INSTITUTE
OF ECONOMIC STUDIES
Faculty of Social Sciences
Charles University

DIVERSIFICATION AMONG CRYPTOASSETS: BITCOIN MAXIMALISM, ACTIVE PORTFOLIO MANAGEMENT, AND SURVIVAL BIASS

Weizhi Sun
Ladislav Kristoufek

IES Working Paper 31/2021

Institute of Economic Studies,
Faculty of Social Sciences,
Charles University in Prague

[UK FSV – IES]

Opletalova 26
CZ-110 00, Prague
E-mail : ies@fsv.cuni.cz
http://ies.fsv.cuni.cz

Institut ekonomických studií
Fakulta sociálních věd
Univerzita Karlova v Praze

Opletalova 26
110 00 Praha 1

E-mail : ies@fsv.cuni.cz
http://ies.fsv.cuni.cz

Bibliographic information:
Sun W. and Kristoufek L. (2021): "Diversification Among Cryptoassets: Bitcoin Maximalism, Active Portfolio Management, and Survival Bias" IES Working Papers 31/2021. IES FSV. Charles University.

Diversification Among Cryptoassets: Bitcoin Maximalism, Active Portfolio Management, and Survival Bias

Weizhi Sun[a]
Ladislav Kristoufek[b]

[a]Institute of Economic Studies, Faculty of Social Sciences, Charles University, Prague, Czech Republic, Email: weizhi.sun@fsv.cuni.cz
[b]The Czech Academy of Sciences, Institute of Information Theory and Automation & Institute of Economic Studies, Faculty of Social Sciences, Charles University, Prague, Czech Republic, Email: LK@fsv.cuni.cz

September 2021

Abstract:
Cryptoassets, particularly Bitcoin, have attracted the attention of institutional investors during the latest price rallies of 2020 and 2021. The need for cryptoassets apart from Bitcoin in their portfolios is mostly unexplored in the current literature, and the general perception of diversification benefits within cryptomarkets mostly builds on popular beliefs. The current study is a deep dive into active and passive investment strategies focusing on specifics of cryptoassets, the most important of which is the survival bias in the portfolio dataset construction and its implications. We show that survival bias does in fact drive the results at their very core and that the differences between using the backward-looking subset of assets and actual assets available at the time of portfolio construction are substantial and lead to completely different implications and investment suggestions. It turns out that active portfolio management does not pay off in most instances compared to simply holding Bitcoin.

JEL: G11, G15, G19, G23
Keywords: cryptocurrencies, cryptoassets, Bitcoin, diversification, portfolio management, survival bias

Acknowledgements: The financial support was provided by the Grant Agency of Charles University (grant number 328321).

1. Introduction

Interest in cryptoassets has been rather cyclical since the foundation and inception of Bitcoin in 2008 and the genesis block mined on 3 January 2009 (Nakamoto, 2008). However, it seems that after the last full cycle starting with the "altcoin season" of 2017[1], going through the bear market from mid-2018 until the lows of the first half of 2020, the situation has changed structurally as institutional investors have started publicly endorsing cryptoassets (mostly Bitcoin) and thus making them more trustworthy. With the increasing capital inflows into the system and thus also increasing liquidity of not only Bitcoin but also other cryptoassets, the question of their possible portfolio usefulness is considered. There have been two natural streams of literature on cryptoassets portfolio utility: purely cryptoasset portfolios and adding cryptoassets to standard financial portfolios.

Platanakis et al. (2018) were the first to investigate whether forming a portfolio of the four popular cryptocurrencies is worthwhile and whether optimal (Markowitz) or naïve (1/N) diversification generates better performance for investors. Due to the limitations of the Sharpe ratio, they applied the Omega ratio (Shadwick and Keating, 2002) as an additional risk-adjusted measure. The empirical results and robustness checks confirm that there is little difference between optimal and naïve diversification, except for different levels of risk aversion and an alternative estimation window. Liu (2019) investigated the investability and role of diversification in cryptocurrency market, and the conclusions show that portfolio diversification across various cryptocurrencies can significantly improve the investment results. The evidence shows that the minimum variance model is less risky, with the smallest maximum drawdown, and the maximum utility model possesses higher return and utility. However, most of the models cannot challenge the naïve 1/N rule under the Sharpe ratio criterion. Contrary to the previous two studies that found few benefits in active portfolio management, Brauneis and Mestel (2019) connected the risk and return of different mean-variance portfolio strategies to single cryptocurrency investments and two benchmarks (the naïvely diversified portfolio and Cryptocurrency Index) and found substantial potential for risk reduction when several cryptocurrencies are combined in a portfolio. In other words, mixing cryptocurrencies enriches the set of "low"-risk cryptocurrency investment opportunities from the aspect of transaction costs.

In another group of studies, Ma et al. (2020) examined the effect of diversification with the addition of five cryptocurrencies to four traditional asset portfolios. The conclusions indicated that diversified investment increased the returns in most of the cases

[1] "Altcoins" is an abbreviation for alternative coins to Bitcoin. These cover most cryptoasset-related items apart from Bitcoin, though the definition develops with new concepts as they are introduced in the cryptomarkets. Currently, "altcoins" usually refers to proof-of-work cryptocurrencies such as Ethereum, Bitcoin Cash, Dogecoin, Litecoin, Zcash, Monero, and Dash; proof-of-stake cryptocurrencies such as Cardano, Tron, Tezos, and EOS; and various tokens built on smart-contract protocols such as Ethereum, Binance Smart Chain, and Wanchain such as Augur, Bancor, Uniswap, Cake, and WanSwap; as well as other cryptoassets that are not easy to sort such as Stellar, XRP, and NEO. In addition, there is a subgroup of stablecoins that form a cryptomarket fiat or numeraire. The currently popular non-fungible tokens (NFTs) are not considered altcoins.

and simultaneously decreased the volatility in all portfolios. Based on the traditional Markowitz mean-variance framework, they indicated that higher returns were linked with a diversified portfolio with cryptocurrencies under the same level of risk. In addition, they pointed out that diversifying an existing portfolio with several cryptocurrencies has a comparative advantage when it comes to diversification with only one single cryptoasset. In addition, they suggested that compared to Bitcoin, it is a better choice for investors to include Ethereum, which offers higher returns for the existing portfolio. Similar evidence was provided by Briere et al. (2013), who added Bitcoin to portfolios that provide better mean-variance trade-offs than portfolios without Bitcoin. However, this was a very early study of the cryptomarket in 2013 and before. Newer results by Mensi et al. (2021) concluded otherwise, that is, that adding Bitcoin to a portfolio does not deliver the sought after diversification benefits, while other cryptoassets delivered better results. Anyfantaki et al. (2018) employed a stochastic spanning method to construct optimal portfolios with and without cryptocurrencies, assessing their performance both in and out of sample. The result suggested that the expanded investment with cryptocurrencies dominates the traditional one with only stocks, bonds, and cash yielding potential diversification benefits and offering better investment opportunities for risk-averse investors. Corbet et al. (2018) also indicated that cryptoassets may offer diversification benefits for investors with short investment horizons.

Even though the literature on various types of interconnections is quite rich (Kumar and Anandarao, 2019; Katsiampa et al., 2019; Kyriazis, 2019; Li et al., 2020; Wang and Ngene, 2020; Xu et al., 2021; Moratis, 2021), the research on actual practical cryptoasset utility in portfolio construction is rather limited. Because such a small set of studies focus on the latter, it is natural to find important differences in dataset construction and methodological approach. With respect to the data, most of the existing literature applied mean-variance spanning tests or comparison between naïve (1/N) and minimum-variance portfolios on the selected data. Brauneis and Mestel (2019) studied daily data of the 500 most capitalized cryptoassets, while Platanakis et al. (2018) summarized inconsistent conclusions using weekly data for only four popular cryptoassets. Both researchers applied similar methodology. Liu et al. (2019) covered the 10 most capitalized cryptoassets.

Here, we present a robust study of realistic portfolio construction within cryptoassets. We focus on the out-of-sample performance of various active portfolio management strategies and compare them with Bitcoin and 1/N portfolio, i.e., passive strategies. As robustness checks, we present several directions: different rebalancing and estimation times, different starting periods, and a comparison of actual and post hoc cryptoasset selection into the starting set of assets. In the following section, we briefly introduce the portfolio approaches and performance measures that are standard in the topical literature. The crucial parts of research follow. Even though the dataset selection is not often interesting in the standard financial assets, for cryptoasset portfolios, this is of upmost importance due to survival bias. In the results and discussion sections, we detail the findings and provide a broader perspective toward the cryptoasset markets and the realistic diversification possibilities within. Overall, we show that the survival bias is in fact driving the results at the very core and that the differences between using the backward-looking subset of assets and the actual assets available (or more precisely, visible on top of the rankings) at the time of portfolio construction are substantial and lead to completely different implications and investment suggestions. It turns out that active portfolio management does not pay off in most instances compared to simply holding Bitcoin.

2. Methodology

There are many different types of performance measures that can be utilized to compare portfolio strategies with different ideas of what an ideal portfolio should approach. We examine the following set of performance measures: mean return, standard deviation, Sharpe ratio, Treynor ratio, Sortino ratio, and Information ratio.

In addition to the standard trio of the mean return $\bar{\mu}$, standard deviation SD, and Sharpe ratio $\frac{\bar{\mu}-\bar{r}_f}{\widehat{SD}}$, where r_f is the return of a risk-free asset (Sharpe, 1994), we use other alternative measures. The Treynor ratio (Brown and Reilly, 2012) is similar to the Sharpe ratio in that it standardizes the portfolio return. However, instead of standardizing using the standard deviation as in the Sharpe ratio, the Treynor ratio uses the portfolio beta as a volatility measure so that it equals $\frac{\bar{\mu}-\bar{r}_f}{\hat{\beta}_p}$, where $\hat{\beta}_p = \frac{\widehat{cov}(r_p,r_m)}{\widehat{var}(r_m)}$ with r_p as a portfolio return and r_m as the market return. The latter thus considers systematic risk only instead of the total risk of the former. The Sortino ratio (Sortino, 1994) corrects the Sharpe ratio for its symmetry. When diversifying a portfolio, one is mostly concerned about the downside risk, i.e., negative shocks, but the Sharpe ratio (and the Treynor ratio) penalizes for the risk in both tails. The Sortino ratio is then a ratio of the return excess to the "minimum acceptable return" (MAR) over the semideviation (square root of semivariance) below the MAR. In our application, we set $MAR = r_f = \bar{r}_{USDT}$, i.e., the minimum acceptable return is set to the mean return of Tether as the most prominent stablecoin, i.e., holding the cryptoequivalent of USD, which is also set as the risk-free rate when necessary. Note that $\bar{r}_{USDT} \approx 0$. The Information ratio (Sharpe, 1994) substitutes the risk-free rate in the original Sharpe ratio by the benchmark return so that the ratio is formed of the active premium (portfolio return minus benchmark return) over the tracking error (square root of the difference between portfolio and benchmark returns) together as $\frac{\bar{\mu}-\bar{r}_m}{\widehat{SD}(r_p-r_m)}$. In our application, we use the capitalization-weighted portfolio as the benchmark when needed.

The portfolios are constructed with five different optimization approaches: minimal standard deviation (*min* σ), minimal expected shortfall at 95% (*min ES*), maximal Sharpe ratio (*max SR*), maximal STARR (excess returns over expected shortfall at 95%, *max STARR*), and maximal constant relative risk aversion up to the fourth moment with the risk aversion parameter $\lambda = 10$ (Martellini and Ziemann, 2010; Boudt et al., 2015) (*max CRRA*). As "naïve" methods, we use a single-asset portfolio of Bitcoin and the uniform $1/N$ portfolio.

3. Data

Even though data availability is an oft-noted quality of the cryptoassets as various measures can be obtained directly from the given blockchain or through various data providers harvesting the data and constructing both simple and complex metrics of blockchain activity, it becomes troublesome when considering more assets in time. Most studies focused either on Bitcoin solely; on a limited set of assets such as the “big three” of Bitcoin, Ethereum, and XRP; or ad hoc sets such as the Top 10 most capitalized cryptoassets at some point in time. When analyzing portfolio performance, one wants to have a wide set of assets with a reasonable history of observations. However, this can become tricky when considering cryptoassets. When looking at the Top 200 cryptoassets with respect to the market capitalization as of the beginning of 2021, only 16 date back to the beginning of 2016; moreover only 12 in the Top 100 and only 8 in the Top 30 date back to the beginning of 2016. This makes any analysis susceptible to survival bias because if one selects the set of interest with respect to the current position in the cryptoasset ranking and then filters with respect to the data availability, the final set will consist only of the winners that made it and survived to the top ranks. However, the actual selection of an investor at the beginning of the examination period can and mostly will be very different. We thus construct two portfolio sets: one with the Top 30 cryptoassets with respect to the market capitalization as of the beginning of 2016 and one with the cryptoassets in the Top 100 as of the beginning of 2021 that have data available back to the beginning of 2016[2]. The former portfolio is composed of Bitcoin (BTC), XRP (XRP), Litecoin (LTC), Ethereum (ETH), Dash (DASH), Dogecoin (DOGE), Peercoin (PPC), BitShares (BTS), Stellar (XML), Nxt (NXT), MaidSafeCoin (MAID), Namecoin (NMC), Factom (FCT), Bytecoin (BCN), Monero (XMR), Rubycoin (RBY), Emercoin (EMC), Clams (CLAM), BlackCoin (BLK), YbCoin (YBC), MonaCoin (MONA), NEM (XEM), Startcoin (START), Counterparty (XCP), Global Currency Reserve (GCR), Novacoin (NVC), Ixcoin (IXC), NeuCoin (NEU), CasinoCoin (CSC), and Tether (USDT). The latter portfolio consists of Bitcoin, XRP, Litecoin, Ethereum, Dash, Dogecoin, Stellar, Monero, NEM, Siacoin (SC), DigiByte (DGB), and Tether. Tether as a stablecoin is used as the risk-free asset when needed and is not included in the default set for portfolio construction (as at least the minimum variance and minimum expected shortfall portfolios would degenerate to all-Tether solutions). We can see that many of the Top 30 cryptoassets of 2016 actually remained at the same or nearly the same position. However, many of them fell deep, e.g., Emercoin fell to a rank of approximately 1500, Clams fell to a rank below 5000, and YbCoin and NeuCoin were actually delisted[3]. Our datasets cover raw close-open returns between 1 January 2016 and 31 March 2021, totaling 1917 daily observations[4].

[2]The ranking snapshots are available at weekly frequency at coinmarketcap.com.

[3]When assets are delisted, i.e., they cannot be traded on any centralized exchange, and there is no liquidity pool on decentralized exchanges. The one after the last available observation is set to -100%, and the rest of the observations are not included.

[4]The time series were obtained from coinmarketcap.com and double-checked against livecoinwatch.com and coingecko.com for series with missing observations.

4. Results

4.1. Portfolio performances

We construct portfolios using five approaches – minimal variance, minimal expected shortfall, maximal Sharpe ratio, maximal excess return over expected shortfall, and maximal constant relative risk aversion – as a default with the Bitcoin and 1/N portfolios as benchmarks. Portfolio weights are constructed on 180 daily observations, and positions are made and held for a month, after which the positions are rebalanced. The resulting out-of-sample performances are summarized in Table 1. Looking only at actual actively managed portfolios (i.e., without the two benchmarks), we see that the most profitable is that based on minimizing the expected shortfall with an annualized return of 149%, closely followed by the maximum STARR portfolio, with an annualized return of 141%. However, return is only a single angle of portfolio construction, so we turn to the measures associated with or incorporating the risk factor. The minimum-variance portfolio has the lowest out-of-sample standard deviation of the actively managed portfolios, with a value of 0.80, which is quite closely followed by the maximum Sharpe ratio portfolio. The portfolios with the highest return have also much higher variance, which is mostly visible for the maximum STARR portfolio, which has a standard deviation more than twice that of the minimum-variance portfolios. By combining the risk and return, the highest Sharpe ratio is connected to the portfolios being rebalanced with respect to the minimum variance. However, the situation changes when we focus on subsets of the overall risk captured by the Sharpe ratio. If only the systematic (Treynor ratio) and the downward (Sortino ratio) risks are taken into consideration, it is the minimum expected shortfall and maximum STARR, respectively, that come out on top. When comparing the performance with the market portfolio, it is only these two that beat the benchmark market portfolio; i.e., their information ratio is positive. We thus see that the optimal strategies vary quite considerably with respect to the performance metric. It is only the maximum CRRA portfolios that are evidently underperforming, suggesting that including four rather than two moments into the optimization procedure does not pay off. This is most likely due to the erratic behavior that is experienced by many of the cryptoassets included in the study. This can lead to a problematic estimation of these higher moments.

How do these active portfolio strategies compare to the two benchmarks, namely, the Bitcoin maximalism, i.e., simply holding Bitcoin and nothing else, and the naïve 1/N approach, when we split the starting capital uniformly across all assets in the Top 30 (not including Tether)? The last two rows of Table 1 provide the answer. Starting with the Bitcoin-only position, we see that return-wise, Bitcoin underperforms all other portfolio strategies except the maximum CRRA strategy. It is thus less profitable over the analyzed period. However, it is also considerably less risky than all active portfolio approaches – where the least risky has a value of 0.80 standard deviations compared with Bitcoin, with a value of 0.64. Even though the Sharpe ratio of Bitcoin (1.40) is lower than that for the minimum variance, minimum expected shortfall, and maximum Sharpe ratio, it is quite close to them, and it outperforms the maximum STARR and CRRA approaches. However, in the other metrics considering different components of risk, Bitcoin underperforms.

However, this is not the end of the story. The 1/N portfolio almost completely beats all the other portfolio methods. Apart from the portfolio standard deviation, which is practically the same as that for the minimum variance portfolios, the naïve strategy strongly outperforms, with an annualized average return of 485% and Sharpe ratio of almost 6. This portfolio also strongly outperforms the market portfolio with an information ratio of 6.39. Even the Sortino ratio, which covers the downward risk, is almost twice the best Sortino ratio of the other strategies, with a value of 0.28.

method	μ	SD	Sharpe	Treynor	Sortino	Information
min σ	1.2867	**0.8023**	**1.6038**	1.4198	0.1414	-0.0372
min ES	**1.4880**	1.0241	1.4530	**1.5261**	0.1472	**0.2107**
max SR	1.1919	0.8356	1.4264	1.2185	0.1341	-0.1944
max STARR	1.4097	1.7147	0.8221	1.2960	**0.1569**	0.0632
max CRRA	0.4583	1.3048	0.3513	0.4648	0.0988	-0.7199
Bitcoin	0.8965	***0.6417***	1.3971	0.8830	0.1214	-1.9475
1/N	***4.8542***	0.8141	***5.9625***	***4.9201***	***0.2800***	***6.3868***

Table 1: **Out-of-sample portfolio performance.** Performance metrics are shown for portfolios based on 180-day windows with rebalancing every month. The portfolio is based on the top 30 cryptoassets at the beginning of 2016. **Bold** numbers highlight the best performance for the given metric, and ***bold italics*** highlight the best performance in the benchmark portfolios (Bitcoin and 1/N portfolio).

Even though the uniform portfolio is the clear winner of the race, one must admit that realistically, almost nobody would have invested in such a portfolio in 2016. Looking at the components of the Top 30 in 2016 (we compare the 1/N portfolio with Bitcoin in a later section), it is difficult to imagine that an investor would lay the same amount of capital to Bitcoin and BlackCoin or CasinoCoin (one could imagine a 1/N portfolio of BTC, XRP, ETH, and likely DASH and LTC). It thus makes sense to further investigate the details of the actively managed portfolios that come out on top.

Based on Table 1, the minimum expected shortfall approach delivers the most profitable strategy (mean return and the Treynor and information ratios), the minimum variance approach yields the highest standardized return (the Sharpe ratio), and the maximum STARR gives the best trade-off between returns and downward risk (the Sortino ratio). Fig. 1 presents the dynamics of portfolio weights for these three strategies. The weights are presented so that only the components with average weights over 1% are shown; the small components below 1% are accumulated in the "rest". In addition, to highlight the differences, this separation between small and other components is based on the weights for the minimum standard deviation portfolios but is manifested in the other two as well. The minimum variance and minimum expected shortfall portfolios show rather similar weight dynamics. The position of Bitcoin in the entire portfolio evolved strongly in time. At the beginning (2016), it was only a small part of the optimal portfolios. For the expected shortfall positions, it even was not part of the portfolio at all for most of 2016. Starting in 2017, the position of Bitcoin started becoming more important and kept growing over 2017 into 2018, where its position solidified at between 60% and 70% of the optimal portfolios.

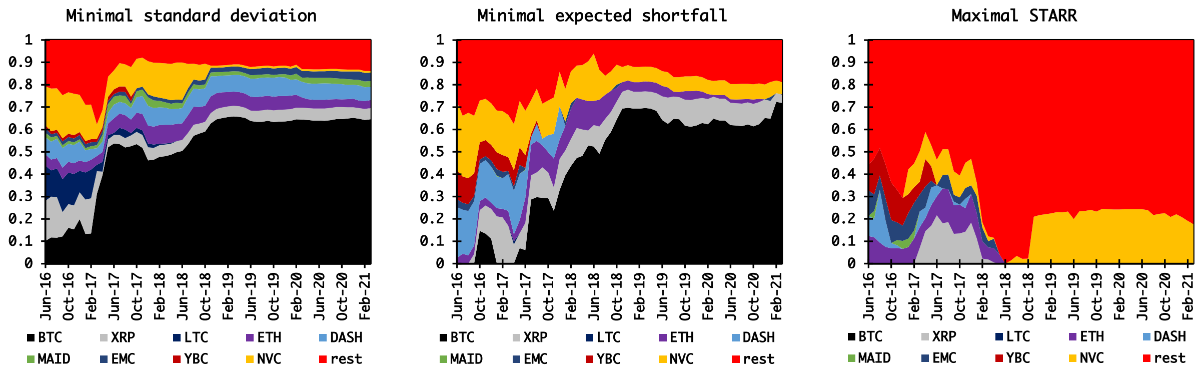

Figure 1: **Portfolio weights dynamics.** Portfolios are based on 180-day windows with rebalancing every month. Only cryptoassets with an average weight of more than 1% are included in the charts. The small-weight cryptoassets are accumulated in the "rest".

From the historical "big three" of BTC, ETH, and XRP, the position of ETH is generally weaker than of XRP. This can be attributed to the position of ETH as following BTC (correlation of 0.54 over the entire period), albeit with more pronounced swings both up and down, while XRP is more detached from the general market (correlation of 0.31 over the entire period). Outside of the "big three", DASH plays an important role in the minimum-variance portfolios and played quite an important one in the minimum expected shortfall as well, albeit only at the beginning between 2016 and 2018. Among the small cryptoassets, Novacoin (NVC) stands out in all three strategies. NVC is practically uncorrelated with BTC (0.04) and has a rather high average return over the period (average 2.1% daily return compared to 0.3% of BTC) both due to some large price swings. Thus, it serves as a general diversifier in these portfolios.

A completely different picture is given by the maximal STARR portfolios. There is no Bitcoin position in the portfolios over the entire period, and these are dominated by the small caps starting their weight at around 50% in 2016-17, almost completely taking over the portfolios in 2018, and finally pushed back slightly to approximately 80% of the capital, not by the large caps but again by NVC. To further illustrate the differences between the portfolios and to actually present the drivers of the maximum STARR positions, Fig. 2 shows three pie charts with average weights in the three approaches, again showing only the ones with an average weight above 1%. The pie charts for the minimum-variance and minimum-shortfall portfolios show what we mostly observed in Fig. 1, i.e., the Bitcoin dominance and rather diversified remains. For the maximal STARR portfolios, we see no BTC and only tiny portions of XRP and ETH, and five cryptoassets with average weights between 10% and 20%: Bytecoin (19%), NEM (12%), NVC (14%), Ixcoin (16%), and CasinoCoin (14%).

A complete picture of the different approaches in overall performance, focusing on the return, is presented in Fig. 3. The three successful active portfolio strategies compared put side-by-side with the naïve strategies. Even though this picture in a way only presents

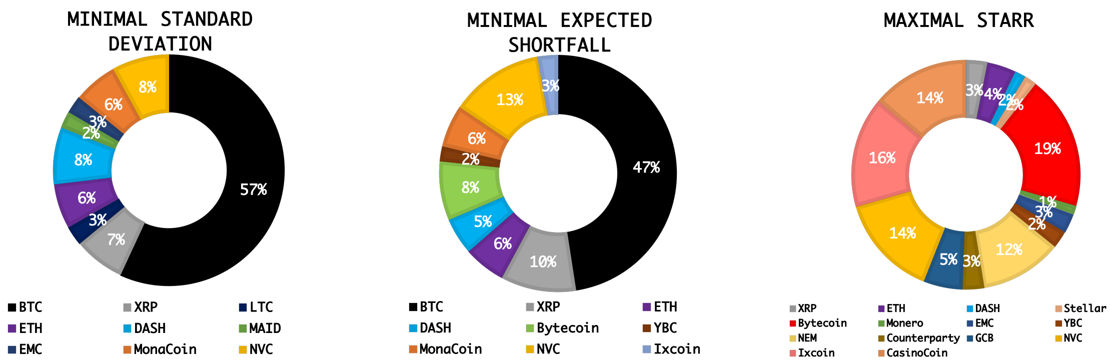

Figure 2: **Portfolio average weights.** Portfolios are based on 180-day windows with rebalancing every month. Only the cryptoassets with the average weight of more than 1% are included in the charts.

the mean return results of Table 1, observing the actual dynamics in time might help to understand why some strategies outperform the others and/or when the detachment, if any, took place. For a complete perspective, we also add the market portfolio given as the capitalization-weighted one. There are two evident detachments or separations of the dynamics visible by the naked eye. The "altcoin season of 2017" presents itself in all portfolios shooting away from Bitcoin. Remember that this period is characterized by low weights of Bitcoin in all portfolios, while its dominance occurred in 2018 and later (at least optimal portfolios wise). The minimum variance and minimum expected shortfall strategies were thus able to take advantage of the "altcoin season" with unprecedented hikes in the non-Bitcoin cryptoassets while slowly building up a position in Bitcoin as the low-variance part (for the cryproasset scale) of the portfolio so that after the altcoins started correcting more than Bitcoin, they had already left their dominant positions for Bitcoin as an anchor. That is why we do not observe Bitcoin catching back up to the active portfolio strategies because it was already a dominant part of them. The 1/N portfolio is apparently off the charts. Not only had it outperformed Bitcoin, market and all other active portfolio strategies during the "altcoin season", but it also never came back. It even survived the bear markets of 2018 and 2019 with the smallest losses to completely take over after the COVID-19 correction in March 2020 and the following boom and new all-time-highs of BTC and ETH.

Apart from the already mentioned trickiness of the 1/N portfolio, as it is difficult to imagine that someone would have taken this strategy in reality at the beginning of 2016, there are also the issues of liquidity and exchanges. When we look at the bottom of the historical Top 30 back at the beginning of 2016, we have CasinoCoin, NeuCoin, and Ixcoin. Currently, CasinoCoin is listed on only one reasonable exchange (Bitrue) with a liquidity of around \$100k if someone wants to sell with an impact of less than 2% of the price. NeuCoin was delisted straight in the second half of 2016; i.e., it delivered a complete loss. However, this turned out not to be that problematic, as it happened before the price rocketing. Ixcoin is now listed on two obscure exchanges (YoBit and FreiExchange)

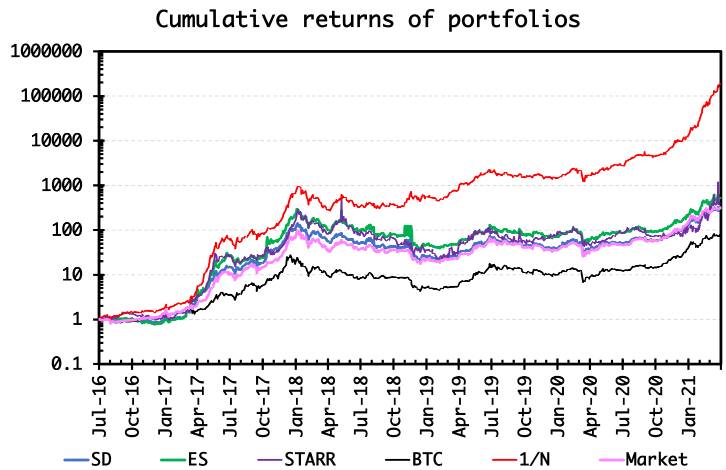

Figure 3: **Cumulative returns.** Cumulative raw returns starting at the value of 1, in a semilogarithmic form. "SD", "ES", and "STARR" represent portfolios based on the minimal variance/SD, minimal expected shortfall, and maximal excess return over expected shortfall, respectively. "BTC" is a single-asset portfolio formed of only Bitcoin. "1/N" is a uniform portfolio, and "Market" is the market capitalization weighted portfolio.

with practically no liquidity and with a price difference between the two exchanges of approximately 100%; i.e., the liquidity is so low that it is not even arbitraged away. Even if we go up the original Top 30 just below the Top 6 of BTC, XRP, LTC, ETH, DASH, and DOGE that all survived in the top positions to the current day, the challenges do not disappear. Just below Dogecoin, we have Peercoin and BitShares. Peercoin is now listed on several exchanges, some even with a good name like Bittrex and HitBTC, and maybe Hotbit. However, the daily volume is still below $100k, and the market depth for selling is only approximately $25k, with an impact below 2%. BitShares is then an example of a cryptoasset that fell from the top but still remains reasonably liquid thanks to being listed on big exchanges such as Binance and Huobi, with over 50 trading pairs listed on several exchanges. The point is that even though the 1/N portfolio is clearly the best on paper, it might be problematic when the profits are to be converted either back to fiat or even to BTC or other dominant cryptoassets. We will return to this in the discussion when we consider it together with other findings presented below.

Optimal portfolios and their performance are based on several important parameters that are selected ad hoc. These are the training/in-sample/estimation period, in which the optimal weights for the given method are calculated, and the rebalancing frequency. In the default setting, we calculate the optimal weights in the 180-day windows and rebalance at the beginning of each month. Table A1 shows the performance measures for a shorter training period of 90 days, and Table A2 presents them for a lower frequency of rebalancing of one quarter. The results qualitatively follow those of the default setting.

4.2. Post hoc portfolio construction

We have stressed that the selection of assets in cryptoasset research might be partially flawed by the survival bias as the assets in the studies are often selected on a post hoc basis. Specifically, one looks at the current ranking with respect to market capitalization and filters based on the data availability until the desired size/width of the dataset is obtained. This can lead to selection of a cryptoasset that is now in the Top 100, for example, but a general investor will rarely invest into it in 2016 or 2017 even if the data were available then simply because it could have been an obscure coin or token at rank 5000 with a market capitalization of a few thousand dollars. Inclusion of this asset will artificially boost the returns of the portfolio because without abnormal returns it would never have made it to the Top 100. In the previous section, we used a snapshot of capitalization ranking as it were at the beginning of 2016 and based the portfolio strategies on the actual Top 30 back then. Now, we focus on the post hoc selection of the assets and examine the differences. As described in the Data section, there are only 12 cryptoassets in the 2021 Top 100 that have a data history back to 2016.

method	μ	SD	Sharpe	Treynor	Sortino	Information
min σ	1.2936	**0.6590**	1.9629	1.2670	0.1510	0.1638
min ES	**1.6286**	0.7557	**2.1551**	**1.5739**	**0.1723**	**0.8962**
max SR	1.1978	0.6902	1.7354	1.1260	0.1408	-0.2389
max STARR	0.6123	0.8633	0.7093	0.5640	0.0921	-1.0911
max CRRA	0.6389	0.8644	0.7391	0.5697	0.0949	-1.0905
Bitcoin	0.8965	***0.6417***	1.3971	0.8890	0.1214	-1.7835
1/N	1.1382	0.7808	1.4577	1.0339	0.1275	-0.3113

Table 2: **Out-of-sample portfolio performance (post hoc portfolio).** Performance metrics are shown for portfolios based on 180-day windows with rebalancing every month. The portfolio is based on the top 100 cryptoassets as of the beginning of 2021 with the data history back to the beginning of 2016, totaling 11 assets. **Bold** numbers highlight the best performance for the given metric, and ***bold italics*** highlight the best performance in the benchmark portfolios (Bitcoin and 1/N portfolio).

By applying the same procedures, we arrive at the portfolio performances summarized in Table 2. There are clear differences. First, the 1/N portfolio does not stand out. Even though its statistics are better than for two of the five actively managed portfolios, it does not beat the minimum-variance, minimum-expected-shortfall, or maximum-Sharpe-ratio strategies. Even though it is again the minimum variance and minimum expected shortfall portfolios that come out on top, their performance is artificially boosted thanks to selection/survival bias. Even though the difference between the annualized return of 163% (post hoc) and 149% (actual) might seem small, the gap widens when propagated over five years. The annualized standard deviation is underestimated by around 20% when the minimum variance portfolios performance are compared.

The dominance of Bitcoin in the optimal portfolios follow a similar path as the original dataset (Fig. 4) but the positions of XRP, ETH, and also DASH are now more prominent. This is highlighted in the pie charts in Fig. 5. Again, the assets with average weights below

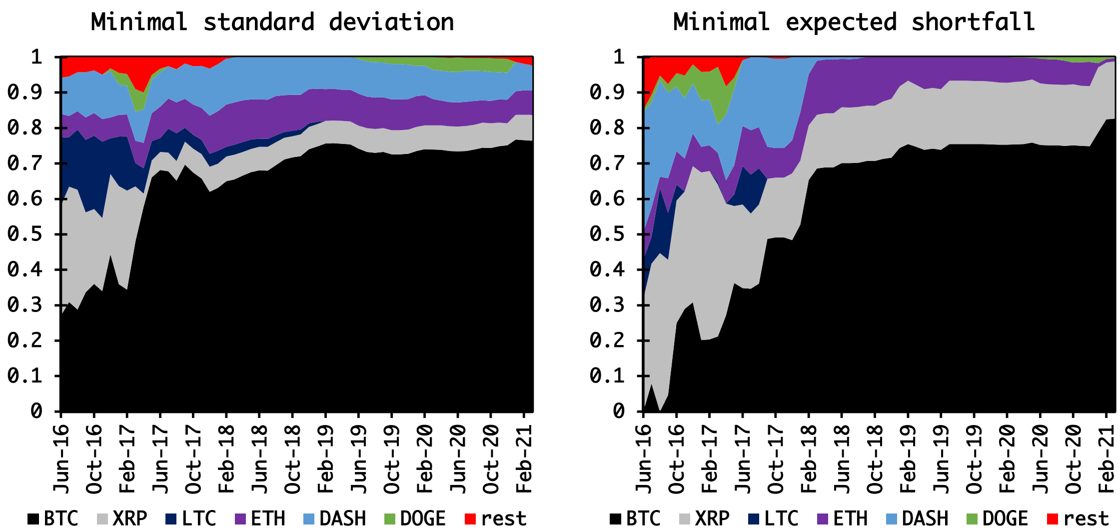

Figure 4: **Portfolio weights dynamics (post hoc).** Portfolios are based on 180-day windows with rebalancing every month. Only cryptoassets with an average weight of more than 1% are included in the charts; the small-weight cryptoassets are accumulated in the "rest".

1% are not shown. The selection and survival bias thus overreport the average return and underreport the actual risk of portfolios but also overrepresent the position of the high caps in the optimal portfolios. Fig. 2 looks more like the textbook chart where the small assets are also represented than Fig. 5.

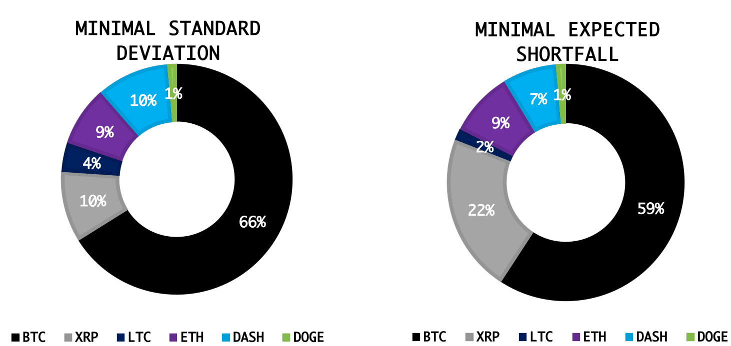

Figure 5: **Portfolio average weights (post hoc portfolios).** Portfolios are based on 180-day windows with rebalancing every month. Only cryptoassets with an average weight of more than 1% are included in the charts.

4.3. 1/N over Bitcoin all the way?

The uniform weight (1/N) portfolio completely beat the competition in all analyzed settings. Its inclusion also highlighted how much its performance remains hidden when post

year	portfolio	μ	SD	Sharpe	Treynor	Sortino	Information
2016	Bitcoin	0.8704	0.6275	1.3872	0.8583	0.1210	-2.0801
	1/N (Top 5)	1.2664	**0.3961**	1.8192	1.2166	0.1431	-0.1274
	1/N (Top 10)	1.3506	0.7438	1.8158	1.2744	0.1460	0.1004
	1/N (Top 30)	**5.2010**	0.7977	**6.5204**	**5.4180**	**0.2972**	**6.9423**
2017	Bitcoin	0.9240	**0.6707**	1.3777	0.9020	0.1205	-2.0643
	1/N (Top 5)	**1.2800**	0.7555	1.6942	1.1629	**0.1366**	**-0.3234**
	1/N (Top 10)	1.1110	0.7541	1.4732	1.0241	0.1217	-0.7711
	1/N (Top 30)	1.2278	0.7041	**1.7438**	**1.2387**	0.1337	-0.4429
2018	Bitcoin	**0.3489**	**0.6274**	**0.5561**	**0.3788**	**0.0726**	**0.0017**
	1/N (Top 5)	0.0887	0.7523	0.1179	0.0825	0.0440	-1.0078
	1/N (Top 10)	0.1075	0.7601	0.1415	0.1007	0.0462	-0.8261
	1/N (Top 30)	0.1386	0.7559	0.1833	0.1325	0.0489	-0.6715
2019	Bitcoin	**1.3341**	0.6043	**2.2075**	**1.2940**	**0.1631**	**-0.1846**
	1/N (Top 5)	0.7303	0.6924	1.0546	0.6425	0.1025	-2.3247
	1/N (Top 10)	0.7210	0.6429	1.1214	0.7039	0.1070	-2.2753
	1/N (Top 30)	1.0199	**0.5963**	1.7103	1.0916	0.1323	-1.2062
2020	Bitcoin	2.1547	0.6339	**3.3994**	2.0739	0.2001	-3.0379
	1/N (Top 5)	1.4120	**0.5837**	2.5191	1.5637	0.1633	-4.6092
	1/N (Top 10)	1.6047	0.6792	2.3625	1.5347	0.1608	-3.4671
	1/N (Top 30)	**2.4280**	0.7780	3.1206	**2.3154**	**0.2029**	**-0.2898**

Table 3: **Comparison of Bitcoin and 1/N portfolio performance throughout the years.** The 1/N portfolios are based on uniform weights over the 5, 10, and 30 most capitalized cryptoassets at the beginning of the given year. The **bold** numbers highlight the best performance for the given metric.

hoc asset selection is used. However, the question of whether this is a general characteristic of the cryptoasset portfolios and markets or the result of the beginning of the analyzed period remains. As discussed above, for the liquidity of smaller cap assets, we inspect the performance of three different 1/N portfolios based on the Top 5, Top 10, and Top 30 most capitalized cryptoassets at the beginning of the given year, and compare them with the performance of Bitcoin explicitly and implicitly with the market portfolio through the information ratio. We do this for the starting years of 2016-2020. Table 3 presents the results in the same form as for the original portfolios. We see that the starting year of 2016 is a clear outlier on the list. In addition, the differences between the Top-5- and Top-10-asset portfolios compared to the Top 30 one are also striking even though they both still beat the Bitcoin benchmark in almost all metrics. In addition, both the Top-5 and Top-10 portfolios perform similarly to the market portfolio with an information ratio close to zero. In 2017, the year of altcoins, the uniform portfolios still beat Bitcoin in the profit-oriented metrics (Bitcoin has a lower standard deviation than all three 1/N portfolios). However, the difference is clearly not as pronounced as that for 2016. For the portfolios uniformly constructed based on the rankings of 2018 and 2019, Bitcoin clearly outperforms all three uniform portfolios. The situation again reverses, albeit not as profoundly, when the starting year and thus the starting ranking is based on 2020. The Top-30 portfolio comes out on the top even though Bitcoin quite closely follows, beating the former in the Sharpe ratio and standard deviation, with similar figures for the Sortino ratio controlling for the downward risk. The results and over-/underperformance comparisons between both naïve portfolio approaches thus strongly depends on the starting period and thus mostly on the dominance of general market sentiment. As the years 2016, 2017, and 2020 can be easily labeled as the bull markets, and the years 2018 and 2019 as the bear markets, it is evident that diversification benefits strongly depend on these. In the bear markets, Bitcoin by itself mostly covers the overall market dynamics, as can be seen from the Information ratios of 0.0017 and -0.1846 in 2018 and 2019, respectively. Note that the Information ratio can be seen approximately as the t-statistic comparing the mean returns of the given asset or portfolio and the overall market (represented by the capitalization-weighted portfolio of the Top 30 assets for the given starting year ranking). Thus, Bitcoin overall returns starting from either 2018 or 2019 cannot be distinguished from the overall market, at least with respect to the expected return. From an investor's perspective, it seems that if the investor enters the market in an already running bull market (which might be most of the retail investors), it does not pay off to diversify, and one can simply buy and hold Bitcoin. If the investor enters during calm or purely bear periods, it seems more reasonable to diversify, waiting for another bull market to arrive. Naturally, this holds only for investors with medium- or long-term investment horizons and not speculators or chartists who seek profits in short-term horizons.

4.4. Survival bias over the years

The passive or naïve investment strategies have varying performances depending on the market state, as shown in the previous section. We now focus on active investment strategies in different starting years. The starting years mean that the dataset contains cryptoassets that were in the Top 30 most capitalized ones[5] at the beginning of the given year the same way as in the previous section with passive portfolio strategies. The other setting is the default setting with 180 days in the estimation period and monthly rebalancing. We thus present the results for the starting years 2016-2019. The last two possible starting years – 2020 and 2021 – are omitted as the out-of-sample periods would be too short. Table 4 summarizes the performance measures. For brevity, we only present the minimum standard deviation and minimum expected shortfall as these show the best performances anyway. The results are again rather dependent on the starting years. For the starting year of 2017, the minimum-variance portfolios deliver the lowest variance in the out-of-sample race as well but are dominated by Bitcoin in all other metrics. None of the strategies beats the hypothetical market portfolio as the information ratio is negative for all. For the starting years of 2018 and 2019, however, the minimum-variance portfolios beat the other strategies across all metrics but the standard deviation and even outperform the market portfolio. What message does this send to investors?

The investment horizon length plays an essential role. If one is interested in collecting within one market cycle and is lucky enough to identify the plateau before the bull market starts, then there exist active diversification strategies that can clearly deliver much higher returns in almost any metric compared to the passive ones. This is evident when looking at the results of the starting year of 2019, where both active strategies deliver annualized returns over 200% while the passive ones are below 100%. The active strategies are around 50% riskier, but in the overall performance this is overpowered by the returns so that all metrics controlling for various types of risk clearly come up better for the active strategies. Even the market portfolio is clearly beaten by both, with information ratios of 1.86 and 1.27 for the minimum-variance and minimum-expected-shortfall strategies, respectively. Such dominance is not visible for the starting year of 2018 even though the minimum variance strategies still dominate. However, the minimum expected shortfall strategy does not outperform Bitcoin in any metric but the standard deviation. The starting year of 2017 can be seen as representative of a long-term holder/investor (and years 2016 and earlier as early adopters with all of the challenges of interpretation and liquidity issues) as the period covers the bull run of 2017, the correction of 2018 and the following tranquil period, over the Covid-19-induced drop in 2020, up to the current new all-time-highs. For this long period (even though four years would hardly be considered a long period for the traditional financial markets, it covers almost half of a relevant existence of the cryptomarkets), simply holding Bitcoin is the best investment strategy as it beats the other strategies in almost all metrics and also closely follows the overall performance of the market portfolio with an Information ratio of -0.23. Fig. 6 shows the structural differences in the portfolio weights for the minimum-variance portfolio over the starting years. It is clear that Bitcoin serves as an anchor for the entire cryptomarket. Once the portfolios include the correction periods, Bitcoin plays a very important role. This is because altcoins often follow Bitcoin

[5] In a parallel manner to removing Tether (USDT) from the dataset for the 2016 starting year, we remove all stablecoins in the given starting years, specifically TrueUSD (TUSD) and USD Coin (USDC).

year (method)	portfolio	μ	SD	Sharpe	Treynor	Sortino	Information
2017 – actual	min σ	0.5990	**0.6081**	0.9850	0.6361	0.0952	-1.0058
	min ES	0.4949	0.6319	0.7833	0.5515	0.0866	-0.9249
	Bitcoin	**0.7698**	0.6773	**1.1366**	**0.7393**	**0.1099**	**-0.2328**
	1/N	0.4523	0.7007	0.6456	0.4370	0.0762	-1.0645
2017 – post hoc	min σ	**1.5904**	0.6838	**2.3259**	**2.1313**	**0.1829**	**1.3733**
	min ES	1.3748	0.6635	2.0719	2.1056	0.1648	0.8947
	Bitcoin	0.7698	0.6773	1.1366	0.7348	0.1099	-0.3642
	1/N	0.9931	**0.6519**	1.5235	1.1163	0.1253	0.4106
2018 – actual	min σ	**0.8514**	0.6250	**1.3623**	**0.9067**	**0.1301**	**0.6045**
	min ES	0.5663	**0.5582**	1.0145	0.7361	0.1035	-0.4035
	Bitcoin	0.7629	0.5934	1.2858	0.8043	0.1183	0.3716
	1/N	0.4875	0.6846	0.7121	0.4888	0.0833	-0.7296
2018 – post hoc	min σ	1.5926	0.7666	**2.0774**	2.1412	0.1988	**1.3196**
	min ES	**1.7035**	0.9144	1.8629	**2.5035**	**0.2051**	1.1494
	Bitcoin	0.7629	**0.5934**	1.2858	0.7526	0.1183	0.1918
	1/N	0.6147	0.6329	0.9713	0.6041	0.0940	-0.4503
2019 – actual	min σ	**1.9665**	0.8147	**2.4139**	**2.4205**	**0.2188**	**1.3386**
	min ES	1.6258	0.8184	1.9865	2.1435	0.1978	0.8017
	Bitcoin	0.8620	**0.6143**	1.4031	0.8190	0.1222	-0.9697
	1/N	0.9181	0.6173	1.4872	0.9592	0.1204	-0.2015
2019 – post hoc	min σ	**1.2219**	0.8139	1.5013	**1.2683**	**0.1592**	0.2403
	min ES	1.0437	0.8915	1.1707	1.1274	0.1459	-0.0449
	Bitcoin	0.8620	**0.6143**	1.4031	0.8199	0.1222	-1.1321
	1/N	1.2148	0.6165	**1.9704**	1.2552	0.1418	**0.7931**

Table 4: **Comparison of active and passive portfolio strategy performance throughout the years (both actual and post hoc set construction). Bold** numbers highlight the best performance for the given metric. For active strategies, the default setting of a 180-day estimation period and monthly rebalancing is retained. The "actual" label signifies that the assets that form the portfolios were in the Top 30 most capitalized cryptoassets at the beginning of the given year. The "post hoc" label signifies that the assets that form the portfolios were in the Top 30 most capitalized cryptoassets at the beginning of 2021 and have a data history down to the beginning of the given year. The search for the latter extends to the Top 100 until 30 cryptoassets are found.

in price hikes, usually surpassing it in the late phases of the bull cycle but correcting or deflating more during market corrections and bear markets. Even though this statement needs further validation in the years to come and more specifically more market cycles to pass, it tracks with what we observe in the optimal portfolio weights. Again, for investors, this mostly implies that timing is everything. If an investor enters the market in the early phases of a coming bull run, then diversification and low weights of Bitcoin pay off. However, if an investor enters the market during other phases, Bitcoin should play a central role in the portfolio.

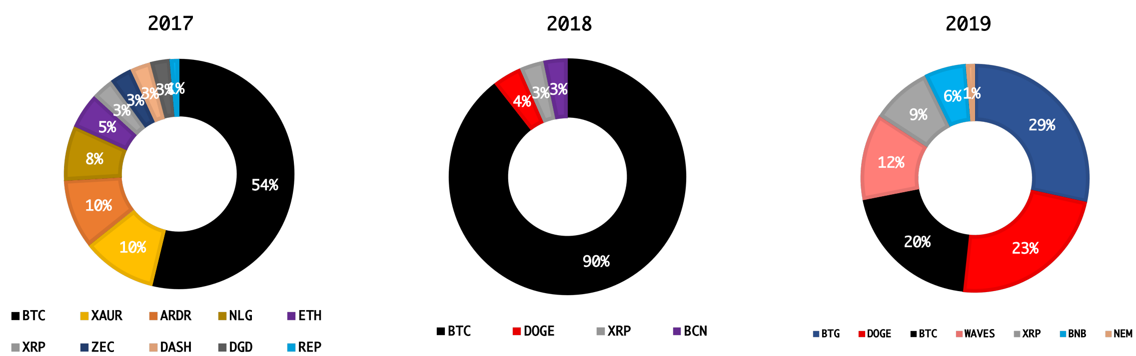

Figure 6: **Portfolio average weights for different starting years.** Portfolios are based on 180-day windows with rebalancing every month. Only cryptoassets with an average weight of more than 1% are included in the charts.

Table 4 presents the performance measures for the post hoc portfolios for different starting years. Here, the portfolios are constructed using the set of cryptoassets that were in the Top 30 at the beginning of 2021 and have a data history down to either 2017, 2018, or 2019. If not all of the Top 30 assets have a long enough data history, then we browse down the market capitalization ranking of 2021 and keep adding assets with the needed length until we either collect 30 assets or we get down to the Top 100. For the 2017 starting year, there are only 23 assets that meet the criteria, and for the other two years, we obtained the full 30 assets. This approach mimics an often applied procedure of dataset construction in the cryptoasset literature. Comparing the actual and post hoc performances throughout the years provides strong evidence that post hoc dataset construction leads to a strong overreporting (or the reporting of better results) of portfolio performance. In a hypothetical situation of a study constructing its dataset using the current Top 30 cryptoassets with data history down to 2017, the comparison with a dataset based on the Top 30 at which an actual investor in 2017 was looking is striking. The best portfolio utilizing the minimum-variance approach and based on the post hoc dataset reports annualized returns almost three times as high as the strategy applied on the actually available portfolio delivered in reality. Similar differences are reported for the portfolios with the minimum expected shortfall. In addition, both active portfolio strategies based on the post hoc data beat the hypothetical market portfolio, with the Information ratios at around 1. However, the actual performance shows that the active portfolio did not beat the market. The naïve 1/N post hoc portfolio delivers more than twice-as-high annualized returns compared to the actual naïve portfolio. Very similar results and striking differences are reported for the starting year of 2018, where the best active post hoc portfolio shows more than three times the actual attainable returns were the actual available dataset used. Interestingly, we do not find such sharp differences with the starting year of 2019, where the proper active portfolios actually outperform the post hoc ones. This is certainly interesting, specifically with the original comparison between the actual and post hoc dataset construction as reported in Tables 1-2 for the original starting year 2016, where the differences were present but not as striking as for starting years 2017 and 2018. We attribute this to the different phases of the market cycle. For the bear markets, the post hoc dataset selection oversells the benefits of diversification and the possible returns of such strategies, even suggesting that such active portfolio management can outperform the market portfolio that they in fact mostly cannot attain. Conversely for the bull markets, the overselling of such strategies is not as evident or clear. In either case, the survival bias in the dataset construction and asset selection can manipulate the results considerably and needs to be taken into consideration in further research on diversification benefits and general portfolio management in the cryptomarkets.

5. Discussion and conclusions

Assessing active portfolio management strategies in the cryptomarkets is associated with various challenging specifics. Most important, the type of datasets used for such study is crucial for the final results as well as potential investment advice. Being realistic and including only the assets that were available or "visible" in the sense of being in the top tier of market capitalization ranking back then gives very different results compared to using the current top-tier cryptoassets and using them for pseudo-out-of-sample exercises. Apart from the very top tiers, which remain rather stable in their ranking, the situation is much more volatile outside of the Top 10. The result is that apart from the most recent data covering mostly the latest bull run, the post hoc dataset construction and resulting portfolio strategies are biased upward. The most contradictory outcome is found for probably the most likely starting year of portfolio studies: 2017. This "year of altcoins" makes good sense as a starting point because practically all of the popular old-timers are already part of the portfolio, well established and high in the ranking. The Top 5 at the beginning of 2017 includes Bitcoin, Ethereum, XRP, Litecoin, and Monero. Even Dogecoin is already at rank 14. All of these will be in the dataset, and it will sound plausible to analyze. When the dataset is examined, the active portfolio strategies clearly dominate the passive ones with an out-of-sample annualized return of 159% for the minimum-variance portfolios compared to 77% for Bitcoin. The active portfolio strategy then dominates the others in all performance metrics except the general risk measured by standard deviation, which is at similar levels for all compared strategies. The message is clear: diversify and actively manage your crypto-portfolio. However, these 21 assets that ranked in the Top 100 at the beginning of 2021 and have data history dating back the beginning of 2017 are quite different from the actual Top 30 that an investor was looking at at the beginning of

2017. Only 16 of the 2017 Top 30 (Augur, Bitcoin, Dash, Dogecoin, Ethereum, Ethereum Classic, Lisk, Litecoin, MaidSafeCoin, Monero, NEM, Neo, Stellar, Tether, XRP, and Zcash) ranked in the Top 100 in 2021. If a real investor in 2017 started with active portfolio strategies, it would not have been worth it. Simply holding Bitcoin with the already mentioned annualized return of 77% clearly outperforms the minimum variance (60%) and minimum expected shortfall (49%) strategies and even practically copies the performance of a hypothetical market portfolio. Thus, the message is completely opposite: buy and hold Bitcoin.

The year of 2017 is actually quite important and specific here because the portfolios learn during the 180-day windows and rebalance every month (in the default setting), which means that the active portfolios in this period started learning in the early months of the bull run. Thus, the profitability of appreciating altcoins is already accounted for here. In addition, this contains the big corrections in the first half of 2018 from the back-then all-time highs at the break of 2017 and 2018. It thus seems that the large gains of the "altcoin season" were mostly diminished by the corrections, at least compared to the gains and corrections of Bitcoin. If the investor started in 2018, then the situation logically improves with respect to the data availability, but still, one needs to reach a rank of 66 at the beginning of 2021 to get 30 assets with a history down to the beginning of 2018. Again, only 17 of the Top 30 at the beginning of 2018 made it to the Top 66 in 2021. Even here, the best strategy in the post hoc selection delivers twice (minimum expected shortfall, 170% annualized return) the returns of the actually available portfolio (minimum variance, 85%). The post hoc selection gives the impression that the active strategies easily outperform the passive ones, with more than twice the annualized returns and clearly better ratios. However, the feasible portfolio construction suggests less-polarized outcomes. Even though it is an active portfolio (minimum variance) that wins the race, it is not by much compared to simply holding Bitcoin (85% vs. 76% annualized returns and 0.6 vs. 0.37 Information criteria). The survival bias that translates into the selection bias in the asset pool that is used for portfolio construction thus very markedly biases the true results and favors active portfolio management over simply holding Bitcoin even though the reality suggests either directly otherwise or minimally the two approaches are comparable depending on the starting year.

The role of Bitcoin is thus much stronger than one might think based on the backward-looking datasets. However, this has not always been true. Maybe even surprisingly, its weakest position in the system, at least with respect to portfolio construction, was recorded at the beginning of the analyzed period in 2016. Its benefits kept growing during 2017 and solidified in 2018 and later at over 50% weights in the portfolios. The ideal strategy in the bull run of 2017 thus seems to be reallocating profits from altcoins to Bitcoin as an anchor of the entire system. Interestingly, this is not observed in the price hikes of 2020 and 2021 when Bitcoin rallied from the local low of around \$5k in March 2020 (the "Covid correction") to almost \$60k in March 2021, reaching similar levels of Bitcoin dominance (the share of Bitcoin market capitalization in the overall cryptoassets capitalization) as in the rally of 2017 (around 40%). However, the starting positions were different. In 2016 and the beginning of 2017, the market was almost completely dominated by Bitcoin, with its dominance mostly above 90%, while it never broke 70% after 2017. The potential for altcoins to grow and contribute to portfolios was much higher back then compared to the more recent years of cryptomarkets.

Apart from Bitcoin, the role of other big players in the field is surprisingly weak. Even though there is a general historical perception of the cryptomarket of the "big three" of Bitcoin, Ethereum, and XRP (with Bitcoin playing the dominant role) plus "the others", the role of Ethereum and XRP in the optimal portfolio places them in the latter group, namely, there is Bitcoin, and there are the others, without much in between. Ethereum and XRP thus evidently do not offer sufficient diversification benefits. This was also reflected in the passive 1/N portfolios, where the larger pools mostly outperformed those with only the very top ranking assets.

There are also important limitations that are mostly inherent to the cryptomarket structure. The cryptomarket is still young, which leads to several issues that are very important for practical portfolio management. Newly launched as well as obsolete projects and low liquidity are two that stand up among the others. The former comes in hand with one of the essential topics of this study: survival bias. There are projects that shoot up and become irrelevant in matter of months, sometimes even weeks or days. These are practically impossible to cover in active portfolio management and of course neither in the passive one. Retail investors might have specific strategies such as regularly playing odds with new projects (a.k.a. "aping" into projects), which might be very similar to gambling. Nevertheless, this is unimaginable with larger investors. Seeing projects with thousands-of-percentage growths in a range of days is not completely unseen, but these are again another manifestation of the survival bias because the investors (mostly the retail ones) do not see the multitude of projects that failed, either fairly or unfairly (currently mostly represented by "rug pulled" liquidity on decentralized exchanges).

The youth of the cryptomarket also makes it difficult to assess its cyclicality and infer suggestions based on different phases of the cycle. There is a popular belief that Bitcoin (and with it the entire market) follows a 4-year cycle connected to halving rewards of Bitcoin mining. However, with respect to portfolio management, the market becomes interesting only from 2016 or maybe even 2017 because before that the cryptomarket was practically only Bitcoin with 90% or higher dominance. Therefore, even if there was a 4-year cycle, there has been only a single one during the period plausible for portfolio diversification studies. Thus, implications made based on difference cycle phases must be taken with a grain of salt.

The liquidity issues were discussed in detail for the 2016 active portfolios. Even though the issue certainly gets better over time, even the starting ranking of 2017 has two cryptoassets that were delisted (Iconomic and Swisscoin) and three that dropped in ranking considerably. These were not listed on large exchanges (or having large liquidity pools on decentralized exchanges) and had liquidity only in the low tens of thousands of USD within the 2 % price impact (GameCredits, Xaurum, and Gulden). Even though five problematic assets sounds like a low number, two of them – Xaurum (XAUR) and Gulden (NLG) – were identified as important parts of the 2017 portfolio strategies with average portfolio weights of approximately 10%, higher than those of Ethereum and XRP. This only magnifies the dominance of Bitcoin over the active strategies for 2017. In 2018, only Bytecoin (BCN) dropped from its Top-30 position out of the Top 500 and lost most of its liquidity. This makes the optimal strategy for the starting year of 2018 even closer to solely Bitcoin even though the optimal portfolio based on all considered assets already has an average of 90% Bitcoin anyway. Furthermore, BitConnect (BCC), an actual Ponzi scheme that collapsed to zero, had practically zero weight in the portfolios, so its demise does not affect the results in any way.

Overall, the survival bias affects the results substantially. Not only does it report higher returns and other performance measures that are more favorable than what could be realistically attained with cryptoasset rankings on the top at the beginning of the portfolio construction period, but it also falsely makes the active portfolio management seem more attractive than simply holding Bitcoin. However, our results suggest that the Bitcoin strategy outperforms the active strategies in most cases and mostly in the long-term horizon (through the cryptoasset lens). There can be benefits from more active diversification and portfolio management in the short term, specifically if an investor hits an incoming bull market, but these are strongly dependent on the timing and existence of the Bitcoin (or cryptoassets in general) cycle. The risks and uncertainties mostly connected to illiquidity of smaller cryptoassets do not seem to sufficiently compensated in their returns and risk diversification compared to Bitcoin.

Acknowledgments

Support from the Charles University PRIMUS program (project PRIMUS/19/HUM/17) and the Czech Science Foundation (project 20-17295S) is highly appreciated.

References

Anyfantaki, S., S. Arvanitis, and N. Topaloglou (2018). Diversification, integration and cryptocurrency market. *Bank of Greece Working Paper 244*, 1–38.

Boudt, K., W. Lu, and B. Peeters (2015). Higher order comoments of multifactor models and asset allocation. *Finance Research Letters 13*(C), 225–233.

Brauneis, A. and R. Mestel (2019). Cryptocurrency-pertfolios in a mean-variance framework. *Finance Research Letters 28*, 259–264.

Briere, M., Oosterlinck, and A. Szafarz (2013). Virtual currency, tangible return: Portfolio diversification with Bitcoin. *Journal of Asset Management 16*(6), 365–373.

Brown, K. and F. Reilly (2012). *Analysis of Investments and management of portfolios.* Cengage Learning.

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

Katsiampa, P., S. Corbet, and B. Lucey (2019). Volatility spillover effects in leading cryptocurrencies: A BEKK-MGARCH analysis. *Finance Research Letters 29*, 68–74.

Kumar, A. and S. Anandarao (2019). Volatility spillover in crypto-currency markets: Some evidences from GARCH and wavelet analysis. *Physica A: Statistical Mechanics and its Applications 524*(15 June), 448–458.

Kyriazis, N. (2019). A survey on empirical findings about spillovers in cryptocurrency markets. *Journal of Risk and Financial Management 12*(4), 170.

Li, Z., Y. Wang, and Z. Huang (2020). Risk connectedness heterogeneity in the cryptocurrency markets. *Frontiers in Physics 8*, 243.

Liu, W. (2019). Portfolio diversification across cryptocurrencies. *Finance Research Letters 29*, 200–205.

Liu, Y., A. Tsyvinski, and X. Wu (2019). Common risk factors in cryptocurrency. *NBER Working Paper Series 25882*, 1–25.

Ma, Y., F. Ahman, M. Liu, and Z. Wang (2020). Portfolio optimization in the era of digital financialization using cryptocurrencies. *Technological Forecasting and Social Change 161*, 120265.

Martellini, L. and V. Ziemann (2010). Improved estimates of higher-order comoments and implications for portfolio selection. *Review of Financial Studies 23*, 1467–1502.

Mensi, W., K. Al-Yahyaee, I. Al-Jarrah, X. Vo, and S. Kang (2021). Does volatility connectedness across major cryptocurrencies behave the same at different frequencies? A portfolio risk analysis. *International Review of Economics and Finance 76*, 96–113.

Moratis, G. (2021). Quantifying the spillover effect in the cryptocurrency market. *Finance Research Letters 38*(January), 101534.

Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system. http://bitcoin.org/bitcoin.pdf.

Platanakis, E., C. Sutcliffe, and A. Urquhart (2018). Optimal vs naÏve diversification in cryptocurrencies. *Economics Letters 171*, 93–96.

Shadwick, W. and C. Keating (2002). A universal performance measure. *Journal of Performance Measurement 6*, 59–84.

Sharpe, W. (1994). The Sharpe ratio. *Journal of Portfolio Management 21*(1), 49–58.

Sortino, F. (1994). Performance measurement in a downside risk framework. *Journal of Investing 3*, 50–58.

Wang, J. and G. Ngene (2020). Does Bitcoin still own the dominant power? an intraday analysis. *International Review of Financial Analysis 71*(October), 101551.

Xu, Q., Y. Zhang, and Z. Zhang (2021). Tail-risk spillovers in cryptocurrency markets. *Finance Research Letters 38*(January), 101453.

Appendix

portfolio	method	μ	SD	Sharpe	Treynor	Sortino	Information
actual	min σ	1.2013	**0.7858**	**1.5288**	1.3419	0.1377	-0.2639
	min ES	1.5168	1.0358	1.4644	**1.6047**	0.1484	**0.1805**
	max SR	1.1167	0.7735	1.4436	1.2046	0.1279	-0.4346
	max STARR	**1.6096**	1.7239	0.9337	1.5087	**0.1631**	0.1564
	max CRRA	0.7577	1.4533	0.5213	0.7866	0.1169	-0.4459
	Bitcoin	0.9444	***0.6351***	1.4870	0.9321	0.1262	-1.9249
	1/N	***4.9973***	0.8095	***6.1732***	***5.1573***	***0.2886***	***6.4421***
post hoc	min σ	1.2666	**0.6470**	1.9577	1.2530	0.1510	-0.1797
	min ES	**1.5703**	0.7428	**2.1141**	**1.5381**	**0.1709**	**0.6354**
	max SR	1.3181	0.6510	2.0248	1.2892	0.1520	0.0532
	max STARR	0.9428	0.8863	1.0638	0.8859	0.1160	-0.5793
	max CRRA	1.4365	0.9550	1.5042	1.2980	0.1459	0.1893
	Bitcoin	0.9444	***0.6351***	1.4870	0.9385	0.1262	-1.7606
	1/N	1.2103	0.7682	1.5754	1.1167	0.1331	-0.2273

Table A1: **Out-of-sample portfolio performance (robustness check I).** Performance metrics are shown for portfolios based on 90-day windows with rebalancing every month. The "actual" portfolio is based on the top 30 cryptoassets at the beginning of 2016. The "ex post" portfolio is based on the top 100 cryptoassets at the beginning of 2021 with the data history back to the beginning of 2016, totaling 11 assets. **Bold** numbers highlight the best performance for the given metric, and ***bold italics*** highlight the best performance in the benchmark portfolios (Bitcoin and 1/N portfolio).

portfolio	method	μ	SD	Sharpe	Treynor	Sortino	Information
actual	min σ	**1.4115**	**0.8337**	**1.6931**	**1.5024**	0.1474	**0.1632**
	min ES	1.3774	1.1181	1.2320	1.3471	0.1461	0.0725
	max SR	1.3753	0.9007	1.5269	1.4448	0.1503	0.0941
	max STARR	1.1116	2.2749	0.4886	0.9878	**0.1709**	-0.0907
	max CRRA	0.7069	1.1151	0.6340	0.8067	0.1084	-0.6039
	Bitcoin	0.8965	***0.6417***	1.3971	0.8830	0.1214	-1.9475
	1/N	***4.8542***	0.8141	***5.9625***	***4.9201***	***0.2800***	***6.3868***
post hoc	min σ	1.2722	**0.6787**	1.8745	1.2329	0.1481	0.0583
	min ES	**1.4600**	0.7683	**1.9003**	**1.3948**	**0.1600**	**0.4757**
	max SR	1.2186	0.6849	1.7793	1.1572	0.1425	-0.1545
	max STARR	0.8101	0.8729	0.9281	0.7487	0.1056	-0.7499
	max CRRA	0.7919	0.9597	0.8251	0.6725	0.1062	-0.6901
	Bitcoin	0.8965	***0.6417***	1.3971	0.8890	0.1214	-1.7835
	1/N	1.1382	0.7808	1.4577	1.0339	0.1275	-0.3113

Table A2: **Out-of-sample portfolio performance (robustness check II.** Performance metrics are shown for portfolios based on 180-day windows with rebalancing every quarter. The "actual" portfolio is based on the top 30 cryptoassets at the beginning of 2016. The "ex post" portfolio is based on the top 100 cryptoassets at the beginning of 2021 with the data history back to the beginning of 2016, totalling 11 assets. **Bold** numbers highlight the best performance for the given metric, and ***bold italics*** highlight the best performance in the benchmark portfolios (Bitcoin and 1/N portfolio).

IES Working Paper Series

2021

1. Mahir Suleymanov: *Foreign Direct Investment in Emerging Markets: Evidence from Russia since the 2000s*
2. Lenka Nechvátalová: *Multi-Horizon Equity Returns Predictability via Machine Learning*
3. Milan Scasny, Matej Opatrny: *Elasticity of Marginal Utility of Consumption: The Equal-Sacrifice Approach Applied for the Czech Republic*
4. Javier Garcia-Bernardo, Petr Jansky and Vojtech Misak: *Common Agricultural Policy Beneficiaries: Evidence of Inequality from a New Data Set*
5. Petr Jakubik, Saida Teleu: *Suspension of Insurers' Dividends as a Response to the Covid-19 Crisis: Evidence from Equity Market*
6. Boris Fisera, Menbere Workie Tiruneh, David Hojdan: *Currency Depreciations in Emerging Economies: A Blessing or a Curse for External Debt Management?*
7. Vojtech Molnar: *Price Level Targeting with Imperfect Rationality: A Heuristic Approach*
8. Alex Cobham, Tommaso Faccio, Javier Garcia-Bernardo, Petr Jansky, Jeffery Kadet, Sol Picciotto: *A Practical Proposal to End Corporate Tax Abuse: METR, a Minimum Effective Tax Rate for Multinationals*
9. Evžen Kočenda, Ichiro Iwasaki: *Bank Survival Around the World: A Meta-Analytic Review*
10. Michal Kuchta: *Scenario Generation for IFRS9 Purposes using a Bayesian MS-VAR Model*
11. Jozef Barunik, Josef Kurka: *Frequency-Dependent Higher Moment Risks*
12. Petr Pleticha: *Who Benefits from Global Value Chain Participation? Does Functional Specialization Matter?*
13. Alex Cobham, Petr Jansky, Chris Jones, Yama Temouri: *An Evaluation of the Effects of the European Commission's Proposals for the Common Consolidated Corporate Tax Base*
14. Javier Garcia-Bernardo, Petr Jansky: *Profit Shifting of Multinational Corporations Worldwide*
15. Tomas Domonkos, Boris Fisera and Maria Siranova: *Income Inequality as Long-term Conditioning Factor of Monetary Transmission to Bank Interest Rates in EA Countries*
16. Petr Jansky, Natalia Li: *Improving the Corruption Perceptions Index: Additional Data Sources and Their Effects*
17. Dominika Ehrenbergerova, Josef Bajzik, Tomas Havranek: *When Does Monetary Policy Sway House Prices? A Meta-Analysis*
18. Daniel Kolář: *Inequality in Pre-Industrial Urban Bohemia: The City of Budweis*
19. Barbora Malinska: *Forecasting Sovereign Bond Realized Volatility Using Time-Varying Coefficients Model*

20. Jan Pintera: *Regional Convergence in the European Union: What are the Factors of Growth?*
21. Jiří Witzany, Martin Diviš: *Interest Rate Risk of Savings Accounts*
22. Tommaso Faccio, Sarah Godar, Petr Janský, Oliver Seabarron: *How Much Multinational Corporations Pay in Taxes and Where: Evidence from their Country-by-Country Reports*
23. Ondřej Schneider: *Labor Migration in the European Union: The case of Central and Eastern Europe*
24. Alex Cobham, Javier Garcia-Bernardo, Petr Janský, Miroslav Palanský: *Statistical Measurement of Illicit Financial Flows in Sustainable Development Goals: Tax Avoidance by Multinational Corporations*
25. Petr Jakubik, Saida Teleu*: Impact of EU-wide insurance stress tests on equity prices and systemic risk*
26. Alex Cobham, Petr Janský, Jan Mareš: *Illicit Financial Flows and Trade Mispricing: Decomposing the Trade Reporting Gap*
27. Salim Turdaliev: *Increasing Block Rate Electricity Pricing and Propensity to Purchase Electric Appliances: Evidence from a Natural Experiment*
28. Katerina Kroupova, Tomas Havranek, Zuzana Irsova: *Student Employment and Education: A Meta-Analysis*
*29. M*atthew Greenwood-Nimmo, Evžen Kočenda, Viet Hoang Nguyen: *Does the Spillover Index Respond Significantly to Systemic Shocks? A Bootstrap-Based Probabilistic Analysis*
30. Julien Pinter and Evžen Kočenda: *Media Treatment of Monetary Policy Surprises and Their Impact on Firms' and Consumers' Expectations*
31. Weizhi Sun, Ladislav Kristoufek: *Diversification Among Cryptoassets: Bitcoin Maximalism, Active Portfolio Management, and Survival Bias*

All papers can be downloaded at: http://ies.fsv.cuni.cz.

Univerzita Karlova v Praze, Fakulta sociálních věd
Institut ekonomických studií [UK FSV – IES] Praha 1, Opletalova 26
E-mail : ies@fsv.cuni.cz http://ies.fsv.cuni.cz