

Erasmus University Rotterdam

Erasmus School of Economics

**Cryptocurrency market factors: Evidence from the cross-section of 417
cryptocurrencies**

Name student: Albert Krištof

Student ID number: 507365

Supervisor: Simon Mayer

Second assessor: Jan Lemmen

Date final version: 21-01-2020

*The content of this thesis is the sole responsibility of the author and does not reflect the view
of either Erasmus School of Economics or Erasmus University.*

Contents

1	Introduction	2
2	Data	2
3	Examined factors	3
3.1	Size	3
3.2	Volume	4
3.3	Momentum	5
4	Cross-sectional results	6
4.1	One-factor model	9
4.2	Two-factor models	10
4.3	Three-factor model	19
5	Three-factor model risk premia	21
6	Conclusion	22
7	Appendix	23
7.1	Data - Details	23
7.2	Methodology	26

1 Introduction

This thesis focuses on the behaviour of returns of cryptocurrencies. While "cryptos" other than Bitcoin emerged as an asset class only recently, they have already managed to attract attention of both institutional and retail investors to an extent that led to a public "crypto" mania in the fall of 2017. Even though the initial hype has ceased and prices deflated from their all-time-highs, it is important to examine the behaviour of cryptocurrency returns in the light of evidence from the stock market to assess whether participants in the cryptocurrency market follow the same behavioral patterns as stock market participants. Our work in principle follows on the work of Liu, Tsyvinski, and Wu (2019).

We inspect a set of market factors observed in the stock market, namely size, volume, and momentum, and test whether such factors exist in the cryptocurrency return data. We first construct sorted portfolios of cryptocurrencies based on cryptocurrency size, volume, and past returns. Next, to proxy for market factors, we develop a long-short strategy for each set of portfolios, that goes long the top performing portfolio and short the worst performing portfolio. We find statistically significant long-short strategies for size and volume factors, and also for momentum among high volume cryptocurrencies and large market capitalisation cryptocurrencies.

After identifying the significant long-short strategies, we proceed to cross-sectionally explain the returns of these strategies and corresponding portfolios. We test the explanatory power of 1 One-factor model, 5 Two-factor models, and 1 Three-factor model. Our independent variables include CMKT - a cryptocurrency market factor; CSMB - a cryptocurrency size factor; CMOM - a cryptocurrency momentum factor; BTC_ret - the return of Bitcoin; and, a novelty of this paper, two variables relating to cryptocurrency hash rate, BTCHR_change - a change in bitcoin hash rate; and CHR - a value weighted change in hash rate composed of hash rate data for 17 cryptocurrencies in our sample. The data in our sample show that CSMB factor has got the highest explanatory power regarding returns of long-short strategies and sorted portfolios. On the other hand, CMKT factor does a poor job in explaining variation in returns, and we cannot conclude that our hash rate factors help in explaining returns of cryptocurrencies either. Overall, we report that the largest portion of variation in returns is captured by a Three-factor model consisting of CMKT, CSMB and CMOM, a result in line with Liu et al. (2019). In the last section of this paper, we look at the risk premia relating to the cryptocurrency Three-factor model. Our findings show support for risk premia for market exposure, size and momentum.

As the literature on cryptocurrency asset-pricing is scarce, this paper contributes to the field of research by providing further evidence that statistically significant long-short strategies exist in cryptocurrency data. Moreover, as we require each coin in the sample to have a median weekly trading volume larger or equal to \$100K, we believe our findings are also of practical nature.

2 Data

The data we use are daily cryptocurrency prices, market capitalisation, trading volume, and hash rates. Prices, market capitalisation and trading volume were retrieved from Coinmarketcap.com, an aggregator of cryptocurrency data across the most important exchanges. Data on hash rates were collected from bitinfocharts.com, a provider of cryptocurrency hash rates and other cryptocurrency data. We initially collect prices, market capitalisations and trading volume for

Table 1: **Panel Summary** This table reports weekly mean and median trading volume and market capitalisation for each year in our panel. The column on the very right reports the number of distinct cryptocurrencies in our sample per year.

Year	Trading Volume		Market Capitalisation		Distinct coins per year
	<i>Mean</i>	<i>Median</i>	<i>Mean</i>	<i>Median</i>	<i>N</i>
2017	46 989 772	904 253	1 114 647 844	38 096 592	199
2018	41 705 510	1 196 941	843 594 047	30 275 372	417
2019	79 071 435	581 879	449 518 240	9 927 764	416

2310 cryptocurrencies, and reduce the sample subject to the following conditions:

1. Keep coins with median weekly trading volume larger or equal to \$100K
2. Keep coins with at least 51 weekly observations between 01/01/2017 and 28/07/2019

Using these criteria, we end up with 417 distinct cryptocurrencies, and conduct the analysis at the time period between 01/01/2017 and 28/07/2019. Table 1 presents the descriptive statistics of our sample. We can clearly see that the mean trading volume increased from 2017 to 2019, and that market capitalisations decreased from 2017 to 2019, a phenomenon one would expect to occur after a big public hype. While the market capitalisations decreased from 2017 to 2019, the trading volume increased, and so did the number of coins in our sample, suggesting a larger activity on the market. To see a detailed list of cryptocurrencies in our sample, the number of coins per each month of our sample period, and the methodology used to convert daily data to weekly data refer to the Appendix (Section 7).

3 Examined factors

As we hypothesize that cryptocurrency market data may uncover return predicting patterns other than the market index itself, we analyze factors constructible solely based on market information. In our case, that information includes market capitalisation, trading volume and price. We hence examine the effect of size, trading volume and price momentum ¹.

3.1 Size

To analyze the effect of cryptocurrency size, we use two measures of market capitalisation. Firstly, we use the average market capitalisation in the formation week, and secondly, we use the last day of week market capitalisation. Coins are allocated according to the market cap measure into quintile value-weighted portfolios each week, and returns of these portfolios are then measured over the subsequent week. We further construct a zero-net-investment strategy buying the biggest coins (5th quintile) and selling the smallest coins (1st quintile), this portfolio serves as a size factor.

¹The analysis presented in the paper uses quintile portfolios. However, to check the robustness of our results, we also construct factors based on terciles and deciles. The results hold even when we use tercile and decile portfolios.

Table 2: **Size factors** This table reports mean weekly excess returns on 5 size value-weighted portfolios. Cryptocurrencies are allocated to portfolios at the end of each week based on their size, and the return of portfolios in the following week is measured. T-statistics reported in parentheses; *, **, *** denote significance at 10%, 5% and 1% confidence intervals.

Size	1 Small	2	3	4	5 Big	5-1 Big-Small
avg_mktcap	0,118*** (3,306)	0,056*** (3,102)	0,043** (2,408)	0,047** (2,319)	0,032** (2,021)	-0,086*** (-2,811)
mktcap_7	0,118*** (3,334)	0,055*** (2,972)	0,046** (2,529)	0,045** (2,228)	0,032** (2,060)	-0,086*** (-2,802)

Table 2 suggests that small coins perform on weekly basis on average better than large capitalisation coins. The return of the 5-1 ("Big-Small") portfolio is -8,6 percent per week for both of our market capitalisation measures. The returns of quintile portfolios are almost identical for both size measures. The portfolio of smallest cryptocurrencies on average returns 11,8 percent per week, whereas the portfolio of the largest cryptos returns 3,2 percent, using both average market cap and last day of week market cap.

The results are highly statistically significant and are in line with Liu et al. (2019) who also find a negative return on a 5-1 size value-weighted portfolio, using a last day of week market cap as a measure of market capitalisation. Their average weekly return is, however, somewhat smaller, -3,4 percent per week.

3.2 Volume

Next, we examine the role of trading volume and its ability to predict returns among cryptocurrencies. We consider the dollar trading volume as a measure of volume in the cryptocurrency market. Liu et al. (2019) find that coins with low formation week volume perform on average on weekly basis better than high volume coins. The data in our sample supports this finding. We further provide evidence that 2, 3, 4 and 5 week trading volume also leads to statistically significant returns one week after the formation period. Table 3 presents the results.

The effect of past trading volume is the most pronounced when we use 1 week trading volume. The 5-1 ("High-Low") strategy results in a weekly average return of -8,3 percent, putting forward that low 1 week volume coins experience higher returns than high volume coins. We obtain similar results for 2, 3, 4 and 5 week volume. The returns for 5-1 strategy decrease with longer formation period, -7,9 percent for 2 week trading volume through -7,4 percent for 5 week volume. Similarly, t-statistics of these strategies decrease with the length of the formation period. Nevertheless, results for all formation periods are statistically significant on at least 5% level; 1, 2, 3 week trading volume 5-1 strategies being significant at 1% level. Out of all considered portfolios, the highest return, 11,9 percent, is produced by the portfolio of coins with the lowest 1 week trading volume. The returns of this and all other formation period low volume portfolios are significant at 1% level.

Table 3: **Volume factors** This table reports weekly excess returns on 5 volume value-weighted portfolios. Cryptocurrencies are allocated to portfolios at the end of each week based on their past n week average dollar trading volume, and the return of portfolios in the following week is measured. T-statistics reported in parentheses; *, **, *** denote significance at 10%, 5% and 1% confidence intervals.

Trading Volume	1 Low	2	3	4	5 High	5-1 High-Low
1 week	0,119*** (3,462)	0,051*** (2,988)	0,047** (2,497)	0,039** (2,117)	0,036** (2,050)	-0,083*** (-2,792)
2 week	0,113*** (3,340)	0,050*** (2,951)	0,042** (2,326)	0,047** (2,252)	0,034** (2,047)	-0,079*** (-2,716)
3 week	0,111*** (3,328)	0,051*** (3,004)	0,043** (2,287)	0,046** (2,273)	0,033** (2,015)	-0,078*** (-2,703)
4 week	0,113*** (3,289)	0,054*** (3,208)	0,042** (2,212)	0,044** (2,197)	0,035** (2,148)	-0,078** (-2,607)
5 week	0,113*** (3,307)	0,052*** (3,012)	0,043** (2,406)	0,038* (1,969)	0,039** (2,252)	-0,074** (-2,428)

3.3 Momentum

While analyzing momentum effect in our sample, we look at 1, 2, 3, 4 and 5 week formation period as a determinant of the following week returns. To incorporate more information while constructing quintile portfolios, we look at, apart from pure price momentum, at additional two strategies - volume-based momentum, and size-based momentum. We shall first present our findings for pure price momentum.

On the contrary to Liu et al. (2019), we do not find evidence supporting statistically significant existence of a zero-net-investment momentum strategy in our sample for any formation week period. The data, however, point out to highly statistically significant past loser and past winner portfolios. The loser portfolios generate between 4,8 (1 week momentum) and 6 percent (4 week momentum) return (significant at 1% level). Winner portfolios produce returns between 7,2 (1 week momentum) and 8,3 percent (2 & 5 week momentum), all significant at 5% level.

As we cannot find support for pure price momentum, we try to further break down momentum portfolios based on past trading volume and size. We therefore first split coins into 3 tercile portfolios according to past trading volume (size), and then split each of these portfolios into 5 momentum portfolios. We thus end up with 15 portfolios for both volume-momentum and size-momentum. We further construct a long-short momentum strategy for each volume (size) group, e.g. buying low volume winners and selling low volume losers, and a long-short strategy for each momentum quintile, e.g. buying high volume winners and selling low volume winners. The strategy 5-1 High-Low in Tables 5 & 7 buys high volume winners and low volume losers, and sells high volume losers and low volume winners.

Our attention will be pointed towards long-short portfolios only. Specifically, we focus on strategies that buy winners and sell losers in each trading volume or size tercile. For example,

Table 4: **Pure price momentum** This table reports weekly excess returns on 5 momentum value weighted portfolios. Cryptocurrencies are allocated to portfolios at the end of each week based on their n week return, and the return of portfolios in the following week is measured. T-statistics reported in parentheses; *, **, *** denote significance at 10%, 5% and 1% confidence intervals.

	1	2	3	4	5	5-1
Momentum	Losers				Winners	Win-Los
1 week	0,048*** (2,736)	0,040** (2,301)	0,052*** (2,969)	0,071*** (3,007)	0,072** (2,472)	0,024 (1,039)
2 week	0,050*** (2,825)	0,042** (2,444)	0,046** (2,601)	0,060*** (3,109)	0,083** (2,407)	0,033 (1,116)
3 week	0,050*** (2,854)	0,048*** (2,710)	0,056*** (2,771)	0,043*** (2,615)	0,082** (2,338)	0,032 (1,045)
4 week	0,060*** (3,042)	0,046*** (2,658)	0,049*** (2,690)	0,045** (2,426)	0,080** (2,455)	0,019 (0,663)
5 week	0,059*** (3,175)	0,042** (2,469)	0,051*** (2,858)	0,045** (2,504)	0,083** (2,397)	0,025 (0,837)

a strategy in the top left corner of the Table 5 buys low volume 1 week winners and sells low volume 1 week losers, generating statistically insignificant -21,9 percent weekly return. We only find statistical support for momentum when we buy high volume winners and sell high volume losers formed on 2 week trading volume, the results for the 5 quintile portfolios belonging to this strategy are reported in Table 6. This finding suggests that incorporating more information during momentum portfolio construction can lead to statistically significant strategies as market participants may deem past trading volume a proxy for visibility and liquidity of the coin.

The last momentum type analyzed is size-based momentum, the results reported in Table 7. Similarly to volume-based momentum, we split coins each week into 15 portfolios based on size and momentum, and construct long-short strategies. Likewise to volume-momentum, strategy 5-1 Big-Small buys high market cap winners and low market cap losers, and sells high market cap losers and low market cap winners. Out of all considered strategies, we only find momentum among high 3 week average market cap coins - this strategy results in a weekly excess return of 3,1 percent, significant at 10% level (results for the quintile portfolios relating to this strategy can be found in Table 8). A longer period market capitalisation may serve as a proxy for the visibility of the coin, and market participants therefore buy primarily coins with such an attribute, driving the return momentum.

4 Cross-sectional results

In this section, we attempt to examine how significant zero-net-investment strategies found in the section 3 fare cross-sectionally vis-à-vis cryptocurrency market factors. We try to explain the returns of long-short strategies using a cryptocurrency market factor CMKT, cryptocurrency size factor CSMB and cryptocurrency momentum factor CMOM. The novelty of this paper is our attempt to use returns of Bitcoin `BTC_ret`, and the change in Bitcoin hash rate `BTCHR_change`

Table 5: **Volume-based momentum** This table reports weekly excess returns on zero-net-investment value weighted portfolios constructed on volume momentum. Cryptocurrencies are allocated to 3 tercile portfolios based on their past n week average volume, and each of these portfolios is further split into 5 momentum portfolios. Subsequently, the return of portfolios in the following week is measured. Reported in this table are portfolios that buy winners and sell losers in each trading volume tercile. The last column of the table, 5-1, is long high volume winners and low volume losers, and short high volume losers and low volume winners. T-statistics reported in parentheses; *, **, *** denote significance at 10%, 5% and 1% confidence intervals.

Volume-Momentum	1 Low	2	3 High	High-Low
1 week	0,219	-0,009	0,017	-0,202
5-1	(1,114)	(-0,486)	(1,273)	(-1,024)
2 week	0,101	0,042	0,031**	-0,070
5-1	(1,101)	(1,383)	(2,158)	(-0,777)
3 week	0,066	0,029	0,017	-0,049
5-1	(0,897)	(1,220)	(1,068)	(-0,667)
4 week	0,152	0,014	-0,018	-0,170
5-1	(1,235)	(0,775)	(-0,697)	(-1,354)
5 week	0,157	0,017	0,001	-0,156
5-1	(1,601)	(0,714)	(0,081)	(-1,597)

Table 6: **2 Week Volume-Momentum - Large Market Cap coins** This table reports mean weekly excess returns on 5 volume-momentum value weighted portfolios. We specifically consider 2 Week Volume-Momentum among High Volume coins since we found a significant long-short strategy for this formation period and volume group (see Table 5). Cryptocurrencies are allocated to portfolios at the end of each week based on their volume and momentum, and the return of portfolios in the following week is measured. T-statistics reported in parentheses; *, **, *** denote significance at 10%, 5% and 1% confidence intervals.

VolMom_2 week High Volume coins	1	2	3	4	5	5-1
mean return	0,007	0,031*	0,040*	0,066**	0,038*	0,031**
	(0,435)	(1,690)	(2,068)	(2,526)	(1,957)	(2,158)

Table 7: **Size-based momentum** This table reports weekly excess returns on zero-net-investment value weighted portfolios constructed on size momentum. Cryptocurrencies are allocated to 3 tercile portfolios based on their past n week average market capitalisation, and each of these portfolios is further split into 5 momentum portfolios. Subsequently, the return of portfolios in the following week is measured. Reported in this table are portfolios that buy winners and sell losers in each size tercile. The last column of the table, 5-1, is long large cap winners and small cap losers, and short large cap losers and small cap winners. T-statistics reported in parentheses; *, **, *** denote significance at 10%, 5% and 1% confidence intervals.

	1	2	3	
Size-Momentum	Small		Big	Big-Small
1 week	0,090	-0,009	0,012	0,078
5-1	(0,990)	(-0,644)	(0,709)	(0,848)
2 week	0,062	-0,005	0,026	0,036
5-1	(1,106)	(-0,236)	(1,555)	(0,656)
3 week	0,049	0,014	0,031*	0,018
5-1	(0,852)	(0,692)	(1,773)	(0,309)
4 week	0,090	-0,015	0,001	0,089
5-1	(1,175)	(-0,590)	(0,063)	(1,141)
5 week	0,068	-0,003	0,002	0,065
5-1	(1,030)	(-0,130)	(0,142)	(0,972)

Table 8: **3 Week Size-Momentum - Large Market Cap coins** This table reports mean weekly excess returns on 5 size-momentum value weighted portfolios. We specifically consider 3 Week Size-Momentum among Large Cap coins since we found a significant long-short strategy for this formation period and size group (see Table 7). Cryptocurrencies are allocated to portfolios at the end of each week based on their size and momentum, and the return of portfolios in the following week is measured. T-statistics reported in parentheses; *, **, *** denote significance at 10%, 5% and 1% confidence intervals.

SizeMom_3 week Large Cap coins	1	2	3	4	5	5-1
mean return	0,015	0,027	0,038**	0,050**	0,046**	0,031*
	(0,906)	(1,601)	(2,001)	(2,371)	(2,067)	(1,773)

as additional factors with the potential to explain returns of our significant long-short strategies. Lastly, we collect hash rate data for 17 coins in our sample and construct a value weighted index of change in hash rates, CHR, which we use as our last cryptocurrency market factor.

We first derive a one-factor model using a cryptocurrency market index CMKT. Subsequently, we develop two-factor models using a combination of CMKT and one of the constructed cryptocurrency factors. And finally, we take a three-factor model using CMKT, CSMB and CMOM, and test its explanatory power. Our main focus is on the R^2 measure of each model.

4.1 One-factor model

The one-factor model does not do a good job in explaining returns of our long-short strategies. As can be seen in the Table 9, the average R^2 across all portfolios of a given strategy ranges from 1,3 percent to 1,9 percent. Alphas of all strategies are significant, and betas of only a handful of portfolios are significant. When we consider the CMKT betas that are significant, we notice that their value is positive. We can hence conclude that the performance of some of our examined strategies to some extent moves with the market.

Table 9: **One-Factor model**

$$R_i - R_f = \alpha_i + \beta_{CMKT}^i * CMKT + \epsilon_i$$

This table presents results of regressions of nine significant long-short strategies outlined in the Section 3 on the market factor CMKT. T-statistics reported in parentheses; *, **, *** denote significance at 10%, 5% and 1% confidence intervals.

		1	2	3	4	5	5-1	\bar{R}^2
avg_mkt_cap	α	0,101*** (2,744)	0,048** (2,557)	0,035* (1,885)	0,038* (1,806)	0,026 (1,606)	-0,075** (-2,354)	0,019
	β_{CMKT}	0,280* (1,757)	0,139* (1,706)	0,137* (1,699)	0,153* (1,669)	0,091 (1,304)	-0,189 (-1,367)	
	R^2	0,023	0,022	0,021	0,021	0,013	0,014	
mkt_cap.7	α	0,102*** (2,785)	0,046** (2,409)	0,037* (1,975)	0,036* (1,732)	0,027* (1,657)	-0,075** (-2,358)	0,019
	β_{CMKT}	0,270* (1,698)	0,149* (1,803)	0,147* (1,818)	0,146 (1,607)	0,089 (1,252)	-0,181 (-1,313)	
	R^2	0,021	0,024	0,024	0,019	0,012	0,013	
Volume_1 week	α	0,102*** (2,884)	0,043** (2,430)	0,038** (1,984)	0,032 (1,654)	0,029 (1,593)	-0,073** (-2,375)	0,019
	β_{CMKT}	0,278* (1,808)	0,137* (1,781)	0,138 (1,646)	0,124 (1,485)	0,117 (1,468)	-0,161 (-1,207)	
	R^2	0,024	0,023	0,020	0,016	0,016	0,011	
Volume_2 week	α	0,098*** (2,815)	0,041** (2,362)	0,034* (1,841)	0,037* (1,715)	0,029* (1,699)	-0,069** (-2,292)	0,018
	β_{CMKT}	0,241 (1,585)	0,146* (1,921)	0,126 (1,554)	0,166* (1,776)	0,077 (1,033)	-0,163 (-1,247)	
	R^2	0,019	0,027	0,018	0,023	0,008	0,012	
Volume_3 week	α	0,097*** (2,805)	0,042** (2,397)	0,035* (1,834)	0,036* (1,762)	0,027 (1,602)	-0,070** (-2,318)	0,018
	β_{CMKT}	0,237 (1,581)	0,152** (1,997)	0,119 (1,421)	0,149* (1,665)	0,095 (1,299)	-0,142 (-1,085)	
	R^2	0,019	0,029	0,015	0,021	0,013	0,009	

Table 9: (Continued)

		1	2	3	4	5	5-1	$\overline{R^2}$
Volume_4 week	α	0,097*** (2,742)	0,045** (2,604)	0,035* (1,804)	0,035* (1,686)	0,029* (1,714)	-0,068** (-2,201)	0,018
	β_{CMKT}	0,259* (1,690)	0,147* (1,952)	0,106 (1,249)	0,149* (1,672)	0,100 (1,367)	-0,159 (-1,186)	
	R^2	0,021	0,028	0,012	0,021	0,014	0,011	
	α	0,097*** (2,762)	0,044** (2,454)	0,036* (1,919)	0,031 (1,553)	0,032* (1,782)	-0,065** (-2,069)	
β_{CMKT}	0,257* (1,679)	0,137* (1,773)	0,125 (1,548)	0,113 (1,312)	0,118 (1,495)	-0,139 (-1,020)		
R^2	0,021	0,023	0,018	0,013	0,017	0,008		
α	0,005 (0,316)	0,022 (1,160)	0,029 (1,488)	0,054** (2,011)	0,034* (1,690)	-0,060 (-0,635)	0,013	
β_{CMKT}	0,028 (0,384)	0,149* (1,814)	0,170* (1,977)	0,193 (1,654)	0,064 (0,726)	-0,172 (-0,421)		
R^2	0,001	0,024	0,029	0,020	0,004	0,001		
α	0,013 (0,769)	0,020 (1,177)	0,031 (1,544)	0,037* (1,711)	0,042* (1,821)	0,007 (0,123)		0,013
β_{CMKT}	0,029 (0,381)	0,104 (1,396)	0,127 (1,479)	0,215** (2,293)	0,063 (0,625)	0,170 (0,656)		
R^2	0,001	0,015	0,016	0,038	0,003	0,003		

4.2 Two-factor models

Two-factor models explain cross-sectional returns of all strategies comparatively better than the one-factor model. Especially, when we employ CSMB or CMOM, the average R^2 of the models goes substantially higher in comparison to the sole CMKT.

Table 10 illustrates the regression results for CMKT and CSMB factor model. The average R^2 ranges from 10,3 percent for 3 week Size-Momentum among Large Cap coins, to 31,8 percent for the last day of week market capitalisation (mkt_cap.7). The model does extremely well in explaining the returns of the lowest quintile portfolios of all strategies (portfolio 1) except for the Volume Momentum and the Size Momentum. Not taking into account Volume Momentum and Size Momentum, the lowest R^2 for any portfolio 1 is 72,3 percent (1 Week Volume), and the highest is 76,7 percent (Last day of week market capitalisation). R^2 for 5-1 strategies varies from 10,3 percent for Size Momentum to 96,5 percent for last week average market capitalisation (avg_mkt_cap). CSMB betas for all 5-1 strategies are highly significant. While CSMB betas are significant even for portfolios 2 and 3, the model can tell little about overall returns of portfolios 2 through 5 as the R^2 for these portfolios does not exceed 10 percent. Furthermore, the significance of alphas is very much reduced.

Table 11 provides an insight into the performance of the second two-factor model, that uses CMKT and CMOM as explanatory variables. The average R^2 of the model is slightly lower than R^2 of the previous model. However, the CMKT CMOM model still performs much better than the one-factor model.

The average R^2 ranges from 11,4 percent for Size Momentum, to 25,6 percent for Last week average market capitalisation. The model, again, can explain returns of portfolios 1 and portfolios 5-1, however, R^2 measures for portfolios 2 through 5 remain low. When we consider

portfolios 1, the model achieves R^2 of 61 percent for Average last week market capitalisation, and achieves a similar R^2 for other factors, too, except for the two momentum factors. Compared to CSMB model, the CMOM model increases R^2 for both momentum portfolio 5 strategies. Overall, the highest R^2 for a 5-1 strategy is 75,2 percent for Average last week market capitalisation, and the lowest 47,1 percent for Size Momentum. Compared to CSMB, CMOM does not decrease the significance of alphas to the same extent as CSMB does.

Table 10: **Two-Factor model A**

$$R_i - R_f = \alpha_i + \beta_{CMKT}^i * CMKT + \beta_{CSMB}^i * CSMB + \epsilon_i$$

This table presents results of regressions of nine significant long-short strategies outlined in the Section 3 on the market cryptocurrency market factor CMKT and cryptocurrency market size factor CSMB. T-statistics reported in parentheses; *, **, *** denote significance at 10%, 5% and 1% confidence intervals.

		1	2	3	4	5	5-1	$\overline{R^2}$
avg_mkt_cap	α	0,019 (1,014)	0,039** (2,078)	0,023 (1,257)	0,032 (1,471)	0,024 (1,477)	0,005 (0,861)	0,317
	β_{CMKT}	0,102 (1,267)	0,120 (1,487)	0,112 (1,411)	0,139 (1,512)	0,088 (1,248)	-0,014 (-0,532)	
	β_{CSMB}	1,556*** (19,774)	0,162** (2,055)	0,224*** (2,905)	0,122 (1,361)	0,027 (0,394)	-1,529*** (-59,636)	
	R^2	0,755	0,052	0,081	0,034	0,014	0,965	
	α	0,020 (1,084)	0,037* (1,939)	0,026 (1,389)	0,030 (1,401)	0,025 (1,495)	0,005 (0,824)	
β_{CMKT}	0,091 (1,162)	0,130 (1,588)	0,123 (1,550)	0,132 (1,451)	0,084 (1,181)	-0,007 (-0,251)		
β_{CSMB}	1,564*** (20,453)	0,161** (2,013)	0,207*** (2,674)	0,120 (1,352)	0,038 (0,539)	-1,527*** (-58,974)		
R^2	0,767	0,053	0,075	0,033	0,014	0,964		
Vol_1 week	α	0,025 (1,299)	0,032* (1,812)	0,030 (1,520)	0,023 (1,197)	0,028 (1,489)	0,003 (0,342)	0,307
	β_{CMKT}	0,110 (1,333)	0,113 (1,499)	0,119 (1,431)	0,106 (1,270)	0,115 (1,423)	0,004 (0,120)	
	β_{CSMB}	1,465*** (18,165)	0,210*** (2,857)	0,163** (2,009)	0,162** (1,995)	0,022 (0,277)	-1,443*** (-40,544)	
	R^2	0,723	0,081	0,049	0,045	0,017	0,927	
	Vol_2 week	α	0,022 (1,164)	0,033* (1,846)	0,025 (1,335)	0,029 (1,322)	0,027 (1,541)	
β_{CMKT}		0,073 (0,923)	0,127* (1,686)	0,106 (1,317)	0,149 (1,591)	0,073 (0,967)	0,000 (-0,011)	
β_{CSMB}		1,463*** (18,855)	0,167** (2,269)	0,176** (2,243)	0,152* (1,667)	0,038 (0,512)	-1,425*** (-42,259)	
R^2		0,736	0,064	0,054	0,044	0,010	0,932	
Vol_3 week		α	0,021 (1,142)	0,034* (1,905)	0,025 (1,269)	0,030 (1,438)	0,025 (1,465)	0,004 (0,515)
	β_{CMKT}	0,072 (0,915)	0,134* (1,773)	0,096 (1,157)	0,136 (1,513)	0,092 (1,239)	0,020 (0,543)	
	β_{CSMB}	1,446*** (18,955)	0,157** (2,135)	0,206** (2,557)	0,115 (1,311)	0,031 (0,430)	-1,415*** (-39,479)	
	R^2	0,738	0,062	0,062	0,033	0,014	0,923	

Table 10: (Continued)

		1	2	3	4	5	5-1	$\overline{R^2}$
Vol_4 week	α	0,019 (1,028)	0,038** (2,145)	0,024 (1,225)	0,029 (1,396)	0,027 (1,582)	0,008 (0,902)	0,303
	β_{CMKT}	0,090 (1,121)	0,131* (1,744)	0,081 (0,975)	0,137 (1,534)	0,097 (1,311)	0,007 (0,178)	
	β_{CSMB}	1,476*** (18,774)	0,142* (1,940)	0,214*** (2,637)	0,101 (1,158)	0,028 (0,388)	-1,448*** (-38,938)	
	R^2	0,735	0,055	0,061	0,031	0,015	0,921	
	α	0,020 (1,065)	0,035* (1,973)	0,026 (1,377)	0,025 (1,213)	0,032* (1,699)	0,012 (1,148)	
β_{CMKT}	0,088 (1,101)	0,119 (1,553)	0,103 (1,295)	0,100 (1,151)	0,116 (1,463)	0,028 (0,645)		
β_{CSMB}	1,474*** (18,833)	0,155** (2,070)	0,189** (2,433)	0,120 (1,416)	0,012 (0,155)	-1,462*** (-34,802)		
R^2	0,736	0,054	0,060	0,028	0,017	0,903		
VolMom_2 week High Vol coins	α	0,005 (0,306)	0,019 (0,985)	0,031 (1,499)	0,050* (1,813)	0,024 (1,199)	0,153*** (3,334)	0,149
	β_{CMKT}	0,028 (0,380)	0,143* (1,725)	0,172** (1,984)	0,185 (1,566)	0,043 (0,489)	0,292 (1,490)	
	β_{CSMB}	0,000 (0,006)	0,054 (0,666)	-0,020 (-0,237)	0,076 (0,665)	0,184** (2,170)	-4,056*** (-21,259)	
	R^2	0,001	0,028	0,029	0,024	0,039	0,776	
	SizeMom_3 week Large Cap coins	α	0,015 (0,845)	0,021 (1,161)	0,028 (1,380)	0,038* (1,709)	0,028 (1,196)	
β_{CMKT}		0,033 (0,428)	0,105 (1,391)	0,122 (1,403)	0,217** (2,294)	0,031 (0,316)	-0,060 (-0,320)	
β_{CSMB}		-0,033 (-0,448)	-0,006 (-0,075)	0,047 (0,562)	-0,019 (-0,207)	0,278*** (2,891)	2,014*** (10,925)	
R^2		0,003	0,015	0,019	0,039	0,063	0,478	

Table 11: **Two-Factor model B**

$$R_i - R_f = \alpha_i + \beta_{CMKT}^i * CMKT + \beta_{CMOM}^i * CMOM + \epsilon_i$$

This table presents results of regressions of nine significant long-short strategies outlined in the Section 3 on the market cryptocurrency market factor CMKT and cryptocurrency market momentum factor CMOM. T-statistics reported in parentheses; *, **, *** denote significance at 10%, 5% and 1% confidence intervals.

		1	2	3	4	5	5-1	$\overline{R^2}$
avg_mkt_cap	α	0,070*** (2,979)	0,045** (2,390)	0,031* (1,670)	0,035 (1,654)	0,025 (1,532)	-0,045*** (-2,788)	0,256
	β_{CMKT}	0,207** (2,041)	0,131 (1,622)	0,127 (1,598)	0,145 (1,593)	0,089 (1,265)	-0,118* (-1,693)	
	β_{CMOM}	1,350*** (14,045)	0,147* (1,914)	0,197*** (2,621)	0,142 (1,647)	0,045 (0,677)	-1,305*** (-19,758)	
	R^2	0,610	0,048	0,070	0,041	0,016	0,752	

Table 11: (Continued)

		1	2	3	4	5	5-1	$\overline{R^2}$
mkt_cap_7	α	0,071*** (3,040)	0,042** (2,244)	0,033* (1,780)	0,033 (1,569)	0,026 (1,565)	-0,045*** (-2,716)	0,252
	β_{CMKT}	0,197* (1,947)	0,141* (1,721)	0,137* (1,725)	0,138 (1,526)	0,086 (1,204)	-0,111 (-1,540)	
	β_{CMOM}	1,345*** (14,024)	0,145* (1,871)	0,174** (2,307)	0,154* (1,796)	0,059 (0,877)	-1,286*** (-18,765)	
	R^2	0,609	0,049	0,063	0,043	0,018	0,732	
	α	0,072*** (3,151)	0,040** (2,266)	0,035* (1,806)	0,028 (1,469)	0,028 (1,493)	-0,045*** (-2,616)	
β_{CMKT}	0,208** (2,089)	0,129* (1,700)	0,129 (1,559)	0,115 (1,394)	0,113 (1,415)	-0,095 (-1,277)		
β_{CMOM}	1,281*** (13,564)	0,133* (1,843)	0,159** (2,028)	0,165** (2,107)	0,075 (0,984)	-1,207*** (-17,106)		
R^2	0,594	0,048	0,050	0,049	0,023	0,694		
α	0,069*** (3,076)	0,039** (2,214)	0,031* (1,665)	0,033 (1,532)	0,028 (1,611)	-0,041** (-2,586)	0,249	
β_{CMKT}	0,171* (1,763)	0,140* (1,847)	0,118 (1,466)	0,156* (1,689)	0,074 (0,988)	-0,097 (-1,411)		
β_{CMOM}	1,279*** (13,888)	0,115 (1,602)	0,151** (1,981)	0,183** (2,082)	0,059 (0,828)	-1,220*** (-18,722)		
R^2	0,603	0,046	0,047	0,055	0,013	0,731		
α	0,068*** (3,038)	0,039** (2,240)	0,031 (1,639)	0,033 (1,611)	0,026 (1,511)	-0,042** (-2,541)		0,243
β_{CMKT}	0,169* (1,744)	0,145* (1,920)	0,110 (1,324)	0,142 (1,589)	0,092 (1,251)	-0,077 (-1,067)		
β_{CMOM}	1,254*** (13,659)	0,124* (1,725)	0,179** (2,272)	0,138 (1,625)	0,061 (0,870)	-1,193*** (-17,460)		
R^2	0,595	0,051	0,052	0,040	0,018	0,702		
α	0,067*** (2,966)	0,043** (2,475)	0,031 (1,599)	0,032 (1,542)	0,028 (1,634)	-0,039** (-2,397)	0,247	
β_{CMKT}	0,189* (1,929)	0,142* (1,887)	0,095 (1,145)	0,142 (1,599)	0,098 (1,325)	-0,091 (-1,286)		
β_{CMOM}	1,294*** (13,936)	0,095 (1,325)	0,192** (2,426)	0,129 (1,536)	0,051 (0,732)	-1,243*** (-18,477)		
R^2	0,606	0,041	0,054	0,038	0,018	0,726		
α	0,068*** (2,992)	0,041** (2,305)	0,032* (1,729)	0,028 (1,412)	0,031* (1,711)	-0,036** (-2,079)		0,241
β_{CMKT}	0,187* (1,908)	0,130* (1,697)	0,116 (1,454)	0,107 (1,240)	0,115 (1,458)	-0,072 (-0,945)		
β_{CMOM}	1,288*** (13,872)	0,118 (1,620)	0,167** (2,214)	0,122 (1,496)	0,047 (0,625)	-1,242*** (-17,237)		
R^2	0,603	0,042	0,053	0,029	0,020	0,696		
α	0,007 (0,391)	0,022 (1,158)	0,030 (1,521)	0,051* (1,894)	0,027 (1,388)	0,025 (0,476)	0,150	
β_{CMKT}	0,032 (0,425)	0,149* (1,809)	0,172** (1,992)	0,186 (1,594)	0,046 (0,553)	0,029 (0,125)		
β_{CMOM}	-0,057 (-0,810)	-0,006 (-0,074)	-0,038 (-0,460)	0,129 (1,163)	0,329*** (4,183)	-3,693*** (-16,881)		
R^2	0,006	0,024	0,030	0,030	0,121	0,685		

Table 11: (Continued)

		1	2	3	4	5	5-1	$\overline{R^2}$
	α	0,014 (0,819)	0,021 (1,235)	0,029 (1,465)	0,038* (1,736)	0,033 (1,518)	-0,037 (-0,852)	
SizeMom_3 week Large Cap coins	β_{CMKT}	0,031 (0,410)	0,107 (1,428)	0,124 (1,437)	0,217** (2,304)	0,041 (0,438)	0,064 (0,340)	0,114
	β_{CMOM}	-0,043 (-0,590)	-0,050 (-0,698)	0,060 (0,728)	-0,036 (-0,401)	0,396*** (4,425)	1,935*** (10,766)	
	R^2	0,004	0,018	0,020	0,039	0,133	0,471	

Next, we turn to models that use either the return of Bitcoin or cryptocurrency hash-rates as explanatory variables. First, let us look at Table 12 presents our findings relating to the model that uses CMKT and a weekly bitcoin return (BTC_ret) as explanatory variables.

The model cannot explain much variation in the returns of cryptocurrencies, and does not reduce the significance of alphas across the board. The maximum average R^2 for any of the factors is 2,1 percent, while the lowest average R^2 is 1,8 percent. Furthermore, none of the BTC_ret betas is significant.

Table 13 contains the results for model D obtained by using CMKT and bitcoin has-rate change BTCHR_change as explanatory variables. Model D does a better job than the model C that uses BTC_ret, however, the overall average R^2 of the model D is still low - its highest average R^2 is 3,6 percent, and the lowest R^2 is 2,9 percent. Model D reduces the significance of alphas for portfolios 3 through 5, and some betas of BTCHR_change are significant, however, no clear systematic influence of BTCHR_change can be clearly seen. Moreover, Model D, similarly to model C, does not help in explaining returns of 5-1 portfolios for which alphas remain significant (except for the momentum portfolios).

Figures in the Table 14 show the results for our last two-factor model, Model E, that uses CMKT and CHR, a value-weighted index of hash-rate changes for 18 cryptocurrencies in our sample. Model E, like its two discussed predecessors, achieves only low levels of average R^2 . Out of the three considered models, however, model E produces the highest average R^2 - 4,2 percent for Last day of week market capitalisation. On the other hand, the lowest average R^2 for any factor is 3,8 percent. The model slightly reduces alphas for 5-1 strategies, in comparison to the previous two models. Moreover, betas for CHR are in some instances highly significant. However, only one CHR beta for portfolio 1 is significant, and no CHR beta for the portfolio 5-1 is significant.

CSMB and CMOM apparently provide a good insight into the behaviour of cryptocurrency returns. We cannot, however, conclusively say the same about BTC_ret, BTCHR_change and CHR. Taking into consideration the significance of betas, only CHR could potentially serve as an explanatory variable when assessing cryptocurrency returns. Perhaps collecting data on more hash-rates could provide better results.

Table 12: **Two-Factor model C**

$$R_i - R_f = \alpha_i + \beta_{CMKT}^i * CMKT + \beta_{BTC_{ret}}^i * BTC_{ret} + \epsilon_i$$

This table presents results of regressions of nine significant long-short strategies outlined in the Section 3 on the cryptocurrency market factor $CMKT$ and the weekly return of Bitcoin BTC_{ret} . T-statistics reported in parentheses; *, **, *** denote significance at 10%, 5% and 1% confidence intervals.

		1	2	3	4	5	5-1	$\overline{R^2}$
avg_mkt_cap	α	0,100*** (2,726)	0,048** (2,565)	0,036* (1,915)	0,038* (1,800)	0,026 (1,596)	-0,075** (-2,338)	0,021
	β_{CMKT}	0,246 (1,210)	0,177* (1,701)	0,207** (2,018)	0,158 (1,352)	0,084 (0,934)	-0,163 (-0,923)	
	$\beta_{BTC_{ret}}$	0,093 (0,269)	-0,104 (-0,587)	-0,193 (-1,103)	-0,015 (-0,073)	0,022 (0,141)	-0,072 (-0,238)	
	R^2	0,023	0,024	0,030	0,021	0,013	0,014	
	α	0,102*** (2,770)	0,046** (2,411)	0,037** (2,006)	0,036* (1,724)	0,027 (1,647)	-0,075** (-2,347)	
β_{CMKT}	0,257 (1,265)	0,175* (1,664)	0,218** (2,123)	0,143 (1,234)	0,081 (0,895)	-0,176 (-0,999)		
$\beta_{BTC_{ret}}$	0,036 (0,104)	-0,073 (-0,405)	-0,196 (-1,121)	0,008 (0,039)	0,021 (0,139)	-0,015 (-0,049)		
R^2	0,021	0,025	0,034	0,019	0,012	0,013		
α	0,102*** (2,876)	0,043** (2,440)	0,039** (2,004)	0,032 (1,646)	0,029 (1,576)	-0,073** (-2,379)	0,021	
β_{CMKT}	0,295 (1,504)	0,176* (1,798)	0,194* (1,823)	0,122 (1,142)	0,086 (0,850)	-0,208 (-1,229)		
$\beta_{BTC_{ret}}$	-0,048 (-0,142)	-0,108 (-0,648)	-0,156 (-0,857)	0,006 (0,035)	0,085 (0,488)	0,132 (0,457)		
R^2	0,024	0,027	0,026	0,016	0,018	0,012		
α	0,098*** (2,800)	0,042** (2,402)	0,035* (1,858)	0,037* (1,703)	0,029* (1,688)	-0,069** (-2,280)		0,021
β_{CMKT}	0,225 (1,161)	0,225** (2,331)	0,176* (1,708)	0,151 (1,259)	0,070 (0,730)	-0,155 (-0,928)		
$\beta_{BTC_{ret}}$	0,043 (0,131)	-0,218 (-1,321)	-0,139 (-0,790)	0,044 (0,214)	0,021 (0,128)	-0,023 (-0,079)		
R^2	0,019	0,040	0,023	0,024	0,008	0,012		
α	0,097*** (2,792)	0,042** (2,429)	0,036* (1,847)	0,036* (1,751)	0,027 (1,593)	-0,070** (-2,308)	0,020	
β_{CMKT}	0,232 (1,212)	0,221** (2,283)	0,164 (1,531)	0,140 (1,225)	0,092 (0,979)	-0,140 (-0,841)		
$\beta_{BTC_{ret}}$	0,014 (0,042)	-0,190 (-1,151)	-0,123 (-0,673)	0,025 (0,129)	0,010 (0,062)	-0,004 (-0,014)		
R^2	0,019	0,039	0,018	0,021	0,013	0,009		
α	0,097*** (2,734)	0,046*** (2,621)	0,035* (1,814)	0,034* (1,676)	0,029* (1,706)	-0,068** (-2,196)		0,019
β_{CMKT}	0,275 (1,404)	0,195** (2,033)	0,144 (1,333)	0,138 (1,214)	0,099 (1,061)	-0,175 (-1,026)		
$\beta_{BTC_{ret}}$	-0,043 (-0,130)	-0,133 (-0,810)	-0,105 (-0,572)	0,030 (0,154)	0,002 (0,015)	0,046 (0,157)		
R^2	0,021	0,033	0,014	0,021	0,014	0,011		

Table 12: (Continued)

		1	2	3	4	5	5-1	$\overline{R^2}$
Vol.5 week	α	0,097*** (2,753)	0,044** (2,479)	0,036* (1,936)	0,031 (1,539)	0,032* (1,774)	-0,065** (-2,064)	0,019
	β_{CMKT}	0,267 (1,367)	0,197** (2,008)	0,174* (1,691)	0,091 (0,823)	0,115 (1,146)	-0,152 (-0,872)	
	β_{BTC_ret}	-0,028 (-0,084)	-0,166 (-0,995)	-0,135 (-0,770)	0,063 (0,333)	0,007 (0,041)	0,035 (0,118)	
	R^2	0,021	0,031	0,022	0,014	0,017	0,008	
	α	0,005 (0,320)	0,022 (1,172)	0,030 (1,505)	0,054** (2,003)	0,033* (1,658)	-0,058 (-0,617)	
β_{CMKT}	0,041 (0,434)	0,186* (1,776)	0,221** (2,022)	0,196 (1,315)	-0,039 (-0,349)	0,017 (0,033)		
β_{BTC_ret}	-0,035 (-0,216)	-0,102 (-0,572)	-0,142 (-0,760)	-0,008 (-0,032)	0,283 (1,493)	-0,523 (-0,589)		
R^2	0,001	0,027	0,033	0,020	0,021	0,004		
α	0,014 (0,771)	0,021 (1,192)	0,031 (1,541)	0,038* (1,748)	0,041* (1,790)	0,006 (0,099)	0,019	
β_{CMKT}	0,041 (0,424)	0,144 (1,511)	0,137 (1,249)	0,309** (2,597)	-0,060 (-0,475)	-0,012 (-0,038)		
β_{BTC_ret}	-0,033 (-0,202)	-0,109 (-0,673)	-0,027 (-0,147)	-0,259 (-1,277)	0,340 (1,568)	0,503 (0,896)		
R^2	0,001	0,018	0,016	0,050	0,021	0,009		

Table 13: **Two-Factor model D**

$$R_i - R_f = \alpha_i + \beta_{CMKT}^i * CMKT + \beta_{BTCHR_change}^i * BTCHR_change + \epsilon_i$$

This table presents results of regressions of nine significant long-short strategies outlined in the Section 3 on the market cryptocurrency market factor CMKT and the change in the hashrate of Bitcoin BTCHR_change. T-statistics reported in parentheses; *, **, *** denote significance at 10%, 5% and 1% confidence intervals.

		1	2	3	4	5	5-1	$\overline{R^2}$
avg_mkt_cap	α	0,094** (2,509)	0,039** (2,062)	0,029 (1,515)	0,029 (1,364)	0,020 (1,227)	-0,074** (-2,274)	0,036
	β_{CMKT}	0,277* (1,736)	0,135* (1,680)	0,134* (1,672)	0,149 (1,642)	0,089 (1,274)	-0,188 (-1,360)	
	β_{BTCHR_change}	0,180 (0,778)	0,256** (2,196)	0,183 (1,564)	0,256* (1,949)	0,165 (1,635)	-0,015 (-0,075)	
	R^2	0,027	0,056	0,039	0,048	0,032	0,014	
	α	0,096** (2,560)	0,038* (1,959)	0,029 (1,554)	0,027 (1,288)	0,021 (1,270)	-0,075** (-2,299)	
β_{CMKT}	0,267* (1,678)	0,145* (1,777)	0,144* (1,791)	0,142 (1,579)	0,086 (1,222)	-0,181 (-1,309)		
β_{BTCHR_change}	0,166 (0,719)	0,231* (1,946)	0,212* (1,824)	0,257* (1,966)	0,171* (1,670)	0,005 (0,023)		
R^2	0,025	0,051	0,049	0,047	0,032	0,013		

Table 13: (Continued)

		1	2	3	4	5	5-1	$\overline{R^2}$
Vol.1 week	α	0,096*** (2,649)	0,037** (2,063)	0,032 (1,625)	0,022 (1,120)	0,022 (1,164)	-0,074** (-2,365)	0,036
	β_{CMKT}	0,275* (1,787)	0,134* (1,755)	0,135 (1,619)	0,120 (1,457)	0,114 (1,439)	-0,161 (-1,208)	
	β_{BTCHR_change}	0,169 (0,758)	0,165 (1,491)	0,181 (1,497)	0,291** (2,444)	0,218* (1,898)	0,048 (0,249)	
	R^2	0,028	0,040	0,037	0,059	0,042	0,011	
Vol.2 week	α	0,092** (2,569)	0,037** (2,069)	0,026 (1,376)	0,027 (1,227)	0,023 (1,325)	-0,069** (-2,219)	0,034
	β_{CMKT}	0,238 (1,564)	0,144* (1,897)	0,122 (1,525)	0,162* (1,751)	0,075 (1,002)	-0,163 (-1,241)	
	β_{BTCHR_change}	0,182 (0,827)	0,123 (1,115)	0,240** (2,067)	0,295** (2,200)	0,173 (1,601)	-0,009 (-0,049)	
	R^2	0,024	0,036	0,049	0,058	0,027	0,012	
Vol.3 week	α	0,091** (2,582)	0,036** (2,012)	0,028 (1,407)	0,026 (1,261)	0,021 (1,223)	-0,070** (-2,276)	0,035
	β_{CMKT}	0,234 (1,562)	0,149* (1,972)	0,116 (1,392)	0,145 (1,639)	0,092 (1,269)	-0,142 (-1,083)	
	β_{BTCHR_change}	0,154 (0,708)	0,175 (1,594)	0,226* (1,867)	0,290** (2,263)	0,173 (1,633)	0,018 (0,096)	
	R^2	0,022	0,048	0,041	0,057	0,032	0,009	
Vol.4 week	α	0,092** (2,543)	0,039** (2,195)	0,026 (1,342)	0,025 (1,220)	0,023 (1,323)	-0,069** (-2,192)	0,036
	β_{CMKT}	0,257* (1,671)	0,144* (1,927)	0,102 (1,217)	0,144 (1,645)	0,098 (1,337)	-0,159 (-1,186)	
	β_{BTCHR_change}	0,133 (0,596)	0,186* (1,709)	0,249** (2,054)	0,265** (2,082)	0,179* (1,686)	0,045 (0,233)	
	R^2	0,024	0,049	0,043	0,052	0,035	0,011	
Vol.5 week	α	0,092** (2,550)	0,037** (2,072)	0,028 (1,475)	0,021 (1,047)	0,026 (1,411)	-0,066** (-2,049)	0,034
	β_{CMKT}	0,254* (1,660)	0,134* (1,746)	0,121 (1,519)	0,109 (1,281)	0,115 (1,467)	-0,140 (-1,020)	
	β_{BTCHR_change}	0,147 (0,660)	0,175 (1,574)	0,226* (1,951)	0,284** (2,303)	0,179 (1,581)	0,033 (0,164)	
	R^2	0,024	0,041	0,046	0,051	0,035	0,008	
VolMom_2 week High Vol coins	α	-0,002 (-0,093)	0,016 (0,841)	0,024 (1,207)	0,047* (1,696)	0,025 (1,222)	-0,060 (-0,622)	0,029
	β_{CMKT}	0,025 (0,345)	0,146* (1,788)	0,168* (1,953)	0,190 (1,628)	0,060 (0,687)	-0,172 (-0,420)	
	β_{BTCHR_change}	0,200* (1,883)	0,163 (1,375)	0,144 (1,157)	0,215 (1,267)	0,264** (2,092)	0,012 (0,021)	
	R^2	0,027	0,038	0,039	0,032	0,036	0,001	
SizeMom_3 week Large Cap coins	α	0,005 (0,293)	0,015 (0,865)	0,024 (1,215)	0,032 (1,443)	0,034 (1,429)	-0,005 (-0,074)	0,029
	β_{CMKT}	0,025 (0,336)	0,102 (1,369)	0,124 (1,452)	0,212** (2,269)	0,059 (0,590)	0,164 (0,635)	
	β_{BTCHR_change}	0,237** (2,181)	0,145 (1,338)	0,173 (1,390)	0,145 (1,064)	0,244* (1,684)	0,340 (0,903)	
	R^2	0,036	0,028	0,031	0,047	0,024	0,009	

Table 14: **Two-Factor model E**

$$R_i - R_f = \alpha_i + \beta_{CMKT}^i * CMKT + \beta_{CHR}^i * CHR + \epsilon_i$$

This table presents results of regressions of nine significant long-short strategies outlined in the Section 3 on the cryptocurrency market factor $CMKT$ and an index of changes in 16 cryptocurrency hashrates CHR . T-statistics reported in parentheses; *, **, *** denote significance at 10%, 5% and 1% confidence intervals.

		1	2	3	4	5	5-1	$\overline{R^2}$
avg_mkt_cap	α	0,079* (1,925)	0,029 (1,411)	0,020 (0,948)	0,010 (0,453)	0,010 (0,551)	-0,069* (-1,938)	0,041
	β_{CMKT}	0,245 (1,509)	0,108 (1,321)	0,112 (1,368)	0,107 (1,177)	0,065 (0,920)	-0,180 (-1,274)	
	β_{CHR}	0,548 (1,141)	0,474* (1,951)	0,393 (1,623)	0,704** (2,608)	0,410* (1,961)	-0,138 (-0,330)	
	R^2	0,032	0,049	0,041	0,069	0,041	0,015	
	α	0,083** (2,028)	0,024 (1,123)	0,023 (1,119)	0,008 (0,356)	0,011 (0,584)	-0,073** (-2,034)	
β_{CMKT}	0,239 (1,478)	0,112 (1,357)	0,125 (1,521)	0,100 (1,103)	0,062 (0,863)	-0,178 (-1,260)		
β_{CHR}	0,474 (0,987)	0,568** (2,318)	0,344 (1,417)	0,718*** (2,680)	0,421** (1,990)	-0,053 (-0,126)		
R^2	0,029	0,062	0,039	0,070	0,041	0,013		
α	0,078* (1,976)	0,029 (1,459)	0,019 (0,879)	0,014 (0,657)	0,006 (0,301)	-0,072** (-2,091)	0,040	
β_{CMKT}	0,239 (1,530)	0,113 (1,459)	0,106 (1,255)	0,095 (1,124)	0,079 (0,991)	-0,160 (-1,175)		
β_{CHR}	0,606 (1,311)	0,362 (1,569)	0,496** (1,988)	0,455* (1,817)	0,593** (2,513)	-0,013 (-0,033)		
R^2	0,037	0,041	0,049	0,041	0,061	0,011		
α	0,078** (1,994)	0,024 (1,246)	0,017 (0,828)	0,010 (0,416)	0,012 (0,616)	-0,066* (-1,953)		0,040
β_{CMKT}	0,207 (1,343)	0,118 (1,538)	0,098 (1,193)	0,122 (1,301)	0,049 (0,644)	-0,159 (-1,186)		
β_{CHR}	0,516 (1,129)	0,438* (1,926)	0,438* (1,808)	0,693** (2,501)	0,447** (2,003)	-0,069 (-0,174)		
R^2	0,028	0,054	0,042	0,068	0,037	0,012		
α	0,077* (1,978)	0,026 (1,345)	0,016 (0,766)	0,008 (0,350)	0,010 (0,525)	-0,067* (-1,967)	0,041	
β_{CMKT}	0,204 (1,336)	0,126 (1,640)	0,088 (1,041)	0,103 (1,149)	0,067 (0,906)	-0,137 (-1,024)		
β_{CHR}	0,517 (1,144)	0,402* (1,766)	0,486* (1,937)	0,729*** (2,756)	0,440** (2,012)	-0,077 (-0,195)		
R^2	0,028	0,052	0,042	0,074	0,042	0,009		
α	0,076* (1,926)	0,030 (1,570)	0,016 (0,747)	0,006 (0,275)	0,012 (0,617)	-0,065* (-1,862)		0,041
β_{CMKT}	0,225 (1,444)	0,123 (1,610)	0,074 (0,873)	0,102 (1,154)	0,072 (0,970)	-0,154 (-1,122)		
β_{CHR}	0,525 (1,135)	0,378* (1,675)	0,485* (1,919)	0,726*** (2,771)	0,445** (2,031)	-0,080 (-0,197)		
R^2	0,031	0,048	0,039	0,075	0,044	0,011		

Table 14: (Continued)

		1	2	3	4	5	5-1	$\overline{R^2}$
Vol_5 week	α	0,074*	0,031	0,017	0,009	0,007	-0,067*	0,040
		(1,877)	(1,579)	(0,846)	(0,395)	(0,356)	(-1,891)	
	β_{CMKT}	0,219	0,117	0,095	0,077	0,076	-0,143	
		(1,406)	(1,489)	(1,167)	(0,886)	(0,974)	(-1,021)	
	β_{CHR}	0,594	0,311	0,466*	0,568**	0,645***	0,051	
	(1,290)	(1,342)	(1,931)	(2,210)	(2,787)	(0,122)		
	R^2	0,033	0,037	0,045	0,048	0,072	0,008	
VolMom_2 week High Vol coins	α	-0,002	0,005	-0,004	0,031	0,018	-0,036	0,038
		(-0,083)	(0,220)	(-0,170)	(1,043)	(0,797)	(-0,335)	
	β_{CMKT}	0,017	0,120	0,115	0,156	0,037	-0,132	
		(0,225)	(1,452)	(1,370)	(1,317)	(0,417)	(-0,317)	
	β_{CHR}	0,178	0,442*	0,847***	0,583*	0,414	-0,619	
	(0,798)	(1,802)	(3,394)	(1,663)	(1,569)	(-0,500)		
	R^2	0,006	0,048	0,107	0,041	0,022	0,003	
SizeMom_3 week Large Cap coins	α	-0,002	0,002	-0,002	0,026	0,028	-0,003	0,038
		(-0,088)	(0,102)	(-0,108)	(1,071)	(1,079)	(-0,040)	
	β_{CMKT}	0,004	0,074	0,073	0,197**	0,040	0,153	
		(0,052)	(0,987)	(0,866)	(2,062)	(0,387)	(0,580)	
	β_{CHR}	0,387*	0,468**	0,840***	0,280	0,362	0,256	
	(1,704)	(2,104)	(3,367)	(0,992)	(1,194)	(0,327)		
	R^2	0,023	0,047	0,095	0,045	0,014	0,004	

4.3 Three-factor model

In the last part of this section, we test a three-factor model of cryptocurrency returns that uses CMKT, CSMB, and CMOM. The three-factor model performs well in explaining returns of portfolios 1 and 5-1. Its highest average R^2 32,1 percent, and its lowest average R^2 12,5 percent are the best results we have obtained.

The model reduces the alphas of 5-1 strategies to minimum (except for the momentum strategies). While alphas for the two momentum strategies are not reduced, the three-factor model increases the R^2 for these two strategies, compared to CMKT CSMB or CMKT CMOM models. Betas for both CSMB and CMOM are highly significant for all 5-1 strategies except for 1 and 3-week Volume. Overall, the combination of CMKT CSMB and CMOM can explain returns well.

Table 15: **Three-Factor model**

$$R_i - R_f = \alpha_i + \beta_{CMKT}^i * CMKT + \beta_{CSMB}^i * CSMB + \beta_{CMOM}^i * CMOM + \epsilon_i$$

This table presents results of regressions of nine significant long-short strategies outlined in the Section 3 on the cryptocurrency market factor CMKT, cryptocurrency size factor CSMB, and cryptocurrency momentum factor CMOM. T-statistics reported in parentheses; *, **, *** denote significance at 10%, 5% and 1% confidence intervals.

		1	2	3	4	5	5-1	$\overline{R^2}$
avg_mkt_cap	α	0,025 (1,299)	0,041** (2,095)	0,024 (1,287)	0,035 (1,608)	0,026 (1,564)	0,002 (0,268)	0,320
	β_{CMKT}	0,113 (1,411)	0,123 (1,503)	0,114 (1,427)	0,146 (1,582)	0,092 (1,294)	-0,021 (-0,845)	
	β_{CSMB}	1,342*** (9,013)	0,121 (0,802)	0,185 (1,256)	-0,012 (-0,070)	-0,046 (-0,346)	-1,388*** (-29,627)	
	β_{CMOM}	0,243* (1,686)	0,047 (0,320)	0,044 (0,309)	0,152 (0,921)	0,083 (0,648)	-0,160*** (-3,535)	
	R^2	0,760	0,053	0,081	0,041	0,017	0,968	
	mkt_cap_7	α	0,025 (1,321)	0,038* (1,957)	0,026 (1,378)	0,035 (1,594)	0,027 (1,608)	
β_{CMKT}		0,100 (1,280)	0,132 (1,602)	0,124 (1,546)	0,141 (1,549)	0,089 (1,241)	-0,011 (-0,427)	
β_{CSMB}		1,388*** (9,559)	0,121 (0,791)	0,196 (1,323)	-0,054 (-0,322)	-0,052 (-0,392)	-1,440*** (-29,560)	
β_{CMOM}		0,201 (1,428)	0,046 (0,307)	0,013 (0,088)	0,199 (1,213)	0,102 (0,792)	-0,099** (-2,093)	
R^2		0,770	0,054	0,075	0,044	0,019	0,965	
Vol_1 week		α	0,031 (1,607)	0,029 (1,600)	0,032 (1,599)	0,026 (1,311)	0,033* (1,720)	0,001 (0,170)
	β_{CMKT}	0,123 (1,490)	0,106 (1,407)	0,123 (1,472)	0,111 (1,328)	0,124 (1,542)	0,001 (0,041)	
	β_{CSMB}	1,229*** (8,067)	0,336** (2,404)	0,083 (0,538)	0,060 (0,390)	-0,159 (-1,067)	-1,388*** (-20,456)	
	β_{CMOM}	0,268* (1,818)	-0,144 (-1,061)	0,091 (0,604)	0,116 (0,770)	0,206 (1,425)	-0,063 (-0,952)	
	R^2	0,730	0,089	0,052	0,050	0,032	0,928	
	Vol_2 week	α	0,028 (1,482)	0,031* (1,710)	0,026 (1,336)	0,034 (1,521)	0,030 (1,645)	0,002 (0,227)
β_{CMKT}		0,086 (1,083)	0,123 (1,627)	0,107 (1,320)	0,159* (1,692)	0,078 (1,023)	-0,008 (-0,234)	
β_{CSMB}		1,230*** (8,398)	0,238* (1,695)	0,156 (1,044)	-0,032 (-0,182)	-0,051 (-0,363)	-1,281*** (-20,405)	
β_{CMOM}		0,265* (1,867)	-0,081 (-0,596)	0,022 (0,151)	0,209 (1,243)	0,101 (0,742)	-0,164*** (-2,693)	
R^2		0,743	0,067	0,054	0,055	0,014	0,936	
Vol_3 week		α	0,026 (1,411)	0,033* (1,841)	0,025 (1,281)	0,034 (1,583)	0,028 (1,609)	0,002 (0,252)
	β_{CMKT}	0,082 (1,050)	0,133* (1,748)	0,097 (1,165)	0,143 (1,587)	0,097 (1,313)	0,016 (0,422)	
	β_{CSMB}	1,249*** (8,641)	0,176 (1,249)	0,180 (1,165)	-0,021 (-0,128)	-0,081 (-0,589)	-1,330*** (-19,554)	
	β_{CMOM}	0,224 (1,603)	-0,021 (-0,156)	0,030 (0,202)	0,155 (0,958)	0,127 (0,957)	-0,097 (-1,473)	
	R^2	0,743	0,062	0,062	0,040	0,021	0,924	

Table 15: (Continued)

		1	2	3	4	5	5-1	\bar{R}^2
Vol_4 week	α	0,026 (1,362)	0,036** (2,002)	0,025 (1,265)	0,033 (1,555)	0,030* (1,689)	0,004 (0,448)	0,308
	β_{CMKT}	0,103 (1,289)	0,127* (1,684)	0,084 (0,999)	0,145 (1,615)	0,102 (1,367)	-0,001 (-0,037)	
	β_{CSMB}	1,231*** (8,300)	0,214 (1,528)	0,166 (1,070)	-0,046 (-0,275)	-0,062 (-0,446)	-1,292*** (-18,644)	
	β_{CMOM}	0,279* (1,945)	-0,082 (-0,602)	0,055 (0,363)	0,167 (1,037)	0,102 (0,763)	-0,177*** (-2,641)	
	R^2	0,742	0,058	0,062	0,039	0,019	0,925	
	Vol_5 week	α	0,026 (1,382)	0,035* (1,892)	0,027 (1,402)	0,027 (1,287)	0,035* (1,836)	
β_{CMKT}		0,101 (1,261)	0,117 (1,521)	0,105 (1,310)	0,104 (1,190)	0,122 (1,535)	0,022 (0,506)	
β_{CSMB}		1,240*** (8,391)	0,185 (1,297)	0,153 (1,028)	0,044 (0,272)	-0,106 (-0,717)	-1,346*** (-16,935)	
β_{CMOM}		0,266* (1,860)	-0,035 (-0,252)	0,041 (0,287)	0,086 (0,551)	0,134 (0,938)	-0,132* (-1,717)	
R^2		0,743	0,055	0,061	0,030	0,023	0,905	
VolMom_2 week High Vol coins		α	0,001 (0,031)	0,015 (0,758)	0,029 (1,386)	0,056** (1,985)	0,039** (2,022)	0,124*** (2,787)
	β_{CMKT}	0,019 (0,252)	0,134 (1,621)	0,169* (1,931)	0,196 (1,656)	0,072 (0,882)	0,233 (1,246)	
	β_{CSMB}	0,183 (1,329)	0,213 (1,392)	0,047 (0,293)	-0,135 (-0,614)	-0,381** (-2,510)	-2,943*** (-8,493)	
	β_{CMOM}	-0,208 (-1,558)	-0,182 (-1,224)	-0,077 (-0,491)	0,240 (1,132)	0,643*** (4,376)	-1,266*** (-3,773)	
	R^2	0,019	0,039	0,031	0,033	0,162	0,798	
	SizeMom_3 week Large Cap coins	α	0,014 (0,761)	0,017 (0,934)	0,030 (1,437)	0,036 (1,603)	0,042* (1,852)	-0,075* (-1,723)
β_{CMKT}		0,030 (0,392)	0,097 (1,288)	0,125 (1,433)	0,214** (2,244)	0,059 (0,624)	-0,014 (-0,078)	
β_{CSMB}		0,015 (0,103)	0,138 (0,988)	-0,018 (-0,109)	0,045 (0,254)	-0,255 (-1,457)	1,135*** (3,332)	
β_{CMOM}		-0,055 (-0,396)	-0,164 (-1,207)	0,074 (0,473)	-0,073 (-0,426)	0,606*** (3,572)	0,999*** (3,027)	
R^2		0,004	0,026	0,020	0,040	0,147	0,513	

5 Three-factor model risk premia

Finally, we want to find out whether the data in our sample support the existence of risk premia based on the Three-factor model outlined in Table 15. In other words, our aim is to examine whether there are risk premia in the cryptocurrency market similar to premia observed in the stock market. To achieve this result, we employ a procedure in nature identical to Fama and MacBeth (1973). If risk premia are present in our sample, the factor betas of individual cryptocurrencies should serve as predictors of returns. We expect a positive relationship between cross-sectional returns and magnitude of factor betas - a higher exposure to CMKT should result in a positive premium; a higher loading on CSMB should convey a positive premium, too; and the same applies to CMOM.

Due to the length of our sample, we estimate 1 time-series regression for returns of each cryptocurrency:

$$R_{i,t} - R_{f,t} = \alpha_i + CMKT_t * \beta_{CMKT}^i + CSMB_t * \beta_{CSMB}^i + CMOM_t * \beta_{CMOM}^i + \epsilon_{i,t} \quad (1)$$

where $R_{i,t}$ is a return of a cryptocurrency i at time t , $CMKT_t$ is a market excess return, $CSMB_t$ is a value of the CSMB size factor at time t , $CMOM_t$ is a value of the CMOM cryptocurrency momentum factor at time t and $\epsilon_{i,t}$ is a standard error of the regression.

Once we obtain time-series factor betas for all cryptocurrencies, we run a cross-sectional regression of cryptocurrency mean returns on factor betas:

$$\bar{R}_i = \lambda_0 + \lambda_1 * \beta_{CMKT}^i + \lambda_2 * \beta_{CSMB}^i + \lambda_3 * \beta_{CMOM}^i + \eta_i \quad (2)$$

where \bar{R}_i is a mean return of a cryptocurrency i ; λ_0 , λ_1 , λ_2 , λ_3 are estimates of risk premia for given factors, and η_i is a standard error.

Our results support the existence of risk premia for all the three factors. With a 100bps higher exposure to the market, a cryptocurrency in our sample on average returns additional 2,1 percentage points in returns. We find that a 100bps increase in the size beta results in a 1,2 percentage point increase in returns. Further, a 100bps gain in momentum beta results in a 0,9 percentage point return decrease - this is a result slightly difficult to interpret but our view is that coins with higher momentum exposure experience stronger reversal and hence negative premium for momentum.

Table 16: Cryptocurrency risk premia This table reports the risk premia found among cryptocurrencies in our sample. We first estimate time-series betas for each coin, and then run a cross-sectional regression $\bar{R}_i = \lambda_0 + \lambda_1 * \beta_{CMKT}^i + \lambda_2 * \beta_{CSMB}^i + \lambda_3 * \beta_{CMOM}^i + \eta_i$. Lambdas represent our estimated risk premia. T-statistics reported in parentheses; *, **, *** denote significance at 10%, 5% and 1% confidence intervals.

Risk premia	λ_0	λ_1	λ_2	λ_3
Premium	-0,016***	0,021***	0,012***	-0,009***
T-stat	(-2,86)	(4,79)	(4,32)	(-2,65)
Standard Error	0,006	0,004	0,003	0,003
N=417				

6 Conclusion

This paper provided a further insight into the behaviour of cryptocurrency returns. We found a significant support for the existence of cryptocurrency size and momentum factors. On the other hand, we found that cryptocurrency hash rates do not help with explaining the cross-section of cryptocurrency returns. We can, however, surely conclude that cryptocurrency returns follow patterns observable in the stock market, hence there are similarities among these two asset classes. We also find risk premia attributable to exposure to market, size factor and momentum. We are just a little bit puzzled by the lack of presence of pure momentum long-short strategy in our sample, perhaps an analysis using different data interval may uncover different results. This topic, however, and other issues relating to the cryptocurrency market should be a topic for other research.

7 Appendix

In this Appendix, we attempt to provide further details on our approach. Our aim was to maintain the main part of the paper as concise as possible, thus we list all the necessary technical details here.

7.1 Data - Details

Table 17 presents a detailed description of our sample regarding the number of coins used in the analysis. As can be seen, 65 cryptocurrencies satisfied our conditions outlined in Section 2 at the beginning of 2017 when the cryptocurrency market was still to attract massive attention. The number of cryptos in our sample reaches 199 by the end of 2017, 360 by mid-2018, and from September 2018 onwards our sample includes at least 415 coins. Even though the number of coins in our sample considerably varies over time, we believe the constraints we imposed on the liquidity and number of observations per coin ensure that our sample is a good approximation of readily investable universe of cryptocurrencies, and that our results are not skewed by less liquid, and hence volatile, coins. If we find significant long-short strategies among coins shortlisted according to our criteria, we thus find a stronger support for market behaviour supporting the existence of a given factor - if such behaviour occurs even for fairly traded coins, our results are more robust.

Table 18 lists all the cryptocurrencies used in our panel. As mentioned in Section 2, we require each coin to have at least 51 weekly observations between 2017 and the end of 7/2019 in order to be included in our sample. There is in total 63 coins that appear over the whole sample period, i.e. they have 134 observations. Our requirement for a coin to have at least 51 observations was mainly motivated by the fact that risk premia are calculated using a linear regression, and a low number of observations per coin could render the coefficients of the regression analysis meaningless.

Lastly, we want to share the cryptocurrencies that are included in the Cryptocurrency Hash-Rate Change Index (CHR). Table 19 lists the 17 coins in our sample for which we could obtain the hash-rate data.

Table 17: Detailed Panel Summary This table summarizes the time variation of the number of coins in our sample. The left column denotes each month in our sample, and the right column reports the number of cryptocurrencies occurring in each month of the sample.

Period	Number of coins
2017m1	65
2017m2	66
2017m3	68
2017m4	76
2017m5	84
2017m6	93
2017m7	114
2017m8	127
2017m9	139
2017m10	163
2017m11	179
2017m12	199

Table 17: (Continued)

Period	Number of coins
2018m1	232
2018m2	256
2018m3	292
2018m4	321
2018m5	342
2018m6	360
2018m7	386
2018m8	412
2018m9	416
2018m10	416
2018m11	416
2018m12	416
2019m1	416
2019m2	416
2019m3	416
2019m4	416
2019m5	416
2019m6	415
2019m7	415
2019m8	415

Table 18: **Detailed Panel Summary** This table summarizes the time variation of the number of coins in our sample. The left column denotes each month in our sample, and the right column reports the number of cryptocurrencies occurring in each month of the sample.

Ox	103	digibyte	134	matrixx	74	ruff	71
Oxbtc	61	digitalnote	134	measurable-data-	75	salt	97
Oxcert	54	digitex-futures	63	medical-chain	76	santiment	108
aaave	87	digixdao	134	medishares	81	scryinfo	72
abyss-token	60	dignity	52	medx	57	seele	52
ace	82	district0x	105	melon	125	selfkey	80
achain	92	dmarket	71	mercurlet	58	selfsell	65
acute-angle-clou	51	doc-com-token	65	mercury	123	sentinel-protoco	55
adtoken	109	dock	67	metal	109	sharder	66
adx-net	108	dogecoin	134	metaverse	106	siacoin	134
aelf	84	dragonchain	87	metronome	54	silent-notary	61
aeron	91	dropil	71	mithril	71	singularDTV	134
aeternity	100	echolink	77	mixin	67	singularitynet	79
agrello-delta	100	edc-blockchain	134	mobilego	112	sirin-labs-token	83
aichain	82	edgeless	122	mobius	75	skrumble-network	53
aidoc	71	educare	69	moeda-loyalty-po	98	skycoin	120
aion	87	egretia	55	monacoin	134	smartcash	106
airswap	94	eidoo	94	monero	134	smartlands	77
all-sports	78	einsteinium	134	monetha	100	smartmesh	74
alphacat	73	elastos	70	morpheus-network	53	smartshare	59
amber	92	electronium	86	moss-coin	56	sonm	107
apex	67	emercoin	134	mtc-mesh-network	54	sophiatx	82
apis	60	endor-protocol	59	mysterium	112	spacechain	74
appcoins	82	energo	80	naga	83	spartyco	86
aragon	116	enigma	95	namecoin	134	status	110
arcblock	74	enjin-coin	90	nano	124	steem	134
ardor	134	eos	109	napoleonx	67	steem-dollars	134
ark	124	eosdac	63	nasdacoins	51	stellar	134
asch	121	ethereum	134	nav-coin	134	stk	77
atbcoin	97	ethereum-classic	134	naviaddress	62	storiqa	74
augur	134	etherparty	89	neblio	99	storj	110
aurora	53	ethos	107	nebulas-token	88	storm	84
b2bx	87	everex	95	nem	134	stox	106
bancor	110	expanse	134	neo	134	stratis	134
bankex	74	factom	134	network	72	streamr-datacoin	91
basic-attention-	114	firstblood	134	nexo	65	substratum	97
bezant	58	fortuna	73	nexty	57	suncontract	105
bezop	75	fox-trading	54	nexus	134	swftcoin	79
bhp-coin	52	fsbt-api-token	57	nimiq	53	synereo	134
bibox-token	81	funfair	110	nkn	62	synthetix-networ	73
bigbom	62	fusion	74	noah-coin	56	syscoin	134
binance-coin	106	game	81	nucleus-vision	73	taas	118
bit-z-token	53	gamecredits	134	nuls	85	tael	86
bitcny	134	gas	105	numeraire	111	telcoin	81

Table 18: (Continued)

bitcoin	134	gems-protocol	61	nxt	134	tenx	109
bitcoin-cash	105	genaro-network	73	oax	104	tezos	57
bitcoin-diamond	72	genesis-vision	90	octoin-coin	70	thekey	72
bitcoin-gold	89	gifo	83	odem	67	theta	80
bitcoin-private	70	gnosis-gno	118	odyssey	79	tierion	102
bitcore	111	gochain	57	olympus-labs	80	time-new-bank	88
bitmart-token	54	golem-network-to	140	omisego	108	tokencard	118
bitshares	134	gonetwork	56	oneledger	53	tokenclub	73
bitusd	134	groestlcoin	134	oneroof-network	81	tokenomy	67
blackcoin	134	guppy	120	ontology	73	tokenpay	68
blackmoon	98	gxchain	101	origin-sport	57	tomochain	71
blockmason	94	haven-protocol	67	ormeus-coin	85	transcodium	64
blockport	81	hi-mutual-societ	74	ost	85	traxia	53
blocktix	105	high-performance	81	own	66	tron	97
blox	102	hollywoodcoin	85	pal-network	64	truechain	74
bluzelle	78	holo	65	particl	107	trueusd	73
bnktothefuture	66	hoqu	69	pascal-coin	134	trust	121
bobs-repair	58	humaniq	117	patientory	113	trustnote	58
bottos	77	huobi-token	67	patron	60	ttc	51
bread	84	hydro-protocol	78	pchain	57	turtlecoin	54
burst	134	hydrogen	65	peercoin	134	u-network	67
bytecoin-bcn	134	hypercash	101	phantasma	59	ugchain	69
bytom	104	icon	84	phore	88	unibright	63
cappasity	81	ignis	79	pivx	134	unikoin-gold	89
cardano	96	igtoken	51	poa-network	75	uptoken	73
cashaa	62	iht-real-estate-	74	poet	100	uquid-coin	82
chainlink	98	ink	88	polymath-network	77	ustrust	84
chronobank	128	insolar	81	popchain	54	vechain	53
cindicator	95	insurepal	79	populous	108	verge	134
civic	107	internet-node-to	81	potcoin	134	vericoins	134
cloakcoin	134	iostoken	80	power-ledger	91	veritaseum	112
constellation	59	iot-chain	84	primas	101	vertcoin	134
content-neutrali	53	iota	112	primecoin	134	viacoin	134
contentbox	53	iotex	62	prochain	81	vibe	97
cortex	68	jibrel-network	78	profile-utility-	80	viberate	96
cos	97	kickico	97	propy	98	vinchain	52
cosmo-coin	54	kin	97	pundi-x	57	vite	54
cpchain	75	komodo	131	qash	88	waltonchain	101
credits	74	kucoin-shares	92	qbao	80	wanchain	69
crowd-machine	61	kyber-network	98	qlink	81	waves	134
crpt	74	latoken	91	qtum	108	wax	84
crypto-com	109	leocoin	112	quantstamp	89	waykichain	66
cryptonex	91	libra-credit	53	quantum-resistan	113	webcoin	54
cube	74	library-credit	134	quarkchain	61	wepower	77
cybermiles	84	linkeye	74	qunqun	81	whitecoin	134
cybervein	67	lisk	134	radium	134	wings	119
dadi	76	litecoin	134	raiden-network-t	91	xinfin-network	68
daex	63	litecoin-cash	68	rate3	57	xmax	57
dai	84	local-coin-swap	54	ravencoin	72	yee	72
dash	134	lockchain	85	rchain	90	yoyow	89
data	76	loom-network	72	realchain	56	zcash	134
data-transaction	55	loopring	101	red-pulse	93	zclassic	134
datarius-credit	64	loyalcoin	61	reddcoin	134	zcoin	134
datum	85	lunyr	118	refereum	74	zebi	66
datx	68	lykke	120	remme	74	zeepin	77
decent	110	lympo	73	ren	73	zencash	113
decentraland	97	maidsafecoin	134	request	94	zeusshield	92
decred	134	mainframe	57	revain	92	zilliqa	79
deepbrain-chain	83	maker	81	ripio-credit-net	91		
delphy	89	mark-space	66	ripple	134		
dent	104	matrix-ai-networ	71	rlc	120		

Table 19: List of Cryptocurrencies constituting the Hash-Rate Change Index (CHR)

This table lists all the cryptocurrencies for which we obtain hash-rate data and subsequently construct the Cryptocurrency Hash-Rate Change Index CHR

Cryptocurrency
Bitcoin
Blackcoin
Bitcoin Cash
Bitcoin Gold
Dash
Dogecoin
Ethereum Classic
Ethereum
Feathercoin
Litecoin
Monero
Namecoin

Table 19: (Continued)

Cryptocurrency
Novacoin
Peercoin
Reddcoin
Vertcoin
ZCash

7.2 Methodology

We now want to clarify how we arrived to weekly data from our originally retrieved daily datapoints.

Weekly returns

We first convert daily prices of cryptocurrency i to daily returns (t denotes time):

$$R_{i,d} = \frac{P_{i,t}}{P_{i,t-1}} - 1 \quad (3)$$

once we obtain the returns, we calculate a weekly return as a product of daily returns from Monday to Sunday:

$$R_{i,w} = \left[\prod_{d=1}^7 (1 + R_{i,d}) \right] - 1 \quad (4)$$

where d is a day in the week starting with Monday.

Market capitalisation measures

We use two measures of weekly market capitalisation - average weekly market capitalisation and last day of week market capitalisation. The latter is simply the market cap observed at the end of each Sunday. The former, average weekly market capitalisation, is calculated as follows:

$$avg_mkt_cap_{i,w} = \frac{\sum_{d=1}^7 market_cap_{i,d}}{7} \quad (5)$$

Weekly trading volume

As a measure of weekly trading volume, we use average weekly trading volume. The formula concurs with the equation 5, we just use trading volume instead of market capitalisation:

$$avg_trading_volume_{i,w} = \frac{\sum_{d=1}^7 trading_volume_{i,d}}{7} \quad (6)$$

Weekly hash-rates

Weekly hash-rates are calculated in an identical fashion as the two equations above:

$$avg_hash_rate_{i,w} = \frac{\sum_{d=1}^7 hash_rate_{i,d}}{7} \quad (7)$$

Weekly risk-free rate

As we use excess returns for our portfolios, i.e. portfolio returns minus risk-free rate, we need a measure of a risk-free return - we proxy for this using 1 Month US Treasury Bill yields. We obtain weekly risk-free rates followingly:

$$weekly_Rf = \frac{monthly_Rf}{365} * 7 \quad (8)$$

where *monthly_Rf* stands for 1 Month US Treasury Bill yield.

References

- Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, 81(3), 607-636. Retrieved from <http://www.jstor.org/stable/1831028>
- Liu, Y., Tsyvinski, A., & Wu, X. (2019, May). Common risk factors in cryptocurrency [Working Paper]. (25882). Retrieved from <http://www.nber.org/papers/w25882>