conley, 2017; Catalani and Gans, 2019; Hahn and Wons, 2018).

Although the emergence of token sales has aroused the attention of investors and policy, peer-reviewed literature on ICOs is still very scarce at the moment. The work of Conley (2017), Catalani and Gans (2019), Kranz *et al.* (2019), Conley (2017), Amsden and Schweizer (2018), Howell *et al.* (2018) and Adhami *et al.* (2018) provide a general introduction to the foundations of the subject area. They also analyze the success determinants of ICOs and find that monetary theory, financial economics and game theory play an important role in the token sales' triumph. Besides, they observe a negative linear relationship of venture uncertainty, while higher venture quality is positively associated with ICO success. Another overarching empirical study (Cai and Gomaa, 2019) deals with the dynamics of a token launch from a behavioral point of perspective and provides evidence that "investor sentiment and investor awareness are determinants of the amounts raised in an ICO." In contrast, Bouchagiar (2018) sheds light on key attributes of ICOs and examines potential risks, as well as the transformation from classic mechanisms to cryptocurrencies.

However, with the introduction of new financing tools and its associated promises, also challenges in terms of regulatory uncertainty, cost level and large risk of scams emerge (Wiśniewska, 2018). Against this backdrop, some research (Rohr and Wright, 2017; Zhang *et al.*, 2018; Dobrauz–Saldapenna and Klebeck, 2019) particularly devoted to the legal and regulatory challenges that token sales entail and provide potential guidelines and insights on how to tackle these problems to improve investor protection.

At present, investors keep facing legal, regulatory and fiscal uncertainties, as no comprehensive regulatory frameworks in the cryptocurrency market exist. Chiefly, participating in a token-sale involves tremendous financial risk, as these projects most likely turn out to be scams with the imposter running away with the investor's money. For this reason, investors are required to be wary before investing in a token-sale. Various empirical studies (Dyhrberg, 2016a; Cermak, 2017; Katsiampa, 2017; Pichl and Kaizoji, 2017; Klein *et al.*, 2018; Charles and Darné, 2019) confirm the large volatility in the cryptocurrency market, which represent another dangerous risk for investors. Allocating various cryptocurrencies to a portfolio can reduce the overall risk. Furthermore, the optimal selection of single weights in the portfolio can further enhance performance. The mean-variance model based on the portfolio selection theory introduced by the economist Harry Markowitz (1952, 1959) is a well-established method in finance to optimize a portfolio.

The optimization of a portfolio consisting of cryptocurrencies presents an emerging field of research. Previous studies examined the portfolio diversification effects of Bitcoin not only with other financial assets (Wu and Pandey, 2014; Eisl *et al.*, 2015; Kajtazi and Moro, 2019) but also that of a blended cryptocurrency portfolio (Liu, 2018; Platanakis *et al.*, 2018; Brauneis and Mestel, 2019). However, these studies rather focused on a general cryptocurrency portfolio than explicitly distinguishing between them. As identified above, a major differentiation of cryptocurrencies can be made between coins and tokens.

As the current literature investigates only the diversification effects of mixed cryptocurrency portfolios, rather than making an explicit distinction, this article is one of the first to examine the investability and role of diversification of coins and tokens using a classic Markowitz approach. That is to say, to construct two different portfolios of which one consists exclusively of coins and the other purely of tokens. This paper aims to examine whether a coin or token portfolio optimized by maximizing the Sharpe ratio is able to outperform benchmark portfolios. The result of this study was to show, which of the coin or token portfolios is more profitable or less risky, thus helping investors to make more informed investment decisions. Against this background, the empirical study delineates from other related work and contributes to the knowledge gap by exploring the investability and diversification, chiefly, in the distinction of coin and token portfolios.

To find significant empirical evidence, the analysis follows the approach of Eisl *et al.* (2015) and partially adopts specific measures of the studies mentioned previously that dealt with the portfolio diversification of cryptocurrencies. This empirical study applies an extension of the traditional mean-variance approach (Markowitz, 1952, 1959) over both portfolios, as the optimal portfolio weights are calculated by maximizing the Sharpe ratio (Sharpe, 1966).

The findings for all models examined exhibit negative performance measures, particularly, in Sharpe, Sortino and utility ratio, which is due to an overall market downturn during the back-testing period. However, the empirical results demonstrate that the best coin portfolio is reflected in the maximum utility (MU) model, with $\lambda = 10$. The market cap portfolio and other more sophisticated models considerably outperform the Sharpe ratio portfolio, which reports feeble performance. In contrast, the global minimum variance portfolio consisting of tokens reports superior performance compared to alternative frameworks. Further, the Sharpe ratio, market cap and 1/N model do not account for an ideal investment opportunity. Overall, the coin MU portfolio, with $\lambda = 10$, is preferable over the token GMV, in particular, with respect to its Omega ratio. The empirical findings prove to be robust to that extent as identical results for each tested model are obtained when calculating the maximized utility for different levels of risk aversion.

This manuscript is structured as follows: Section 2 provides a brief overview of the research conducted on the economics and finance of Bitcoin and particularly its effect on portfolio diversification. Subsequently, Section 3 illustrates the methodology and data used in this empirical study. Section 4 presents descriptive statistics of the single constituents for the cryptocurrency portfolios and Section 5 discusses the empirical results of the analysis over the out-of-sample period. Ultimately, Section 6 concludes the study.

2. Literature review

Many cryptocurrencies allow the transfer of virtual money in a peer-to-peer network. To ensure the integrity of the data in a distributed system, cryptographic hash functions are used. Another important feature of cryptocurrency functionality is the consensus protocol, which provides an agreement between anonymous nodes on the current status of the transaction history stored in a distributed ledger, commonly referred to as a blockchain. New blocks are added by certain nodes (miners) on the network and cryptographically linked to previous blocks of data, making the blockchain tamper-proof and accessible to all on the network (Nakamoto, 2008). Given these properties, the need for a centralized and trustworthy third party such as a bank or a state institution becomes obsolete making cryptocurrencies attractive to everyone.

In the past couple of years, public interest in Bitcoin and other cryptocurrencies has vastly grown, which is mainly reflected in the sharp rise of the cryptocurrency market in 2017, reaching a total of US$825bn in early January 2018. Individual cryptocurrency prices such as those for Bitcoin or Ethereum, rose at levels of over 1,700% and 5,400% during this period, respectively[3]. The remarkable development of the cryptocurrency market caught the attention of investors, regulators and academics, casting doubts on an emerging bubble across the entire market that menaces the wealth of private and institutional investors. Notably, the market for cryptocurrencies collapsed shortly after its peak in January plummeting to a total market capitalization of less than US$300bn in February 2018[3].

High speculation in the cryptocurrency market creating a huge bubble, in particular, regarding Bitcoin, has been empirically proved by Cheah and Fry (2015), Corbet *et al.* (2017), Fry (2018) and Bouri *et al.* (2019d). More recent publications (da Fonseca and da Fonseca, 2019; Chaim and Laurini, 2019) use different stochastic models to demonstrate the existence of bubbles in Bitcoin prices. They find bubble-like behavior, primarily, in the early stages of Bitcoin, but find no evidence from 2016 onward. Furthermore, findings by Kallinterakis (2019) reveal that the cryptocurrency market is significantly subject to herd behavior of investors, especially during upswings, low volatility and high volume days. Bouri *et al.*

(2019a) find similar results and conclude that herding specifically occurs when uncertainty increases. According to studies by Karalevicius *et al.* (2018), the Bitcoin price is sensitive to media sentiment, leading to the overreactions of investors in the short-term.

Early tests on the market efficiency of Bitcoin resulted in the assumption that the efficient market hypothesis is not satisfied over long-term periods (Urquhart, 2016). However, later studies by Nadarajah and Chu (2017) find that simple power transformation of the Bitcoin returns leads to market efficiency without loss of information, especially, in recent years. Further authors, as Vidal-Tomás and Ibañez (2018) prove evidence that monetary policy news does not affect Bitcoin price, but events in cryptocurrency markets do, concluding that efficiency has improved over time. Similarly, Brauneis and Mestel (2018), Khuntia and Pattanayak (2018), Tiwari *et al.* (2018) and Othman *et al.* (2019) discover that market efficiency has considerably evolved with time.

Concerning the price discovery of Bitcoin, Ciaian *et al.* (2016) observe that market forces and Bitcoin attractiveness substantially affect prices, however, with variation over time. Current studies (Kapar and Olmo, 2019) unveil that introducing Bitcoin futures dominates the price discovery process, which is mainly driven by a combination of Bitcoin's futures and spot price. Urquhart (2017) finds strong evidence of price clustering in Bitcoin around whole numbers, with over 10% of prices ending with two zero decimal digits. Baig *et al.* (2019) use investor sentiment to derive price clustering in Bitcoin and confirm previous studies, as investors tend to settle on round prices.

Multiple studies have examined cryptocurrencies, in particular, with focus on Bitcoin, for their price changes over both short and long-term periods, finding that volatility for cryptocurrencies is larger than that of other financial assets (Dyhrberg, 2016a; Cermak, 2017; Katsiampa, 2017; Pichl and Kaizoji, 2017; Klein *et al.*, 2018; Charles and Darné, 2019). Katsiampa (2017) explores different competing GARCH-type models to explain the volatility of Bitcoin's price, concluding with the AR-CGARCH as the optimal model for goodness-of-fit to the data. A replication study by Charles and Darné (2019) partially validates the findings as mentioned earlier of Katsiampa (2017), however, the authors turn down all tested GARCH models after conducting a robustness analysis. Similar scholarly work is conducted by Tiwari *et al.* (2019), who attempts to find the best fit model for returns of Bitcoin and Litecoin comparing a set of different GARCH models with stochastic volatility framework. The findings of this study reveal that for Bitcoin the stochastic volatility-*t* approach shows best fit while for Litecoin the GARCH-*t* almost always outperforms other models. Recent findings by Sosa *et al.* (2019) show that the E-GARCH under generalized error distribution exhibits the best model to forecast Bitcoin conditional volatility.

In general, the literature on forecasting volatility of Bitcoin returns is expanding to a large extent at the moment. Urquhart (2018) identify that the attention of Bitcoin is boosted, chiefly, by previous day volatility and volume, as well as two days previous returns. Yu *et al.* (2019) investigate the dynamic volatility of Bitcoin using high-frequency data. The author's findings show that the leverage effect considerably affects future volatility, thus making it more powerful in forecasting Bitcoin volatility. Additionally, Chaim and Laurini (2018) examine the dynamics of Bitcoin's daily returns and volatility, concluding "that introducing a time-varying average volatility component reduces temporal persistence of the autoregressive volatility process." Further research on the economics of Bitcoin identifies (adaptive) long memory in the volatility of Bitcoin returns (Bouri *et al.*, 2018b; Khuntia and Pattanayak, 2018). More recent academic work of Katsiampa (2018) studies the volatility dynamics of Bitcoin and Ether, noticing that conditional volatility and correlation of both react to major news. Furthermore, he infers that Ether serves as an effective hedge against Bitcoin in a portfolio.

The decentralized nature of cryptocurrencies and the high speculation in the market raises the question of how to categorize cryptocurrencies. For this reason, the relevant literature regards Bitcoin and other cryptocurrencies as a speculative investment due to their high volatility, especially when compared to traditional currencies (Glaser *et al.*, 2014; Bouoiyour *et al.*, 2014; Wu and Pandey, 2014; Baek and Elbeck, 2015; Baur *et al.*, 2018b; Hao, 2018). Early works of Dyhrberg (2016b) suggest that Bitcoin represents something between gold and currencies. However, subsequent studies (Baur *et al.*, 2018a; Stavroyiannis, 2018) reject this hypothesis, as Bitcoin's returns, standard deviation and correlation differ clearly from that of gold, the S&P 500 and the American dollar. More recent studies of Lambrecht and Larue (2018), who analyze Bitcoin regarding its functioning as a currency from a philosophical point of view, conclude that the cryptocurrency most likely cannot fulfil its promises as traditional currency. Moreover, current research (Corbet *et al.*, 2019b) confirms that Bitcoin is a speculative asset even after the introduction of futures trading. Further evidence (Haiss and Schmid–Schmidsfelden, 2018) corroborate previous studies that found cryptocurrencies are more of a token and extremely volatile asset class of their own, however, indicate that Bitcoin cash may best meet the properties of a currency at the moment. Primarily, due to the decentralized design, Ram (2019) classifies Bitcoin as a distinct alternative asset class.

Another field of research on the economics and finance of cryptocurrencies concerns the capabilities of hedging and diversification benefits of Bitcoin in an investment portfolio. Against this background, Nadarajah and Chu (2017) and Dyhrberg *et al.* (2018) acknowledge the investment grade of Bitcoin. Unlike Dyhrberg (2016a) and Klein *et al.* (2018) find differences in the structure of Bitcoin against gold and other assets and, therefore, Bitcoin does not provide stable hedging capabilities, as does the gold in a global portfolio. According to Bouri *et al.* (2017), Bitcoin acts as a suitable diversifier, but is only effective as a hedge and safe haven against Asia Pacific stocks, while further studies prove evidence that Bitcoin is a powerful hedge against various indices such as the euro STOXX, Nikkei, Shanghai A-share, S&P 500 and the TSX index using monthly data (Chan *et al.*, 2019). Extended analysis (Bouri *et al.*, 2019b) confer hedging capabilities of several cryptocurrencies beyond Bitcoin, especially, against US equity indices. Moreover, in a more recent study by Bouri *et al.* (2019c), the authors find further evidence of diversifying and hedging abilities of major cryptocurrencies, including Bitcoin, Ethereum and Litecoin specifically against Asian Pacific and Japanese equities. Given these properties, investors can effectively benefit from diversifying portfolios by combining cryptocurrencies with equity investments. Conversely, Fang *et al.* (2019) find hedging properties of Bitcoin only applies in uncertain economic situations. Similarly, Shahzad *et al.* (2019) propose that Bitcoin does not always behave like a safe haven.

Against this background, a broad range of academic work has focused on the inclusion of cryptocurrencies to a global portfolio and its effects on portfolio diversification. Initial studies (Wu and Pandey, 2014; Eisl *et al.*, 2015) use slightly different versions of the mean-variance framework for optimizing a globally diversified portfolio and find positive effects on the overall portfolio performance when including Bitcoin. Different studies (Brière *et al.*, 2015; Carrick, 2016; Pinudom *et al.*, 2018; Symitsi and Chalvatzis, 2019) confirm the benefits of including Bitcoin as a complement to a well-diversified portfolio. Furthermore, several works aim at examining the positive impact of portfolios, including Bitcoin and other altcoins using a classical Markowitz model (Markowitz, 1952, 1959). Notably, Liu (2018), Platanakis and Urquhart (2019,; Kajtazi and Moro (2019) and Brauneis and Mestel (2019) find evidence that the inclusion of Bitcoin and other cryptocurrencies to a global portfolio improves overall portfolio performance, however, sophisticated portfolio optimization models such as the aforementioned mean-variance analysis introduced by Markowitz, cannot beat a naïvely diversified portfolio in regard of Sharpe ratio (Sharpe, 1966), which confirms previous findings by DeMiguel *et al.* (2009).

The literature also embraces the investigation of the relationship between Bitcoin and other financial assets using different statistical tools. Kristjanpoller and Bouri (2019) examines cross-correlations between traditional currencies and cryptocurrencies and identify "significant asymmetric characteristic from the cross-correlation, that is, found to be persistent and multifractal in most of the cases." Further studies reveal considerably negative dependencies between currencies and cryptocurrencies (Baumöhl, 2019; Uyar, 2019).

In this context, the spillover effects of cryptocurrencies to other financial assets are particularly expanding in literature at present. Findings by Corbet *et al.* (2018), Alfieri (2019) demonstrate potential diversification effects of cryptocurrencies in relationship with other financial assets. Identical results in the work of Guesmi *et al.* (2018), Bouri *et al.* (2018a) and Qarni *et al.* (2019) discover the return and volatility spillover effects of Bitcoin to financial markets using different statistical models. Research by Katsiampa *et al.* (2019) and Kumar and Anandarao (2019) provide significant evidence that spillover effects occur even among cryptocurrencies themselves.

Regarding the transaction costs of cryptocurrencies, especially, those of Bitcoin, Kim (2017) indicate lower levels of fees compared to retail foreign exchange markets and Dyhrberg *et al.* (2018) to major equity exchanges.

Currently, a new field of research on Bitcoin and cryptocurrencies is emerging that deals with the effectiveness of technical analysis in the cryptocurrency market. Notably, several studies (Alaoui *et al.*, 2018; Hudson and Urquhart, 2019; Corbet *et al.*, 2019a) have provided significant predictive power for the application of technical trading rules for cryptocurrencies, opening up new opportunities for investors and future research.

Concluding, Corbet *et al.* (2019c) present a detailed overview of research conducted in the field of cryptocurrencies. Still, academic work in the economics of Bitcoin and Altcoins is vastly expanding, which calls for further systematic reviews to pool pertinent literature.

3. Methodology and data

As with Wu and Pandey (2014), Platanakis *et al.* (2018), Liu (2018), Brauneis and Mestel (2019) and Kajtazi and Moro (2019), this research is exploratory, however, distinguishes itself in detail by optimizing two distinct portfolios, i.e. of coins and tokens, rather than a well-diversified portfolio including Bitcoin, Altcoins and/or other financial assets. This empirical study applies a slight variation of the traditional mean-variance approach (Markowitz, 1952, 1959) over both portfolios. The optimal weight allocation is generated by maximizing the Sharpe ratio of the constituent cryptocurrency (Sharpe, 1966). Additionally, the optimization process produces efficient frontiers of portfolios, which can be all considered as optimal in terms of the risk-return ratio as for any given level of risk the return is maximized.

Subsequently, the analysis evaluates the performance of such optimized Sharpe ratio portfolios in comparison to alternative portfolio strategies for specific performance measures not only such as annualized return and volatility but also the Sortino and Omega ratios [Equations (3) and (4)]. Furthermore, the maximized utility is computed with distinct levels of the risk aversion parameter to demonstrate that the empirical findings are robust. The objective of this work is to examine whether the optimization of specific cryptocurrency portfolios using a classic mean-variance framework can outperform varied benchmark portfolios. The terms "optimal" and "optimized" are used interchangeably throughout this paper to refer to such portfolios.

3.1 Data

Daily market prices of cryptocurrencies were retrieved from the online platform www.coinmarketcap.com on which current average prices of all cryptocurrencies are freely available. Taking extreme values into account during the market turmoil from 2017 to 2018 reflects a realistic scenario that aims to provide investors with a better understanding of the particular characteristics of cryptocurrencies to make more informed investment decisions. However, historical data, particularly on token prices, is limited since most of the larger tokens have been issued in mid-2017, thus reducing the available set of data. Furthermore, to ensure a homogeneous sample period, the sampling started on August 1, 2017, and ended on May 31, 2018, t = 303 for both coins and tokens, covering the most significant ups and downs of the cryptocurrency market in recent history. The authors are aware of the relatively short sampling period but refer to the limited data available. Optimal portfolio weights, which are generated from the recorded in-sample data, will be back-tested in an out-of-sample period from June 1, 2018 to May 31, 2019, to mimic a realistic investment case using predefined portfolio strategies. This approach is in contrast to the work of Kajtazi and Moro (2019), who renounce to factor this volatile period.

The empirical analysis includes in total 20 cryptocurrencies, separated into two portfolios consisting of 10 coins and 10 tokens each. The total market cap of cryptocurrencies determines the selection process of the single cryptocurrencies, which totals US$331.3bn as of the first investment date June 1, 2018. Against this background, the 10 most significant coins and tokens according to their market value are selected and allocated to the portfolios. The study comprises the following coins: Bitcoin, Ethereum, XRP, Bitcoin cash, EOS, Litecoin, Stellar, IOTA, NEO and Dash and the following tokens: Tether, Golem, Augur, DigixDAO, Basic Attention Token, Gas, OmiseGO, status, populous and MaidSafeCoin to the empirical analysis.

3.2 The mean-variance approach

Investing one's wealth in merely one asset might yield tremendous returns, however, it also bears a considerable amount of risk of losing the entire investment. The adage to "never put all your eggs into one basket" becomes true in this context. To put it differently, an investor should construct a portfolio of diverse or ideally, uncorrelated assets to spread the individual risk of each asset, thus, reducing overall risk. According to the pioneer of modern portfolio theory Harry Markowitz (1952, 1959), the risk-return ratio can be increased through optimal diversification. In essence, he emphasized that an investor should differentiate the risks associated with a single asset from a multi-asset portfolio confirming that uncertainty or risk, is considerably reduced. Moreover, Markowitz provided a quantitative framework defined as the mean-variance portfolio analysis, to estimate the risk, denoted by σ and the return, denoted by R, of a portfolio. In mathematical notation, optimal diversification is achieved by maximizing the expected quadratic utility function, $E(U)$, where U (x) = $1 - e^{-\lambda x}$ assuming the random vector, R, to follow a multivariate normal distribution [$R \sim N(\mu, \Sigma)$]:

$$E\left(U\left(R_p\right)\right) = w^T \mu - \frac{\lambda}{2} w^T \sum w \tag{1}$$

where the vector of portfolio weights is denoted by w. Solving the utility function requires historical sample data to estimate the mean, μ and the covariance matrix, $\sum$. Further, the mean-variance model depends upon the individual degree of the investor's risk aversion, denoted by the parameter λ. However, unlike Brauneis and Mestel (2019), Platanakis *et al.* (2018); Liu (2018), in which different levels of the risk aversion parameter were assumed, this empirical study aims to optimize the constituent weightings in the portfolios by maximizing the Sharpe ratio. The Sharpe ratio portfolio (Sharpe, 1966), also known as the tangency portfolio, comprises the largest risk-reward combination and is deemed to be an extension to the classic mean-variance model. Specifically, maximizing the Sharpe ratio, which is the mean return per unit standard deviation, can be defined as follows in the optimization process:

$$\mathrm{Max}\left[\frac{r_P - r_f}{s_P}\right] \quad | \quad \forall\,\text{Portfolios P with}:\begin{cases} \sum_i w_{pi} = 1 \\ w_{pi} \geq 0 \end{cases} \tag{2}$$

The objective is to maximize the fraction resulting from the numerator, $r_P - r_f$, which represents the average portfolio return less the risk-free rate[4]. The denominator, s_P, gives the portfolio's standard deviation, thereby producing the optimal weights in terms of the risk-adjusted excess return. In addition, all portfolios constructed in the optimization process are subject to certain constraints, i.e. to the full investment constraint, denoted by $\sum_i w_{pi} = 1$ and the long-only constraint, $w_{pi} \geq 0$. In light of the nascent stage of the cryptocurrency market, short sales[5] are neglected in the cadre of this empirical study.

Although the mean-variance framework is a widely used method to optimizing portfolio allocation, internal flaws in the model limit its usefulness (Black and Litterman, 1992; Kan and Zhou, 2007). Studies by DeMiguel *et al.* (2009) show that portfolios subject to a mean-variance optimization model result in poorer portfolio performance compared to a naïvely diversified portfolio (1/*N*) due to internal estimation errors in the model's parameters. Furthermore, more recent studies by Platanakis and Urquhart (2019) show that the Black–Littermann model with variance-based constraints conveys superior risk-adjusted returns and lower volatilities compared to a 1/*N* portfolio strategy and a classic Markowitz mean-variance portfolio approach.

Excess kurtosis and fat-tailed distribution account for another decisive drawback of the Markowitz model and can lead to less robust results in a mean-variance environment, in which a normal distribution of returns is assumed. Consistent with previous findings (Brière *et al.*, 2015; Wu and Pandey, 2014; Guesmi *et al.*, 2018; Platanakis *et al.*, 2018; Brauneis and Mestel, 2019), observed returns of Bitcoin and other cryptocurrencies in this empirical study show high excess kurtosis and heavily skewed distributions (Table 2). Recent studies by Mba *et al.* (2018) propose a GARCH-differential evolution *t*-copula-based approach to portfolio optimization to significantly increase the yield of a cryptocurrency portfolio with fat tail distributions and, thus, controlling the associated risk. Moreover, alternative risk measures may be considered to estimate variance such as value-at-risk (VaR) and expected shortfall (ES)[6] to provide more reliable optimization parameters for cryptocurrency returns (Kajtazi and Moro, 2019).

3.3 Evaluating portfolio performance

The maximized Sharpe ratio portfolios are back-tested over a period of one year from June 1, 2018 to May 31, 2019 (out-of-sample period) excluding any rebalancing, as opposed to the work of Platanakis *et al.* (2018), Liu (2018), Kajtazi and Moro (2019) and Brauneis and Mestel (2019), as the results show added value using (monthly) rebalancing of single weights not only for the optimized Sharpe ratio portfolio but also other sophisticated models. It can be concluded, allowing for transaction costs might have had an even more negative effect on portfolio performance.

This empirical study attempts to create a realistic case for investors, i.e. the required inputs of the optimal portfolio such as expected return and covariance matrix, are calculated on a historical base from the out-of-sample data set (Liu, 2018, who estimated out-of-sample results via a rolling window). This approach is in contrast to a purely theoretical in-sample estimation, in which both historical and future data are already available for any given point of time.

The performance of the optimized coin and token portfolios is evaluated against benchmark portfolios in terms of statistics (the portfolio mean return and standard deviation) and specific evaluation ratios such as annualized measures for return, standard deviation and Sharpe ratio. Furthermore, the Sortino and Omega ratios of such portfolios are measured, as the former ratios rely on portfolio mean and variance, which provide less robust results in the event of non-normal distributed returns. As a modification of the Sharpe ratio, the Sortino ratio (Sortino and Meer, 1991; Sortino and Price, 1994) aims to quantify negative movements, more specifically the downward deviation, denoted by DR_P, in the denominator of the following formula:

$$\text{Sortino} = \frac{r_P - \text{MAR}}{\mathrm{DR}_P} \tag{3}$$

The nominator gives the excess return, where MAR originally indicates the minimum acceptable return. In this analysis, the MAR is to be assumed the risk-free asset over the back-testing period.

The Omega ratio (Keating and Shadwick, 2002) captures all higher moment effects by partitioning the average gain over the average loss using a predetermined threshold, r, which is usually set to zero[7]. In accordance with Wu and Pandey (2014), Platanakis *et al.* (2018) and Kajtazi and Moro (2019), the target rate, r, is set to zero. The mathematical notation of the Omega ratio can be defined as follows:

Table 1.
List of different portfolio strategies examined in this empirical study

#	Model	Abbreviation	Objective function	Type
1	Markowitz maximum Sharpe	Max SR	$(r_p - r_f)/s_p$	Maximize
2	Naïve diversification	1/N		
3	Market capitalization	MC		
4	Minimum variance	GMV	$w^T \sum w$	Minimize
5.1	MU, with $\lambda = 0.1$	MU(0.1)	$w^T \mu - 0.05 w^T \sum w$	Maximize
5.2	MU, with $\lambda = 1$	MU(1)	$w^T \mu - 0.5 w^T \sum w$	Maximize
5.3	MU, with $\lambda = 10$	MU(10)	$w^T \mu - 5 w^T \sum w$	Maximize
5.4	MU, with $\lambda = 50$	MU(50)	$w^T \mu - 25 w^T \sum w$	Maximize
6	Market benchmark	Index		

$$\Omega(r) = \frac{\int_r^b [1 - F(x)]dx}{\int_a^r F(x)dx} \tag{4}$$

The cumulative distribution F encompasses the interval (a, b) and does not depend upon normally distributed returns.

Additionally, the annual maximized utility for each model is calculated, giving the empirical results more robustness. In the final analysis of this empirical study, performance-related measures of the optimized Sharpe ratio portfolios for coins and tokens with alternative portfolio strategies and a market index for cryptocurrencies are compared. Table 1 shows the different portfolio strategies, plus the market benchmark for cryptocurrencies, that are examined in this empirical analysis.

4. Descriptive statistics

Panels 2a and 2b of Table 2 report the descriptive statistics for coins and tokens, respectively, selected in this study over the entire sample period. As for coins, the observation confirms findings by Liu (2018), who also examined daily statistics and correlations of nine coins, but only one token (Tether). Bitcoin reports the lowest risk measures of all coins, specifically, regarding standard, semi and downside deviation, historical VaR and ES. Similar results by Miglietti *et al.* (2019) indicate that Bitcoin has a rather low-risk profile compared to other cryptocurrencies such as Litecoin. Because of the fact, Bitcoin was the first cryptocurrency launched and, thus, making it the most matured of all, investors highly appreciate it as a safe haven, which has also been empirically proved (Bouri *et al.*, 2017; Chan *et al.*, 2019). Besides, Bitcoin still accounts for approximately two-third of the total value of the cryptocurrency market[8] which, in turn, ensures a high level of liquidity for investors. Conversely, Bitcoin cash and Stellar represent the most volatile coins in this analysis with daily standard deviations of above 10%, which is analog to findings by Gkillas and Katsiampa (2018). In general, the coins observed in this study show a standard deviation between 5.5% to 10.7% with Bitcoin the lowest and Stellar the highest, which is consistent with recent findings of Bouri *et al.* (2019c). The statistics further indicate that XRP (90.59%) and Bitcoin cash (90.16%) experienced the largest maximal draw-down during the sample period. Despite its speculative nature, Stellar shows the best risk-return profile, in particular, for the Sharpe, Sortino and Omega ratios, which are the highest among all coins. Regarding heavy tails of returns, 8 out of 10 coins indicate positively skewed distributions. Occurring heavy tails of cryptocurrencies are empirically confirmed by Chan *et al.* (2017), who suggest that certain cryptocurrencies require a particular distribution to provide good fits. Great excess kurtosis is monitored with Dash ($5.3 - 3$) Stellar ($5.5 - 3$), Litecoin ($6 - 3$) and XRP ($10.7 - 3$). The statistics contrast those of Phillip *et al.* (2018), who assert that Ethereum and Dash have lower kurtosis than Bitcoin.

In line with the findings of Liu (2018), Tether behaves in an atypical manner compared to the remaining tokens in the analysis indicating a stable price development expressed in a zero daily mean (rounded number) and low-risk measures. The remaining tokens in this examination involve significant risk, as daily volatility ranges from 8.1% to 12.9% with MaidSafeCoin the less (Tether) and Gas the riskiest. Regarding the maximum loss during one day through the sample period, DigixDAO reports a decrease of −46.02% in one day. However, also extreme returns are observable in the cryptocurrency market as can be seen with Gas, whose highest daily return gauges 75.03%. These statistics inevitably point to the

Table 2. Descriptive statistics: Panel 2a shows the stats of coins and Panel 2b that of tokens

a) Coins:	Bitcoin	Ethereum	XRP	Bitcoin cash	EOS	Litecoin	Stellar	IOTA	NEO	Dash
Mean (%)	0.33	0.31	0.41	0.32	0.64	0.33	0.93	0.59	0.63	0.17
Min (%)	−20.75	−25.89	−35.33	−44.60	−38.50	−39.52	−32.83	−37.70	−32.85	−24.32
Max (%)	22.51	23.47	60.69	43.16	34.73	38.93	66.69	38.40	50.89	43.78
Standard deviation (%)	5.51	6.06	9.04	10.53	9.86	7.67	10.77	9.64	9.80	7.33
Semi deviation (%)	3.94	4.37	5.45	6.87	6.47	5.05	6.84	6.55	6.25	4.86
Downside deviation (%)	3.77	4.23	5.25	6.71	6.14	4.88	6.34	6.23	5.90	4.77
Maximum drawdown (%)	72.80	77.90	90.59	90.16	80.41	78.65	85.00	88.54	82.87	87.41
Historical VaR (%)	−8.40	−9.85	−11.70	−13.43	−13.57	−10.19	−14.39	−14.28	−12.40	−11.85
Historical ES (%)	−12.01	−14.32	−17.26	−21.81	−20.22	−15.43	−20.24	−19.63	−18.53	−15.79
Modified VaR (%)	−8.62	−9.84	−7.69	−14.40	−13.73	−9.97	−11.99	−14.01	−12.33	−9.38
Modified ES (%)	−12.57	−15.42	−7.69	−16.63	−17.22	−9.97	−11.99	−18.62	−13.40	−9.38
Std dev Sharpe (%)	5.99	5.02	4.48	2.97	6.42	4.28	8.55	6.10	6.38	2.21
ES Sharpe (%)	2.63	1.97	5.26	1.88	3.67	3.29	7.69	3.16	4.66	1.73
Sortino ratio	0.0875	0.0719	0.0772	0.0466	0.1031	0.0673	0.1454	0.0944	0.1058	0.0340
Omega	1.1801	1.1553	1.1586	1.0932	1.2039	1.1366	1.2785	1.1800	1.1974	1.0682
Skewness	−0.0758	−0.2882	16.686	0.5661	0.4593	0.5986	1.0826	0.2858	0.8220	0.7701
Kurtosis	1.7924	2.3373	10.6957	3.8096	2.4114	5.9943	5.5286	2.1169	3.5569	5.3236

b) Tokens:	Tether	Golem	Augur	DigixDAO	Basic attention	Gas	OmiseGO	Status	Populous	MaidSafeCoin
Mean (%)	0.00	0.28	0.25	0.21	0.28	0.71	0.68	0.20	0.41	0.13
Min (%)	−4.74	−35.88	−31.18	−46.02	−35.44	−31.70	−28.46	−28.71	−25.92	−37.94
Max (%)	5.72	48.45	65.35	57.95	27.44	75.03	54.16	73.99	38.89	28.50
Standard deviation (%)	0.87	9.46	8.78	9.09	9.11	12.92	9.71	10.67	9.86	8.07
Semi deviation (%)	0.60	6.68	5.82	6.25	6.52	7.48	6.38	6.56	6.59	6.00
Downside deviation (%)	0.60	6.53	5.70	6.14	6.37	7.06	6.02	6.46	6.35	5.94
Maximum drawdown (%)	9.05	89.74	86.53	84.81	87.12	91.90	76.88	91.49	91.11	87.21
Historical VaR (%)	−1.00	−15.68	−12.95	−13.85	−14.23	−15.37	−13.58	−14.13	−14.12	−14.56
Historical ES (%)	−2.09	−20.96	−18.90	−19.49	−19.73	−20.61	−19.04	−21.16	−18.64	−19.29
Modified VaR (%)	−1.14	−14.48	−9.33	−12.18	−14.97	−11.59	−12.43	−9.96	−14.36	−13.78
Modified ES (%)	−1.14	−20.62	−9.33	−12.18	−20.41	−23.30	−13.55	−9.96	−17.67	−21.56
Std dev Sharpe	−0.005	0.0293	0.0276	0.0228	0.0297	0.0546	0.0699	0.0183	0.0413	0.0149
ES Sharpe	−0.0038	0.0134	0.026	0.017	0.0132	0.0303	0.0501	0.0196	0.0231	0.0056

(*continued*)

Sortino ratio	−0.0073	0.0424	0.0426	0.0337	0.0424	0.0998	0.1127	0.0303	0.0641	0.0203
Omega	1.0016	1.0850	1.0866	1.0703	1.0821	1.1752	1.2181	1.0587	1.1155	1.0428
Skewness	0.4423	0.1024	1.1165	0.4588	−0.1630	1.7350	0.7157	1.5868	0.4348	−0.4515
Kurtosis	10.0702	2.5511	10.3237	7.0763	0.7269	6.8094	3.8184	9.3510	0.7740	2.1501

Notes: Data was collected over a sample period from August 1, 2017 to May 31, 2018, $t = 303$. All metrics rely upon daily logarithmic returns and are reported daily. Skewness is calculated using the Pearson estimator. VaR and ES measures are estimated at a 95 confidence level and modified VaR and ES apply the Cornish–Fisher method. Downside deviation, Sharpe and Sortino ratio requires the indication of the risk-free rate, $r_f = 1.20$, with Sortino using r_f as the input for the MAR parameter. When calculating the Omega ratio, a threshold of zero is assumed

Table 2.

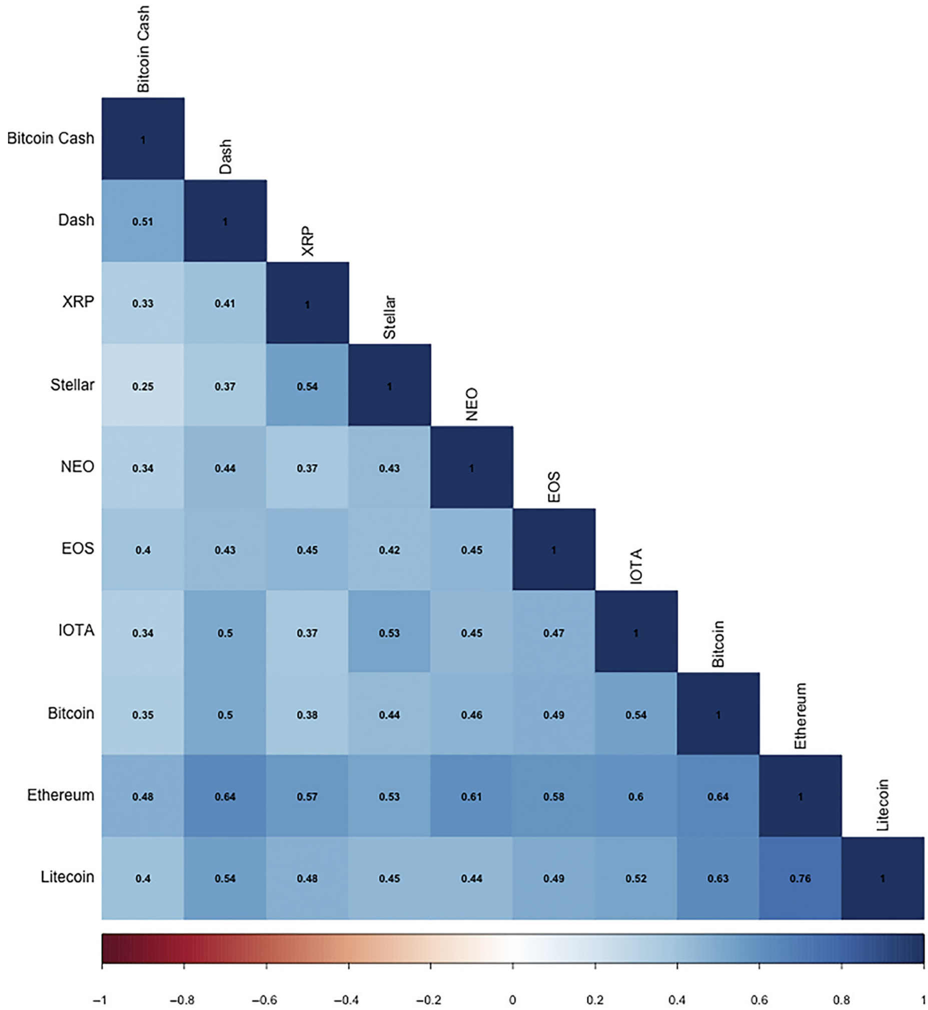

Figure 1.
Coin correlation matrix

enormous speculative power in the cryptocurrency market, specifically, regarding tokens. For risk-adjusted performance measures, OmiseGO trumps the rest of tokens in terms of Sharpe ratios (standard deviation and CVaR), Sortino and Omega ratio. The distribution of returns by virtually all tokens shows strong tails on the right, indicating more higher positive returns, only except for Basic Attention tokens and MaidSafeCoin. Further, Panel 2b reveals that more than half of the tokens show a leptokurtic distribution.

The correlation coefficient parameters of the single coins and tokens are displayed in Figures 1 and 2, respectively. The coefficient parameters are clustered by the density of their correlation. The correlation matrix unequivocally demonstrates positive moderate to strong co-movements between all coins indicating correlation coefficients in the range of 0.25 to 0.76. In particular, Bitcoin, Ethereum and Litecoin tend to strongly correlate (>0.6) with each other, which is in accordance with the studies of Platanakis *et al.* (2018) and Liu (2018).

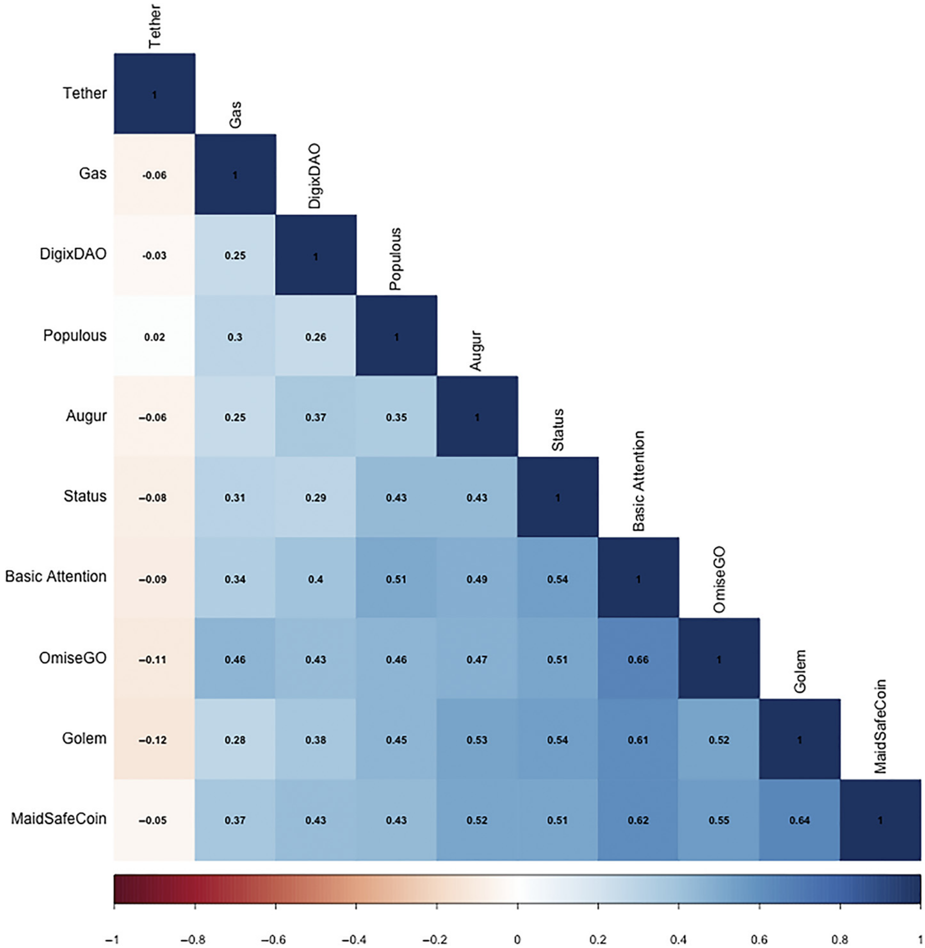

Figure 2.
Token correlation matrix

Under these circumstances, diversification benefits purely among cryptocurrencies will most likely be difficult to realize.

The observation demonstrates that Tether token is highly uncorrelated to the remaining tokens in the portfolio. Correlation coefficients between −0.12 and 0.02 confirm the findings of Liu (2018) that, notably, Tether behaves similarly to a traditional currency, thus allowing for effective diversification. In addition, the Basic Attention Token greatly connects to OmiseGO (0.66), Golem (0.61) and MaidSafeCoin (0.62). Overall, the correlation matrix shows that, except for the aforementioned Tether, tokens pose a moderate positive linear relationship between 0.25 and 0.66.

The efficient frontiers of the cryptocurrencies examined in this work are plotted in Figures 3 and 4. Generating the efficient frontier requires a certain number of potential portfolio allocations that constitute the efficient frontier. The optimization process produces 500 different portfolios and displays the optimal portfolio for a pure coin and token investment, which is constructed by maximizing the Sharpe ratio as mentioned previously.

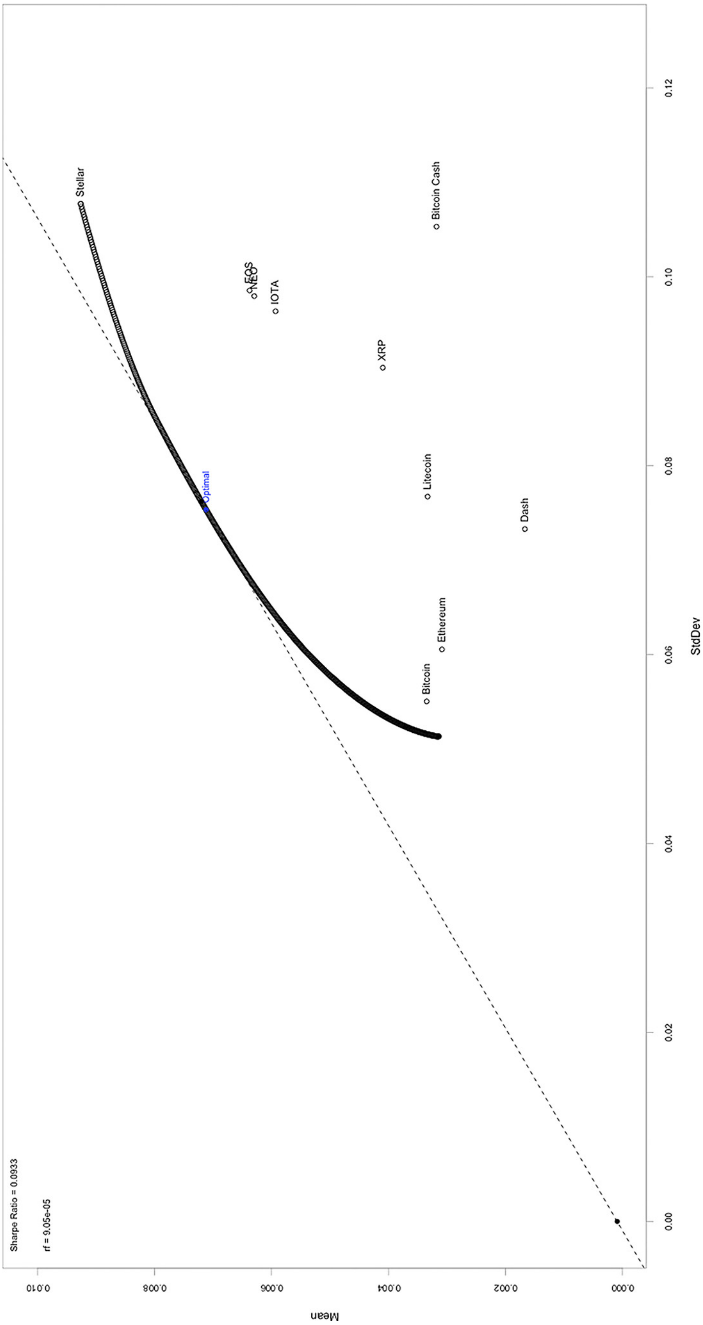

Figure 3.
Coin efficient frontier

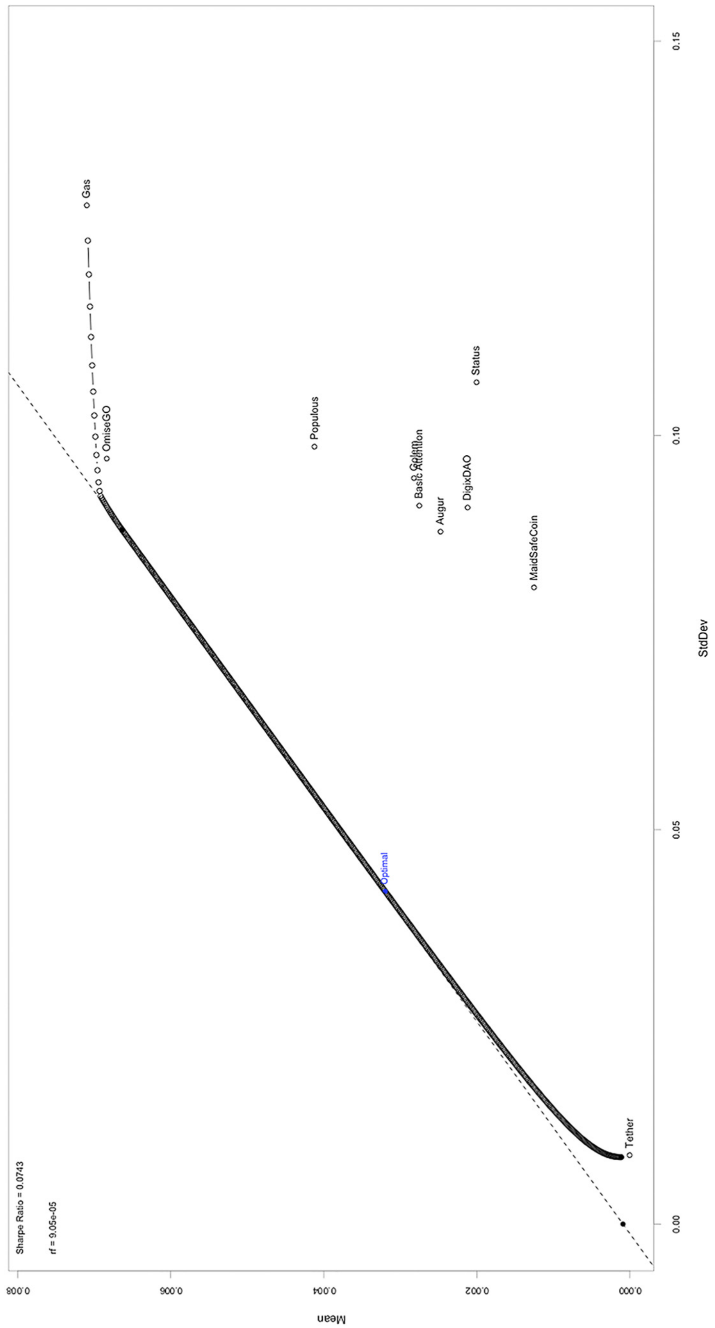

Figure 4.
Token efficient
frontier

The optimal coin portfolio shows a Sharpe ratio of 0.0933, while the token equivalent reports a risk-return ratio of 0.0743. These portfolios are optimal as they locate at the efficient frontier and have the highest Sharpe ratios among all efficient frontier portfolios and portfolios with only one cryptocurrency constituent. This observation confirms the assumption of the Markowitz model that allocating assets to a portfolio reduces the overall risk compared to the individual risk of these related assets. The optimization process results into a mean of 0.71% and a volatility of 7.54% for the optimal coin portfolio. The optimal token portfolio displays a mean of 0.32% and a standard deviation of 4.22%. Further, the maximized return portfolios comprise the full invested (i.e. 100%) Stellar and Gas portfolio for coins and tokens. However, the maximized return portfolio will not serve as a benchmark portfolio in this analysis. In line with Platanakis *et al.* (2018) and Brauneis and Mestel (2019), the diversification effect of constructing portfolios of cryptocurrencies, in this case, coins and tokens, significantly reduces risk irrespective of significant correlation among the cryptocurrencies chosen in this analysis.

5. Results and discussion

In this section, the performance of the different portfolio strategies over the out-of-sample period for various statistical and performance-related measures are analyzed. Additionally, the maximized utility with distinct levels of the risk aversion parameter is calculated, λ, to obtain more robust results to validate the findings in the empirical study.

5.1 Performance evaluation

Table 3 depicts the empirical performance of cryptocurrency portfolio strategies applied in this study. The results of the portfolio strategies regarding coins are exhibited in Panel 3a. Chiefly, unfavorable results for each coin portfolio strategy is found, which can be traced back to the general market downturn during the back-testing period. The negative performance of the entire cryptocurrency market is reflected, in particular, in the weak performance of the cryptocurrency index used in this analysis. Taking a closer look at the statistical and performance-related metrics of the coin portfolios, different outcomes for each portfolio strategy are discerned, however, a very consistent picture across all measures is prevalent.

Although all portfolios have led to unfavorable results, four portfolio strategies show superior performance compared to the remaining ones. Notably, the portfolios with a lower proportion of risky associated coins, namely, the GMV, MU(10), MU(50) and the MC portfolio performed best. The portfolios mentioned above comprise a significant amount of Bitcoin, Ethereum and Dash, which, as displayed in Table 2a, record the lowest standard deviation among the coins selected in this empirical analysis. The portfolios can benefit from hedging activities, as according to Katsiampa (2018), the optimal portfolio weights of Bitcoin should outweigh that of Ethereum, which is indeed the case in this analysis. Further observations demonstrate that specifically the GMV, MU(10) and MU(50) indicate virtually identical results not only for the daily mean and volatility but also all performance measures such as the annualized Sharpe and Omega ratio. This observation follows the Markowitz' minimum variance framework, which tries to build up a portfolio by minimizing the associated risk and the maximized utility portfolios, which penalizes the portfolio return given a large λ. Overall, the MU(10) outperforms the alternative portfolio strategies examined in this empirical study, as it reports the lowest volatility (3.72%), the less weakest portfolio return (−19.44%) and the highest Omega ratio with 0.9576 of all coin portfolios.

The performance of the MU(10) substantially outweighs the market index, which shows moderate results and ends up with a midfield position in the ranking. In contrast, the worst

Table 3. Empirical performance of cryptocurrency portfolio strategies

Statistical performance measure	Max SR	1/N	MC	GMV	$\lambda = 0.1$	$\lambda = 1$	$\lambda = 10$	$\lambda = 50$	Index
a) Coins:				Maximized utility portfolios					
Mean (%)	−0.18	−0.18	−0.08	−0.06	−0.21	−0.11	−0.05	−0.06	−0.13
Standard deviation (%)	4.52	4.63	3.95	3.73	4.90	4.04	3.72	3.73	4.13
Annualized log return (%)	−66.65	−63.83	−27.61	−20.50	−77.46	−41.11	−19.44	−20.29	−49.01
Annualized simple return (%)	−48.65	−47.18	−24.12	−18.53	−53.91	−33.71	−17.67	−18.36	−38.74
Annualized std dev (%)	86.36	88.46	75.52	71.32	93.55	77.14	71.11	71.28	78.85
Annualized sharpe	−0.8121	−0.7609	−0.4103	−0.3345	−0.8656	−0.5772	−0.3206	−0.3317	−0.6651
Utility	−1.0400	−1.0300	−0.5600	−0.4600	−1.2100	−0.7100	−0.4500	−0.4600	−0.8000
Sortino ratio	−0.0570	−0.0538	−0.0294	−0.0240	−0.0629	−0.0407	−0.0230	−0.0238	−0.0466
Omega	0.8903	0.8952	0.9441	0.9555	0.8849	0.9212	0.9576	0.9559	0.9094
b) Tokens				Maximized utility portfolios					
Mean (%)	−0.23	−0.31	−0.23	−0.01	−0.45	−0.20	−0.03	−0.01	−0.13
Standard deviation (%)	2.66	4.37	2.99	0.56	5.52	2.41	0.64	0.57	4.13
Annualized log return (%)	−81.95	−114.08	−84.38	−3.90	−163.70	−73.88	−10.00	−5.36	−49.01
Annualized simple return (%)	−55.94	−68.04	−56.99	−3.82	−80.54	−52.23	−9.52	−5.21	−38.74
Annualized std dev (%)	50.78	83.48	57.18	10.68	105.55	46.06	12.17	10.88	78.85
Annualized sharpe	−1.6832	−1.4100	−1.5377	−0.6755	−1.5865	−1.6801	−1.0958	−0.7971	−0.6651
Utility	−0.9500	−1.4900	−1.0100	−0.0400	−2.2000	−0.8500	−0.1100	−0.0600	−0.8000
Sortino ratio	−0.1135	−0.0922	−0.1010	−0.0483	−0.1077	−0.1132	−0.0761	−0.0565	−0.0466
Omega	0.7889	0.8152	0.8019	0.9408	0.7969	0.7900	0.8832	0.9229	0.9094

Notes: Panel 3a compares the maximized Sharpe ratio portfolio with alternative coin portfolio strategies and Panel 3b analogously, but for tokens. The evaluation of performance metrics is recorded during the back-testing period from June 1, 2018, through May 31, 2019, t = 365. Daily mean and standard deviation are calculated using logarithmic returns. Annualized simple returns are converted back from annualized logarithmic returns with exp^R_log-1 to obtain comparable values for better interpretation. The annualized Sharpe and Sortino ratio requires the risk-free interest rate of the off-sample period, r_f = 2.28, with r_f in Sortino serving as the MAR. The utility is measured in annual numbers and requires the risk aversion parameter, λ, which is set to 1. We use a target threshold of zero for the Omega ratio portfolio is reflected by the risky MU(0.1), resulting in a portfolio, that is, highly prone to market turbulence. The portfolio to be tested in this study, the Max SR and the naïvely diversified portfolio report rather weak numbers, in particular, concerning daily logarithmic means of −0.18% for both. However, under the Sharpe, Sortino and Omega ratio criterion, the 1/*N* performs marginally better compared to that of the Max SR. Assuming the Max SR as the central mean-variance model, the findings are consistent to that of DeMiguel *et al.* (2009), who found that sophisticated portfolio optimization models do not record superior risk-return patterns compared to a 1/*N* rule. The results validate the findings of Platanakis *et al.* (2018), Liu (2018), Brauneis and Mestel (2019) and Kajtazi and Moro (2019). However, as the studies mentioned above did not include negative market developments in their back-testing periods, the results are more significant in such periods. When extending the spectrum of sophisticated optimization models to the maximized utility portfolios, plus the minimum variance portfolio, the findings prove that a naïve diversification is worse, especially, in market downturns compared to the former portfolio strategies regarding all performance evaluation measures. Moreover, if, for example, the MU portfolio models would entirely be excluded from analysis, the results become even more evident. The Max SR and the 1/*N* rule would have indicated by far the worst portfolio investments in such a case. Further evidence, of the naïvely diversified portfolio being the worst investment choice in the sample, is displayed in the greatest loss (86.13%) after a peak during the back-testing period in comparison to other portfolio approaches. Consistent with the findings, the GMV, MU(10) and MU(50) indicate the lowest draw-downs (≤75%).

In light of the persistently substantial volatility in cryptocurrency markets, the empirical findings assert that portfolio managers are advised to construct a global minimum variance portfolio. In the absence of sophisticated optimization models, private investors can invest according to the market values of cryptocurrencies. As implied above, the findings indicate the GMV, MU(10) and MU(50) are the best coin portfolio choices for investors under these market circumstances. Notably, the MC portfolio can be considered as a potential alternative portfolio strategy in the absence of more sophisticated portfolio optimization models. Conversely, the tangency and the equally weighted portfolio should be dismissed. Certainly, the authors are aware of the difficulty to interpret performance measures with negative results in the case of Sharpe and Sortino. For instance, negative Sortino occurs mainly due to negative portfolio returns, r_P, in the numerator of the Sortino ratio for all coin portfolios [Equation (3)].

As for the token portfolios, a similar picture to coins is observed (Panel 3b). As pointed out before, the entire cryptocurrency market experienced a downturn during the sample period, which also affected the performance of tested token portfolio strategies. Each token portfolio in this empirical analysis reports negative returns, Sharpe and Sortino ratio. Notably, the findings exhibit that the individual performance drifts more apart for tokens as in comparison to coins. Annualized simple returns range from −3.82% and −80.54% while volatility lies between 10.68% and 105.55% for the GMV and MU(0.1), respectively. Given the seemingly risk-less properties of Tether as described in Table 2b, an increasing share of this token in one's portfolio will necessarily reduce the vulnerability of the overall portfolio, in particular, during market turmoil. Indeed this is the case with the GMV, which has a share of Tether of >97%. By contrast, the MU(0.1) consists of solely Gas and OmiseGO, which are among the most volatile tokens recognized in this study. Even though GMV is more resilient in market turbulence and, therefore, limits overall portfolio risk, it is assumed that in favorable market conditions larger returns will be most likely not realized.

When comparing performance-related measures, the cryptocurrency index outperforms each token portfolio strategy with respect to Sharpe and Sortino. Regarding the maximized utility, assuming a λ of one, the results confirm that the GMV indicates the best ratio (−0.0448). The same holds for the Omega ratio, for which the GMV reports 0.9408 and, therefore, outweighs the residual portfolio strategies. However, it should be noted, that the MU(50), which implies a high aversion of risk such as the GMV, shows a higher Omega ratio of 0.9229 than the cci30 with 0.9094.

Moreover, MC and Max SR underperform the 1/*N* rule in terms of Sharpe, Sortino and Omega ratio. Similar to the performance of coin portfolios, naïve diversification dominates a classic mean-variance portfolio and, surprisingly, the market cap portfolio, which has proven to be a good alternative investment in pure coin portfolios. In the event of those conditions, results obtained verify previous studies by DeMiguel *et al.* (2009), analogously to the results for coins.

Finally, not only the GMV but also the MU(50), as the best portfolio option in times of unfavorable market conditions in a sheer token investment world. Contrarily, the Max SR, MC and the 1/*N* should be removed from the list of potential token portfolio strategies.

If an investor has to decide between a pure coin or a token portfolio, the MU(10) for coins as the first choice, as it reports the highest performance ratios, in particular, with regard to the Sharpe (−0.3206), Sortino (−0.0230) and Omega ratio (0.9576). As it comes to the comparison of coin and tokens portfolios, the coin portfolios generally expose superior performance for each portfolio methodology in terms of Sharpe, Sortino and Omega. Moreover, the empirical results suggest that investors should rather favor a blended cryptocurrency portfolio, represented by the market index, before investing in a pure token portfolio.

It should be noted, however, that results for both coins and tokens are related to the downtrend in the cryptocurrency market and should, therefore, be viewed with caution. It is to be assumed that the performance of the individual portfolios could differ significantly in subsequent periods and, therefore, the findings may be misleading for investors. This empirical study is the first of its kind to test coin and token portfolios and provide investors, regulators and scholars with sound evidence of the behavior of these specially created portfolios. Against this backdrop, further research in this area is strongly recommended, specifically, with regard to extending the sample periods.

5.2 Maximized utility

In addition to the performance ratios mentioned above, the annual maximized utility is calculated for each portfolio model, giving the empirical results more robustness. The study requires a certain level of the risk aversion parameter, λ, for each coin and token portfolio over the entire out-of-sample period. For this reason, different levels of λ are assumed. In general, a risk aversion parameter of zero indicates a risk-seeking mentality and, thus, results in the maximum expected return portfolio. On the other side, increasing λ to an exorbitant large number returns the minimum variance portfolio. Following Liu (2018), the two extreme cases are used; $\lambda = 0$ and $\lambda = \infty$, where the latter is represented by $\lambda = 10^6$ in this empirical analysis. Furthermore, a remaining set for $\lambda = \{0.1, 0.2, 0.5, 1, 10, 50\}$ is assumed and tested for its annual maximized utility. The maximized utility is computed as defined in equation (1) and annualized by multiplying with 365.

Panels 4a and 4b report the annualized maximized utility with a different selection of risk aversion parameters for coin and token portfolios. As emphasized above, all portfolio strategies report negative utility for both coins and tokens due to the constant downturn in the entire cryptocurrency market. Nonetheless, the findings are consistent with the former empirical results as the estimated maximized utilities validate the performance measures. As for coins, MC shows considerably better utility than Max SR, 1/*N* and the market index

Table 4.
Back-testing maximized utility

Level of risk aversion	Max SR	1/N	MC	GMV	ƛ = 0.1	ƛ = 1	ƛ = 10	ƛ = 50	Index
a) Coins				Maximized utility portfolios					
ƛ = 0	−0.67	−0.64	−0.28	−0.21	−0.78	−0.41	−0.19	−0.20	−0.49
ƛ = 0.1	−0.71	−0.68	−0.31	−0.23	−0.82	−0.44	−0.22	−0.23	−0.52
ƛ = 0.2	−0.74	−0.72	−0.33	−0.26	−0.86	−0.47	−0.25	−0.25	−0.55
ƛ = 0.5	−0.85	−0.84	−0.42	−0.33	−1.00	−0.56	−0.32	−0.33	−0.65
ƛ = 1	−1.04	−1.03	−0.56	−0.46	−1.21	−0.71	−0.45	−0.46	−0.80
ƛ = 10	−4.40	−4.55	−3.13	−2.75	−5.15	−3.39	−2.72	−2.74	−3.60
ƛ = 50	−19.31	−20.20	−14.54	−12.92	−22.65	−15.29	−12.84	−12.90	−16.03
ƛ = 10^6	−3.73 × 10^5	−3.91 × 10^5	−2.85 × 10^5	−2.54 × 10^5	−4.38 × 10^5	−2.98 × 10^5	−2.53 × 10^5	−2.54 × 10^5	−3.11 × 10^5
b) Tokens				Maximized utility portfolios					
ƛ = 0	−0.82	−1.14	−0.85	−0.04	−1.64	−0.74	−0.10	−0.05	−0.49
ƛ = 0.1	−0.83	−1.18	−0.86	−0.04	−1.70	−0.75	−0.10	−0.05	−0.52
ƛ = 0.2	−0.85	−1.21	−0.88	−0.04	−1.75	−0.76	−0.10	−0.05	−0.55
ƛ = 0.5	−0.89	−1.32	−0.93	−0.04	−1.92	−0.79	−0.10	−0.06	−0.65
ƛ = 1	−0.95	−1.49	−1.01	−0.04	−2.20	−0.85	−0.11	−0.06	−0.80
ƛ = 10	−2.11	−4.63	−2.48	−0.10	−7.21	−1.80	−0.17	−0.11	−3.60
ƛ = 50	−7.27	−18.56	−9.02	−0.32	−29.49	−6.04	−0.47	−0.35	−16.03
ƛ = 10^6	−1.29 x 10^5	−3.48 x 10^5	−1.63 x 10^5	−5.70 x 10^3	−5.57 x 10^5	−1.06 x 10^5	−7.40 x 10^3	−5.92 x 10^3	−3.11 x 10^5

Notes: Panels 4a and 4b report the annualized maximized utility with a different selection of risk aversion parameters for coin and token portfolios. The maximized utility is calculated by the corresponding ƛ in each row and then multiplied by 365 to obtain annual utility for each given λ. In particular, once $\lambda \geq 10$, the $1/N$ rule starts to underperform the Max SR model. However, the risky MU(0.1) reports the lowest utility. Conversely, GMV, MU(10) and MU(50) share virtually identical utilities, which are superior to the models mentioned before (Table 4).

Similar to coins, only negative maximized utilities for each level of λ for token portfolios are found. As opposed to coins, where the market index was outperformed by more than half of the models, the market benchmark was only beaten by three token portfolio models. Among the portfolios with the best utility measure are the GMV, MU(10) and MU(50) for which the former reports the best utility for each level of risk aversion.

On the other hand, high risky portfolios such as the MU(0.1), show considerably weak maximized utilities. Interestingly, the token portfolio optimized by maximizing the Sharpe ratio outperforms the naïve diversification at a significant level. For higher levels of λ, this becomes even more evident, while for coins these models tend to hold very similar results irrespective of λ.

The coin portfolios exhibit better utility on average against their token counterparts, knowing that only negative numbers are reported. Moreover, the market index serves as a good benchmark for testing portfolio performance as it reports average results for both coin and token portfolios. In general, increasing the parameter for risk aversion leads to a lower utility for coins and tokens, as found by Liu (2018) for blended cryptocurrency portfolios.

Regarding the research objective, whether the optimized Sharpe ratio portfolios exhibit positive diversification effects, the findings clearly indicate that such portfolios do not add value to an investor's portfolio. Instead, investors are advised to construct their portfolios using alternative optimization models, for example, the maximized utility framework.

The empirical results provide sound evidence that the less risky MU(10) and GMV are the preferred portfolio choices for coins and tokens, respectively. Against this backdrop, investments in cryptocurrencies are more reasonable for risk-averse investors due to the inefficient risk-return trade-off in high market periods, as proposed in Othman *et al.* (2019). Arguably, a portfolio should consist of a high proportion of less risky cryptocurrencies to be less prone to large systematic market crashes.

6. Conclusion

The findings obtained by this empirical study contribute to the literature of cryptocurrencies and portfolio diversification, in particular, aiming at the distinction of coin and tokens portfolios. For portfolio performance evaluation, the GMV, MU(10) and MU(50) model are the best choices for investors when investing in a coin portfolio. On the other hand, as for token portfolios, the GMV and MU(50) portfolio report superior performance measures in unfavorable market conditions. The portfolios optimized by maximizing the Sharpe ratio for both coins and tokens should be disregarded as an investment, as the results exhibit no value-added for these models. However, if an investor has to decide between a pure coin or token portfolio, the MU(10) for coins should be the first choice because of its superior performance ratios. The results obtained in this empirical analysis are robust, as calculating maximized utility for each portfolio strategy validates previous findings. In this context, increasing the risk aversion parameter leads to a lower utility for coins and tokens.

In light of the persistently substantial volatility in cryptocurrency markets, the empirical findings assert that professional portfolio managers are advised to construct a global minimum variance portfolio. However, in the absence of sophisticated optimization models, individual investors should invest in market cap portfolios of coins rather than tokens because of the higher Omega ratio. Although the simple portfolio strategies indicate higher standard deviations for coins, the token alternatives should be handled with care, especially with regard to almost non-fluctuating Tether token, which undoubtedly distorts overall portfolio metrics. Given the speculative nature of the cryptocurrency market, it is generally recommendable to all types of investors to optimize portfolios by minimizing variance to enhance the performance.

Besides, the results of this study can be valuable for policymakers around the world. Despite minor differences in the risk and reward ratios of the portfolios tested, tokens tend to be more speculative, especially if the Tether token is excluded. In these circumstances, regulators are advised to improve supervision and, in particular, to make greater efforts to gain a full understanding of this new type of asset to ultimately increase investor protection.

Further investigation is strongly recommended as tokens represent a new phenomenon in the cryptocurrency universe, for which only a limited amount of data is available, which restricts the sampling. Besides, future research should expand on the question of the investment-grade of tokens. In this context, the pertinent literature on ICOs is very limited and should be amplified. Moreover, future research on the examination of other sophisticated models such as the Black and Litterman model (Black and Litterman, 1992; Platanakis and Urquhart, 2019) and the inclusion of different constraints in portfolio optimization like in Kajtazi and Moro (2019) for both coin and token portfolios will contribute to further closing the knowledge gap in this area. Last but not least, the increasing number of studies in the field of Bitcoin and cryptocurrencies finally (2017, p. 86, 2018, p. 258, 2019, p. 345)[9] calls for more future research. For this reason, carrying out systematic reviews are worth-wile to pool the relevant literature, providing scholars with a structured overview of knowledge gained and the current development of research in this subject area.

Notes

1. Retrieved from www.coinmarketcap.com as of November 20th, 2019.
2. See www.icodata.io/stats
3. See www.coinmarketcap.com
4. The risk-free rate was extracted from www.treasury.gov, specifying the daily interest rates for the yield curve: 1.20% for the sample and 2.28% for the back-testing period.
5. Technically, short selling is feasible for large financial institutions via OTC markets (Meyer and Stafford, 2017).
6. VaR measures the minimum potential loss for a given probability and time horizon whereas ES looks beyond the VaR threshold calculating the average loss.
7. The target ratio, r, set up to zero indicates a special case of the Gain-Loss-ratio by Bernardo and Ledoit (2000).
8. Bitcoin dominance ≥ 66% of the entire cryptocurrency market in November 2019.
9. Retrieved from Web of Science as of November 20, 2019.

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