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Bachelor Thesis

Identification of Risk Factors for Predicting Cryptocurrency Returns

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Declaration of Authorship

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“We have tasted freedom and will not give up.”

Volodymyr Zelenskyy

UKRAINIAN CATHOLIC UNIVERSITY

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Identification of Risk Factors for Predicting Cryptocurrency Returns

by Alisa Balakirska

Abstract

In this research we consider a comprehensive list of price- and market-related return predictors in the cryptocurrency market. Using the long-short strategies we formed a set of available characteristics at the daily and weekly frequencies. We further implement equal- and value-weighted portfolios and find a number of cryptocurrency characteristics that are successfully predicting their returns. Specifically, a number of cryptocurrency characteristics form successful long-short strategies that generate sizable and statistically significant returns.

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Dedicated to my lovely family

Chapter 1

Introduction

1.1 Introduction

Investors become more and more interested in the cryptocurrency market. The primary reason is the fact that cryptocurrencies have exhibited extremely superior performance compared to paltry and negative yields on offer from the investments in more traditional asset classes. Today the total market capitalization of the cryptocurrency is already above 2 trillion USD, which is comparable to the G7 economies. However, opinions about the relevance of cryptocurrencies vary between two main ideas. The first one is that the cryptocurrency market is a bubble. People see an increase in the crypto prices, think that it is justified, they are buying crypto and then they find out that it was just a bubble after the price crash. The second idea claims that blockchain technology is an innovation that will become popular in the near future and cryptocurrency will represent a stake in this technology. In this thesis, we will examine the properties of the cryptocurrencies as a form of investment.

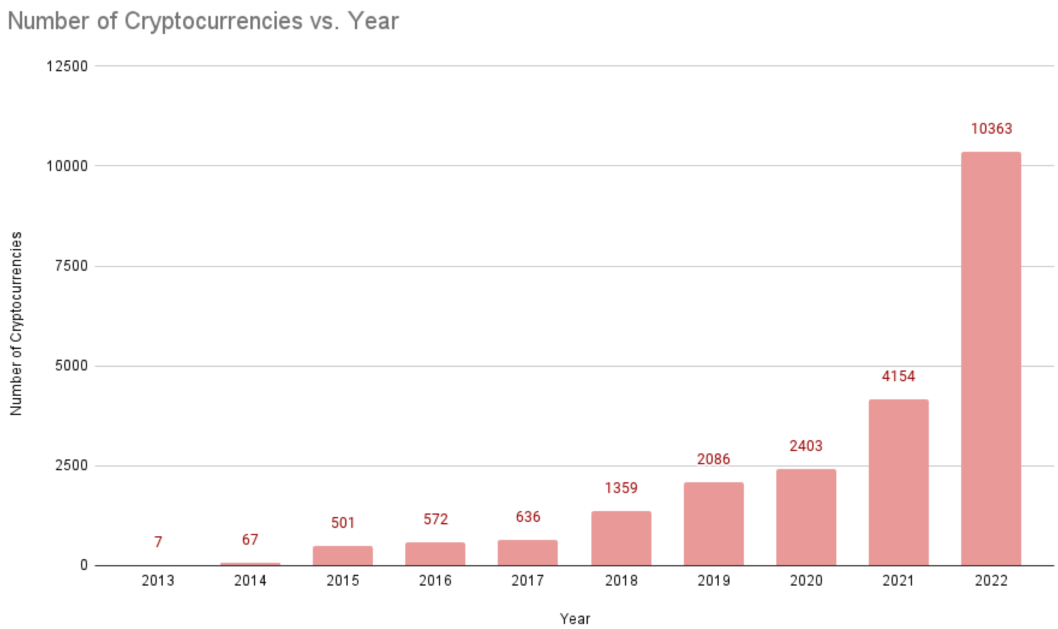

Figure 1.1: Number or Cryptocurrencies

There are a lot of cryptocurrencies on the market and at the same time - the amount of them increased from 7 in 2013 to more than 10000 in 2021 (excluding the dead cryptocurrencies). Unfortunately, there is no such cryptocurrency that will fit everyone. A lot of tips for selecting a cryptocurrency can help investors, most techniques use historical data, reputation, exploring its creators, etc. Using historical data to predict the future prices of cryptocurrencies is a controversial method, because historical data may not capture current or future trends. In this paper, we want to explore the cryptocurrency market using standard empirical asset pricing tools and test the usefulness of a wide range of cryptocurrency characteristics for predicting their future returns.

1.2 Goals

The main goals of this paper are:

1. To find out which characteristics are usually used by investors while selecting a cryptocurrency
2. To examine which characteristics of cryptocurrencies are significant for predicting their returns

1.3 Motivation

Nowadays cryptocurrency is a popular form of investment. A lot of factors depend on the price of cryptocurrencies - such as supply and demand, cost of production, availability, among others. Also, an important factor now is popularity. If a celebrity like Elon Musk mentions crypto on Twitter, its price tend fluctuate in response to the news immediately. Overall, it is hard to predict cryptocurrency prices. In this work, we want to find out which characteristics can be useful for predicting cryptocurrency returns. This research can help investors find the characteristics by which they can choose in which cryptocurrency they should invest and which they have to sell.

Chapter 2

Data description

2.1 Data pre-processing

In this section, we describe the data we used for the research. We collected the cryptocurrency price data from CryptoCompare.com. The advantage of this source is that it searches a lot of exchange websites and provides an accurate measure of the characteristics of each cryptocurrency. On-chain measures we collected from IntoTheBlock.com. From all existing cryptocurrencies, we selected only crypto with a market capitalization above one million dollars. In the data, we use the returns of these cryptocurrencies daily from January 2018 to March 2021. By taking historical data only for the last 4 years, we filtered the dead cryptocurrencies by excluding coins that had a price or trading volume of 0 on any day, so only active crypto left. We also took all available factors for each cryptocurrency and divided them into 4 groups - on-chain characteristics, trading frictions, characteristics that describe past returns, and other.

2.2 Data

Our data consists of 332 different cryptocurrencies, their prices daily from January 2018 to March 2021, and 30 characteristics for each cryptocurrency. We selected characteristics as was introduced by Feng, Giglio, and Xiu (2017)[7] and Chen and Zimmermann (2018)[3] and divided them into 4 groups - on-chain measures, trading frictions, past returns, and others.

The data has the name of the cryptocurrency asset (**ticker**), the date (**DATE**), the return on investment of a given asset (**return**) and its 30 characteristics for the given day.

On-chain characteristics describe the movements of coins and individual wallets. We used these characteristics to exclude dead cryptocurrencies from our data. On-chain factors consist of **active addresses** - the number of addresses that made at least one transaction during the day and **new addresses** - the number of new addresses created during the day.

Market-based characteristics describe the financial analysis of the cryptocurrencies - their capitalization, trading volume, volatility, etc. They are useful for us because we can estimate the size of cryptocurrencies. Market-based factors consist of **marketcap** - total market capitalization - which is calculated by multiplying the price of cryptocurrency by the number of coins in the market, **bm** - network to market value - the cumulative number of unique addresses over the current available supply times the current USD price, daily trading volume - the amount of given cryptocurrency, which was purchased during the day, expressed in millions of USD which was firstly documented by Banz (1981) [2] and Fama and French (1992)[6](**volumeto**), the last day trading volume over the current available supply (**turnover**), Amihud illiquidity measure - the absolute return divided by the dollar trading volume for each day (**Ahcc**), the daily average between two different synthetic bid-ask spread measures as proposed by Corwin and Schultz (2012)[5] and Abdi and Ranaldo (2017)[1] - the difference between the highest price that a buyer is willing to pay for an asset and the lowest price that a seller is willing to accept (**bidask**), a detrended measure of trading volume based on two different trending periods (30 and 60 days) as proposed by Llorente et al. (2002)[9] (**volshocksSTD30**, **volshocksSTD60**), 30-day rolling-window estimates of the CAPM alpha (**capm alpha**), idiosyncratic volatility (**idio vol**), the daily realized volatility estimate as in Yang and Zhang (2000)[10] (**yzvol**), the standard deviation of the residuals from a 30-day rolling window regression of daily turnover on a constant as in Chordia et al. (2001)[4] (**std to**), The standard deviation of the residuals from a 30-day rolling window regression of daily trading volume on a constant as in Chordia et al. (2001)[4] (**std vol**).

Past returns can help us identify if the cryptocurrency price changes significantly during the given time period. Characteristics consist of cumulative returns from 1, 7, 13, 22, and 31 days before the return prediction to two days before as introduced by Jegadeesh and Titman (2001)[8] (**r1**, **r7**, **r 13**, **r 22**, **r 31**), we define intermediate momentum as the cumulative returns from 30 days before prediction to 14 days before (**r30 14**), we define long-term reversal is the cumulative return from 180 days before the return prediction to 60 days before (r180 60), the maximum trading value for last 7, 14, 21, 30 days (**max 7**, **max 14**, **max 21**, **max 30**), the mean of 1, 2, 4, 8, 16 maximum trading values over last 30 days (**max 30 m1**, **max 30 m2**, **max 30 m4**, **max 30 m8**, **max 30 m16**).

Other characteristics consist of the 5 percents historical value-at-risk based on 90 days of realized returns (**var95**) and 30-day rolling-window estimates of the CAPM beta (**capm beta**).

Chapter 3

Methodology

In this section, we describe the methodology used in this work.

Firstly, we find the data which has cryptocurrency returns on daily basis and its different characteristics. To have relevant data we did the data pre-processing and found 332 relevant cryptocurrencies for this research.

For every time period (day or week), we sort each cryptocurrency into quintile portfolios based on the value of given characteristics. In this research we use the first and last 20 percent of the sorted data - so we have 1st and 5th portfolios of the data.

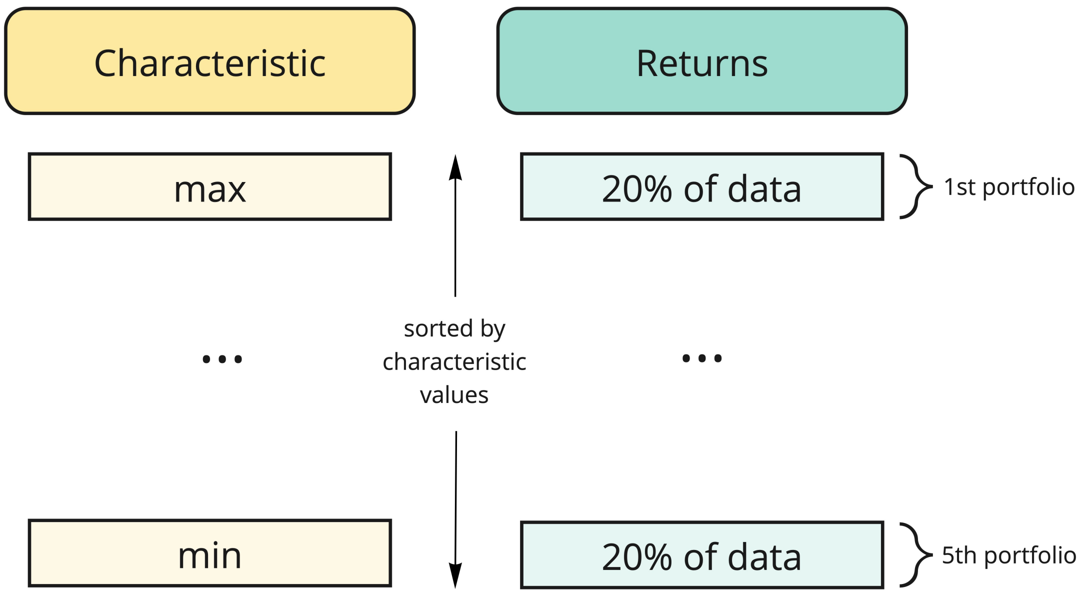

Figure 3.1: Methodology

Then we apply the long-short strategy - we sell the portfolio with high characteristic values and we buy a portfolio with low characteristic values. We implement the analysis with equal-weighted portfolio and with value-weighted portfolio. This research we made for 2 time periods - day and week, to see also if there is a significant difference depending on the trading period. The idea is that if the characteristic is significant, the returns of 1st and 5th portfolios should be significantly different over all time, so we can have profit using the long-short strategy based on the given characteristics.

There are several methods of identifying if sample groups are significantly different: Z-test, T-test, ANOVA, and Chi-Square test. Our next step was to identify which of these methods suits the situation.
ANOVA, or analysis of variance, is used to compare three or more samples, but in our case, we have only 2.
Chi-Square test is applicable only to categorical variables, so it is also not our case.
Z-test is used to find out if two samples are different from each other, but it doesn't tell how much they are different. Also for accurate Z-test big samples is a need.
The only suitable method is to use the T-test - it is applicable to 2 samples and it can tell how much two samples differ from each other using the significance level.
The formula for the T-value:

$$T = (meanoverall - meandiff)/(SD/\sqrt{(n)}$$

So for calculating the $\mathbf{t-value}$ we need:
mean overall - mean of the overall sample
mean diff - the difference between means of first and second portfolios
SD - standard deviation of the sample
n - number of data samples

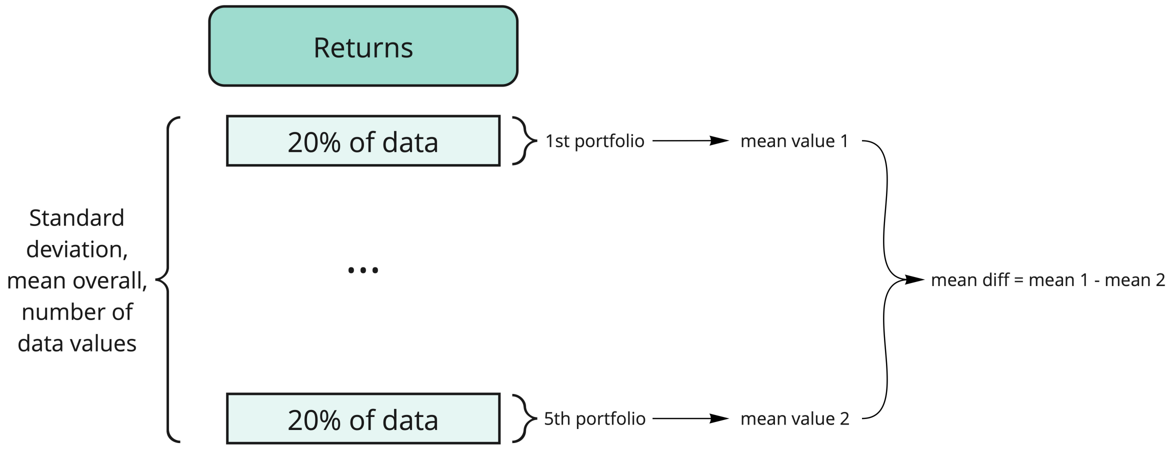

Figure 3.2: T-value

After we calculate the t-value for each portfolio we evaluate the significance of the results by significance levels - for 10 percent the t-value should be more than 1.64, for 5 percent the t-value should be more than 1.96 and for 1 percent it should be more than 2.57.

We repeated this procedure for each characteristic for every time period and you can see the results in the next section.

Chapter 4

Results

We analyzed the performance of all factors and found which are significant. Firstly, we calculated the results for daily trading and then for weekly trading. For each characteristic group we created the equal-weighted portfolio and value-weighted portfolio. The reason for doing 2 portfolios is that in real life we cannot use the equal-weighted portfolio at least because of the price difference of the coins. It mean that we cannot invest in Bitcoin and in some other unknown coin the same amount of money. In this situation the value-weighted portfolio can save us - we just divide the amount of money we invest proportionally to the price of the coins in the portfolio. The results for all characteristics you can find in Appendices. The results for significant characteristics you can find in the tables below.

4.1 Daily trading

On − chain characteristics
For on-chain characteristics we found that only network-to-market value - the cumulative number of unique addresses over the currently available supply times the current USD price (**bm**) is a significant characteristic in an equal-weighted portfolio. For the network-to-market value the differences in average returns are -120.23 for the first portfolio and 55.47 for the fifth portfolio. So the low-high difference is -175.7, which is statistically significant at the 1 percent significance level.
Unfortunately, we cannot use the equal-weighted portfolio strategy in real life, so we did the same analysis for a value-weighted portfolio. After we did it, we found that this characteristic is no longer significant for predicting returns. We also found that for daily trading none of the on-chain characteristics is significant in a value-weighted portfolio.
You can find the results on the tables below.

- Equal-weighted portfolio

	bm
	Mean (%)
Low	-120,23
2.0	-85,46
3.0	-104,13
4.0	-77,61
High	55,47
Low-High difference	-175,7
t-stat	-10,4

Table 4.1: On-chain characteristics daily trading equal-weighted portfolio

- Value-weighted portfolio

None of characteristics found to be significant.

Trading frictions

From trading frictions, we also can see that not all characteristics which are significant for an equal-weighted portfolio remain significant for a value-weighted portfolio.
The most significant characteristics for equal-weighted portfolio are **market capitalization**, **idiosyncratic volatility**, **yzvol** and **volumneto**. For the **market capitalization** the differences in average returns are 65.36 for the first portfolio and -70.03 for the fifth portfolio. So the low-high difference is 135.39, which is statistically significant at the 1 percent significance level. For the **idiosyncratic volatility** the results are -12.79 for the first portfolio, -120.31 for the fifth portfolio, and the difference is 107.52, which is significant at the 1 percent significance level. Almost all factors that are significant for the equal-weighted portfolio are significant at the 1 percent significance level, except **std to** and **std vol**, which are significant at 5 percent significance level.
For the value-weighted portfolio the most significant factors are **idiosyncratic volatility**, **yzvol** and **std vol**. For **yzvol**, **bidask**, **idiosyncratic volatility** and **std vol** the significance increased for value-weighted portfolio.
In the results for the most significant factors in the value-weighted portfolio we can see the dynamics of returns growth from low to high portfolio - it is also a good metric.
You can find the results on the tables below.

- Equal-weighted portfolio

	Marketcap	yzvol	bidask	turnover	Idio vol	std to
	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)
Low	65,36	-11,06	-43,43	-37,39	-12,79	-66,92
2.0	-111,52	-43,66	-48,48	-44,1	-42,93	-41,8
3.0	-109,31	-60,2	-69,65	-34,84	-64,01	-58,4
4.0	-106,2	-99,72	-66,86	-42,52	-87,81	-64,6
High	-70,03	-112,93	-107,1	-110,3	-120,31	-91,7
Low-High difference	135,39	101,87	63,66	72,91	107,52	24,78
t-stat	8,29	6,99	3,74	3,81	7,11	1,82

Table 4.2: Trading frictions daily trading equal-weighted portfolio

	std vol	volumeto
	Mean (%)	Mean (%)
Low	-48,82	35,7
2.0	-49,82	-91,1
3.0	-57,46	-66,39
4.0	-89,07	-71,77
High	-79,92	-82,36
Low-High difference	31,1	118,06
t-stat	2,47	5,91

Table 4.3: Trading frictions daily trading equal-weighted portfolio

- Value-weighted portfolio

	yzvol	bidask	turnover	Idio vol	std vol
	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)
Low	14,8	-22,83	-134,84	12,86	11,46
2.0	-40,9	-5,39	-52,86	-52,99	-55,3
3.0	-81,39	-49,28	9,75	-77,9	-96,32
4.0	-159,05	-78,3	-9,37	-152,29	-109,98
High	-294,53	-244,05	-73,21	-341,74	-170,32
Low-High difference	309,33	221,22	-61,63	354,6	181,78
t-stat	7,94	4,71	-1,8	8,5	5,44

Table 4.4: Trading frictions daily trading value-weighted portfolio

Past returns

For past returns, a lot of characteristics remain significant for the value-weighted portfolio, especially from the characteristics which contain the mean of maximum values from the last 30 days. As for cumulative returns, **r7** and **r13** are significant for both equal-weighted and value-weighted portfolios. All characteristics which are significant for the equal-weighted portfolio are significant at the 1 percent significance level.

For the value-weighted portfolio we can see that the long-term reversal is the cumulative return from 180 days before the return prediction to 60 days before found to be significant. The significance of all cumulative returns for the value-weighted portfolio decreased from the 1 percent significance level to 5 percent.
Also for the value-weighted portfolio, all factors which contain the mean of maximum values from the last 30 days are significant at the 1 percent significance level.
You can find the results on the tables below.

- Equal-weighted portfolio

	r1	r7	r13	r22	r31
	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)
Low	-36,47	-24,71	-8,86	-15,64	-25,61
2.0	-38,63	-51,78	-45,62	-45,69	-40,02
3.0	-44,01	-42,95	-53,14	-43,02	-43,19
4.0	-51,65	-47,48	-51,28	-66,33	-68,99
High	-163,66	-165,27	-169,09	-158,11	-150,02
Low-High difference	127,19	140,57	160,23	142,47	124,41
t-stat	6,03	6,97	7,96	7,08	6,36

Table 4.5: Past returns daily trading equal-weighted portfolio

	Max 7	Max 14	Max 21	Max 30	Max 30 m1	Max 30 m2
	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)
Low	-42,57	-33,58	-28,94	-25,98	-25,98	-18,24
2.0	-31,75	-37,61	-33,76	-30,35	-30,35	-41,38
3.0	-35,67	-45,31	-51,38	-57,66	-57,66	-55,52
4.0	-60,08	-66,12	-71,35	-81,7	-81,7	-78,52
High	-161,17	-146,79	-143,89	-131,78	-131,78	-133,95
Low-High difference	118,6	113,21	114,95	105,79	105,79	115,71
t-stat	7,5	7,48	8,02	7,37	7,37	7,28

Table 4.6: Past returns daily trading equal-weighted portfolio

	Max 30 m4	Max 30 m8	Max 30 m16
	Mean (%)	Mean (%)	Mean (%)
Low	-18,69	-24,19	-25,19
2.0	-41,76	-40,54	-37,35
3.0	-53,24	-49,4	-62,38
4.0	-75,49	-70,99	-55,86
High	-138,45	-142,73	-147,18
Low-High difference	119,75	118,54	121,99
t-stat	7,63	7,33	7,29

Table 4.7: Past returns daily trading equal-weighted portfolio

- Value-weighted portfolio

	r7	r13	r180 60	Max 7	Max 14	Max 21
	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)
Low	-165,96	-132,5	-108,58	-19,81	-14,65	2,35
2.0	-67,79	-67,75	-46,71	-13,74	-5,48	5,95
3.0	-19,79	-29,51	-38,98	-3,97	-9,68	-18,73
4.0	14,43	22,63	-15,07	-56,28	-65,74	-123,23
High	-63,56	-40,53	-16,73	-249,46	-315,36	-286,92
Low-High difference	-102,4	-91,97	-91,85	229,66	300,71	289,26
t-stat	-2,33	-2,34	-2,86	5,75	7,36	6,87

Table 4.8: Past returns daily trading value-weighted portfolio

	Max 30	Max 30 m1	Max 30 m2	Max 30 m4	Max 30 m8	Max 30 m16
	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)
Low	12,16	12,16	13,24	14,36	16,2	8,9
2.0	-7,2	-7,2	-11,75	-23,11	-27,58	-0,88
3.0	-47,41	-47,41	-50,26	-29,56	-32,76	-50,15
4.0	-142,82	-142,82	-132,32	-147,52	-127,09	-102,02
High	-267,51	-267,51	-294,08	-294,24	-304,01	-292,09
Low-High difference	279,67	279,67	307,32	308,61	320,21	300,99
t-stat	7,37	7,37	8,2	7,93	8,01	7,66

Table 4.9: Past returns daily trading value-weighted portfolio

Other

For other characteristics, the situation changed - for the equal-weighted portfolio only **capm aplha** - the excess return from a CAPM, calculated based on a 30-day rolling window, is significant at the 1 percent significance level, but for the value-weighted portfolio we can see that only the historical Value-at-Risk at the 5 percent calculated based on past 90-day returns (**var95**) is significant at the 1 percent significance level. You can find the results on the tables below.

- Equal-weighted portfolio

	Capm alpha
	Mean (%)
Low	-22,28
2.0	-44,52
3.0	-41,75
4.0	-66,08
High	-152,98
Low-High difference	130,7
t-stat	6,62

Table 4.10: Other characteristics daily trading equal-weighted portfolio

- Value-weighted portfolio

	var95
	Mean (%)
Low	-264,77
2.0	-109,19
3.0	-96,03
4.0	-42,75
High	11,22
Low-High difference	-275,99
t-stat	-7,16

Table 4.11: Other characteristics daily trading value-weighted portfolio

4.2 Weekly trading

For weekly trading, we apply the same thing - form the long-short strategy, find the first and fifth portfolios, and calculate their difference, but we trade once a week. After that we evaluate the significance for each factor using the t-value.
We calculated the returns over all week and did the same research with the equal-weighted portfolio and the value-weighted portfolios.

On – chain characteristics

From on-chain characteristics, only network-to-market value - the cumulative number of unique addresses over the current available supply times the current USD price

(**bm**) is significant in equal-weighted portfolio. The results for **bm** are -78.65 for the first portfolio, -47.3 for the fifth portfolio, and their difference is -31.35, which is significant at the 5 percent significance level.
But in the value-weighted portfolio it is no longer significant. For the value-weighted portfolio we didn't find any on-chain characteristics to be significant.
You can find the results on the tables below.

- Equal-weighted portfolio

	BM
	Mean (%)
Low	-78,65
2.0	-66,22
3.0	-69,02
4.0	-73,52
High	-47,3
Low-High difference	-31,35
t-stat	-2,22

Table 4.12: On-chain characteristics weekly trading equal-weighted portfolio

- Value-weighted portfolio

None of characteristics found to be significant.

Trading frictions

For trading frictions for weekly trading, the situation with factor significance changed a lot - some characteristics which are not significant for the equal-weighted portfolio became significant for the value-weighted portfolio - such as market capitalization (**marketcap**), the standard deviation of the residuals from a 30-day rolling window regression of daily trading volume (**std vol**), trading volume (**volumeto**). Also some factors like **turnover** and **std to** were significant at the 5 percent significance level for the equal-weighted portfolio, but in value-weighted they are no longer significant.
Realised volatility (**yzvol**), the bid-ask spread (**bidask**) and idiosyncratic volatility (**idio vol**) remain significant for both portfolios at the 1 percent significance level.
You can find the results on the tables below.

- Equal-weighted portfolio

	yzvol	Bidask	turnover	Idio vol	std to
	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)
Low	-21,96	-43,54	-62,98	-21,63	-64,52
2.0	-50,22	-52,22	-66,52	-39,98	-50,78
3.0	-66,37	-63,56	-45,33	-74,24	-57,98
4.0	-97,46	-67,15	-58,51	-89,69	-70,84
High	-94,76	-111,38	-95,34	-105,12	-85,99
Low-High difference	72,8	67,84	32,35	83,49	21,47
t-stat	4,84	4,73	2,55	5,39	1,79

Table 4.13: Trading frictions weekly trading equal-weighted portfolio

- Value-weighted portfolio

	Marketcap	yzvol	Bidask	Idio vol	std vol	volumeto
	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)
Low	-69,95	13,73	2,32	11,25	8,46	-83,6
2.0	-79,41	-41,14	-38,89	-48,2	-35,54	-82,71
3.0	-78,13	-81,84	-27,92	-88,67	-72,93	-75,1
4.0	-68,13	-119,59	-64,31	-121,98	-83,53	-46,81
High	0,2	-111,3	-142,02	-154,84	-102,28	5,22
Low-High difference	-70,15	125,03	144,34	166,1	110,74	-88,82
t-stat	-2,64	3,36	3,4	4,16	3,01	-3,32

Table 4.14: Trading frictions weekly trading value-weighted portfolio

Past returns

As for past returns, all cumulative returns are significant for equal-weighted portfolio at the 1 percent significance level, but for the value-weighted only **r13** remain to be significant.
Also a lot of characteristics with mean of maximum returns for the last 30 days are significant for both equal-weighted and value-weighted portfolios at the 1 percent significance level. The factors **Max 30 m2** and **Max 30 m4** are significant for the equal-weighted portfolio, but found not to be significant for the value-weighted portfolio. For the value-weighted portfolio we can see that **Max 7** became significant at the 1 percent significance level.
You can find the results on the tables below.

- Equal-weighted portfolio

	r1	r7	r13	r22	r31	Max 7
	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)
Low	-62,84	-53,37	-62,37	-50,57	-51,47	-49,94
2.0	-57,39	-58,67	-53,19	-61,04	-53,57	-38,7
3.0	-46,41	-51,22	-57,4	-48,74	-59,27	-55,36
4.0	-59,76	-62,09	-49,2	-63,18	-61,47	-65,03
High	-111,65	-110,24	-113,63	-110,75	-104,96	-127,95
Low-High difference	48,81	56,87	51,26	60,19	53,49	78,01
t-stat	3,57	3,38	3,46	4,1	3,19	5,7

Table 4.15: Past returns weekly trading equal-weighted portfolio

	Max 14	Max 21	Max 30	Max 30 m1	Max 30 m2	Max 30 m4
	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)
Low	-40,62	-34,66	-29,02	-29,02	-25,08	-24,54
2.0	-42,65	-47,14	-38,31	-38,31	-44,06	-46,64
3.0	-58,53	-50,43	-60,99	-60,99	-58,95	-55,66
4.0	-72,55	-79,97	-90,19	-90,19	-92,56	-92,59
High	-120,97	-122,11	-112,06	-112,06	-109,83	-111,22
Low-High difference	80,35	87,45	83,05	83,05	84,75	86,68
t-stat	5,22	5,58	5,53	5,53	5,26	5,38

Table 4.16: Past returns weekly trading equal-weighted portfolio

	Max 30 m8	Max 30 m16
	Mean (%)	Mean (%)
Low	-27,44	-27,49
2.0	-47,66	-48,84
3.0	-49,29	-50,41
4.0	-89,24	-85,9
High	-117,25	-118,23
Low-High difference	89,81	90,74
t-stat	5,51	5,28

Table 4.17: Past returns weekly trading equal-weighted portfolio

- Value-weighted portfolio

	r13	Max 7	Max 14	Max 21	Max 30	Max 30 m1
	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)
Low	-116,81	-16,98	-12,15	8,62	10,06	10,06
2.0	-31,25	-2,85	2,67	1,73	-21,37	-21,37
3.0	-42,05	-23,13	-18,03	-26,73	-57,9	-57,9
4.0	-9,02	-36,34	-93,44	-108,06	-109,17	-109,17
High	-52,72	-175,79	-180,4	-172,39	-137,38	-137,38
Low-High difference	-64,09	158,81	168,25	181.0	147,44	147,44
t-stat	-1,82	4,47	4,6	5.0	3,42	3,42

Table 4.18: Past returns weekly trading value-weighted portfolio

	Max 30 m2	Max 30 m4	Max 30 m8	Max 30 m16
	Mean (%)	Mean (%)	Mean (%)	Mean (%)
Low	-0,3	8,08	8,13	11,97
2.0	-11,87	-6,12	-25,38	-18,13
3.0	-76,74	-58,11	-54,41	-50,35
4.0	-78,79	-101,77	-110,98	-94,53
High	-171,18	-160,61	-171,29	-172,54
Low-High difference	170,88	168,69	179,41	184,51
t-stat	4,49	4,52	4,5	4,9

Table 4.19: Past returns weekly trading value-weighted portfolio

Other

From other characteristics, for the equal weighted portfolio **capm aplha** and **var95** are significant at the 1 percent significance level.
For the value-weighted only **var95** remain significant at the 1 percent significance level with results of -50.99 for the first portfolio, -109.05 for the fifth portfolio, and 58.05 for their difference. **Capm aplha** is no longer significant for the value-weighted portfolio.
You can find the results on the tables below.

- Equal-weighted portfolio

	Capm alpha	var95
	Mean (%)	Mean (%)
Low	-50,99	-77,79
2.0	-59,11	-78.0
3.0	-56,35	-72,05
4.0	-55,26	-62,81
High	-109,05	-31,23
Low-High difference	58,05	-46,56
t-stat	3,43	-3,61

Table 4.20: Other characteristics weekly trading equal-weighted portfolio

- Value-weighted portfolio

	var95
	Mean (%)
Low	-120,1
2.0	-81,42
3.0	-65,79
4.0	-57,86
High	10,26
Low-High difference	-130,36
t-stat	-3,37

Table 4.21: Other characteristics weekly trading value-weighted portfolio

Chapter 5

Conclusion

The results of this thesis show that we can use the cryptocurrency characteristics for predicting their returns. Market-based characteristics or trading frictions were found to be important measures. Past returns were found to be significant predictors for all time periods for both equal- and value-weighted portfolios. In contrast, we can see that on-chain factors, such as the number of new addresses and the number of addresses on which at least one transaction was made during the day, are not a significant measure for predicting the returns.

By using a certain set of characteristics the investor can buy portfolios using the long-short strategy and have profit from the returns. The set of characteristics should be chosen depending on the trading period. In this paper we used daily and weekly trading. We also found that set of significant characteristics changes if we change the portfolio strategy - equal- or value-weighted. The set of significant characteristics can be used for predicting cryptocurrency returns and using the long-short strategy for selecting cryptocurrencies.

Chapter 6

Further model improvement

As an improvement for future research, the model with all significant factors can be created. The importance of the characteristic can be calculated by analyzing its significance, which can be taken from this research. We also understand that this research is actual right now and can be actual only for the near future - a couple of years. As the cryptocurrency market changes rapidly, we cannot make research and found characteristics that will be significant for this market for a long time. Also for improving the model analyzing current trends could be done. As we already mentioned in this paper, cryptocurrency is hard to predict because of its unpredictable risks - such as promotion on social media, statements of big companies, or some famous people.

Appendix A

Tables with statistic for all characteristics for equal-weighted portfolio for daily trading.

	Active addresses	Bidask	BM	Capm alpha	Capm beta	Idio vol
	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)
Low	-40,31	-43,43	-120,23	-22,28	-82,32	-12,79
2.0	-45.0	-48,48	-85,46	-44,52	-63,28	-42,93
3.0	-72,34	-69,65	-104,13	-41,75	-47,97	-64,01
4.0	-83,65	-66,86	-77,61	-66,08	-57,6	-87,81
High	-64,88	-107,1	55,47	-152,98	-76,27	-120,31
Low-High difference	24,57	63,66	-175,7	130,7	-6,05	107,52
t-stat	1,01	3,74	-10,4	6,62	-0,39	7,11

Table 1: All characteristics for equal-weighted portfolio for daily trading

	Marketcap	Max 7	Max 14	Max 21	Max 30	Max 30 m1
	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)
Low	65,36	-42,57	-33,58	-28,94	-25,98	-25,98
2.0	-111,52	-31,75	-37,61	-33,76	-30,35	-30,35
3.0	-109,31	-35,67	-45,31	-51,38	-57,66	-57,66
4.0	-106,2	-60,08	-66,12	-71,35	-81,7	-81,7
High	-70,03	-161,17	-146,79	-143,89	-131,78	-131,78
Low-High difference	135,39	118,6	113,21	114,95	105,79	105,79
t-stat	8,29	7,5	7,48	8,02	7,37	7,37

Table 2: All characteristics for equal-weighted portfolio for daily trading

	Max 30 m2	Max 30 m4	Max 30 m8	Max 30 m16	New addresses	r1
	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)
Low	-18,24	-18,69	-24,19	-25,19	-49,44	-36,47
2.0	-41,38	-41,76	-40,54	-37,35	-49,26	-38,63
3.0	-55,52	-53,24	-49,4	-62,38	-69,14	-44,01
4.0	-78,52	-75,49	-70,99	-55,86	-86,24	-51,65
High	-133,95	-138,45	-142,73	-147,18	-65,61	-163,66
Low-High difference	115,71	119,75	118,54	121,99	16,17	127,19
t-stat	7,28	7,63	7,33	7,29	0,57	6,03

Table 3: All characteristics for equal-weighted portfolio for daily trading

	r7	r13	r22	r30 14	r31	r180 60
	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)
Low	-24,71	-8,86	-15,64	-74,07	-25,61	-79,74
2.0	-51,78	-45,62	-45,69	-63,25	-40,02	-55,33
3.0	-42,95	-53,14	-43,02	-42,73	-43,19	-50,32
4.0	-47,48	-51,28	-66,33	-64,9	-68,99	-66,09
High	-165,27	-169,09	-158,11	-82,24	-150,02	-59,29
Low-High difference	140,57	160,23	142,47	8,16	124,41	-20,46
t-stat	6,97	7,96	7,08	0,47	6,36	-1,29

Table 4: All characteristics for equal-weighted portfolio for daily trading

	std to	std vol	turnover	var95	volumeto	yzvol
	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)
Low	-66,92	-48,82	-37,39	-54,29	35,7	-11,06
2.0	-41,8	-49,82	-44,1	-85,64	-91,1	-43,66
3.0	-58,4	-57,46	-34,84	-73,04	-66,39	-60,2
4.0	-64,6	-89,07	-42,52	-66,93	-71,77	-99,72
High	-91,7	-79,92	-110,3	-37,35	-82,36	-112,93
Low-High difference	24,78	31,1	72,91	-16,94	118,06	101,87
t-stat	1,82	2,47	3,81	-1,17	5,91	6,99

Table 5: All characteristics for equal-weighted portfolio for daily trading

Appendix B

Tables with statistic for all characteristics for value-weighted portfolio for daily trading.

	Active addresses	Bidask	BM	Capm alpha	Capm beta	Idio vol
	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)
Low	-7,13	-22,83	-57,72	-99,43	-94,49	12,86
2.0	-47,61	-5,39	-39,21	-73,6	-26,34	-52,99
3.0	-104,89	-49,28	-61,81	-19,98	-19,3	-77,9
4.0	-96,7	-78,3	-23,39	1,82	-14,95	-152,29
High	4,67	-244,05	-28,88	-63,31	-109,12	-341,74
Low-High difference	-11,8	221,22	-28,84	-36,12	14,63	354,6
t-stat	-0,39	4,71	-0,97	-0,92	0,38	8,5

Table 6: All characteristics for value-weighted portfolio for daily trading

	Marketcap	Max 7	Max 14	Max 21	Max 30	Max 30 m1
	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)
Low	-7,98	-19,81	-14,65	2,35	12,16	12,16
2.0	-103,5	-13,74	-5,48	5,95	-7,2	-7,2
3.0	-109,49	-3,97	-9,68	-18,73	-47,41	-47,41
4.0	-102,55	-56,28	-65,74	-123,23	-142,82	-142,82
High	0,7	-249,46	-315,36	-286,92	-267,51	-267,51
Low-High difference	-8,68	229,66	300,71	289,26	279,67	279,67
t-stat	-0,39	5,75	7,36	6,87	7,37	7,37

Table 7: All characteristics for value-weighted portfolio for daily trading

	Max 30 m2	Max 30 m4	Max 30 m8	Max 30 m16	New addresses	r1
	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)
Low	13,24	14,36	16,2	8,9	-26,39	-142,81
2.0	-11,75	-23,11	-27,58	-0,88	-65,46	-33,07
3.0	-50,26	-29,56	-32,76	-50,15	-105,96	-17,88
4.0	-132,32	-147,52	-127,09	-102,02	-95,59	-2,3
High	-294,08	-294,24	-304,01	-292,09	4,87	-103,54
Low-High difference	307,32	308,61	320,21	300,99	-31,26	-39,28
t-stat	8,2	7,93	8,01	7,66	-1,16	-0,99

Table 8: All characteristics for value-weighted portfolio for daily trading

	r7	r13	r22	r30 14	r31	r180 60
	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)
Low	-165,96	-132,5	-104,53	-115,82	-103,31	-108,58
2.0	-67,79	-67,75	-48,69	-59,59	-63,25	-46,71
3.0	-19,79	-29,51	-56,76	-7,52	-30,1	-38,98
4.0	14,43	22,63	-8,7	-33,8	-12,2	-15,07
High	-63,56	-40,53	-52,95	-67,86	-42,27	-16,73
Low-High difference	-102,4	-91,97	-51,58	-47,96	-61,03	-91,85
t-stat	-2,33	-2,34	-1,37	-1,19	-1,62	-2,86

Table 9: All characteristics for value-weighted portfolio for daily trading

	std to	std vol	turnover	var95	volumeto	yzvol
	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)
Low	-61,48	11,46	-134,84	-264,77	-226,88	14,8
2.0	-11,78	-55,3	-52,86	-109,19	-121,86	-40,9
3.0	7,79	-96,32	9,75	-96,03	-89,94	-81,39
4.0	-46,63	-109,98	-9,37	-42,75	-60,37	-159,05
High	-86,56	-170,32	-73,21	11,22	7,51	-294,53
Low-High difference	25,07	181,78	-61,63	-275,99	-234,39	309,33
t-stat	0,7	5,44	-1,8	-7,16	-6,29	7,94

Table 10: All characteristics for value-weighted portfolio for daily trading

Appendix C

Tables with statistic for all characteristics for equal-weighted portfolio for weekly trading.

	Active addresses	Bidask	BM	Capm alpha	Capm beta	Idio vol
	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)
Low	-61,58	-43,54	-78,65	-50,99	-74,81	-21,63
2.0	-54,83	-52,22	-66,22	-59,11	-62,23	-39,98
3.0	-80,49	-63,56	-69,02	-56,35	-57,39	-74,24
4.0	-69,39	-67,15	-73,52	-55,26	-53,03	-89,69
High	-58,11	-111,38	-47,3	-109,05	-83,3	-105,12
Low-High difference	-3,47	67,84	-31,35	58,05	8,49	83,49
t-stat	-0,17	4,73	-2,22	3,43	0,55	5,39

Table 11: All characteristics for equal-weighted portfolio for weekly trading

	Marketcap	Max 7	Max 14	Max 21	Max 30	Max 30 m1
	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)
Low	-50,31	-49,94	-40,62	-34,66	-29,02	-29,02
2.0	-78,57	-38,7	-42,65	-47,14	-38,31	-38,31
3.0	-79,54	-55,36	-58,53	-50,43	-60,99	-60,99
4.0	-75,59	-65,03	-72,55	-79,97	-90,19	-90,19
High	-50,89	-127,95	-120,97	-122,11	-112,06	-112,06
Low-High difference	0,58	78,01	80,35	87,45	83,05	83,05
t-stat	0,04	5,7	5,22	5,58	5,53	5,53

Table 12: All characteristics for equal-weighted portfolio for weekly trading

	Max 30 m2	Max 30 m4	Max 30 m8	Max 30 m16	New addresses	r1
	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)
Low	-25,08	-24,54	-27,44	-27,49	-51,26	-62,84
2.0	-44,06	-46,64	-47,66	-48,84	-55,42	-57,39
3.0	-58,95	-55,66	-49,29	-50,41	-75,5	-46,41
4.0	-92,56	-92,59	-89,24	-85,9	-72,08	-59,76
High	-109,83	-111,22	-117,25	-118,23	-57,15	-111,65
Low-High difference	84,75	86,68	89,81	90,74	5,9	48,81
t-stat	5,26	5,38	5,51	5,28	0,18	3,57

Table 13: All characteristics for equal-weighted portfolio for weekly trading

	r7	r13	r22	r30 14	r31	r180 60
	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)
Low	-53,37	-62,37	-50,57	-68,66	-51,47	-75,25
2.0	-58,67	-53,19	-61,04	-56,25	-53,57	-62,4
3.0	-51,22	-57,4	-48,74	-49,17	-59,27	-48,92
4.0	-62,09	-49,2	-63,18	-69,53	-61,47	-60,79
High	-110,24	-113,63	-110,75	-87,12	-104,96	-63,59
Low-High difference	56,87	51,26	60,19	18,46	53,49	-11,66
t-stat	3,38	3,46	4,1	1,48	3,19	-0,69

Table 14: All characteristics for equal-weighted portfolio for weekly trading

	std to	std vol	turnover	var95	volumeto	yzvol
	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)
Low	-64,52	-53,61	-62,98	-77,79	-61,19	-21,96
2.0	-50,78	-52,29	-66,52	-78.0	-71,93	-50,22
3.0	-57,98	-68,1	-45,33	-72,05	-60,59	-66,37
4.0	-70,84	-83,7	-58,51	-62,81	-67,43	-97,46
High	-85,99	-73,9	-95,34	-31,23	-70,31	-94,76
Low-High difference	21,47	20,29	32,35	-46,56	9,12	72,8
t-stat	1,79	1,62	2,55	-3,61	0,74	4,84

Table 15: All characteristics for equal-weighted portfolio for weekly trading

Appendix D

Tables with statistic for all characteristics for value-weighted portfolio for weekly trading.

	Active addresses	Bidask	BM	Capm alpha	Capm beta	Idio vol
	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)
Low	10,28	2,32	-46,01	-44,91	-54,51	11,25
2.0	-51,82	-38,89	-34,03	-59,77	-39,87	-48,2
3.0	-47,92	-27,92	-51,95	-27,79	-12,71	-88,67
4.0	-94,18	-64,31	-29.0	2,2	-19,37	-121,98
High	2,76	-142,02	-32,34	-49,56	-102,63	-154,84
Low-High difference	7,52	144,34	-13,67	4,65	48,12	166,1
t-stat	0,23	3,4	-0,46	0,14	0,97	4,16

Table 16: All characteristics for value-weighted portfolio for weekly trading

	Marketcap	Max 7	Max 14	Max 21	Max 30	Max 30 m1
	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)
Low	-69,95	-16,98	-12,15	8,62	10,06	10,06
2.0	-79,41	-2,85	2,67	1,73	-21,37	-21,37
3.0	-78,13	-23,13	-18,03	-26,73	-57,9	-57,9
4.0	-68,13	-36,34	-93,44	-108,06	-109,17	-109,17
High	0,2	-175,79	-180,4	-172,39	-137,38	-137,38
Low-High difference	-70,15	158,81	168,25	181.0	147,44	147,44
t-stat	-2,64	4,47	4,6	5.0	3,42	3,42

Table 17: All characteristics for value-weighted portfolio for weekly trading

	Max 30 m2	Max 30 m4	Max 30 m8	Max 30 m16	New addresses	r1
	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)
Low	-0,3	8,08	8,13	11,97	-14,03	-87,87
2.0	-11,87	-6,12	-25,38	-18,13	-30,69	-55,49
3.0	-76,74	-58,11	-54,41	-50,35	-62,96	-3,73
4.0	-78,79	-101,77	-110,98	-94,53	-85,92	-32,16
High	-171,18	-160,61	-171,29	-172,54	2,87	-47,57
Low-High difference	170,88	168,69	179,41	184,51	-16,9	-40,31
t-stat	4,49	4,52	4,5	4,9	-0,55	-1,13

Table 18: All characteristics for value-weighted portfolio for weekly trading

	r7	r13	r22	r30 14	r31	r180 60
	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)
Low	-112,72	-116,81	-84,76	-69,23	-59,53	-63,07
2.0	-38,28	-31,25	-31,43	-57.0	-42,97	-45,14
3.0	-19.0	-42,05	-46,72	11,62	-39,03	-15,57
4.0	9,47	-9,02	5,24	-17,32	-20,43	-12,24
High	-64,95	-52,72	-63,34	-70,61	-53,38	-15,62
Low-High difference	-47,78	-64,09	-21,43	1,38	-6,15	-47,45
t-stat	-1,4	-1,82	-0,63	0,03	-0,18	-1,59

Table 19: All characteristics for value-weighted portfolio for weekly trading

	std to	std vol	turnover	var95	volumeto	yzvol
	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)	Mean (%)
Low	-63,76	8,46	-86,26	-120,1	-83,6	13,73
2.0	-17,08	-35,54	-60,42	-81,42	-82,71	-41,14
3.0	4,1	-72,93	-1,62	-65,79	-75,1	-81,84
4.0	-43,49	-83,53	-1,22	-57,86	-46,81	-119,59
High	-69,66	-102,28	-65,94	10,26	5,22	-111,3
Low-High difference	5,89	110,74	-20,32	-130,36	-88,82	125,03
t-stat	0,2	3,01	-0,82	-3,37	-3,32	3,36

Table 20: All characteristics for value-weighted portfolio for weekly trading

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