iranpaper Downloaded from https://iranpaper.ir

Economics Letters 171 (2018) 93–96

Contents lists available at ScienceDirect

Economics Letters

journal homepage: www.elsevier.com/locate/ecolet

Optimal vs naïve diversification in cryptocurrencies

Emmanouil Platanakis [a], Charles Sutcliffe [b], Andrew Urquhart [c,*]

[a] School of Management, University of Bath, Claverton Down, 8 West, Bath, United Kingdom
[b] ICMA Centre, Henley Business School, University of Reading, Whiteknights, Reading, United Kingdom
[c] Centre of Digital Finance, Southampton Business School, University of Southampton, Southampton, United Kingdom

HIGHLIGHTS

- We examine the diversification benefits of cryptocurrencies.
- We employ weekly data for four popular cryptocurrencies.
- We show little difference between naïve and optimal diversification.
- Our results hold for different levels of risk-aversions and estimation windows.

ARTICLE INFO

Article history:
Received 19 June 2018
Received in revised form 6 July 2018
Accepted 11 July 2018
Available online xxxx

Keywords:
Cryptocurrencies
Optimal diversification
Naïve diversification
Portfolio optimization

ABSTRACT

This paper contributes to the literature on cryptocurrencies by examining the performance of naïve (1/N) and optimal (Markowitz) diversification in a portfolio of four popular cryptocurrencies. We employ weekly data with weekly rebalancing and show there is very little to select between naïve diversification and optimal diversification. Our results hold for different levels of risk-aversion and an alternative estimation window.

© 2018 Published by Elsevier B.V.

1. Introduction

Since the seminal work by Nobel Prize winner Harry Markowitz on mean–variance portfolio construction, a large literature has examined whether this method of optimal diversification outperforms naïve diversification. Black and Litterman (1992) and Kan and Zhou (2007) show that mean–variance struggles with estimation errors in the parameters of the model, while DeMiguel et al. (2009) show that employing estimated means and variances performs worse than a naïve strategy of simply holding equal positions in every asset (1/N). However recently, Ackermann et al. (2017) show that mean–variance analysis does outperform the naïve 1/N strategy in currency markets, since interest rates provide a predictor of future returns that are free of estimation error.

We add to the debate by examining the performance of optimal and naïve diversification in cryptocurrency markets. Cryptocurrencies have attracted a lot of attention from investors, regulators and the media since the first cryptocurrency, Bitcoin, was proposed by Nakamoto (2008). For example, from December 2016 to December 2017 the price of Bitcoin grew by 1300%, while the total market capitalization of all cryptocurrencies was over $230 billion in December 2017. Given this surge of interest, there has consequently been a stream of literature examining the properties of cryptocurrencies, documenting bubbles in Bitcoin (Cheah and Fry, 2015; Corbet et al., 2017), the market efficiency of Bitcoin (Urquhart, 2016; Nadarajah and Chu, 2017; Tiwari et al., 2018; Khuntia and Pattanayak, 2018), the hedging and diversification benefits of Bitcoin (Bouri et al., 2017; Corbet et al., 2018a), the unique features of cryptocurrencies (Gkillas and Katsiampa, 2018; Phillip et al., 2018), the relationship between transaction activity and Bitcoin returns (Koutmos, 2018) and price clustering within Bitcoin prices (Urquhart, 2017).[1]

Given the huge surge of interest by investors in cryptocurrencies, this is the first paper to examine whether forming a portfolio of the four main cryptocurrencies is worthwhile, and whether optimal or naïve diversification generates better performance for investors. Cryptocurrencies have been shown to be held by investors as speculative assets (Baur et al., 2018), rather than used as a medium of exchange. Therefore, investors hold portfolios

* Corresponding author.
E-mail addresses: E.Platanakis@bath.ac.uk (E. Platanakis), c.sutcliffe@icmacentre.ac.uk (C. Sutcliffe), a.j.urquhart@soton.ac.uk (A. Urquhart).

https://doi.org/10.1016/j.econlet.2018.07.020
0165-1765/© 2018 Published by Elsevier B.V.

[1] See Corbet et al. (2018b) for a complete review of the literature on cryptocurrencies.

iranpaper Downloaded from https://iranpaper.ir

of cryptocurrencies, and we examine whether naïve or optimal diversification produces the best performance for investors. We find very little difference in terms of expected returns, Sharpe ratio and Omega ratio between naïve diversification and optimal diversification indicating that the gain from optimal diversification is more than offset by estimation error, consistent with the findings of DeMiguel et al. (2009) for equities.

2. Data and methodology

We collected weekly data on the four most liquid and long-standing cryptocurrencies, namely Bitcoin, Litecoin, Ripple and Dash from http://www.coinmarketcap.com over the period 21st February 2014 to 26th January 2018.[2] We also collected the risk-free rate the Kenneth French database.[3] Descriptive statistics of the simple returns on the four cryptocurrencies in this study are reported in Table 1. Dash has the highest mean return and standard deviation, while Bitcoin has the smallest mean return and standard deviation. Bitcoin has slight positive skewness and a normal distribution (according to the kurtosis), while the other cryptocurrencies exhibit strong positive skewness and excess kurtosis, indicating a leptokurtic distribution. Panel B of Table 1 reports the correlation matrix between the cryptocurrencies. We find that most pairs are positively correlated, with a correlation coefficient between 0.1125 and 0.5473, while Ripple and Dash have a negative correlation of −0.0001. Therefore, since the correlation between these cryptocurrencies is not highly positive, it is plausible that investing in a portfolio of cryptocurrencies provides meaningful diversification benefits.

2.1. Mean–variance portfolio optimization (optimal diversification)

Investors optimize the trade-off between the mean and variance of returns in the mean–variance portfolio optimization model of Markowitz (1952). We estimate the vector of portfolio weights (decision variables), denoted by $\mathbf{x}$, by maximizing the following quadratic utility function with respect to the vector of asset weights ($\mathbf{x}$):-

$$U = \mathbf{x}^{\mathrm{T}}\boldsymbol{\mu} - \frac{\lambda}{2}\mathbf{x}^{\mathrm{T}}\boldsymbol{\Sigma}\mathbf{x}. \tag{1}$$

We use sample (historical) estimates for the mean ($\boldsymbol{\mu}$) and covariance matrix ($\boldsymbol{\Sigma}$), while the parameter λ denotes the investor's risk aversion. We additionally impose non-short selling constraints, as well as normalization of the portfolio weights. Hence, the optimization problem for the mean–variance diversification can be described as follows:

$$\begin{aligned} &\max_{\mathbf{x}} \left\{ \mathbf{x}^{\mathrm{T}}\boldsymbol{\mu} - \frac{\lambda}{2}\mathbf{x}^{\mathrm{T}}\boldsymbol{\Sigma}\mathbf{x} \right\} \\ &s.t.\ \mathrm{x}_i \geq 0,\ \forall i \\ &\sum_{i=1}^{N} \mathrm{x}_i = 1 \end{aligned} \tag{2}$$

2.2. Equally weighted portfolio (naïve diversification)

A portfolio weight of 1/N is assigned to each asset in our portfolio, and we use 1/N with re-balancing as in DeMiguel et al. (2009), e.g. $\mathrm{x}_i = \frac{1}{\mathrm{N}}\ \forall i$. Hence, the asset weights are independent of the value of λ.

[2] The sample period start date is determined by the available of data for all four cryptocurrencies.

[3] Available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

2.3. Performance metrics

The Sharpe ratio (Sharpe, 1966), which is a standard metric for measuring risk-adjusted performance, is defined as the average excess return above the risk-free rate per unit of risk (standard deviation) and is computed as follows:-

$$SR = \frac{\overline{R}_p - \overline{R}_f}{\sigma_p}, \tag{3}$$

where $\overline{R}_p - \overline{R}_f$ is the average portfolio return in excess of the risk-free rate computed over the entire out-of-sample period, and σ_p represents the portfolio standard deviation estimated over the same out-of-sample period.

However, the Sharpe ratio has its limitations since it depends on only the first two moments, (see, for instance, the discussion in Oikonomou et al. (2018), Platanakis and Sutcliffe (2017b), and Platanakis et al. (2017a), for alternative performance metrics). For this reason we also use the Omega ratio (Shadwick and Keating, 2002) as an additional risk-adjusted measure. The Omega ratio is also known as the gain–loss ratio since it is defined as the ratio of the average gain to the average loss, and is computed as follows:-

$$Omega = \frac{\frac{1}{\mathrm{T}}\sum_{t=1}^{\mathrm{T}} \max\left(0, +R_{p,t}\right)}{\frac{1}{\mathrm{T}}\sum_{t=1}^{\mathrm{T}} \max\left(0, -R_{p,t}\right)}. \tag{4}$$

The main advantage of the Omega ratio is that it does not require any assumption about the underlying distribution of returns.

2.4. Transaction costs

When examining any investment strategy transaction costs are vital since any profit gained may be extinguished by the inclusion of appropriate transaction costs. Therefore we include transaction costs of 50 basis points for all cryptocurrencies, consistent with Lintilhac and Tourin (2017). We incorporate transaction costs by subtracting the total transaction costs from the portfolio returns. Total transaction costs (TC_t) at time t are computed as follows:-

$$\mathrm{TC}_t = \sum_{i=1}^{N} \mathrm{T}_i \left(\left| \mathrm{x}_{i,t} - \mathrm{x}^{+}_{i,t-1} \right| \right), \tag{5}$$

where $\mathrm{x}^{+}_{i,t-1}$ denotes the weight of the ith asset at the end of the period $t-1$, and T_i is the proportionate transaction cost of trading the ith cryptocurrency.

3. Empirical results

Figs. 1 and 2 report the Sharpe and Omega ratios respectively for a 26-week expanding estimation window, rebalanced every week. The difference between naïve diversification (1/N) and optimal diversification (Markowitz) is very small and statistically insignificant, indicating that there is very little to select between these two methods of diversification. These figures also show that risk-adjusted performance is insensitive to λ. To add robustness to our findings, Figs. 3 and 4 report the re-estimation of our models with a 52-week expanding window, rather than a 26-week expanding window. These results are consistent with those for a 26-week expanding window.

4. Conclusions

We add to the literature on cryptocurrencies and portfolio management by examining the performance of naïve diversification (1/N) and optimal diversification (Markowitz) in the context of a portfolio consisting of four popular cryptocurrencies. We find very little difference in performance between the two construction

Downloaded from https://iranpaper.ir

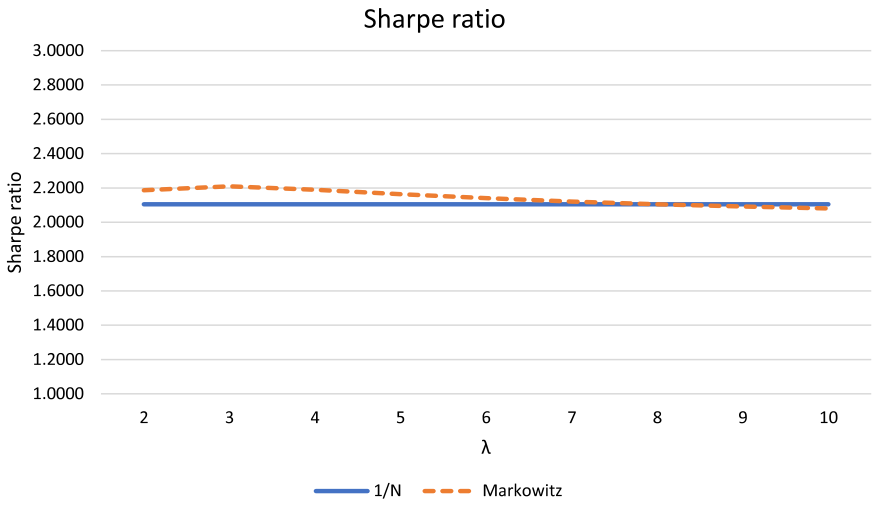

Fig. 1. The Sharpe ratio of the naïve diversification (1/N) and optimal diversification (Markowitz) portfolios at different levels of risk-aversion, inclusive of transaction costs, for a 26-week expanding window.

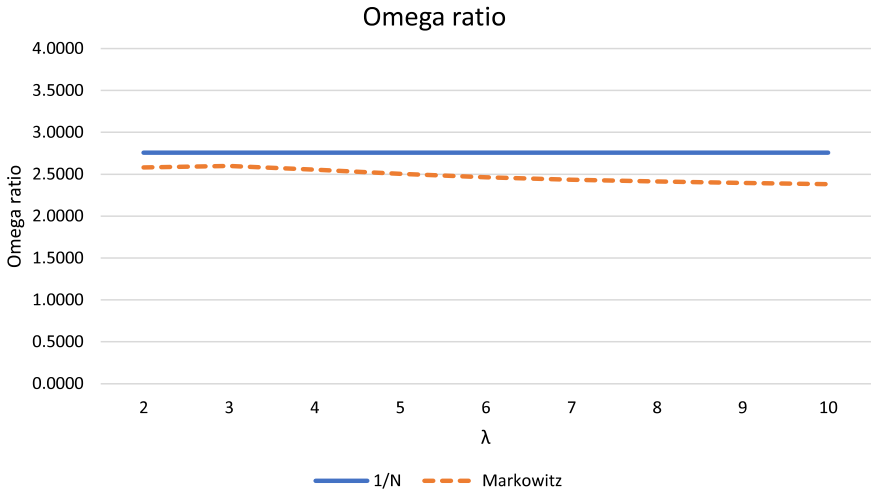

Fig. 2. The Omega ratio of the naïve diversification (1/N) and optimal diversification (Markowitz) portfolios at different levels of risk-aversion, inclusive of transaction costs, for a 26-week expanding window.

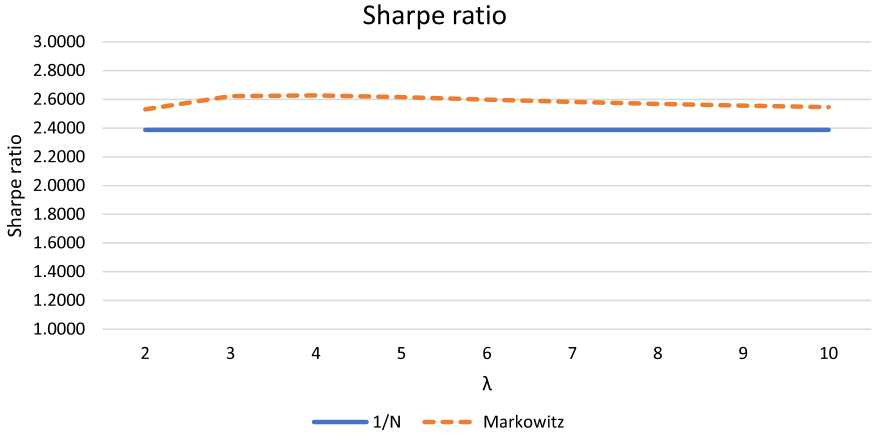

Fig. 3. The Sharpe ratio of the naïve diversification (1/N) and optimal diversification (Markowitz) portfolios at different levels of risk-aversion, inclusive of transaction costs, for a 52-week expanding window.

iranpaper Downloaded from https://iranpaper.ir

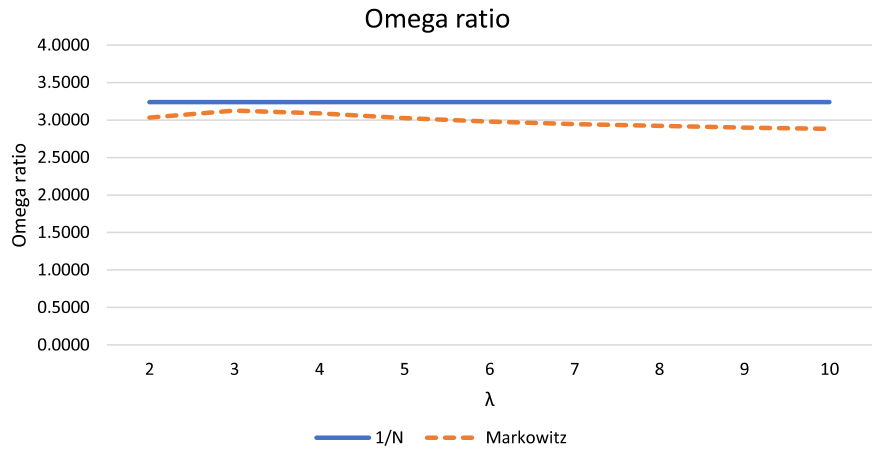

Fig. 4. The Omega ratio of the naïve diversification (1/N) and optimal diversification (Markowitz) portfolios at different levels of risk-aversion, inclusive of transaction costs, for a 52-week expanding window.

Table 1
Descriptive statistics of the returns of the cryptocurrencies employed in this study, and their correlation matrix.

	Bitcoin	Litecoin	Ripple	Dash
Panel A: Descriptive statistics				
Mean	0.01866	0.02352	0.04656	0.06352
Std. Dev.	0.10098	0.17652	0.27585	0.27900
Min	−0.28343	−0.29293	−0.52026	−0.51269
Max	0.50966	1.40112	1.99923	2.02120
Skew	0.75464	3.44920	3.46105	3.60369
Kurt	3.00297	20.79265	16.61553	18.75829
Panel B: Correlation matrix				
Bitcoin	1			
Litecoin	0.4922	1		
Ripple	0.2132	0.5473	1	
Dash	0.1293	0.1125	−0.0001	1

techniques, supporting the findings of DeMiguel et al. (2009) that naïve diversification is as good, if not better, than optimal diversification.

References

Ackermann, F., Pohl, W., Schmedders, K., 2017. Optimal and naive diversification in currency markets. Manage. Sci. 63, 3347–3360.

Baur, D.G., Hong, K., Lee, A.D., 2018. Bitcoin: Medium of exchange or speculative assets? J. Int. Financ. Mark. Inst. Money 54, 177–189.

Black, F., Litterman, R., 1992. Global portfolio optimization. Financ. Anal. J. 48, 28–43.

Bouri, E., Molnár, P., Azzi, G., Roubaud, D., Hagfors, L.I., 2017. On the hedge and safe haven properties of bitcoin: Is it really more than a diversifier? Finance Res. Lett. 20, 192–198.

Cheah, E.-T., Fry, J., 2015. Speculative bubbles in bitcoin markets? an empirical investigation into the fundamental value of bitcoin. Econom. Lett. 130, 32–36.

Corbet, S., Larkin, C., Lucey, B., Meegan, A., Yarovaya, L., 2018a. Exploring the dynamic relationships between cryptocurrencies and other financial assets. Econom. Lett. 165 (1), 28–34.

Corbet, S., Lucey, B., Urquhart, A., Yarovaya, L., 2018b. Cryptocurrencies as a Financial Asset: A systematic analysis. Available at SSRN: https://ssrn.com/abstract=3143122.

Corbet, S., Lucey, B., Yarovaya, L., 2017. Datestamping the Bitcoin and Ethereum bubbles. Finance Res. Lett. (forthcoming).

DeMiguel, V., Garlappi, L., Uppal, R., 2009. Optimal versus naive diversification: How inefficient is the 1/N portfolio strategy? Rev. Financ. Stud. 22, 1915–1953.

Gkillas, K., Katsiampa, P., 2018. An application of extreme value theory to cryptocurrencies. Econom. Lett. 164, 109–111.

Kan, R., Zhou, G., 2007. Optimal portfolio choice with parameter uncertainty. J. Financ. Quant. Anal. 42, 621–656.

Khuntia, S., Pattanayak, J.K., 2018. Adaptive market hypothesis and evolving predictability of bitcoin. Econom. Lett. 167, 26–28.

Koutmos, D., 2018. Bitcoin returns and transaction activity. Econom. Lett. 167, 81–85.

Lintilhac, P.S., Tourin, A., 2017. Model-based pairs trading in the bitcoin market. Quant. Finance 17 (5), 703–716.

Markowitz, H., 1952. Portfolio selection. J. Finance 7, 77–91.

Nadarajah, S., Chu, J., 2017. On the inefficiency of bitcoin. Econom. Lett. 150, 6–9.

Nakamoto, S., 2008. Bitcoin: A peer-to-peer electronic cash system. Available at https://Bitcoin.org/Bitcoin.pdf.

Oikonomou, I., Platanakis, E., Sutcliffe, C., 2018. Socially responsible investment portfolios: Does the optimization process matter? Br. Account. Rev. 50, 379–401.

Phillip, A., Chan, J., Peiris, S., 2018. A new look at cryptocurrencies. Econom. Lett. 163, 6–9.

Platanakis, E., Sakkas, A., Sutcliffe, C., 2017a. Harmful Diversification: Evidence from Alternative Investments, ICMA Centre Discussion Paper Number: ICM-2017-09. Available at SSRN: https://ssrn.com/abstract=2911212.

Platanakis, E., Sutcliffe, C., 2017b. Asset–Liability modelling and pension schemes: the application of robust optimization to USS. Eur. J. Finance 23, 324–352.

Shadwick, W.F., Keating, C., 2002. A universal performance measure. J. Perform. Meas. 6, 59–84.

Sharpe, W.F., 1966. Mutual fund performance. J. Bus. 39, 119–138.

Tiwari, A.K., Jana, R., Das, D., Roubaud, D., 2018. Informational efficiency of bitcoin - an extension. Econom. Lett. 163, 106–109.

Urquhart, A., 2016. The inefficiency of bitcoin. Econom. Lett. 148, 80–82.

Urquhart, A., 2017. Price clustering in bitcoin. Econom. Lett. 159, 145–148.