UNIVERSITY OF GOTHENBURG
SCHOOL OF BUSINESS, ECONOMICS AND LAW

Master's Thesis in Finance, 30 hec

Graduate School

Common risk factors in the cross-section of cryptocurrency returns

An empirical study on different types of cryptocurrency anomalies: size, momentum, volatility and trend

Authors:
Dan Luo
Sebastian Andersson

Supervisor:
Adam Farago

Spring 2021

Abstract

This paper identifies three common risk factors in the returns on cryptocurrencies. The three common risk factors are the market factor, size factor, and momentum factor. Investigating a collection of 461 cryptocurrencies, we find that the size factor impacts the size-related anomalous returns, and the momentum factor affects the volatility-related anomalous returns. Moreover, the proposed three-factor model has satisfied explanatory power on the cross-section of cryptocurrency returns.

Acknowledgement

First, we would want to thank our supervisor, Adam Farago, for the valuable guidance and feedback throughout the project. We also thank our fellow students in the finance lab for all the good memories made along the way. Furthermore, we are grateful for all the supports we have received from our friends and families.

Table of Contents

List of Tables

List of Figures

1 Introduction

Over the past few decades, financial researchers have examined numerous risk factors that capture the cross-sectional returns on stocks (Schwert, 2003; Hou et al., 2020). In contrast, far fewer investigations are constructed to identify the risk factors in the cross-section of cryptocurrency returns. Sovbetov (2018) mentions that most financial economists ignore the capabilities of the broad cryptocurrency market, even if the cryptocurrency market represents one of the most trending topics nowadays. Liu et al. (2019) conduct the first comprehensive study that analyzes the cross-section of cryptocurrency returns and finds significant size and momentum effects.

What common risk factors affect the cross-sectional cryptocurrency returns? Inspired by Liu et al. (2019), this paper conducts a detailed investigation of common risk factors based on two methods. First, we examine a wide range of cryptocurrency anomalies (factors), which overlap in the literature on various stock anomalies. Second, to analyze the classical equity-based risk factors in cryptocurrency returns, we take the market return, size, and momentum into account as our common risk factors. We show that our proposed size- and momentum factors capture the cross-sectional cryptocurrency returns.

1.1 The short history of cryptocurrency

Since 2013, the cryptocurrency market has experienced rapid growth over the last few years. Although cryptocurrencies are still considered to be in their nascent stage, they are recognized as one of the most trending topics in academia (Sovbetov, 2018). This part will discuss the short history of the cryptocurrency market, strengthening the fact that investigations on cryptocurrencies are essential.

The financial crisis of 2008 created the Great Recession in the foreign exchange market, stock market, and many other financial markets in the world (Athreye et al., 2021). During the Great Recession, the pull factor [1] of the traditional financial markets was extremely weak (Dwyer and Tkac, 2009), with a direct acceleration effect of currency devaluation (Fratzscher, 2009). In the same year, Bitcoin was created as the first cryptocurrency in the world. Bitcoin has dramatically changed the financial world because it is a new way of payment without having any authorities involved (Ammous, 2018). In November 2008, Satoshi Nakamoto, the creator of Bitcoin, published a whitepaper called "Bitcoin: A Peer-to-Peer Electronic Cash System" [2] to a digital currency mailing list. In the middle of 2009, the whitepaper delivered its first formation of the Bitcoin Blockchain.[3] Little is known about Nakamoto's identity. According to Wikipedia, Nakamoto might be an individual, a team, or even an institution. However, the early use of Bitcoin started in 2011, when more people realized Bitcoin could be used as a payment method as well as a profitable investment.

[1] Pull factor: i.e., factors that are specific to countries themselves, which have been driving capital flows over the past few years. A weak pull factor might lead to poverty, fear, disasters, and unemployment (ECB).

[2] The whitepaper: https://bitcoin.org/bitcoin.pdf.

[3] A decentralized computation network of autonomous hubs, more information see Wikipedia.

1.1.1 The rapid growth of the cryptocurrency market

Since the genesis of Bitcoin twelve years ago, numerous new digital currencies have been released. In 2011, both Litecoin and Namecoin were released as two new cryptocurrencies. Until today, Litecoin remains one of the top 20 cryptocurrencies by market capitalization. In 2012, Peercoin was created as the fourth cryptocurrency. Interestingly, Peercoin has died out because investors do not find potential in it anymore. After 2012, the amount of new cryptocurrencies increases day by day, including Dogecoin, one of the phenomenon cryptocurrencies. According to CoinGecko[4], Dogecoin was released in 2013, and after years of being unknown to the public, in 2021, it attracted millions of investors' attention suddenly. As a consequence, Dogecoin experienced a one-year price increase of 20,459% in 2021.[5] Figure 1 shows the number of cryptocurrencies listed on CoinMarketCap[6] from June 2013 to May 2021. We can see that the number of new cryptocurrencies increases every year, where the total amount of cryptocurrencies increased from 66 in June 2013 to 9,527 in May 2021.

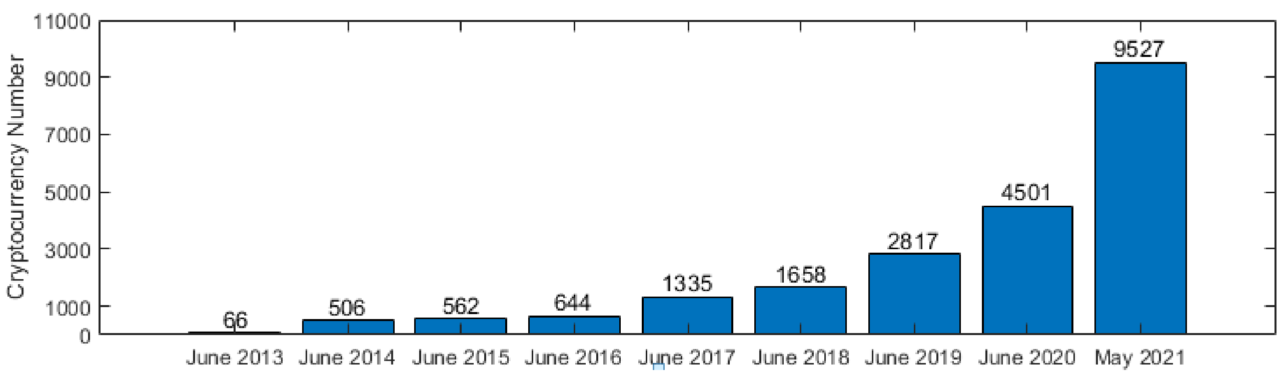

Figure 1: Number of cryptocurrencies worldwide from 2013 to 2021. Source: Statista

The rapid expansion of the cryptocurrency market in recent years has created investment opportunities for individual investors, institutions, and major companies (Yermack, 2015). On 08 April 2021, the total cryptocurrency market capitalization exceeds $2 trillion in the global market, while it was just $1.39 billion at the beginning of April 2013. During this time, Bitcoin dominated the cryptocurrency market by market capitalization and encountered a 72,186% (almost 722 times) market capitalization expansion (from $1.5 billion at the beginning of April 2013 to $1.08 trillion in May 2021).

To put that into relation, Figure 2 compares the market capitalization of Bitcoin, the whole cryptocurrency market, and the largest banks worldwide. The subplot on the left-hand side shows that the cryptocurrency market has a total market capitalization of more than 700 billion dollars at the beginning of 2021, which is higher than the combined market capitalization of the three largest banks. Just four months later, at the beginning of May 2021, the market capitalization of the whole cryptocurrency market (2.35 trillion dollars according to CoinGecko) surpassed the combined market capitalization of ten largest banks worldwide (2.26 trillion dollars according to Bloomberg). The subplot on the right-hand side of Figure

[4] The world's largest independent cryptocurrency data aggregator.

[5] $0.00203745 on April 20, 2020 and $0.41888 per Dogecoin on April 20, 2021.

[6] The world's most-referenced value-tracking website for cryptocurrencies in the rapidly developing cryptocurrency market.

2 compares the market capitalization of Bitcoin and the largest three banks (Industrial and Commercial Bank of China (ICBC), JPMorgan Chase (JPM), and Bank of America (BAC)). The market capitalization of Bitcoin in December 2020 was around \$536 billion, which is higher than that of JPM (\$387.33 billion), BAC (\$262.2billion), and ICBC (\$262.4 billion).

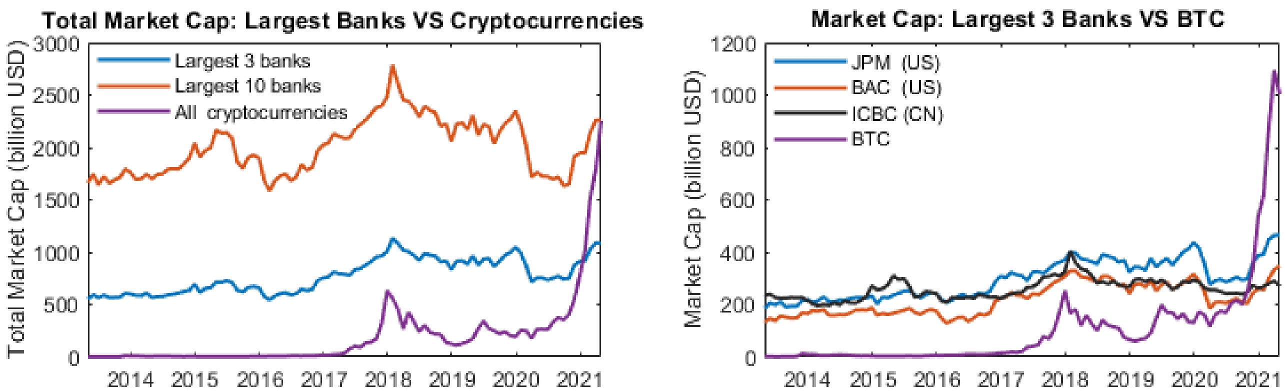

Figure 2: Market capitalization comparison from April 2013 to May 2021
Data Source: CoinGecko and Bloomberg

What is the reason for the rapid growth of the cryptocurrency market? Some of the incredible market development for cryptocurrencies are related to countries like Japan and South Korea's acceptance of Bitcoin as a payment method (Cointelegraph, 2017). As the supply of bitcoin is relatively fixed (21 million offerings in total), a higher demand than supply creates price pressure upward. Another essential driver of commercialization is the creation of the Enterprise Ethereum Alliance in 2019, an ecosystem of banks and companies that use Ethereum's blockchain technology in their daily business operations (Entethalliance, 2021). However, Bitcoin's value mainly lies in its safe technology rather than effective transactions. In 2021, large corporations like Tesla and MicroStrategy have bought Bitcoin as a store of value on their balance sheet instead of holding cash in fiat currency (Decrypt, 2021).

Therefore, researchers need to pay more attention to this area, considering the rapid expansion of the cryptocurrency market and investors' increasing interest in cryptocurrencies.

1.1.2 The legal status of cryptocurrencies

Even though cryptocurrencies constitute an important financial innovation in recent times, one may doubt that cryptocurrencies provide a reasonable investment opportunity for investors since the legal status of cryptocurrencies differs substantially across countries (Stolbov and Shchepeleva, 2020). However, according to Forkast News, more and more countries suffering from hyperinflation start to use cryptocurrency as their shelter amidst inflation turmoil. Moreover, Ammous (2018) explains that the more central banks dilute their currency supply, the stronger the case of other investment options like gold and Bitcoin will attract investors' attention. For example, the Argentine central bank is known as one of the world's most prolific money printers, and the country has suffered from recession and hyperinflation since 2018. Investors in Argentina are placing their faith in cryptocurrency for monetary freedom as their home country's economy crumbles with currency devaluation, runaway inflation, and surges in prices for basic goods.

It is undeniable that cryptocurrency is a new type of economy representing an advanced payment method (Bziker, 2021). However, due to the existing evidence on price manipulation in the cryptocurrency market, e.g., Bitcoin (Gandal et al., 2018), it is crucial to concern political and economic policies against the cryptocurrency market (Colon et al., 2021). Authorities on both national and regional levels keep working on their laws and policies to regulate cryptocurrencies. The legal status of cryptocurrencies shifts from jurisdiction to jurisdiction regarding the various government-issued notices. According to the Library of Congress, central banks play an important role in issuing notifications about the pitfalls of cryptocurrency investments, aiming to educate citizens about risks resulting from the highly volatile cryptocurrency market. Some jurisdictions focus on imposing restrictions on cryptocurrency investments. For instance, countries like Bolivia, Pakistan, Morocco, Algeria, Nepal, and Vietnam have banned all activities related to cryptocurrencies. There are also additional nations that do not ban citizens from cryptocurrency investments. Instead, they put out indirect laws or policies restricting financial institutions inside their countries from facilitating cryptocurrency transactions (Colombia, Iran, Bangladesh, China, Lithuania, Etc.).[7] While in most of the countries, the existence and circulation of cryptocurrencies stays in a fuzzy border between legal and illegal (e.g., Luxembourg, the Cayman Islands, Belarus, and Spain).

Indeed, cryptocurrency investors should be aware of the notifications issued by authorities since the cryptocurrency market is relatively underdeveloped comparing to the traditional financial markets (Li et al., 2021). However, we cannot deny that cryptocurrencies are a new global investment class, which creates opportunities for investors worldwide (Celeste et al., 2020). Omane-Adjepong and Alagidede (2019) further emphasize the importance of investigating the cryptocurrency market since it is an innovative and essential element of global financial markets. Overall, both policymakers and researchers should expand their studies on the attributes of the cryptocurrency market (Klarin, 2020). To further check cryptocurrency's legal status, we present an overview of cryptocurrencies' legal status across the largest 15 economies by gross domestic product (GDP) in Table A1 Appendix B.[8]

1.2 Problem discussion and research question

In this subsection, we discuss existing problems in the cryptocurrency market and present the motivation for our research question.

1.2.1 Problem discussion

A decentralized financial market for a new investment class has emerged from the active trading of major cryptocurrencies, which removes the need for a centralized governing body (Manavi et al., 2020). While investigations are ongoing whether a cryptocurrency is an asset or not, Liu et al. (2020) argue that cryptocurrencies could be considered a different asset class type. Therefore, they suggest that cryptocur-

[7]Cryptocurrency regulations around the world.

[8]The website to check the largest 15 economies by GDP.

rencies can diversify both investors' and institutions' portfolios to spread risks. Similarly, Platanakis and Urquhart (2020) and Brière et al. (2018) also claim that cryptocurrencies differentiate from traditional financial assets, which might help to improve an investor's overall portfolio performance.

As discussed in Section 1.1, investors and institutions are increasingly interested in the cryptocurrency market (Celeste et al., 2020); thus, it is crucial for researchers to expand their studies on this area and provide more professional insights for cryptocurrency holders (Klarin, 2020). Nonetheless, the cryptocurrency investment strategies may differentiate from the investment strategies of traditional financial assets. From the finance viewpoint, it is essential to understand the risk factors that drive cryptocurrency returns. Hence, a relevant question that emerges is the connection between risk factors and cryptocurrency returns. It has been proven that the cryptocurrency market is differentiated from the traditional financial markets (Baur et al., 2018; Liu and Tsyvinski, 2018). Specifically, Baur et al. (2018) point out that cryptocurrencies remain independent from traditional financial assets, like stocks or commodities. In addition, Liu and Tsyvinski (2018) conduct the first comprehensive investigation on whether major cryptocurrencies co-move with traditional financial markets. They examine the risk factors from the cryptocurrency market, stock market, commodity market, and central banks. Their findings show that the return on cryptocurrency investments can only be predicted by cryptocurrency market-related factors. However, it is always an open challenge what cryptocurrency-related risk factors should be considered in a cryptocurrency asset pricing model to capture returns. This study aims to research the common risk factors that affect the cross-section of cryptocurrency returns, and help investors to understand this nascent cryptocurrency market better.

1.2.2 Research question and purpose

Research question:
Are there any common risk factors that drive the cryptocurrency anomalous returns?

Our paper tries to address this question and clearly specify in the light of existing research. To this day, factors affecting portfolio returns to the stock market have been deeply explored and understood. Due to the novelty of digital assets as a new investment class, only a limited amount of studies aims to uncover a more detailed understanding of the drivers behind the cross-sectional cryptocurrency returns. The validity of portfolio theories and asset pricing models in the cryptocurrency market remains an exciting and needed topic of academic discourse. Inspired by Liu et al. (2019), our research project examines the cross-section of cryptocurrency returns. The primary purpose is to investigate the cryptocurrency market-related risk factors, using asset pricing tools with inspiration from the Capital Asset Pricing Model (CAPM), Fama-French model, and Carhart four-factor model. In particular, we aim to identify common risk factors in cryptocurrency anomalous returns. On the other hand, we try to replicate Liu et al.'s (2019) study by compiling an extensive cryptocurrency data set with 31 anomalies (factors). The 31 anomalies are synthesized by the trading strategies based on size-, momentum-, volatility- and trend signals in the cryptocurrency market. In other words, we attempt to test whether attributes that are considered significant in the cross-section of stock markets are likewise presented in the cryptocurrency returns. Hence, we contribute to the literature by extending the branch of investigations on cryptocurrency returns. Additionally, with the use of the market factor from the CAPM, size factor from the Fama-French three-factor model, and the momentum factor from the Carhart four-factor model (Lintner, 1965; Mossin, 1966; Fama and French, 1993; Carhart, 1997), we further contribute by studying whether the cryptocurrency market functions similarly to stock markets.

1.3 Preview of our results

This part briefly previews the empirical results of our study. With a sample data set of 500 cryptocurrencies, including information from January 2017 through January 2021. We first find that 17 out of 31 long-short trading strategies can yield significant economic gains. The 17 trading strategies refer to our cryptocurrency factors (anomalies). Next, we examine whether these 17 cross-sectional cryptocurrency anomalies are exposed to three common risk factors (market return, size- and momentum- factors). Our second main result shows us a preferable three-factor model explaining the cross-sectional cryptocurrency returns, as we find that several anomalies have significant exposures to the size and momentum risks. In other words, the proposed three-factor model outperforms the cryptocurrency-CAPM (C-CAPM) and the two-factor models in capturing the cross-section of the cryptocurrency returns.

1.4 Delimitation

This paper analyzes the data on a weekly basis over a short time frame, as the cryptocurrency market is very new (data available from 2013 to 2021, at the moment of writing). Compared to the stock market, the time frame can be traced back to the year 1611 (the first modern stock trading in the Netherlands). In the future, one may engage in a more profound examination of the data with lower (monthly) or even higher (daily) frequencies over a longer time frame.

In addition to the short time frame, the lack of recently updated data might be another limitation of our study. This paper collects the sample data at the beginning of February 2021, and cryptocurrencies with a market capitalization smaller than 1 million dollars are excluded. Nevertheless, at the moment of writing (May 2021), some excluded cryptocurrencies are being actively traded with a market capitalization of more than 1 million. For example, QuickSwap, which was released at the end of February 2021 with a zero dollar market cap, is now ranked as the 339th largest cryptocurrency by market capitalization ($133.7 million in May 2021). The rapid growth of the cryptocurrency market leads to the active replacement of major cryptocurrencies. The 500 largest cryptocurrencies (by market cap) we collected in February 2021, are likely a limitation because it does not permit us to consider new upcoming cryptocurrencies in our study. From the econometrics perspective, our empirical model might lead to bias (either overestimate or underestimate the effects) due to the lack of recently updated data.

2 Literature review

2.1 Traditional financial markets

In the traditional financial markets, research for asset pricing models is widely examined. Sharpe (1964), Lintner (1965) and Mossin (1966) introduced the Capital Asset Pricing Model (CAPM), a model developed on Markowitz's (1952) research within modern portfolio theory. Markowitz (1952) argues that systematic risk cannot be diversified away. Therefore investors seek a portfolio with the highest expected return related to the expected risk. Given a set of portfolios with the same expected return, the portfolio with the lowest risk is preferred (Markowitz, 1952). CAPM is a way to measure systematic risk and estimate the compensation level needed for taking additional risk (Sharpe, 1964). Banz (1981) performs the first research on tracking the size effect in the stock market, showing that small stocks tend to outperform large stocks. Banz (1981) argues the CAPM is misspecified because they find size effect in the stock market, while CAPM only considers market effect.

Motivated by Banz (1981), Fama and French (1992, 1993) examine the CAPM. Their findings display that market β in the model has low explanatory power on changes in excess return. Therefore, adding more factors to the CAPM could enhance the explanatory power of the model. Fama and French (1993) argue that the addition of a size and a value factor into the CAPM could increase the model's predicting power, as the findings by Fama and French (1992) indicate that both the size and value factors predict the cross-section of average stock returns. On average, the CAPM suffers from high absolute pricing errors compared to a three-factor model (Fama and French, 1993). The additional risk factors are represented by small-minus-big (SMB) and high-minus-low (HML). SMB explains the size effect, and a small market capitalization stock earns higher returns than a large market capitalization stock. HML visualizes the value effect, and a stock with a low price-to-book ratio has superior performance than a stock with a high price-to-book ratio. Based on the literature by Fama and French (1993), the Fama-French three-factor model divides into three factors: Rm-Rf (market risk), SMB (market size), and HML (market value).

Moreover, Jegadeesh and Titman (1993) argue that trading strategies can perceive abnormal returns if the strategy buys past winners and sells past losers. Related to the momentum theory, Carhart (1997) creates a four-factor model including a cross-sectional momentum factor, winner-minus-loser (WML). The creation of the momentum factor is based on the theory that winners will keep winning in the future and losers will keep underperforming (Carhart, 1997). Carhart (1997) finds a momentum effect, the effect of positive return on an asset can influence it for up to twelve months. The four-factor model decreases most of the pricing errors indicating that it outperforms the CAPM and the three-factor model (Carhart, 1997).

Novy-Marx (2013) and Titman et al. (2003) find evidence that the Fama-French three-factor model is incomplete in capturing expected returns. More recent research by Fama and French (2015) results in a five-factor model, with two additional variables to the three-factor model, robust-minus-weak (RMW) and conservative-minus-aggressive investment (CMA). RMW indicates that stocks with higher profits perform better than stocks with lower profits, also called the profitability factor. CMA indicates that stocks of a company with high total asset growth have below-average returns, also called the investment factor. Fama and French (2015) find the value factor to be redundant when including the investment and profitability factors.

Asset pricing models that capture expected returns have been widely explored in the stock market. However, the replication of anomalies is not common in the finance field (Hou et al., 2020). Our paper conducts a comprehensive replication of several published anomalies in the stock market. We find it interesting to briefly review the literature that examines hundreds of different stock anomalies. Schwert (2003) explains that anomalies refer to empirical results, which are likely to be inconsistent with persevered theories of asset pricing behaviors. By testing a broad list of stock anomalies, all his empirical findings indicate that anomalous stock returns are likely to be more apparent than real. Furthermore, Hou et al. (2020) deliver the largest-to-date replication in the finance field. They test a wide range of data libraries with 447 anomalies and find that 161 anomalies are significant. They also conclude that it is possible to increase the credibility of the anomalies literature by connecting with economic theories. Hence, the literature by Schwert (2003) and Hou et al. (2020) gives us inspirations for using cryptocurrency anomalies in the first place.

2.2 The cryptocurrency market

Dyhrberg et al. (2018) take a view on Bitcoin's investment potential by measuring its trading dynamics and microstructure. Their research proposes that Bitcoin has a lower effective spread than spreads on major equity exchanges. They also find that Bitcoin has increased volatility during US market trading hours and most trades executed are non-algorithmic. It is interesting because it gives value to the fact that Bitcoin is a potential investment alternative to the equity market, even if the cryptocurrency market structure is fundamentally different. Additionally, literature from Liu and Tsyvinski (2018) and Baur et al. (2018) suggest that Bitcoin is mainly a speculative investment. Because of its relatively low market capitalization, it is not endangering the stability of the traditional financial system. Despite the increasing investigations on the pricing mechanisms of cryptocurrencies (Dyhrberg et al., 2018; Liu and Tsyvinski, 2018; Baur et al., 2018), only a limited amount of research has been dedicated to the co-integration between cryptocurrency returns and the stock market. Liu and Tsyvinski (2018) research how the cryptocurrency returns respond to shocks from the traditional financial markets. They tested whether there is co-movement between the cryptocurrency market and several traditional markets, and suggest that only the cryptocurrency market-related factors can affect the behavior of cryptocurrency returns. Similar results have been found by Corbet et al. (2018) , who argue that the cryptocurrency market is relatively isolated and might offer short-term diversification advantages for investors. However, Kurka's (2019) findings show volatility spillover effects between Bitcoin and the traditional financial markets when market shocks occur, implying that the cryptocurrency market is not independent. Moreover, Gil-Alana et al. (2020) detail the evidence that there is a low association between the stock market and the cryptocurrency market. In relation to previous research (Liu and Tsyvinski, 2018; Corbet et al., 2018; Kurka, 2019; Gil-Alana et al., 2020), we find it is more interesting to look at the cryptocurrency market-related factors than to check the connections between the traditional financial markets and the cryptocurrency market, as there seems to be a low linkage between them.

A rapid increase in both supply and variation of cryptocurrencies impacts the need to evaluate cryptocurrency asset pricing models and long-short strategy characteristics further. With modest research in this area, Liu et al. (2019) manage to perform a single sorted cross-sectional analysis on an index containing 1707 different cryptocurrencies. However, for being one of the pioneers, they came up with exciting results. Findings by Liu et al. (2019) suggest that a three-factor model consisting of the cryptocurrency market, size, and momentum can apprehend most of the cross-sectional expected cryptocurrency returns. Their study finds that known characteristics from the equity market could be found in long-short strategies for cryptocurrencies. In similarity to Liu et al. (2019), Liu et al. (2020) investigate a cryptocurrency asset pricing model but argue that the choice of sorting process influences the correlation between common risk factors. Moreover, Liu et al. (2020) examine both the Fama–MacBeth regression and a time-series regression. Their findings contribute to further research, as 93.99% of the 78 cryptocurrencies in the sample period could be explained by the cryptocurrency three-factor model consisting of market, size, and momentum factors. Eventually, more researchers found the subject interesting. Shen et al. (2020) state that the cryptocurrency three-factor model outperforms the cryptocurrency-CAPM in capturing returns. Their results indicate that these factors capture cryptocurrency anomalous returns when incorporating size and reversal factors into C-CAPM. Furthermore, Shen et al. (2020) find that small cryptocurrencies tend to outperform large ones and that reversal returns increase from big to small cryptocurrencies. Contributions to literature by Liu et al. (2019), Liu et al. (2020) and Shen et al. (2020), create a ground for us to build further on. Our research follows the same template as Liu et al. (2019), but we differentiate from their study on a few notes:

1. Newer sample period
2. Implementation of trend strategies (trend factors)
3. More comprehensive research for the volatility strategies (volatility factors)

Our trading strategies are categorized as size, momentum, volatility, and trend. We are the first researchers to implement trend strategies in the cryptocurrency market. The trend strategies are implemented based on Han et al.'s (2013) research from the stock market that moving average strategies are uncorrelated with momentum strategies, even if both are trend-following. Moreover, Brock et al. (1992) argue that the moving average strategies have strong support in the results from the stock market, and Lo et al. (2000) consider that moving averages can be beneficial to use in a trend-following trading strategy. This paper's size, momentum, and volatility strategies are based on Liu et al.'s (2019) research from the cryptocurrency market. They find that size and momentum factors are significant for apprehending the cross-section of cryptocurrency returns.

3 Data

We collect trading data of the top 500 cryptocurrencies on 5-February-2021, based on market capitalization from Coingecko.com. Coingecko is a leading cryptocurrency source aggregator that provides an in-depth view of the digital cryptocurrency market. It lists over 6400 cryptocurrencies from over 400 major exchanges (13 May 2021), which all meet the platform's requirements. Examples of requirements are: reaching Coingecko's application programming interface (API) standards, listed on at least one of Coingecko's integrated exchanges, and have visible calculations for its market capitalization. In contrast to other researchers that use Coinmarketcap.com for data collection (Liu and Tsyvinski, 2018; Liu et al., 2019), we found out that Coinmarketcap's free API had expired and that Coingecko was a better source aggregator to manually download from. Moreover, CoinGecko is an independent website, while Coinmarketcap is owned by Binance (a cryptocurrency exchange). We do not use Coinmarketcap as we think there might be bias towards some cryptocurrencies or new projects.

Each cryptocurrency is collected from its first trading day, and our data set ranges from 29-April-2013 to 5-February-2021, a total of 2898 trading days. Our data contains information on the daily close price and market capitalization. In the cleaning process, a problem arose. Even with strict requirements from Coingecko, data in 39 cryptocurrencies were insufficient on either daily close price or market capitalization. Therefore, our final data set decreased to 461 cryptocurrencies as we require the sample to have information on both sections. The summary statistics are presented in Table 1, which reports the number of sample cryptocurrencies, total market capitalization, and the mean value of our sample cryptocurrencies at the end of each year. As we can see, only a few cryptocurrencies appear between 2013 and 2016 since our data set gets more relevant in recent times. The number of sample cryptocurrencies in the first four years is too few to conduct a cross-sectional study. Therefore, we only use part of the data set containing a four-year time frame from January 2017 to January 2021. Since a five-year time frame (2014 to 2018) is used by Liu et al. (2019) and a three-year time frame (2015 to 2018) is used by Liu et al. (2020), we find a four-year time frame is enough to conduct our investigation.

Table 1: Summary statistics

Year	Number of coins	Market Cap (million $)	Mean Market CAP (million $)
2013	4	10,025.27	2,506.32
2014	18	5,306.34	294.80
2015	24	6,981.32	290.89
2016	37	17,386.05	469.89
2017	102	590,970.18	5,793.83
2018	194	124,022.18	639.29
2019	294	189,450.25	644.39
2020	451	761,291.29	1,688.01
Full	461	1,113,873.02	2,416.21

We structure the final data set in Matlab and examine the patterns of average returns in a weekly horizon. Weekly returns and corresponding anomaly variables are converted from the daily data of each cryptocurrency, from Monday close price to Monday close price next week. Our choice of constructing weekly data instead of monthly data comes from the short sample period of only four years. We could use daily data for our construction process, but there is a risk that our sample cryptocurrencies will be noisy and that the transaction costs will influence the results too much. When choosing weekly data, the construction process follows the ones implemented by previous researchers (Liu et al., 2019, 2020; Shen et al., 2020).

The converted data leads to 209 weekly observations, where we exclude cryptocurrencies with a market capitalization below $1,000,000 and cryptocurrencies with missing price values. Figure 3 vitalizes the sample cryptocurrencies traded in our portfolios each week, from January 2017 to January 2021.

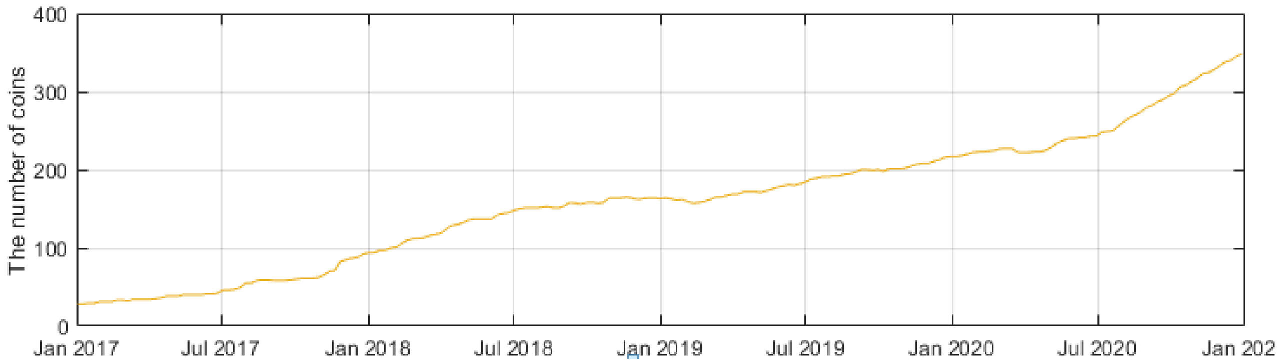

Figure 3: The number of cryptocurrencies used for each formation week

4 Methodology

Our common risk factor tests in the cryptocurrency market are presented from two different methods. First, we explain in detail the methodology of our cross-sectional cryptocurrency factor (anomalies) construction process. Second, we consider three established common risk factors and use nested factor models to run time-series regressions on our cross-section cryptocurrency factors (Fama and French, 1992, 1993; Novy-Marx, 2013; Titman et al., 2003). Therefore, we will have two types of factors involved in the study. The first type of factor is the cross-sectional cryptocurrency factors used as response variables, standing for anomaly returns of a certain trading strategy. The second type is the common risk factors used as explanatory variables in the proposed factor models. Based on previous studies, we construct market return, size, and momentum as our cryptocurrency-specific common risk factors.

4.1 The cross-section of cryptocurrency factors (31 in total)

This part discusses the construction processes of the cross-section of cryptocurrency factors. We will use a single sorting process to construct our cryptocurrency factors and focus on a comprehensive list of 31 previously investigated factors based on the standard long-short procedure, attributed to the studies of Liu et al. (2019), Brock et al. (1992), Lo et al. (2000), Han et al. (2013) and Neely et al. (2014). Table 2 presents the definition of all the 31 factors, where we categorize them as four types: size, momentum, volatility, and trend. Note that each factor is constructed under a given sorting variable (anomalous variable), and the last column of Table 2 stands for the definition of each sorting variable.

Table 2: The 31 factors and the corresponding sorting variables

Category	Factor	The sorting variable used for the factor
Panel A: Size Factor		
Size	MCAP	Last day market capitalization in the formation week
Size	PRICE	Last day price in the formation week
Size	MAXPRICE 1w	The maximum daily price over the past formation week
Size^{new}	MAXPRICE 2w	The maximum daily price over the past two weeks
Panel B: Momentum Factor		
Momentum	$MOM1$	One week momentum
Momentum	$MOM2$	Two week momentum
Momentum	$MOM3$	Three week momentum
Momentum	$MOM4$	Four week momentum
Panel C: Volatility Factor		
Volatility	RETSTD 1w	The standard deviation of one-week daily returns
Volatility^{new}	RETSTD 2w	The standard deviation of two-week daily returns
Volatility^{new}	RETSTD 3w	The standard deviation of three-week daily returns
Volatility^{new}	RETSTD 4w	The standard deviation of four-week daily returns
Volatility	RETSKEW 1w	The skewness of one-week daily returns
Volatility^{new}	RETSKEW 2w	The skewness of two-week daily returns
Volatility^{new}	RETSKEW 3w	The skewness of three-week daily returns
Volatility^{new}	RETSKEW 4w	The skewness of four-week daily returns
Volatility	RETKURT 1w	The kurtosis of one-week daily returns
Volatility^{new}	RETKURT 2w	The kurtosis of two-week daily returns
Volatility^{new}	RETKURT 3w	The kurtosis of three-week daily returns
Volatility^{new}	RETKURT 4w	The kurtosis of four-week daily returns
Volatility	MAXRET 1w	Maximum daily return over the past formation week
Volatility^{new}	MAXRET 2w	Maximum daily return over the past two weeks

Table 2 continued

Category	Factor	The sorting variable used for the factor
Panel D: Trend Factor		
Trend^{new}	MA3	The normalized three-day moving average price
Trend^{new}	MA5	The normalized five-day moving average price
Trend^{new}	MA7	The normalized seven-day moving average price
Trend^{new}	MA10	The normalized ten-day moving average price
Trend^{new}	MA20	The normalized twenty-day moving average price
Trend^{new}	MA30	The normalized thirty-day moving average price
Trend^{new}	MA50	The normalized fifty-day moving average price
Trend^{new}	MA100	The normalized one-hundred-day moving average price
Trend^{new}	ER	The expected return from the cross-sectional regression of cryptocurrency returns on observed normalized MA signals

Notably, we differentiate from Liu et al. (2019) both with a newer sample period and with new factors. That is, we test some new size and volatility factors on different time horizons. In addition, we introduce advanced trend factors in our study, aiming to capture the cryptocurrency price information from a trend perspective (Han et al., 2016). All new factors investigated by this paper are marked as new in Table 2.

4.2 Factor construction process

This part explains the construction process applied for the 31 factors. Following the method outlined in Liu et al. (2019), we implement the zero-investment long-short strategies to construct our factors.

Each Monday, we use a one-dimensional sort on the traded cryptocurrencies and rank them in ascending order based on a given sorting variable, as shown in Table 2. We then obtain five quintile portfolios every week, and the given factor is the weekly return differences between the fifth quintile portfolio and the first quintile portfolio (5-1). Table 3 shows the sorting process for constructing our cryptocurrency factors (anomalies) regarding a given sorting variable. Note that the return differences of the long-short investing strategies are interpreted as the weekly returns on all factors.

Table 3: Quintile portfolio returns after sorting on a given variable

First quintile	Second quintile	Third quintile	Fourth quintile	Fifth quintile
Lowest 20% (**L**)	20% - 40%	40% - 60%	60% - 80%	Highest 20% (**H**)
Factor = H - L = Highest 20% - Lowest 20%				

Following Liu et al. (2019), we use a value-weighted allocation strategy. The formula for the weight of cryptocurrency i at the beginning of week t (w_{it}) for each value-weighted quintile portfolio:

$$w_{it} = \frac{Cap_{i,t}}{TotalCap_t} \tag{1}$$

$$0 < w_{it} < 1 \tag{2}$$

The portfolio return in week t after the portfolio allocation strategy is:

$$R_{pt} = \sum_{i=1}^{N} w_{it} R_{it} \tag{3}$$

Where w_{it} denotes the investment weight of cryptocurrency i at the beginning of week t, Cap_t is the market capitalization of cryptocurrency i at the beginning of week t, and $TotalCap_t$ stands for the total market capitalization of the traded cryptocurrencies in the quintile portfolio at the beginning of week t. Note that the weight (w_{it}) on each cryptocurrency is positive. R_{pt} is the quintile portfolio return in week t after rebalancing on a weekly basis, R_{it} is the return on cryptocurrency i in week t. Note that the weight formula and the formula for portfolio returns are used in all factor construction processes.

4.2.1 Size factor

Each of the cryptocurrency size factors is based on a given size-related sorting variable: market capitalization, close price, maximum daily close price over the past formation week, and maximum daily close price over the past two weeks, respectively. Table 4 shows the construction results of all significant size factors[9], reported as the average weekly returns on the value-weighted quintile portfolios and their t-test statistics.[10] At a 10% significance level, we find statistically significant weekly average returns on the value-weighted portfolios. It is worth noting that the mean returns decrease from the first to the fifth for all quintile portfolios indicating negative weekly return differences for our size factors. The return differences are -5.25% for MCAP, -5.05% for PRICE, -5.03% for MAXPRICE1w and -5.04% for MAX-PRICE 2w. The negative average returns of the zero-investment long-short strategies tell us there could be a positive economic gain if we short the portfolio with the largest size and long the portfolio with the smallest size(1-5). As expected, the results show that the cryptocurrency with a smaller size is more likely to have higher returns than the returns on cryptocurrency with a larger size. The size effect in our case is corresponding to the findings from Fama and French (1992, 1993), Novy-Marx (2013), Titman et al. (2003) and Liu et al. (2019), where they see significant size effects either in the stock market or the cryptocurrency market.

[9]Note that we report all the insignificant size factors later in Section 4.2.5.

[10]Test the null hypothesis (H_0) that the sample portfolio return comes from a population with a mean equals to zero.

Table 4: Size factor construction results

This table reports the mean quintile portfolio returns based on market capitalization, close price on Monday, maximum daily price over the past one week, and the maximum daily price over the past two weeks, respectively. The mean returns are the time-series averages of weekly value-weighted portfolio returns. Newey-West (1987) t-statistics are in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level respectively. The sample period is from January 2017 through January 2021.

			Weekly Quintile Portfolio Returns					**Factor**
			1	2	3	4	5	5-1
SIZE	MCAP	Mean	0.0742***	0.0487***	0.0342**	0.0224**	0.0217***	-0.0525***
		t(Mean)	(4.8757)	(3.5299)	(2.3148)	(2.1069)	(2.7741)	(-4.5692)
	PRICE	Mean	0.0721**	0.0387**	0.0241**	0.0208**	0.02167***	-0.0505*
		t(Mean)	(2.4836)	(2.2395)	(2.0945)	(2.1782)	(2.7820)	(-1.9268)
	MAXPRICE 1w	Mean	0.0720**	0.0352**	0.0252**	0.0210**	0.0217***	-0.0503*
		t(Mean)	(2.4737)	(2.0024)	(2.0983)	(2.2305)	(2.7798)	(-1.9172)
	MAXPRICE 2w	Mean	0.0721**	0.0370**	0.0224**	0.0204**	0.0217***	-0.0504*
		t(Mean)	(2.4766)	(2.0785)	(1.9436)	(2.1687)	(2.7836)	(-1.9199)

Following Moskowitz et al. (2012), He et al. (2017) and Cooper et al. (2004), we check the weekly cumulative returns to backtest the performance of each trading strategy. Note that the weekly returns of our long-short trading strategy based on size are negative (5-1 factor). Therefore, we check the profitability performance by longing the first quintile portfolio and shorting the fifth quintile portfolio (1-5), which yields positive economic gains.[11] Figure 4 illustrates the weekly cumulative returns of each size strategy from January 2017 to January 2021. Note that the left y-axis shows the log-scaled cumulative returns, and the right y-axis shows the corresponding weekly cumulative returns. We can see that the cumulative returns on all size factors have experienced rapid growth from January 2017 to January 2018. The rapid growth is reasonable since the total cryptocurrency market capitalization has appreciated more than 1,200% during that year.[12] Due to the common use of price information, it is not surprising to see that the log-scaled return streams of PRICE, MAXPRICE 1w, and MAX-PRICE 2w have experienced similar paths. Compering to the return streams of other size strategies, the return stream of MCAP has the least volatile upward trend, generating the highest profitability during the past four sample years. Therefore, the trading strategy based on MCAP is the preferable one in this case.

[11]The same method is applied for the trend factor later in Section 4.1.4, and we check the 1-5 long-short strategy instead of 5-1.

[12]Source from: Forbes

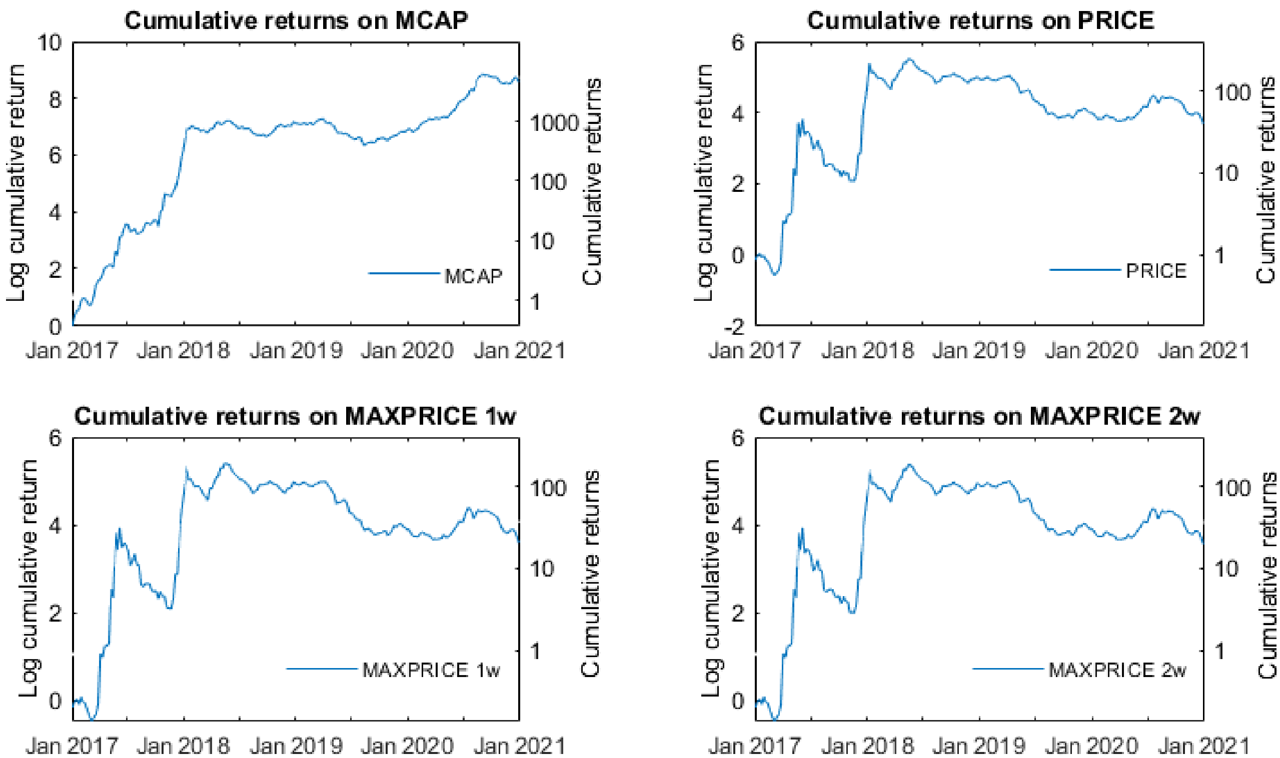

Figure 4: Cumulative returns on size factors (both log-scaled and normal)

4.2.2 Momentum factor

Each of the cryptocurrency momentum factors is based on a given momentum-related sorting variable: one-week momentum, two-week momentum, three-week momentum, and four-week momentum. Same as the methodology by Liu et al. (2019), our momentum variables represent the past returns. The formula for the s-week momentum is the return on cryptocurrency i for the past s weeks (MOM_{it}^{s}):

$$MOM_{it}^{s} = PastReturn_{it}^{s} = \frac{P_i^t}{P_i^{t-s}} - 1 \qquad (i = 1, \ldots, n, n = 461) \tag{4}$$

MOM_{it}^{s} denotes the s-week of past return for cryptocurrency i at week t, s= 1,2,3,4, representing one-, two-, three- and four-week momentum, respectively. P_i^t is the close price of cryptocurrency i on Monday within the formation week t, and P_i^{t-s} is the closing price of cryptocurrency i on Monday within the formation week $t-s$, $s = 1, 2, 3, 4$.

Following the factor construction process introduced in Section 4.2, Table 5 visualizes the construction results of all significant momentum factors[13], reported as the mean weekly returns and the mean weekly return difference of the value-weighted quintile portfolios. Compared to Liu et al. (2019), our one- and four-week momentum strategies do not show significant results. The last column is the weekly return difference between the fifth and the first quintile portfolio, representing the corresponding momentum factor

[13]Note that we report all the insignificant momentum factors later in Section 4.2.5.

(5-1). We can see that the average weekly returns are monotonically increasing from the first to the fifth quintile portfolio. In other words, at a significance level of 10%, all the mean weekly return differences (5-1) are positive and statistically significant. The weekly return differences are 3.38% and 2.01% for MOM2 and MOM3, respectively. On the one hand, the positive average weekly return differences indicate economic gain if we long the portfolio with the highest momentum (the highest past returns) and short the portfolio with the lowest momentum (the lowest past returns). On the other hand, cryptocurrencies with higher momentum are more likely to have higher returns, and cryptocurrencies with lower momentum are more likely to have lower returns. The momentum effect, in this case, is supporting the findings from Fama and French (1992, 1993), Novy-Marx (2013), Titman et al. (2003) and Liu et al. (2019).

Table 5: Momentum factor construction results

This table reports the mean quintile portfolio returns based on the one- and two-week momentum, respectively. The mean returns are the time-series averages of weekly value-weighted portfolio returns. Newey-West (1987) t-statistics are in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level respectively. The sample period is from January 2017 through January 2021.

			Weekly Quintile Portfolio Returns					**Factor**
			1	2	3	4	5	5-1
MOM	r 2,0	Mean	0.0058	0.0139	0.0332***	0.0354**	0.0396***	0.0338***
		t(Mean)	(0.5479)	(1.1538)	(2.9844)	(2.1504)	(3.3733)	(3.0918)
	r 3,0	Mean	0.0161	0.0178	0.0305**	0.0360***	0.0362***	0.0201*
		t(Mean)	(1.2742)	(1.4768)	(2.2150)	(3.3440)	(2.8749)	(1.8049)

Figure 5 presents the significant momentum strategies' performances by plotting weekly cumulative returns for each long-short strategy. Note that the left y-axis shows the log-scaled cumulative returns, and the right y-axis shows the corresponding cumulative returns. As we can see, our long-short trading strategy based on the two-week momentum outperforms the strategy based on the three-week momentum. In other words, the return stream of MOM2 is less volatile and has higher profitability than that of MOM3, resulting in more cumulative compounding over time. Specifically, between the middle of 2017 to the beginning of 2020, the log-scaled cumulative returns on MOM3 are negative, indicating a trading loss over time. For example, assume we invested $1 in the strategy based on MOM3 in January 2017, it would give us positive gains until the middle of 2017. However, we would suffer losses between the middle of 2017 and the middle of 2020. Thus, the momentum trading strategy based on MOM2 is the best one in this case as it has a stable upward trend.

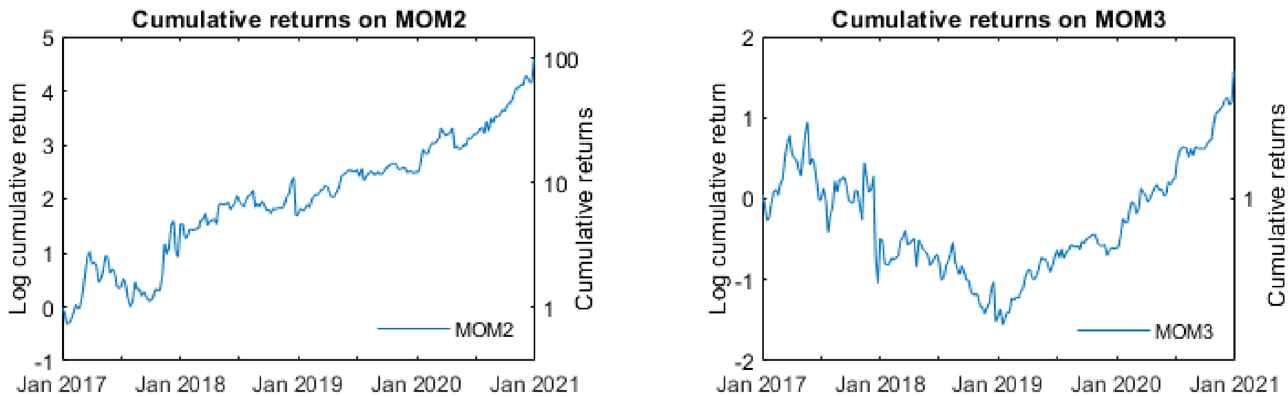

Figure 5: Cumulative returns on momentum factors (both log-scaled and normal)

4.2.3 Volatility factor

In similarity to Liu et al. (2019), the skewness of returns, maximum daily returns, kurtosis of returns, and standard deviation of returns cover the performance of our volatility-related factors. Amaya et al. (2015) and Bali et al. (2011) study the volatility-related factors in the equity market, and their research constructs a framework for our volatility factors. Each of the volatility factor construction processes is based on a given volatility-related variable: the standard variation of returns (one-, two-, three- and four-week, respectively), the skewness of returns (one-, two-, three- and four-week, respectively), the kurtosis of returns (one-, two-, three- and four-week, respectively), the maximum daily return (one- and two-week). Table 6 shows the construction results of the significant volatility factors, and all the insignificant volatility factors are reported later in Section 4.2.5. The last column in Table 6 reports the weekly return differences between the fifth and the first quintile portfolios, representing our volatility factors. Compared to the insignificant results of Liu et al. (2019), our volatility factors based on the skewness of returns (one- and two-week) and maximum returns (one- and two-week) are significant. The weekly mean returns are positive and statistically significant for RETSKEW 1w, RETSKEW 2w, MAXRET 1w, and MAXRET 2w, with a weekly mean return of 2.14%, 2.26%, 3.28%, and 2.58% respectively. There is no clear monotonically trend between the quintile portfolios under a given trading strategy, but the volatility factors indicate economic power in the long-short strategies. In other words, cryptocurrencies with high volatility are more likely to get higher returns than that of low volatility cryptocurrencies. In contrast to the stock market, where Conrad et al. (2013) argue that ex-ante negatively skewed returns yield high returns, investors on the cryptocurrency market seem to be attracted to investments with positive skewness of return and high volatility. With positive skewness, cryptocurrency investors prefer more lottery-like payoffs (Langlois, 2020). There are probably several explanations for this phenomenon, but one of the most substantial reasons might be the lack of financial institutions in the cryptocurrency market. On the stock market, Boyer et al. (2010) argue that stocks with high volatility get lower expected returns. Related to Favre and Signer (2002) study on mutual funds, investment decisions typically go towards investment opportunities with negative skewness and low volatility. Therefore, with the low amount of institutions acting in the cryptocurrency market, the investment characteristics differentiate as retail investors provide most of the liquidity. With a low amount of institutional buyers, our strategy proves that the greatest portfolio return is made in cryptocurrencies with high volatility and positive skewness.

Table 6: Volatility factor construction results

This table reports the mean quintile portfolio returns based on one-week skewness of returns, two-week skewness of returns, one-week maximum daily return, and two-week maximum daily return, respectively. The mean returns are the time-series averages of the weekly value-weighted portfolio returns. Newey-West (1987) t-statistics are in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level respectively. The sample period is from January 2017 through January 2021.

			Weekly Quintile Portfolio Returns					**Factor**
			1	2	3	4	5	5-1
Volatility	RETSKEW 1w	Mean	0.0164*	0.0337***	0.0248**	0.0440**	0.0377***	0.0214**
		t(Mean)	(1.6823)	(2.9476)	(2.0146)	(2.3532)	(2.9494)	(2.3226)
	RETSKEW 2w	Mean	0.0152*	0.0325**	0.0361***	0.0076	0.0378**	0.0226**
		t(Mean)	(1.6695)	(2.6002)	(2.9261)	(0.8216)	(2.5631)	(1.9730)
	MAXRET 1w	Mean	0.0137*	0.0247**	0.0357***	0.0243**	0.0464**	0.0328*
		t(Mean)	(1.6648)	(2.3806)	(2.7627)	(1.9846)	(2.4222)	(1.8511)
	MAXRET 2w	Mean	0.0152*	0.0368**	0.0332**	0.0167	0.0410**	0.0258*
		t(Mean)	(1.9347)	(2.5639)	(2.3892)	(1.4486)	(2.3338)	(1.7261)

As we can see in Figure 6, the cumulative returns on the volatility factors are similar at the end of the sample period (January 2021). Note that the left y-axis shows the log-scaled cumulative returns, and the right y-axis shows the corresponding cumulative returns. However, all four volatility trading strategies experience different return streams. The strategy based on RETSKEW 1w is least volatile over the whole period, as the other three strategies create most of their return gains in the first year. Moreover, it is not surprising to see similar return streams between MAXRET 1w and MAXRET 2w since both of the long-short trading strategies use the information of maximum daily returns. Overall, the strategy based on RETSKEW 1w is preferable as it has an upward sloping trend during the whole sample period.

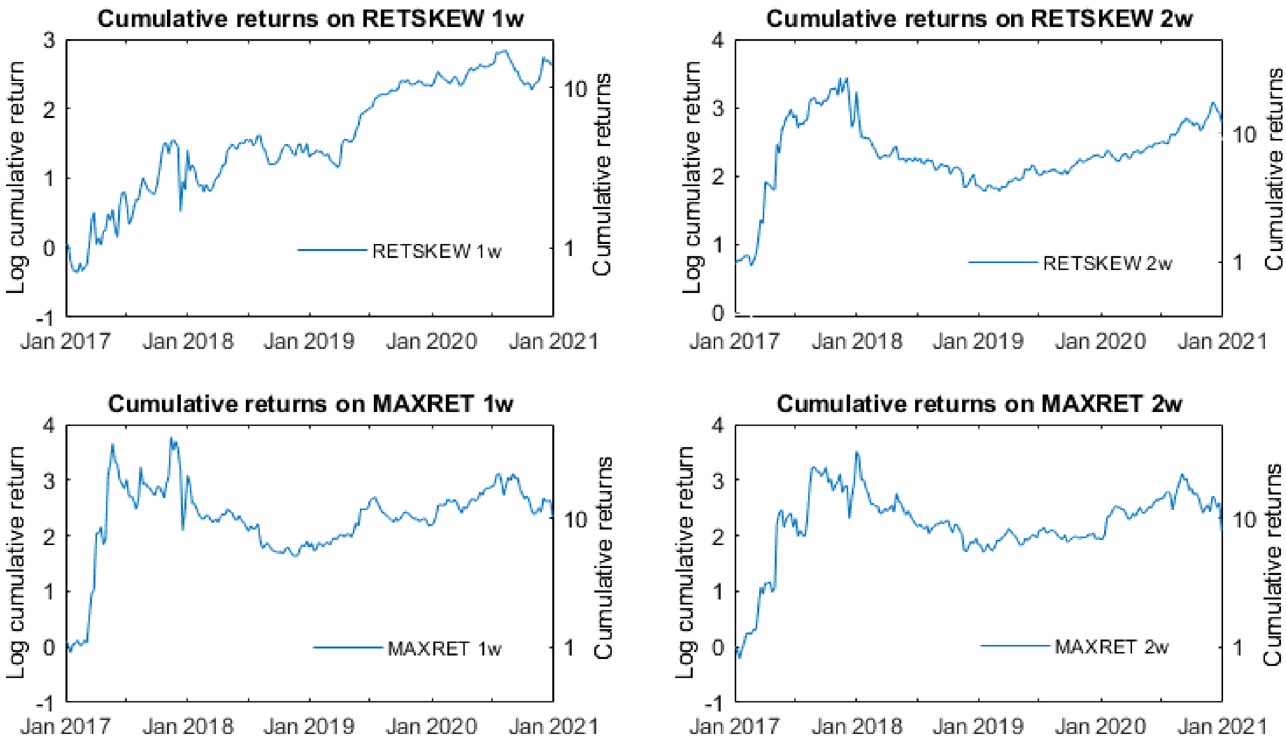

Figure 6: Cumulative returns on volatility factors (both log-scaled and normal)

4.2.4 Trend factor

Inspired by Han et al.'s (2016) investigation on the trend factor from the stock market, we analyze several trend factors in the cryptocurrency market. The trend factor is defined to capture the price trend of our sample cryptocurrencies. We analyze two types of trend factors that are differentiated from the calculation methods. The First type of trend factor is the long-short trend strategy based on normalized moving average prices of cryptocurrencies ($\widetilde{MA}$). The reason for our choice is attributed to the research by Brock et al. (1992), Lo et al. (2000), Han et al. (2013), Han et al. (2016) and Neely et al. (2014). Their research provides reliable evidence on the forecasting power of moving average prices on the stock market. The second type of trend factor is the long-short trend strategy based on predicted expected returns ($E_t[r_{i,t+1}]$). The construction of $E_t[r_{i,t+1}]$ is established from a more far-reaching method by Han et al. (2016), where they conduct the first comprehensive paper to construct $E_t[r_{i,t+1}]$ as a new trend indicator. Han et al. find that this new type of trend factor can well explain the performance of cross-sectional stock returns. Therefore, we find it interesting to examine such a factor to capture the cross-section of cryptocurrency return performances.

Using the same procedure as Han et al. (2016) have done to the stock returns, we compute different types of sorting variables to construct our trend factors: normalized moving average prices ($\widetilde{MA}$) and the predicted expected returns ($E_t[r_{i,t+1}]$) . To construct the normalized moving average prices ($\widetilde{MAs}$), we first calculate the moving average (MA) prices on the last trading day in the formation week. The MA on the last trading day d in the formation week t with L days lag is defined as:

$$MA_{it,L} = \frac{P^t_{i,d-L+1} + P^t_{i,d-L+2} + ... + P^t_{i,d-1} + P^t_{i,d}}{L} \tag{5}$$

Where $P^t_{i,d}$ denotes cryptocurrency i's closing price on the last trading day d of the formation week t with a lag length of L days. Then, we normalize the moving average prices of cryptocurrency i on the last trading day d in the formation week t with a lag of L days:

$$\widetilde{MA}_{it,L} = \frac{MA_{it,L}}{P^t_{i,d}} \tag{6}$$

After the construction of $\widetilde{MA}$, we follow Han et al.'s (2016) three-step procedure to create our cryptocurrency related $E_t[r_{i,t+1}]$. The cryptocurrency related $E_t[r_{i,t+1}]$ is used as a trend signal to indicate the cross-sectional cryptocurrency predicted returns.

In the first step, for each formation week t, we compute all the observed $\widetilde{MA}_{it,L}$ signals for the returns of cryptocurrency i and run the following cross-sectional regression to derive the coefficients ($\boldsymbol{\gamma}$) on the $\widetilde{MA}_{it,L}$ variables:

$$r_{i,t} = \gamma_{0,t} + \sum_{j=1} \gamma_{j,t} \widetilde{MA}_{it-1,L_j} + \varepsilon_{i,t} \qquad (i = 1, \ldots, n) \tag{7}$$

Where $r_{i,t}$ denotes the return (in percent) on cryptocurrency i at the formation week t, $\gamma_{0,t}$ is the intercept at week t, $\widetilde{MA}_{it-1,L_j}$ is the trend driver at week $t-1$ for cryptocurrency i with a lag length of L_j, $\gamma_{j,t}$ is the coefficient of $\widetilde{MA}_{it-1,L_j}$ at week t, n denotes the number of cryptocurrencies we use.

Han et al. (2016) point out that using a long lag length might increase overlapping problems, which could lead to highly correlated predictors. Hence, for regression (7), we use non-overlapping moving average prices which have fewer lags. The lag lengths are 3-, 5-, 7-, 10-, 20-, 30-, 50- and 100 days respectively, following the research by Brock et al. (1992) and Han et al. (2016).

Then, in the second step, we collect the time-series of the coefficients ($\gamma_{j,t}$) of the normalized moving average prices of various time length ($\widetilde{MA}_{it,L}$) and calculate the estimated expected coefficients $E_t[\gamma_{i,t+1}]$. Note that we use a one-year horizon to obtain $E_t[\gamma_{i,t+1}]$, which is the average of the estimated coefficients over the past 52 weeks (Han et al., 2016; Liu et al., 2020).

$$E_t[\gamma_{i,t+1}] = \frac{1}{52} \sum_{w=1}^{52} \gamma_{j,t+1-w} \tag{8}$$

In the last step, we derive the predicted (forecast) expected return by using the estimated expected coefficients $E_t[\gamma_{i,t+1}]$ and the normalized moving average prices $\widetilde{MA}_{it,L_j}$. $E_t[\gamma_{i,t+1}]$ is given by:

$$E_t[r_{i,t+1}] = \sum_{j=1} E_t[\gamma_{i,t+1}] \widetilde{MA}_{it,L_j} \tag{9}$$

Where $E_t[r_{i,t+1}]$ denotes the predicted expected return on cryptocurrency i at week $t+1$. We do not take the intercept into consideration since the intercept is exactly the same for all cryptocurrencies in the same cross-section of regression.

Table 7: Trend factor construction results

This table reports the mean quintile portfolio returns based on normalized moving average with 3-, 5-, 7-, 10-, 20-, 30-day lag lengths and the predicted returns ($E_t[r_{i,t+1}]$), respectively. The mean returns are the time-series averages of the weekly value-weighted portfolio returns. Newey-West (1987) t-statistics are in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level respectively. The sample period is from January 2017 through January 2021.

			Weekly Quintile Portfolios Returns					**Factor**
			1	2	3	4	5	5-1
Trend	MA3	Mean	0.0316***	0.0332***	0.0369***	0.0140	0.0025	-0.0291***
		t(Mean)	(2.7315)	(3.1516)	(2.8788)	(1.2163)	(0.2592)	(-3.1447)
	MA5	Mean	0.0452***	0.0312***	0.0258**	0.0078	0.0072	-0.0380***
		t(Mean)	(3.0993)	(3.1632)	(2.5687)	(0.7765)	(0.7038)	(-3.3988)
	MA7	Mean	0.0325***	0.0497***	0.0212**	0.0178*	0.0073	-0.0252***
		t(Mean)	(2.9353)	(3.8187)	(2.2312)	(1.7005)	(0.6747)	(-3.0205)
	MA10	Mean	0.0342***	0.0446***	0.0245**	0.0196*	0.0023	-0.0319***
		t(Mean)	(3.0703)	(3.5740)	(2.1615)	(1.7016)	(0.2338)	(-3.4751)
	MA20	Mean	0.0383***	0.0448**	0.0293***	0.0179	0.0067	-0.0316**
		t(Mean)	(2.9500)	(2.4177)	(2.7491)	(1.6151)	(0.6432)	(-2.5574)
	MA30	Mean	0.0365***	0.0431**	0.0302***	0.0127	0.0112	-0.025***
		t(Mean)	(3.4718)	(2.5488)	(2.7051)	(1.1041)	(1.0620)	(-2.5182)
	ER	Mean	0.0365**	0.0273***	0.0249***	0.0194**	0.0114	-0.0252**
		t(Mean)	(2.3223)	(2.7436)	(2.6844)	(1.9970)	(1.0363)	(-1.9439)

Each of the cryptocurrency trend factors is based on a given trend-related variable: normalized moving average with L day lag length ($\widetilde{MA}_{it,L}$)[14] and their expected returns ($E_t[r_{i,t+1}]$), respectively. To simplify the expressions, we refer to our trend factors as MA3, MA5, MA7, MA10, MA20, MA30, MA50, MA100 and ER, respectively. Following the factor construction process introduced in Section 4.2, Table 7 presents the factor construction results. We can see that the trend factors based on MA3, MA5, MA7, MA10, M20, MA30, and ER could generate returns with statistically significant t-statistics.[15] The negative mean return

[14] $\widetilde{MA}_{it,L}$: $\widetilde{MA}_{3d}$, $\widetilde{MA}_{5d}$, $\widetilde{MA}_{7d}$, $\widetilde{MA}_{10d}$, $\widetilde{MA}_{20d}$, $\widetilde{MA}_{30d}$, $\widetilde{MA}_{50d}$, $\widetilde{MA}_{100d}$

[15] The insignificant trend factors are reported in Section 4.2.5

differences on the trend factors indicate the average portfolio returns decrease from the first quintile to the fifth quintile. Specifically, a cryptocurrency with high normalized moving average prices $\widetilde{MAs}$ or high expected (forecast) returns ($E_t[r_{i,t+1}]$) is more likely to have low returns. Our finding is different from Han et al.'s (2016) finding in the stock market, where they conclude that stocks with high forecast returns ($E_t[r_{i,t+1}]$) are more likely to yield high future returns. Furthermore, it is not surprising that the mean return differences on trend factors are similar since all trend factors use price-related characteristics to capture information (moving average prices with various time lengths).

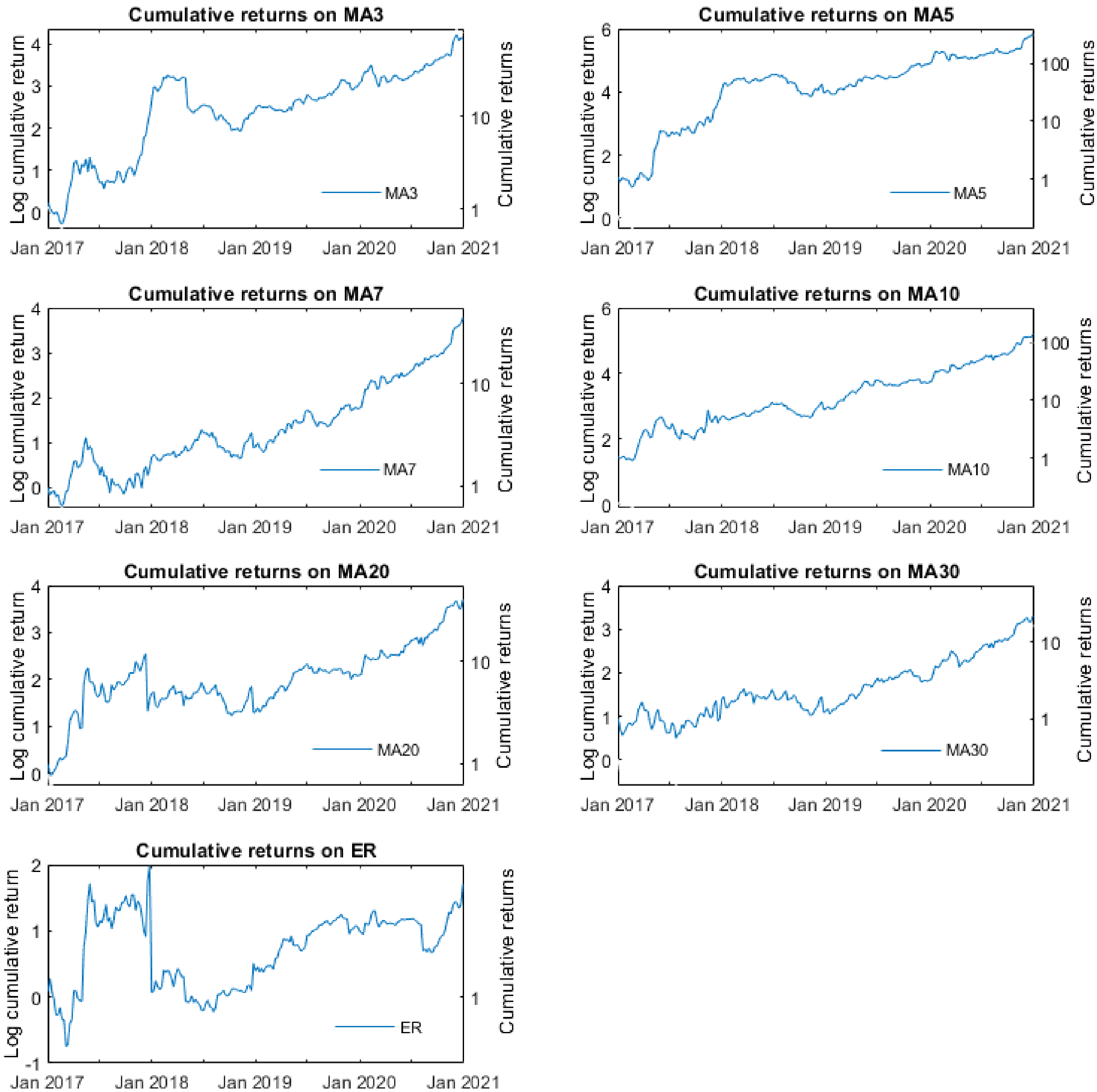

Figure 7: Cumulative returns on trend factors (both log-scaled and normal)

In addition, Figure 7 displays the cumulative returns on the trend factors over time. Note that the left y-axis shows the log-scaled cumulative returns, and the right y-axis shows the corresponding cumulative returns. We can see that the return streams of all trend trading strategies are more volatile between January 2017 to January 2019, but start to have higher profitability and yield more cumulative compounding after January 2019. Nevertheless, the trend strategy based on expected returns (ER) does not outperform other trend strategies based on moving average prices with various time lengths. One possible reason might be the short sample period, making it difficult to draw a proper conclusion. It would be interesting to test the trading strategy's performance based on ER with a more extended sample period. However, it is still nice to see that the trend strategies based on MA5 and MA10 are the preferable ones since they have a generally upward trend with the highest cumulative returns (at the end of the sample period).

4.2.5 Insignificant factors

This section reports the construction results for the factors that do not yield statistically significant returns (at a significance level of 10%). Following the factor construction process introduced in Section 4.2, we find that there are fourteen insignificant factors. Each of the insignificant factors is based on a given sorting variable: one-week momentum, two-week momentum, the standard deviation of returns (one-, two-, three- and four-week), the kurtosis of returns (one-, two-, three- and four-week), 50- and 100-day moving average prices, respectively. Table 8 shows the construction results of our insignificant factors, and none of the factors generates significant long-short trading returns. From Table 8, we can see that the average return differences of the fifth and the first quintile portfolios (5-1) are statistically insignificant and very small. For example, the 100-day moving average (MA100) long-short strategy generates a statistically insignificant mean return of -0.91%.

Table 8: Insignificant factors

This table reports the mean quintile portfolio returns based on the insignificant factors. The mean returns are the time-series averages of the weekly value-weighted portfolio returns. Newey-West (1987) t-statistics are in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level respectively. The sample period is from January 2017 through January 2021.

		Weekly Quintile Portfolio Returns					**Factor**
		1	2	3	4	5	5-1
MOM1	Mean	0.0118	0.0156	0.0275	0.0345	0.0360	0.0242
	t(Mean)	(0.8962)	(1.5615)	(2.3889)	(2.9666)	(2.5050)	(1.5523)
MOM4	Mean	0.0136	0.0243	0.0388	0.0373	0.0229	0.0094
	t(Mean)	(1.3804)	(1.8512)	(2.3547)	(2.9704)	(2.1582)	(0.9667)
RETSTD 1w	Mean	0.0209	0.0317	0.0319	0.0348	0.0384	0.0174
	t(Mean)	(2.4635)	(2.6692)	(2.5509)	(2.3444)	(2.0796)	(1.0234)
RETSTD 2w	Mean	0.0221	0.0369	0.0216	0.0376	0.0212	-0.0009
	t(Mean)	(2.8290)	(2.3173)	(1.9195)	(2.3811)	(1.5267)	(-0.0807)
RETSTD 3w	Mean	0.0232	0.0319	0.0262	0.0334	0.0224	-0.0008
	t(Mean)	(2.7716)	(2.7431)	(2.5306)	(1.9235)	(1.5187)	(-0.0669)
RETSTD 4w	Mean	0.0231	0.0297	0.0416	0.0230	0.0221	-0.0009
	t(Mean)	(2.7707)	(2.5797)	(2.8660)	(1.7187)	(1.5205)	(-0.0775)
RETSKEW 3w	Mean	0.0204	0.0310	0.0233	0.0228	0.0297	0.0093
	t(Mean)	(2.0684)	(2.5161)	(2.2728)	(2.0581)	(2.0191)	(0.6872)
RETSKEW 4w	Mean	0.0325	0.0227	0.0281	0.0176	0.0339	0.0015
	t(Mean)	(2.4945)	(2.2983)	(2.6599)	(1.6154)	(2.2821)	(0.0980)
RETKURT 1w	Mean	0.0251	0.0399	0.0208	0.0288	0.0269	0.0018
	t(Mean)	(2.3658)	(2.4649)	(1.9210)	(2.9425)	(2.4425)	(0.2038)
RETKURT 2w	Mean	0.0224	0.0283	0.0162	0.0322	0.0180	-0.0044
	t(Mean)	(2.2199)	(2.3748)	(1.6963)	(2.0341)	(1.5145)	(-0.4208)
RETKURT 3w	Mean	0.0200	0.0224	0.0305	0.0244	0.0321	0.0121
	t(Mean)	(1.7889)	(2.1205)	(2.7719)	(2.2779)	(2.1793)	(0.9945)
RETKURT 4w	Mean	0.0286	0.0303	0.0228	0.0172	0.0311	0.0025
	t(Mean)	(2.6245)	(2.6022)	(2.1933)	(1.9779)	(2.1935)	(0.2090)
MA50	Mean	0.0361	0.0437	0.0305	0.0100	0.0230	-0.0131
	t(Mean)	(2.4898)	(2.3697)	(2.7910)	(1.0796)	(1.7232)	(-0.9693)
MA100	Mean	0.0324	0.0290	0.0308	0.0283	0.0227	-0.0097
	t(Mean)	(2.3471)	(2.6270)	(2.4530)	(2.0569)	(1.6926)	(-0.6355)

4.3 The common risk factor model

This part introduces our factor models that consider three common risk factors, aiming to analyze whether these common risk factors can capture the cross-sectional cryptocurrency returns (returns on the 17 significant anomalies see Section 4.1). Following Fama and French (1992, 1993), Novy-Marx (2013) and Titman et al. (2003), we consider the market returns, size, and momentum as our cryptocurrency common risk factors. It is worth noting that the construction processes of the cryptocurrency common risk factors are based on the methods by Liu et al. (2019).

4.3.1 Three common risk factors

The first type of the common risk factor is the value-weighted cryptocurrency market returns, which is given by:

$$CMKT_t = \sum_{i=1}^{N} R_{it} * \frac{Cap_{i,t}}{TotalCap_t} \qquad (i = 1, \ldots, N) \tag{10}$$

Where $CMKT_t$ stands for the returns of the market portfolio in week t, R_{it} represents the return on cryptocurrency i at the beginning of week t, Cap_t is the market capitalization of cryptocurrency i at the beginning of week t, $TotalCap_t$ stands for the total market capitalization of all sample cryptocurrencies at the beginning of week t. N denotes the number of traded cryptocurrencies in week t.

We use a long-short strategy to construct the other two common risk factors: size (CSMB) and momentum (CMOM). As discussed in Section 4.1, we first construct portfolios by sorting cryptocurrencies in an ascending order based on a given sorting variable. Following Liu et al. (2019), the same one-dimensional sorting process is used, and all cryptocurrencies are sorted into three groups instead of five. The sorting variable is based on market capitalization and one-week momentum (one-week past return), respectively (Liu et al., 2019).

To construct the cryptocurrency size factor (CSMB), each Monday, we categorize the traded cryptocurrencies into three size groups in ascending order. Figure 9 shows the three cryptocurrency portfolios from the sorting process based on market capitalization information. The three portfolios are: portfolio with small size cryptocurrencies (bottom 30%, **Small**), portfolio with medium size cryptocurrencies (medium 40%, **Medium**) and portfolio with large size cryptocurrencies (top 30%, **Big**).

Table 9: Three portfolios formed on market capitalization

Bottom 30%	Medium 40%	Top 30%
Small(**S**)	Medium (**M**)	Big (**B**)

CSMB is the return difference between the value-weighted portfolio with a small size and the value-weighted portfolio with a large size. The formula for CSMB is:

$$CSMB_t = \mathbf{S} - \mathbf{B} \tag{11}$$

Moreover, the momentum factor (CMOM) is created based on the information of one-week momentum. Each Monday, we sort the traded cryptocurrencies into three momentum groups in ascending order, and CMOM is the weekly return differences between the first and the third momentum groups. Table 10 shows the three cryptocurrency portfolios we construct after the sorting process: portfolio with the lowest momentum cryptocurrencies (bottom 30%, **Loser**), portfolio with medium momentum cryptocurrencies (medium 40%, **Neutral**), and portfolio with the highest momentum cryptocurrencies (top 30%, **Winner**).

Table 10: Three portfolios formed on one-week momentum (one-week past return)

Bottom 30%	Medium 40%	Top 30%
Loser (**L**)	Neutral (**N**)	Winner (**W**)

CMOM is the weekly value-weighted returns of the winner cryptocurrency portfolio minus the weekly value-weighted returns of the loser cryptocurrency portfolio. The formula for CMOM is:

$$CMOM_t = \mathbf{W} - \mathbf{L} \tag{12}$$

Note that the reason for using value-weighted portfolio returns is because we want to make sure the risk factors are more robust to the outliers (Liu et al., 2020).

Table 11: Descriptive statistics for three common risk factors

This table reports the descriptive statistics for three common risk factors. Panel A shows the summary statistics, and the mean returns are the time-series averages of weekly value-weighted portfolio returns. Panel B reports the correlation matrix of the three factors. The sample period is from January 2017 through January 2021.

	Panel A: Summary statistics				Panel B: Correlation		
	Mean	Std	Skew	Kurt	CMKT	CSMB	CMOM
CMKT	0.022	0.114	0.022	3.940	1.000		
CSMB	0.040	0.161	3.301	17.436	0.226	1.000	
CMOM	0.028	0.188	3.514	47.607	-0.074	0.062	1.000

Table 11 provides descriptive statistics for the three common risk factors we construct. From the results in Panel A, we can see that all three factors show high average weekly returns (2.2% for CMKT, 4.0% for CSMB, and 2.8% for CMOM). Moreover, the size factor (CSMB) performs the highest average return, and the market factor (CMKT) performs the lowest average return. In other words, CSMB and CMOM account for a wider range of cross-sectional variations than CMKT. Additionally, all three factors have positive skewness and positive kurtosis. Panel B in Table 11 exhibits the correlation matrix of CMKT, CSMB, and CMOM. We can see that CSMB and CMKT are nearly uncorrelated to CMOM, with correlation coefficients around 0.062 and -0.074, respectively. Moreover, there is a low positive correlation between CSMB and CMKT, with a value of 0.226. The low level of correlations between the common risk factors implies that multicollinearity has little impact on the estimated model loadings (Shen et al., 2020).

4.3.2 The proposed factor models

We consider four types of cryptocurrency factor models. First, we analyze a single factor model similar to the classic CAPM, which only considers the cryptocurrency market factor. Similar to Shen et al. (2020) and Liu et al. (2019), we refer to the one-factor model as the cryptocurrency-CAPM (C-CAPM). The C-CAPM can be written as:

$$R_{pt}^{(j)} = \alpha_j + \beta_{CMKT} * CMKT_t + \varepsilon_t \tag{13}$$

Secondly, a two-factor model is applied by adding the cryptocurrency size factor into the C-CAPM, which can be written as:

$$R_{pt}^{(j)} = \alpha_j + \beta_{CMKT} * CMKT_t + \beta_{CSMB} * CSMB_t + \varepsilon_t \tag{14}$$

Thirdly, another two-factor model is applied by adding the cryptocurrency momentum factor into the C-CAPM, which can be written as:

$$R_{pt}^{(j)} = \alpha_j + \beta_{CMKT} * CMKT_t + \beta_{CMOM} * CMOM_t + \varepsilon_t \tag{15}$$

Lastly, we consider a three-factor model that combines all three common risk factors: market, size, and momentum. The three-factor model can be written as:

$$R_{pt}^{(j)} = \alpha_j + \beta_{CMKT} * CMKT_t + \beta_{CSMB} * CSMB_t + \beta_{CMOM} * CMOM_t + \varepsilon_t \tag{16}$$

Where: $R_{pt}^{(j)}$ is the portfolio return on factor j in week t.[16] CMKT is cryptocurrency market factor, and β_{CMKT} stands for the market exposure. CSMB defines the cryptocurrency size factor, and β_{CSMB} stands for the size exposures. CMOM is the cryptocurrency momentum factor, and β_{CMOM} stands for the momentum exposure. ε_t is the error term.

[16]See significant factors from table 4, table 5,table 6, and table 7.

5 Results

5.1 The one-factor model: C-CAPM

We consider the one-factor model based on the cryptocurrency market factor (CMKT) on our 17 zero-investment long-short strategies. Panel A in Table 12 shows the C-CAPM regression results. At a significance level of 10%, 11 out of 17 C-CAPM alphas are statistically significant, indicating a low explanatory power of the model. Moreover, only the size-related cryptocurrency factors (MCAP, PRICE, MAXPRICE 1w, MAXPRICE 2w) have statistically significant market risk exposures (β_{CMKT}). For example, PRICE has a significant market risk exposure of -1.1751, suggesting that the returns on PRICE decrease if the market rises. Each insignificant β_{CMKT} means the corresponding factor is insignificantly exposed to the cryptocurrency market risk.

The question is, can C-CAPM explain the return on the 17 significant cryptocurrency factors?[17] To answer this question, we analyze the results from Panel A in Table 12 for each category. Inspired by Fama and French (2015), Han et al. (2016) and Shen et al. (2020), we check the model performance from two perspectives. First, we check the number of significant alphas to see the overall performance of the model. Second, we compare the alphas with unadjusted average returns to see if the model has a certain explanatory power in capturing the cross-sectional returns. For instance, based on the results of a given time series regression, Shen et al. (2020) note that the model can capture part of the cross-sectional returns if the alpha is lower (higher) than the positive (negative) unadjusted average return. Therefore, for the size factors, only MCAP has a significant C-CAPM alpha (-0.0449), which is almost 15% lower than the unadjusted average return (-0.0525 in Table 4, noted as $mean$). This indicates that the model can explain a sizable portion of the return on the zero-investment long-short size strategies. In addition, all the momentum factors have significant C-CAPM alphas, with nearly the same values as the unadjusted average returns in Table 5.[18] This indicates that C-CAPM cannot explain the return on our zero-investment long-short momentum strategies. Our results are consistent with the results from Liu et al. (2019). Moreover, two out of four volatility factors have significant C-CAPM alphas (RETSKEW 1w, RETSKEW 2w), but with alphas that are lower than the unadjusted average returns reported in Table 6.[19] Therefore, it is hard to check the explanatory power of C-CAPM towards the returns on the volatility factors. For the trend factors, it is notable that six out of seven C-CAPM alphas are statistically significant, and the six C-CAPM alphas are only slightly different from the unadjusted average returns.[20] In other words, the C-CAPM cannot explain the return on the trend factors. This finding is consistent with the finding from Han et al. (2016) in the stock market. Han et al. (2016) indicate that CAPM and other complex asset pricing models are unlikely to explain the trend factor, as the MAs information are usually not incorporated into the common risk variables of those models (see similar finding from Neely et al., 2014).

In addition, since the R^2 values for all the 17 zero-investment long-short strategies we construct are rela-

[17]Categorized as size, momentum, volatility, and trend.

[18]MOM2: α = 0.0350 V.S. mean return = 0.0338; MOM3: α = 0.0208 V.S. mean return = 0.0201.

[19]RETSKEW 1w: α =0.0181 V.S. mean return = 0.0214; RETSKEW 2w: α = 0.0184 V.S. mean return = 0.0226.

[20]The unadjusted average returns on the trend factors are shown in Table 5, noted as $mean$.

tively low[21], we infer that the C-CAPM lacks the power to explain the zero-investment long-short strategy returns in the cryptocurrency market.[22]

Inspired by Liu et al. (2019), we demonstrate the mean absolute pricing errors (m.a.e) and the mean value of R^2s ($\bar{R}^2$) for each portfolio strategy, to measure how much of the cryptocurrency quintile portfolio returns can be explained by a given model. The detailed regression results for each quintile portfolio under the C-CAPM are reported in Table B1, Appendix B. The mean of the absolute pricing errors (m.a.e) and ($\bar{R}^2$) for each strategy are given by:

$$m.a.e_j = \bar{\alpha}_j = \frac{|\alpha_{j1}| + |\alpha_{j2}| + |\alpha_{j3}| + |\alpha_{j4}| + |\alpha_{j5}|}{5} \tag{17}$$

$$\bar{R_j^2} = \frac{R_{j1}^2 + R_{j2}^2 + R_{j3}^2 + R_{j4}^2 + R_{j5}^2}{5} \tag{18}$$

Where: m.a.e is the average of five absolute intercepts, where $|\alpha_{j1}|$, $|\alpha_{j2}|$, $|\alpha_{j3}|$, $|\alpha_{j4}|$ and $|\alpha_{j5}|$ stand for the absolute values of the intercepts by regressing the five quintile portfolios on the proposed common risk factors, under a given trading strategy j. $\bar{R}^2$ is the mean of the five R^2s by regressing the five quintile portfolios on CMOM and CSMB, regarding a given strategy j.

The last two columns from Panel A in Table 12 report the final results for m.a.e and $\bar{R}^2$ under the C-CAPM. We can see that the m.a.e ranges from 0.52% for the trend strategy (ER) to 1.45% for MCAP. Moreover, the R^2 is above 50% under all 17 trading strategies, ranging from 51.12% for MOM2 to 62.49% for MCAP. In other words, under a given strategy, the results of C-CAPM R^2 from Table 12 show that the overall measure of the C-CAPM can explain more than 50% of the return variation for each portfolio. We conclude that strong co-movements exist between different cryptocurrencies, which supports the findings by Liu et al. (2019).

5.2 The two-factor model: CMKT CSMB

From Panel B in Table 12, we can see the time series regression results of the 17 cryptocurrency factors on two common risk factors (CMKT and CSMB). There are very few changes happening in the alphas in comparison with the C-CAPM alphas. Due to the additional size factor in this model, no C-CAPM alphas in the long-short strategy transform from being significant to insignificant. From the perspective of risk exposures on the two factors, CMKT and CSMB, we see that this two-factor model performs better than the C-CAPM in explaining the returns of the four size factors: MCAP, PRICE, MAXRET 1w, and MAXRET 2w. This is illustrated briefly by the statistically significant coefficient of the cryptocurrency size factor, retrieving larger R_2s on all size-related long-short strategies compared to the results from the C-CAPM. The negative exposures on size are not surprising, given the fact that our long-short size strategies are based on the size-related sorting variables (i.e., market capitalization). Interestingly, all non-size

[21]Ranging from zero percent for a trend factor (MA7) to 12.7% for a size factor (MAXRET 2w).

[22]Ranging from zero percent for the trend factor based on seven-day moving average (MA7) to 12.7% for another size factor based on two-week maximum price (MAXRET 2w).

strategies have no exposure on neither CMKT nor CSMB, indicating that the two-factor model does not show a good fit to the returns on non-size related strategies.

In comparison to the C-CAPM, the average absolute pricing errors clearly decreased for almost all quintile portfolios with slightly increasing $\bar{R}^2$s. This indicates that the two-factor model containing CMKT and CSMB performs better in capturing the returns on quintile portfolios. For example, the m.a.e for MAXRET 1w drops from 0.61% to 0.39%, with a $\bar{R}^2$ rises from 58.85% to 64.11% in the two-factor model. The detailed regression results for each quintile portfolio under the two-factor model (CMKT and CSMB) are reported in Table B2, Appendix B.

5.3 The two-factor model: CMKT CMOM

From Panel C in Table 12, we see the time series regression results of the 17 cryptocurrency factors on the market (CMKT) and momentum (CMOM) factors. Due to the additional momentum factor in this model, alphas in four long-short strategies transform from being significant under the C-CAPM to insignificant (RETSKEW 2w, MAXPRICE 1w, MAXPRICE 2w, and MOM3). For example, the C-CAPM alpha for MOM3 drops from a significant value of 0.0208 to an insignificant value of 0.0121 under the two-factor model. Furthermore, we can see that all size strategies except for MCAP have significant market risk exposures. Surprisingly, both momentum strategies have statistically insignificant exposures to the cryptocurrency momentum factor, which is different from the findings in Liu et al. (2019). A likely explanation is that the sample cryptocurrencies allocated in our long-short momentum strategy portfolio (5-1) are very different from the sample cryptocurrencies allocated in our common momentum factor (3-1). This might lead to totally unrelated return differences. For volatility strategies, only RETSKEW 1w and MAXRET 1w have significant momentum risk exposures. At a significance level of 10%, almost all the trend strategies have statistically significant momentum risk exposures, except MA30 and ER. In other words, the two-factor model with CMKT and CMOM outperforms the C-CAPM in explaining the returns of the trend strategies (MA3, MA5, MA7, MA10, and MA20).

In addition, R^2s ranges from 3.12% for RETSKEW 1w, to 36.17% for MAXRET 1w. Almost all time series regressions develop higher R^2s in comparison to R^2s under C-CAPM. Moreover, m.a.e ranges from 0.39% for MAXRET 1w to 1.50% for MCAP, and almost all m.a.e decrease compared to m.a.e from C-CAPM. All $\bar{R}_s^2$ are above 53%, ranging from 53.97% for MAXPRICE 1w to 64.53% for MA5. These results tell us that under a given strategy, the overall measure of the two-factor (CMKT and CMOM) model can explain more than 53% of the return variation for each portfolio, which is an improvement from C-CAPM. Our results are similar to the findings by Liu et al. (2019), that is, there are strong co-movements between different cryptocurrencies. Note that the detailed regression results for each quintile portfolio under the two-factor model (CMKT and CMOM) are reported in Table B3, Appendix B.

5.4 The three-factor model: CMKT CSMB CMOM

Finally, we consider the three-factor model that contains the cryptocurrency momentum, size, and market factor. Panel D in Table 12 presents the time-series regression results of the 17 strategies. With successive decreases in the number of significant alphas with largely rising R^2s on the 17 factors, we further conclude that the three-factor model outperforms the models we reported earlier. For example, at a significance level of 5%, there are eight statistically significant C-CAPM alphas.[23] However, the number of significant alphas reduce from eight to five[24] by the use of the three-factor model. Turning now to the evidence on the risk exposures, first, the risk exposures on size (β_{CSMB}) are significant at the 1% confidence level for all zero-investment long-short size strategies and the strategy based on MA7. Furthermore, the risk exposures on momentum (β_{CMOM}) are significant at a confidence level of 5% for the zero-investment long-short strategies based on RETSKEW 2w, MAXPRICE 1w, MA3, MA7, and MA10. Interestingly, none of our 17 zero-investment long-short strategies are observed to have statistically significant market risk exposures at the confidence level of 5%. Together these results provide important insights that both the cryptocurrency size factor and cryptocurrency momentum factor are crucial indicators of the cross-sectional returns on cryptocurrencies.

In contrast to the results from the C-CAPM and the two-factor models, almost all m.a.e significantly decrease, with largely increasing $\bar{R}^2$s under the three-factor model. For example, the m.a.e for MCAP are 1.45% under C-CAPM, 1.50% under the two-factor model (CMKT and CSMB), 0.94% under the alternative two-factor model (CMKT and CMOM) and 0.89% under the three-factor model, with $\bar{R}^2$s of 64.12%, 64.32%, 84.44% and 85.01% respectively. These results provide important insights that under a given strategy, the overall measure of the three-factor model performs better than other models in capturing the return variation for each quintile portfolio. Note that the detailed regression results for each quintile portfolio under the three-factor model are reported in Table B4, Appendix B.

[23] Significant C-CAPM alphas on the zero-investment long-short strategies based on MCAP, MOM2, MA3, MA5, MA7, MA10, MA20, MA30.

[24] Significant alphas on MCAP, MOM2, $\widetilde{MA}_5$, $\widetilde{MA}_7$ and $\widetilde{MA}_{10}$.

Table 12: Regression results from the proposed factor models

C-CAPM: $R_{pt}^{(j)} = \alpha_j + \beta_{CMKT} * CMKT_t + \varepsilon_t$

Two-factor model ❶: $R_{pt}^{(j)} = \alpha_j + \beta_{CMKT} * CMKT_t + \beta_{CSMB} * CSMB_t + \varepsilon_t$

Two-factor model ❷: $R_{pt}^{(j)} = \alpha_j + \beta_{CMKT} * CMKT_t + \beta_{CMOM} * CMOM_t + \varepsilon_t$

Three-factor model: $R_{pt}^{(j)} = \alpha_j + \beta_{CMKT} * CMKT_t + \beta_{CSMB} * CSMB_t + \beta_{CMOM} * CMOM_t + \varepsilon_t$

This table reports intercepts and coefficients from nested factor models in regressions to explain weekly value-weighted returns on our 17 significant cryptocurrency factors. Panel A shows the regression results under the one-factor model produced by the cryptocurrency market return. Panel B and Panel C show regression results under the two-factor models, adding CSMB and CMOM to the model of C-CAPM, respectively. Panel D shows the regression results under the proposed three-factor model. *, **, *** denote significance levels at the 10%, 5%, and 1%. m.a.e and $\bar{R}^2$ are the mean of the absolute pricing errors and the average R^2 of the five portfolios, respectively. The sample period is from January 2017 through January 2021, 209 weeks

Factor (5-1)		Panel A (C-CAPM)			Panel B (Two-factor model ❶)			Panel C (Two-factor model ❷)			Panel D (Three-factor model)		
		Estimator	m.a.e	$\bar{R}^2$	Estimator	m.a.e	$\bar{R}^2$	Estimator	m.a.e	$\bar{R}^2$	Estimator	m.a.e	$\bar{R}^2$
MCAP	α	-0.0449***			-0.0141***			-0.0451***			-0.0160***		
	β_{CMKT}	-0.3478*			-0.0547			-0.3471*			-0.0441		
	β_{CSMB}		1.45%	64.12%	-0.9242***	0.94%	84.44%	α	1.50%	64.32%	-0.9308***	0.89%	85.01%
	β_{CMOM}							0.0057			0.0687		
	R^2	0.0572			0.8138			0.0572			0.8198		
PRICE	α	-0.0246			0.0205			-0.0172			0.0247		
	β_{CMKT}	-1.1751*			-0.7448*			-1.2050*			-0.7682*		
	β_{CSMB}		0.70%	55.54%	-1.3568***	0.72%	62.98%		0.56%	55.82%	-1.3420**	0.79%	63.12%
	β_{CMOM}							-0.2436			-0.1528		
	R^2	0.1257			0.4399			0.1403			0.4455		
MAXPRICE1	α	-0.0243			0.0210			-0.0169			0.0252		
	β_{CMKT}	-1.1822*			-0.7500*			-1.2120*			-0.7734*		
	β_{CSMB}		0.68%	53.47%	-1.3624***	0.68%	60.52%		0.55%	53.97%	-1.3476**	0.74%	60.85%
	β_{CMOM}							-0.2435			-0.1523		
	R^2	0.1268			0.4423			0.1412			0.4480		
MAXPRICE2	α	-0.0244			0.0210			-0.0170			0.0252		
	β_{CMKT}	-1.1848*			-0.7522*			-1.2146*			-0.7756*		
	β_{CSMB}		0.65%	54.12%	-1.3638***	0.71%	61.14%		0.53%	54.46%	-1.3490**	0.78%	61.33%
	β_{CMOM}							-0.2436			-0.1523		
	R^2	0.1270			0.4426			0.1415			0.4482		
MOM2	α	0.0350***			0.0367***			0.0250**			0.0275**		
	β_{CMKT}	-0.0571			-0.0412			-0.0166			0.0103		
	β_{CSMB}		1.21%	51.12%	-0.0502	1.14%	55.15%		0.87%	58.20%	-0.0828	1.02%	62.30%
	β_{CMOM}							0.3302			0.3358		
	R^2	0.0017			0.0042			0.1554			0.1621		
MOM3	α	0.0208*			0.0235*			0.0121			0.0156		
	β_{CMKT}	-0.0311			-0.0050			0.0038			0.0398		
	β_{CSMB}		0.86%	54.60%	-0.0821	0.90%	58.23%		0.57%	57.51%	-0.1105	0.61%	61.32%
	β_{CMOM}							0.2847			0.2922		
	R^2	0.0005			0.0068			0.1103			0.1217		
RETSKEW1	α	0.0181*			0.0157*			0.0207**			0.0182*		
	β_{CMKT}	0.1488			0.1254			0.1382			0.1112		
	β_{CSMB}		0.79%	55.16%	0.0739	0.51%	59.40%		1.08%	59.00%	0.0829	0.71%	63.27%
	β_{CMOM}							-0.0866			-0.0922		
	R^2	0.0163			0.0239			0.0312			0.0406		
RETSKEW2	α	0.0184*			0.0103			0.0046			-0.0017		
	β_{CMKT}	0.1895			0.1126			0.2452			0.1803		
	β_{CSMB}		1.04%	58.92%	0.2424	0.55%	62.33%		0.80%	61.84%	0.1994	0.68%	65.21%
	β_{CMOM}							0.4548***			0.4413***		
	R^2	0.0171			0.0697			0.2829			0.3183		

Table 12 continued

Factor (5-1)		Panel A (C-CAPM)			Panel B (Two-factor model ❶)			Panel C (Two-factor model ❷)			Panel D (Three-factor model)		
		Estimator	m.a.e	$\bar{R}^2$	Estimator	m.a.e	$\bar{R}^2$	Estimator	m.a.e	$\bar{R}^2$	Estimator	m.a.e	$\bar{R}^2$
	α	0.0227			0.0135			-0.0008			-0.0071		
	β_{CMKT}	0.4595			0.3722			0.5540*			0.4885		
MAXRET1	β_{CSMB}		0.61%	58.85%	0.2750	0.61%	63.26%		0.39%	64.11%	0.2014	0.56%	68.54%
	β_{CMOM}							0.7714***			0.7578***		
	R^2	0.0421			0.0704			0.3617			0.3767		
	α	0.0138			0.0063			0.0084			0.0019		
	β_{CMKT}	0.5482*			0.4766			0.5697*			0.5013		
MAXRET2	β_{CSMB}		0.60%	54.93%	0.2260	0.48%	58.10%		0.54%	56.46%	0.2103	0.67%	59.59%
	β_{CMOM}							0.1751			0.1609		
	R^2	0.0839			0.1106			0.1069			0.1299		
	α	-0.0256**			-0.0260**			-0.0179*			-0.0191*		
	β_{CMKT}	-0.1605			-0.1648			-0.1916			-0.2041*		
MA3	β_{CSMB}		1.08%	57.51%	0.0135	0.90%	61.88%		0.57%	62.07%	0.0384	0.79%	66.42%
	β_{CMOM}							-0.2533**			-0.2559**		
	R^2	0.0188			0.0190			0.1447			0.1467		
	α	-0.0310***			-0.0308**			-0.0261**			-0.0263**		
	β_{CMKT}	-0.3167			-0.3144			-0.3367			-0.3395		
MA5	β_{CSMB}		1.16%	62.40%	-0.0073	1.13%	65.76%		0.96%	64.53%	0.0086	1.05%	67.96%
	β_{CMOM}							-0.1629			-0.1635		
	R^2	0.0501			0.0502			0.0858			0.0859		
	α	-0.0253**			-0.0281***			-0.0144*			-0.0182**		
	β_{CMKT}	0.0063			-0.0205			-0.0373			-0.0764		
MA7	β_{CSMB}		1.13%	61.68%	0.0845	1.25%	65.21%		0.85%	64.18%	0.1199*	0.91%	67.94%
	β_{CMOM}							-0.3563**			-0.3645***		
	R^2	0.0000			0.0121			0.3078			0.3319		
	α	-0.0322***			-0.0340***			-0.0215**			-0.0242**		
	β_{CMKT}	0.0164			0.0002			-0.0269			-0.0549		
MA10	β_{CSMB}		1.14%	59.89%	0.0513	1.37%	64.45%		0.95%	62.70%	0.0862	1.01%	67.55%
	β_{CMOM}							-0.3533**			-0.3592**		
	R^2	0.0002			0.0039			0.2496			0.2598		
	α	-0.0308**			-0.0314***			-0.0178*			-0.0197*		
	β_{CMKT}	-0.0336			-0.0396			-0.0861			-0.1060		
MA20	β_{CSMB}		1.11%	54.59%	0.0189	1.26%	61.40%		0.94%	57.12%	0.0609	0.92%	64.20%
	β_{CMOM}							-0.4285*			-0.4326*		
	R^2	0.0005			0.0007			0.2033			0.2061		
	α	-0.0269**			-0.0288**			-0.0166*			-0.0195*		
	β_{CMKT}	0.0729			0.0544			0.0315			0.0016		
MA30	β_{CSMB}		1.13%	54.61%	0.0584	1.08%	59.88%		0.57%	60.37%	0.0918	0.99%	65.60%
	β_{CMOM}							-0.3379			-0.3441		
	R^2	0.0033			0.0072			0.1935			0.2032		
	α	-0.0165			-0.0112			-0.0201			-0.0148		
	β_{CMKT}	-0.3951			-0.3449			-0.3804			-0.3246		
ER	β_{CSMB}		0.52%	62.49%	-0.1584	0.71%	66.52%		0.65%	62.83%	-0.1712	0.60%	67.03%
	β_{CMOM}							0.1203			0.1319		
	R^2	0.0582			0.0757			0.0727			0.0931		

6 Robustness checks

When looking for specification issues, a check for robustness is usually a standard procedure when changes are made to the model's specification. A model is considered to pass the robustness check when the variables of interest uphold the same sign and level of significance as different combinations of control variables are added to the model. In this section, we consider our robust tests from three aspects. Firstly, we test if the model specifications from section 4[25] are robust to alternative formations. Secondly, we investigate whether the transaction costs are an issue for the proposed models since there is a debate going on whether transaction costs are of concern for a given profitable trading strategy (Barroso and Santa-Clara, 2015). Lastly, we discuss the portfolio allocation issues and present an analysis of equal-weighted portfolio returns to mitigate the concerns.

6.1 Alternative formations: double sorting

We create two new common risk factors (size and momentum) in the cryptocurrency market using double sorts. First, the double sorting is performed on the traded cryptocurrency returns based on information of the market capitalization (size) and one week past return (momentum). The construction process is shown in Table 13, which derives six different portfolios.

Table 13: Two-dimensional sorts on size and one-week momentum

		Market Capitalization	
		Bottom 50%	Top 50%
	Bottom 30%	Small Loser (**SL**)	Big Loser (**BL**)
One-week Momentum	Neutral 40%	Small Neutral (**SN**)	Big Neutral (**BN**)
	Top 30%	Small Winner (**SW**)	Big Winner (**BW**)

CMKT remains the same as in the previous Section 4.3.1 (see equation 10), which represents the weekly returns on the value-weight cryptocurrency market portfolio.

$CSMB^{new}$ is the new cryptocurrency size factor, which stands for the mean returns differences between the total weekly returns on the three value-weighted small cryptocurrency portfolios and the total weekly returns on the three big cryptocurrency portfolio returns:

$$CSMB_t^{new} = \frac{1}{3}(SL + SN + SW) - \frac{1}{3}(BL + BN + BW). \tag{19}$$

$CMOM^{new}$ is the new cryptocurrency momentum factor, which stands for the average return differences between the total weekly returns on the two winner portfolios and the total weekly returns on the three loser portfolios:

$$CMOM_t^{new} = \frac{1}{2}(SW + BW) - \frac{1}{2}(SL + BL). \tag{20}$$

[25]The C-CAPM (equation 13), the two-factor models (equation 14 and 15) and the three-factor model (equation 16).

Table 14: The robustness check using double sorting

C-CAPM: $R_{pt}^{(j)} = \alpha_j + \beta_{CMKT} * CMKT_t + \varepsilon_t$

Two-factor model ❶: $R_{pt}^{(j)} = \alpha_j + \beta_{CMKT} * CMKT_t + \beta_{CSMB}^{new} * CSMB_t^{new} + \varepsilon_t$

Two-factor model ❷: $R_{pt}^{(j)} = \alpha_j + \beta_{CMKT} * CMKT_t + \beta_{CMOM}^{new} * CMOM_t^{new} + \varepsilon_t$

Three-factor model: $R_{pt}^{(j)} = \alpha_j + \beta_{CMKT} * CMKT_t + \beta_{CSMB}^{new} * CSMB_t^{new} + \beta_{CMOM}^{new} * CMOM_t^{new} + \varepsilon_t$

This table reports intercepts (α) from nested factor models in regressions to explain weekly value-weighted returns on our 17 significant cryptocurrency factors. Panel A shows the regression results under the new one-factor model produced by the cryptocurrency market return. Panel B and Panel C show the regression results under the two-factor models when adding the new CSMB and the new CMOM to the model of C-CAPM, respectively. Panel D shows regression results under the proposed three-factor model. *, **, *** denote significance levels at the 10%, 5%, and 1%. m.a.e and $\bar{R}^2$ are the mean of the absolute pricing errors and the average R^2 of the five portfolios, respectively. The sample period is from January 2017 through January 2021, 209 weeks

17 Factors (5-1)	Panel A C-CAPM			Panel B Two-factor model ❶			Panel C Two-factor model ❷			Panel D Three-factor model		
Panel A: Size Factor	α on Factor	m.a.e	$\bar{R}^2$	α on Factor	m.a.e	$\bar{R}^2$	α on Factor	m.a.e	$\bar{R}^2$	α on Factor	m.a.e	$\bar{R}^2$
MCAP	-0.0449***	1.45%	64.12%	-0.0275*	0.85%	69.19%	-0.0449***	1.42%	65.07%	-0.0086	0.91%	76.12%
PRICE	-0.0246	0.70%	55.54%	-0.0233	0.77%	57.66%	-0.0210	0.65%	58.08%	0.0223	0.88%	61.71%
MAXPRICE1	-0.0243	0.68%	53.47%	-0.0234	0.89%	56.16%	-0.0206	0.65%	56.37%	0.0227	0.87%	59.93%
MAXPRICE2	-0.0244	0.65%	54.12%	-0.0234	0.92%	56.74%	-0.0207	0.61%	56.96%	0.0225	0.91%	60.50%
Panel B: Momentum Factor												
MOM2	0.0350***	1.21%	51.12%	0.0359***	1.06%	52.34%	0.0347***	1.19%	51.84%	0.0324**	0.88%	53.22%
MOM3	0.0208*	0.86%	54.60%	0.0246*	1.11%	56.58%	0.0199	0.83%	56.79%	0.0182	0.87%	58.05%
Panel C: Volatility Factor												
RETSKEW1	0.0181*	0.79%	55.16%	0.0197**	0.83%	55.92%	0.0181*	0.74%	57.26%	0.0220**	0.79%	58.54%
RETSKEW2	0.0184*	1.04%	58.92%	0.0168	1.04%	59.95%	0.0174	1.00%	61.36%	0.0031	0.98%	63.31%
MAXRET1	0.0227	0.61%	58.85%	0.0137	0.60%	60.39%	0.0222	0.60%	59.89%	-0.0024	0.44%	61.80%
MAXRET2	0.0138	0.60%	54.93%	0.0022	0.58%	56.81%	0.0142	0.60%	55.42%	-0.0058	0.65%	57.18%
Panel D: Trend Factor												
MA3	-0.0256**	1.08%	57.51%	-0.0246**	0.98%	58.27%	-0.0259**	1.07%	58.12%	-0.0277**	0.74%	59.46%
MA5	-0.0310***	1.16%	62.34%	-0.0310***	1.05%	64.38%	-0.0304***	1.17%	63.83%	-0.0200*	1.01%	65.42%
MA7	-0.0253**	1.13%	61.68%	-0.0240**	1.17%	63.15%	-0.0252**	1.11%	62.41%	-0.0212*	0.92%	64.13%
MA10	-0.0322***	1.14%	59.89%	-0.0355***	1.19%	62.06%	-0.0316***	1.15%	61.45%	-0.0308**	1.02%	63.40%
MA20	-0.0308**	1.11%	54.59%	-0.0277**	1.30%	56.41%	-0.0300**	1.03%	58.31%	-0.0150	0.62%	60.06%
MA30	-0.0269**	1.13%	54.61%	-0.0289**	1.23%	55.51%	-0.0262**	1.07%	2.00%	-0.0229*	0.79%	57.56%
ER	-0.0165	0.52%	62.49%	-0.0169	0.57%	63.30%	-0.0165	0.53%	63.17%	-0.0176	0.74%	64.51%
Significant alpha at 10% level	11			10			9			7		
Significant alpha at 5% level	8			8			8			4		

Table 14 provides the estimation results from our three double-sorted factor models. From the α_s presented in Table 14, we can see that the trend factors have significant αs under all the models, meaning that the proposed factor models have weak explanation power to the cross-sectional returns based on trend. However, we find that there is a decrease in the number of significant α_s on the 17 factors when we increase the number of the explanatory variables (from the one-factor model to the three-factor model). That is, at a significance level of 5%, the number of significant α_s decreases from eight under the C-CAPM to four under the three-factor model. These findings are similar to the findings from the result section (Section 5).

Additionally, the results for the mean absolute pricing errors (m.a.e) and $\bar{R}^2$ are consistent with the results from Table 12. In comparison to the C-CAPM and the two-factor models, we find all the m.a.e largely decrease under the three-factor model, with rising $\bar{R}^2$s. Together with all the findings, we further conclude that under a given strategy, with exceptions of trend strategies, the overall measure of the three-factor model performs better than other models in capturing the return variation for cryptocurrency portfolios.

The conclusion holds no matter we use double sorts or single sort to construct our explanatory variables.

6.2 Transaction costs

In this subsection, we assess the profitability of our zero-investment long-short strategies by considering transaction costs. Since we re-balance the portfolio on a weekly basis, the portfolio weights are under a constant change every week, and thus, we compute them as the hold portfolio weights (Brandt et al., 2009; Barroso and Santa-Clara, 2015). According to these studies, a hold portfolio weight denotes the weight on cryptocurrency i of a given strategy j at the beginning of week t right before the trading happens, which is the same as the portfolio at time $t-1$ with the weights changed by the returns from $t-1$ to t:

$$\tilde{w}_{it}^{j} = w_{it-1}^{j} \frac{1 + R_{it-1}}{1 + R_{pt-1}^{j}} \tag{21}$$

Note that when t equals to 1, $\tilde{w}_{i1}^{j}$ is corresponding to our first re-balancing week (5/1/2017), which is calculated by $\tilde{w}_{i0}^{j}$ based on the inputs corresponding to the week before the first re-balancing week (t=0 refer to 4/24/2017).

By re-balancing the portfolio at the beginning of each week, we further report the turnover-series for each allocation strategy j at week t, which can be calculated by:

$$T_t^{(j)} = \frac{1}{2}\sum_{i=1}^{N} |w_{it}^{j} - \tilde{w}_{it}^{j}| \tag{22}$$

After obtaining the hold portfolio weights $\tilde{w}_{it}^{j}$ and turnover rates $T_t^{(j)}$, we then calculate the transaction cost adjusted portfolio return at week t under a given zero-investment trading strategy j:

$$\tilde{R}_{pt}^{(j)} = \sum_{i=1}^{N} (w_{it}^{j} R_{it} - c * |w_{it}^{(j)} - \tilde{w}_{it}^{(j)}|) \tag{23}$$

Note that c is the one-way proportional transaction cost and that c = 0.3% in our case. The level of transaction cost is based on the 2021 Crypto-Exchange Fee Comparison [26], where we consider an average level of the transaction costs across the 41 most commonly traded exchanges.

6.2.1 Turnover rates and mean returns on the trading strategies

In this part, we explore the turnover rates and the return characteristics of the zero-investment long-short strategies (factors). Due to the page limit, we only report 8 out of 17 significant factors (see section 4), which represent the four types of trading strategies (Size, Momentum, Volatility and Trend). The eight chosen factors are: MCAP and PRICE (size strategy), MOM2 (momentum strategy), RETSKEW 2w

[26] The 2021 Crypto-Exchange Fee Comparison: https://www.cointracker.io/blog/2019-crypto-exchange-fee-comparison.

(volatility strategy) and we have four trend factors that stands for trend strategy (MA3, MA10, MA30 and ER). As mentioned in Section 4.2.1, the negative average weekly return difference on our zero-investment long-short strategies (5-1) tells that there would be positive economical gains by shorting the fifth quintile portfolio and longing the first quintile portfolio (1-5). Therefore, we adjust our long-short strategy from 5-1 to 1-5 for the factor with negative weekly returns (MCAP, PRICE, MA3, MA10, MA30 and ER).

Table 15: Turnover rates and weekly mean returns on the eight factors

Factor	$\bar{R}_{pt}^{(j)}$	**Cost-adjusted** $\bar{R}_{pt}^{(j)}$	$\bar{T}_{t}^{(j)}$
MCAP	5.25%	4.96%	22.81%
PRICE	5.05%	4.64%	26.81%
MOM2	3.38%	2.40%	72.62%
RETSKEW2	2.26%	1.19%	76.62%
MA3	2.91%	1.88%	74.38%
MA10	3.19%	2.28%	75.81%
MA30	2.53%	1.60%	69.87%
ER	2.52%	1.43%	75.81%

Table 15 reports the turnover rate of each factor and the corresponding weekly mean return. We can see that MCAP has a turnover rate of only 22.81%, and the turnover rate of PRICE is 26.81%. Moreover, the mean returns on MCAP and PRICE decrease slightly after the full consideration of transaction cost (reduces from 5.25% to 4.96% for MCAP, from 5.05% to 4.64% for PRICE). On the one hand, the relatively low turnover rates indicate low transaction costs. On the other hand, a low turnover rate specifies a "buy-and-hold" allocation strategy for each formation week (Hui and Chan, 2019). In other words, the investment weight on each cryptocurrency changes slightly when we continuously re-balance our portfolio on a weekly basis. However, the high turnover rates of other factors (ranging from 69.87% for MA30 to 76.62% for RETSKEW2) in Table 15 suggest that the investment weights on each traded cryptocurrency change dramatically on a weekly basis, which result in high transaction costs. Therefore, the profitability of those factors decreases a lot (almost 1% decease on the weekly average returns). Why the turnover rates on the momentum, volatility and trend factors are higher than that of the size factors? Han et al. (2016) provides a reasonable explanation because they find that a factor is likely to have a higher turnover rate if that factor incorporates more information across different investment horizons. This is true in our case because we use more complicated information to construct our momentum, volatility, and trend factors. In contrast, the size factors are either based on the value of the price or the market capitalization value.

Inspired by He et al. (2017) and Cooper et al. (2004), we compare the performance of our zero-investment long-short strategies without applying the transaction costs to the performance of our zero-investment long-short strategies with the implementation of transaction costs. Following He et al. (2017) and Cooper et al. (2004), we examine the cumulative returns on our the long-short strategies. Figure 8 demonstrates the cumulative returns of the long-short strategies with and without transaction costs, respectively. Note that the left y-axis shows the log-scaled cumulative returns, and the right y-axis shows the corresponding cumulative returns. Our findings are consistent with the findings from Table 15. After considering the transaction costs, the profitability changes are relatively small for the size-related factors (MCAP and PRICE). However, the profitability changes are large for other factors with the full consideration of transaction costs.

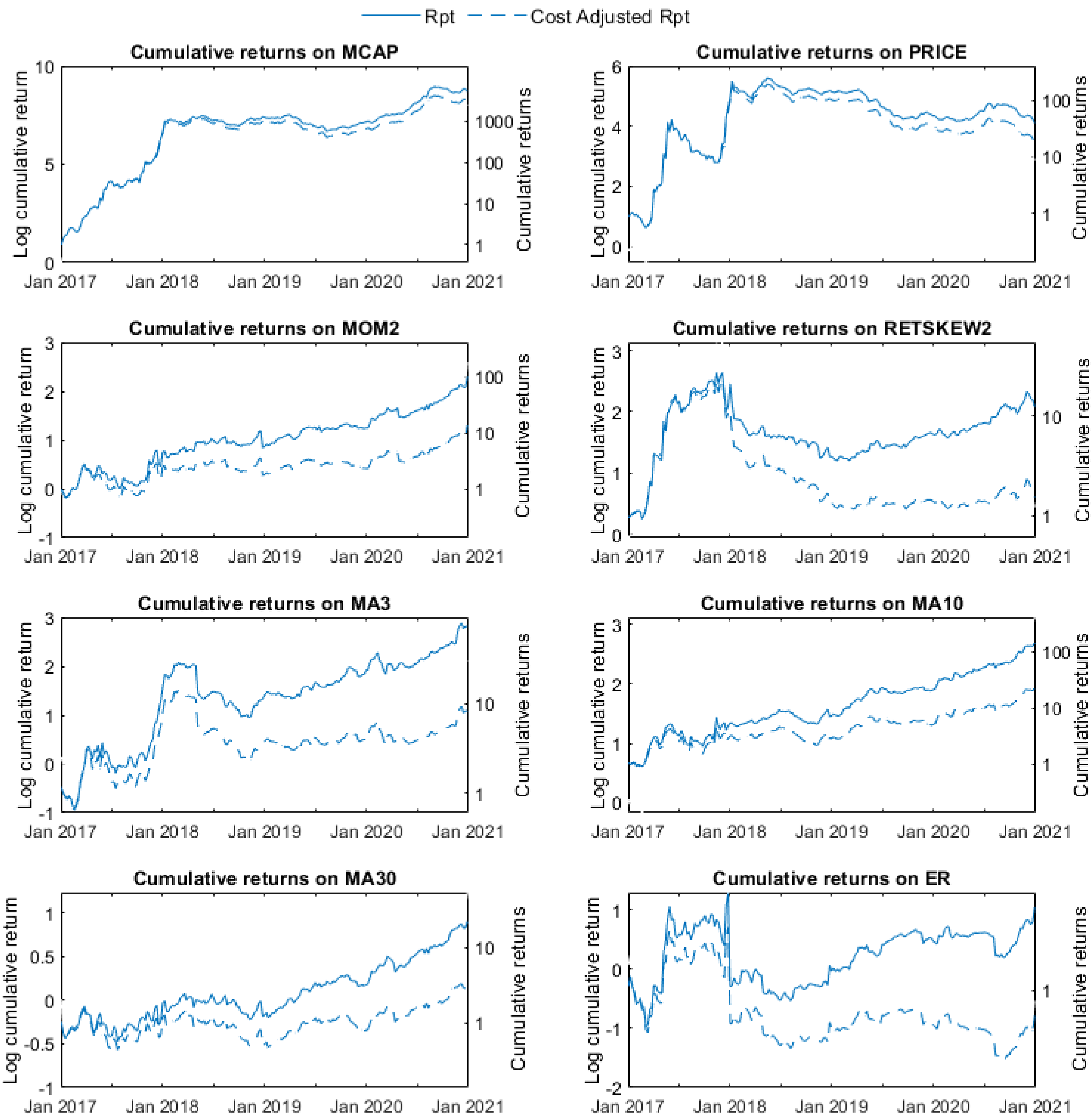

Figure 8: Cumulative returns: R_{pt} v.s. cost adjusted R_{pt}

6.3 Alternative formations: equal-weighted portfolios

Fama and French (2015) argue that value-weighted portfolios in the stock market tend to be underestimated because big stocks might dominate the value-weighted portfolio returns, whereas small stocks are the most challenging part for asset pricing models. To check if this concern exists in the cryptocurrency market or not, we test the performance of the proposed factor models on equal-weighted anomalous returns.

Following the method by Liu et al. (2020), we first construct equal-weighted weekly returns for the quintile portfolios, we then use the zero-investment long-short strategy to construct new cryptocurrency factors (anomalies: 5-1) formed on the anomalous variables (see Table 2). Surprisingly, we only find 12 factors that are significant under the equal-weighted allocation strategy, and 19 factors that are insignificant at a 10% significant level. Thus, in this part, we use the 12 significant equal-weighted anomalies to conduct our robustness check. The 12 significant cryptocurrency factors are MCAP, PRICE, MAXPRICE 1w, MAXPRICE 2w, MOM2, RETSKEW 1w, RETSKEW 2w, MAXRET 1w, MAXRET 2w, MA3, MA20, and MA30. The formula for equal-weighted portfolio returns looks as follows:

$$R_{pt}^{EW} = \sum_{i=1}^{N} w_{it} * R_{it} \tag{24}$$

$$w_{it} = \frac{1}{N} \tag{25}$$

Where R_{pt}^{EW} is the equal-weighted quintile portfolio return in week t after rebalancing on a weekly basis, R_{it} is the return on cryptocurrency i in week t. w_{it} denotes the investing weight of cryptocurrency i at the beginning of week t. Note that the w_{it} is a scalar ($\frac{1}{N}$) at the beginning of week t, since all the traded cryptocurrencies are equally weighted.

Lastly, we regress the 12 significant anomalies on the three common risk factors. The three common risk factors are the market, size, and momentum. Following Liu et al. (2020), the alternative formation aims to test the equal-weighted anomalous returns (different dependent variables) without changing the construction methods of the common risk factors (same independent variables). Thus, the three common risk factors remain the same as reported in Section 4.3. Table 16 reports the regression results from the proposed factor models to explain weekly equal-weighted anomalous returns. At a significance level of 10%, α_s presented in table 16 indicate that the two-factor model formed on size and market and the three-factor model outperform the other two models. These findings differ from the findings in Table 12, where we find the three-factor model performs the best in capturing the cryptocurrency anomalous returns.

Additionally, the results for the mean absolute pricing errors (m.a.e) and the mean of R^2s ($\bar{R}^2$) are inconsistent with the findings from Table 12. That is, in comparison to the C-CAPM and the two-factor model with CMKT and CMOM, we find that all the m.a.e largely decrease under the factor models that include size factor (CSMB), and the $\bar{R}^2$s are increasing at the same time. To summarize, the overall measure of the models that consider CSMB outperforms the other models that do not consider CSMB.

It is reasonable to find strong existing size effects in the equal-weighted anomalies since small cryptocurrencies play an essential role in capturing anomalous returns. Additionally, the equal-weighted anomalous returns do not co-move with the market and momentum factor since mismatching exists in the proposed models. For instance, the common risk factors (CMKT and CMOM) used as the independent variables are based on the value-weighted portfolios, while the new cryptocurrency anomalies used as the dependent variables are based on equal-weighted portfolios. Therefore, to avoid mismatching issues, we conclude that the value-weighted allocation strategy is more relevant in our case than using the equal-weighted allocation strategy. This robustness check further supports the researches by Liu et al. (2020), Liu et al. (2019) and Shen et al. (2020), where they use proposed factor pricing models to capture the value-weighted anomalous returns instead of the equal-weighted ones.

Table 16: The robustness check using equal-weighted portfolios

C-CAPM: $R_{pt}^{(j,new)} = \alpha_j + \beta_{CMKT} * CMKT_t + \varepsilon_t$

Two-factor model ❶: $R_{pt}^{(j,new)} = \alpha_j + \beta_{CMKT} * CMKT_t + \beta_{CSMB} * CSMB_t + \varepsilon_t$

Two-factor model ❷: $R_{pt}^{(j,new)} = \alpha_j + \beta_{CMKT} * CMKT_t + \beta_{CMOM} * CMOM_t + \varepsilon_t$

Three-factor model: $R_{pt}^{(j,new)} = \alpha_j + \beta_{CMKT} * CMKT_t + \beta_{CSMB} * CSMB_t + \beta_{CMOM} * CMOM_t + \varepsilon_t$

This table reports intercepts (α) from nested factor models in regressions to explain weekly equal-weighted returns on 12 significant cryptocurrency factors. Panel A shows the regression results under the new one-factor model produced by the cryptocurrency market return. Panel B and Panel C show regression results under the two-factor models when adding the new CSMB and the new CMOM to the model of C-CAPM, respectively. Panel D shows regression results under the proposed three-factor model. *, **, *** denote significance levels at the 10%, 5%, and 1%. m.a.e and $\bar{R}^2$ are the mean of the absolute pricing errors and the average R^2 of the five portfolios, respectively. The sample period is from January 2017 through January 2021, 209 weeks

12 Factors (5-1)	Panel A C-CAPM			Panel B Two-factor model ❶			Panel C Two-factor model ❷			Panel D Three-factor model		
Panel A: Size Factor	α on Factor	m.a.e	$\bar{R}^2$	α on Factor	m.a.e	$\bar{R}^2$	α on Factor	m.a.e	$\bar{R}^2$	α on Factor	m.a.e	$\bar{R}^2$
MCAP	-0.0613***	1.93%	54.65%	-0.0237**	0.31%	78.05%	-0.0636***	2.1%	55.0%	-0.0278**	1.08%	78.82%
PRICE	-0.0433*	1.92%	53.29%	0.0060	0.31%	72.42%	-0.0428*	2.0%	53.7%	0.0037	0.29%	73.16%
MAXPRICE1	-0.0354*	1.91%	49.28%	0.0115	0.32%	67.67%	-0.0347	2.0%	49.7%	0.0094	0.59%	68.40%
MAXPRICE2	-0.0346*	1.91%	49.22%	0.0123	0.32%	67.59%	-0.0340	2.0%	49.6%	0.0102	0.55%	68.31%
Panel B: Momentum Factor												
MOM2	0.0239**	1.65%	52.42%	0.0081	0.49%	75.33%	0.0218**	1.8%	52.7%	0.0071	0.40%	76.11%
Panel C: Volatility Factor												
RETSKEW1	0.0212*	1.94%	48.38%	0.0163*	0.29%	70.11%	0.0219*	2.1%	48.9%	0.0172*	0.66%	70.91%
RETSKEW2	0.0189*	1.91%	49.36%	0.0022	0.32%	72.59%	0.0171*	2.0%	49.6%	0.0015	0.32%	73.27%
MAXRET1	0.0328*	1.91%	51.87%	0.0050	0.32%	74.55%	0.0304*	2.0%	52.3%	0.0044	0.41%	75.39%
MAXRET2	0.0346**	1.93%	48.47%	0.0069	0.30%	70.71%	0.0409**	2.0%	49.0%	0.0141	0.57%	71.53%
Panel D: Trend Factor												
MA3	0.0226	1.92%	50.70%	0.0040	0.31%	73.92%	0.0268*	2.0%	51.6%	0.0088	0.35%	75.29%
MA20	-0.0178*	1.64%	52.17%	-0.0111	0.48%	74.46%	-0.0128	1.8%	52.8%	-0.0070	0.45%	75.56%
MA30	-0.0189*	1.62%	53.26%	-0.0095	0.52%	77.08%	-0.0169*	1.8%	53.7%	-0.0082	0.38%	78.04%
Significant alpha at 10% level	11			2			9			2		
Significant alpha at 5% level	3			1			3			1		

7 Discussion

As mentioned in the methodology part (Section 4), we have two different types of factors in our paper: factors used as dependent variables and common risk factors used as independent variables. To simplify the explanation, we call the 17 dependent cryptocurrency factors anomalies in the discussion and conclusion part. Therefore, the returns on our cryptocurrency factors are defined as the anomalous returns (Hou et al., 2020).

This study contributes with empirical results to analyze the classical equity-based risk factors in the cross-sectional cryptocurrency anomalous returns. The classical equity-based risk factors, also called common risk factors, used in this paper are: market, size, and momentum. Based on the anomalies literature in the traditional financial markets, we first compile 31 cryptocurrency anomalies. After controlling for the value-weighted returns, 17 out of 31 anomalies are observed to be significant at the 10% level. Thereafter, with the use of time-series regressions, we find associations between the 17 significant anomalies and the common risk factors. As discussed before, the empirical results reported in the previous section were substantially conclusive. In the test of CAPM, we find cryptocurrency market premiums in anomalous returns. In other words, those anomalies are observed to be exposed to the cryptocurrency market risk under the cryptocurrency-CAPM (C-CAPM). For example, the cross-section of cryptocurrency anomalous returns on MAXRET2 increase with the market returns. Moreover, when adding the size factor into the empirical time-series regression model (two-factor model), the market factor shows less explanatory power to the anomalous returns. Instead, under the two-factor model consisting of the market and size factor, the size factor is dominant to explain the cross-sectional variation in cryptocurrency returns based on size-related anomalies. Our findings are consistent with the results from Shen et al. (2020), that is, the C-CAPM is found to have poor performance in explaining the cross-sectional cryptocurrency returns. Moreover, the size effect that is commonly reported as an indicator of the cryptocurrency returns does not capture the cross-sectional anomalous returns based on momentum, volatility, and trend.

Our findings on the momentum factor stand out, as there are no momentum effects on our momentum anomalies. The findings deviate from previous researches (Liu et al., 2019; Liu and Tsyvinski, 2018; Liu et al., 2020). One reason for this might be the use of a different cryptocurrency sample and a newer sample period, as our sample period contains the most volatile years of the historical cryptocurrency market. The market volatility impacts both the price and market capitalization of each cryptocurrency, as there are substantial movements on a daily basis. However, it is reasonable that our momentum risk factor (CMOM) based on the one-week past returns cannot explain the momentum anomalies based on the information from the two- and three-week past returns. Therefore, the inclusion of the momentum risk factor in the two- and three-factor models do not give additional explanatory power for momentum anomalies. However, CMOM creates additional explanatory power for the two- and three-factor models in capturing the anomalous returns based on the information of the one-week maximum returns. Our findings are equivalent to previous research by Carhart (1997). The question is then, why does CMOM add no additional explanatory power for the anomaly based on two-week maximum returns? As the construction for the CMOM is based on one-week information (Monday-Monday), it might impact our anomalous returns based on the information of the one-week price or one-week returns. The regression results from the anomaly based on the 7-day moving average prices (MA7) support this explanation. Because CMOM captures the anomalous returns based on the information of the 7-day moving average prices (one week) with a higher significance level of the coefficients than that of anomalies based on other moving average prices. To summarize, the common momentum risk factor based on the one-week past returns can capture part of the cross-sectional returns for trend and volatility anomalies.

In addition, the results for the anomalies based on trend are unique because our findings show that almost all of the trend anomalies have no significant risk exposure to either the market, size, or momentum factor. This further supports Han et al.'s (2016) finding from the stock market, where the existing factor models are not capable of capturing the extra returns on the trend anomalies. An intuitive reason might be that the trend anomalies use the information from moving average prices, and moving average prices are less likely to be integrated with the common risk factors of the existing models (see, e.g., Neely et al., 2014).

8 Conclusion

In this paper, we extend the findings of Liu et al. (2019) and Shen et al. (2020) by investigating the effects of common risk factors on the cross-sectional cryptocurrency anomalous returns. Following the approach by Liu et al. (2019), we evaluate the performance of 17 anomalies (cryptocurrency factors), using both the methods of a cross-sectional study and time-series regressions. The results clearly show size effects and momentum effects in the cryptocurrency market. In addition, the three-factor model has more satisfying explanation power than the C-CAPM and the two-factor models. After reconstructing the common risk factors using a double-sorting process, we find that the three-factor model still outperforms the other three models. Therefore, we conclude that the standard asset pricing tools can meaningfully capture the cross-section of cryptocurrency returns.

The complexities of the cryptocurrency market are far away from completely investigated (Liu et al., 2020). Even though we find significant size effects and momentum effects in the cryptocurrency returns, numerous new risk factors from the traditional financial market could be implemented in the future. Considering that we are the first ones to construct the cryptocurrency trend anomalies, and with findings presented that the nested factor models cannot capture anomalous returns based on trend, our investigation could act as a benchmark for recognizing the trend factors as an extra risk factor in the cryptocurrency market.

References

1. Diego Amaya, Peter Christoffersen, Kris Jacobs, and Aurelio Vasquez. Does realized skewness predict the cross-section of equity returns? *Journal of Financial Economics, Vol. 118, No. 1, 135-167*, 2015. URL https://www.sciencedirect.com/science/article/pii/S0304405X15001257.

2. Saifedean Ammous. The bitcoin standard: The decentralized alternative to central banking. *Hoboken, N.J.: Wiley, ISBN 978119473916, the first edition*, 2018. URL https://rk2bukz.cf/book.php?id=Sw5TDwAAQBAJ.

3. Suma Athreye, Abubakr Saeed, and Muhammad Saad Baloch. Financial crisis of 2008 and outward foreign investments from china and india. *Journal of World Business, Vol 56, Issue 3, 101190*, 2021. URL https://www.sciencedirect.com/science/article/pii/S109095162100002X#!

4. Turan.G. Bali, Nusret Cakici, and Robert.F. Whitelaw. Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics, Vol. 99, No. 2, 427-446*, 2011. URL https://www.sciencedirect.com/science/article/pii/S0304405X1000190X#aep-article-footnote-id1.

5. Rolf.W. Banz. The relationship between return and market value of common stocks. *Journal of Financial Economics, Vol. 9, No. 1, 3-18*, 1981. URL https://www.sciencedirect.com/science/article/pii/0304405X81900180.

6. Pedro Barroso and Pedro Santa-Clara. Momentum has its moments. *Journal of Financial Economics,Volume 116, Issue 1, Pages 111-120*, 2015. URL https://www.sciencedirect.com/science/article/pii/S0304405X14002566#!

7. Dirk G. Baur, KiHoon Hong, and Adrian D. Lee. Bitcoin: Medium of exchange or speculative assets? *Journal of International Financial Markets, Institutions Money, Vol. 54, pp. 177–189*, 2018. URL researchgate.net/publication/321988034_Bitcoin_Medium_of_Exchange_or_Speculative_Assets/link/5d8c2c0392851c33e93c63a0/download.

8. Brian Boyer, Todd Mitton, and Keith Vorkink. Expected idiosyncratic skewness. *The Review of Financial Studies, Vol 23, No 1, Pages 169-202*, 2010. URL https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1089071.

9. Michael W. Brandt, Pedro Santa-Clara, and Rossen I. Valkanov. Parametric portfolio policies: Exploiting characteristics in the cross-section of equity returns. *The Review of Financial Studies, Vol 22, Issue 9, Pages 3411–3447*, 2009. URL https://academic.oup.com/rfs/article-abstract/22/9/3411/1572695.

10. Marie Brière, Kim Oosterlinck, and Ariane Szafarz. Virtual currency, tangible return: Portfolio diversification with bitcoin. *Journal of Asset Management, vol 16, 365–373*, 2018. URL https://link.springer.com/article/10.1057/jam.2015.5.

11. W. Brock, J. Lakonishok, and B. LeBaron. Simple technical trading rules and the stochastic properties of stock returns. *The Journal of Finance, Vol. 47, No. 5, pp. 1731-1764*, 1992. URL https://www.jstor.org/stable/2328994.

12. Zakaria Bziker. The status of cryptocurrency in morocco. *Research in Globalization, Vol 3, 100040*, 2021. URL https://www.sciencedirect.com/science/article/pii/S2590051X21000058.

13. Mark.M. Carhart. On persistence in mutual fund performance. *The Journal of Finance, Vol. 52, No. 1, 57-82*, 1997. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.1997.tb03808.x.

14. Valerio Celeste, Shaen Corbet, and Constantin Gurdgiev. Fractal dynamics and wavelet analysis: Deep volatility and return properties of bitcoin, ethereum and ripple. *The Quarterly Review of Economics and Finance Vol 76, Pages 310-324*, 2020. URL https://www.sciencedirect.com/science/article/pii/S1062976919300730?via%3Dihub.

15. Francisco Colon, Chaehyun Kim, and Wonjoon Kim. The effect of political and economic uncertainty on the cryptocurrency market. *Finance Research Letters, Vol 39, 101621*, 2021. URL https://www.sciencedirect.com/science/article/pii/S1544612320301707#!

16. Jennifer Conrad, Robert Dittmar, and Eric Ghysels. Ex ante skewness and expected stock returns. *The journal of finance, Vol 68, No 1, Pages 85-124*, 2013. URL https://www.jstor.org/stable/23324392?seq=1.

17. Michael J. Cooper, Roberto C. Gutierrez Jr., and Allaudeen Hameed. Market states and momentum. *The Journal of Finance, Vol LIX, NO. 3*, 2004. URL https://www.nber.org/papers/w25882.

18. Shaen Corbet, Andrew Meegan, Charles Larkin, Brian Lucey, and Larisa Yarovaya. Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economic Letters, Vol. 165,*, 2018. URL https://www.sciencedirect.com/science/article/pii/0304405X93900235?via%3Dihub.

19. Gerald P. Dwyer and Paula Tkac. The financial crisis of 2008 in fixed-income markets. *Journal of International Money and Finance, Vol 28, Pages 1293-1316*, 2009. URL https://www.sciencedirect.com/science/article/pii/S0261560609000977#!

20. Anne H. Dyhrberg, Sean Foley, and Jiri Svec. How investible is bitcoin? analyzing the liquidity and transaction costs of bitcoin markets. *Economics Letters, vol 171, 140-133*, 2018. URL https://www.sciencedirect.com/science/article/pii/S0165176518302921.

21. Eugene Fama and Kenneth French. The cross-section of expected stock returns. *The Journal of Finance, Vol. 47, No 2, 427-465*, 1992. URL https://www.jstor.org/stable/2329112?seq=1#metadata_info_tab_contents.

22. Eugene Fama and Kenneth French. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics, Vol. 33, No 1, 3-56*, 1993. URL https://www.sciencedirect.com/science/article/pii/0304405X93900235?via%3Dihub.

23. Eugene Fama and Kenneth French. A five-factor asset pricing model. *Journal of Financial Economics, Vol. 116, No.1, 1-22*, 2015. URL https://www.sciencedirect.com/science/article/pii/S0304405X14002323.

24. Laurent Favre and Andreas Signer. The difficulties of measuring the benefits of hedge funds. *The Journal of Alternative Investments, Vol 5, No 1, Pages 31-41, DOI 10.3905/jai.2002.319041*, 2002. URL https://www.researchgate.net/publication/242074961_The_Difficulties_of_Measuring_the_Benefits_of_Hedge_Funds.

25. Marcel Fratzscher. What explains global exchange rate movements during the financial crisis? *Journal of International Money and Finance, Vol 28, Issue 8, Pages 1390-1407*, 2009. URL https://www.sciencedirect.com/science/article/pii/S0261560609000990#!

26. Neil Gandal, JT Hamrick, Tyler Moore, and Tali Oberman. Price manipulation in the bitcoin ecosystem. *Journal of Monetary Economics, Vol 95, pages 86-96*, 2018. URL https://www.sciencedirect.com/science/article/pii/S0304393217301666.

27. Luis Alberiko Gil-Alana, Emmanuel Joel Aikins Abakah, Charles Larkin, and María Fátima Romero Rojo. Cryptocurrencies and stock market indices. are they related? *Research in International Business and Finance, Vol 51, 101063*, 2020. URL https://www.sciencedirect.com/science/article/pii/S0275531919303472#\protect\leavevmode@ifvmode\kern-.1667em\relax

28. Y. Han, K. Yang, and G. Zhou. A new anomaly: the cross-sectional profitability of technical analysis. *Journal of Financial and Quantitative Analysis, Vol. 48, pp. 1433-1461*, 2013. URL https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1656460.

29. Yufeng Han, Guofu Zhou, and Yingzi Zhu. A trend factor: Any economic gains from using information over investment horizons? *Journal of Financial Economics, Vol122, Issue 2, Pages 352-375*, 2016. URL https://www.sciencedirect.com/science/article/pii/S0304405X16301271#!

30. Xue-Zhong He, Kai Li, and Youwei Li. Asset allocation with time series momentum and reversal. *SSRN Electronic Journal, DOI 10.2139/ssrn.2919122*, 2017. URL https://www.researchgate.net/publication/314904164_Asset_Allocation_with_Time_Series_Momentum_and_Reversal.

31. Kewei Hou, Chen Xue, and Lu Zhang. Replicating anomalies. *The Review of Financial Studies, Volume 33, Issue 5, May 2020, Pages 2019–2133*, 2020. URL https://academic.oup.com/rfs/article/33/5/2019/5236964.

32. Eddie Chi Man Hui and Ka Kwan Kevin Chan. Alternative trading strategies to beat "buy-and-hold". *Physica A: Statistical Mechanics and its Applications, Vol 534, 120800*, 2019. URL https://www.sciencedirect.com/science/article/pii/S0378437119304108#!

33. Narasimhan Jegadeesh and Sheridan Titman. Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance, Vol. 48, No.1, 65-91*, 1993. URL https://www.jstor.org/stable/2328882?seq=25#metadata_info_tab_contents.

34. Anton Klarin. The decade-long cryptocurrencies and the blockchain rollercoaster: Mapping the intellectual structure and charting future directions. *Research in International Business and Finance, Vol 51, 101067*, 2020. URL https://www.sciencedirect.com/science/article/pii/S0275531919300558?via%3Dihub#!

35. Josef Kurka. Do cryptocurrencies and traditional asset classes influence each other? *Finance Research Letters, Vol 31, 38-46*, 2019. URL https://www.sciencedirect.com/science/article/pii/S154461231830477X.

36. Hugues Langlois. Measuring skewness premia. *Journal of Financial Economics, Vol 135, Pages 399-424*, 2020. URL https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1089071.

37. Rong Li, Sufang Li, Di Yuan, and Huiming Zhu. Investor attention and cryptocurrency: Evidence from wavelet-based quantile granger causality analysis. *Research in International Business and Finance, Vol 56, 101389*, 2021. URL https://www.sciencedirect.com/science/article/pii/S0275531921000106.

38. John Lintner. The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *The Review of Economics and Statistics, Vol. 47, No. 1, 13-37*, 1965. URL https://www.jstor.org/stable/1924119?seq=1#metadata_info_tab_contents.

39. Weiyi Liu, Xuan Liang, and Guowei Cui. Common risk factors in the returns on cryptocurrencies. *Economic Modelling, Vol. 86, pp. 299-305*, 2020. URL https://www.sciencedirect.com/science/article/pii/S026499931931020X.

40. Yukun Liu and Aleh Tsyvinski. Risk and returns of cryptocurrency. *[Forthcoming] Review of Financial Studies*, 2018. URL https://economics.yale.edu/sites/default/files/files/Faculty/Tsyvinski/cryptoreturns%208-7-2018.pdf.

41. Yukun Liu, Aleh Tsyvinski, and Xi Wu. Common risk factors in cryptocurrency. *[Forthcoming] Journal of Finance*, 2019. URL https://www.nber.org/papers/w25882.

42. Andrew W. Lo, Harry Mamaysky, and Jiang Wang. Foundations of technical analysis: Computational algorithms, statistical inference, and empirical implementation. *National Bureau of Economic Research, WORKING PAPER 7613, DOI 10. 3386/w7613*, 2000. URL https://www.nber.org/papers/w7613.

43. Seyed Alireza Manavi, Gholamreza Jafari, Shahin Rouhanib, and Marcel Ausloos. Demythifying the belief in cryptocurrencies decentralized aspects. a study of cryptocurrencies time cross-correlations with common currencies, commodities and financial indices. *Physica A: Statistical Mechanics and its Applications, Vol 556, 124759.*, 2020. URL https://www.sciencedirect.com/science/article/pii/S0378437120303836.

44. Harry Markowitz. Portfolio selection. *The Journal of Finance, Vol. 7, No. 1, 77-91*, 1952. URL https://www.jstor.org/stable/2975974?seq=1#metadata_info_tab_contents.

45. Tobias J. Moskowitz, Yao Hua Ooi, and Lasse Heje Pedersen. Time series momentum. *Journal of Financial Economics, Vol 104, Issue 2, Pages 228-250*, 2012. URL https://www.sciencedirect.com/science/article/pii/S0304405X11002613#!

46. Jan Mossin. Equilibrium in a capital asset market. *Econometrica, Vol. 34, No. 4, 768-783*, 1966. URL https://www.jstor.org/stable/1910098?seq=1#metadata_info_tab_contents.

47. Christopher J. Neely, David E. Rapach, Jun Tu, and Guofu Zhou. Forecasting the equity risk premium: The role of technical indicators. *Management Science, Vol 60, 1772-1791*, 2014. URL https://pubsonline.informs.org/doi/abs/10.1287/mnsc.2013.1838.

48. Whitney K. Newey and Kenneth D. West. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica, Vol 55, pp. 703-708*, 1987. URL https://www.jstor.org/stable/1913610?origin=crossref&seq=1#metadata_info_tab_contents.

49. Robert Novy-Marx. The other side of value: The gross profitability premium. *Journal of Financial Economics 108(1), 1-28*, 2013. URL https://www.sciencedirect.com/science/article/abs/pii/S0304405X13000044.

50. Maurice Omane-Adjepong and Imhotep Paul Alagidede. Multiresolution analysis and spillovers of major cryptocurrency markets. *Research in International Business and Finance, Vol 49, Pages 191-206*, 2019. URL https://www.sciencedirect.com/science/article/pii/S0275531919302375?via%3Dihub#!

51. Emmanouil Platanakis and Andrew Urquhart. Should investors include bitcoin in their portfolios?a portfolio theory approach. *The British Accounting Review, vol 52, 100837*, 2020. URL https://www.sciencedirect.com/science/article/pii/S0890838919300605.

52. G. William Schwert. Chapter 15 anomalies and market efficiency. *Handbook of the Economics of Finance, Vol 1, Part B, Pages 939-974*, 2003. URL https://www.sciencedirect.com/science/article/pii/S1574010203010240.

53. William.F. Sharpe. Capital asset prices: a theory of market equilibrium under conditions of risk. *Journal of Finance, Vol. 19, No. 3, 425-442*, 1964. URL https://onlinelibrary.wiley.com/doi/full/10.1111/j.1540-6261.1964.tb02865.x.

54. Dehua Shen, Andrew Urquhart, and Pengfei Wan. A three-factor pricing model for cryptocurrencies. *Finance Research Letters, vol 34, 101248*, 2020. URL https://www.sciencedirect.com/science/article/pii/S1544612319304519.

55. Yhlas Sovbetov. Factors influencing cryptocurrency prices: Evidence from bitcoin, ethereum, dash, litcoin, and monero. *Journal of Economics and Financial Analysis, Vol 2, Issue 2, Pages 1-27*, 2018. URL https://www.researchgate.net/publication/323243426_Factors_Influencing_Cryptocurrency_Prices_Evidence_from_Bitcoin_Ethereum_Dash_Litcoin_and_Monero.

56. Mikhail Stolbov and Maria Shchepeleva. What predicts the legal status of cryptocurrencies? *Economic Analysis and Policy, Vol 67, Pages 273-291*, 2020. URL https://www.sciencedirect.com/science/article/pii/S0313592620304057#!

57. Sheridan Titman, John Wei, and Feixue Xie. Capital investments and stock returns. *Journal of Financial and Quantitative Analysis 39, 677-700*, 2003. URL https://www.nber.org/papers/w9951.

58. David Yermack. Is bitcoin a real currency? an economic appraisal. *National Bureau of Economic Research, No 19747*, 2015. URL https://www.nber.org/papers/w19747.

A Appendix A

A.1 Web links

Binance: https://www.binance.com/en

Bloomberg: https://www.bloomberg.com/markets/rates-bonds

Coin.Dance: https://coin.dance/stats/marketcaptoday

CoinGecko: https://www.coingecko.com/en/coins/dogecoin

Coinmarketcap.com: https://coinmarketcap.com/

Cointelegraph (2017):
https://cointelegraph.com/news/south-korea-officially-legalizes-bitcoin-huge-market-for-traders

Decrypt (2021): https://decrypt.co/47061/public-companies-biggest-bitcoin-portfolios

Entethalliance (2021): https://entethalliance.org/

Kenneth French online data library:
https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Library of Congress:
https://www.loc.gov/law/help/cryptocurrency/world-survey.php

The 2021 Crypto-Exchange Fee Comparison:
https://www.cointracker.io/blog/2019-crypto-exchange-fee-comparison

The whitepaper by Satoshi Nakamoto: https://bitcoin.org/bitcoin.pdf

Worldometers (checking GDP by country): https://www.worldometers.info/gdp/gdp-by-country/

A.2 Cryptocurrencies' legal status across the largest 15 economies

Table A1 presents an overview of cryptocurrencies' legal status across the largest 15 economies by gross domestic product (GDP).

Table A1: Cryptocurrency regulation around the world

Country	Cryptocurrency	Exchanges	Central Bank Digital Currency
USA	Illegal; accepted by some retailers	Legal; regulation various by state	Digital US dollar (in designing process)
China	Bitcoin considered property; illegal as tender	Illegal but workarounds possible	Digital yuan/DCEP (official trails in April 2020)
Japan	Legal; treated as property	Legal; must re-register with FSA	Digital yen (legislative deliberation)
Germany	Gray area	Gray area	Digital euro considering (ECB)
India	Effectively illegal; ban under consideration	Legal but hard to operate	Digital rupee considering
UK	Not legal; considered "assets"	Legal; must register with FCA	Digital pound being considered
France	Gray area	Gray area	Digital euro considering (ECB)
Brazil	Legal but cannot be classified as financial assets	Legal, must register with COAF	Digital Brazilian real considering
Italy	Gray area but initial coin offering not allowed	Gray area	Digital euro considering (ECB)
Canada	Illegal; accepted by some retailers	Legal; regulation varies by place	Digital Canadian dollar considering
Russia	Illegal	Gray area; must get registered	Digital rubble considering
South Korea	Illegal; considered "financial assets"	Legal; must register with FSS	Digital won (2-year pilot scheme)
Australia	Legal; treated as property	Legal; must register in AUSTRAC	Digital Australian dollar considering
Spain	Gray Area	Legal	Digital euro considering (ECB)
Mexico	Legal	Legal	Might consider digital peso soon

B Appendix B

B.1 Tables for detailed OLS regression results

Table B1-B3 reports the detailed regression results involved in this study (Section 5).

Table B1: The cryptocurrency-CAPM (C-CAPM)

$$R_{pt}^{(j)} = \alpha_j + \beta_{CMKT} * CMKT_t + \varepsilon_t$$

		Quintile Portfolios					Factor	Based on 1 to 5	
		1	2	3	4	5	5-1	m.a.e	$\bar{R}^2$
MCAP	α	0.0448***	0.0213*	0.0044	-0.0021	-0.0000	-0.0449***	1.45%	64.12%
	β_{CMKT}	1.3357***	1.2482***	1.3609***	1.1165***	0.9878***	-0.3478*		
	R^2	0.4811	0.5107	0.5283	0.6873	0.9986	0.0572		
PRICE	α	0.0251	0.0060	0.0026	0.0009	0.0005	-0.0246	0.70%	55.54%
	β_{CMKT}	2.1398***	1.4847***	0.9795***	0.9083***	0.9646***	-1.1751*		
	R^2	0.3389	0.4641	0.4535	0.5627	0.9577	0.1257		
MAXPRICE1	α	0.0248	0.0031	0.0042	0.0016	0.0005	-0.0243	0.68%	53.47%
	β_{CMKT}	2.1477***	1.4609***	0.9571***	0.8817***	0.9656***	-1.1822*		
	R^2	0.3402	0.4324	0.3968	0.5468	0.9575	0.1268		
MAXPRICE2	α	0.0249	0.0049	0.0014	0.0009	0.0005	-0.0244	0.65%	54.12%
	β_{CMKT}	2.1503***	1.4643***	0.9569***	0.8863***	0.9655***	-1.1848*		
	R^2	0.3403	0.4218	0.4309	0.5556	0.9576	0.1270		
MOM2	α	-0.0165*	-0.0110*	0.0089	0.0054	0.0186*	0.0350***	1.21%	51.12%
	β_{CMKT}	1.0140***	1.1322***	1.1082***	1.0921***	0.9569***	-0.0571		
	R^2	0.5698	0.5525	0.6186	0.3997	0.4152	0.0017		
MOM3	α	-0.0073	-0.0076	0.0023	0.0123*	0.0135	0.0208*	0.86%	54.60%
	β_{CMKT}	1.0622***	0.9755***	1.2811***	1.1259***	1.0312***	-0.0311		
	R^2	0.4426	0.6818	0.5409	0.6455	0.4190	0.0005		
RETSKEW1	α	-0.0066	0.0081	0.0019	0.0113	0.0115	0.0181*	0.79%	55.16%
	β_{CMKT}	1.0463***	1.1637***	1.0413***	1.4890***	1.1951***	0.1488		
	R^2	0.7236	0.6480	0.4460	0.3957	0.5449	0.0163		
RETSKEW2	α	-0.0067	0.0082	0.0105	-0.0147***	0.0117	0.0184*	1.04%	58.92%
	β_{CMKT}	0.9948***	1.1085***	1.1655***	1.0160***	1.1843***	0.1895		
	R^2	0.7475	0.4900	0.5568	0.7480	0.4037	0.0171		
MAXRET1	α	-0.0059	-0.0002	0.0073	-0.0004	0.0168	0.0227	0.61%	58.85%
	β_{CMKT}	0.8920***	1.1370***	1.2913***	1.1237***	1.3515***	0.4595		
	R^2	0.7343	0.7481	0.6234	0.5266	0.3101	0.0421		

Table B1 continued

		Quintile Portfolios					Factor	Based on 1 to 5	
		1	2	3	4	5	5-1	m.a.e	$\bar{R}^2$
	α	-0.0040	0.0063	0.0053	-0.0049	0.0097	0.0138		
MAXRET2	β_{CMKT}	0.8753***	1.3915***	1.2656***	0.9851***	1.4236***	0.5482*	0.60%	54.93%
	R^2	0.7769	0.5861	0.5194	0.4541	0.4099	0.0839		
	α	0.0075	0.0086	0.0110	-0.0086	-0.0181**	-0.0256**		
MA3	β_{CMKT}	1.0992***	1.1215***	1.1810***	1.0318***	0.9387***	-0.1605	1.08%	57.51%
	R^2	0.5624	0.7060	0.5300	0.5005	0.5767	0.0188		
	α	0.0164*	0.0087	0.0031	-0.0154***	-0.0146*	-0.0310***		
MA5	β_{CMKT}	1.3097***	1.0261***	1.0305***	1.0590***	0.9930***	-0.3167	1.16%	62.40%
	R^2	0.5044	0.6747	0.6583	0.6885	0.5939	0.0501		
	α	0.0087	0.0243**	-0.0003	-0.0066	-0.0166**	-0.0253**		
MA7	β_{CMKT}	1.0823***	1.1564***	0.9708***	1.1129***	1.0887***	0.0063	1.13%	61.68%
	R^2	0.5973	0.4930	0.6606	0.7050	0.6279	0.0000		
	α	0.0128	0.0174**	0.0004	-0.0068	-0.0194***	-0.0322***		
MA10	β_{CMKT}	0.9727***	1.2403***	1.0954***	1.2035***	0.9891***	0.0164	1.14%	59.89%
	R^2	0.4768	0.6165	0.5834	0.6821	0.6356	0.0002		
	α	0.0147*	0.0129	0.0050	-0.0067	-0.0161**	-0.0308**		
MA20	β_{CMKT}	1.0722***	1.4528***	1.1039***	1.1219***	1.0386***	-0.0336	1.11%	54.59%
	R^2	0.4258	0.3837	0.6707	0.6375	0.6117	0.0005		
	α	0.0158*	0.0137	0.0044	-0.0114*	-0.0111	-0.0269**		
MA30	β_{CMKT}	0.9433***	1.3362***	1.1767***	1.0996***	1.0162***	0.0729	1.13%	54.61%
	R^2	0.5022	0.3899	0.6932	0.5680	0.5773	0.0033		
	α	0.0054	0.0043	0.0029	-0.0024	-0.0111	-0.0165		
ER	β_{CMKT}	1.4183***	1.0477***	1.0035***	0.9956***	1.0232***	-0.3951	0.52%	62.49%
	R^2	0.5074	0.6930	0.7296	0.6526	0.5418	0.0582		
	α	0.0148***	0.0003	-0.0177**	-0.0136***	0.0007***	-0.0141***		
MCAP	β_{CMKT}	1.0491***	1.0485***	1.1506***	1.0067***	0.9944***	-0.0547	0.94%	84.44%
	β_{CSMB}	0.9034***	0.6298***	0.6631***	0.3461***	-0.0207***	-0.9242***		
	R^2	0.8937	0.7545	0.7634	0.8112	0.9994	0.8138		

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table B2: The two-factor model: CMKT and CSMB

$$R_{pt}^{(j)} = \alpha_j + \beta_{CMKT} * CMKT_t + \beta_{CSMB} * CSMB_t + \varepsilon_t$$

		Quintile Portfolios					Factor	Based on 1 to 5	
		1	2	3	4	5	5-1	m.a.e	$\bar{R}^2$
PRICE	α	-0.0187	-0.0066	-0.0052	-0.0037	0.0018	0.0205	0.72%	62.98%
	β_{CMKT}	1.7223***	1.3654***	0.9059***	0.8642***	0.9776***	-0.7448*		
	β_{CSMB}	1.3160**	0.3762**	0.2319**	0.1392	-0.0408**	-1.3568***		
	R^2	0.5792	0.5200	0.5012	0.5875	0.9609	0.4399		
MAXPRICE1	α	-0.0192	-0.0054	-0.0049	-0.0028	0.0018	0.0210	0.68%	60.52%
	β_{CMKT}	1.7286***	1.3803***	0.8709***	0.8397***	0.9786***	-0.7500*		
	β_{CSMB}	1.3213***	0.2543	0.2718**	0.1321	-0.0411**	-1.3624***		
	R^2	0.5816	0.4569	0.4567	0.5698	0.9608	0.4423		
MAXPRICE2	α	-0.0191	-0.0042	-0.0070	-0.0035	0.0019	0.0210	0.71%	61.14%
	β_{CMKT}	1.7307***	1.3783***	0.8773***	0.8439***	0.9785***	-0.7522*		
	β_{CSMB}	1.3227***	0.2709	0.2511**	0.1336	-0.0410**	-1.3638***		
	R^2	0.5818	0.4488	0.4865	0.5793	0.9608	0.4426		
MOM2	α	-0.0241***	-0.0176***	0.0007	-0.0019	0.0125	0.0367***	1.14%	55.15%
	β_{CMKT}	0.9408***	1.0690***	1.0306***	1.0231***	0.8996***	-0.0412		
	β_{CSMB}	0.2309***	0.1995	0.2445**	0.2175	0.1807*	-0.0502		
	R^2	0.6251	0.5847	0.6751	0.4294	0.4430	0.0042		
MOM3	α	-0.0178**	-0.0132**	0.0021	0.0063	0.0058	0.0235*	0.90%	58.23%
	β_{CMKT}	0.9623***	0.9223***	1.2787***	1.0689***	0.9573***	-0.0050		
	β_{CSMB}	0.3151*	0.1675**	0.0075	0.1797*	0.2330*	-0.0821		
	R^2	0.5156	0.7194	0.5410	0.6763	0.4591	0.0068		
RETSKEW1	α	-0.0103*	-0.0015	-0.0043	-0.0040	0.0053	0.0157*	0.51%	59.40%
	β_{CMKT}	1.0111***	1.0721***	0.9815***	1.3436***	1.1364***	0.1254		
	β_{CSMB}	0.1110	0.2886***	0.1887	0.4581*	0.1850	0.0739		
	R^2	0.7388	0.7227	0.4734	0.4659	0.5694	0.0239		
RETSKEW2	α	-0.0086*	0.0006	0.0001	-0.0164***	0.0018	0.0103	0.55%	62.33%
	β_{CMKT}	0.9768***	1.0361***	1.0664***	0.9997***	1.0894***	0.1126		
	β_{CSMB}	0.0568	0.2284	0.3123**	0.0516	0.2991**	0.2424		
	R^2	0.7520	0.5290	0.6318	0.7516	0.4519	0.0697		
MAXRET1	α	-0.0097**	-0.0036	-0.0048	-0.0085	0.0038	0.0135	0.61%	63.26%
	β_{CMKT}	0.8559***	1.1047***	1.1761***	1.0468***	1.2281***	0.3722		
	β_{CSMB}	0.1139*	0.1019	0.3634***	0.2424*	0.3890*	0.2750		
	R^2	0.7568	0.7594	0.7159	0.5725	0.3583	0.0704		
MAXRET2	α	-0.0058	-0.0003	-0.0063	-0.0109	0.0005	0.0063	0.48%	58.10%
	β_{CMKT}	0.8589***	1.3291***	1.1550***	0.9281***	1.3354***	0.4766		
	β_{CSMB}	0.0519	0.1970*	0.3488**	0.1797	0.2778*	0.2260		
	R^2	0.7820	0.6081	0.5934	0.4824	0.4391	0.1106		

Table B2 continued

		Quintile Portfolios					Factor	Based on 1 to 5	
		1	2	3	4	5	5-1	m.a.e	$\bar{R}^2$
MA3	α	-0.0007	0.0028	0.0027	-0.0119	-0.0267***	-0.0260**	0.90%	61.88%
	β_{CMKT}	1.0215***	1.0661***	1.1028***	1.0006***	0.8566***	-0.1648		
	β_{CSMB}	0.2451*	0.1748**	0.2465*	0.0985	0.2587***	0.0135		
	R^2	0.6148	0.7381	0.5733	0.5091	0.6588	0.0190		
MA5	α	0.0116	0.0014	-0.0010	-0.0231***	-0.0192***	-0.0308**	1.13%	65.76%
	β_{CMKT}	1.2643***	0.9566***	0.9912***	0.9861***	0.9500***	-0.3144		
	β_{CSMB}	0.1429	0.2191**	0.1239	0.2299*	0.1356	-0.0073		
	R^2	0.5157	0.7323	0.6761	0.7494	0.6146	0.0502		
MA7	α	0.0040	0.0165*	-0.0041	-0.0139**	-0.0241***	-0.0281***	1.25%	65.21%
	β_{CMKT}	1.0374***	1.0817***	0.9340***	1.0436***	1.0169***	-0.0205		
	β_{CSMB}	0.1418	0.2355***	0.1158*	0.2184**	0.2263***	0.0845		
	R^2	0.6165	0.5313	0.6782	0.7559	0.6788	0.0121		
MA10	α	0.0098	0.0091	-0.0093*	-0.0162***	-0.0242***	-0.0340***	1.37%	64.45%
	β_{CMKT}	0.9435***	1.1612***	1.0024***	1.1141***	0.9437***	0.0002		
	β_{CSMB}	0.0918	0.2496**	0.2935**	0.2817*	0.1431*	0.0513		
	R^2	0.4847	0.6633	0.6619	0.7522	0.6605	0.0039		
MA20	α	0.0112	-0.0132	0.0012	-0.0172***	-0.0202***	-0.0314***	1.26%	61.40%
	β_{CMKT}	1.0384***	1.2047***	1.0670***	1.0223***	0.9988***	-0.0396		
	β_{CSMB}	0.1064	0.7821*	0.1165	0.3138***	0.1253	0.0189		
	R^2	0.4336	0.5922	0.6847	0.7310	0.6284	0.0007		
MA30	α	0.0116	-0.0062	-0.0001	-0.0191***	-0.0172**	-0.0288**	1.08%	59.88%
	β_{CMKT}	0.9033***	1.1459***	1.1339***	1.0267***	0.9577***	0.0544		
	β_{CSMB}	0.1260	0.6001**	0.1352*	0.2300*	0.1844*	0.0584		
	R^2	0.5190	0.5373	0.7104	0.6146	0.6129	0.0072		
ER	α	-0.0055	0.0004	-0.0035	-0.0096*	-0.0167**	-0.0112	0.71%	66.52%
	β_{CMKT}	1.3143***	1.0104***	0.9426***	0.9275***	0.9695***	-0.3449		
	β_{CSMB}	0.3277*	0.1176	0.1919***	0.2147**	0.1693*	-0.1584		
	R^2	0.5581	0.7094	0.7796	0.7095	0.5696	0.0757		

$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Table B3: The two-factor model: CMKT and CMOM

$$R_{pt}^{(j)} = \alpha_j + \beta_{CMKT} * CMKT_t + \beta_{CMOM} * CMOM_t + \varepsilon_t$$

		Quintile Portfolios					Factor	Based on 1 to 5	
		1	2	3	4	5	5-1	m.a.e	$\bar{R}^2$
MCAP	α	0.0450***	0.0218*	0.0073	-0.0009	-0.0001	-0.0451***	1.50%	64.32%
	β_{CMKT}	1.3352***	1.2462***	1.3488***	1.1115***	0.9881***	-0.3471*		
	β_{CMOM}	-0.0039	-0.0164	-0.0983	-0.0406	0.0019	0.0057		
	R^2	0.4811	0.5110	0.5357	0.6898	0.9986	0.0572		
PRICE	α	0.0182	0.0066	0.0012	0.0010	0.0010	-0.0172	0.56%	55.82%
	β_{CMKT}	2.1676***	1.4821***	0.9850***	0.9079***	0.9626***	-1.2050*		
	β_{CMOM}	0.2267	-0.0214	0.0454	-0.0038	-0.0169	-0.2436		
	R^2	0.3492	0.4644	0.4561	0.5628	0.9585	0.1403		
MAXPRICE1	α	0.0179	0.0055	0.0013	0.0019	0.0010	-0.0169	0.55%	53.97%
	β_{CMKT}	2.1755***	1.4512***	0.9686***	0.8804***	0.9635***	-1.2120*		
	β_{CMOM}	0.2266	-0.0791	0.0932	-0.0099	-0.0169	-0.2435		
	R^2	0.3504	0.4358	0.4069	0.5470	0.9583	0.1412		
MAXPRICE2	α	0.0180	0.0059	-0.0006	0.0012	0.0010	-0.0170	0.53%	54.46%
	β_{CMKT}	2.1780***	1.4601***	0.9647***	0.8850***	0.9634***	-1.2146*		
	β_{CMOM}	0.2267	-0.0340	0.0635	-0.0111	-0.0169	-0.2436		
	R^2	0.3505	0.4224	0.4360	0.5559	0.9583	0.1415		
MOM2	α	-0.0122	-0.0014	0.0092	-0.0077	0.0128	0.0250**	0.87%	58.20%
	β_{CMKT}	0.9967***	1.0936***	1.1068***	1.1445***	0.9800***	-0.0166		
	β_{CMOM}	-0.1414	-0.3152	-0.0110	0.4278	0.1888	0.3302		
	R^2	0.5996	0.6679	0.6188	0.5649	0.4588	0.1554		
MOM3	α	0.0010	-0.0063	0.0026	0.0057	0.0131	0.0121	0.57%	57.51%
	β_{CMKT}	1.0290***	0.9700***	1.2800***	1.1524***	1.0328***	0.0038		
	β_{CMOM}	-0.2712	-0.0442	-0.0090	0.2162***	0.0136	0.2847		
	R^2	0.5203	0.6855	0.5410	0.7096	0.4192	0.1103		
RETSKEW1	α	-0.0055	0.0105	-0.0098	0.0129	0.0152	0.0207**	1.08%	59.00%
	β_{CMKT}	1.0418***	1.1542***	1.0886***	1.4825***	1.1800***	0.1382		
	β_{CMOM}	-0.0363	-0.0772	0.3860	-0.0527	-0.1229	-0.0866		
	R^2	0.7259	0.6557	0.6110	0.3970	0.5604	0.0312		
RETSKEW2	α	-0.0042	0.0112	0.0118	-0.0123**	0.0004	0.0046	0.80%	61.84%
	β_{CMKT}	0.9847***	1.0962***	1.1604***	1.0064***	1.2299***	0.2452		
	β_{CMOM}	-0.0827*	-0.1002	-0.0415	-0.0789*	0.3722***	0.4548***		
	R^2	0.7614	0.5008	0.5587	0.7601	0.5110	0.2829		
MAXRET1	α	-0.0022	0.0013	0.0090	0.0042	-0.0030	-0.0008	0.39%	64.11%
	β_{CMKT}	0.8771***	1.1309***	1.2845***	1.1051***	1.4311***	0.5540*		
	β_{CMOM}	-0.1217	-0.0503	-0.0557	-0.1515	0.6497***	0.7714***		
	R^2	0.7712	0.7520	0.6265	0.5524	0.5032	0.3617		

Table B3 continued

		Quintile Portfolios					Factor	Based on 1 to 5	
		1	2	3	4	5	5-1	m.a.e	$\bar{R}^2$
MAXRET2	α	-0.0024	0.0129	0.0006	-0.0051	0.0060	0.0084	0.54%	56.46%
	β_{CMKT}	0.8689***	1.3647***	1.2849***	0.9860***	1.4386***	0.5697*		
	β_{CMOM}	-0.0525	-0.2192	0.1570	0.0074	0.1226	0.1751		
	R^2	0.7844	0.6252	0.5410	0.4542	0.4181	0.1069		
MA3	α	0.0039	0.0082	0.0011	-0.0015	-0.0139*	-0.0179*	0.57%	62.07%
	β_{CMKT}	1.1135***	1.1233***	1.2208***	1.0030***	0.9219***	-0.1916		
	β_{CMOM}	0.1165	0.0146	0.3249	-0.2346*	-0.1368**	-0.2533**		
	R^2	0.5794	0.7063	0.6380	0.5702	0.6096	0.1447		
MA5	α	0.0116	0.0090	-0.0020	-0.0108*	-0.0145*	-0.0261**	0.96%	64.53%
	β_{CMKT}	1.3290***	1.0247***	1.0512***	1.0402***	0.9923***	-0.3367		
	β_{CMOM}	0.1574	-0.0112	0.1691*	-0.1535***	-0.0055	-0.1629		
	R^2	0.5241	0.6749	0.7060	0.7275	0.5939	0.0858		
MA7	α	0.0043	0.0215**	0.0023	-0.0041	-0.0101	-0.0144*	0.85%	64.18%
	β_{CMKT}	1.1000***	1.1678***	0.9605***	1.1026***	1.0627***	-0.0373		
	β_{CMOM}	0.1443	0.0925	-0.0835	-0.0844	-0.2120*	-0.3563**		
	R^2	0.6259	0.5015	0.6737	0.7159	0.6921	0.3078		
MA10	α	0.0065	0.0160**	0.0055	-0.0046	-0.0150**	-0.0215**	0.95%	62.70%
	β_{CMKT}	0.9981***	1.2459***	1.0752***	1.1945***	0.9712***	-0.0269		
	β_{CMOM}	0.2076*	0.0457	-0.1653	-0.0735	-0.1457***	-0.3533**		
	R2	0.5353	0.6188	0.6192	0.6890	0.6727	0.2496		
MA20	α	0.0083	0.0170	0.0057	-0.0066	-0.0094	-0.0178*	0.94%	57.12%
	β_{CMKT}	1.0980***	1.4361***	1.1011***	1.1213***	1.0119***	-0.0861		
	β_{CMOM}	0.2108*	-0.1360	-0.0231	-0.0047	-0.2177*	-0.4285*		
	R^2	0.4701	0.3928	0.6715	0.6376	0.6841	0.2033		
MA30	α	0.0099	0.0015	0.0073	-0.0032	-0.0067	-0.0166*	0.57%	60.37%
	β_{CMKT}	0.9669***	1.3856***	1.1650***	1.0666***	0.9983***	0.0315		
	β_{CMOM}	0.1920	0.4031	-0.0956	-0.2699	-0.1458	-0.3379		
	R2	0.5582	0.4854	0.7055	0.6601	0.6093	0.1935		
ER	α	0.0092	0.0050	0.0045	-0.0027	-0.0110	-0.0201	0.65%	62.83%
	β_{CMKT}	1.4031***	1.0446***	0.9970***	0.9969***	1.0227***	-0.3804		
	β_{CMOM}	-0.1242	-0.0251	-0.0530	0.0100	-0.0039	0.1203		
	R^2	0.5178	0.6941	0.7351	0.6528	0.5418	0.0727		

$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Newey-West (1987) t-statistics in parentheses

Table B4: The three-factor model: CMKT, CSMB and CMOM

$$R_{pt}^{(j)} = \alpha_j + \beta_{CMKT} * CMKT_t + \beta_{CSMB} * CSMB_t + \beta_{CMOM} * CMOM_t + \varepsilon_t$$

		Quintile Portfolios					Factor	Based on 1 to 5	
		1	2	3	4	5	5-1	m.a.e	$\bar{R}^2$
	α	0.0165***	0.0019	-0.0138**	-0.0119**	0.0006**	-0.0160***		
	β_{CMKT}	1.0391***	1.0393***	1.1284***	0.9968***	0.9949***	-0.0441		
MCAP	β_{CSMB}	0.9098***	0.6356***	0.6771***	0.3524***	-0.0211***	-0.9308***	0.89%	85.01%
	β_{CMOM}	-0.0654	-0.0594	-0.1441**	-0.0645	0.0033	0.0687		
	R^2	0.9994	0.8198	0.7793	0.8173	0.9994	0.8198		
	α	-0.0225	-0.0053	-0.0060	-0.0034	0.0022	0.0247		
	β_{CMKT}	1.7436***	1.3582***	0.9105***	0.8621***	0.9754***	-0.7682*		
PRICE	β_{CSMB}	1.3025**	0.3808**	0.2290**	0.1404	-0.0394*	-1.3420**	0.79%	63.12%
	β_{CMOM}	0.1386	-0.0471	0.0299	-0.0133	-0.0142	-0.1528		
	R^2	0.5830	0.5212	0.5023	0.5878	0.9615	0.4455		
	α	-0.0230	-0.0028	-0.0069	-0.0022	0.0022	0.0252		
	β_{CMKT}	1.7498***	1.3654***	0.8825***	0.8368***	0.9764***	-0.7734*		
MAXPRICE1	β_{CSMB}	1.3079**	0.2637	0.2645**	0.1340	-0.0397*	-1.3476**	0.74%	60.85%
	β_{CMOM}	0.1381	-0.0969	0.0753	-0.0190	-0.0142	-0.1523		
	R^2	0.5853	0.4620	0.4633	0.5705	0.9613	0.4480		
	α	-0.0229	-0.0027	-0.0083	-0.0030	0.0022	0.0252		
	β_{CMKT}	1.7519***	1.3703***	0.8844***	0.8408***	0.9763***	-0.7756*		
MAXPRICE2	β_{CSMB}	1.3093**	0.2760	0.2465**	0.1355	-0.0397*	-1.3490**	0.78%	61.33%
	β_{CMOM}	0.1381	-0.0527	0.0468	-0.0203	-0.0142	-0.1523		
	R^2	0.5855	0.4503	0.4893	0.5801	0.9614	0.4482		
	α	-0.0198***	-0.0086	0.0015	-0.0132	0.0077	0.0275**		
	β_{CMKT}	0.9165***	1.0182***	1.0264***	1.0869***	0.9268***	0.0103		
MOM2	β_{CSMB}	0.2462***	0.2316*	0.2472**	0.1771	0.1634**	-0.0828	1.02%	62.30%
	β_{CMOM}	-0.1580*	-0.3309*	-0.0277	0.4159	0.1778	0.3358		
	R^2	0.6622	0.7109	0.6761	0.5844	0.4813	0.1621		
	α	-0.0097	-0.0117*	0.0024	0.0007	0.0058	0.0156		
	β_{CMKT}	0.9171***	0.9138***	1.2772***	1.1004***	0.9569***	0.0398		
MOM3	β_{CSMB}	0.3437*	0.1729**	0.0084	0.1597*	0.2332*	-0.1105	0.61%	61.32%
	β_{CMOM}	-0.2944	-0.0559	-0.0096	0.2054***	-0.0022	0.2922		
	R^2	0.6066	0.7254	0.5411	0.7338	0.4591	0.1217		
	α	-0.0091*	0.0011	-0.0146*	-0.0017	0.0090	0.0182*		
	β_{CMKT}	1.0043***	1.0572***	1.0391***	1.3307***	1.1155***	0.1112		
RETSKEW1	β_{CSMB}	0.1153	0.2980***	0.1522*	0.4663*	0.1982	0.0829	0.71%	63.27%
	β_{CMOM}	-0.0441	-0.0973	0.3757	-0.0842	-0.1363	-0.0922		
	R^2	0.7423	0.7348	0.6287	0.4693	0.5883	0.0406		

Table B4 continued

		Quintile Portfolios					Factor	Based on 1 to 5	
		1	2	3	4	5	5-1	m.a.e	$\bar{R}^2$
RETSKEW2	α	-0.0062	0.0037	0.0018	-0.0142**	-0.0079	-0.0017		
	β_{CMKT}	0.9634***	1.0182***	1.0567***	0.9870***	1.1437***	0.1803		
	β_{CSMB}	0.0652	0.2397	0.3185**	0.0596	0.2647**	0.1994	0.68%	65.21%
	β_{CMOM}	-0.0871*	-0.1164	-0.0631	-0.0829*	0.3542***	0.4413***		
	R^2	0.7673	0.5434	0.6362	0.7649	0.5485	0.3183		
MAXRET1	α	-0.0061	-0.0021	-0.0026	-0.0039	-0.0133	-0.0071		
	β_{CMKT}	0.8359***	1.0959***	1.1637***	1.0208***	1.3243***	0.4885		
	β_{CSMB}	0.1266**	0.1075	0.3712***	0.2588*	0.3280**	0.2014	0.56%	68.54%
	β_{CMOM}	-0.1303	-0.0576	-0.0808	-0.1690	0.6275***	0.7578***		
	R^2	0.7987	0.7645	0.7224	0.6044	0.5372	0.3767		
MAXRET2	α	-0.0042	0.0061	-0.0099	-0.0108	-0.0024	0.0019		
	β_{CMKT}	0.8502***	1.2931***	1.1756***	0.9274***	1.3515***	0.5013		
	β_{CSMB}	0.0574	0.2197*	0.3358*	0.1802	0.2677*	0.2103	0.67%	59.59%
	β_{CMOM}	-0.0564	-0.2341*	0.1342	-0.0048	0.1045	0.1609		
	R^2	0.7906	0.6524	0.6090	0.4824	0.4451	0.1299		
MA3	α	-0.0034	0.0027	-0.0057	-0.0053	-0.0225***	-0.0191*		
	β_{CMKT}	1.0369***	1.0665***	1.1504***	0.9633***	0.8328***	-0.2041*		
	β_{CSMB}	0.2354*	0.1745**	0.2164*	0.1221	0.2738***	0.0384	0.79%	66.42%
	β_{CMOM}	0.1006	0.0027	0.3102	-0.2429*	-0.1553***	-0.2559**		
	R^2	0.6274	0.7381	0.6712	0.5833	0.7010	0.1467		
MA5	α	0.0076	0.0021	-0.0054	-0.0185***	-0.0188**	-0.0263**		
	β_{CMKT}	1.2872***	0.9525***	1.0160***	0.9600***	0.9477***	-0.3395		
	β_{CSMB}	0.1285	0.2217**	0.1082*	0.2465**	0.1371	0.0086	1.05%	67.96%
	β_{CMOM}	0.1487	-0.0262	0.1617*	-0.1702***	-0.0148	-0.1635		
	R^2	0.5331	0.7335	0.7195	0.7969	0.6150	0.0859		
MA7	α	0.0003	0.0144	-0.0016	-0.0112*	-0.0179***	-0.0182**		
	β_{CMKT}	1.0582***	1.0935***	0.9199***	1.0283***	0.9818***	-0.0764		
	β_{CSMB}	0.1286	0.2280***	0.1248*	0.2282**	0.2486***	0.1199*	0.91%	67.94%
	β_{CMOM}	0.1356	0.0771	-0.0919	-0.0998	-0.2289**	-0.3645***		
	R2	0.6416	0.5372	0.6940	0.7711	0.7530	0.3319		
MA10	α	0.0042	0.0083	-0.0043	-0.0137**	-0.0199***	-0.0242**		
	β_{CMKT}	0.9746***	1.1656***	0.9738***	1.0998***	0.9197***	-0.0549		
	β_{CSMB}	0.0721	0.2468**	0.3116**	0.2908*	0.1583*	0.0862	1.01%	67.55%
	β_{CMOM}	0.2027*	0.0290	-0.1864	-0.0932	-0.1564***	-0.3592**		
	R^2	0.5401	0.6642	0.7071	0.7632	0.7030	0.2598		
MA20	α	0.0056	-0.0080	0.0020	-0.0165**	-0.0140**	-0.0197*		
	β_{CMKT}	1.0699***	1.1755***	1.0622***	1.0183***	0.9639***	-0.1060		
	β_{CSMB}	0.0865	0.8006*	0.1195	0.3163***	0.1474*	0.0609	0.92%	64.20%
	β_{CMOM}	0.2050*	-0.1902	-0.0312	-0.0261	-0.2276*	-0.4326*		
	R2	0.4753	0.6098	0.6861	0.7320	0.7070	0.2061		

Table B4 continued

		Quintile Portfolios					Factor	Based on 1 to 5	
		1	2	3	4	5	5-1	m.a.e	$\bar{R}^2$
ER	α	-0.0015	0.0013	-0.0017	-0.0094*	-0.0163**	-0.0148	0.60%	67.03%
	β_{CMKT}	1.2917***	1.0053***	0.9324***	0.9268***	0.9671***	-0.3246		
	β_{CSMB}	0.3420*	0.1208	0.1984***	0.2152**	0.1708*	-0.1712		
	β_{CMOM}	-0.1473	-0.0333	-0.0664	-0.0045	-0.0154	0.1319		
	R^2	0.5728	0.7113	0.7882	0.7095	0.5699	0.0931		
MA30	α	0.0066	-0.0162	0.0027	-0.0113*	-0.0129*	-0.0195*	0.99%	65.60%
	β_{CMKT}	0.9317***	1.2018***	1.1177***	0.9826***	0.9333***	0.0016		
	β_{CSMB}	0.1081	0.5646**	0.1455*	0.2580*	0.1999*	0.0918		
	β_{CMOM}	0.1847	0.3649	-0.1054	-0.2873*	-0.1594*	-0.3441		
	R^2	0.5705	0.6150	0.7252	0.7183	0.6509	0.2032		

$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$