Cryptocurrency Portfolios Using Heuristics

Emmanouil Platanakis*

Charles Sutcliffe$

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* University of Bath, School of Management, Claverton Down, Bath, BA2 7AY, UK, email: E.Platanakis@bath.ac.uk, Tel: +44 (0) 1225 386207

$ The ICMA Centre, Henley Business School, University of Reading, PO Box 242, Reading, RG6 6BA, UK, email: c.m.s.sutcliffe@rdg.ac.uk, Tel +44 (0) 118 378 6117

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Abstract

Given the support from academic studies for heuristic (naive) asset allocation strategies, this study compares the performance of seven heuristics, including four new heuristics, in forming a portfolio of six popular cryptocurrencies. As many cryptocurrency traders are retail investors, they are likely to use heuristics, rather than sophisticated optimization procedures. Our empirical analysis shows little difference in the out-of-sample performance of these seven strategies, indicating that it does not matter which heuristic is used by cryptocurrency investors. Therefore retail investors might as well use the simplest heuristic (*1/N*) strategy, whose performance has been widely studied and found to be comparable with that of portfolio optimization models.

Key words: Cryptocurrencies; Heuristic Asset Allocation Strategies; Portfolio Management

JEL: G11

Highlights

- We compare seven heuristics in forming portfolios of six cryptocurrencies.
- Heuristics are relevant for the retail investors who dominate cryptocurrencies.
- There is little out-of-sample performance difference between the seven heuristics.
- We suggest using the widely studied and very simple $1/N$ heuristic.

1. Introduction

The main problem with Markowitz (1952) portfolio theory is that parameter estimation errors often lead to poor out-of-sample performance, and this phenomenon has been extensively investigated; e.g. Kan and Zhou (2007), Platanakis and Sutcliffe (2017), Platanakis et al (2019), and Platanakis et al (2021), among others. For this reason, several influential academic studies support using heuristic asset allocation strategies (e.g. $1/N$). For instance, DeMiguel et al (2009) show that $1/N$ with re-balancing is not consistently beaten by any of 14 portfolio optimization methods across seven datasets in an out-of-sample setting. Kirby and Ostdiek (2012) propose two heuristic portfolio strategies, volatility timing and reward-to-risk timing, that beat $1/N$ in the presence of transaction costs; while Hsu et al (2018) evaluate the out-of-sample performance of several portfolio construction techniques relative to $1/N$, and find that none can consistently beat $1/N$ after controlling for data-snooping biases.

Cryptocurrencies have attracted much attention from individual investors, fund managers, academics and the media; and in June 2019 the total market capitalization of cryptocurrencies was over $330 billion[1]. Since many cryptocurrency traders are retail investors (Dyhrberg et al 2018), they are unlikely to use sophisticated portfolio optimization procedures, and rely on a heuristic. Therefore the performance of heuristics is of particular importance in cryptocurrency markets.

This is the first paper to apply a wide range of heuristics to forming portfolios of cryptocurrencies, and to investigate whether any heuristic is superior. We build on Platanakis et al (2018), who showed there is very little difference in performance between the $1/N$ rule and Markowitz when applied to cryptocurrency portfolios. We apply three popular heuristics ($1/N$, risk-parity and reward-to-risk timing), together with four new heuristics which we propose, to a portfolio of six

[1] For a review of the cryptocurrency literature, see Corbet et al (2019).

popular and very liquid cryptocurrencies (Bitcoin, Litecoin, Ripple, Dash, Stellar and Monero). Overall, our results show there is little to choose between these seven heuristics.

The rest of this paper is organized as follows. Section 2 presents our data and methodology, Section 3 contains a description of our performance metrics and transaction costs, and Section 4 presents our results. We conclude in Section 5.

2. Data and Methodology

2.1. Data

We analyse weekly data on Bitcoin, Litecoin, Ripple, Dash, Stellar and Monero over the period 15th August 2014 to 22nd February 2019 (237 weeks/observations) from www.coinmarketcap.com.[2] The risk-free rate is from the Kenneth French website. Table 1 reports the correlations, and the means, standard deviations and Sharpe ratios of the six cryptocurrencies. The highest correlation is between Ripple and Stellar at 0.5859, and the lowest is between Stellar and Dash at 0.1629.

2.2. Methodology: Portfolio Construction Techniques

1/N. We apply the *1/N* heuristic with re-balancing, as in DeMiguel et al (2009), which assigns a weight of *1/N* to each asset at every re-balancing:

$$x_i^{1/N} = \frac{1}{N}, \forall i \tag{1}$$

where x_i^j represents the portfolio weights for each asset i and heuristic j. N denotes the total number of assets.

[2] Consistent with Platanakis and Urquhart (2020), we use weekly rather than monthly returns since monthly returns would not provide an adequate number of observations.

Risk-Parity (RP). Risk-parity has the intuitive appeal of achieving an equal contribution by each asset to total portfolio risk. We use a simplified version of the risk-parity method, as in Oikonomou et al (2018). The portfolio weights are:

$$x_i^{RP} = \frac{1/\sigma_\iota^2}{\sum_{\iota=1}^{N}\left(1/\sigma_\iota^2\right)}, \forall i \tag{2}$$

where σ_ι^2 denotes the sample variance of asset i.

Reward-to-Risk Timing (RRT). Reward-to-risk timing assigns greater weight to assets with a higher sample reward-to-risk ratio, and is characterized by lower turnover than other approaches. The RRT asset weights are:

$$x_i^{RRT} = \frac{\mu_\iota^+ / \sigma_\iota^2}{\sum_{\iota=1}^{N}\left(\mu_\iota^+ / \sigma_\iota^2\right)}, \forall i \tag{3}$$

where σ_ι^2 is the sample variance of asset i, and $\mu_\iota^+ = max(0, \mu_i)$ to avoid short-selling (μ_i denotes the historical (sample) mean return of asset i).

Value-at-Risk Heuristic (VaRH). The value-at-risk heuristic is based on the value-at-risk (VaR) of each asset. Inspired by the risk-parity approach, we overweight assets with lower VaR at the 99% percentile. This is particularly important since cryptocurrencies are much riskier than traditional assets, e.g. equities, and can generate huge losses (Chaim and Laurini, 2018; Fry, 2018). The VaR asset weights of this new heuristic are:[3]

$$x_i^{VaRH} = \frac{1/VaR_{99\%,i}}{\sum_{\iota=1}^{N}\left(1/VaR_{99\%,i}\right)}, \forall i \tag{4}$$

[3] None of the values of $VaR_{99\%,i}$ is positive

Reward-to-VaR Timing (RVT). We propose a reward-to-VaR timing heuristic, which is an extension of the RRT heuristic. We use the VaR as a risk measure instead of the sample variance. Since cryptocurrencies are more exposed to extreme events, the VaR may be a more appropriate risk measure than the sample variance. The RVT asset weights are:

$$x_i^{RVT} = \frac{\mu_i^+ / VaR_{99\%,i}}{\sum_{i=1}^{N}\left(\mu_i^+ / VaR_{99\%,i}\right)}, \ \forall i \tag{5}$$

where $\mu_i^+ = max(0, \mu_i), \ \forall i,$ to prohibit short-selling.

Naïve Combination (NC) and Optimal Combination (OC) Heuristics. We also propose two more heuristics that are based on a combination of the five heuristics we have described so far (1/N, RP, RRT, VaRH and RVT). We take the average of the asset weights across these five heuristics in an attempt to diversify away the estimation errors of each heuristic.

We compute the portfolio weights for the naïve (equally) weighted combination heuristic as:

$$x_i^{NC} = \frac{1}{5}\times\left(x_i^{1/N} + x_i^{RP} + x_i^{RRT} + x_i^{VaRH} + x_i^{RVT}\right), \ \forall i \tag{6}$$

We compute the portfolio weights for the optimal combination heuristic (OC) as:

$$x_i^{OC} = \left(\alpha_1 x_i^{1/N} + \alpha_2 x_i^{RP} + \alpha_3 x_i^{RRT} + \alpha_4 x_i^{VaRH} + \alpha_5 x_i^{RVT}\right), \ \forall i \tag{7}$$

where $\alpha_i \geq 0, \ \forall i.$ The OC heuristic is attractive since it applies the shrinkage approach directly to the portfolio weights by computing the optimal combination of the five heuristic portfolios. The coefficients (α_i) for the OC heuristic are computed by minimizing the portfolio variance, subject to no-short selling and normalization of the portfolio weights. Hence, the optimization problem for the OC heuristic is:

$$\begin{aligned}&\min_{\mathbf{x}^{OC}} \left\{ \left(\mathbf{x}^{OC}\right)^{\mathrm{T}} \mathbf{\Sigma}\mathbf{x}^{OC} \right\} \\ &s.t. \quad \mathrm{x}_i^{OC} \geq 0, \ \forall i \ , \\ &\qquad \sum_{i=1}^{N} \mathrm{x}_i^{OC} = 1\end{aligned} \tag{8}$$

3. Performance Metrics and Transaction Costs

3.1 Performance Metrics

The Sharpe ratio (Sharpe, 1966) is probably the most popular metric for measuring portfolio risk-adjusted performance, and is computed as the average out-of-sample portfolio excess return, divided by the out-of-sample portfolio standard deviation. We also use certainty equivalent returns (CERs) as an additional performance metric. Assuming mean-variance investors, this is computed as:

$$CER = \bar{\mu}_{portfolio} - \frac{\lambda}{2}\sigma^2_{portfolio}, \tag{9}$$

where $\bar{\mu}_{portfolio}$ denotes the average out-of-sample portfolio return, and $\sigma_{portfolio}$ represents the out-of-sample portfolio standard deviation. Following DeMiguel et al (2009), we set the risk aversion parameter (λ) to unity.

We also compute the Omega ratio (Shadwick and Keating, 2002) as our third risk-adjusted performance metric. This ratio does not depend on any assumption about the distribution of asset returns, and is computed as:

$$Omega = \frac{\frac{1}{\mathrm{T}}\sum_{t=1}^{\mathrm{T}} \max\left(0, +R_{p,t}\right)}{\frac{1}{\mathrm{T}}\sum_{t=1}^{\mathrm{T}} \max\left(0, -R_{p,t}\right)}, \tag{10}$$

where $R_{p,t}$ is the portfolio return at time *t*.

3.2 Transaction Costs

Total transaction costs, which are subtracted from portfolio returns, are computed as:-

$$\mathrm{TC}_t = \sum_{i=1}^{N} \mathrm{T}_i \left(\left| \mathrm{x}_{i,t} - \mathrm{x}_{i,t-1}^{+} \right| \right). \tag{11}$$

We follow Platanakis et al (2018) and Platanakis and Urquhart (2019) and set T_i (proportional transaction costs) to 50 bps (0.5%) for all the cryptocurrencies. $\mathrm{x}_{i,t}^{+}$ denotes the weight of asset i in the portfolio at the end of period t (just before re-balancing).

4. Results

We use a 52-week (1-year) expanding estimation window with weekly re-balancing. Figures 1 to 3 plot the annualized out-of-sample Sharpe ratios, CERs and Omega ratios, allowing for transactions costs. These show very little difference between the seven heuristics. Table 2 has the mean values of the seven strategies in Figures 1 to 3. VaRH has the highest Sharpe ratio, while *1/N* is the best heuristic according to both the CERs and Omega ratios. But using the test of Lo (2012), there are no significant differences between the seven Sharpe ratios. In Table 3 we report the means and standard deviations of the portfolio weights of the seven strategies; and Figures 4 to 9 plot the asset allocation over the entire out-of-sample period for each heuristic. The portfolio weights differ across the seven heuristics, with Bitcoin having the highest average weight for every heuristic except *1/N*, and Stellar having the lowest average weight for four heuristics. Bitcoin has the lowest average return (98%) and standard deviation (36%); while Stellar has the highest average return (712%) and standard deviation (102%). So Bitcoin has the greatest appeal to more risk averse investors, and Stellar has the least appeal. These differences in portfolio weights do not have a significant impact on out-of-sample performance.

5. Conclusions

Given the strong support from influential studies for easily-implemented asset allocation strategies, we contribute to the cryptocurrency literature by comparing the out-of-sample performance of seven heuristics for forming portfolios of six popular cryptocurrencies. Although they have different average asset allocations, using three performance metrics we find very little difference in the out-of-sample performance of these seven heuristics. Our findings imply that unsophisticated retail investors can use *1/N*, the simplest heuristic, to form cryptocurrency portfolios; although this may not lead to superior performance.

Table 1: Correlation matrix of cryptocurrency returns, and annualized means and standard deviations and Sharpe ratios

Correlation Matrix	Bitcoin	Litecoin	Ripple	Dash	Stellar	Monero
Bitcoin	1.0000	-	-	-	-	-
Litecoin	0.5535	1.0000	-	-	-	-
Ripple	0.2866	0.5639	1.0000	-	-	-
Dash	0.3755	0.3376	0.1742	1.0000	-	-
Stellar	0.3333	0.3015	0.5859	0.1629	1.0000	-
Monero	0.4209	0.3048	0.1679	0.4300	0.1700	1.0000
Mean return %	97.71	186.36	698.81	233.54	712.02	381.56
SD of returns %	35.57	60.77	92.36	57.70	102.03	72.53
Sharpe ratio	2.73	3.05	7.56	4.03	6.97	5.25

Table 2: Mean annualized out-of-sample performance of the seven heuristics.

	1/N	RRT	RP	VaRH	RVT	NC	OC
Mean Sharpe ratio	1.7059	1.5476	1.7410	1.7438	1.5369	1.6826	1.7148
Mean CER	1.2470	1.0407	1.1297	1.2057	1.0783	1.1614	1.1837
Mean Omega ratio	2.0974	1.8753	2.0361	2.0865	1.9046	2.0154	2.0436

Table 3: Portfolio weights for the seven heuristics.

		Bitcoin	Litecoin	Ripple	Dash	Stellar	Monero
1/N	Mean	0.1667	0.1667	0.1667	0.1667	0.1667	0.1667
	SD	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
RRT	Mean	0.2265	0.0899	0.2116	0.2047	0.1368	0.1306
	SD	0.1277	0.0614	0.1677	0.0891	0.1007	0.0659
RP	Mean	0.4688	0.1651	0.0710	0.1430	0.0571	0.0950
	SD	0.0322	0.0201	0.0091	0.0230	0.0130	0.0230
VaRH	Mean	0.2994	0.1760	0.1181	0.1675	0.1042	0.1347
	SD	0.0135	0.0091	0.0065	0.0124	0.0109	0.0152
RVT	Mean	0.1231	0.0824	0.2507	0.1950	0.1823	0.1664
	SD	0.0703	0.0592	0.1465	0.0842	0.0958	0.0931
NC	Mean	0.2569	0.1360	0.1636	0.1754	0.1294	0.1387
	SD	0.0407	0.0233	0.0626	0.0350	0.0392	0.0261
OC	Mean	0.2776	0.1418	0.1478	0.1750	0.1190	0.1388
	SD	0.0290	0.0163	0.0378	0.0267	0.0241	0.0177

Figure 1: Out-of-sample Sharpe ratios (annualized) of the seven heuristics

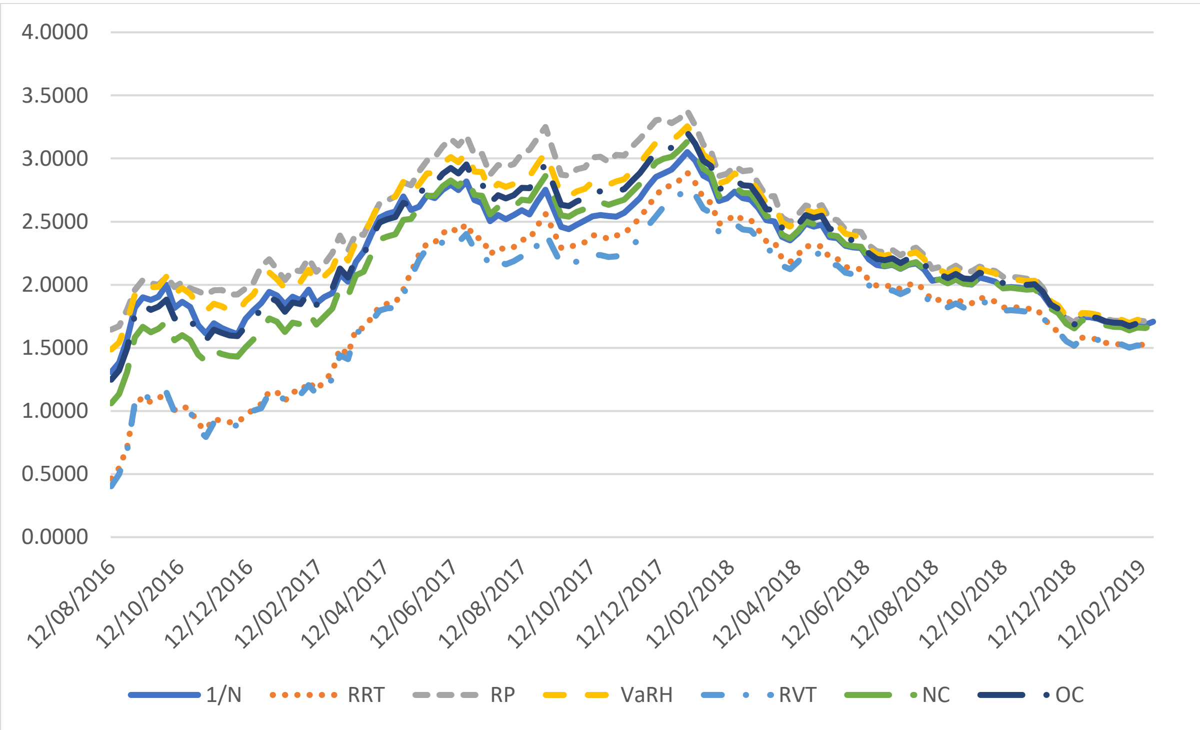


Figure 2: Out-of-sample CERs (annualized) of the seven heuristics.

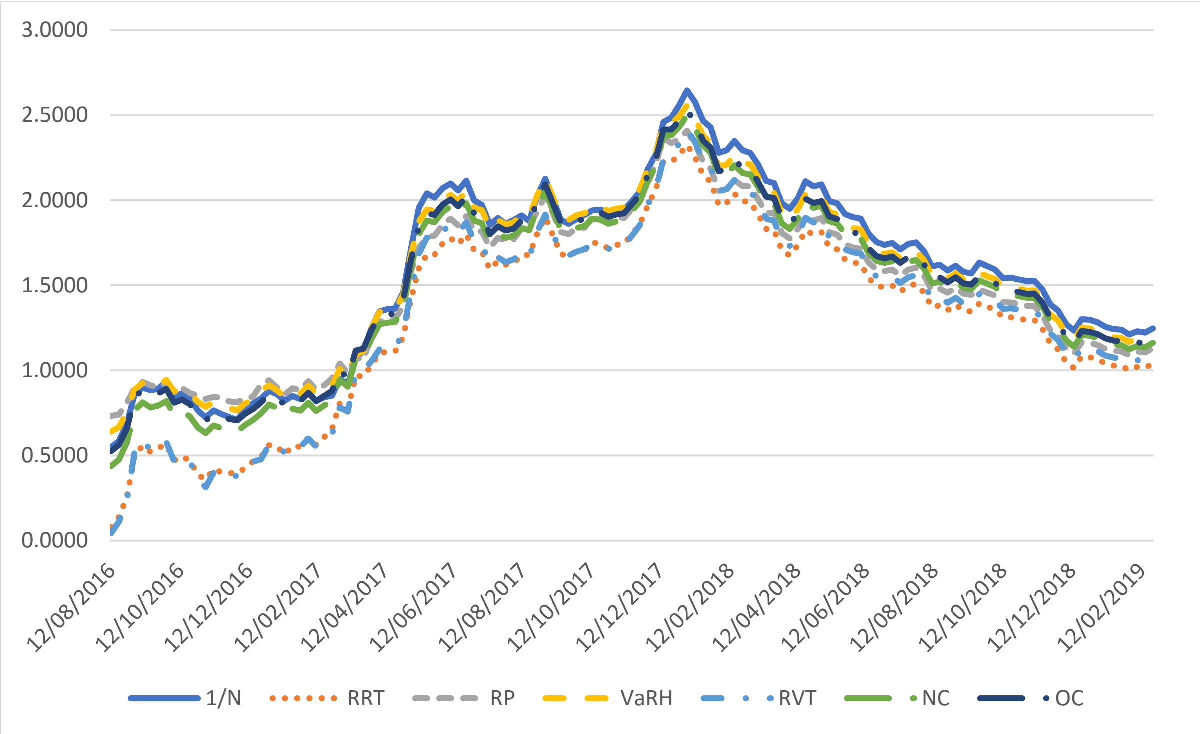


Figure 3: Out-of-sample Omega ratios (annualized) of the seven heuristics

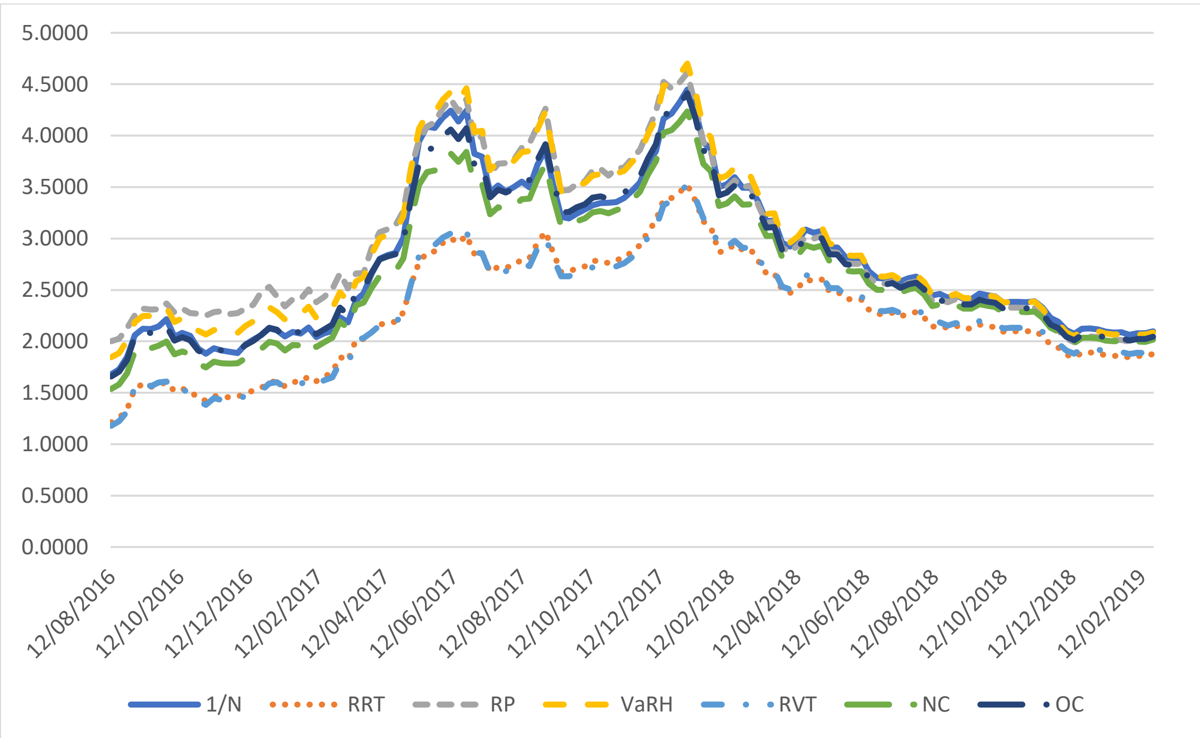


Figure 4: Asset allocation for RRT

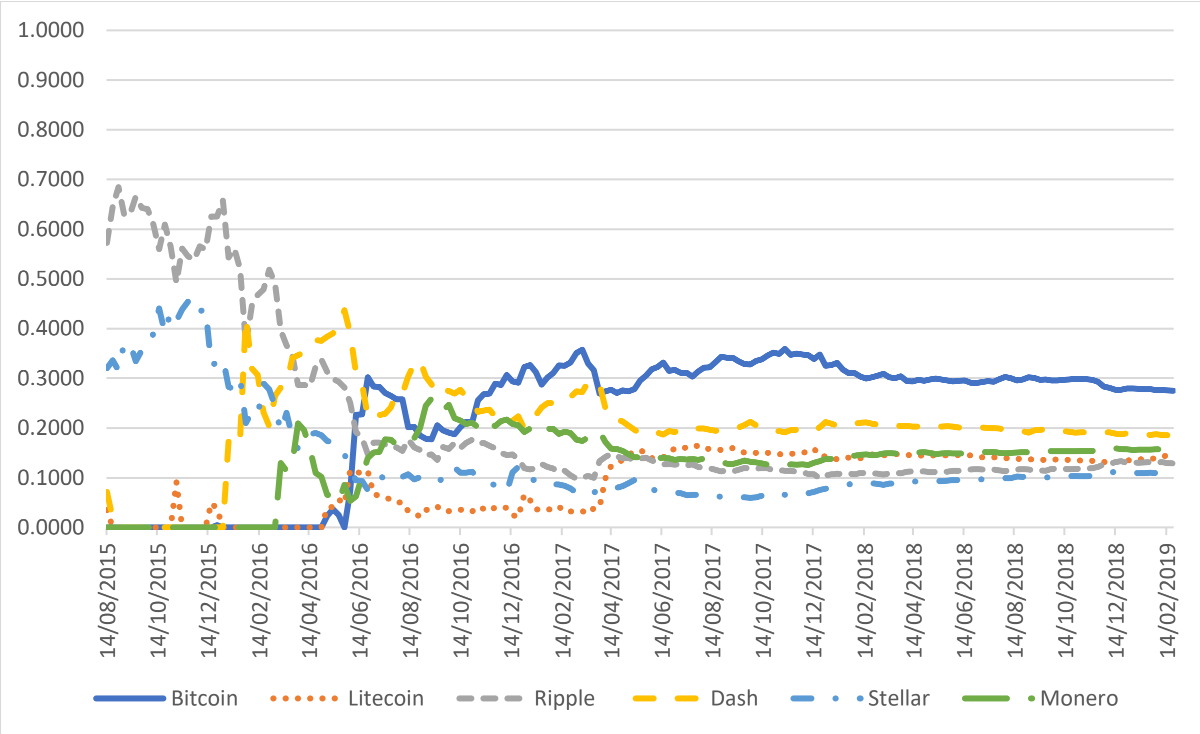


Figure 5: Asset allocation for RP

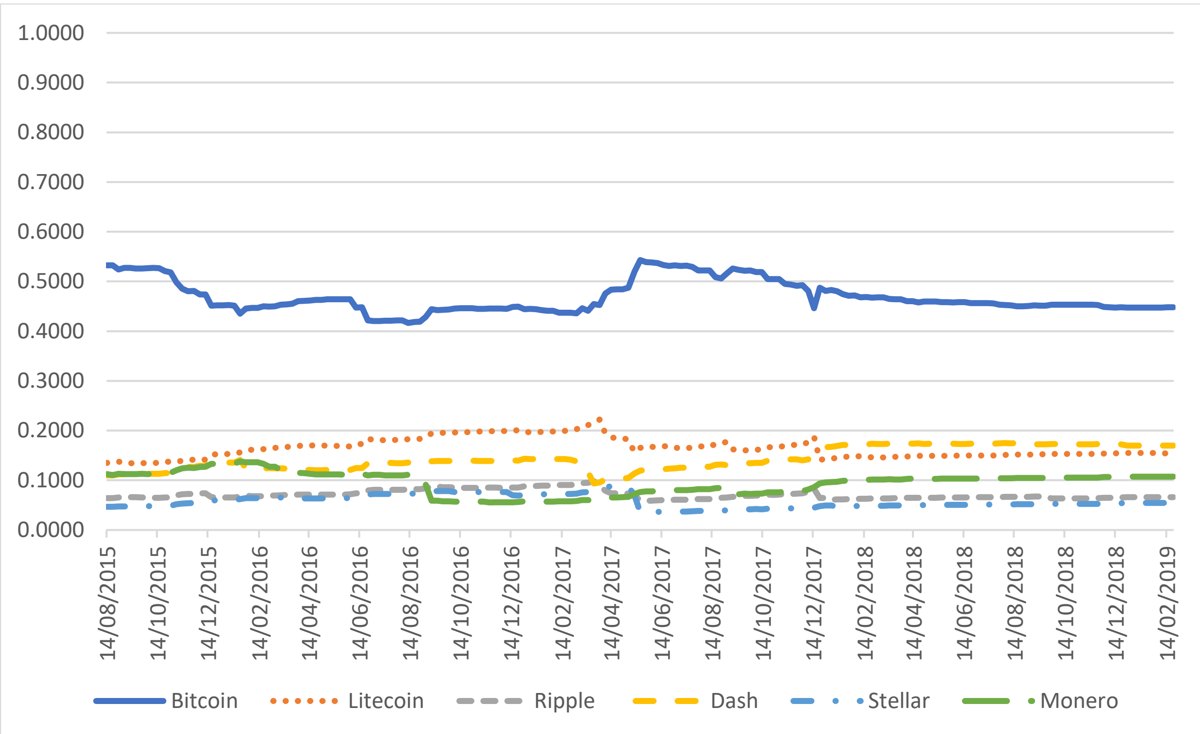


Figure 6: Asset allocation for VaRH

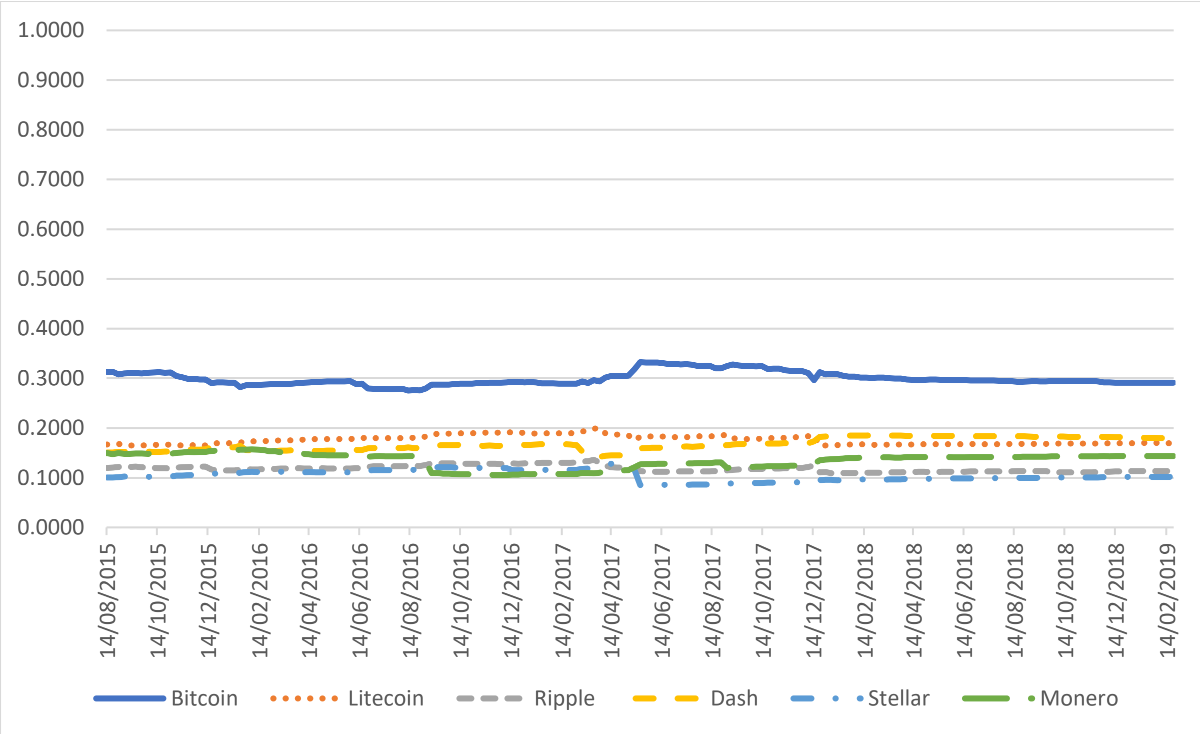


Figure 7: Asset allocation for RVT

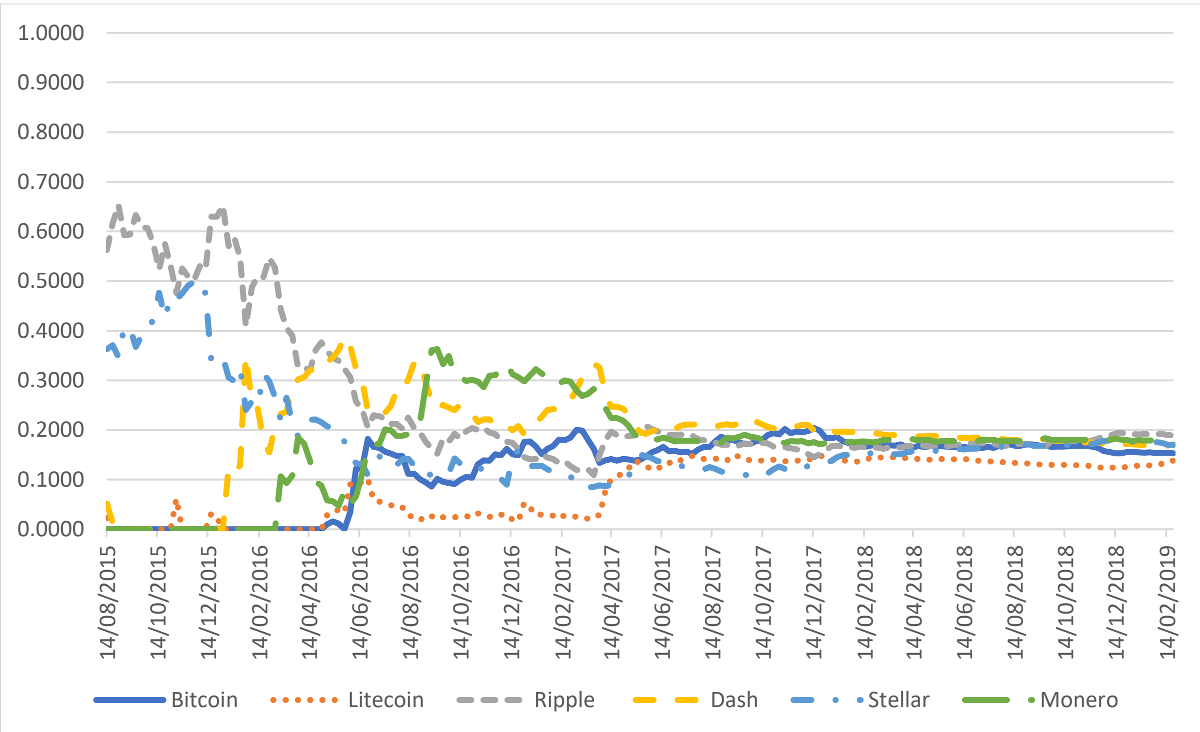


Figure 8: Asset allocation for NC

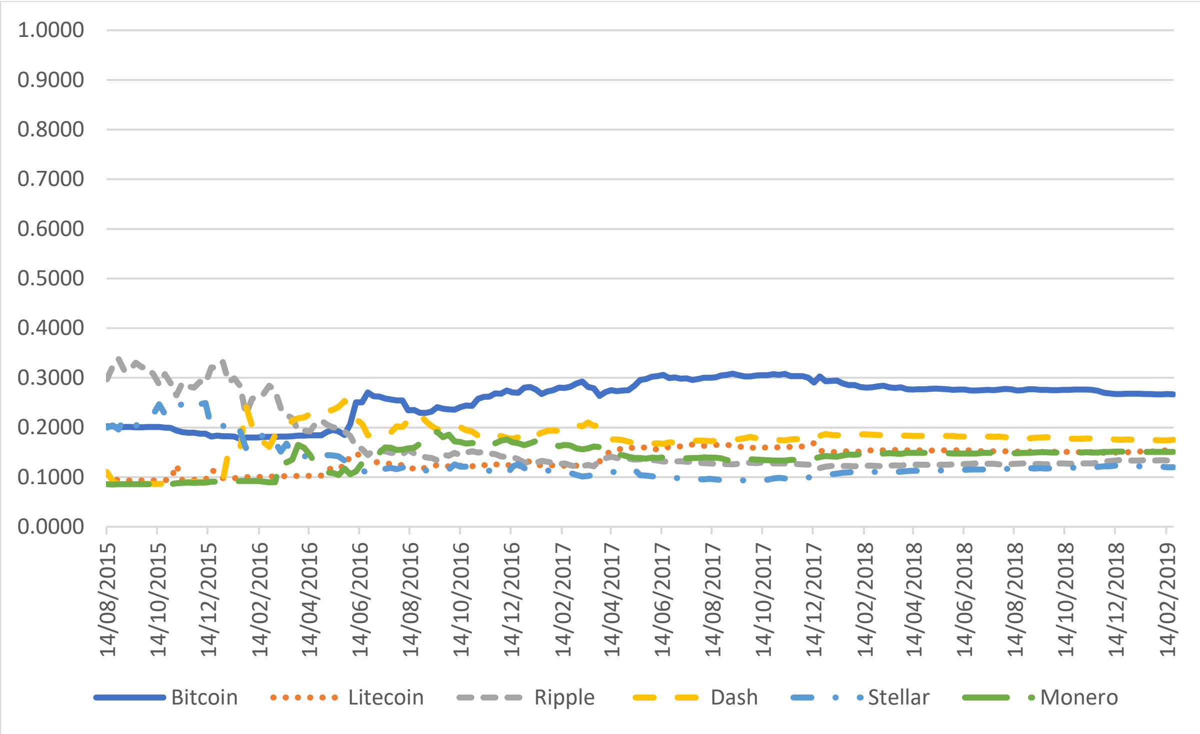
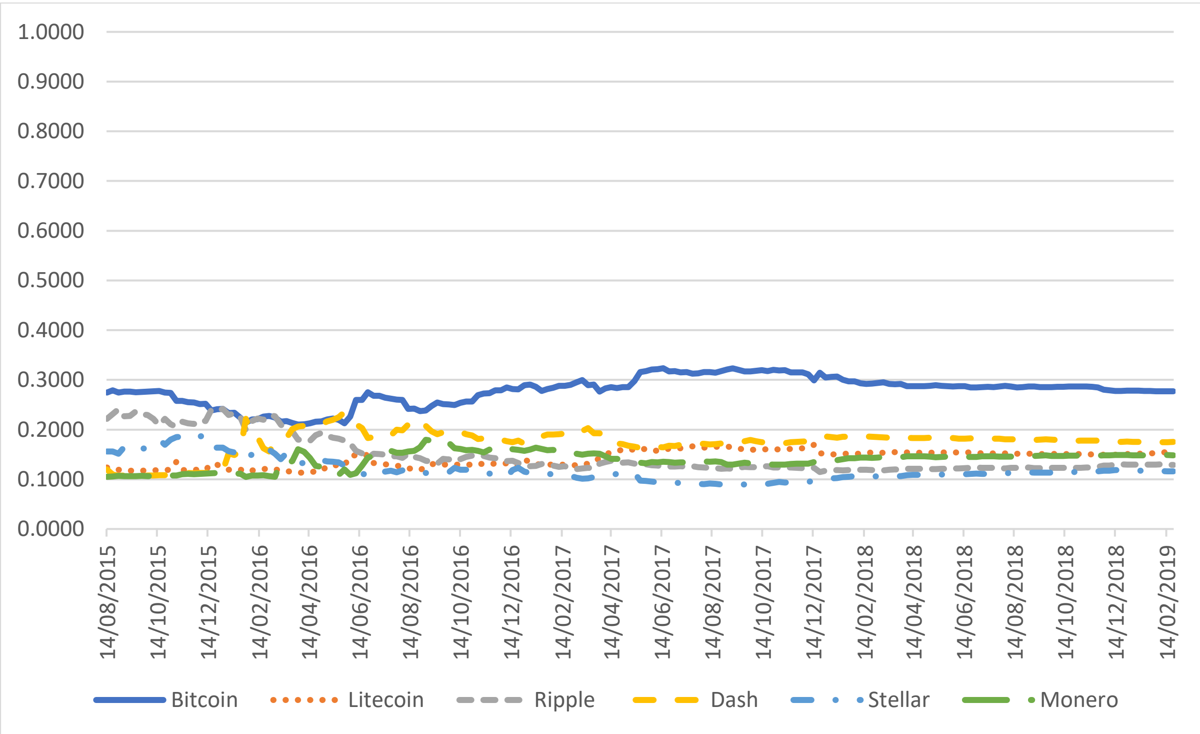


Figure 9: Asset allocation for OC



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