Physica A 523 (2019) 691–701

Contents lists available at ScienceDirect

Physica A

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

Momentum and contrarian effects on the cryptocurrency market ☆

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HIGHLIGHTS

- Strong short-term contrarian effect can be observed on the cryptocurrency market.
- Momentum/contrarian strategies achieve abnormal rates of return in comparison to S&P500.
- Values of performance indicators are high and not achievable on classical markets.
- Significant diversification effect of crypto-assets in reference to the classical assets.

ARTICLE INFO

Article history:
Received 16 March 2018
Received in revised form 28 December 2018
Available online 5 March 2019

Keywords:
Cryptocurrencies
Bitcoin
Momentum and contrarian effect
Investment strategies
Efficient market hypothesis
Modern asset allocation

ABSTRACT

We report the results of investigation of the momentum and contrarian effects on cryptocurrency markets. The investigated investment strategies involve 100 (amongst over 1200 present as of date Nov 2017) cryptocurrencies with the largest market cap and average 14-day daily volume exceeding a given threshold value. Investment portfolios are constructed using different assumptions regarding the portfolio reallocation period, width of the ranking window, the number of cryptocurrencies in the portfolio, and the percent transaction costs. The performance is benchmarked against: (1) equally weighted and (2) market-cap weighted investments in all of the ranked assets, as well as against the buy and hold strategies based on (3) S&P500 index, and (4) Bitcoin price. Our results show a clear and significant dominance of the short-term contrarian effect over both momentum effect and the benchmark portfolios. The information ratio coefficient for the contrarian strategies often exceeds two-digit values depending on the assumed reallocation period and the width of the ranking window. Additionally, we observe a significant diversification potential for all cryptocurrency portfolios with relation to the S&P500 index.

1. Introduction

During recent years, and especially in 2017 we clearly could have witnessed the violent and abrupt development of the cryptocurrency markets. Each and every week new crypto-assets arise — many of them tempt potential investors with some great opportunities but often bring to the table exactly as many promises as legal and ethical doubts. Cryptocurrencies and the blockchain – the underlying technology – are being investigated since the moment when the bitcoin creator/creators manifesto has been published [1]. However, the most of the previous research focused

☆ The authors are grateful to Quantitative Finance Research Group at University of Warsaw and Labyrinth HF project for their support and encouraging comments.

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https://doi.org/10.1016/j.physa.2019.02.057
0378-4371/

mostly on technical [2] and legal [3] aspects of the cryptocurrencies and blockchain. It was only quite recently when the cryptocurrency market started to be perceived as a serious, albeit controversial and risky, candidate for a new asset class [4,5]. The general consensus amongst the researchers is that the highly volatile cryptocurrency market currently can be used mostly for the speculative and short-term hedging purposes [6–9] and that volume can predict returns while it cannot help predict the volatility of Bitcoin returns [10]. The mainstream media each and every day report about yet another speculative bubble on bitcoin to pop anytime soon, and the scientific evidence on such bubbles seems to be sound [11]. Among the most recent research on the econometrics of cryptocurrencies are approaches using the autoregressive models [12–14] or papers analysing some stylised facts of the Bitcoin markets [15]. On the other hand we observe more pessimistic analysis of cryptocurrency environment especially if we focus on the mining profitability and its consequence on the ability of the next blocks to be mined further [16].

One may suspect that the cryptocurrency markets are currently on the similar stage of development as the financial markets have been during the first few decades of the 20th century. In this context, questions about the current degree of informational efficiency of the cryptocurrency markets arise quite naturally. Are the anomalies known from the regulated markets also present in the cryptocurrency markets? If yes, then to what degree? How strong are these? Would it be possible to employ such effects to construct an investment strategy giving excessive returns? The topic of informational efficiency of the Bitcoin market was previously undertaken by Bariviera [17].

Amongst the most classical historical anomalies present on young and inefficient markets we definitely can distinguish the momentum and contrarian effects. Their presence on the regulated markets is widely known and accepted. However, at the same time the amplitude of these effects is very limited due to the high efficiencies of the classical markets. The momentum effect is often used by investors and can be roughly defined as a tendency for the price trends to increase in the short or medium perspective (from 3 to 12 months — [18]). On the other hand, the contrarian effect can be seen as a tendency to reverse the trends of price changes in a long (from 3 to 5 years — [19,20]) or a very short (up to 1 month — [21,22] time frame). The very existence of such market anomalies can give an opportunity to predict the direction of change of prices and as such, to obtain the excessive rates of return.

Our working hypothesis is formulated in the following way: 'The strong momentum and contrarian effects are observed on the cryptocurrency markets'. Therefore, in this article we will benchmark the efficiency of investment strategies based on the momentum and contrarian effects on the cryptocurrency markets against the reference strategies and determine their potential to generate the excessive rates of returns. These concepts were widely analysed for the classical financial markets (among others Chan et al. [23], Moskowitz [24] as well as authors mentioned above), but has not yet been investigated in the context of the new crypto-asset class. Therefore, our research contributes to the verification of the efficient market hypothesis on young and dynamically developing cryptocurrency market instead of classical assets from the regulated markets.

The article is organised in the following way. In Section 2 we introduce the research methodology and the process of portfolio creation. In Section 3 we describe and discuss the data we used in our investigation. In Section 4 we present the results, while in the conclusion section we briefly restate and summarise the key aspects of our results presenting outlook to some further interesting developments.

2. Methodology

The main idea behind the momentum strategy is to achieve excessive returns via investment in assets that have recently obtained the highest rates of return. On the other hand, the contrarian strategy assumes exactly the opposite: one should invest in the assets that recently have declined the most. It is important to note that at the beginning in the both cases we have to define a set of assumptions that, however arbitrary, are key to the quantification of profitability of investigated strategies. Among such assumptions we may have:

- the length of portfolio reallocation period,
- the length of the ranking window which is used to determine the groups of assets exhibiting the strongest gains/losses,
- the percentage value of transaction costs that decreases the gross return,
- the threshold value of the moving average volume filter.

2.1. Portfolio construction

The reallocation day can be understood as a day on which our portfolio composition is revised. The revision is based on a given cryptocurrency ranking (for a given measure, e.g. market cap or daily rates of return) in a given period of time, called the ranking window (RA). During the reallocation day, we liquidate the asset that does not score high enough to be placed in the ranking list, as well as we invest in the new asset present on the list, and balance our shares in the asset that has remained. The time interval between two neighbouring reallocation days is called the reallocation period (RE). Both the ranking window RA and the reallocation period RE do not necessarily have to be of equal length.

To ensure the minimum liquidity of the investment portfolio, only assets for which the 14-day moving average of volume exceeds the filter threshold of 100 USD (VF) are qualified into our investment spectrum on each reallocation day.

Then, a ranked set of 100 cryptocurrencies with the largest market cap is chosen from the qualified assets. The ranking is calculated daily for the in-sample data and from now on will be referred to as the 'TOP100'. Another important aspect that we consider during the construction and evaluation of our portfolios are the total (percent) transaction costs (TC). These include both the unit transaction costs that are paid directly to the exchange as well as the bid–ask spreads present in the cryptocurrency market quotes.

The TOP100 ranking is then used to construct momentum/contrarian portfolios as well as the reference ones using the following procedure:

1. The **Momentum** portfolio is created as an equally-weighted investment in %N = 25% cryptocurrencies with the highest weekly rate of return (RA = 1 w) in TOP100. The reallocation period is set to 1 week (RE = 1 w), the percent transaction costs are taken as 1% of the portfolio value (TC = 1%),
2. The **Contrarian** portfolio is created as an equally-weighted investment in %N = 25% cryptocurrencies with the lowest weekly rate of return (RA = 1 w) in TOP100. The reallocation period is set to 1 week (RE = 1 w), the percent transaction costs are taken as 1% of the portfolio value (TC = 1%),
3. The reference portfolio **EqW** is created as an equally-weighted investment in all the assets present in TOP100 during the reallocation day. The reallocation period and the percent transaction costs are set to 1 week (RE = 1 w) and 1% of the portfolio value (TC = 1%), respectively, exactly as in the benchmarked momentum and contrarian portfolios,
4. The reference portfolio **McW** is created as the market-cap weighted investment in all the assets present in TOP100 during the reallocation day. The reallocation period and the percent transaction costs are set to 1 week (RE = 1 w) and 1% of the portfolio value (TC = 1%), respectively, exactly as in the benchmarked momentum and contrarian portfolios.

The EqW and McW reference strategies were used as benchmarks to judge the relative efficiency of the Momentum and Contrarian portfolios. To obtain the full picture on the performance of our portfolios in the cryptocurrency world we also have compared the results to the buy and hold strategy on Bitcoin price (BTC B&H). The buy and hold strategy on the S&P500 index (S&P B&H) has been calculated as a usual benchmark for investment strategies involved on the regulated markets. Both B&H strategies were calculated on the same simulation horizon as the former strategies. The sensitivity analysis of the momentum and contrarian strategies was performed for the following parameters: %N (the percentage of cryptocurrencies out of the TOP100 kept in the portfolio), RE (the reallocation period), RA (the width of the ranking window), and TC (the percentage value of the transaction costs).

2.2. Portfolio performance

For a given portfolio p in the period $t \in [0, \ldots, T]$, its gross rate of return $R_{0,T}^{(p)}$ can be defined as:

$$R_{0,T}^{(p)} = \prod_{t=0}^{T} \left(1 + \sum_{i=1}^{N} w_{i,t} r_{i,t} - \Delta W_t^R \cdot TC \right) - 1 \,, \tag{1}$$

where N is the total number of assets; T is the investment's total time horizon (measured in days herein); $w_{i,t}$ is the percentage (weight) of the ith asset in the whole portfolio p on day t; $r_{i,t}$ is the simply accruing daily rate of return of the ith asset on day t; ΔW_t^R is the total portfolio turnover rate (in percent) on day t; and TC is the total percent transaction costs.

The weights evolve according to the following formula (we assume $w_{i,t}$ sum up to 100% for each recurrence step):

$$w_{i,t} = \left(1 + r_{i,t}\right) w_{i,t-1} \,, \tag{2}$$

and after the portfolio performance evaluation on the reallocation day $t = t_R$ they are set to:

$$w_{i,t_R} = \begin{cases} \dfrac{1}{N} & \longrightarrow \quad \text{for equally weighted portfolio} \\ \dfrac{\mathrm{MC}_{i,t}}{\sum_i^N \mathrm{MC}_{i,t}} & \longrightarrow \quad \text{for market-cap weighted portfolio} \end{cases} \tag{3}$$

The portfolio composition changes on the reallocation day. Some assets leave the TOP100, some other assets score high enough to enter the ranking, and the remaining assets stay on the list, albeit with new weights. To quantify the change in the portfolio we need to calculate the turnover ratio $\Delta W_{t_R}^R$ (with the implicit assumption that $w_{i,t}$ sum up to unity):

$$\Delta W_{t_R}^R = \sum_{i=1}^{N} |w_{i,t} - w_{i,t_R}| \,. \tag{4}$$

The above quantity may be of any value in the range from 0% (no change in comparison to the previous reallocation day) to 200% (complete reallocation of all assets in the portfolio). The total portfolio reallocation cost can be calculated by taking the product of ΔW_t^R and the total percent transaction cost TC, which includes the unit transaction costs of the exchange as well as an estimate of the assets' bid–ask spreads. The real values of TC on the crypto markets can usually range between 0.2% and 2.0% of the transaction value depending on the specific asset's liquidity. For all of the base strategies described in this paper we have set the total percent transaction costs to 1.0%.

2.3. Descriptive statistics

To get a deeper evaluation and understanding of our portfolios' efficiency we have also employed the following measures:

- the annualised rate of change (ARC):

$$\mathrm{ARC} = \left(1 + \frac{P_T}{P_0}\right)^{\frac{365}{T}} - 1\,, \tag{5}$$

where P_i stands for the portfolio value after the ith period,

- the annualised standard deviation of daily returns (ASD):

$$\mathrm{ASD} = \sqrt{\frac{365}{T}\sum_{t=1}^{T}(r_t - \bar{r})^2},\ r_t = \frac{P_t}{P_{t-1}} - 1 \tag{6}$$

- the maximum drawdown coefficient (MDD):

$$\mathrm{MDD}\,(T) = \max_{\tau\in[0,T]}\left(\max_{t\in[0,\tau]} P_t - P_\tau\right) \tag{7}$$

- the information ratio coefficients (IR1, IR2) — quantifying the risk-weighted gain:

$$\mathrm{IR1} = \mathrm{ARC}/\mathrm{ASD}\,, \tag{8}$$

$$\mathrm{IR2} = \mathrm{sign(ARC)ARC}^2/(\mathrm{ASD}\cdot\mathrm{MDD})\,, \tag{9}$$

where sign(x) stands for the negative or positive sign of value x.

3. Data

Number of cryptocurrencies and their market capitalisation nowadays are growing extremely rapidly. The total market cap of the cryptocurrency market has increased from 17 billion USD to over 200 billion USD in the 12 month period ending on 2017-10-28 equalling 0.3%/0.5% of total world/USA stock markets capitalisation.[1] The total market cap of 100 largest cryptocurrencies was approx. 170 billion USD at the end of the above mentioned period but almost 90% of the total value was provided only by 10 cryptocurrencies, amongst which Bitcoin (BTC) dominates (56% of total market cap). The remaining set of 1200 cryptocurrencies beyond the 10 largest ones (often called 'altcoins') consists of assets significantly less liquid and much more volatile than Bitcoin. These altcoins constitute the most interesting observations characterised by the annualised rates of return and risk-weighted ratios not present on regulated markets. Table 1 shows a set of descriptive statistics for the 10 largest and 10 smallest cryptocurrencies for as of date 2017-10-28.

As one can see from Table 1, magnitudes and spreads of values in the sets of %ARC, %ASD and information ratios are huge, starting from small cryptos like `kin` and `aragon` which could bring heavy loses through `bitcoin-cash`, which although quite large, turn out to be barely close to profitable, ending on `bitconnect` which in this very snapshot of time exhibited absurdly high rate of growth. The maximum drawdown values are also quite large — each cryptocurrency in the set has %MDD greater than 50% while 5 out of 20 have noted drawdown greater than 90%. For comparison purposes — the S&P500 index has noted 'only' 14% drawdown in the same simulation horizon (see Table 3). It is worth to note that the differences in values of market cap and daily volume between the head and tail of this table (`bitcoin` vs `kin`) is 3 and 4 orders of magnitude, respectively. All of these observations taken along with the fact that we have chosen approximately the largest 10% of all cryptos for the given day make, in our opinion, quite a strong and vivid suggestion on how non-uniform and volatile the crypto market is today.

In our investigation, the TOP100 ranking has been constructed using all cryptocurrency data provided by www.coinmarketcap.com. The TOP100 set has been then used to construct specific investment portfolios. The open, high, low,

[1] Estimates based on data provided by: www.coinmarketcap and World Bank: data.worldbank.org/indicator/CM.MKT.TRAD.CD. Stock market cap for 2016 equals 77.507 and 42.071 trillion USD for world and USA, respectively.

Table 1
Descriptive statistics for 10 first and last cryptocurrencies on TOP100, snapshot as of date 2017-10-28.

Name	%ARC	%ASD	%MDD	IR1	IR2	Date of Start	MarketCap [USD]	Volume (24 h) [USD]	%MISS
First 10 cryptocurrencies in TOP100 AOD 2017-10-28									
bitcoin	109.8	66.4	73.3	1.7	2.5	2014-05-12	96,369,600,000	1,403,920,000	0
ethereum	714.8	154.9	84.3	4.6	39.1	2015-08-08	28,410,400,000	264,424,000	0
ripple	176.6	155.0	85.4	1.1	2.4	2014-05-12	7,806,200,000	26,864,900	0
bitcoin-cash	9.7	245.9	58.5	0.0	0.0	2017-08-02	6,183,520,000	781,037,000	0
litecoin	61.4	110.5	90.0	0.6	0.4	2014-05-12	2,966,700,000	71,063,200	0
dash	289.8	147.2	92.9	2.0	6.1	2014-05-12	2,152,090,000	47,092,100	0
nem	1,246.5	180.1	75.0	6.9	115.1	2015-04-01	1,781,830,000	4,671,300	0
bitconnect	Inf	206.5	51.6	6,212.7	Inf	2017-01-20	1,558,580,000	10,550,800	0
neo	2,989.8	270.8	85.6	11.0	385.4	2016-10-26	1,443,000,000	25,368,200	0
monero	218.6	155.4	95.5	1.4	3.2	2014-05-21	1,327,650,000	25,397,400	0
Last 10 cryptocurrencies in TOP 100 AOD 2017-10-28									
Name	%ARC	%ASD	%MDD	IR1	IR2	Date of Start	MarketCap [USD]	Volume (24 h) [USD]	%MISS
zencash	288.7	386.5	82.7	0.7	2.6	2017-06-07	49,749,900	1,464,900	0
edgeless	18,466.6	377.6	70.8	48.9	12,752.3	2017-04-07	49,017,500	961,797	0
aragon	−11.4	188.6	65.6	−0.1	−0.0	2017-05-20	48,817,400	376,313	0
rlc	339.1	213.9	77.0	1.6	7.0	2017-04-22	48,397,600	231,263	0
taas	2,726.2	149.6	59.0	18.2	842.2	2017-05-12	46,407,500	230,103	0
nolimitcoin	8,500.0	635.2	92.0	13.4	1,236.6	2016-09-12	45,917,600	84,228	0
nav-coin	396.0	472.9	94.9	0.8	3.5	2014-06-12	45,209,300	502,409	0
loopring	718.2	343.1	73.2	2.1	20.5	2017-09-03	42,275,700	188,744	0
wings	4,405.1	291.0	73.1	15.1	911.7	2017-04-28	41,613,800	434,531	0
kin	−100.0	180.3	56.9	−0.6	−1.0	2017-09-28	39,996,200	38,250	0

Legend: %ARC — annualised rate of return (percent), %ASD — annualised standard deviation (percent), %MDD — maximum drawdown of capital (percent), IR1, IR2 — information ratios calculated in two ways described in formulas (8) and (9), 'Date of Start' — date of first observation on TOP100 ranking, %MISS — percentage of missing data. Values higher than 100,000 have been replaced with 'Inf'.

close, volume and market cap data have been downloaded and cleaned. The opening date of the simulation horizon was chosen as 2014-05-12 — this was the first Monday in our historical data when more than 130 close prices have been found[2]. The end date was chosen as 2017-10-28 as the date when we started our calculations. The TOP100 ranking was recalculated for each day of the simulation. From the set of 1223 unique cryptocurrencies only 450 have entered the TOP100 ranking for at least one day and had the 14-day moving average of daily volume higher than 100 USD (we used such filter to exclude the least liquid assets from the final set).

As the cryptocurrency market is young and dynamic, data taken from it may require some additional cleaning process. For example, some cryptocurrencies, especially the smallest and the youngest ones, sometimes exhibit discontinuities in the time series of the closing prices, daily volume, or market cap. Short and sudden spikes in the closing prices can occasionally be observed and it is difficult to judge whether these are the result of real market movements or just spurious outliers. Statistics describing the data completeness can be found on Fig. 1.

Usually, the youngest cryptocurrencies (around their ICO) have the least trustworthy and the most difficult data to analyse. Their time series contain missing values of market cap for the whole simulation horizon, and the daily volume values, if reported, are tiny. Such cryptocurrencies, so far have very limited liquidity and are not yet suitable for trading and practical investments. They may evolve and develop into more liquid assets or may as well become the so-called 'trash-coins'. Coins and tokens on this stage of development are very susceptible to market price manipulations and other unethical activities. Even if the initial turbulences pass and a cryptocurrency stays in the market quotes for several more months, some periods of missing data still can occur and might be followed by strong price movements (e.g. `pluton`). The most developed cryptocurrencies with more than year of quoting and a solid, reasonable daily volume (e.g. `dash`, `monero`, `monacoin`) in general provide the most stable time series data. The most frequent data failure cases the reason of only short gaps (1–2 days) in the daily series, almost exclusively affecting the market cap. The longer the asset is quoted, the higher probability that it will provide stable data. In the set of more than 1200 cryptoassets, approximately 20 assets older than 1 year had very unstable data (e.g. `virtualcoin`, `flappycoin`, `elacoin`) or very long periods of unavailable data (e.g. `dopecoin`).

To address these problems with data, we have applied a filter which discards a cryptocurrency from the ranking if the mean 14-day moving average of daily volume is lower than VF = 100 USD. In this way we were able to remove all the most pathological cases of some low-liquidity thrash altcoins from our research and to smooth our daily volume data by

[2] This day is not associated with any specific historical event — our intention was to add a small safety margin to avoid adding outliers and spurious assets to the TOP100 set.

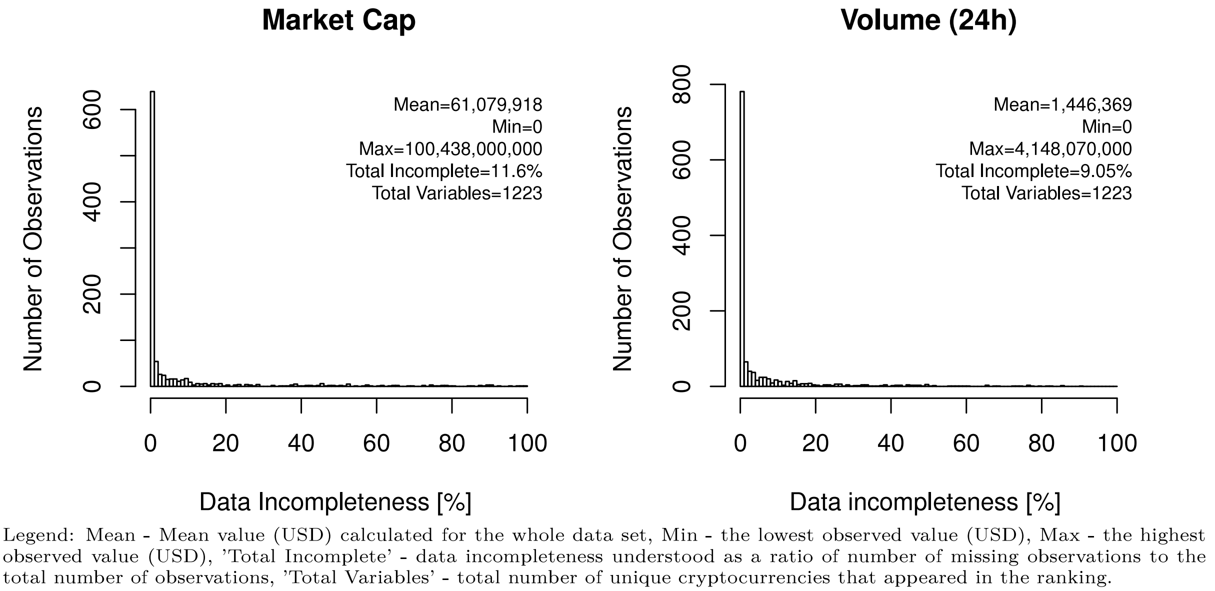


Fig. 1. MarketCap and Volume data completeness histograms for the whole cryptocurrency set AOD 2017-10-28. Legend: Mean — Mean value (USD) calculated for the whole data set, Min — the lowest observed value (USD), Max — the highest observed value (USD), 'Total Incomplete' — data incompleteness understood as a ratio of number of missing observations to the total number of observations, 'Total Variables' — total number of unique cryptocurrencies that appeared in the ranking.

replacing the single missing values with the moving averages. The missing market cap data for stable cryptocurrencies were estimated using the constant circulating supply approximation:

$$\frac{\mathrm{MC}_t}{\mathrm{Close}_t} \approx \frac{\mathrm{MC}_{t-1}}{\mathrm{Close}_{t-1}} \,. \tag{10}$$

In other words, if the amount of currency in the circulating supply is constant, then we can take the missing market cap value as:

$$\mathrm{MC}_t = (1 + r_t)\,\mathrm{MC}_{t-1} \,. \tag{11}$$

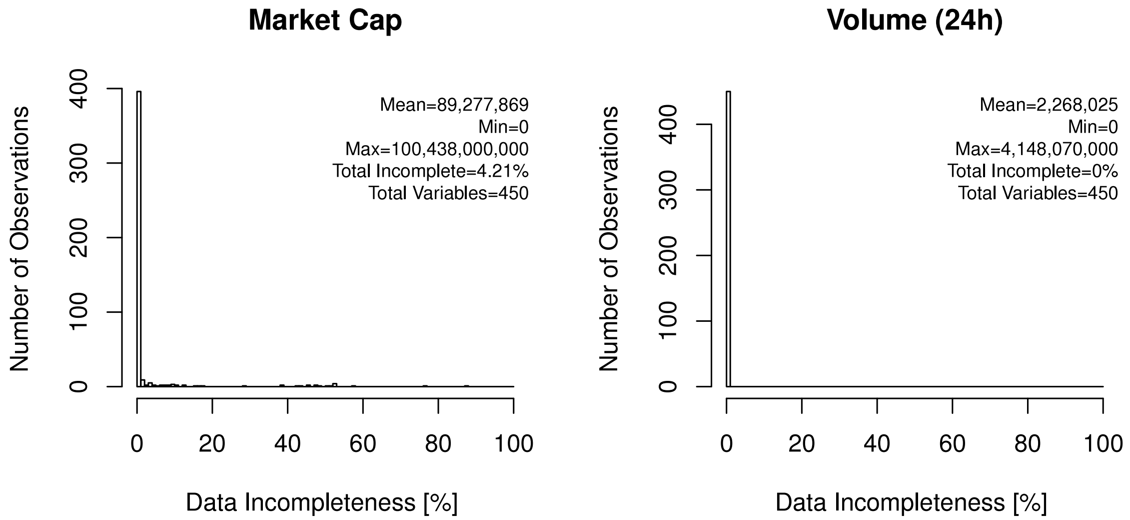
In the case when the close price of a given cryptocurrency at a given day is missing, the asset is not included in the ranking at all. Another corner case may happen if we encounter a missing value of the close price for a cryptocurrency that is currently present in our investment portfolio. In such situation we assume the exit close price equal to the last observed close price carried forward. This assumption is necessary in order to provide the results for strategies exhibiting longer reallocation periods (e.g. monthly). Fig. 2 shows completeness analysis of filtered and cleaned data.

4. Results

The descriptive statistics for the momentum, contrarian, and reference strategies are shown on Table 2. Plots of the equity lines (i.e. the cumulative rate of return) and equity drawdowns for momentum and contrarian strategies in comparison with the reference strategies can be found on Figs. 3 and 4, respectively.

4.1. Verification of the working hypothesis

The buy and hold strategy (B&H) on the Bitcoin gives approximately 10 times larger ARC with 5 times larger risk (both in terms of %ASD and %MDD) than B&H on S&P500 index, resulting in 2 and 5 times larger values of IR1 and IR2, respectively. The market cap weighted strategy is slightly more effective than BTC B&H which is intuitively correct — the dominant part of the McW portfolio consists of Bitcoin while contributions from other currencies participate in the reduction of portfolio specific risk. Information ratios IR1/IR2 for the equally weighted strategy are equal to 2.7 and 9.0, respectively (discussion on the controversially high values of these indicators can be found in Section 4.2), and EqW is the strongest benchmark for the verification of momentum/contrarian strategies performance. The substantial difference between EqW and McW benchmark strategies can be attributed to the diversification phenomenon. This potential is much higher in case of EqW portfolio which contains broader set of investment in single cryptocurrencies in comparison to McW portfolio which is heavily overweight by one cryptocurrency i.e. Bitcoin.



Legend: Mean - Mean value (USD) calculated for the whole data set, Min - the lowest observed value (USD), Max - the highest observed value (USD), 'Total Incomplete' - data incompleteness understood as a ratio of number of missing observations to the total number of observations, 'Total Variables' - total number of unique cryptocurrencies that appeared in the ranking.

Fig. 2. MarketCap and Volume data completeness histograms for the data set of 100 largest cryptocurrencies after volume filtering and filling of the missing market cap data. Legend: Mean — Mean value (USD) calculated for the whole data set, Min — the lowest observed value (USD), Max — the highest observed value (USD), 'Total Incomplete' — data incompleteness understood as a ratio of number of missing observations to the total number of observations, 'Total Variables' — total number of unique cryptocurrencies that appeared in the ranking.

Table 2
Descriptive statistics of momentum and contrarian strategies compared with the reference strategies.

Nazwa	%N	RE	RA	%KT	VF	%ARC	%ASD	%MDD	IR1	IR2	%MT
S&P B″	–	–	–	–	–	9.3	12.3	14.2	0.8	0.5	0.0
BTC B&H	–	–	–	–	–	109.6	66.3	73.3	1.7	2.5	0.0
McW	100	1 w	–	1.0	100	117.8	64.7	71.2	1.8	3.0	0.5
EqW	100	1 w	–	1.0	100	239.4	88.9	72.0	2.7	9.0	3.8
Momentum	25	1 w	1 w	1.0	100	20.9	111.1	88.4	0.2	0.0	21.8
Contrarian	25	1 w	1 w	1.0	100	273.2	128.0	60.3	2.1	9.7	23.3

Legend: McW — market cap weighted strategy, EqW — equally weighted strategy, %N — the amount (percentage) of currencies with the highest/lowest rate of return used to construct portfolio, RE — the width of the period between the cyclical portfolio reallocation, RA — the width of the timeframe used to construct the highest/lowest rate of returns ranking, %TC — the total transaction costs taken as the percentage of the total transaction value, VF — the threshold value (USD) of the 14-day moving average of daily volume, %ARC — annualised rate of return (percent), %ASD — annualised standard deviation (percent), %MDD — the maximum drawdown of capital (percent), IR1, IR2 — information ratios calculated in two ways described in formulas (8) and (9), %MDD — maximum drawdown coefficient (percent), %MT — the mean portfolio turnover ratio (percent).

The momentum strategy underperforms all the benchmark strategies with IR1/IR2 values of 0.2 and 0.0, respectively, while the contrarian strategy exhibits similar performance as the equally weighted strategy, albeit with slightly higher volatility yet more favourable drawdown profile, resulting in IR1/IR2 equal to 2.1 and 9.7, respectively. These values suggest that the short-term contrarian effect is present and quite strong on the cryptocurrency market. At the same time, there is no direct proof of existence of analogous momentum effect.

4.2. Sensitivity analysis

The sensitivity analysis has been performed in a way to include at least one value of parameter lower and one higher than the one initially selected for the calculation purposes. The following parameters and their respective values were used in Table 3:

- Percentage of currencies with the highest/lowest rate of return from TOP100%N = 5%, 10%, 25%, 50%
- Reallocation period RE = 1 d, 1 w (7 d), 1 m (30 d)
- Width of the ranking window RA = 1 d, 1 w (7 d), 1 m (30 d)
- Total transaction costs TC = 0.5%, 1.0%, 2.0%

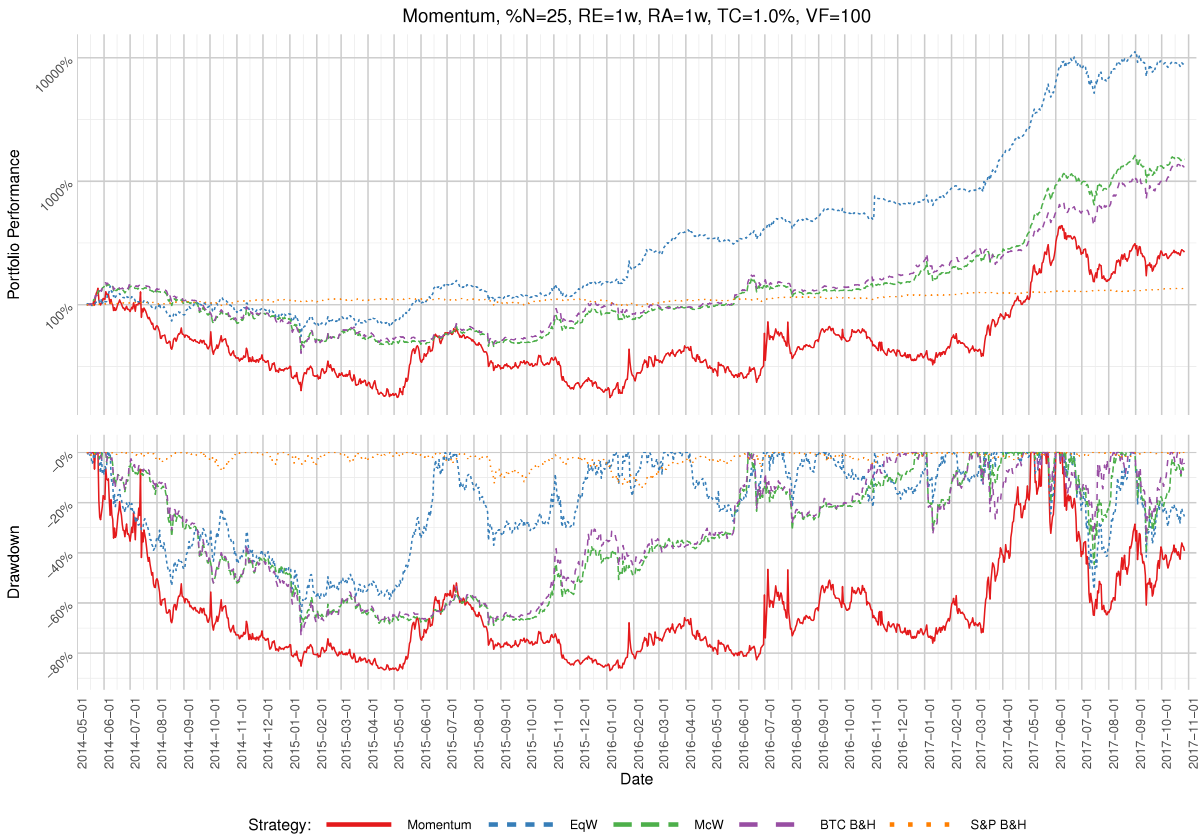


Fig. 3. Equity line and drawdowns of the momentum strategy in comparison with the reference strategies.

It is not difficult to find out that for both momentum and contrarian strategies we would have $2 \cdot 4 \cdot 3^3 = 216$ combinations to present and discuss. Due to the limited amount of space we have, we only present analysis for the 1st rank parameter combinations.

Values of rates of return and information ratios IR1/IR2 decrease with the increase of frequency of portfolio reallocation (RE) for momentum strategy while for contrarian exactly the opposite is true. In the case of contrarian strategy with 1-day reallocation period the ARC coefficient exceeds 100,000% resulting in abnormally high values of IR1 and IR2. We can observe analogous effect if we change the width of the ranking window (RA) performance of the contrarian portfolio increases as we tighten the ranking window while profitability of the momentum strategy declines at the same time. We can also see exactly the same trend in the case of maximum drawdown parameters. For RA = 30-day we can observe the maximal efficiency of the momentum strategies. Increasing the %N parameter increases efficiency of momentum strategy while hampers the gains from contrarian. One also cannot ignore the importance of the total transaction costs %TC for the global portfolio performance. An increase in %TC monotonically decreases all performance indicators for all investigated strategies without changing the portfolio mean turnover rate, which is reasonable and intuitive. Also, the values of %MT are systematically higher for contrarian strategies which can be explained easily by greater relative growth of contrarian assets which forces larger movements in portfolio allocation.

Abnormally high rates of return for the contrarian strategy with short reallocation and ranking periods and small number of assets were a large concern for us at first. But after a more detailed analysis it became evident that these are a perfectly legitimate consequence of occasional, albeit very strong jumps in prices of single currencies in contrarian portfolios. For example:

- AOD 2014-08-04 we can observe the first sharp jump in the contrarian portfolio value. Amongst the 25 cryptoassets on the ranking list for this day, 13 have noted loses (mean daily loss of 8.5%), 3 of them did not gain nor lose, while the remaining 9 currencies have achieved gains. The top performer was eccoin (ECC) which gained 1000% in value and pushed the daily portfolio value gain to approximately 40% in a single day.
- Between 2017-05-20 and 2017-05-23 we can observe yet another strong gain which is clearly visible on Fig. 4. The majority of assets in the portfolio have suffered losses, except for 4 cryptocurrencies: zetacoin (ZET), infinitecoin (IFC), fedoracoin (TIPS), and worldcoin (WDC). Each of these has appreciated approximately by 100%.

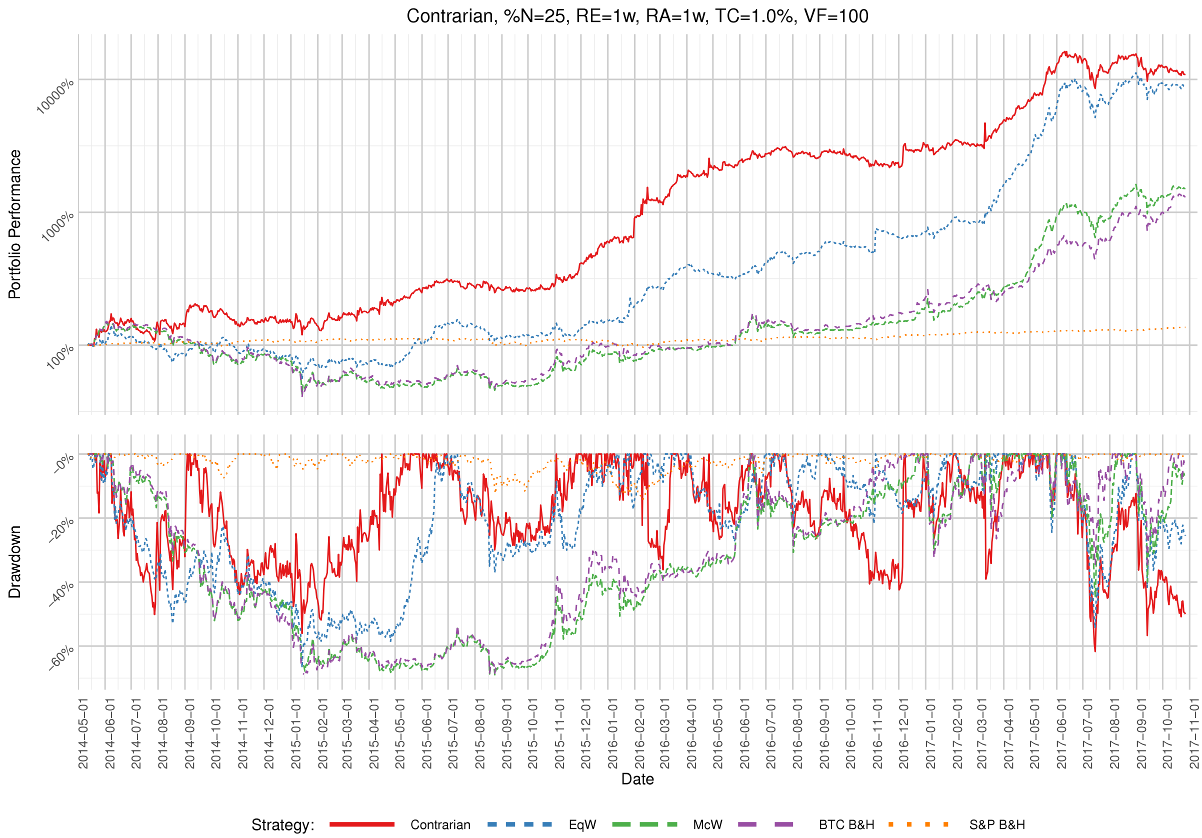


Fig. 4. Equity line and drawdowns of the contrarian strategy in comparison with the reference strategies.

Similar examples are very common in the investigated data. All of these examples have two common components: they seem to be completely unrelated random spikes in prices and they happen mostly for less known cryptocurrencies/altcoins with moderate/low market cap and liquidity. Strictly speaking, the general cause of such abnormally high rates of return can be seen as a result of very strong positive skewness of the rate of return distribution on the cryptocurrency market. The lower %N of the strategy the stronger impact such random spikes have on the overall portfolio value. Additionally, the shorter the ranking window, the quicker we can detect sharp and abrupt falls which are the basis for the contrarian strategy. In other words, we just need to put the current worst performing assets into a bag and wait for the price of at least one of them to spike up manyfold driving very high gains on the portfolio level — and we have a rational basis to believe that it really will happen because of very high positive skewness of returns distribution of these assets.

While analysing cryptocurrency market it is easy to notice a significant diversification effect in reference to the classical assets. Table 4 shows that correlation coefficients between S&P500 and various cryptocurrency strategies are slightly negative or close to zero. This effect combined with information about risk-weighted returns of S&P500 buy&hold strategy (Table 3) creates a potential for increasing the efficiency of well-balanced portfolios constructed from classical asset classes by enabling the maximisation of profit/risk ratio through the best combination of all accessible investment alternatives.

5. Conclusions

In our paper we report the results of investigation of the presence and strength of momentum and contrarian effects in the set of over 1200 cryptocurrencies in the period between 2014-05-12 and 2017-10-28. Our results clearly show existence of strong contrarian effect (with the strongest one observed on the daily level — Table 3) and lack of the analogous momentum effect on the cryptocurrency market. Therefore, referring to our research questions we can say that anomalies known from the regulated markets are currently present in the cryptocurrency markets. Our results at the same time generally do not resemble the results on momentum and contrarian effects observed historically on the classical regulated markets [18–20]. Additionally, we have shown that investment strategies employing momentum and contrarian effects achieve abnormal risk-weighted rates of return in comparison to the S&P500 B&H strategy (taken as a benchmark of classical markets) and, in many parametrisation variants, the cryptocurrency market benchmarks as well.

Values of performance indicators of the investigated portfolios are often suspiciously high and are not achievable on the classical markets even by the most sophisticated algorithmic strategies. However we are aware of the fact that such

Table 3
Descriptive statistics for momentum (left panel) and contrarian (right panel) strategies. Descriptive statistics for the reference strategies have been duplicated in both panels for reader's convenience.

Reference strategies																	
Name					%ARC	%ASD	%MDD	IR1	IR2	%MT	%ARC	%ASD	%MDD	IR1	IR2	%MT
S&P B&H					9.3	12.3	14.2	0.8	0.5	0.0	9.3	12.3	14.2	0.8	0.5	0.0
BTC B&H					109.6	66.3	73.3	1.7	2.5	0.0	109.6	66.3	73.3	1.7	2.5	0.0
McW					117.8	64.7	71.2	1.8	3.0	0.5	117.8	64.7	71.2	1.8	3.0	0.5
EqW					239.4	88.9	72.0	2.7	9.0	3.8	239.4	88.9	72.0	2.7	9.0	3.8
Parameters					Momentum strategy						Contrarian strategy					
%N	RE	RA	%TC	VF	%ARC	%ASD	%MDD	IR1	IR2	%MT	%ARC	%ASD	%MDD	IR1	IR2	%MT
25	1 d	1 w	1.0	100	−96.5	125.8	100.0	−0.8	0.7	69.6	19,319.2	107.1	57.3	180.4	60,836.3	81.6
25	1 w	1 w	1.0	100	20.9	111.1	88.4	0.2	0.0	21.8	273.2	128.0	60.3	2.1	9.7	23.3
25	1 m	1 w	1.0	100	199.2	117.2	79.6	1.7	4.3	5.3	103.3	138.8	77.9	0.7	1.0	5.4
25	1 w	1 d	1.0	100	−12.2	107.8	89.2	−0.1	0.0	21.4	429.5	173.5	77.2	2.5	13.8	21.9
25	1 w	1 w	1.0	100	20.9	111.1	88.4	0.2	0.0	21.8	273.2	128.0	60.3	2.1	9.7	23.3
25	1 w	1 m	1.0	100	170.7	114.9	65.0	1.5	3.9	11.9	208.9	111.3	87.6	1.9	4.5	13.3
1	1 w	1 w	1.0	100	−100	805.3	100.0	0.0	0.0	27.0	4,787.8	1,003.8	99.6	4.8	229.3	27.8
2	1 w	1 w	1.0	100	−99.5	415.2	100.0	−0.2	−0.2	26.5	9,013.1	674.5	96.4	13.4	1,249.6	27.6
3	1 w	1 w	1.0	100	−95.4	361.5	100.0	−0.3	−0.3	26.4	6,233.0	474.1	92.6	13.1	885.3	27.3
4	1 w	1 w	1.0	100	−76.9	298.0	100.0	−0.3	−0.2	26.2	4,587.4	380.8	83.6	12.0	661.2	27.3
5	1 w	1 w	1.0	100	−68.3	250.3	99.9	−0.3	−0.2	25.9	3,992.2	322.1	78.4	12.4	631.3	27.2
10	1 w	1 w	1.0	100	−11.9	168.7	96.7	−0.1	0.0	24.3	1,460.0	211.0	70.1	6.9	144.0	26.4
25	1 w	1 w	1.0	100	20.9	111.1	88.4	0.2	0.0	21.8	273.2	128.0	60.3	2.1	9.7	23.3
50	1 w	1 w	1.0	100	77.8	89.6	85.7	0.9	0.8	15.8	199.0	112.6	62.8	1.8	5.6	16.9
25	1 w	1 w	0.5	100	80.6	110.7	84.8	0.7	0.7	21.8	474.4	127.5	58.0	3.7	30.5	23.3
25	1 w	1 w	1.0	100	20.9	111.1	88.4	0.2	0.0	21.8	273.2	128.0	60.3	2.1	9.7	23.3
25	1 w	1 w	2.0	100	−46.4	112.5	98.2	−0.4	0.2	21.8	55.8	129.6	72.3	0.4	0.3	23.3
10	1 d	1 d	1.0	100	−100.0	231.5	100.0	−0.4	0.4	172.0	Inf	219.9	76.1	Inf	Inf	182.0
25	1 w	1 w	1.0	100	20.9	111.1	88.4	0.2	0.0	21.8	273.2	128.0	60.3	2.1	9.7	23.3
50	1 m	1 m	1.0	100	240.0	94.2	61.5	2.5	9.9	3.9	151.9	115.2	81.9	1.3	2.4	4.2

Legend: McW — market cap weighted strategy, EqW — equally weighted strategy, %N — the amount (percentage) of currencies with the highest/lowest rate of return used for portfolio construction, RE — the width of the period between cyclic portfolio reallocations, RA — the width of the timeframe used to construct the highest/lowest rate of returns ranking, %TC — the total transaction costs taken as the percentage of the total transaction value, VF — the threshold value (USD) of the 14-day moving average of daily volume, %ARC — annualised rate of return (percent), %ASD — annualised standard deviation (percent), %MDD — the maximum drawdown of capital (percent), IR1, IR2 — information ratios calculated in two ways described in formulas (8) and (9), %MDD — maximum drawdown coefficient (percent), %MT — the mean portfolio turnover ratio (percent). Values higher than 100,000 have been replaced with 'Inf'.

Table 4
Correlation matrix between Momentum/Contrarian strategies and the benchmark strategies.

	S&P B&H	BTC B&H	McW	EqW	Momentum	Contrarian
S&P B&H	1.0000	−0.0169	−0.0126	−0.0104	−0.0427	0.0127
BTC B&H	−0.0169	1.0000	0.9475	0.6090	0.4900	0.4237
McW	−0.0126	0.9475	1.0000	0.6785	0.5412	0.4748
EqW	−0.0104	0.6090	0.6785	1.0000	0.6672	0.5950
Momentum	−0.0427	0.4900	0.5412	0.6672	1.0000	0.3335
Contrarian	0.0127	0.4237	0.4748	0.5950	0.3335	1.0000

Legend: McW — market cap weighted strategy, EqW — equally weighted strategy. Momentum and Contrarian strategies have been constructed using 7-day reallocation period, 7-day ranking period and based on 25% of cryptocurrencies from TOP100 having highest/lowest rates of return.

results characterise markets in their early stage of development which are currently not informationally efficient and that such phenomenon cannot be treated as a sustainable price pattern. Therefore, referring to the research questions stated at the beginning we can say that currently we observe high degree of informational inefficiency on cryptocurrency market and that it is possible to construct an investment strategy giving excessive returns. The rational justification of such high risk-weighted returns of tested strategies can be given briefly as: (1) the cryptocurrency market is still quite young and unstable, (2) there are severe limitations in the market liquidity which make investments of several bln USD virtually impossible to perform, (3) regulations and security of investments on the cryptocurrency market are in a very early stage which practically eliminates the possibility of large institutional investors entering the market, (4) infrastructural and technical solutions on crypto markets, e.g. very liberal rules regarding the portfolio margining, enforce the loss socialisation and severely impair the possibility of applying more advanced algorithmic strategies based on e.g. inter-exchange arbitrage opportunities.

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