The Cross-Section of Cryptocurrency Risk and Return

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Zusammenfassung: Wir untersuchen den Querschnitt von über 1200 Kryptowährungen, gesammelt von 350 Handelsplätzen, in der Zeitspanne von Januar 2014 bis Juni 2020. Im speziellen untersuchen wir, ob weit verbreitete Charakteristika, wie Beta (Fama/MacBeth (1973)), Size (Banz (1981)) oder Momentum (Jegadeesh/Titman (1993)) – die bereits intensiv in der Aktienliteratur untersucht werden – den Querschnitt der Kryptowährungsrenditen erklären können. Wir verwenden den Monotonic Relationship (MR) Test von Patton und Timmermann (2010) um auf Abhängigkeiten zwischen Charakteristika und durchschnittlichen Portfoliorenditen sowie Standardabweichungen zu testen. Wir erweitern die bestehende Literatur, indem wir zahlreiche Charakteristika identifizieren, die Risiko und Renditen von Kryptowährungen erklären können.

Summary: We analyze the cross-section of more than 1200 cryptocurrencies derived from 350 exchanges in the time period from January 2014 to June 2020. Specifically, we investigate whether well-known cross-sectional characteristics like beta (Fama/MacBeth (1973)), size (Banz (1981)) or momentum (Jegadeesh/Titman (1993)) – which have been intensively investigated in the equities literature – explain the cross-section of cryptocurrency returns. We apply the monotonic relationship (Mr.) test developed by Patton and Timmermann (2010) to test for dependencies between characteristics and average portfolio returns and standard deviations. We extend the existing literature on cryptocurrencies showing that there are various characteristics which are able to explain cryptocurrency risk and return.

→ JEL classification: Cryptocurrency, Cryptocurrency risk, Portfoliorendite
→ Keywords: G10, G11, G15

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1 Introduction

Since 2008 and the famous Bitcoin Whitepaper "A peer-to-peer electronic cash system" written under the pseudonym "Satoshi Nakamoto", a new asset class augmented the financial industry. Following the criteria by Sharpe (1992), an asset class is characterized by being mutually exclusive, comprehensive and possessing uncorrelated returns.[1] Cryptocurrencies are comprehensive and as a whole, something new. The returns are indeed uncorrelated with traditional asset classes, which makes them very interesting for portfolio diversification.[2] Today, scientific literature mostly agrees that cryptocurrencies form a new asset class.[3] In total, cryptocurrencies accumulate a market capitalization of $260 billion with a share of nearly 60 % Bitcoin, 9 % Ethereum, 3.5 % Tether and 3.1 % Ripple.[4] The number of cryptocurrencies varies depending on the data source. While coinmarketcap counts 5800 cryptos, coingecko displays over 7800. Nevertheless, the ICO platform ICObench alone counted over 5725 ICOs until today.[5]

In this study, we investigate the cross-section of cryptocurrency risk and return. The cross-sectional analysis of returns is a commonly known topic with respect to other asset classes, including stocks, bonds, commodities, currencies and interest rate futures.[6] Today, investors are facing a massive amount of strategies and market anomalies. Starting with the influential work of Fama and French (1992, 1993) and the equity market, they augmented the famous CAPM by two more risk factors, namely size and value. Momentum was later introduced by Jegadeesh and Titman (1993) and added to a four-factor model by Carhart (1997). Pástor and Stambaugh (2003) finally introduced liquidity as a fifth risk factor. Fama and French (2015) themselves published a five-factor model, including market beta, value, size, profitability and investment.[7] Over the decades, several hundreds of research papers have been published investigating new risk factors.[8] This is often referred to as the "Factor Zoo".[9] Nevertheless it is an ongoing scientific debate if the covariances (loadings of an asset on risk factors which investors seek compensation for) or the firms characteristics explain the cross-section of returns.[10] The former implies risk compensation while the latter mispricing. From a multi-asset perspective, Asness et al. (2013) find especially value and momentum return premia in eight markets and asset classes. Accordingly, Asness et al. (2015) identify four investment opportunities, called "styles", which are stable over asset classes, markets and time periods. Those styles – value, momentum, carry and defensive – generate positive average returns over the risk-free rate for

1 Sharpe (1992, p. 8).

2 See Brauneis and Mestel (2019), Kuo Chuen et al. (2017), Bianchi (2020) among others.

3 Corbet et al. (2019).

4 www.coingecko.com; 30. 07. 2020.

5 www.icobench.com; 30. 07. 2020.

6 See Asness et al. (2015, p. 29), Asness et al. (2013), Frazzini and Pedersen (2014) among others.

7 Fama and French (2013, pp. 1–2).

8 See Green et al. (2017), Harvey et al. (2016) or McLean and Pontill (2016) for a broad overview of characteristics.

9 Cochrane (2011, p. 1063).

10 Daniel and Titman (1997), Davis et al. (2000), Lin and Zhang (2013) among others.

an investor.[11] They find strong diversification benefits when combining all styles in a portfolio, as well as statistically significant alphas when leaving out styles from the analysis.[12]

Asness et al. (2015) document the importance for investors and predictive power of styles across multiple asset classes. To investigate such styles in cryptocurrencies, we need to examine the cross-section of cryptocurrency risk and return. Therefore, we build 38 characteristics solely out of price, 24-hour turnover and market capitalization data. We then form quintile portfolios based on and sorted by the cryptocurrencies characteristic values. We expect a steady increase or decrease in the average portfolio risk or return depending on the characteristic under investigation. To test for statistical significance, we apply the monotonic relationship test (MR-test) by Patton and Timmermann (2010). The monotonic relationship test not only tests the hypothesis of a significant difference between the highest and lowest portfolio (a t-test would be sufficient for returns, an F-test for standard deviations)[13], but includes all the portfolios in between.

Our analysis contributes to the young and increasing field of cryptocurrency research especially by showing that cryptocurrency risk and return can be partly explained by solely market-based characteristics. Furthermore, the use of the Patton and Timmermann (2010) test shows not only clear evidence of return spreads in the long-short portfolio but as well monotonic relations in between them. Specifically, we find several characteristics to explain cross-sectional return and risk spreads. We find the short-term reversal to be the dominating characteristic in the cross-section of expected returns. We further show huge differences between value-weighted and equally-weighted portfolios. Risk can partly be explained especially by size and risk related characteristics. We do not find characteristics that increase returns and decrease risk simultaneously.

The paper is structured as follows: Section 2 reviews the literature and section 3 describes the data, characteristics and methodology. Section 4 presents the results, while section 5 concludes.

2 Literature Review

The cryptocurrency market, although relatively young, is a growing field of empirical finance research. Especially since the 2017/2018 hype and an increasing cross-section as well as longer time-series, researchers picked up interest. The study of several cross-sectional anomalies are at the center of market efficiency debates and asset pricing studies.[14] With no warranty for completeness, we want to give an overview over the existing literature especially from firstly the perspective of cryptocurrency market efficiency and secondly cryptocurrency return characteristics. Makarov and Schoar (2020) examine arbitrage opportunities and find large price spreads across countries but smaller deviations within regions and between cryptocurrencies. For a sample until February 2018, they find a co-movement of opening arbitrage spreads across countries especially during times of large Bitcoin appreciation. While the spread of exchanges within a country does not exceed 1 %, the

11 Asness et al. (2015, pp. 30–33).

12 Asness et al. (2015, pp. 39–42).

13 Patton and Timmermann (2010, p. 605).

14 Asness et al. (2013, p. 929).

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average difference between the US and Europe (Japan) is 3 % (10 %). Brauneis and Mestel (2018) as well as Wei (2018) find that market efficiency increases with liquidity for a broad cross-section of cryptocurrencies beyond Bitcoin. Köchling et al. (2019) examine the delay of price reactions to unexpected new information and find it to be highly correlated with market capitalization and liquidity. Hu et al. (2019), Tran and Leirvik (2020) as well as Al-Yahyaee et al. (2020) find the cryptocurrency market to be inefficient, while the latter two as well report time-varying efficiency. Zargar and Kumar (2019) find information inefficiency in higher frequency Bitcoin data, vanishing at daily level data. Zhang et al. (2020) and Kristoufek and Vosvrda (2019) find the cryptocurrencies to be more efficient in bull markets than bear markets. Accordingly, Bouri et al. (2019a), da Gama Silva et al. (2019) and Ballis and Drakos (2020) find evidence for herding behavior and contagion. Following Bikhchandani and Sharma (2001), herding behavior is defined as a state, in which a group of investors ignore their own information and simply follow market expectations. Herding can have significant impact on price and volatility of assets.[15] Several other publications focus on diversification effects, momentum trading, one day momentum effects, seasonality and day-of-the-week effect, trading volume and price predictability are mentioned without further insights.[16] Given the former findings on partial market inefficiencies, we hypothesize that market anonmalies should be observable.

Compared to the time-series anomalies described above, studies on cross-sectional anomalies are significantly fewer. Y. Liu and Tsyvinski (2018) show little risk exposures to common factors derived from the stock market (i. e. CAPM market factor and the Fama-French five factors), currencies and metals. They therefore construct crypto-specific factors and show strong predictive ability of momentum and investor attention.[17] Y. Liu et al. (2019) analyses the performance of 25 characteristic-based zero-investment long-short portfolios and find especially several size and momentum characteristics creating spreads in the returns. A three-factor asset pricing model including size, reversal and market is proposed by Shen et al. (2020) for a large cross-section of cryptocurrencies. Again W. Liu et al. (2020) find significant size and momentum effects, contrary Glas (2019) reports short-term reversal effects. In summary, scientific research is especially lacking a commonly accepted factor model. Although papers have been published about cryptocurrency specific characteristics, it is still not known which characteristics really matter. One major reason is the use of relatively small datasets in previous publications, regarding the time-series as well as the cross-section. This is naturally due to the short existence of this asset class. By taking a most recent and publicly available dataset, as well as a transparent methodology, we further shed light not only on the cross-section of cryptocurrency return but as well risk. Specifically, we choose characteristics commonly known from the stock market, as they are widely used and studied. As cryptocurrencies do not offer any pendant to firm specific fundamentals, we are limited to characteristics retrieved from closing prices, trading volumes and market capitalizations. Specifically, we calculate size, volatility, volume, reversal and several momentum characteristics, which are presented in detail in the next section.

15 Bouri et al. (2019a, p. 216).

16 Glas and Poddig (2018), Chu et al. (2020), Caporale and Plastum (2019a), Kaiser (2019), Caporale and Plastum (2019b), Bouri et al. (2019b), respectively.

17 The authors including momentum, investor attention and Bitcoin wallet users as a proxy for value in their model.

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3 Data and Methodology

We collect daily data from the platform coingecko.com. Coingecko offers a public API with historical data on the price, 24-hour turnover volume, and market capitalization. All data is freely available without any API-Key. The platform collects data from about 350 exchanges and calculates the spot prices as the volume-weighted averages. Outliers from an exchange are defined as a price change of at least 100 times the previous one.[18] In total, we queried the PVM[19] series for 6004 cryptocurrencies on a daily basis from January 2014 to June 2020. For reproducibility reasons, the following describes the data preprocessing.

We queried only cryptos with at least one year of trading, an average market capitalization of at least one million US-Dollar[20] and set every value smaller or equal to zero to missing. We calculate discrete returns and further performed cross-sectional winsorizing. After cleaning, the dataset includes a total of 1267 cryptocurrencies. The trading restriction of 365 days was a particular burden. Figure 1 plots time-series for an equally-weighted and value-weighted market index. The risk-free rate is the 3-Month Treasury Bill with Constant Maturity, retrieved from FRED database.[21] The market is calculated as the equally-weighted average of all returns at time t. The following Table 1 presents the main descriptive statistics of the dataset. The mean (median) of monthly log returns is 3.37 % (2.65 %) for Bitcoin, with a standard deviation of 22.14 %. Bitcoin is furthermore the only one of the four major currencies with a positive median monthly return. Ethereum (ETH) has the highest monthly average return and overall performance with 6.56 % (16,593 %), respectively. The high difference in total cumulative return can be explained by the fact that Ethereum was published relatively late (July 2015) and therefore the full price history is included. Bitcoin's first price datapoint in our sample already starts at $767.74, as we cut off data prior to 2014 for comparison reasons and due to the small amount of existing cryptocurrencies.[22]

Litecoin (LTC) has a mean monthly return of 0.87 %, with a standard deviation of 31.43 % and median monthly return of -2.36 %. Ripple's (XRP) standard deviation is even higher at 46.08 %, along with an average mean monthly return of 2.57 % and a median value of -6.67 %. Furthermore, interesting is the good performance of the value-weighted market index with an average monthly return of 4.41 % and 25.47 % standard deviation, compared to its equally-weighted counterpart. This is mostly due to Bitcoins index domination and induces poor performance of cryptocurrencies with low market capitalization.

To discover the risk and return behavior of a large number of cryptocurrencies, we calculate a variety of cross-sectional characteristics. Specifically, we calculate size, volatility, volume, reversal and several momentum characteristics, which are presented in detail in the following: Table 2 lists all reversal and momentum characteristics used in this study. Momentum was initially introduced by Jegadeesh and Titman (1993) for the stock market. Nevertheless, there exists a large range of

18 https://www.coingecko.com/en/methodology; 01.08.2020.

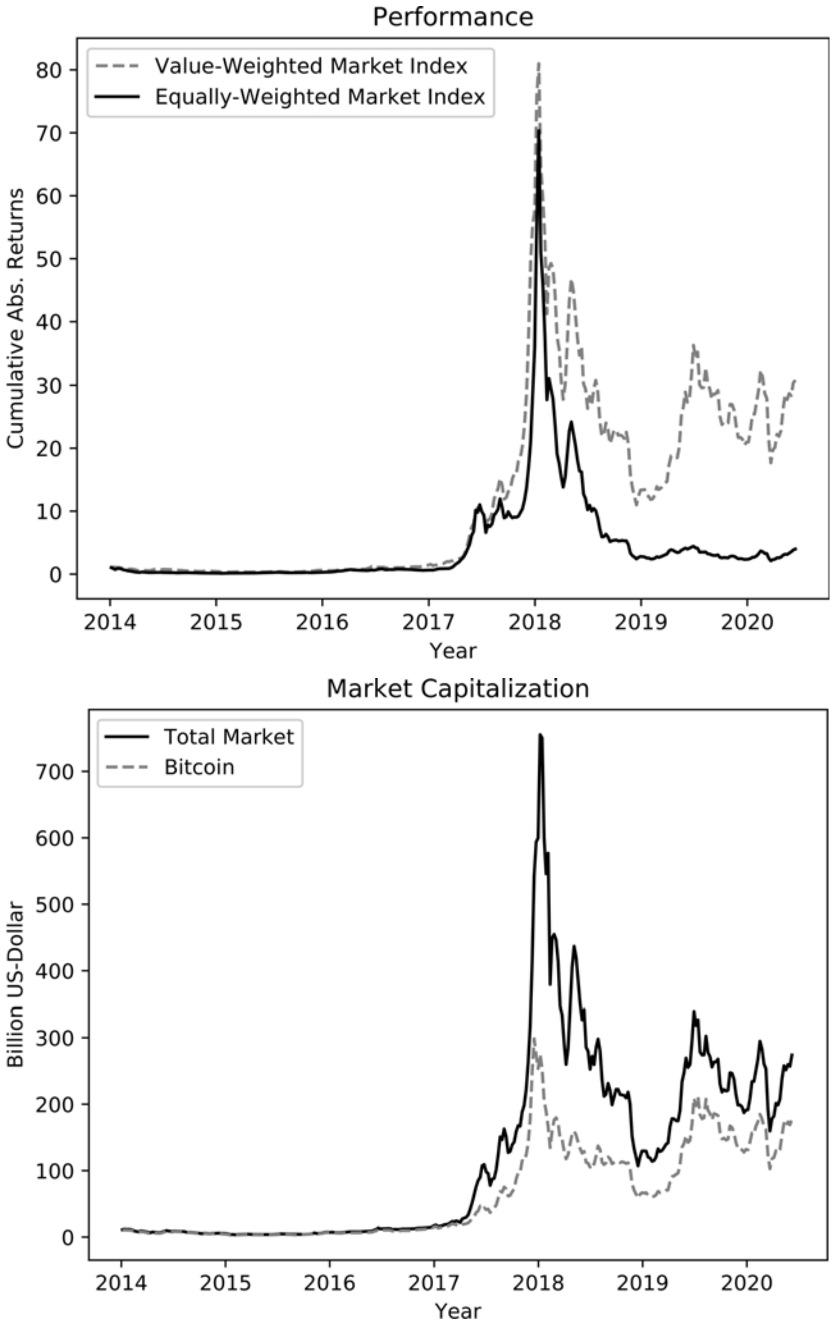
19 Price-Volume-Market Capitalization.

20 Following Y. Liu et al. (2019) for comparison purposes.

21 https://fred.stlouisfed.org/series/DGS3MO.

22 See e.g. Y. Liu et al. (2019).

Figure 1



(a): Equally-weighted and value-weighted market index. The plot shows cumulative discrete daily returns, beginning on 2014 – 01 – 01 until 2020 – 06 – 10. Equally-weighted denotes the average cross-sectional return of all cryptocurrencies at time t, accumulated over t=1,...,T. Value-weighted denotes the weighted cross-sectional average of all returns by the share of market capitalization at time t accumulated over t = 1,...,T. (b): Market capitalization of the whole cryptocurrency market and Bitcoin, in billion US-Dollar.

Table 1

Asset	Mean (%)	Median (%)	Std (%)	Total (%)	p(t)	Sharpe	Skew	Kurt
BTC	3.37	2.65	22.14	1287.20	0.18	0.15	0.16	-0.35
ETH	6.56	0.00	35.71	16592.75	0.11	0.18	0.78	1.52
LTC	0.87	–2.36	31.43	96.58	0.81	0.03	0.89	1.15
XRP	2.57	–6.67	46.08	639.60	0.62	0.06	2.26	7.35
IndexEW	1.79	–0.31	31.01	303.26	0.61	0.06	0.51	1.79
IndexVW	4.41	2.76	25.47	3007.14	0.13	0.17	0.66	1.36

Descriptive statistics of the four major cryptocurrencies, equally-weighted market index ($Index^{EW}$), and value-weighted market index ($Index^{VW}$). The data ranges from 2014 – 01 – 01 until 2020 – 06 – 10, with daily frequency. Ethereum (ETH) starts at 2015 – 08 – 08. 'Mean/Median (%)' is the mean/median of monthly log returns. 'Std (%)' is the standard deviation of monthly log returns. 'Total' denotes the overall cumulative discrete return. 'Skew'/'Kurt' denotes the skewness/kurtosis of monthly log returns, respectively. 'p(t)' is the p-value of the corresponding t-test of monthly zero average log returns. 'Sharpe' is the Sharpe ratio.

Table 2

Characterisitc	Description	Methodology
ΔMV	Change in market value	$\Delta MV_t = MV_t/MV_{t-1} - 1$
Reversal	Short-term reversal	$Reversal_t = P_t/P_{t-6} - 1$
Mom^{2w}	2-week momentum	$Mom_t^{2w} = P_{t-7}/P_{t-14} - 1$
Mom^{3w}	3-week momentum	$Mom_t^{3w} = P_{t-7}/P_{t-21} - 1$
Mom^{4w}	4-week momentum	$Mom_t^{4w} = P_{t-7}/P_{t-30} - 1$
Mom^{8w}	8-week momentum	$Mom_t^{8w} = P_{t-7}/P_{t-52} - 1$
Mom^{16w}	16-week momentum	$Mom_t^{16w} = P_{t-7}/P_{t-112} - 1$
Mom^{52w}	52-week momentum	$Mom_t^{52w} = P_{t-7}/P_{t-365} - 1$
$Mom^{52w\text{-}4w}$	52-week momentum – 4-weeks	$Mom_t^{52w-4w} = P_{t-28}/P_{t-365} - 1$

All momentum characteristics used in this study. The index t in the methodology column refers to days. Weeks include holidays and weekends.

literature on momentum in many asset classes.[23] We distinguish between momentum and (short-term) reversal effects. Under the momentum effect, past winners will continue to outperform past losers. However, the (short-term) reversal states a mean reversion of past winners in the short-term which results in an underperformance. Both, momentum and reversal are widely accepted in the literature and found as well in cryptocurrencies.[24] We expect the reversal to be of very short range, following the results of Glas (2019), Y. Liu et al. (2019) and Shen et al. (2020). Former find especially momentum between 1- to 4-weeks significant, while Glas (2019) and Shen (2020) find especially a (shortterm) reversal but no momentum. Thus, we focus on several momentum characteristics with a short-term reversal effect that should take place within the week before portfolio formation.

23 See Asness et al. (2013), Moskowitz et al. (2012) among others.

24 See section 2.

Specifically, momentum is calculated as the cumulative (discrete) return over a certain period, i. e.:

$$Mom_t^{2w} = \frac{P_{t-7}}{P_{t-14}} - 1 \tag{1}$$

where P_t is the price in period t. The excluded reversal effect should take place in the past week before portfolio formation, i. e.:

$$Reversal_t = \frac{P_t}{P_{t-6}} - 1 \tag{2}$$

Note that the characteristic ΔMV from Table 2 falls in the span of the short-term reversal. As market value is calculated as the current coin supply times the price, it can be interpreted as a one-day reversal. The change in number of coins is negligibly small, thus leaving a pure price effect in the characteristic. We extend the momentum lags up to one year to capture long-term effects. The one-year momentum is calculated both with one-week and four-week reversal excluded for comparison reasons, as the latter is the classical momentum by Jegadeesh and Titman (1993) and standard in research of other asset classes. As cryptocurrencies are traded without any break, holidays and weekends are included in our calculations.

Table 3 lists all characteristics regarding size. Size was first documented by Banz (1981) and heavily studied in asset pricing. We consider characteristics regarding the market value and price of the previous day, as well as the number and change in coins of a cryptocurrency.

Table 3

Characterisitc	Description	Methodology
MV	Market value	$MV_{i,\,t}$
Price	Price	$P_{i,\,t}$
MaxP^{1w}	Max. price of prev. week	$MaxP_t^{1w} = \max\left(P_{i,\ t:t-7}\right)$
Age	Weeks of trading	$Age_t = \frac{\#Days}{7}$
ΔNumCoins	Change in coins	$\Delta NumCoins_t = \frac{NumCoins_{i,\,t}}{NumCoins_{i,\,t-1}}$

All size characteristics used in this study. The index t refers to days.

The amount of coins of a cryptocurrency is calculated by dividing the market value by the price. Note that this will include coins from lost wallets as well; the proxy therefore does not reflect the actual circulating supply. However, precise data is not available for the large cross-section.

The smallest group of characteristics is volume-based and summarized in Table 4. Volume was initially mentioned by Datar et al. (1998) and Amihud (2002)

We consider the US-Dollar volume from the previous day, the US-Dollar volume from the previous week, and value-weighted US-Dollar volume as possible predictors for risk and return. We expect volume characteristics to co-move with size as smaller, unpopular cryptocurrencies should have lower turnover rates, and vice versa. The illiquidity proxy by Amihud (2002) is expected to have a

Table 4

Characterisitc	Description	Methodology
\$Vol	US-Dollar volumen	$\$Vol_{i,\,t}$
\$Vol[1w]	US-Dollar volumen prev. week	$\$Vol_{i,\,t-7}$
\$Vol[VW]	US-Dollar volumen value-weighted	$\$Vol_t^{VW} = \$Vol * \frac{MV_{i,\,t}}{\sum_{i=1}^{I} MV_{i,\,t}}$
Amihud	Amihud illiquidity measure	$Amihud_t = \frac{1}{14} * \sum_{t-14}^{t} \frac{\lvert R_{i,\,t}\rvert}{\$Vol_{i,\,t}}$

All volume characteristics used in this study. The index t refers to days.

negative direction of action as the proxy is by construction inverse to the turnover volume (i. e. more illiquid stocks generate higher returns).

The last group of characteristics we consider are risk based and put together in Table 5. Beta was introduced by Black et al. (1972), volatility by Blitz and van Vliet (2007), skewness by Harvey and Siddique (2000) and recently examined by Amaya et al. (2015), kurtosis by Fang and Lai (1997) and again recently examined by Amaya et al. (2015). All volatility characteristics are calculated for 182 days (6 month) and 365 days (1 year).

Table 5

Characterisitc	Description	Methodology
Std	Return std deviation	$Std_t = \sqrt{\frac{\sum_{t=1}^{t}(r_t-\bar{r})^2}{t}}$
SR	Sharpe ratio	$SR_t = \frac{\bar{r}}{Std_{i,\,t}}$
Skew	Return skewness	$Skew_t = \frac{1}{t}\sum_{t=1}^{t}\left(\frac{r_t-\bar{r}}{Std_t}\right)^3$
Kurt	Return kurtosis	$Kurt_t = \frac{1}{t}\sum_{t=1}^{t}\left(\frac{r_t-\bar{r}}{Std_t}\right)^4$
Beta	Market beta	$r_{i,\,t} - r_t^f = \alpha_{i,\,t} + \beta_{i,\,t}(r_{i,\,t} - r_{m,\,t}) + \varepsilon_{i,\,t}$
Alpha	Jensen's alpha	$r_{i,\,t} - r_t^f = \alpha_{i,\,t} + \beta_{i,\,t}(r_{i,\,t} - r_{m,\,t}) + \varepsilon_{i,\,t}$
ResStd	Idiosyncratic risk	$r_{i,\,t} - r_t^f = \alpha_{i,\,t} + \beta_{i,\,t}(r_{i,\,t} - r_{m,\,t}) + \varepsilon_{i,\,t}$
ResSkew	Residual skewness	$r_{i,\,t} - r_t^f = \alpha_{i,\,t} + \beta_{i,\,t}(r_{i,\,t} - r_{m,\,t}) + \varepsilon_{i,\,t}$
ResKurt	Residual kurtosis	$r_{i,\,t} - r_t^f = \alpha_{i,\,t} + \beta_{i,\,t}(r_{i,\,t} - r_{m,\,t}) + \varepsilon_{i,\,t}$

All risk characteristics used in this study. The index t refers to days. All higher central moment characteristics in the upper part refer to returns, the lower part to the residuals of the CAPM regression.

Characteristics are calculated and portfolios are rebalanced on a daily basis. For each asset $i = 1,\dots,I$ and period $t = 1,\dots,T$ we calculate the value of the characteristics as presented above. For example, we estimate the market beta using the past 365 days for each cryptocurrency in rolling window regressions on an equally-weighted market index. For each period, we sort the cryptocurrencies according to their beta and split the portfolio in quintiles (i. e. assets exhibiting the lowest 20 % up to the highest 20 % of market exposure). We then observe the returns in the next period, rebalance the portfolios, and average the results over all timesteps. If a characteristic has predictive power, it should create a spread in average risk and return over the risk-free rate between the quintile

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portfolios.[25] For the explicit example and by following traditional finance literature, we would expect an increase of risk and return for higher beta portfolios.[26]

To test for statistical significance, we use the monotonic relation test (MR-test) by Patton and Timmermann (2010). Only if a monotonic increase/decrease from the lowest to the highest portfolio is found, the null hypothesis of no significant spread in risk or returns is rejected. This method clearly reduces false positives as random fluctuations could spread the highest and lowest portfolio without any meaning to the characteristic.[27] The next section describes the results with respect to portfolio returns and portfolio risk.

4 Results

4.1 Returns

This section describes the results, beginning with the cryptocurrency returns. Table 6 displays all characteristics with a significant and monotone spread in between the quantile portfolios.

The cryptocurrency returns in the portfolios are equally weighted, following standard cryptocurrency literature.[28] We show absolute average returns of the long-short portfolio. An investor would therefore short-sell assets in the quantile portfolio with the lowest realized return and go long assets in the quantile portfolio with the highest realized return. As the cryptocurrency industry is fairly new and sorting directions are not adapted, we sort cryptocurrencies by their characteristics' values from low to high. The sign of the long-short portfolio returns then points the right direction of sorting. However, the hedge-portfolio returns outside the tables are referenced to in absolute terms.

The cross-section of cryptocurrency returns can partly be explained especially by reversal characteristics and higher central moments of the CAPM regression residuals and return distribution. Cryptocurrencies with the smallest change in market value, ΔMV, generate an average return of 1.74 % in the next period. Therefore, a last periods high change in market value results in an average drawdown of -1.04 %. The long-short position has a return of 2.76 % and is highly significant. In line with that finding, the Reversal characteristic, i. e. past seven days of returns, has a payout in the long-short position of 1.97 %. The only significant momentum characteristic, Mom^{16w}, is unexpectedly negative and smaller by a factor of nearly 20. This can be interpreted as a longterm reversal. All other momentum characteristics commonly found significant in the literature, especially those of short-term up to 4-weeks, fail significance in our analysis.

Next to the reversal, we find a *low price* effect in the characteristics Price and MaxP^{1w}. Both leave a similar pattern with returns in the long-short portfolio of 0.55 % and 0.43 %, respectively. Following

25 Asness et al. (2015, p. 33).

26 However, Haugen and Heins (1972) first discovered the low beta anomaly in stock markets which clearly contradicts the CAPM.

27 Patton and Timmermann (2010, p. 607).

28 See Y. Liu et al. (2019) among others.

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Table 6

Characteristic	Low	2	3	4	High	H-L	p(MR)
ΔMV	1.74	0.26	0.05	−0.12	−1.04	−2.79	0.00
Price	0.57	0.18	0.17	0.04	0.02	−0.55	1.00
MaxP^{1w}	0.50	0.20	0.16	0.08	0.07	−0.43	1.20
Reversal	1.39	0.29	0.09	−0.17	−0.58	−1.97	0.00
Mom^{16w}	0.34	0.22	0.19	0.20	0.19	0.15	4.50
\$Vol^{1w}	0.52	0.32	0.12	0.03	0.02	−0.50	0.20
ResStd^{6m}	0.11	0.14	0.13	0.17	0.34	0.23	2.20
ResSkew^{1y}	0.31	0.21	0.17	0.16	0.16	−0.15	2.80
ResKurt^{6m}	0.26	0.21	0.19	0.12	0.09	−0.17	0.60
ResKurt^{1y}	0.30	0.20	0.18	0.18	0.14	−0.17	0.03
Std^{6m}	0.10	0.13	0.15	0.15	0.35	0.25	1.20
Skew^{6m}	0.23	0.25	0.19	0.12	0.07	−0.17	4.00
Kurt^{6m}	0.25	0.22	0.16	0.12	0.11	−0.15	0.00
Kurt^{1y}	0.32	0.18	0.17	0.18	0.15	−0.17	2.00

All characteristics with a significant spread in returns. The first column provides the name of the characteristic, 'Low' refers to the average daily returns of the portfolios containing the 20 % assets exhibiting the lowest characteristic values each period. Accordingly, 'High' refers to the portfolio with the 20 % of assets exhibiting the highest characteristic values each period. All returns are without transaction fees. p(MR) is the p-value (%) of the monotonic relation test by Patton and Timmermann (2010). Significance level is α= 5 %. 'Res' refers to the residuals of the CAPM regression, whereas no prefix on the central moment characteristics refers to the returns.

the previous results, we expect low price cryptocurrencies to have a lower average turnover rate, therefore to co-move with a *low volume* effect. Indeed, the past weeks US-Dollar volume characteristic creates a similar spread of 0.50 % and is highly significant.

The higher central moments of both, regression residuals and returns, show the same and expected sign. Idiosyncratic risk, as well as return volatility, can both explain parts of cryptocurrency return and have similar spreads of 0.25 % and 0.23 %, respectively.[29] In any case, we can not find a low-volatility effect, as commonly observed on the stock market. Cryptocurrency returns increase with their volatility. However, the 1-year counterparts of both volatility characteristics fail to produce significant premiums. We next analyze the data with respect to the higher moment of skewness. We expect lower (left) skewed assets to pay higher returns as investors will ask a premium for the higher tail risk in the assets.[30] We observe this in both, the return skewness and the residual skewness, with spreads of 0.15 % and 0.17 %, respectively. Surprisingly, and not in line with literature, the correlation of kurtosis with expected stock returns is negative. Amaya et al. (2015) find a strong negative relation between skewness and expected stock returns, but a positive relation between kurtosis and expected stock returns, although the latter is not very strong. The kurtosis in cryptocurrency returns and residuals, independent of their time horizon, creates long-short spreads between 0.15 % and 0.17 %. Although the overall effect is small, based on finance literature we expected it to be positive.

29 See Merton (1987) why idiosyncratic risk should be priced.

30 Amaya et al. (2015).

4.2 Risk

Next to the returns, Table 7 presents the results regarding risk.[31] Risk in the cross-section of cryptocurrencies can partly be explained by the market value as well as last period's price, the market beta and several central moments from the residual as well as the return distribution. The market value (MV) and price information (Price and MaxP^{1w}) from the previous periods have negative signs, meaning the portfolio risk decreases with higher market value, price and maximum price. We thus find a size effect (Banz (1981)) in the cross-section of cryptocurrency risk, with co-moving returns.

Table 7

Characteristic	Low	2	3	4	High	H-L	p(MR)
MV	5.10	4.58	4.55	4.54	4.28	3.91	2.40
Price	5.19	4.76	4.40	4.35	4.12	3.61	0.10
MaxP^{1w}	5.09	4.79	4.38	4.35	4.13	3.50	0.60
ResStd^{6m}	3.75	4.32	4.53	4.58	4.79	3.00	0.10
ResStd^{1y}	3.86	4.39	4.57	4.63	4.78	2.87	0.00
Std^{6m}	3.56	4.33	4.49	4.67	4.88	3.00	0.00
Std^{1y}	3.75	4.36	4.57	4.76	4.80	2.88	0.00
Beta^{6m}	3.67	4.31	4.50	4.61	4.81	3.10	0.00
Kurt^{6m}	4.58	4.44	4.35	4.31	4.17	2.71	0.00

All characteristics with a significant spread in portfolio risk. The first column provides the name of the characteristic, 'Low' refers to the average standard deviation of the portfolio containing the 20 % assets exhibiting the lowest characteristic values each period. Accordingly, 'High' refers to the portfolio with the 20 % of assets exhibiting the highest characteristic values each period. 'H-L' is the long-short zero investment portfolio. p(MR) is the p-value (%) of the monotonic relation test by Patton and Timmermann (2010). Significance level is $\alpha = 5\,\%$. 'Res' refers to the residuals of the CAPM regression, whereas no prefix on the central moment characteristics refer to the returns.

The effects of all size characteristics are quite similar, reducing the standard deviation from highest 5.19 % down to lowest 4.12 %. The portfolio risk of cryptocurrencies further increases with the 6-month market beta from 3.67 % to 4.81 %, leaving the long-short portfolio at 3.10 % standard deviation. Similar to size, we do not observe any related pattern in the portfolio returns. From untabulated results, we report that both 6-month and 1-year betas (and alphas) are U-shaped, with long-short portfolio returns close to zero. A low beta anomaly is therefore not present in crypto-currencies. The idiosyncratic volatility obviously increases portfolio risk, from 3.75 % up to about 4.79 %. Further, the increase in portfolio risk accompanies with higher expected returns of 0.23 % (see Table 6). A similar picture can be seen for the return volatility. The standard deviation increases from 3.56 % (3.75 %) up to 4.88 % (4.80 %) for the 6-month (1-year) horizon. Again, the 6-month return volatility characteristic accompanies with an increase in returns of 0.25 %. The risk-portfolios build on the kurtosis of cryptocurrency returns co-move with their return counterparts. Along with the unexpected decrease in portfolio returns from 0.32 % down to 0.15 % comes a decrease in portfolio risk from 4.58 % to 4.17 %. The overall spread however is small. The return volatility, the idiosyncratic risk, and characteristics regarding size are useful predictors, with all having the expected direction of action. Nevertheless, skewness does not play a role in the cross-section of

31 We define risk as the standard deviation of quantile portfolio returns of all periods.

cryptocurrency risk despite creating significant spreads in expected returns. The risk for all momentum strategies and the reversal remains similar over portfolios and lags between 4 % and 5 %.

4.3 Reversal and Momentum in Cryptocurrencies – a closer look

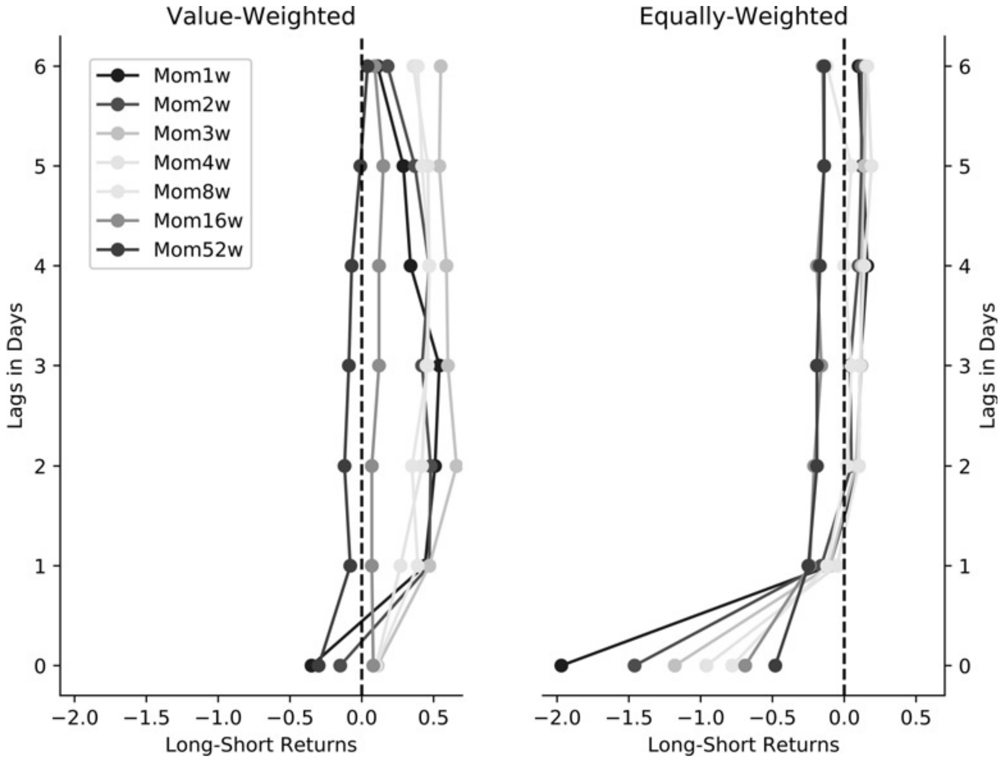
The reversal effect in cryptocurrencies is strong and worth a closer look. As mentioned above, the portfolios are equally weighted for comparison reasons, as this is the standard in cryptocurrency literature.[32] However, Figure 1 indicates a tremendous difference in equally versus value-weighted market index returns. While the value-weighted index partly recovered after the 2018 crash, the equally-weighted index continued losing value. This is due to the equal weights of low capitalized and high capitalized returns. On the other hand, especially Bitcoin is the main driver of value-weighted indexes. The question might arise with respect to how results are affected if the portfolio weights are changed from equal- to value-weighted. Figure 2 plots the momentum portfolio returns for equally-weighted and value-weighted cryptocurrencies with different lag length.

Specifically, we create momentum portfolios from 1-week up to 52-weeks and omit an increasing number of days (lags) in the portfolio formation. The goal is to extract only the reversal and calculate a pure momentum. The value of a 2-week momentum portfolio in t+1 with lag $L = 2$ is calculated from returns of periods t-14 : t-2. This leaves two data points, t and t-1, out of the calculation for the reversal effect to take place. The reversal effect is especially strong for the equally-weighted portfolios and decreasing over the period length of the momentum characteristic. The 8-week momentum (Mom^{8w}) is less affected by the reversal than the 4-week momentum (Mom^{4w}). With a lag length of two days, the reversal loses influence and short-term portfolio returns are mostly positive, but small. Interestingly, in the long-run returns remain negative. A different picture comes with the value-weighted portfolios. The reversal itself is weaker which initially leaves only the 1-week and 2-week momentum portfolios negative if the reversal is included (L=0). The long-short portfolio returns of the ΔMV characteristic is -1.05 % (-2.76 % for equally-weighted, see Table 6). The reversal itself seems to disappear as well after latest 2 days, leaving a pure momentum with average returns ranging between 0.1 % and 0.6 %. However, the 1-year momentum is mostly negative similar to the equally-weighted portfolios. The classical momentum by Jegadeesh and Titman (1993) for cryptocurrencies, i. e. 1-year momentum excluding the last month, is insignificant with -0.16 % average returns for equally-weighted and -0.13 % for value-weighted long-short portfolios.

We follow the results from Figure 2 and create value-weighted momentum portfolios with a reversal of two days. We find four momentum portfolios with significant monotonic patterns and spreads in the long-short position up to 0.66 %. For equally-weighted portfolios and a lag of two days, we only find significance for the 1-year period. All characteristics with a 1-year horizon (equally- and value-weighted) show an inverse pattern in returns and can therefore be seen as a long-term reversal. Further, all momentum characteristics show high volatility. While the standard deviations across the portfolios are similar for longer ranging momentums (around 4.5 % – 5.5 %), the short-term characteristics are U-shaped and exhibit standard deviations between 6 % – 7 % in the high and low portfolios. Compared to other asset classes, momentum and reversal are very short. Next, the

32 E. g. W. Liu et al. (2020), Y. Liu et al. (2019) use equally-weighted portfolios.

Figure 2



Long-short returns of momentum portfolios (x-axis) with different reversals (y-axis). The lag of one/two day(s) means the momentum is calculated until t-1 / t-2, with one/two day(s) reversal effect, respectively. The left figure contains all value-weighted portfolios, while the right figure all equally-weighted portfolios.

Table 8

Characteristic	Low	2	3	4	High	H-L	p(MR)
Mom^{1w-2d}	−0.16	−0.12	0.05	0.30	0.35	0.51	0.00
Mom^{2w-2d}	−0.18	0.04	0.06	0.35	0.30	0.48	19.90
Mom^{3w-2d}	−0.25	−0.02	0.08	0.21	0.41	0.66	0.00
Mom^{4w-2d}	−0.07	−0.08	−0.01	0.25	0.35	0.42	4.40
Mom^{8w-2d}	−0.05	0.09	0.13	0.15	0.31	0.35	0.10
Mom^{16w-2d}	0.18	0.07	0.07	0.17	0.25	0.07	66.00
Mom^{52w-2d}	0.23	0.12	0.09	0.21	0.10	−0.12	29.70
Mom^{52w-4w}	0.21	0.32	0.12	0.15	0.08	−0.13	55.10

All momentum characteristics with significant spread in value-weighted portfolio returns. The reversal is set to the previous two days before portfolio formation. The first column provides the name of the characteristic, 'Low' refers to the average daily returns of the portfolios containing the 20% assets exhibiting the lowest characteristic values each period. Accordingly, 'High' refers to the portfolio with the 20% of assets exhibiting the highest characteristic values each period. 'H-L' is the long-short zero investment portfolio. All returns are without transaction fees. p(MR) is the p-value (%) of the monotonic relation test by Patton and Timmermann (2010). Significance level is α= 5%.

reversal is taking place in mostly low capitalized assets. A profitable investing strategy could either lack tradability of assets or produce unprofitably high trading costs.[33]

In summary, short-term reversal is the strongest characteristic in the cross-section of cryptocurrencies, especially in equally-weighted portfolios. The reversal effect disappears completely two days before portfolio formation. Momentum on the other hand can barely be found, despite many publications who claimed differently. However, it is heavily affected by the portfolio weights. While there is no momentum in equally-weighted portfolios (if, then a negative long-run 1-year reversal), value-weighted portfolios do have significant short-term momentums. However, those portfolios are heavily influenced by a handful of large cryptocurrencies and create return spreads similar to the low price and low volume effect.

This finding is important as it is estimated that about 21% of all ICOs listed on Icobench were deleted from at least one of the major exchanges, while 13% were deleted from all major exchanges.[34] The chosen data source, the overall market coverage of a platform and if failed coins are still included or ex-post deleted from the database, can have a massive impact on the results. An ex-post cleaned (i.e. survivorship biased) dataset therefore is closer to value-weighted portfolios, whereas smaller and failed coins drastically lower the overall returns.

4.4 Double Sorts

The previous results indicate that the market capitalization has a major impact on the performance of cryptocurrency characteristics. Therefore, double sorted portfolios are created, firstly on the market capitalization, and secondly on the reversal and momentum characteristics, as these seem to be the most important characteristics for cryptocurrencies. To control for market capitalization ensures that the findings are not exclusively driven by illiquidity and hold for tradeable cryptocurrencies. The relationship of stock return predictability and liquidity is addressed, among others, in Lewellen (2015).[35] To keep consistency with our analysis above, the double sorts are performed with equally-weighted portfolio returns. The sorts are limited to quartiles to ensure a meaningful population in each portfolio. The following Table 9 reports sorts by market capitalization as rows and the reversal as columns. The last column represents the hedge-portfolios of reversal for each market capitalization quartile. The last row represents returns of the market capitalization hedge-portfolios for each reversal quartile.

33 Groot et al. (2011) show that reversal strategies in the stock market can be profitable once limiting the asset universe to large capitalized only.

34 Momtaz (2020, p. 3).

35 Lewellen (2015, p. 24) reports reduced return spreads when using more liquid assets in his analysis.

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Table 9

MV / Reversal	Low	2	3	High	H-L
Low	2.38	.61	0.23	−1.09	−3.46***
2	1.72	0.29	−0.12	−1.12	−2.87***
3	1.12	0.14	−0.17	−1.06	−2.18***
High	0.55	0.09	−0.02	−0.44	−0.93***
H-L	−1.87***	−0.53***	−0.24	0.63**	-

Double sorted average portfolio returns (independent sorting). The returns are sorted firstly by market capitalization (rows) and secondly by momentum (columns). Asterisks mark the significance level of the monotonic relation test by Patton and Timmermann (2010) with significance level ***=1 %, **=5 %.

The returns consistently decrease with the reversal quartiles and result in high absolute hedge-portfolio returns. The returns of the reversal hedge-portfolios decrease with increasing market capitalization. However, the reversal effect exclusively for liquid cryptocurrencies remains very strong. The returns furthermore decrease with higher market capitalization for low reversal portfolios, but switch direction and increase with the high reversal portfolio. Low capitalized cryptocurrencies have on average higher reversal effects and higher following returns. The size effect within the reversal portfolios is decreasing, resulting in absolute hedge portfolio returns falling from 1.86 % to 0.63 % and switching sign. All in all, small cryptocurrencies have a much higher bandwidth, while the reversal is still present within the largest 25 % of cryptocurrencies. From untabulated results it can be reported that the average portfolio risk over every market capitalization quartile monotonically falls from 6.13 % down to 5.20 % for large cryptocurrencies, excluding the hedge-portfolios.

Furthermore, the performance of the double sorted momentum hedge-portfolios are examined. Figure 2 of the previous section revealed momentum effects only in value-weighted sorts, especially for short-term momentum characteristics. The following Table 10 presents aggregated returns for double sorted momentum hedge-portfolios for each market capitalization quartile. The characteristics are calculated with a lag of two days, following the previous findings regarding the duration of the reversal effects. Significant momentum portfolios, in terms of the MR-test, can be found especially in the short-run with high-capitalized cryptocurrencies. The results are consistent with Figure 2 and show increasing hedge-portfolio returns for high capitalized cryptocurrencies, decreasing after 3-weeks.

Table 10

MV / Mom*	1W	2W	3W	4W	8W	16W	52W
Low	0.12	−0.13	−0.13	0.08	−0.12	−0.41	−0.10
2	0.11	−0.06	−0.06	0.08	0.02	0.00	0.17**
3	0.07	0.19	0.25	0.21**	0.22	−0.01	0.11**
High	0.27**	0.37***	0.44***	0.27**	0.15***	−0.10	−0.22

Aggregated results from several double sorted characteristics. The returns are clustered firstly by market capitalization (rows), and secondly by momentum (columns). The values represent the hedge-portfolio returns of momentum. Negative values are interpreted as reversal, positive values as momentum. Asterisks mark the significance level of the monotonic relation test by Patton and Timmermann (2010) with significance level ***=1 %, **=5 %.

The average returns are substantially lower than their value-weighted counterparts from Table 8 even though only the biggest 25 % of cryptocurrencies are considered. Interestingly, a significant positive momentum effect can be found in the long-run for the two middle capitalized cryptocurrencies. This finding is contrary to Table 8 where only negative and insignificant long-run long-short returns are obtained.

This subsection only focused on double sorted portfolios for the most promising characteristics due to spacing limitations. Approaches to control the amount of characteristics are not provided and left for further research. In this field latest publications from the stock market especially focus on machine learning methods (e. g. Gu et al. (2020)) or recently introduced methodologies like the IPCA (Instrumented Principal Component Analysis) by Kelly et al. (2019).

4.5 Transaction Costs

The profitability of cryptocurrency strategies has not been mentioned so far. Despite the questionable tradeability of many cryptocurrencies due to a lack in trading volume and availability, profitability examinations like the parametric portfolio policy by Brandt et al. (2009) is left for further research. Especially the availability of cryptocurrencies may be the biggest issue as the listings of cryptocurrencies on different exchanges are very limited. This circumstance limits the realization of trading strategies. However, as transaction costs are the most important unknown, an indirect measure is given in the following.

Every period and for every characteristic the asset's quantile portfolio is memorized before and after rebalancing. Out of all possibilities, the fraction of actual transitions is calculated and used as a proxy for transaction costs. The following Tables 11–13 present transition matrices obtained for the strongest and most relevant characteristics. Those are the reversal and 3-weeks momentum (Mom^{3w}) excluding reversal effect. The change in market value (ΔMV), as the second strongest characteristic in terms of hedge-portfolio returns, is close to the reversal by construction, which results in nearly identical transition matrices. As a reference characteristic market value (MV) is selected, as short-term fluctuations are expected to be low. The following Table 11 presents the transition matrix of MV as our benchmark.

Table 11

MV		Low	2	3	4	High
Period t	Low	0.94	0.06	0	0	0
	2	0.05	0.90	0.05	0	0
	3	0	0.05	0.91	0.04	0
	4	0	0	0.04	0.93	0.03
	High	0	0	0	0.02	0.98
				Period t+1		

Probability of a cryptocurrency to be sorted in the respective portfolio after rebalancing. The diagonal signifies no change in portfolios after rebalancing. The transition matrix is calculated from single sorts by market capitalization.

The table reads as follows: rows represent time t, columns the next period after rebalancing. On the diagonal the probability of an asset i to stay in the respective quintile is given. Reading row-wise, the matrix gives the probability of an asset to change into the respective portfolio (column) the next

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period. For example, the first row states that 94 % of the assets will stay in the low portfolio and 6 % will change to the second quantile portfolio. The second row states the 5 % of all assets previously being in the second quantile portfolio will transit to the low portfolio, 90 % will stay and 5 % will transit to the 3rd quantile portfolio after rebalancing. As expected the market value matrix is steady, especially in the low (top) diagonal portfolio with only 6 % (2 %) change between periods. Changes greater than one quintile are not present. The highest and lowest diagonal portfolios are those of interest, as an investor would short-sell the low and buy the high return portfolio.

The following Table 12 presents the transition matrix of the reversal effect. Unlike the market value this strategy shows high variation between periods. The diagonal is weakly occupied and most exchange takes place between the two extrema. A high fluctuation especially between the high and low portfolio is by construction the reversal effect. Therefore, investors would face large transaction costs when implementing a reversal strategy.

Table 12

Reversal		Low	2	3	4	High
Period t	Low	0.19	0.15	0.15	0.19	0.32
	2	0.15	0.21	0.23	0.24	0.17
	3	0.14	0.22	0.27	0.23	0.14
	4	0.17	0.24	0.22	0.20	0.17
	High	0.35	0.17	0.13	0.14	0.21
				Period t+1		

Probability of a cryptocurrency to be sorted in the respective portfolio after rebalancing. The diagonal signifies no change in portfolios after rebalancing. The transition matrix is calculated from single sorts by the reversal effect.

The next important characteristic is the 3-week momentum. Unlike the market value, again a much higher variation is obtained including a clearly U-shaped diagonal. The largest values with around 75 % are found for the lowest and highest portfolio. This means an investor would need to change around 25 % of its asset when rebalancing the portfolio daily. Transitions from the highest to the lowest portfolio are rare with around 2 %, and vice versa. This is due to the exclution of the reversal effect which capatured most of the transitions.

Table 13

Mom3w		Low	2	3	4	High
Period t	Low	0.72	0.18	0.05	0.03	0.02
	2	0.18	0.53	0.21	0.06	0.02
	3	0.04	0.21	0.50	0.20	0.05
	4	0.03	0.05	0.20	0.56	0.16
	High	0.02	0.02	0.03	0.16	0.77
				Period t+1		

Probability of a cryptocurrency to be sorted in the respective portfolio after rebalancing. The diagonal signifies no change in portfolios after rebalancing. The transition matrix is calculated from single sorts by the 3-weeks momentum.

In summary the findings show especially steady market value related characteristics, due to the high levels of inproportionality in the market. The high jumps within the reversal quantiles are expected by construction, whereas the high and low portfolio for the 3-weeks momentum shows reasonable results. However, as mentioned in the beginning of this chapter, the transition matrices show the levels of fluctuation within the characteristics and can only be used as a proxy for expected transaction costs when implementing a strategy.

5 Conclusion

In the previous sections we provided insights into the cross-section of cryptocurrency risk and return. We calculated around 40 characteristics out of purely market-based data for 1200 currencies. Referring back to our research question, commonly studied characteristics from a broad variety of asset classes can be found in cryptocurrencies. In the cross-section of returns, we find high exposure to reversal characteristics. This finding is not in line with most of the literature, where a momentum is often observed (only Shen et al. (2020) and Glas (2019) to the best of our knowledge introduce a reversal to their factor models).[36] We find momentum only in value-weighted portfolios, which have heavy exposure to just a handful of cryptocurrencies. Nevertheless, we do see a low price and low volume effect in cryptocurrencies. Both are, despite the reversal, the strongest characteristics in equally-weighted portfolio returns. We further find, in line with financial literature, a low skewness effect, although only creating half of the average returns of low price and low volume characteristics. The kurtosis is unexpectedly negatively related to returns. This is not supported by financial literature, even if publications rarely exceed the third central moment. However, for the portfolio volatility, size and market beta matter as well as common risk measures such as the return volatility or the idiosyncratic risk. Nevertheless, an inverse relation, i. e. lower risk and higher returns can not be found in cryptocurrencies.

All in all, cryptocurrencies are still lacking a commonly accepted factor model. Our results can help to determine what characteristics are applicable to the new asset class. Further, researchers are still looking for a suitable value factor. The commonly known book-to-market ratio from the equity market is not suitable due to missing book values. So far, trials to proxy the latter using blockchain fundamentals like the hash-rate or block-length mostly fail significance.[37] However, despite the poor data availability for such fundamentals for a large cross-section, different blockchain mechanisms (e. g. cryptocurrencies with own/token on a blockchain or different hashing algorithms) complicate research in that field.

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