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Value and Momentum in Cryptocurrency Market Factor Models

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Abstract

Cryptocurrency market is a decentralized, highly speculative, emerging environment, perfect for researching fundamental risk or behavioral biases. The paper attempts to test factor models analogous to other asset classes', most notably by using market-to-volume factor as stock market value counterpart and several momentum strategies, including volume-based momentum. I find size and market to be robust and significant, while conventional momentum strategies and time-series momentum are not. The market-to-volume factor performance is more in line with behavioral and attention explanations. Volume-based momentum factor highly significant and is likely to be related to noise-trader risk, making cryptocurrency returns highly saturated with behavioral anomalies.

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1. Introduction

Bitcoin as a concept of decentralized peer-to-peer digital encrypted currency was created my Nakamoto (2008) and over the years led to the creation of a new cryptocurrency market and expanding into other mediums. At the time of writing the paper the total market capitalization of cryptocurrency market is about 1 trillion USD with its peak of more than 2.9 trillion USD in November 2021. Recently, a new crypto-asset called NFT or non-fungible token has also been on the rise with rapid growth from almost zero to more than 800 billion for art-blocks in just 2021.

The decentralized nature of cryptocurrency also brought change to political landscape around it. As some countries try to embrace the digital currency and support it being used for payments, other countries introduce policies or bans on generating, trading, and keeping cryptocurrencies as an attempt to regulate it. For example China has an absolute ban on cryptocurrencies as of 2022.

Another interesting impact of cryptocurrency market is its effect on tech sector. To generate new cryptocurrencies, a large amount of computing power is required, mainly an extremely large number of simple calculations which are perfectly suited for GPU or graphics processing unit, a common computer part used for rendering images. Cryptocurrency market boom consequently caused an extreme demand on the graphic units, causing the massive shortage of them from year 2017.

With cryptocurrencies getting an increasing recognition in the media and becoming more mainstream, the digital currencies are also getting increased traction in financial research. Cryptocurrency market interesting to research not only as a digital currency with no underlying value phenomenon, but also as an emerging market that is decentralized and highly speculative. Such environment can be perfect for studying both fundamental and behavioral theories.

Due to cryptocurrency imbedded complexity in valuating it as well as distinguishing fundamental risk factors from market-wide behavioral biases the main focus of this paper is to establish a theoretical framework in a form of factor analysis. The paper research question is:

> *What common factors can explain cryptocurrency return variance and are they related to risk?*

To answer this question well established methods in other financial assets, mainly stocks, are used with an addition of the still growing cryptocurrency literature. In the standard financial theory what determines the price of an asset and what drives its returns is the underlying value and risk, therefore it is important to find a risk-return relationship in cryptocurrency space or find alternative explanations of return variance using, for example, behavioral theory. If cryptocurrency market is dominated by sentiment and noise-traders, it might be a good enough deterrent to prevent potential investors to enter it, seeking either high risk – high return opportunities or means of diversification. Results of this paper can help investors to either evaluate their trading strategies or help them make more educated choices on constructing a cryptocurrency portfolio. It is also interesting from an academic perspective to understand the market better from risk-behavioral perspective.

In this research the following factors are tested on average equal-rated returns: market, size, volume, market-to-volume, cross-sectional and time-series momentum, and volume-based momentum. Market and size and widely used risk factors found in many other asset classes. Market-to-volume is defined as a ratio between market capitalization of a coin and its total transactional volume over the same period. It is used like value factor in the stock market, however it can also be interpreted at either a liquidity factor or a proxy for attention factor. Cross-sectional and time-series momentum strategies are primarily a behavioral anomaly that is persistent in most markets across multiple asset classes but more pronounced in emerging markets. Finally, volume-based momentum is a new metric inspired by Jegadeesh and Titman (1993) and Swaminathan (2000) and methodology that is used as an alternative to momentum factor.

The main finding of the research include strong evidence of Market and Size factors explaining return variance and relating to fundamental risk. Similarly, volume-based momentum factor is highly significant and robust and could be related to liquidity premium. Alternatively it can be interpreted as a strong contrarian effect due to noise trader activity (De Long et al, 1990). There is little evidence of 3-12 months classical momentum strategies generating negative returns. Market-to-volume is likely to be more be better explained by investor sentiment and noise-trader risk, than fundamental value or liquidity risk. The factor also makes volume factor redundant as it is better at explaining cross-sectional returns. Short-term momentum and time-series momentum did not produce significant coefficients. Overall, the evidence of fundamental risk in cryptocurrency market is concentrated in saze and market factors, while classical momentum does not to explain returns sufficiently. On the other hand market-to-volume and volume-based momentum factors seem to be more related to behavioral anomalies.

The rest of the paper is structured in the following manner. Section 2 discusses relevant literature, Section 3 is focused on Data and data transformations, Section 4 describes research methodology. Section 5 conducts the empirical results and robustness checks. Section 6 concludes.

2. Literature review

2.1. Efficient Market Hypothesis and CAPM

Efficient Market Hypothesis and Capital Asset Pricing model are models that sit at the core of modern financial economic theory and should serve as a good starting point for investigation on cryptocurrency markets

Still used to this day, the Efficient Market Hypothesis that was independently developed by Fama (1970) and Samuelson (1965). The main assumptions of the hypotheses state that prices reflect the intrinsic value of assets and incorporate all available past and future information, the prices move randomly, and it is impossible to generate returns on mispricings consistently.

The implication of testing EMH is the simultaneous test of the market and the model, thus rejecting it might mean that either the market is inefficient, or the model is inaccurate. (Fama, 1970)

On another other hand Capital Asset Pricing Model was developed by Sharpe (1964) and Lither (1969) as a model for pricing financial assets. The simplicity and elegance of the model's risk and return relationship contributed to both its rapid adaptation into financial world and growing research literature to test and expand it. The central point of CAPM is the Market factor and assets risk-return relationship is described as their sensitivity to market volatility.

2.2. Fama French 3 factor model

The next big step in modern theory development would be the Fama French 3 factor model (Fama and French, 1992). In addition to the market factor, two more were introduced: Size and Value. The new factors occupied new dimensions of risk-return relationship. Size factor is rather straightforward, small companies are less transparent and have more difficulty to obtain financing as bigger companies and therefore they must have a higher rate of return to compensate for it. Value factor is based on the ratio of a firm's equity to its market price. High book-to-market companies or "value" companies on average have higher returns than their "growth" counterparts.

One explanation of the factor could be that growth companies on average perform better in the long ran and have more growth opportunities, so they are safer to invest in. (Fama and French, 1993). An alternative, behavioral explanation can also play a role in explaining both size and value returns. The early work of the impact of investor sentiment on the financial market was documented by Shleifer (2000). Detailed research on the correctional returns was done by Baker and Wurgler (2006). They find that following low investor sentiment the stocks that are small, young, distressed, unprofitable or extremely low in book-to-market experience high returns but also underperform after high sentiment. Low sentiment would forecast that Investors will overreact and gamble on volatile, small stocks that have limited information producing abnormal returns. Lemmon and Portniaguina (2006) also find some limited evidence on the impact of sentiment (measured in institutional ownership) on value firms and zero sensitivity for growth firms. Later research, however, suggests that the impact of sentiment depends on the state of the economy and only have predictive power during expansions (Chung at al, 2012).

2.3. Momentum

Another major factor that got a lot of attention in the literature is momentum. First evidence of it was found in stock market by Jegadeesh and Titman (1993). Momentum is described as a tendency of stocks that outperformed other stocks over a period to continue producing relatively higher returns. Carhart (1997) used momentum as an additional factor in Fama French three-factor model and found evidence of momentum explaining some of the return variance, however he does not provide any interpretation of the nature of momentum. Similarly, Fama and French (2012) study momentum along other factors in four regions globally and find patterns in all markets except Japan which can be attributed to either chance (Fama and French, 2012) or theory of individualism (Chui et al, 2010), which tries to relate cultural differences to trading patterns.

From that point the factor research becomes more saturated. Fama French 5-factor model that includes profitability and investment patterns (Fama and French, 2015), there also have been multiple studies on liquidity and macro-oriented factors.

A major paper by Asness, Moskowitz and Pedersen (2013) studies returns across a number of asset classes and finds strong correlation between momentum and value factors. Additionally they find a negative relationship between the factors and the benefit of combining them to improve market efficiency. Liquidity risk offers a partial explanation for the momentum, but not for value or the combination of the two.

Lee and Swaminathan (2000) documents momentum effects reversing over the 3-5 years, which is faster for high volume stocks. They also reject the notion that volume is simply a liquidity proxy.

A paper Moskowitz et al (2012) also introduced time-series momentum, finding that cumulative returns over a one to twelve months effect the future returns for all 58 liquid securities they tested.

2.4. Cryptocurrency research

Moving to cryptocurrency space, the initial history of cryptocurrencies started with Bitcoin, in paper made by Satoshi Nakamoto in 2008. As the network grew crating its own market, the literature on cryptocurrencies began to emerge as well.

Overall research on cryptocurrencies poses several problems. In addition to the decentralized nature of the asset and limited governance over it, studies like Baek and Elbeck (2015) or Baur et al. (2018) on Bitcoin also show that cryptocurrency market is very speculative in nature.

Early papers like Baur at al (2015) and Elendner at al (2016) however also show that crypto currencies also tend to have very low correlation with other financial assets. This implies that the cryptocurrency can be used for diversification. Elendner at al (2016) also found some evidence for a size effect.

A large highly speculative and decentralized market however opens up research with the focus on behavioral impacts on the assets. If the market is driven by sentiment and speculators, then the behavioral factors will play a bigger role in pricing, than in conventional assets. Conversely, risk-based factors would not be as influential. Unless, of course, factors like size and market are fundamental to the market structure.

Next, I discuss the relevant factor research on cryptocurrency market. One of the first papers that did a factor analysis of cryptocurrencies is done by Hubrich (2017). The factors used in the paper are momentum, value and carry. Momentum factor is described as the last week returns. Value factor poses a challenge due to cryptocurrencies lacking either a book value, or any form of fundamental value that can be estimated. In the paper the value factor is defined as a ratio of market capitalization to the transaction volume of the cryptocurrency. This is based on a notion that the fundamental value of cryptocurrency comes from its economic activity, or in other words the volume of trading relative to its size. Carry factor is supposed to capture how the market would change if the underlying cryptocurrency demand does not change. This metric is based on currency “inflation” as a result of future creation of new coins due to mining. All three factors have statistically significant coefficients, with momentum being the strongest of them all.

In general most papers like Shen at al. (2020) or more recent Liu et al. (2022) focus on market size and momentum factors the most. Market and size are found to have a significant and positive sign, similar to stocks. Most difference in results comes from how researchers estimate momentum. Momentum is one of the most developed directions of research of the asset. There is also a distinction between the cross-sectional and time-series strategies.

A good example of that is the first paper on momentum in cryptocurrencies by Rohbach et al, (2017). The paper documents both strong cross-sectional and time-series momentum effects in cryptocurrencies and emerging market currencies.

A rather classical study on momentum factor was done by Grobys et al (2019). Their portfolios are constructed very similarly to the original Jegadeesh and Titman (1993) methodology, however they do not find significant momentum payoffs, and find limited evidence for a time series momentum.

Other studies like Tzouvanas et al (2020), Wang and Chong (2021) or Liu et al. (2022) focus more on short term momentum based on last one to four weeks and find conflicting results. Tzouvanas et al (2020) find only significant momentum returns up to seven days, but not longer periods. Returns are also not adjusted for other factors. Wang and Chong (2021) also use one week momentum and using Fama–MacBeth regressions the momentum beta is found to be negative or insignificant. Finally, Liu et al. (2022) use three-week momentum and their results on regressing different portfolios on market, size and momentum show positive and significant momentum betas.

Kosc et al. (2018) also document a contrarian effect in cryptocurrencies, which is described as inverted momentum strategy that generates positive returns.

In general, momentum in literature is treated as anomaly, since EMH states that past returns should not predict future returns. Since momentum is still documented in other assets, in particular stocks to this day, its effects must be exacerbated in cryptocurrency market as it is both unregulated and new. To explain the nature of momentum, behavioral theories seem to fit the description the most. Researchers offer several behavioral hypotheses for momentum returns. The most applicable theories for crypto markets seem to be Grinblatt and Han (2005) disposition effect theory, Daniel et al (1998) overconfidence theory, representative heuristic by Barberis, Shleifer and Vishny (1998), gradual information diffusion (Hong and Stein, 1999) or De Long et al. (1990) noise trader risk theory.

Disposition effect is a bias of treating gains and losses differently. In investment is the tendency of traders to hold loser stocks for too long, while selling past winners too early, this leads to the market underreaction and as a result it creates momentum. Overconfidence can be described as self-attribution bias; investors think that positive momentum returns are a result of their skill and not wide-range mispricing and as a result they further invest in momentum. Similarly, representative heuristic is a bias of expecting momentum returns in the future based on the strategy working in the past. Gradual information diffusion theory states that private information is being diffused into the market over time creating the initial underreaction. Knowing this, traders try to arbitrage on this trend leading to long term overreaction. Finally, noise trader risk describe a conflict between noise traders and fundamental traders. If the market is dominated by noise traders, they are likely to create speculative mispricing to the point where fundamental investors are unlikely to oppose it. This can create persistent under or over reaction. One of the crucial differences between the theories is the assumption whether the mispricing is corrected over the longer horizons. Only noise trader risk and disposition effect do not require long term reversals, making them more likely to explain cryptocurrency momentum, as other studies do not find them. Moreover cryptocurrency market does have speculatory and overconfidence traits with a lack of fundamental trading, therefore noise traders might play a big role in momentum returns and other mispricings.

Volume is also a common factor in cryptocurrency literature, which is tied up to liquidity. The risk-based approach suggests that assets with low liquidity should offer premia to compensate for the difficulty and risk attached to dealing with low volatility like high bid-ask spreads or a high price sensitivity, making it more expensive to trade in large volumes. Bianchi and Dickerson (2019) make a good analysis on volume and momentum and find that there is likely a liquidity premium concentrated in cryptocurrencies with low market activity that are small and volatile. Returns of their strategy also seem to generate a significant and positive alpha when regressing them on other factors. Most other studies like by Yang (2019) or Liu et al. (2022) find Volume factor and its alternatives to not be significant.

Cryptocurrency Value factor in this paper is defined as their traded volume divided by their market capitalization which is unique to cryptocurrencies. However, it can also be defined as the cryptocurrency turnover ratio, which is also a common liquidity factor. Long et al. (2020) uses turnover as a factor when regressing their portfolio strategy, they find the coefficient to be mostly insignificant. Yang (2019) regresses value weighted turnover portfolio returns on market and size and finds no significant alpha. Alternatively, a research on stock returns by Lee and Swaminathan (2000) finds that past trading volume (which is estimated as a turnover ratio) negatively impacts returns similarly to value stocks and has a positive impact on momentum return. Another link between turnover ratio and value was made in an article by Vlastelica R. (2017) in a popular cryptocurrency news website MarketWatch. The author made a similar link as Hubrich (2017) suggesting that the ratio represents perceived value of cryptocurrency in the same way as book-to-market for companies.

And interesting study was done by Bhambhwani et al (2019) as they tried to incorporate cryptocurrency specific characteristics, namely network size and computing power into factor analyses. Their results suggest that the factors explain returns as well as the standard market, size, and momentum. They find market and network size to be the most significant out of the five.

From another angle, Shen at al (2019) use twitter data to find a link between the attention Bitcoin is getting to its price movement. They find that previous day trends on twitter correspond to a significant increase of volatility and trading volume of Bitcoin the next day.

3. Data

There has been a lot of uncertainty in the research community on the overall validity and reliability of cryptocurrency data. For example Alexander and Dakos (2020) document that more than 80 academic papers they reviewed had data from questionable sources, unsynchronized data when studying multiple asset classes or errors in time-series analysis. Another important pitfall of using cryptocurrency data is that due to unregulated and decentralized nature of the asset, some information like trading volume is hard to measure reliably. The main reason is that a lot of websites use trading volume as a measure to rank cryptocurrencies, providing the incentive for exchanges with extremely low or absent transaction costs to inflate numbers or "wash trade". Some more reliable sources of cryptocurrency data like CoinMarketCap or CryptoCompare use their own methodology to calculate volume, using only exchanges that have a trading fee and do not incentivize excess trading.

The cryptocurrency data for this research was extracted through CoinMarketCap API. Weekly data was obtained from the 1st of January 2015 till the 1st of January 2022. The main data extracted was the price, market capitalization, traded volume. The data was used to estimate weekly returns and relevant metrics. A total number of time datapoints is 365. Risk-free rate was obtained from 3-month Treasury bill rates.

Several cleaning steps and transformations had to be made to the dataset for it to be tested reliably. First, like most studies, cryptocurrencies with low market capitalization are excluded. For this research the break point of 500 000 dollars was chosen. In addition, top and bottom 0.5% of the returns data were dropped. The reason they were not winsorized as other papers suggest is because after reviewing a sample of extreme returns, most of them reflect pricing errors. For example CoinMarketCap does not adjust for cryptocurrency splits. It is a relatively rare event, however unlike stock splits, the ratio can be a 1 to 1000 split. Finally, datapoints with missing volume or market capitalization data are also dropped and duplicate values are removed.

The final dataset contains 288,901 unique observations. The minimal number of cryptocurrencies in any given week is 38 while the largest is 2100. The overall trend can be seen in Figure 1. There is a relatively sharp increase in the number of new cryptocurrencies in 2017 and after 2020 due to spikes in popularity of the market. Figure 2 shows the total market capitalization in millions. In 2021 the number reached 3 trillion dollars.

Figure 1. The weekly number of unique cryptocurrencies available 2015-2021.

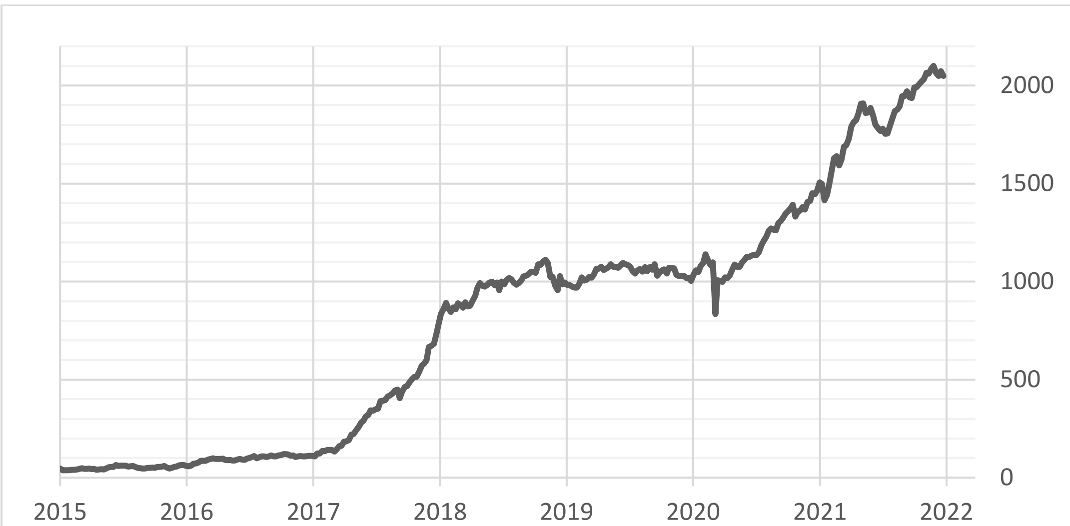
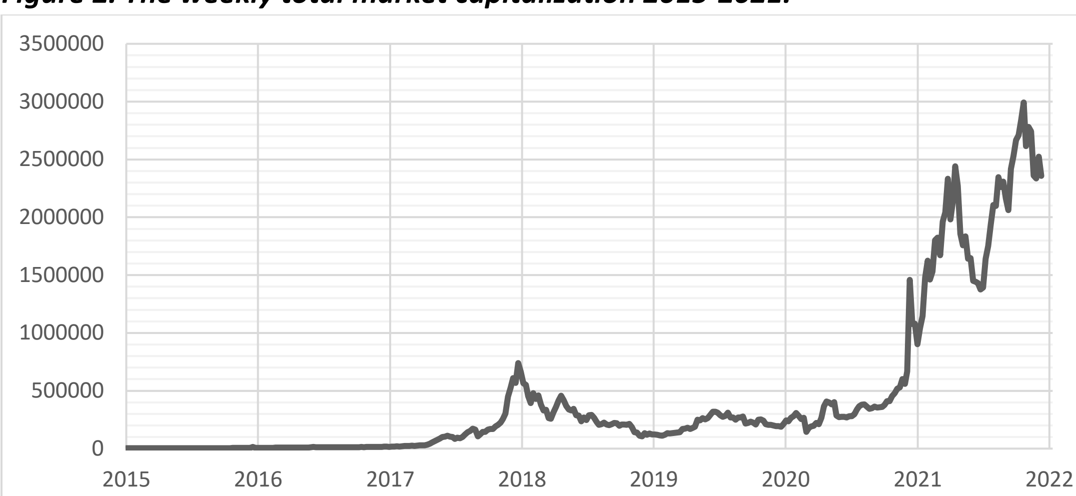


Figure 2. The weekly total market capitalization 2015-2021.



Descriptive statistics of data per year can also be found in Table 1. The average market capitalization of the cryptocurrencies changed a lot over the years, most notably the sharp increase in 2017 with the growth of the market and even bigger increase in 2021. 2018 is the only year with average negative weekly returns. Otherwise the weekly average return on cryptocurrencies is about 4 percent.

Table 1. Descriptive statistics of data on a yearly basis.
Average market capitalization is reported in million dollars.

Year	Avg. obs.	Total obs.	Avg. market cap.	Avg. ret	Std. dev.
2015	50	2574	89.5	0.044	0.304
2016	98	5099	110.2	0.061	0.351
2017	347	18029	372	0.147	0.455
2018	970	50461	311.8	-0.010	0.309
2019	1045	54335	203.5	0.022	0.271
2020	1190	63046	294.6	0.046	0.293
2021	1833	95311	1072.4	0.048	0.337

4. Methodology

The main goal of this paper is to find whether there are factors that describe cryptocurrency returns and get some insight into whether cryptocurrencies are driven more by market risk or behavioral biases. To test this I regress average returns on multiple factors and study their sign, significance, and possible explanations. If prices are driven by sentiment, then returns will have relatively high exposure to these factors.

To construct the Market factor, first weekly value weighted returns are estimated. As expected, since the Bitcoin is by far the largest cryptocurrency, it has always had a significant weight, which is 63% on average. As a result market returns are also highly correlated with Bitcoin at 0.88.

$$R_{it} - r_{ft} = \alpha_i + \beta_{Market}(R_{mt} - r_{ft}) + \varepsilon_{it} \quad (1)$$

Next, I investigate the Size, Volatility and Market-to-Volume factors. They all are constructed following the Fama-French (1992) methodology by sorting cryptocurrencies on the relevant metric on a weekly basis into quintiles and then estimating the average returns of the groups.

The factor portfolio is then the difference of top and bottom groups. In this paper top and bottom 30% performers are used to estimate portfolio returns.

The Size portfolio or SMB is therefore constructed as weekly 30% smallest returns minus 30% largest cryptocurrencies based on their market capitalization. Including it to the regression will have the following formula:

$$R_{it} - r_{ft} = \alpha_i + \beta_{Market}(R_{mt} - r_{ft}) + \beta_{SMB} SMB_t + \varepsilon_{it} \quad (1)$$

The size factor represents the fundamental risk. In stock markets smaller companies are less liquid and have higher trading costs. Another explanation is tied to their flexibility which allows them to generate higher returns during the business cycle. Finally, smaller companies have bigger financing constrains and borrow at higher rates, so they should generate higher returns than bigger counterparts. In cryptocurrency space, liquidity explanation of size effect is the most applicable. In addition, smaller coins are at a higher fundamental risk of disappearing during recessions, since if investors would still want to hold cryptocurrencies in their portfolios, they would be more likely to choose the ones with bigger size.

Analogously to Size, Volume is constructed in the same manner, sorting cryptocurrencies on their trading volume and then estimating returns of the groups. The portfolio is constructed as top 30% highest volume returns minutes the bottom 30%. Volume is based on liquidity risk, suggesting that low volume cryptocurrencies should offer a premium as they have less liquidity and less attention from investors. Therefore the expected factor beta should be negative.

$$R_{it} - r_{ft} = \alpha_i + \beta_{Market}(R_{mt} - r_{ft}) + \beta_{Volume} Volume_t + \varepsilon_{it} \quad (2)$$

For market-to-volume or value factor, is estimated similarly to Majeri and Hafner (2021). Market size is divided by the weekly volume and then sorted from high to low. Then the value portfolio is constructed by taking returns of the top 30% and subtracting the bottom 30% weekly. The economic reasoning behind the cryptocurrency value factor is the assumption that market-to-volume ratio is the reflection of how useful or attractive the cryptocurrency is to investors, when a significant portion of the cryptocurrency market capitalization is traded, it seems more valuable in comparison to others. If the factor follows the similar pattern to the stock book-to-market factor, there should be a risk premium in “value” cryptocurrencies that are undervalued. Such cryptocurrencies then must then have a high market-to-volume ratio, as their market activity is underestimated. Turnover interpretation of the factor would also suggest the same sign, as high market-to-volume means that the cryptocurrency is not liquid enough to its size and therefore should offer a premium. If returns of the portfolio are negative, however, that could suggest that behavior explanation is likely at place and low market-to-volume cryptocurrencies have higher returns due to positive sentiment.

$$R_{it} - r_{ft} = \alpha_i + \beta_{Market}(R_{mt} - r_{ft}) + \beta_{HML}HML_t + \varepsilon_{it} \quad (3)$$

Adding all the factors into a 4-factor regression model will be the last step before introducing momentum.

$$R_{it} - r_{ft} = \alpha_i + \beta_{Market}(R_{mt} - r_{ft}) + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{Volume}Volume_t + \varepsilon_{it} \quad (4)$$

A positive and significant alpha would suggest that there are excess returns that are not explained by the market movement.

This paper presents three measures for momentum strategies, namely classical cross-sectional momentum based on Jaagdesh and Titmann (1993) methodology adjusted for weekly returns and short and medium horizons, then the time-series momentum based on Moskowitz et al. (2012) methodology, and lastly, volume-based momentum, that is similar by design to Jaagdesh and Titmann (1993) or Swaminathan (2000), but portfolios are sorted on past volume, rather than turnover ratio or past returns.

Cross-sectional momentum cumulative returns of cryptocurrencies are estimated over the past J weeks ranging from 1 to 4 and from 12 to 48 weeks to reflect both short term momentum with 1-4 week horizons and more standard 12 to 48 weeks momentum of 3 to 12 months. Based on the cryptocurrency performance 20% top and 20% bottom performers are sorted into winner and loser groups. Similarly, the average returns are then estimated over the next 1-4 and 12-48 weeks. Weekly portfolios are then constructed by subtracting losers from winners.

It should be noted, that unlike other momentum research that also follow Novy-Marx (2012) methodology, 1 week or month waiting period is not implemented, as studying momentum in cryptocurrency literature this step seems to be redundant if not making the portfolios perform worse. Including either of these momentum strategies have a regression model of:

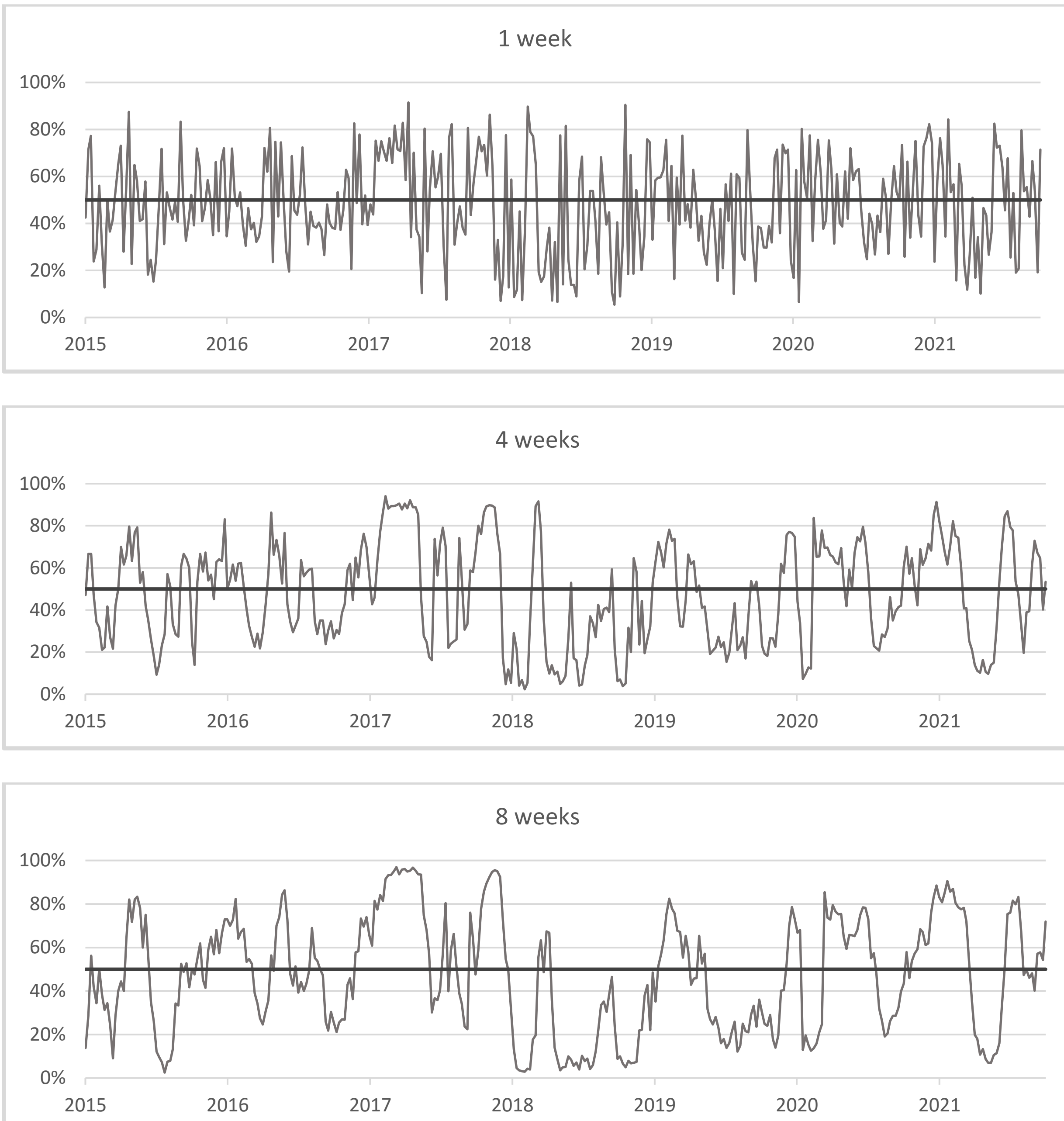
$$R_{it} - r_{ft} = \alpha_i + \beta_{Market}(R_{mt} - r_{ft}) + \beta_{SMB}SMB_t + \beta_{HML}HML_t +$$

$$+ \beta_{Volume}Volume_t + \beta_{MOM}MOM_t + \varepsilon_{it} \quad (5)$$

Next, the time series momentum model is constructed. For each cryptocurrency cumulative returns are estimated over the last J weeks ranging from 1 to 8. Then whether the returns are negative or positive will determine if that cryptocurrency will go into losers or winner's portfolio. The average returns of these portfolios are estimated over the next week. Finally the time series momentum factor is derived from the difference between winner and loser portfolios. Unlike cross-sectional momentum, the winner and loser portfolios are not always equal in size. Figure 3 presents the relative proportion of winners to the total number of cryptocurrencies available for 1-, 4- and 8-week strategies. In some periods up to 97% or as low as 3% of cryptocurrencies are concentrated in the winner group. However, for most of these occurrences there are still at least 20 cryptocurrencies in either group. For more recent years, where there are plenty of cryptocurrencies in circulation, the diversification risk negligible. It can also be seen that as the J increases, the distribution of winner-loser distribution becomes less noisy. The regression model used for time-series momentum as a factor is the same as for cross-sectional momentum (Formula 5).

The final set of cross-sectional returns is estimated for momentum based on Volume. Cryptocurrencies are first sorted on cumulative volume over the previous J weeks, then sorted into high and low volume portfolios and their returns are estimated over the next K weeks. The factor portfolio is constructed by taking the difference of returns of 20% top from 20% bottom performers. The economic reasoning behind the factor resides somewhere between risk and behavioral. Volume-based momentum suggests that cryptocurrencies that showed high past trading volume due to either extreme gain, loses, or sufficient trading activity due to their size will outperform other cryptocurrencies over the next 1 to 4 weeks. If the sign of the factor is negative, it can be interpreted as liquidity premium for risk-related explanation of returns. On the other hand if it is positive, it can also be viewed as a proxy for investor attention or in other words “any news is good news”. The volume momentum uses the same regression model 5. Adding it as an additional factor to momentum would create too many momentum-volume pairs to report, therefore it will be reported in a limited way.

Figure 3. The ratio of cryptocurrencies in winner groups for 1- ,4- and 8-week strategies.



The final analysis will include cumulative average returns of selected momentum groups from both short-term, medium-term, and volume-based momentum strategies. It is done to look for long-term reversals. Depending on results and factor significance, noise trader risk and disposition effect might be possible explanation for the factor returns.

All factor portfolios are constructed using equal-weighted returns, except for the market factor. The reason value-weighted returns are not chosen is due to extreme weights of Bitcoin, making the returns all findings biased towards Bitcoin movement. There are other ways to weight returns, like using the volume weights, however for this research average returns seemed like the most suitable choice. For all regressions Newey-West robust standard errors were used to account for cryptocurrency heteroscedasticity.

5. Results

In this section the focus will be first on Size, Volume and Market-to-Volume with the gradual addition of momentum related factors.

Table 2 shows the average returns of Size, Volume and Market-to-Volume groups. Cryptocurrencies with smaller Market Capitalization seem to have lower returns on average. Currencies with the highest trading volume outperform other groups with average weekly returns of 4.8%, which is logical, considering that the crypto market has been growing a lot over the years, therefore biggest trading patterns are led to gains more often than losses. However, cryptocurrencies with the lowest trading volume have returns very similar to those in 2nd largest group. A similar pattern but in reverse can be seen in Market-to-Volume size groups. Currencies with high weekly trading volume relative to their size, or high turnover on average earn 5.9% weekly.

Table 2. Average returns of Size, Volume and Market-to-Volume per relative size group.

Group	Size	t	Volume	t	Market-to-Volume	t
1 (Smallest)	0.017	(2.85)	0.021	(3.85)	0.059	(6.67)
2	0.017	(2.67)	0.010	(1.71)	0.018	(2.55)
3	0.024	(3.88)	0.014	(2.16)	0.007	(1.18)
4	0.026	(3.96)	0.023	(3.19)	0.007	(1.30)
5 (Biggest)	0.029	(4.43)	0.048	(6.31)	0.022	(4.07)

Results from regressing cryptocurrency returns on the factors and the market returns are shown in Table 3. Despite cryptocurrencies with high market capitalization on average having higher returns than the smallest ones, the Size factor is positive and highly significant in all regression models. This is most likely due to high correlation between the biggest group and the market. Volume factor returns are positive in Model 2 meaning that highly traded liquid cryptocurrencies on average outperform illiquid ones. Market-to-Volume factor is also highly significant but negative. Highly traded relative to their size cryptocurrencies are therefore earn higher returns. Positive sign in volume factor and negative in Market-to-Volume factor both suggest that there is no liquidity premium in cryptocurrencies. Combining all factors into one model makes the Volume factor insignificant, Market-to-Volume factor seem to capture most of its effects. The adjusted R-squared is also slightly higher when Volume factor is excluded.

Table 3. Regression results of multiple factors on average equal-weighted returns.

This table summarizes regression results of average weekly returns on SMB, VOL and MKT-VOL factors for the period from 2015 till the end of 2021. SMB is the size factor, VOL is Volume factor and MKT-VOL is the market-to-volume factor. R-squared is adjusted for adding new factors. T-statistic is reported in parentheses. *, **, *** next to coefficients correspond to 10%, 5% and 1% significance levels.

	(1)	**(2)**	**(3)**	**(4)**
Variables	**SMB**	**VOL**	**MKT-VOL**	**ALL**
Market	0.823***	0.768***	0.759***	0.760***
	(26.99)	(29.52)	(29.66)	(29.62)
SMB	0.061***	0.151***	0.085***	0.090***
	(3.44)	(9.05)	(5.73)	(3.86)
VOL		0.149***		0.011
		(12.12)		(0.28)
MKT-VOL			-0.119	-0.111***
			(-12.90)	(-3.72)
Constant	-0.005*	-0.011***	-0.013***	-0.013***
	(-1.47)	(-3.74)	(-4.56)	(-4.47)
Observations	354	354	354	354
Adj. R-squared	0.676	0.771	0.780	0.779

Next, momentum returns are studied. I first look at short term (1-4 weeks) momentum returns. Average momentum returns are shown in Table 4. All winner and loser average returns are significant, and loser portfolios either outperform the winners or have a statistically similar performance. The momentum portfolios are mostly insignificant except for the returns in the first week. The biggest differences in groups are also concentrated in groups created based on last week performance. On average the strategy yields -1.8% weekly returns.

Table 4. Average short-term momentum returns.

This table summarizes average weekly returns of momentum groups. J is the number of past months used for sorting, and K is the holding period. W is the winner group with 20% top highest cumulative returns over the J number of weeks, L is the bottom 20%. W-L is the difference portfolio of the two. T-statistic is reported in parentheses. *, **, *** next to coefficients correspond to 10%, 5% and 1% significance levels.

J		K =	1	2	3	4
1	W		0.029***	0.033***	0.032***	0.034***
			(4.08)	(5.67)	(6.16)	(6.42)
	L		0.048***	0.036***	0.034***	0.033***
			(7.39)	(6.86)	(6.5)	(6.47)
	W-L		-0.018***	-0.004	-0.002	0
			(-3.77)	(-1.05)	(-0.65)	(0.07)
2	W		0.026***	0.029***	0.029***	0.03***
			(3.53)	(5.28)	(5.76)	(6.1)
	L		0.041***	0.031***	0.032***	0.032***
			(6.61)	(6.09)	(6.08)	(6.34)
	W-L		-0.015***	-0.002	-0.003	-0.002
			(-3.05)	(-0.65)	(-0.91)	(-0.85)
3	W		0.023***	0.027***	0.027***	0.029***
			(3.28)	(4.83)	(5.4)	(5.83)
	L		0.037***	0.03***	0.031***	0.031***
			(6.1)	(5.77)	(6.09)	(6.28)
	W-L		-0.014***	-0.003	-0.004	-0.002
			(-2.82)	(-0.93)	(-1.32)	(-0.65)
4	W		0.023***	0.024***	0.025***	0.025***
			(3.21)	(4.35)	(4.97)	(5.25)
	L		0.035***	0.029***	0.03***	0.031***
			(5.73)	(5.85)	(6.02)	(6.18)
	W-L		-0.012***	-0.006*	-0.005*	-0.006**
			(-2.58)	(-1.68)	(-1.79)	(-2.01)

The negative momentum portfolio returns are caused by strong performance of losing cryptocurrencies. This suggests an immediate first week reversal which is persistent for at least 4 weeks. This could be explained by initial overreaction to negative news with a strong and robust correction in subsequent periods.

Next, momentum portfolios are added to the factor model and coefficients are presented in Table 5. All momentum portfolios are insignificant, even the ones with the shortest term. Therefore there are no significant short term momentum effects on the average cryptocurrency returns. The difference in winner and loser portfolios can also be explained by variance of other factors. Comparing other coefficients to the ones in models without the momentum factor, does not show any noticeable changes. Adding momentum also had no effect on the alpha.

Alternatively, we also look for more classical momentum returns similar to Jagadeesh and Titman (1993) time periods. However, instead of looking at 3-12 months, 12–48-week returns are estimated and presented in Table 6. Results show a pattern close to its short-term counterpart, the difference portfolio yields predominantly negative returns, with higher significance levels. Once again, when adding momentum portfolios into the regression models (Table 7), the momentum factor seem to disappear. The only exceptions are momentum portfolios based on previous 24-48 weeks with the holding period of 12 weeks. Combined they present a weak evidence of reverse medium-term momentum. In addition, for all models the Market-to-Volume factor decreased in both magnitude and significance. It is now significant only at 90% confidence interval.

Table 5. Regression results of multiple factors on average equal-weighted returns.

This table summarizes regression results of average weekly returns on SMB, VOL and MKT-VOL factors for the period from 2015 till the end of 2021. SMB is the size factor, VOL is Volume factor and MKT-VOL is the market-to-volume factor, MOM is the momentum factor, alpha is the regression intercept. J is the number of past months used for sorting, and K is the holding period for momentum portfolios. T-statistic is reported in parentheses. *, **, *** next to coefficients correspond to 10%, 5% and 1% significance levels.

		MOM				Rm-Rf			
J	K =	1	2	3	4	1	2	3	4
1		-0.025	0.028	-0.055	-0.062	0.762***	0.762***	0.759***	0.761***
		(-0.65)	(0.38)	(-0.53)	(-0.7)	(20.51)	(20.64)	(20.62)	(20.36)
2		0.029	0.025	-0.059	0.016	0.761***	0.762***	0.761***	0.762***
		(0.51)	(0.43)	(-0.83)	(0.23)	(20.49)	(20.36)	(20.42)	(20.46)
3		0.035	0.009	-0.068	-0.039	0.76***	0.762***	0.762***	0.761***
		(0.58)	(0.15)	(-1.19)	(-0.77)	(20.61)	(20.2)	(20.68)	(20.36)
4		0.039	0.061	-0.024	0	0.76***	0.763***	0.762***	0.762***
		(0.67)	(0.99)	(-0.36)	(0)	(20.4)	(20.04)	(20.45)	(20.44)

		MKT-VOL				SMB			
J	K =	1	2	3	4	1	2	3	4
1		-0.113***	-0.11***	-0.114***	-0.11***	0.091***	0.088***	0.091***	0.094***
		(-2.81)	(-2.67)	(-2.71)	(-2.85)	(3.54)	(3.52)	(3.58)	(3.75)
2		-0.107***	-0.112***	-0.112***	-0.112***	0.088***	0.087***	0.092***	0.088***
		(-2.74)	(-2.78)	(-2.85)	(-2.8)	(3.38)	(3.4)	(3.56)	(3.45)
3		-0.11***	-0.112***	-0.109***	-0.111***	0.084***	0.088***	0.093***	0.091***
		(-2.79)	(-2.81)	(-2.82)	(-2.81)	(2.95)	(3.36)	(3.63)	(3.58)
4		-0.109***	-0.113***	-0.112***	-0.112***	0.086***	0.086***	0.09***	0.089***
		(-2.77)	(-2.82)	(-2.81)	(-2.77)	(3.22)	(3.29)	(3.52)	(3.47)

		VOL				alpha			
J	K =	1	2	3	4	1	2	3	4
1		0.012	0.011	0.009	0.015	-0.014***	-0.014***	-0.014***	-0.014***
		(0.24)	(0.22)	(0.18)	(0.3)	(-4.74)	(-4.96)	(-5.02)	(-4.86)
2		0.014	0.009	0.011	0.01	-0.013***	-0.014***	-0.014***	-0.014***
		(0.27)	(0.18)	(0.22)	(0.2)	(-3.9)	(-4.9)	(-5.04)	(-4.94)
3		0.009	0.01	0.014	0.012	-0.013***	-0.014***	-0.014***	-0.014***
		(0.16)	(0.19)	(0.28)	(0.24)	(-4.07)	(-4.9)	(-5.03)	(-4.95)
4		0.01	0.007	0.011	0.011	-0.013***	-0.013***	-0.014***	-0.014***
		(0.2)	(0.13)	(0.22)	(0.21)	(-4.2)	(-4.77)	(-5.06)	(-5.04)

Table 6. Average medium-term momentum returns.

This table summarizes average weekly returns of momentum groups. J is the number of past months used for sorting, and K is the holding period. W is the winner group with 20% top highest cumulative returns over the J number of weeks, L is the bottom 20%. W-L is the difference portfolio of the two. T-statistic is reported in parentheses. *, **, *** next to coefficients correspond to 10%, 5% and 1% significance levels.

J		K =	12	24	36	48
12	W		0.04***	0.056***	0.063***	0.087***
			(6.7)	(7.23)	(8.75)	(7.78)
	L		0.056***	0.079***	0.085***	0.143***
			(6.23)	(6.24)	(6.93)	(4.73)
	W-L		-0.016***	-0.023***	-0.021***	-0.056***
			(-3.77)	(-2.85)	(-2.46)	(-2.37)
24	W		0.045***	0.051***	0.062***	0.081***
			(5.91)	(8.15)	(9.46)	(8.71)
	L		0.065***	0.073***	0.07***	0.108***
			(4.47)	(6.7)	(6.64)	(7.06)
	W-L		-0.02***	-0.022***	-0.008	-0.027***
			(-2.33)	(-2.97)	(-1.17)	(-3.33)
36	W		0.037***	0.056***	0.064***	0.085***
			(6.73)	(7.16)	(8.64)	(8.52)
	L		0.065***	0.067***	0.07***	0.105***
			(4.81)	(5.98)	(8.27)	(6.79)
	W-L		-0.028***	-0.011**	-0.007*	-0.021**
			(-2.73)	(-2.12)	(-1.82)	(-2.04)
48	W		0.046***	0.06***	0.072***	0.1***
			(6.27)	(6.94)	(8.44)	(7.61)
	L		0.065***	0.059***	0.056***	0.091***
			(4.48)	(7.29)	(8.75)	(6.62)
	W-L		-0.019**	0.001	0.016***	0.008
			(-2.06)	(0.31)	(3.33)	(0.86)

Table 7. Regression results of multiple factors on average equal-weighted returns.

This table summarizes regression results of average weekly returns on SMB, VOL and MKT-VOL factors for the period from 2015 till the end of 2021. SMB is the size factor, VOL is Volume factor and MKT-VOL is the market-to-volume factor, MOM is the momentum factor, alpha is the regression intercept. J is the number of past months used for sorting, and K is the holding period for momentum portfolios. T-statistic is reported in parentheses. *, **, *** next to coefficients correspond to 10%, 5% and 1% significance levels.

		MOM				Rm-Rf			
J	K =	12	24	36	48	12	24	36	48
12		-0.058	0.001	0.022	0.007	0.758***	0.76***	0.762***	0.761***
		(-0.84)	(0.05)	(0.96)	(0.73)	(18.29)	(18.26)	(18.27)	(18.25)
24		-0.065***	-0.007	0.02	-0.012	0.761***	0.76***	0.763***	0.759***
		(-4.31)	(-0.37)	(1.08)	(-0.45)	(18.33)	(18.17)	(18.15)	(18.11)
36		-0.052***	-0.015	-0.038	0	0.761***	0.76***	0.761***	0.76***
		(-2.62)	(-0.48)	(-0.69)	(-0.02)	(18.43)	(18.24)	(18.34)	(18.21)
48		-0.059***	0.03	-0.035	-0.038	0.764***	0.761***	0.762***	0.763***
		(-2.72)	(0.5)	(-0.57)	(-1.6)	(18.35)	(18.29)	(18.14)	(18.2)

		MKT-VOL				SMB			
J	K =	12	24	36	48	12	24	36	48
12		-0.098*	-0.096*	-0.093*	-0.095*	0.115***	0.117***	0.119***	0.119***
		(-1.83)	(-1.8)	(-1.74)	(-1.78)	(3.18)	(3.23)	(3.3)	(3.28)
24		-0.094*	-0.097*	-0.091*	-0.098*	0.112***	0.117***	0.119***	0.115***
		(-1.8)	(-1.81)	(-1.68)	(-1.83)	(3.09)	(3.2)	(3.29)	(3.15)
36		-0.094*	-0.097*	-0.094*	-0.096*	0.113***	0.117***	0.117***	0.117***
		(-1.8)	(-1.81)	(-1.78)	(-1.8)	(3.11)	(3.23)	(3.24)	(3.23)
48		-0.099*	-0.096*	-0.095*	-0.099*	0.113***	0.116***	0.119***	0.118***
		(-1.87)	(-1.81)	(-1.76)	(-1.85)	(3.11)	(3.17)	(3.19)	(3.25)

		VOL				alpha			
J	K =	12	24	36	48	12	24	36	48
12		0.035	0.04	0.045	0.042	-0.015***	-0.014***	-0.014***	-0.014***
		(0.48)	(0.56)	(0.63)	(0.59)	(-4.47)	(-4.1)	(-4.01)	(-4)
24		0.035	0.039	0.047	0.037	-0.015***	-0.014***	-0.014***	-0.015***
		(0.49)	(0.54)	(0.64)	(0.51)	(-4.46)	(-4.12)	(-4.1)	(-4.15)
36		0.034	0.039	0.041	0.04	-0.015***	-0.014***	-0.014***	-0.014***
		(0.48)	(0.55)	(0.57)	(0.56)	(-4.47)	(-4.14)	(-4.17)	(-4.12)
48		0.029	0.04	0.041	0.035	-0.015***	-0.014***	-0.014***	-0.014***
		(0.4)	(0.56)	(0.57)	(0.49)	(-4.41)	(-4.12)	(-3.62)	(-4)

Before moving to volatility-based momentum, I also investigate time-series momentum returns. The summary of both Winner, Loser and regression results are shown in Table 8. For the regression part, other factors and the constant are not shown due to their coefficients being very similar to short-term momentum counterparts or the ones in the model with no momentum factor present. Overall, there are negative Winners minus Losers portfolio returns, that concentrate at around 6-8 past weeks. This suggests that cryptocurrencies with long negative performance have an increasing probability of outperforming winning counterparts for up to 0.9% weekly on average. Adding the portfolios to the regression models, however, makes the factor insignificant. The time-series momentum factor with the largest significance is the one based on last week performance with t-statistic of (-1.44). Despite it not being significant enough it is more in line with findings of other time-series momentum papers on cryptocurrencies.

Table 8. Average time-series momentum returns.

This table summarizes average weekly returns of momentum groups. J is the number of past months used for sorting, and the holding period is one week. W is the winner group with 20% top highest cumulative returns over the J number of weeks, L is the bottom 20%. W-L is the difference portfolio of the two. Beta is the time-series momentum coefficient of regression of average returns weekly on market, size, volume, market to volume and time-series momentum factors. T-statistic is reported in parentheses. *, **, *** next to coefficients correspond to 10%, 5% and 1% significance levels.

J =	W	L	W-L	Beta
1	0.03***	0.033***	-0.003	-0.084
	(4.66)	(5.43)	(-1.02)	(-1.44)
2	0.027***	0.029***	-0.002	0.066
	(4.12)	(4.82)	(-0.57)	(0.67)
3	0.025***	0.028***	-0.003	0.04
	(3.86)	(4.72)	(-0.88)	(0.4)
4	0.024***	0.026***	-0.003	0.102
	(3.71)	(4.52)	(-0.82)	(1.18)
5	0.022***	0.026***	-0.005	0.028
	(3.41)	(4.66)	(-1.38)	(0.34)
6	0.021***	0.027***	-0.006**	-0.052
	(3.31)	(4.67)	(-2.01)	(-0.92)
7	0.019***	0.029***	-0.009***	0.013
	(3.08)	(4.97)	(-2.89)	(0.12)
8	0.02***	0.029***	-0.009***	0.002
	(3.11)	(4.96)	(-2.53)	(0.04)

The final factor of interest is momentum based on past volume. The average returns are reported in Table 9. Similar to short- and medium-term momentum, average returns of past low volatility is higher for Loser cryptocurrencies. Unlike the short-term momentum results though, the difference portfolio returns are highly significant. The returns are the highest in one-week portfolios with gradual decrease for longer periods. This can have a number of possible explanations. Past winners or cryptocurrencies with high past volatility could be attributed to either extreme gains, extreme losses or the large size or just large trading activity. If it is caused by continuous presence of largest cryptocurrencies, the returns can be explained by market and size factors. Another explanation is that past volume is sensitive to large price reversals and returns in the following weeks are relatively weaker after the initial spike. Finally, negative returns might suggest existence of liquidity premium as low volatility past performers earn higher returns. The winner portfolios are always the lowest at K = 1 and continuously increase for longer periods. Loser portfolios however either decrease or remain relatively stable throughout the weeks following the first.

Next, volume-based momentum portfolios are added to regression models and presented in Table 10. The factors remains highly significant, 14 out of 16 coefficients are significant at 99%. The factor sign is negative, meaning that even after correcting for market, size and turnover rate high past 1 to 4 volatility cryptocurrencies underperform in comparison to low past volatility counterparts. Market-to-volume factor also remains highly significant.

Table 9. Average short-term volume-momentum returns.

This table summarizes average weekly returns of volume-momentum groups. J is the number of past months used for sorting, and K is the holding period. W is the winner group with 20% top highest cumulative returns over the J number of weeks, L is the bottom 20%. W-L is the difference portfolio of the two. T-statistic is reported in parentheses. *, **, *** next to coefficients correspond to 10%, 5% and 1% significance levels.

J		K =	1	2	3	4
1	W		0.017***	0.02***	0.024***	0.026***
			(2.46)	(3.65)	(4.34)	(4.78)
	L		0.049***	0.042***	0.041***	0.039***
			(7.92)	(8.21)	(8.15)	(8.05)
	W-L		-0.032***	-0.022***	-0.018***	-0.013***
			(-6.81)	(-6.02)	(-5.37)	(-4.29)
2	W		0.017***	0.02***	0.023***	0.026***
			(2.44)	(3.55)	(4.28)	(4.76)
	L		0.042***	0.039***	0.038***	0.038***
			(6.83)	(7.4)	(7.65)	(7.91)
	W-L		-0.024***	-0.019***	-0.015***	-0.011***
			(-5.19)	(-5.44)	(-4.77)	(-3.95)
3	W		0.017***	0.02***	0.023***	0.026***
			(2.49)	(3.64)	(4.34)	(4.81)
	L		0.041***	0.037***	0.036***	0.036***
			(6.7)	(7.21)	(7.59)	(7.88)
	W-L		-0.024***	-0.017***	-0.013***	-0.01***
			(-5.29)	(-4.81)	(-3.96)	(-3.2)
4	W		0.018***	0.021***	0.024***	0.027***
			(2.67)	(3.77)	(4.42)	(4.93)
	L		0.039***	0.035***	0.035***	0.035***
			(6.38)	(7.14)	(7.6)	(7.91)
	W-L		-0.02***	-0.014***	-0.011***	-0.008***
			(-4.42)	(-3.93)	(-3.33)	(-2.63)

Momentum portfolios are not included with volume basted momentum as that would create a 16x32 matrix of different regression models. These models were run separately (results are not shown). Overall, short-term momentum stays insignificant, medium-term momentum factors that were significant remained significant, Market-to-Volume also stays significant. Volume based momentum factors have slightly lower t-statistic but still above 95% mark, making them the most robust results.

Table 10. Regression results of multiple factors on average equal-weighted returns.

This table summarizes regression results of average weekly returns on SMB, VOL and MKT-VOL factors for the period from 2015 till the end of 2021. SMB is the size factor, VOL is Volume factor and MKT-VOL is the market-to-volume factor, VOL_MOM is the volume-momentum factor, alpha is the regression intercept. J is the number of past months used for sorting, and K is the holding period for momentum portfolios. T-statistic is reported in parentheses. *, **, *** next to coefficients correspond to 10%, 5% and 1% significance levels.

		VOL_MOM				Rm-Rf			
J	K =	1	2	3	4	1	2	3	4
1		-0.221***	-0.219***	-0.21***	-0.225***	0.759***	0.763***	0.771***	0.771***
		(-2.93)	(-3.63)	(-3.66)	(-3.07)	(21.02)	(23.66)	(24.38)	(22.41)
2		-0.201***	-0.223***	-0.207***	-0.233***	0.757***	0.759***	0.768***	0.772***
		(-2.62)	(-3.93)	(-3.49)	(-3.14)	(20.85)	(23.6)	(24.14)	(22.45)
3		-0.183*	-0.208***	-0.192***	-0.203***	0.758***	0.762***	0.771***	0.773***
		(-1.92)	(-3.48)	(-2.83)	(-2.68)	(20.75)	(23.68)	(23.77)	(22.09)
4		-0.177*	-0.197***	-0.183***	-0.215***	0.763***	0.767***	0.774***	0.778***
		(-1.95)	(-3.55)	(-3.33)	(-3.15)	(20.51)	(23.56)	(23.86)	(22.05)

		MKT-VOL				SMB			
J	K =	1	2	3	4	1	2	3	4
1		-0.133***	-0.115***	-0.112***	-0.109***	0.057**	0.074***	0.078***	0.081***
		(-3.48)	(-3.09)	(-3.08)	(-2.98)	(2.1)	(2.98)	(3.01)	(3.13)
2		-0.12***	-0.108***	-0.106***	-0.107***	0.06**	0.073***	0.078***	0.08***
		(-3.32)	(-3)	(-2.99)	(-2.94)	(2.25)	(2.94)	(3.03)	(3.08)
3		-0.11***	-0.105***	-0.11***	-0.111***	0.065**	0.075***	0.078***	0.08***
		(-3.09)	(-2.88)	(-3.01)	(-2.96)	(2.26)	(2.95)	(2.99)	(3.04)
4		-0.114***	-0.11***	-0.11***	-0.112***	0.064**	0.075***	0.079***	0.078***
		(-3.14)	(-2.98)	(-3.01)	(-2.98)	(2.24)	(2.97)	(3.07)	(3)

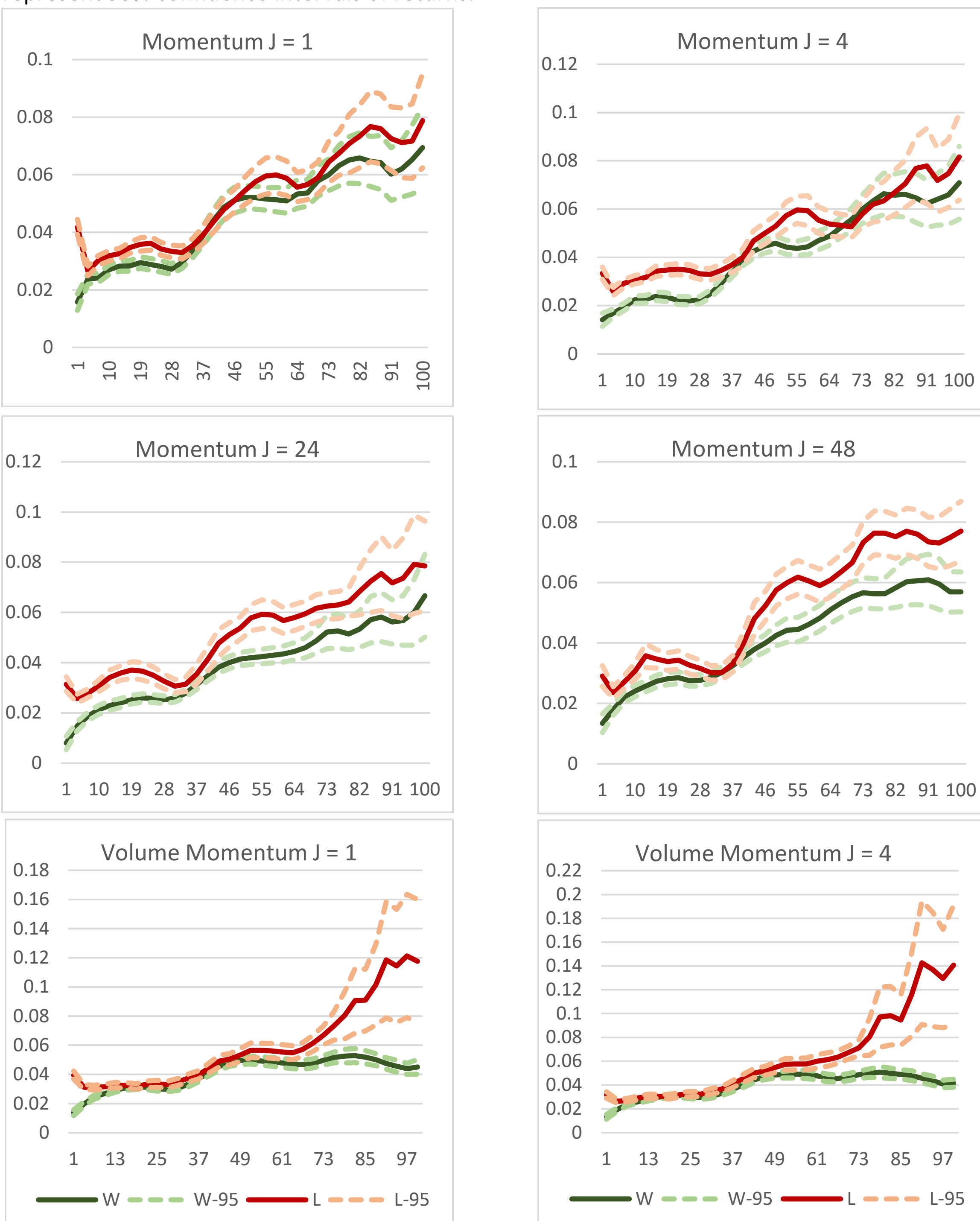
		VOL				alpha			
J	K =	1	2	3	4	1	2	3	4
1		0.029	0.027	0.021	0.02	-0.025***	-0.02***	-0.019***	-0.017***
		(0.66)	(0.58)	(0.44)	(0.42)	(-6.38)	(-6.75)	(-6.46)	(-5.95)
2		0.042	0.035	0.027	0.022	-0.022***	-0.02***	-0.018***	-0.017***
		(0.95)	(0.75)	(0.59)	(0.48)	(-6.15)	(-6.53)	(-6.13)	(-5.91)
3		0.045	0.035	0.021	0.016	-0.021***	-0.019***	-0.017***	-0.016***
		(1.03)	(0.75)	(0.45)	(0.33)	(-5.12)	(-6.25)	(-5.85)	(-5.67)
4		0.038	0.029	0.022	0.015	-0.02***	-0.018***	-0.017***	-0.016***
		(0.88)	(0.62)	(0.46)	(0.31)	(-5.43)	(-6.24)	(-5.91)	(-5.82)

Another point of interest for momentum studies is long-term reversal. To test if there is short- or long-term reversal, average cumulative returns are constructed winner and loser portfolios. A set of J = (1, 4, 24, 48) is selected for cross-sectional momentum and J = (1, 4) for volume-based momentum (Figure 4). The graphs are limited to only the cumulative average returns up to 100 weeks, because after that the confidence intervals of winner and loser groups become too large to interpret the results in a meaningful way. An indicator for long term reversal would be if two lines cross each other and diverge. Despite the lines coming close with multiple strategies, there is no evidence of momentum return reversal for up to 2 years. Volume-momentum returns on the other hand seem to diverge even more over time. Cryptocurrencies with low past volatility overt time have much larger and volatile returns relative to the winner group.

To summarize the results, there is significant and robust evidence of Market, Size, Market-to-Volume and Volume-based momentum factors explaining the cryptocurrency returns. There is some evidence of momentum with 6-12 months formation periods and 3 months holding period. The sign of the factor is negative, mostly due to strong performance of loser portfolios following the formation period. A potential explanation can be formed with a combination of disposition effect and noise-trader risk. Negative returns have a much stronger next week overcorrection that persists indefinitely due to noise trader activity. The absence of long term reversal is in line with this theory. Finally, negative returns on momentum portfolios are also present in other cryptocurrency literature like Kosk et al. (2019) that find evidence of contrarian effects. Short-term momentum returns and time series momentum returns are not significant. Volume-to-Market factor makes the Volume factor redundant. Market and Size and Market-to-Volume explain about 78% of the variance of returns. Adding other factors does not bring the adjusted R-squared above 81% suggesting that momentum effects only marginally improve the model. The sign of Market-to-Volume factor is negative, which contradicts the hypothesis, that it can be interpreted as a Value factor counterpart of stock market factor. Similarly, it also contradicts the hypothesis that Market-to-Volume factor can reflect liquidity premium. The alternative explanation of the factor can be related to behavioral theories. A plausible explanation is that the market-to-volume factor captures investor sentiment or attention.

Figure 4. Cumulative average returns of winner and loser momentum portfolios.

Figures show cumulative average returns on momentum groups up to 100 weeks from the investment point. L is the 20% worst performers over the past J weeks. W is the 20% best performers. Dotted lines represent 95% confidence intervals of returns.



Combined with noise-trader risk, cryptocurrencies with high economic activity would also be the target for speculative trading, and if noise-traders dominate the market, this will cause a long-term mispricing. A good way to test which explanation is more likely is to use a different measure for attention factor, and for example, regress market-to-volume portfolio returns on the one of the factor models, including the new factor. The ideal data for the attention factor would be either twitter or google trends data. However, there is currently no twitter database available that have a large enough cryptocurrency trend data for a cross-sectional study. The alternative is google trends data. However, the way google data is presented is relative to past popularity per search word on a scale from a 100 to 0. The day a certain keyword was at its most popular point becomes the new 100 and the other datapoints scale down according to the new highest value. For time series data, this type of date might have been sufficient, but for cross-sectional analysis 100 points in bitcoin is not comparable to 100 points of any small emerging new coin. However, it is likely that a large enough database with time-series twitter or google data, with absolute metric might appear at some point.

Finally, volume-based momentum factor results are the most interesting discovery in combination with the other factors. The negative sign of the factor suggests that it represents the liquidity premium. Moreover, the cumulative returns over the next two years also makes it behave like a stock market Value factor. To see the exposure of other factors on returns of volume-momentum portfolio returns, the constructed portfolios were regressed by market, size, volume, market-to-volume and momentum factors (not reported). Momentum factors do not produce significant coefficients. Volume and size explain the variance of returns to a limited degree. These factors are significant in only 5 out of 16 regressions (when momentum is excluded), and the adjusted R-squared ranges from 5 to 60%. All models, however, share a significant alpha, suggesting that up to -6.5% weekly returns are not explained by other factors. This suggests that volume-based momentum captures something other than market, size and other factors and might indeed be connected to liquidity premium. It also produces larger and more robust momentum returns than other momentum strategies. An alternative explanation of volume-based momentum can be as another contrarian effect, this interpretation would be more in line with disposition effect and noise trader risk theories, as just like medium-term momentum, there are no long term reversal present. Moreover contrarian effect does show itself in stocks in either very short periods, or very long ones (Kosc et al., 2019).

All results seem to be robust to some changes in methodology and data transformations. Using different group size quintiles for either momentum portfolios or size, volume and market-to-volume does not significantly change the sign or the corresponding t-statistics. Surprisingly, splitting the dataset into two periods, 2015-2018 and 2018-2021 resulted in similar results. The only notable difference is changes in time-series momentum 1 week strategy. In the more recent period the beta becomes significant at 5%, which is more in line with findings of other cryptocurrency research. The difference can be caused by the relatively limited number of cryptocurrencies in the beginning of the dataset, introducing enough idiosyncratic volatility. The best way to test the validity of the results is to use a different dataset, provided by another platform, as they might have different values for prices and especially volume.

6. Conclusion

Cryptocurrency market poses an incredible opportunity to study a decentralized, highly speculative, emerging environment for the presence of either fundamental risk or behavioral biases. The goal of this research paper was to examine the cryptocurrency return on the presence of common risk factors present in stock market and other asset classes as well as momentum and its alternatives.

Market and size risk factors are robust and significant. I found no evidence of short-term momentum or time-series momentum explaining cryptocurrency return variance and some limited evidence of contrarian effect of 3-12 months momentum. And interesting find was using market-to-volume ratio as a factor representing value premium. Instead of reflecting the fundamental value risk or liquidity premium, its performance better fits as an attention factor and behavioral explanations as noise trader activity is likely to be concentrated in high economic activity cryptocurrencies. Market-to-volume also explains returns better than volume factor and makes it redundant.

Finally, volume-based momentum had by far most significant and robust results as a factor. Due to its negative sign it either show strong effect of liquidity premium or a strong contrarian effect based on noise-trader activity. When relating results to other cryptocurrency research, it is likely that behavioral theory is the more likely cause (despite volume-based momentum being robust to other momentum factors) as momentum and behavioral market anomalies are documented in other papers, however finding liquidity premium is not common.

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