Common Risk Factors in Cryptocurrency*

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Abstract

We find that three factors – cryptocurrency market, size, and momentum – capture the cross-sectional expected cryptocurrency returns. We consider a comprehensive list of price- and market-related return predictors in the stock market, and construct their cryptocurrency counterparts. Ten cryptocurrency characteristics form successful long-short strategies that generate sizable and statistically significant excess returns, and we show that all of these strategies are accounted for by the cryptocurrency three-factor model. Lastly, we examine potential underlying mechanisms of the cryptocurrency size and momentum effects.

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1 Introduction

The cryptocurrency market has experienced rapid growth. This market allows companies to raise money without engaging with venture capitalists and to be traded without being listed on stock exchanges.[1] The entire set of coins in the crypto market ranges from well-known currencies such as Bitcoin, Ethereum, and Ripple to much more obscure coins. There are two views on the cryptocurrency market. The first is that most and perhaps all of the coins represent bubbles and fraud. The second is that the blockchain technology embodied in coins may become an important innovation and that at least some coins may be assets that represent a stake in the future of this technology. If the latter case is true, analyzing the cryptocurrency market from the empirical asset pricing point of view is important for two reasons. The first reason is to establish a set of empirical regularities that can be used as stylized facts to assess and develop theoretical models. The second reason is to understand and differentiate the theoretical explanations of the asset pricing factors both in the traditional asset pricing and the newly developed cryptocurrency literature.

We consider all of the coins with market capitalizations above one million dollars and their returns from the beginning of 2014 to July of 2020. The number of such coins grew from 109 in 2014 to 1,559 in 2018, and then dropped to 665 in 2020. The equity market is perhaps the most studied market and the literature established a number of factors that explain the cross-section of stock returns. Among the return predictors compiled by Feng, Giglio, and Xiu (2017) and Chen and Zimmermann (2020), we select those that are constructed based only on price and market information, and construct their cryptocurrency counterparts – 24 such characteristics in total.[2] Out of the 24 cryptocurrency characteristics we considered, ten characteristics form successful long-short strategies generating sizeable and statistically significant excess returns. In particular, three factors – cryptocurrency market, size, and momentum – capture most of the cross-sectional expected returns.

The size and momentum premia are among the most studied effects in asset pricing. Both the traditional asset pricing and the newly developed cryptocurrency literature have proposed theoretical explanations to account for the size and momentum phenomena. For the

[1] An important fraction of cryptocurrencies is issued to raise money. Using the dataset of Momtaz 2021, we find that about 40 percent the cryptocurrencies in our sample went through initial coin offerings.

[2] The use of the equity factors provides discipline against the critique of picking and choosing factors that suit the paper.

cryptocurrency size premium, the findings are potentially consistent with two mechanisms. First, we find evidence that the cryptocurrency size factor may potentially capture the liquidity effect. Second, we provide evidence that the size premium is consistent with a mechanism proposed by the recent cryptocurrency theories: the trade-off between capital gain and convenience yield (e.g., Cong, Li, and Wang 2018; Sockin and Xiong 2018; Prat, Danos, and Marcassa 2019). Investors obtain two benefits from holding cryptocurrencies: capital gain and the convenience from transactions. In equilibrium, the convenience yield of the larger and more mature cryptocurrencies is higher, and thus their capital gain should be lower. For the cryptocurrency momentum premium, the findings are in line with the investor overreaction channel (e.g., Barberis, Shleifer, and Vishny 1998; Daniel, Hirshleifer, and Subrahmanyam 1998; Sockin and Xiong 2018).

We first describe the construction of the 24 cryptocurrency characteristics. There are broadly four groups of characteristics: size, momentum, volume, and volatility. We also construct an index of coin market return using all of the coins for which the data are readily available. The coin market return series comprises 1,827 coins weighted by their market capitalization.

We then analyze the performances of the 24 characteristics in the cryptocurrency market. Each week, we sort the returns of individual cryptocurrencies into quintile portfolios based on the value of a given characteristic. We track the return of each portfolio in the week that follows and calculate the average excess return over the risk-free rate of each portfolio. We then form the long-short strategy based on the difference between the fifth and the first quintiles. We find that the returns of the zero-investment strategies are statistically significant for 10 out of the 24 characteristics. Specifically, these are market capitalization, price, and maximum price; past one-, two-, three-, four-week, and one-to-four-week return; price volume; and standard deviation of price volume. We now turn to the detailed description of the results for each group of strategies.

For the statistically significant size related strategies, a zero-investment long-short strategy that longs the smallest coins and shorts the largest coins generates more than 3 percent excess weekly returns (5.8 percent for the market capitalization, 3.2 percent for the end of week price, and 3.3 percent for the highest price of the week strategies). For the momentum strategies, a zero-investment long-short strategy that longs the coins with comparatively large price increases and shorts the coins with comparatively small increases generates about 3 percent excess weekly returns (2.5 percent for one-week momentum, 3.1 percent for two-week momentum, 3.1 percent for three-week momentum, 2.2 percent for four-week momentum, and 1.7 percent for one-to-four-week momentum strategies). For the volume related strategies, a zero-investment strategy that longs the lowest volume coins and shorts the highest volume coins generates about 3 percent excess weekly returns (3.3 percent for the price volume). For the volatility strategy, a zero-investment strategy that longs the lowest price volume volatility coins and shorts the highest price volume volatility coins generates 3.2 percent excess weekly returns. For all of these strategies, the returns on individual quintile portfolios are almost monotonic with the quintiles. Determining the cryptocurrency characteristics that predict the cross-section of the entire cryptocurrency space is the first main result of the paper.

Next, we investigate whether a small number of factors can span these ten cross-sectional cryptocurrency return predictors. Our second main result is to develop a factor model for the cross-section of the cryptocurrency returns. We first consider a one-factor model with the coin market factor only. This is, in essence, a cryptocurrency CAPM model. The results are similar to those found in other asset classes – the model performs poorly in pricing the cross-section of the coin returns. We next show that a three-factor model with the cryptocurrency market factor (CMKT), a cryptocurrency size factor (CSMB), and a cryptocurrency momentum factor (CMOM) accounts for the excess returns of all of the ten successful zero-investment strategies. Adjusted for the cryptocurrency three-factor model, none of the alphas of the ten strategies remains statistically significant. The CSMB factor accounts for the following strategies: market capitalization, price, maximum day price, price volume, and the standard deviation of price volume. The CMOM factor accounts for the one-week, two-week, three-week, four-week, and one-to-four week momentum strategies.

Moreover, motivated by the Arbitrage Pricing Theory (Ross 1976), we conduct a principal component analysis on the 24 long-short strategies. We show that the first two principal components already account for more than 45 percent of the variations in the 24 long-short strategies. We show that the first and second principal components strongly correlate with the cryptocurrency size and momentum factors, respectively. The cryptocurrency market factor captures the level instead of the long-short strategy premia. Results based on the ten successful long-short strategies show a similar pattern. Furthermore, examining the level of the portfolios for the 24 strategies, we show that the first three principal components account for 73 percent of the variations of the portfolios. These three principal components strongly correlate with the cryptocurrency market, size, and momentum factors. Overall, we conclude that the cryptocurrency three-factor model captures the cross-section of expected returns of cryptocurrencies.

We then examine plausible mechanisms of the cryptocurrency size and momentum factors. For the cryptocurrency size effect, the findings are potentially consistent with two mechanisms. First, it is suggested that part of the size premium captures the illiquidity premium of the market. We find three sets of evidence that are in line with this liquidity view of size premium: (1) the small coins have lower prices and higher Amihud illiquidity measures relative to the large coins; (2) in the cross-section, the cryptocurrency size premium is more pronounced among coins that have high arbitrage costs; and (3) in the time-series, the cryptocurrency size premium is larger at times of high cryptocurrency market volatility. Second, consistent with the recent theories emphasizing the trade-off between capital gain and convenience yield, we show that the size premium is relatively large at times of high Bitcoin transactions.

For the cryptocurrency momentum premium, the evidence is potentially in line with the investor overreaction mechanism (e.g., Daniel, Hirshleifer, and Subrahmanyam 1998; Peng and Xiong 2006). After the initial continuation, prices tend to reverse in the long horizons. Moreover, the cryptocurrency momentum effect is markedly stronger among the large and well-known coins. The momentum strategy in the below-median size group generates statistically insignificant weekly excess returns, whereas the momentum strategy in the above-median size group generates statistically significant 3.2 percent weekly returns. These findings are consistent with the attention-based overreaction-induced momentum effect (Peng and Xiong 2006; Andrei and Hasler 2015). Consistent with these theories, we further find that (1) the cryptocurrency momentum effect is more pronounced among coins that receive high investor attention, and (2) the momentum factor is stronger at times of high investor attention.

We document several additional results. Firstly, we investigate the multiple hypothesis testing problem and test the joint significance of the 10 successful strategies. Using two methods, the k-familywise error rate (k-FWER) method in Lehmann and Romano (2005) and the joint F-test as in Gibbons, Ross, and Shanken (1989), we show that it is difficult to generate the results by chance. Secondly, we study the implementability of the strategies.

As the construction of the long-short strategies relies on the ability to short coins, a natural criticism of our findings is that short selling is either not possible or limited for most of the coins. We thus analyze each strategy that shorts Bitcoin instead of shorting the relevant quintile portfolio. The results virtually do not change. Then, we focus on the 20 largest and most liquid cryptocurrencies and test the trading strategies. We show that using the top 20 coins give qualitatively consistent results. Moreover, we restrict our sample to the cryptocurrencies that are traded against USD in the reputable exchange platforms and find consistent results. We further account for three different trading costs: trading fees, bid-ask spreads, and shorting fees. We show that, although the transaction costs are substantial in the cryptocurrency market, about 90 percent of the long-only strategy returns and about 60 percent of the long-short strategy returns remain after the adjustments.

Thirdly, we discuss the similarity between the cryptocurrency market and the currency market. We note that both the cryptocurrency market and the currency market have clear level factors: Bitcoin and the U.S. dollar. In addition, both markets exhibit momentum effects. Fourthly, we show that the cryptocurrency size and momentum effects are not driven by the surge of initial coin offerings. Fifthly, we show consistent results using the Fama-MacBeth cross-sectional regressions. Sixthly, we show that the stock market factor models, such as the Fama-French 3-factor, Carhart 4-factor, and the Fama-French 5-factor models, do not account for the cross-section of cryptocurrency returns. Lastly, we show that the procedure that removes the unpriced risks similar to Daniel, Mota, Rottke, and Santos (2018) strengthens the cryptocurrency size factor but not the cryptocurrency momentum factor. One possible explanation is that loadings on the cryptocurrency momentum factor are more transient than loadings on the cryptocurrency size factor.

We discuss the relationship of our paper to the literature. Size and momentum are among the most studied strategies in asset pricing. The size effect in the stock market is first documented in Banz (1981). Fama and French (1992) show that size and value are important factors in explaining the cross-section of expected stock returns.[3] Several papers (e.g., Amihud 2002; Pástor and Stambaugh 2003) question the robustness and interpretations of the size effect, suggesting that the size effect may be the result of data mining. Our

[3]The use of factor models to analyze asset returns dates back to the papers of Fama and French (1993) and Fama and French (1996). Lustig, Roussanov, and Verdelhan (2011), Szymanowska, De Roon, Nijman, and Van Den Goorbergh (2014), and Bai, Bali, and Wen (2018) develop factor models for the currency, commodity, and corporate bond markets, respectively.

findings on momentum are related to many papers on the topic such as Jegadeesh and Titman (1993) and Asness, Moskowitz, and Pedersen (2013). Behavioral finance offers several justifications of the momentum effect (e.g., Daniel, Hirshleifer, and Subrahmanyam 1998; Barberis, Shleifer, and Vishny 1998; Hong and Stein 1999). Risk-based explanations of the momentum effect consider the organizations and the cash-flow timing of the companies (e.g., Li 2017). In this paper, we find strong size and momentum effects in the cryptocurrency market. Moreover, we show that the cryptocurrency size factor is potentially consistent with the liquidity view of size premium (e.g., Amihud 2002; Bali, Cakici, Yan, and Zhang 2005; Bali and Cakici 2008) and the cryptocurrency momentum factor is in line with the investor overreaction channel (e.g., Barberis, Shleifer, and Vishny 1998; Daniel, Hirshleifer, and Subrahmanyam 1998; Peng and Xiong 2006).

A number of recent papers develop models of cryptocurrency valuations. Cong, Li, and Wang (2018) is a model about dynamic user adoption, and the main prediction is on the endogenous adoption of cryptocurrency and the price predictions at different stages of the life cycles of cryptocurrencies. Other studies focusing on the network effect of cryptocurrencies include Pagnotta (2018), Pagnotta and Buraschi (2018), and Biais, Bisiere, Bouvard, Casamatta, and Menkveld (2018). Sockin and Xiong (2018) consider the possibility of multiple equilibria in their static model, and emphasize the importance of speculator sentiment in driving cryptocurrency returns. In their model, speculator sentiment is given exogenously, and momentum effect can arise in some specification of the sentiment because users have incorrect expectations about future prices. The mechanism is similar to De Long, Shleifer, Summers, and Waldmann (1990), where irrational noise traders with erroneous stochastic beliefs affect prices so that prices can diverge significantly from fundamental values. Athey, Parashkevov, Sarukkai, and Xia (2016) model bitcoin prices as a function of its usage as payment vehicles. Schilling and Uhlig (2018) consider an economy where both fiat money and cryptocurrency coexist and emphasize the importance of monetary policy in cryptocurrency valuations. We connect our findings to Sockin and Xiong (2018) on investor overreaction in cryptocurrencies, and Cong, Li, and Wang (2018), Sockin and Xiong (2018), and Prat, Danos, and Marcassa (2019) on the trade-off between capital gain and convenience yield.

Several recent papers document empirical facts related to cryptocurrency investments. Liu and Tsyvinski (2018) is the first comprehensive study of the valuations of the cryptocurrency market in the aggregate time-series. They show that the cryptocurrency market returns have low exposures to risk factors of the other markets. However, the aggregate market returns can be predicted by cryptocurrency specific factors such as time-series momentum and investor attention. This paper studies the cross-section of cryptocurrency returns, considering the entire space of available cryptocurrencies. We show that a three-factor model with the cryptocurrency market, size, and momentum factors captures the cross-sectional variations of cryptocurrency returns. Borri (2018) shows that cryptocurrency returns are exposed to the tail-risks within cryptocurrencies but are not exposed to tail-risks concerning other global assets. Makarov and Schoar (2018), Borri and Shakhnov (2018b), and Borri and Shakhnov (2018a) show that there are dispersions of Bitcoin prices across different exchange platforms. Hu, Parlour, and Rajan (2018) show that most cryptocurrency returns have positive correlations with Bitcoin returns.

2 Data

We collect trading data of all cryptocurrencies available from Coinmarketcap.com. Coinmarketcap.com is a leading source of cryptocurrency price and volume data. It aggregates information from over 200 major exchanges and provides daily data on opening, closing, high, low prices, volume, and market capitalization (in dollars) for most of the cryptocurrencies.[4] For each cryptocurrency on the website, its price is calculated by taking the volume-weighted average of all prices reported at each market. A cryptocurrency needs to meet a list of criteria to be listed, such as being traded on a public exchange with an API that reports the last traded price and the last 24-hour trading volume, and having a non-zero trading volume on at least one supported exchange so that a price can be determined. When we started our study, Coinmarketcap.com listed both active and defunct cryptocurrencies, thus alleviating concerns about survivorship bias.[5]

We use daily close prices to construct weekly coin returns. Specifically, we divide each year into 52 weeks. The first week of the year consists of the first seven days of the year. The

[4] Some coins are not tracked by the website because the coins' exchanges do not provide accessible APIs.

[5] In Table IA.1 of the Internet Appendix, we consider the impact of delisting on our results. In the robustness test, we assume a negative 30 percent return if the cryptocurrency is delisted. Shumway (1997) documents that stock delisting is associated with a negative 10 percent return on average, so our choice of a negative 30 percent return is conservative. We find that considering delisting returns has a qualitatively small effect on our results.

first 51 weeks of the year consist of seven days each and the last week of the year consists of the last eight days of the year.[6] Our sample includes 1,827 coins from the beginning of 2014 to July of 2020. The trading volume data became available in the last week of 2013, and thus our sample period starts from the beginning of 2014. We require that the coins have information on price, volume, and market capitalization. We further exclude coins with market capitalizations of less than $1,000,000.

The summary statistics are presented in Panel A of Table 1. The number of coins in our sample that satisfy all the filters increases from 109 in 2014 to 1,559 in 2018. The number of coins in our sample that satisfy all the filters is 665 in 2020. The mean (median) market capitalization in the sample is 353.26 (6.64) million dollars. The mean (median) daily price volume in our sample is 44.99 (0.12) million dollars.

We construct a cryptocurrency market return as the value-weighted return of all the underlying available coins. The cryptocurrency excess market return (CMKT) is constructed as the difference between the cryptocurrency market return and the risk-free rate measured as the one-month Treasury bill rate. The summary statistics are presented in Panel B of Table 1. During the sample period, the average coin market index return is 1.3 percent per week, which is similar to the average Bitcoin return (1.3 percent per week) but is lower than the average Ripple return (2.6 percent per week) or Ethereum return (3.6 percent per week).[7] The weekly standard deviation of the coin market index return is 0.112, which is slightly higher than that of Bitcoin (0.111) but much lower than those of Ripple (0.237) and Ethereum (0.210). The coin market returns have positive skewness and kurtosis. Figure 1 plots the aggregate cryptocurrency market against Bitcoin, Ripple, and Ethereum. The values are presented as the US dollar value of investing one dollar from the inception of the given cryptocurrency to facilitate comparisons. The figure shows strong correlations among the cryptocurrency market index and the investment values of the major coins.

We obtain the stock market factors for the Fama French 3-factor, Carhart 4-factor, and Fama French 5-factor models from the Kenneth French website.

[6] The last week of 2016 consists of the last nine days of the year.

[7] Bitcoin, Ripple, and Ethereum are the three of the largest cryptocurrencies by market capitalization and thus form a natural reference group. During the sample period, the geometric average returns for the coin market index, Bitcoin, Ripple, and Ethereum are 0.7 percent, 0.7 percent, 0.7 percent, and 1.8 percent, respectively.

Table 1: Summary Statistics

Panel A reports the number of coins, the mean and median of market capitalization, and the mean and median of daily trading price volume by year. Panel B reports the characteristics of coin market index returns, Bitcoin returns, Ripple returns, and Ethereum returns. The coin market index returns, Bitcoin returns, and Ripple returns start from the first week of 2014. The Ethereum returns start from the thirty-second week of 2015.

Panel A

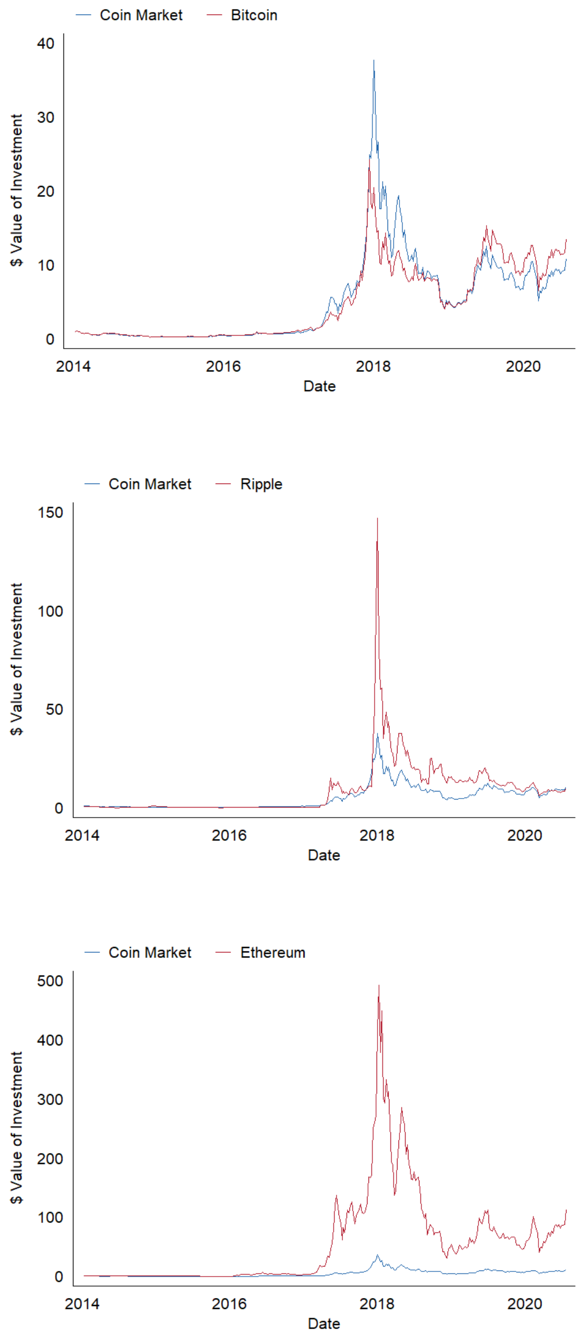
Year	Number of Coins	Market Cap (mil)		Volume (thous)	
		Mean	Median	Mean	Median
2014	109	239.83	3.89	1,146.09	36.24
2015	77	134.53	2.76	1,187.64	11.51
2016	155	160.60	3.41	1,795.03	23.96
2017	795	439.42	9.02	18,661.07	131.36
2018	1,559	363.17	8.85	21,184.20	124.92
2019	1,085	300.52	5.36	59,115.13	139.70
2020	665	440.21	5.38	125,249.20	210.77
Full	1,827	353.26	6.64	44,991.04	121.91

Panel B

	Mean	Median	SD	Skewness	Kurtosis
Coin Market Return	0.013	0.005	0.112	0.234	4.658
Bitcoin Return	0.013	0.001	0.111	0.394	4.749
Ripple Return	0.026	-0.003	0.237	3.890	26.296
Ethereum Return	0.036	0.011	0.210	1.971	12.161

Figure 1: Cryptocurrency Market and Major Coins

This figure plots the aggregate cryptocurrency market against Bitcoin, Ripple, and Ethereum.



3 Cross-Sectional Return Predictors

The equity market is perhaps the most studied market and the literature has uncovered different strategies based on price, return, and volume. Many trading strategies in other asset markets can find their counterparts in the equity market.[8] By applying similar methods of analyzing the equity risk factors to the cryptocurrency market, we establish a set of empirical regularities of cryptocurrencies that can be used as stylized facts to assess and develop theoretical models.

We consider a comprehensive list of the established return predictors in the cross-section of stock returns, compiled by Feng, Giglio, and Xiu (2017) and Chen and Zimmermann (2020). Among these, we select all the characteristics that can be directly constructed using only the information on price, volume, and market capitalization.[9] The reason we consider only the market-based return predictors is that financial and accounting data for the cross-section of coins are either not readily available or not applicable. We hence investigate 24 characteristics that we present in Table 2. We further group them into four broad categories: size, momentum, volume, and volatility. The use of the equity factors provides discipline against the critique of picking and choosing the factors that suit the paper. Specifically, our main goal of using the equity factors is to have a comprehensive, well-established list of factors, all of which we examine.

3.1 Size Characteristics

We analyze the performance of the zero-investment long-short strategies based on the size-related characteristics: market capitalization, price, maximum price, and age. Each week, we sort individual cryptocurrencies into quintile portfolios based on the value of a

[8]Menkhoff, Sarno, Schmeling, and Schrimpf (2012) find that the currency market exhibits a momentum effect, similar to the equity market. Asness, Moskowitz, and Pedersen (2013) show that the value and momentum effects are present not only in the equity market, but also in the currency, commodity, and bond markets.

[9]Several other papers (e.g., McLean and Pontiff 2016; Kozak, Nagel, and Santosh 2018; Hou, Xue, and Zhang 2020) construct different versions of "factor zoos", where the number of factors can be different, but the price, volume, and market capitalization strategies across the different factor zoos are largely consistent.

given characteristic. We track the return of each portfolio in the week that follows. We then calculate the average excess returns over the risk-free rate of each portfolio, and the excess returns of the long-short strategies based on the difference between the fifth and the first quintiles. We find that the first three return predictors generate statistically significant long-short strategy returns. The result of the zero-investment long-short strategy for age is not statistically significant and is summarized in the last part of the section.

Table 3 presents the results. For the first three characteristics, the average mean excess returns decrease from the top to the bottom quintiles. The differences in the average returns of the highest and lowest quintiles are -5.8 percent for market capitalization, -3.2 percent for the end of week price, and -3.3 percent for the highest price of the week. All of these differences are statistically significant at the 5 percent level. In other words, a zero-investment strategy that longs the smallest coins and shorts the largest coins generates more than 3 percent excess weekly returns. Of course, this strategy does not take into account trading costs and the feasibility of short selling. We consider strategies that short Bitcoin, and present results that long the smallest coins and short Bitcoin in Section 6. In Table IA.2 of the Internet Appendix, we also present results based on tercile instead of quintile portfolios.[10] The results based on tercile portfolios are qualitatively similar.

3.2 Momentum Characteristics

We analyze the performance of the zero-investment long-short strategies based on past one-, two-, three-, four-, one-to-four-, eight-, sixteen-, fifty-, and one hundred-week returns. Each week, we sort individual cryptocurrencies into quintile portfolios based on the value of a given characteristic. All strategies are rebalanced weekly. We find that the one-, two-, three-, four-, and one-to-four-week momentum strategies generate statistically significant long-short strategy returns. The results of the zero-investment long-short strategies based on the past eight-, sixteen-, fifty, and one hundred-week returns are not statistically significant and are summarized in the last part of the section.

[10] The same robustness results are presented for all other successful strategies in Table IA.2 of the Internet Appendix.

Table 2: Return Predictor Definitions

Category	Predictor	Reference	Definition
Size	MCAP	Banz (1981)	Log last day market capitalization in the portfolio formation week
Size	PRC	Miller and Scholes (1982)	Log last day price in the portfolio formation week
Size	MAXDPRC	George and Hwang (2004)	The maximum price of the portfolio formation week
Size	AGE	Barry and Brown (1984)	The number of days that have been listed on Coinmarketcap.com
Mom	r 1,0	Jegadeesh and Titman (1993)	Past one-week return
Mom	r 2,0	Jegadeesh and Titman (1993)	Past two-week return
Mom	r 3,0	Jegadeesh and Titman (1993)	Past three-week return
Mom	r 4,0	Jegadeesh and Titman (1993)	Past four-week return
Mom	r 4,1	Jegadeesh and Titman (1993)	Past one-to-four-week return
Mom	r 8,0	Jegadeesh and Titman (1993)	Past eight-week return
Mom	r 16,0	Jegadeesh and Titman (1993)	Past sixteen-week return
Mom	r 50,0	De Bondt and Thaler (1985)	Past fifty-week return
Mom	r 100,0	De Bondt and Thaler (1985)	Past one hundred-week return
Volume	VOL	Chordia, Subrahmanyam, and Anshuman (2001)	Log average daily volume in the portfolio formation week
Volume	PRCVOL	Chordia, Subrahmanyam, and Anshuman (2001)	Log average daily volume times price in the portfolio formation week
Volume	VOLSCALED	Chordia, Subrahmanyam, and Anshuman (2001)	Log average daily volume times price scaled by market capitalization in the portfolio formation week
Vol	BETA	Fama and MacBeth (1973)	The regression coefficient β^i_{CMKT} in $R_i - R_f = \alpha^i + \beta^i_{CMKT} CMKT + \epsilon_i$. The model is estimated using daily returns of the previous 365 days before the formation week.
Vol	BETA2	Fama and MacBeth (1973)	Beta squared
Vol	IDIOVOL	Ang, Hodrick, Xing, and Zhang (2006)	The idiosyncratic volatility is measured as the standard deviation of the residual after estimating $R_i - R_f = \alpha^i + \beta^i_{CMKT} CMKT + \epsilon_i$. The model is estimated using daily returns of the previous 365 days before the formation week.
Vol	RETVOL	Ang, Hodrick, Xing, and Zhang (2006)	The standard deviation of daily returns in the portfolio formation week
Vol	MAXRET	Bali, Cakici, and Whitelaw (2011)	Maximum daily return of the portfolio formation week
Vol	DELAY	Hou and Moskowitz (2005)	The improvement of R^2 in $R_i - R_f = \alpha^i + \beta^i_{CMKT} CMKT + \beta^i_{CMKT_{-1}} CMKT_{-1} + \beta^i_{CMKT_{-2}} CMKT_{-2} + \epsilon_i$, where $CMKT_{-1}$ and $CMKT_{-2}$ are the lagged one and two day coin market index excess returns, compared to using only current coin market excess returns. The model is estimated using daily returns of the previous 365 days before the formation week.
Vol	STDPRCVOL	Chordia, Subrahmanyam, and Anshuman (2001)	Log standard deviation of price volume in the portfolio formation week
Vol	DAMIHUD	Amihud (2002)	The average absolute daily return divided by price volume in the portfolio formation week

Table 3: Size Strategy Returns

This table reports the mean quintile portfolio returns based on the market capitalization, last day price, and maximum day price measures. The mean returns are the time-series averages of weekly value-weighted portfolio excess returns. *, **, *** denote significance levels at the 10%, 5%, and 1%.

	Quintiles					
	1	2	3	4	5	5-1
MCAP	**Low**				**High**	
Mean	0.071***	0.018**	0.013	0.012	0.013**	-0.058**
t(Mean)	(2.84)	(2.00)	(1.62)	(1.59)	(2.16)	(-2.45)
PRC	**Low**				**High**	
Mean	0.045***	0.026**	0.004	0.015	0.013**	-0.032**
t(Mean)	(3.02)	(2.45)	(0.50)	(1.45)	(2.13)	(-2.51)
MAXDPRC	**Low**				**High**	
Mean	0.046***	0.023**	0.004	0.016	0.013**	-0.033**
t(Mean)	(3.05)	(2.17)	(0.50)	(1.51)	(2.13)	(-2.55)

Table 4 presents the results of the successful return predictors for the portfolios sorted in quintiles. For the one-, two-, three-, four-, and one-to-four-week momentum strategies, the average mean excess returns increase with the quintiles. The patterns are almost universally monotonic. The difference in the average returns of the highest and lowest quintiles is about 3 percent for each horizon and statistically significant. In other words, a zero-investment strategy that longs the coins with comparatively large increases and shorts the coins with comparatively small increases generates about 3 percent excess weekly returns. The differences in the average returns of the highest and lowest quintiles are 2.5 percent for the one-week momentum strategy, 3.1 percent for the two-week momentum strategy, 3.1 percent for the three-week momentum strategy, 2.2 percent for the four-week momentum strategy, and 1.7 percent for the one-to-four-week momentum strategy.

Table 4: Momentum Strategy Returns

This table reports the mean quintile portfolio returns based on the past one-week, two-week, three-week, four-week, and one-to-four-week return measures. The mean returns are the time-series averages of weekly value-weighted portfolio excess returns. *, **, *** denote significance levels at the 10%, 5%, and 1%.

	Quintiles					
	1	2	3	4	5	5-1
r 1,0	**Low**				**High**	
Mean	-0.002	0.000	0.010	0.036**	0.023**	0.025**
t(Mean)	(-0.19)	(0.04)	(1.45)	(2.52)	(2.03)	(2.19)
r 2,0	**Low**				**High**	
Mean	0.000	0.005	0.009	0.017**	0.031***	0.031***
t(Mean)	(0.01)	(0.66)	(1.33)	(2.15)	(2.93)	(2.90)
r 3,0	**Low**				**High**	
Mean	0.005	0.002	0.016*	0.017**	0.036***	0.031***
t(Mean)	(0.60)	(0.28)	(1.94)	(2.30)	(3.21)	(2.65)
r 4,0	**Low**				**High**	
Mean	0.002	0.005	0.009	0.020**	0.025**	0.022**
t(Mean)	(0.30)	(0.66)	(1.28)	(2.45)	(2.32)	(2.26)
r 4,1	**Low**				**High**	
Mean	0.003	0.007	0.021**	0.011	0.020**	0.017*
t(Mean)	(0.35)	(0.94)	(2.34)	(1.51)	(2.02)	(1.82)

3.3 Volume Characteristics

We analyze the performance of the volume-related return predictors: volume, price volume, and scaled volume. Each week, we sort individual cryptocurrencies into quintile portfolios based on the value of a given characteristic. All strategies are rebalanced weekly. The price volume strategy generates statistically significant long-short strategy returns. The results of the zero-investment long-short strategies based on the other volume characteristics are not statistically significant and are summarized in the last part of the section. We note that it has been documented that cryptocurrency volume data could be unreliable due to the manipulations of some cryptocurrency exchanges.[11] In the latter part of the paper, we test the robustness of the results using volume data directly from the reputable cryptocurrency exchanges. Moreover, we use alternative measures that do not involve volume information when feasible.

Table 5 presents the results for the portfolios sorted in quintiles based on price volume. The average mean excess returns decrease with the quintiles. The pattern is mostly monotonic from the lowest to the highest quintiles. The difference in the average returns of the highest and lowest quintiles is -3.3 percent for price volume. The difference is statistically significant at the five percent level. In other words, a zero-investment strategy that longs the lowest price volume coins and shorts the highest price volume coins generates 3.3 percent excess weekly returns.

Table 5: Volume Strategy Returns

This table reports the mean quintile portfolio returns based on the price volume measure. The mean returns are the time-series averages of weekly value-weighted portfolio excess returns. *, **, *** denote significance levels at the 10%, 5%, and 1%.

	Quintiles					
	1	2	3	4	5	5-1
PRCVOL	**Low**				**High**	
Mean	0.046***	0.023**	0.015	0.014	0.013**	-0.033**
t(Mean)	(2.97)	(2.28)	(1.59)	(1.49)	(2.15)	(-2.44)

3.4 Volatility Characteristics

We analyze the performance of the volatility-related return predictors: beta, beta squared, idiosyncratic volatility, the standard deviation of returns, maximum day return, delay, the standard deviation of price volume, and Amihud's illiquidity measure.[12] Each week, we sort

[11] For example, see https://medium.com/@sylvainartplayribes/chasing-fake-volume-a-crypto-plague-ea1a3c1e0b5e.

[12] Because the Amihud's illiquidity measure uses volume information and the volume data could be unreliable as noted before, we also use the Abdi and Ranaldo (2017) measure as an alternative illiquidity measure and reach a similar conclusion.

individual cryptocurrencies into quintile portfolios based on the value of a given characteristic. All strategies are rebalanced weekly. The standard deviation of price volume measure generates statistically significant long-short strategy returns, but the other characteristics do not. We summarize the insignificant volatility characteristics in the last part of the section.

Table 6 presents the results for the portfolios sorted in quintiles based on the standard deviation of price volume measure – the only characteristic out of eight in this group that generates statistically significant excess returns on the long-short strategies. For the standard deviation of price volume, the average mean excess returns of the portfolios decrease monotonically with the quintiles and are statistically significant for each quintile. The difference in the average returns of the highest and lowest quintiles is -3.2 percent. In other words, a zero-investment strategy that longs the lowest price volume volatility coins and shorts the highest price volume volatility coins generates 3.2 percent excess weekly returns.[13]

Table 6: Volatility Strategy Returns

This table reports the mean quintile portfolio returns based on the standard deviation of price volume measure. The mean returns are the time-series averages of weekly value-weighted portfolio excess returns. *, **, *** denote significance levels at the 10%, 5%, and 1%.

	Quintiles					
	1	2	3	4	5	5-1
STDPRCVOL	**Low**				**High**	
Mean	0.045***	0.027**	0.019*	0.017*	0.013**	-0.032***
t(Mean)	(3.20)	(2.29)	(1.95)	(1.67)	(2.14)	(-2.65)

[13]For the cross-section of cryptocurrencies, the price volume volatility strongly correlates with size. The reason is that the price volume volatility measure is primarily driven by the differences in the price levels of coins. In the next section, we show that the price volume volatility premium can be accounted for by the cryptocurrency size factor.

Table 7: Insignificant Strategy Returns

This table reports the mean quintile portfolio returns based on the insignificant return predictors. The mean returns are the time-series averages of weekly value-weighted portfolio excess returns. The CAPM adjusted alpha is also reported in the table. *, **, *** denote significance levels at the 10%, 5%, and 1%.

		1	2	3	4	5	5-1	CAPM α
AGE	Mean	0.018	0.009	0.016**	0.012	0.012**	-0.006	-0.005
	t(Mean)	(1.35)	(1.06)	(2.00)	(1.53)	(2.03)	(-0.49)	(-0.44)
r 8,0	Mean	0.016	0.010	0.020**	0.020**	0.019*	0.003	0.003
	t(Mean)	(1.65)	(1.46)	(2.08)	(2.45)	(1.89)	(0.32)	(0.29)
r 16,0	Mean	0.017**	0.014*	0.008	0.014*	0.019*	0.003	0.003
	t(Mean)	(2.03)	(1.86)	(1.07)	(1.74)	(1.88)	(0.24)	(0.33)
r 50,0	Mean	0.015*	0.017**	0.014	0.014*	0.009	-0.006	-0.007
	t(Mean)	(1.86)	(2.21)	(1.61)	(1.78)	(1.04)	(-0.69)	(-0.79)
r 100,0	Mean	0.025***	0.020**	0.021**	0.020**	0.015	-0.008	-0.008
	t(Mean)	(2.95)	(2.51)	(2.05)	(2.09)	(1.55)	(-0.80)	(-0.79)
VOL	Mean	0.024*	0.026*	0.015*	0.012	0.013**	-0.011	-0.012
	t(Mean)	(1.84)	(1.69)	(1.91)	(1.46)	(2.09)	(-0.99)	(-1.06)
VOLSCALED	Mean	0.024*	0.008	0.010	0.009	0.015*	-0.009	-0.007
	t(Mean)	(1.85)	(1.01)	(1.33)	(1.25)	(1.67)	(-0.66)	(-0.56)
BETA	Mean	0.015*	0.025**	0.021**	0.021**	0.009	-0.006	-0.007
	t(Mean)	(1.80)	(2.48)	(2.24)	(2.19)	(1.07)	(-0.68)	(-0.80)
BETA2	Mean	0.016*	0.024**	0.021**	0.021**	0.009	-0.006	-0.007
	t(Mean)	(1.91)	(2.44)	(2.30)	(2.18)	(1.09)	(-0.77)	(-0.90)
IDIOVOL	Mean	0.014**	0.025**	0.020*	0.003	0.015	0.002	0.002
	t(Mean)	(2.23)	(2.47)	(1.83)	(0.33)	(1.29)	(0.19)	(0.17)
RETVOL	Mean	0.013*	0.018**	0.024**	0.018	0.002	-0.010	-0.009
	t(Mean)	(1.88)	(2.11)	(2.18)	(1.34)	(0.19)	(-0.89)	(-0.78)
MAXRET	Mean	0.010	0.018**	0.011	0.027**	0.011	0.001	0.002
	t(Mean)	(1.40)	(2.12)	(1.39)	(1.99)	(0.83)	(0.09)	(0.17)
DELAY	Mean	0.018***	0.023**	0.015	0.023**	0.012	-0.006	-0.006
	t(Mean)	(2.67)	(2.44)	(1.51)	(2.07)	(1.53)	(-0.72)	(-0.73)
DAMIHUD	Mean	0.013**	0.012	0.009	0.024	0.024*	0.011	0.012
	t(Mean)	(2.11)	(1.36)	(1.05)	(1.46)	(1.76)	(0.93)	(0.98)

3.5 Insignificant Strategies

In this subsection, we present the table that summarizes the results for the zero-investment strategies of the characteristics that do not generate statistically significant returns. There are fourteen such characteristics: age; past eight-, sixteen-, fifty-, and one hundred-week returns; volume, and scaled volume; beta, beta squared, idiosyncratic volatility, the standard deviation of returns, maximum day return, delay, and the Amihud's illiquidity measure.

Table 7 presents the results of the performance of the zero-investment long-short strategies. None of the measures generates statistically significant long-short strategy returns. The average mean excess returns do not change monotonically with the quintiles. The differences in the average returns of the highest and lowest quintiles are small and statistically insignificant. For example, the sixteen-week momentum strategy generates statistically insignificant excess returns of 0.3 percent per week on the long-short strategy.

3.6 Discussion of the Successful Predictors

We use return predictors in the equity market to motivate our selection of the 24 cryptocurrency characteristics. In this section, we discuss the behavior of the successful predictors, relative to those in the equity market. The directions of the non-momentum significant predictors in our findings are in line with the findings in the equity market. Consistent with Banz (1981), Miller and Scholes (1982), and George and Hwang (2004), we find that: (1) small coins have higher average returns than large coins, (2) low price coins have higher average returns than high price coins, and (3) low maximum price coins have higher average returns than high maximum price coins. Consistent with Chordia, Subrahmanyam, and Anshuman (2001), we find that: (1) low price volume coins have higher average returns than high price volume coins, and (2) low standard deviation of price volume coins have higher average returns than high standard deviation of price volume coins. Jegadeesh and Titman (1993) find that the momentum effect in the equity market concentrates between the past second month and the past twelfth month, while there is evidence of reversal effect for the past first month. In the cryptocurrency market, however, we find that the momentum effect is at a shorter horizon. In particular, the momentum effect in the cryptocurrency market exists for one to four weeks, the horizons in which there are reversal effects in the equity market. At the horizon that momentum in the equity market is in effect, there is no evidence of cryptocurrency momentum effect.

4 Cryptocurrency Factors

4.1 Cryptocurrency Factor Model

In this section, we investigate whether a small number of factors can span the ten cross-sectional cryptocurrency return predictors that we have identified. We perform an analysis similar to that of Fama and French (1996). We first show that a one-factor model with only the coin market excess return, or the cryptocurrency CAPM, cannot account for most of the excess returns of the ten strategies. Then, we analyze two-factor models: a two-factor model that adds the cryptocurrency size factor and a two-factor model that adds the cryptocurrency momentum factor. The two-factor model with the cryptocurrency market factor and a cryptocurrency size factor can account for the excess returns of five out of the ten zero-investment strategies but cannot explain any of the momentum related strategies. The two-factor model with the cryptocurrency market factor and a cryptocurrency momentum factor can account for the five momentum related strategies but not for any of the other strategies. Finally, we show that a cryptocurrency three-factor model with the market factor, a size factor, and a momentum factor explains the excess returns of all ten strategies.

The construction of the cryptocurrency market excess returns is discussed in Section 2. We construct the cryptocurrency size and momentum factors following the method in Fama and French (1993). Specifically, for size, each week we split the coins into three size groups by market capitalization: bottom 30 percent (small, S), middle 40 percent (middle, M), and top 30 percent (big, B).[14] We then form value-weighted portfolios for each of the three groups. The size factor (CSMB) is the return difference between the portfolios of the small and the big size portfolios. We construct the momentum factor (CMOM) using the three-week momentum and form the momentum factor based on the intersection of 2×3 portfolios.[15] In particular, for each week, we first sort coins into two portfolios based on coin sizes. We then form three momentum portfolios within each size portfolio based on the

[14]We use market capitalization as our main size measure because of the tradition in the stock market size literature. The results are robust to using alternative measures of size.

[15]We use three-week momentum as our main momentum measure because it generates the largest long-short spread in the data. The results are qualitatively similar using alternative measures of momentum.

past three week returns. The first, second, and third momentum portfolios are the bottom 30 percent, middle 40 percent, and top 30 percent of the coins based on past three-week returns. The momentum factor is constructed as the following:

$$\begin{aligned} CMOM &= 1/2\,(Small\ High + Big\ High) \\ &\quad -1/2\,(Small\ Low + Big\ Low) \end{aligned} \tag{1}$$

We first consider a one-factor model with only the cryptocurrency market factor or the cryptocurrency CAPM. The assumption for the cryptocurrency CAPM is that the investors predominantly invested in cryptocurrencies.[16] Table 8 presents the results for all the ten significant zero-investment strategies that we have found in the last section. The alphas for all of the zero-investment long-short strategies remain statistically significant. Moreover, the decreases in magnitude are small compared to the unadjusted excess returns. The average percentage decrease of the zero-investment strategy excess returns for the statistically significant strategies is only 9.50 percent. The strategies have some exposure to the coin market returns. In particular, the zero-investment long-short strategies based on market capitalization, price, maximum day price, price volume, and standard deviation of price volume are significantly exposed to the coin market excess returns. The strategies based on past returns – the one-week momentum strategy, three-week momentum strategy, four-week momentum strategy, and one-to-four-week momentum strategy – are not significantly exposed to the coin market returns. The only exception is the two-week momentum strategy, which positively exposes to the coin market returns. The average of the absolute value of the statistically significant betas is 0.364 (with a range of 0.163 for the two-week momentum strategy to 0.486 for the maximum day price). However, for all the strategies, the one-factor model does not explain a sizable portion of the excess returns, with the zero-investment strategy R^2s ranging from about zero percent for the one-week momentum strategy to 5.2 percent for price and the maximum day price strategies.

[16] We formally test the cryptocurrency market segmentation using the standard technique in the international finance literature that employs measures of segmentation based on the evolution of equity and currency return correlations or systematic risk exposures (see Bekaert, Hodrick, and Zhang 2009 for references). We regress the excess coin market returns on the global Fama-French factors (market, size, value, investment, and profitability factors) and the different major currency returns (Canadian dollar, Singapore dollar, Australian dollar, Euro, and British pound). The results are reported in Table IA.3 of the Internet Appendix. We find that the equity and currency factors account for a small amount of the cross-sectional variation in cryptocurrency returns. Based on the interpretations of the international finance literature, it implies strong market segmentation.

Table 8: Cryptocurrency One-Factor Model

This table reports the results for the cryptocurrency one-factor model adjustment of the ten successful long-short strategies. The pricing model is the following:

$$R_i - R_f = \alpha^i + \beta^i_{CMKT} CMKT + \epsilon_i \tag{2}$$

where $CMKT$ is the cryptocurrency excess market returns. The formation of the quintile portfolios for the ten significant strategies are discussed in Section 3. The t-statistics are reported in the parentheses. *, **, *** 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.

	α	$t(\alpha)$	β_{CMKT}	$t(\beta_{CMKT})$	R^2	m.a.e	$\bar{R^2}$
MCAP	-0.052**	(-2.19)	-0.467**	(-2.24)	0.014	0.011	0.544
PRC	-0.026**	(-2.05)	-0.481***	(-4.32)	0.052	0.009	0.545
MAXDPRC	-0.026**	(-2.09)	-0.486***	(-4.33)	0.052	0.009	0.539
r 1,0	0.025**	(2.17)	0.005	(0.05)	0.000	0.012	0.454
r 2,0	0.029***	(2.69)	0.163*	(1.72)	0.009	0.009	0.503
r 3,0	0.030**	(2.55)	0.072	(0.69)	0.001	0.010	0.484
r 4,0	0.021**	(2.08)	0.128	(1.44)	0.006	0.008	0.536
r 4,1	0.016*	(1.65)	0.127	(1.50)	0.007	0.006	0.525
PRCVOL	-0.029**	(-2.12)	-0.339***	(-2.80)	0.023	0.008	0.519
STDPRCVOL	-0.028**	(-2.37)	-0.249**	(-2.34)	0.016	0.009	0.518

We then consider a two-factor model with the cryptocurrency market factor and the cryptocurrency size factor. Model (1) of Table 9 presents the results for all ten zero-investment long-short strategies adjusting for the two-factor model. The long-short alphas for most of them, with the exception of the momentum strategies, are no longer significant. For example, the absolute value of the alpha for price volume drops from 2.9 percent under the one-factor model to an insignificant 0.7 percent under the two-factor model. Most strategies have significant exposures to the cryptocurrency size factor, with the exception of the two-week momentum strategy. Among the non-momentum strategies, the absolute values of their size factor loadings range from 0.339 for the max day price factor to 1.611 for the market capitalization factor. In other words, the smaller coins are also more illiquid and have lower trading volume, similar to results in the stock market. Among the momentum strategies, the absolute values of their size factor loadings are below 0.144. Many strategies have significant loadings on CMKT, with the exception of the market capitalization, the standard deviation of price volume, the one-, two-, three-, and four-week momentum factors. For all non-momentum strategies, the model explains substantial fractions of the return variations beyond what the coin market factor explains. Among the non-momentum strategies, the zero-investment long-short strategy R^2s range from 19.1 percent for the strategy based on the maximum day price factor to 95.3 percent for the strategy based on the market capitalization factor. However, this two-factor model based on the cryptocurrency market and size falls short in explaining the momentum-based strategies. The alphas on the momentum-based strategies are economically large and statistically significant, adjusting for this two-factor model. Compared to those of the one-factor model, the means of absolute pricing errors decrease dramatically for the non-momentum strategies. For example, the m.a.e of the price volume strategy reduces from 0.8 percent in the one-factor model to 0.3 percent in the two-factor model controlling for the cryptocurrency market and size factors – a 63 percent decrease. The means of absolute pricing errors do not materially change for the momentum strategies controlling for the two-factor model.

We next consider an alternative two-factor model by combining the cryptocurrency market factor and the cryptocurrency momentum factor. Model (2) of Table 9 presents the results for all ten zero-investment long-short strategies adjusting for the alternative two-factor model. This two-factor model performs well in capturing the excess returns of the five momentum factors – one-, two-, three-, four-, and one-to-four-week momentum factors. After controlling for this alternative two-factor model, the alphas for all five momentum strategies are no longer statistically significant. For example, the alpha of the four-week momentum strategy drops from 2.1 percent under the one-factor model to 0.7 percent under this alternative two-factor model. All five momentum strategies have statistically significant exposures to the momentum factor. For these five strategies, their momentum factor loadings range from 0.531 for the one-week momentum to 1.117 for the three-week momentum. All non-momentum strategies have significant exposures to the market. On the other hand, none of the momentum strategies significantly exposes to the cryptocurrency market factor. For the momentum strategies, this alternative two-factor model explains a substantial fraction of the return variations in contrast to the market one-factor model or the market and size two-factor model. The zero-investment strategy R^2s range from 14.0 percent for the one-week momentum to 57.1 percent for the three-week momentum. However, the model underperforms in explaining the return variations of the non-momentum strategies compared to the two-factor model with the cryptocurrency market and the cryptocurrency size factors. The alphas of the non-momentum strategies remain statistically significant. Compared to the one-factor model, the means of absolute pricing errors largely decrease for the momentum factors. For example, the m.a.e of the two-week momentum strategy reduces from 0.9 percent in the one-factor model to 0.4 percent in the two-factor model.

Finally, we consider a three-factor model that combines the cryptocurrency market, size, and momentum factors. Model (3) of Table 9 presents the results for all ten strategies. Adjusted for the cryptocurrency three-factor model, none of the alphas for the ten strategies remains statistically significant. We now turn to the discussion of the exposures to the three factors. The price volume zero-investment long-short strategy is statistically significantly exposed to the size factor but not to the momentum factor. The two-week momentum zero-investment long-short strategy is statistically significantly exposed to the momentum factor but not to the size factor. The other eight long-short strategies are significantly exposed to both the size and momentum factors. None of the strategies is exposed to the market factor only. In other words, both size and momentum are important in explaining the cross-section of expected returns of cryptocurrencies. Compared to the one-factor model, the means of absolute pricing errors largely decrease for all of the ten strategies.

4.2 Principal Component Analysis

The Arbitrage Pricing Theory (Ross 1976) suggests that a small number of risk factors can capture substantial common variations in asset returns. In this section, we conduct principal component analysis on the 24 long-short strategies in the paper. We test whether a small number of principal components can meaningfully capture the variations of the returns of the strategies. We show that two components emerge to explain substantial variations of the long-short strategies. We further examine the correlations between the first two principal components and the three cryptocurrency factors. We find that the first principal component strongly correlates with the cryptocurrency size factor, and the second principal component significantly exposes to the cryptocurrency momentum factor.

Table 9: Cryptocurrency Factor Models

This table reports the results for the cryptocurrency factor adjustments of the ten successful long-short strategies. $CMKT$ is the cryptocurrency excess market returns, $CSMB$ is the cryptocurrency size factor, and $CMOM$ is the cryptocurrency momentum factor. The t-statistics are reported in the parentheses. *, **, *** 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.

		Cons	t	CMKT	t	CSMB	t	CMOM	t	R^2	m.a.e	$\bar{R^2}$
	(1)	-0.000	(-0.05)	-0.025	(-0.54)	-1.611***	(-82.15)			0.953	0.003	0.719
MCAP	(2)	-0.052**	(-2.20)	-0.469**	(-2.24)			0.037	(0.23)	0.015	0.011	0.548
	(3)	-0.002	(-0.32)	-0.030	(-0.64)	-1.611***	(-82.57)	0.072**	(2.07)	0.953	0.001	0.723
	(1)	-0.015	(-1.28)	-0.387***	(-3.75)	-0.342***	(-7.76)			0.195	0.007	0.567
PRC	(2)	-0.029**	(-2.34)	-0.493***	(-4.45)			0.186**	(2.19)	0.065	0.010	0.548
	(3)	-0.019	(-1.60)	-0.400***	(-3.89)	-0.343***	(-7.85)	0.194**	(2.48)	0.210	0.008	0.570
	(1)	-0.016	(-1.32)	-0.393***	(-3.76)	-0.339***	(-7.63)			0.191	0.007	0.560
MAXDPRC	(2)	-0.030**	(-2.36)	-0.497***	(-4.45)			0.177**	(2.06)	0.064	0.009	0.542
	(3)	-0.019	(-1.63)	-0.404***	(-3.89)	-0.341***	(-7.71)	0.184**	(2.33)	0.204	0.007	0.563
	(1)	0.020*	(1.78)	-0.034	(-0.35)	0.144***	(3.41)			0.033	0.012	0.465
r 1,0	(2)	0.014	(1.33)	-0.029	(-0.32)			0.531***	(7.44)	0.140	0.009	0.477
	(3)	0.010	(0.92)	-0.068	(-0.74)	0.141***	(3.59)	0.528***	(7.52)	0.172	0.010	0.487
	(1)	0.028**	(2.57)	0.154	(1.61)	0.035	(0.85)			0.011	0.009	0.507
r 2,0	(2)	0.015	(1.61)	0.117	(1.45)			0.714***	(11.59)	0.290	0.004	0.556
	(3)	0.014	(1.49)	0.108	(1.34)	0.030	(0.87)	0.714***	(11.58)	0.292	0.004	0.559
	(1)	0.033***	(2.77)	0.095	(0.91)	-0.084*	(-1.89)			0.012	0.010	0.491
r 3,0	(2)	0.008	(1.03)	-0.001	(-0.01)			1.117***	(21.23)	0.571	0.006	0.578
	(3)	0.011	(1.41)	0.024	(0.35)	-0.092***	(-3.16)	1.119***	(21.54)	0.584	0.005	0.585
	(1)	0.019*	(1.85)	0.109	(1.23)	0.068*	(1.80)			0.015	0.007	0.540
r 4,0	(2)	0.007	(0.83)	0.082	(1.11)			0.699***	(12.35)	0.315	0.004	0.578
	(3)	0.005	(0.60)	0.065	(0.88)	0.063**	(2.01)	0.698***	(12.38)	0.323	0.003	0.582
	(1)	0.020**	(2.15)	0.165**	(1.98)	-0.140***	(-3.94)			0.051	0.007	0.539
r 4,1	(2)	-0.001	(-0.07)	0.081	(1.12)			0.694***	(11.45)	0.286	0.004	0.561
	(3)	0.004	(0.51)	0.121*	(1.72)	-0.148***	(-4.97)	0.700***	(11.95)	0.335	0.005	0.576
	(1)	-0.007	(-0.73)	-0.150*	(-1.78)	-0.688***	(-19.14)			0.530	0.003	0.601
PRCVOL	(2)	-0.030**	(-2.17)	-0.342***	(-2.82)			0.045	(0.49)	0.023	0.008	0.521
	(3)	-0.008	(-0.85)	-0.154*	(-1.82)	-0.688***	(-19.15)	0.060	(0.94)	0.532	0.003	0.603
	(1)	-0.008	(-1.04)	-0.076	(-1.07)	-0.631***	(-20.91)			0.570	0.004	0.605
STDPRCVOL	(2)	-0.031**	(-2.52)	-0.256**	(-2.40)			0.103	(1.27)	0.020	0.009	0.522
	(3)	-0.011	(-1.33)	-0.083	(-1.18)	-0.632***	(-21.05)	0.117**	(2.18)	0.576	0.004	0.609

Table 10 shows the results of the principal component analysis for the 24 long-short strategies. Panel A of Table 10 shows the eigenvalues and the explanatory power of the first 15 principal components. We omit the remaining components because the first 15 components have already explained the majority of the variations of the 24 long-short strategies. The eigenvalues of the first and second principal components are 6.44 and 4.46, respectively. The eigenvalues of the first two components are much larger than the remaining principal components. The first two principals combined already explain approximately 45 percent of the variations in the 24 long-short strategies.

Panel B of Table 10 reports the correlation matrix of the first three principal components and the three cryptocurrency factors. The first principal component strongly correlates with the cryptocurrency size factor. The absolute value of the correlation is 0.826. The first principal component also negatively correlates with the cryptocurrency market and momentum factors, where the absolute values of the correlations are 0.178 and 0.227, respectively. The second principal component has substantial exposure to the cryptocurrency momentum factor. The correlation between them is 0.662. The second component negatively correlates with the cryptocurrency size factor and has a relatively low correlation with the cryptocurrency market factor. The third principal component has moderate correlation with any of the cryptocurrency factors.

We further apply the principal component analysis on the level of the portfolios for all the 24 strategies. We document the results in Table IA.4 of the Internet Appendix. We find that the first three principal components account for 72.9 percent of the variations of the portfolios. Consistent with the evidence in Table 10, the first principal component strongly correlates with the cryptocurrency market factor (correlation of 94.7 percent), the second principal component strongly correlates with the cryptocurrency size factor (correlation of 87.3 percent), and the third principal component strongly correlates with the cryptocurrency momentum factor (correlation of 57.7 percent). The results show that the cryptocurrency market factor is crucial in explaining the level of the portfolio returns of the quintile portfolios.

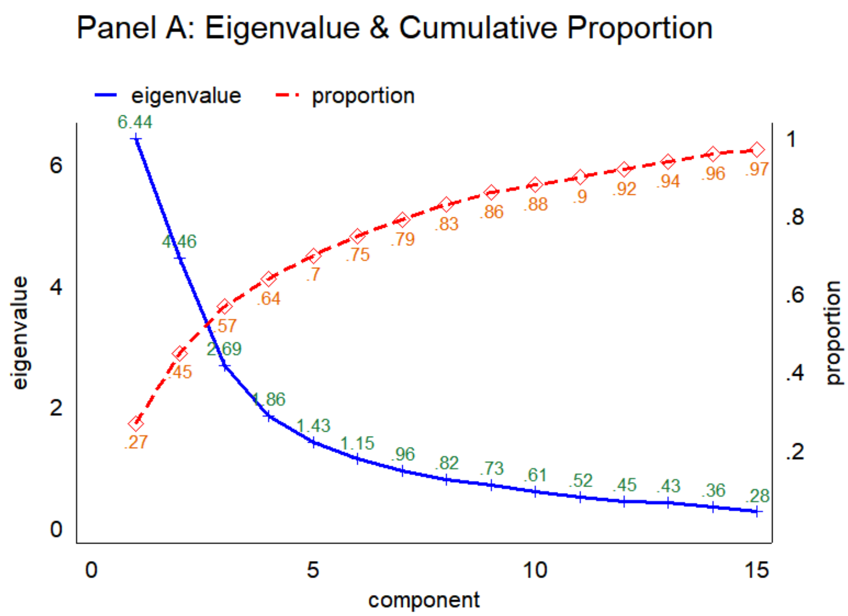
5 Investigating Mechanism

In this section, we explore the potential mechanisms for the cryptocurrency size and momentum effects. Size and momentum effects are two of the most studied phenomena in the stock market and have become the staples of current asset pricing models. The asset pricing literature has proposed various potential explanations and mechanisms for these two strategies. However, a common critique of cross-sectional trading strategies is that the strategies may suffer from data mining or overfitting. In particular, it has been shown that the size effect in the equity market is weak outside of the original Banz (1981) sample.

For the cryptocurrency size effect, our findings are potentially in line with two mechanisms. First, it is suggested that size is a proxy for an illiquidity premium. We show three sets of evidence that are potentially consistent with this liquidity view: (1) the small coins have lower prices and higher Amihud illiquidity measure relative to the large coins; (2) in the cross-section, the cryptocurrency size premium is more pronounced among coins that have high arbitrage costs; and (3) in the time-series, the cryptocurrency size premium is larger at times of high cryptocurrency market volatility. Second, we find that the size premium is also consistent with a mechanism proposed by the recent cryptocurrency theories: the trade-off between capital gain and convenience yield (e.g., Cong, Li, and Wang 2018; Sockin and Xiong 2018; Prat, Danos, and Marcassa 2019). Investors obtain two benefits from holding cryptocurrencies: capital gain and the convenience from transactions. In equilibrium, the convenience yield of the larger and more mature cryptocurrencies is higher, and thus their capital gain should be lower. An important prediction is that the cryptocurrency size premium should be relatively large at times of high demand for transactions. Consistent with this prediction, we show that the size premium is larger at times of relatively high Bitcoin transactions.

Table 10: Principal Component Analysis

This table reports the principal component analysis of the full set of the long-short strategies. Panel A plots the eigenvalues and the cumulative shares of total variation explained for the first fifteen principal components. Panel B reports the correlation matrix of the first two principal components, the cryptocurrency excess market returns, the cryptocurrency size factor, and the cryptocurrency momentum factor.



Panel B						
	PC1	PC2	PC3	CMKT	CSMB	CMOM
PC1	1.000					
PC2	0.000	1.000				
PC3	-0.000	-0.000	1.000			
CMKT	-0.178	0.078	0.357	1.000		
CSMB	-0.826	-0.209	0.211	0.127	1.000	
CMOM	-0.227	0.662	-0.124	0.073	0.006	1.000

The theories of momentum effect commonly involve behavioral explanations. Daniel, Hirshleifer, and Subrahmanyam (1998), Barberis, Shleifer, and Vishny (1998), and Hong and Stein (1999) provide explanations for the momentum effect based on different psychological biases. Both investor overreaction and underreaction are proposed as potential channels to explain the momentum effect. We find that the cryptocurrency momentum effect is plausibly consistent with the investor overreaction mechanism. After the initial continuation, there is a long horizon reversal effect. Moreover, we find that the cryptocurrency momentum effect is markedly stronger among the large and well-known coins. These findings are in line with the attention-based overreaction-induced momentum effect (Peng and Xiong 2006; Andrei and Hasler 2015). Consistent with these theories, we further show that (1) the cryptocurrency momentum effect is more pronounced among coins that receive high investor attention, and (2) the momentum factor is stronger at times of high investor attention.

It is important to note that, although we provide evidence to support some plausible mechanisms underlying the cryptocurrency size and momentum effects, the channels are only possible explanations and do not imply a definitive answer.

5.1 Cryptocurrency Size Effect

Portfolio Characteristics

Firstly, we explore the characteristics of the market capitalization and the three-week momentum quintile portfolios. We calculate the value-weighted characteristics for each of the quintile portfolios. The characteristics include price, Amihud illiquidity, coin age, 7-day return standard deviation, 30-day return standard deviation, and idiosyncratic volatility measures. The results are reported in Table IA.5 of the Internet Appendix.

For the quintile portfolios based on market capitalization, the first quintile portfolio, which is comprised of small coins, has lower average price, relative to the fifth quintile portfolio. Based on the Amihud-illiquidity measure, the coins in the first quintile are much less liquid compared to those in the fifth quintile. Moreover, the coins in the first quintile portfolio are generally younger and have higher volatility than those in the fifth quintile portfolio. In summary, the small coins have lower prices and are less liquid compared to the big coins. The results are consistent with the finding that the cryptocurrency size factor absorbs the return premia of price volume, price, and other size-related strategies. The results on the characteristics of the market capitalization quintile portfolios are consistent with the narrative that size proxies for a liquidity effect.

For the quintile portfolios based on past three-week returns, the average price and age of the fifth portfolio are also larger than those of the first portfolio. The Amihud illiquidity measure of the fifth portfolio is slightly lower than that of the first portfolio. Overall, the results show that the high momentum portfolio contains larger and more liquid coins.

Cost of Arbitrage

Secondly, we test the implications of Shleifer and Vishny (1997) and Pontiff (2006) on the cryptocurrency size effect in the cross-section. These two papers argue that the size premium should be strong among assets that are hard to arbitrage, where the competitive arbitrageurs may not engage in the arbitrage opportunity. We proxy for the cost of arbitrage using a composite index based on the methods of Stambaugh, Yu, and Yuan (2015) and Atilgan, Bali, Demirtas, and Gunaydin (2019). To construct the composite index, we use five underlying measures: idiosyncratic volatility, coin age, Amihud illiquidity, coin price, and volume-volatility measures. The first four measures are the costs of arbitrage measures proposed in the literature. We construct the volume-volatility measure as the ratio between cryptocurrency volume and return volatility, to proxy for the dispersion of investor expectations. This measure is motivated by Biais and Bossaerts (1998), who show that the volume-volatility ratio summarizes the degree of disagreement among the investors and discriminates between genuine disagreement and mere Bayesian learning with agreeing agents. We sort cryptocurrencies into quintiles based on their volatility, Amihud illiquidity, volume-volatility ratio, price and age so that higher quintile indicates higher costs of arbitrage. Then, we assign each cryptocurrency the corresponding score of its quintile rank for all five variables. The cost of arbitrage index is defined as the sum of the five scores, and higher values indicate higher costs of arbitrage.

Then, we double sort cryptocurrencies based on their cost of arbitrage and market capitalization. We document the results in Table IA.6 of the Internet Appendix. Consistent with the implications of Shleifer and Vishny (1997) and Pontiff (2006), we find that the cryptocurrency size effect is more pronounced among coins with higher arbitrage costs. The long-short strategy for the tercile with high arbitrage cost generates a spread of 8.7 percent. The long-short strategy for the low arbitrage cost tercile does not generate a statistically significant return premium. We also find a positive relation between future returns and arbitrage risks among the small size coins.

Moreover, in Table IA.6 of the Internet Appendix, we report double sorting results based on the cost of arbitrage and the cryptocurrency three-week momentum. We find that the cryptocurrency momentum effect does not concentrate on the high arbitrage cost group. In fact, the three-week momentum effect is stronger among the low arbitrage cost group.

Time-Series Analysis

Thirdly, we study the exposures of the cryptocurrency size and momentum factors to the time-series variables. Specifically, we test the exposures of the cryptocurrency size and momentum factors to the Daniel, Hirshleifer, and Sun (2019) behavioral factor model, the Fama-French 3-factor model, the Carhart 4-factor model, the Fama-French 5-factor model, the standard deviations of the cryptocurrency market returns, and the logged Bitcoin transaction amount. The results are summarized in Table IA.7 of the Internet Appendix. The time-series test is performed at the weekly frequency.

The cryptocurrency size and momentum factors do not significantly expose to any of the stock market factors in the time-series. However, the cryptocurrency size factor significantly and positively exposes to the standard deviations of the cryptocurrency market returns, suggesting that the cryptocurrency size factor performs well when the cryptocurrency market is more volatile. The result further supports the liquidity view of the size premium. On the other hand, the momentum factor does not significantly expose to the standard deviations of the cryptocurrency market returns.

Lastly, we test the implications of the trade-off theory between capital gain and convenience yield as proposed by the recent cryptocurrency models (e.g., Cong, Li, and Wang 2018; Sockin and Xiong 2018; Prat, Danos, and Marcassa 2019). Specifically, we examine whether the cryptocurrency size premium is more pronounced at times of high Bitcoin transactions. We regress the cryptocurrency size premium on the log of Bitcoin transaction amount. Consistent with the theory, we find that the cryptocurrency size factor positively exposes to the logged transaction count measure, suggesting that the cryptocurrency size effect is larger when the convenience yield is higher. Unlike the size factor, the momentum factor does not expose to the logged Bitcoin transaction count measure.

Lottery and Skewness Effect

One potential explanation of the size effect is that it captures the lottery or skewness effect among the very small coins. We define a coin's skewness as its return skewness of the past week before the formation time.[17] Each week, we sort coins based on their skewness measure into quintile portfolios. The fifth quintile has the coins with the highest skewness measure, and the first quintile has the coins with the lowest skewness measure. We document the results in Table IA.8 of the Internet Appendix. The average excess return of the fifth quintile is 1.8 percent per week, and the average excess return of the first quintile is 0.9 percent per week. The average long-short strategy return based on skewness is positive (0.9 percent) but is not statistically significant (t-stat=0.98). The evidence is inconsistent with the idea that the lottery or skewness effect generates significant excess returns.

5.2 Cryptocurrency Momentum Effect

The behavioral explanations of the momentum effect (e.g., Barberis, Shleifer, and Vishny 1998; Daniel, Hirshleifer, and Subrahmanyam 1998; Hong and Stein 1999) suggest that the momentum phenomenon could arise as a result of either investors' delayed reaction or overreaction to information. Moreover, the behavioral models on overreaction imply that the momentum effect should be followed by reversals – a phenomenon observed in the equity market. Looking at the relatively long-horizon past returns in the cryptocurrency market, we observe patterns consistent with the long-term reversal effect.

We form portfolios based on 60-week, 70-week, 80-week, 90-week, and 100-week returns. In Table IA.9 of the Internet Appendix, we show that the long-short strategies that buy the long-term winner portfolio and short the long-term loser portfolio generate consistent negative future returns. The magnitude of the long-short strategy spread peaks at the 80-week momentum strategy, which generates a 1.5 percent weekly return and is significant at the 10 percent level. The long-short strategy return spreads of the other strategies are insignificant, plausibly due to the short sample period. This pattern is plausibly consistent with the models based on overreactions.

Recent theories also provide some risk-based explanations of momentum, such as Li (2017), which relies on firms' cash-flow riskiness to get momentum effects. Li (2017) generates

[17]Results are qualitatively similar if we use return skewness in the past month to measure coins' skewness.

momentum effects because, in his model, winner firms have high short-term profitability and investment commitment, which leads to more negative exposures to the price of investment goods than loser firms. This particular risk-based explanation of momentum has difficulty in explaining the cryptocurrency momentum effect because the channel relies on the cash flow riskiness of the winner firms induced by making greater commitments to future capital investment than loser firms. We find that the cryptocurrency momentum effect is strong at the relatively short horizons (less than a month), which is unlikely to match the investment adjustment horizons. Indeed, the momentum effect in the equity market that the cash-flow explanation is based on has a much longer horizon for one year. Additionally, the mechanism in Li (2017) relies on the differential exposures of the winner firms and loser firms to the shocks to the price of investment goods. Therefore, we test whether the cryptocurrency momentum factor exposes to the fluctuations in the price of investment goods. Following Li (2017), we measure the relative price shocks as the changes in the logarithm of the price deflator of investment goods relative to that of nondurable consumption goods. We find that the cryptocurrency momentum factor does not significantly expose to the relative price shocks with a t-statistic of only 0.85.

Relationship Between Cryptocurrency Size and Momentum

A key implication of the behavioral-based underreaction channel is that the momentum effects should be stronger among assets that receive less attention (e.g., small size). The cryptocurrency market consists of both large and well-known coins and small and obscure ones, which provides a sound setting in testing the underreaction-based delay channel. We test whether the cryptocurrency momentum effects are consistent with the underreaction channel by examining the relationship between cryptocurrency momentum and size.

We double sort first on market capitalization into two groups at the median. Then, within each size group, we sort cryptocurrencies based on the past three-week returns into five groups. The results are reported in Table IA.10 of the Internet Appendix. We find that the long-short momentum strategy in the below-median size group generates insignificant weekly returns. In contrast, the long-short momentum strategy in the above-median size group generates statistically significant 3.2 percent weekly returns. This implies that the momentum strategy works better for the larger coins in the cryptocurrency market. This finding is in contrast to the equity market, where momentum strategies work better among smaller stocks (see Hong, Lim, and Stein 2000). The finding that the cryptocurrency momentum effect is concentrated among large coins poses a challenge to the underreaction-based explanations of the momentum effect. In the next subsection, we further investigate the possible mechanism underlying the cryptocurrency momentum effect.

Attention and Momentum

The phenomenon that the momentum effect is concentrated among the large coins is most consistent with recent theories of investor overreaction (Peng and Xiong 2006; Andrei and Hasler 2015). In particular, the idea that the overreaction-induced momentum effect should be more pronounced among high attention assets. In the Peng and Xiong (2006) model when applied to the cryptocurrency market, each coin has fundamental factors that are not directly observable, with positive and negative shocks to the factors at different times. Investors have limited attention and they need to process information to infer the values of cryptocurrencies.[18] Investors are also subject to overconfidence, and thus they overestimate the precision of their acquired information (Daniel, Hirshleifer, and Subrahmanyam 1998; Peng and Xiong 2006). Together the limited attention and overconfidence lead to overreaction-induced momentum effect among cryptocurrencies with high investor attention.

We further test some of the predictions from the attention-driven overreaction-based momentum theories (Peng and Xiong 2006; Hou, Xiong, and Peng 2009). We test the hypothesis that the overreaction-driven momentum effect is stronger among high attention cryptocurrencies. We use two ways to proxy investor attention. For the first one, we follow Hou, Xiong, and Peng (2009) and use volume as a proxy for investor attention. However, as noted before, the volume data may be subject to misreporting. Therefore, we use Google searches as an alternative proxy for investor attention. We summarize the results in Table IA.11 in the Internet Appendix.

Panel A of the table shows the results using volume data. For each week, we first sort individual coins into two portfolios based on their price volume in the week. The first portfolio has coins with below-median price volume, and the second portfolio has coins with above-median price volume. Then, within each volume portfolio, we sort coins into

[18]The investor attention constraint and attention allocation are governed by the entropy concept from information theory in Peng and Xiong (2006).

quintiles based on past three-week returns. The first portfolio has coins with the lowest past three-week returns and the fifth portfolio has coins with the highest past three week returns. Consistent with the hypothesis, the momentum effect is more pronounced among coins with high attention as proxied by trading volume. For the low volume group, the long-short strategy return based on the past three-week return has a statistically insignificant -0.6 percent per week. For the high volume group, the long-short strategy return based on the past three-week return has a statistically significant 3.4 percent per week. The excess returns are monotonically increasing across the quintile portfolios for the high volume subgroup. The results echo the findings of Hou, Xiong, and Peng (2009), who show that the price momentum effect is more pronounced among stocks with high attention as proxied by stock trading volume.

Panel B of the table uses Google searches of individual coins as an alternative proxy for investor attention. The Google search measure is a direct proxy for investor attention of individual coins and does not use the potentially unreliable volume data in the cryptocurrency market. For each week, we first sort individual coins into two portfolios based on their Google search in the week. The first portfolio has coins with below-median Google search, and the second portfolio has coins with above-median Google search. Then, within each Google search portfolio, we sort coins into quintiles based on past three-week returns. Consistent with the hypothesis, the momentum effect is more pronounced among coins with high attention as proxied by Google search. For the low Google search group, the long-short strategy return has a statistically insignificant 1.6 percent per week. For the high Google search group, the long-short strategy return has a statistically significant 3.6 percent per week. The excess returns are monotonically increasing across the quintile portfolios for the high Google search subgroup.

Additionally, as discussed in Hou, Xiong, and Peng (2009), another prediction of Peng and Xiong (2006) is that the overreaction-driven momentum effect should be stronger at times of high investor attention. This is a time-series prediction, as opposed to the cross-sectional prediction above. Following Liu and Tsyvinski (2018), we use Google searches as a measure of aggregate investor attention in the time-series. We count the Google search for the word "blockchain" as the measure of investor attention and denote the variable $\textbf{\textit{Google}}$.[19] To test whether the momentum effect is stronger at times of high investor attention, we regress

[19] Alternatively, using the word "cryptocurrency" generates qualitatively similar results.

the momentum factor on the lagged $Google$ variable. The results are shown in Panel C of the table. Column (1) of Panel C regresses the momentum factor on $Google$ only. The coefficient estimate on $Google$ is positive and statistically significant at the 1 percent level, suggesting that the momentum effect is larger at times of high investor attention as measured by Google search. In Columns (2) and (3), we include cryptocurrency market and size factors as controls. The coefficient estimates on $Google$ remain highly statistically significant and the magnitudes are close to the standalone specification in Column (1). Furthermore, to better gauge the economic magnitude, we create a discrete version of the $Google$ variable by constructing a tercile $Google^{rank}$ variable based on the value of the $Google$ variable. Columns (4)–(6) report the results based on $Google^{rank}$. The coefficient estimates on $Google^{rank}$ are all statistically significant at the 5 percent level. The magnitudes of the coefficient estimates are large. Based on the estimate, the average momentum factor returns of the top tercile, or high attention periods, is about 4 percent higher than the average momentum factor returns of the bottom tercile, or low attention periods. We also use the Twitter posting data as an alternative aggregate attention measure, and the results are summarized in Columns (7)–(9) of the table.[20] Although the economic magnitudes are smaller, the results using Twitter posting data are consistent with the results using Google search data.

Overall, the results suggest that the momentum effect in the cryptocurrency market is more pronounced among high attention coins and during periods of high attention.

6 Additional Results

In this section, we describe seven sets of additional results: the multiple hypothesis testing, the implementability and robustness of the strategies, comparison between cryptocurrency and currency markets, relationship to initial coin offerings, the analysis of the cross-sectional regressions, adjusting the stock market factors, and hedging unpriced risks.

6.1 Multiple Hypothesis Testing

Among the 24 predictors we investigate, ten form successful long-short zero-investment strategies. However, the strategies are not independent of each other. In this subsection, we

[20]We thank William Goetzmann for sharing the Twitter posting data with us.

investigate the multiple hypothesis testing problem and test the joint significance of the set of strategies we study. Using two methods, the k-familywise error rate (k-FWER) method in Lehmann and Romano (2005) and the joint F-test as in Gibbons, Ross, and Shanken (1989), we show that it is difficult to generate the results by chance.

We start by adjusting the p-value using the k-familywise error rate (k-FWER) method in Lehmann and Romano (2005). Our main results show that ten out of the 24 characteristics we considered generate significant long-short strategy returns. We set $k = 10$, which corresponds to the probability under the null of falsely rejecting ten or more hypotheses. Because we start with 24 characteristics or 24 hypotheses, based on the formula in Lehmann and Romano (2005), we need to cut the 5 percent p-value threshold from 0.05 to $0.05 \times 10/24 = 0.021$ and the 10 percent p-value threshold from 0.10 to $0.10 \times 10/24 = 0.042$.

Panel A of Table 11 reports the results and shows the actual p-value of each successful long-short strategy average return and whether the strategy is significant at the 5 percent level (10 percent level) under the k-FWER threshold. All the non-momentum strategies are significant at the 5 percent level under the k-FWER threshold. The two-week and three-week momentum strategies are significant at the 5 percent level under the k-FWER threshold. The one-week and four-week momentum strategies are significant at the 10 percent level under the k-FWER threshold. The only strategy that is not significant at the 10 percent level under the k-FWER threshold is the one-to-four-week momentum strategy.

Additionally, we provide a joint test considering both the significant and insignificant strategies to see whether the mean excess returns are jointly different from the null that they are all zero.[21] The results are reported in Panel B of Table 11. Column (1) of Panel B shows the F-test result that tests whether the mean excess returns of the 24 strategies are jointly different from the null that they are all zero. The p-value is 0.001, suggesting that we can reject the null hypothesis that the mean excess returns are all zero at the 1 percent level. Columns (2) and (3) report the F test results as in Gibbons, Ross, and Shanken (1989), where the factor models used are the Fama-French 6-factor model and the cryptocurrency three-factor model, respectively. The p-value based on the Fama-French 6-factor model is 0.033, suggesting that we can reject the null hypothesis that the alphas of the 24 strategies adjusted for the Fama-French 6-factor model are jointly zero at the 5 percent level. The p-

[21] This joint test does not require us to pick the successful strategies. The additional strategies may provide a more stringent test and higher hurdle for the results.

value based on the cryptocurrency 3-factor model is 0.194, suggesting that we cannot reject the null hypothesis that the 24 alphas adjusted for the cryptocurrency 3-factor model are jointly zero. These results are consistent with the main conclusion in the paper that the cryptocurrency three-factor model is successful in pricing the 24 strategies we considered.

Table 11: Multiple Hypothesis Testing

This table shows the results of multiple hypothesis testing. Panel A reports the results adjusting the p-value for the ten successful long-short strategies using the k-familywise error rate (k-FWER) method in Lehmann and Romano (2005) where $k = 10$. Panel B shows the joint test of significance for the 24 long-short strategies using F tests.

Panel A: k-FWER Adjustment			
	p-value	Adj 5%	Adj 10%
	Actual	0.021	0.042
MCAP	0.015	✓	✓
PRC	0.013	✓	✓
MAXDPRC	0.011	✓	✓
r 1,0	0.029		✓
r 2,0	0.004	✓	✓
r 3,0	0.008	✓	✓
r 4,0	0.025		✓
r 4,1	0.070		
PRCVOL	0.015	✓	✓
STDPRCVOL	0.008	✓	✓
Panel B: Joint Test of Significance			
Join Test	(1)	(2)	(3)
	Mean	FF 6Fac	Cryto 3Fac
p-value	0.001	0.033	0.194

6.2 Implementability and Robustness of the Strategies

We have a short sample of cryptocurrency data spanning from the beginning of 2014 to July of 2020. The short period imposes potential barriers to our study. Moreover, there is a great deal of uncertainty and learning about cryptocurrencies during the period. As argued by Pástor and Veronesi (2003), it takes time for investors to fully learn and understand emerging technologies. For these reasons, one may concern about the results being short-lived.

We partially address these concerns by breaking the sample period into two halves and checking whether our results are stable for these subsamples. During the first half of the sample, there were considerably more uncertainty and learning about cryptocurrency as an asset class. We find that the directions of all of the results are the same for the first and second halves of the sample. There is potentially still a lot of uncertainty and learning about cryptocurrencies today, but the assumption we need for the subsample tests is relatively mild: the uncertainty has decreased from the first half of the sample period to the second half of the sample period.

One concern with constructing the zero-investment strategies in cryptocurrencies is that shorting is not readily available for most of the coins. Based on the cryptocurrency one-factor adjusted alphas in Table 8, we calculate the contributions of the long-end and the short-end to the strategies, relative to the average coin market returns. For the non-momentum strategies, the long-side of the strategies accounts for the majority of the return spreads. The alphas of the long positions are all significantly positive, and the alphas of the short positions are small and insignificant. The results suggest that it is relatively easy to implement the non-momentum strategies because it only requires buying the small coins and shorting Bitcoin.

For the momentum strategies, both the long- and the short-ends account for some of the spreads. For example, in Table 4, the fifth quintile or the long-end of the two-week momentum strategy has an average excess return of 3.1 percent per week and the first quintile or the short-end of the two-week momentum strategy has an average excess return of 0.0 percent per week. However, the level of the excess returns includes the exposures to the average coin market excess returns, which are significantly positive. A portfolio of coins with zero average returns significantly underperforms the average cryptocurrencies. Accordingly, we use the level of coin market returns as the benchmark. Relative to the average coin market returns, as shown in Table 8, the long-end of the two-week momentum strategy has a coin market return adjusted alpha of 1.8 and the short-end has a coin market return adjusted alpha of -1.1. Therefore, the contribution of the long-end (short-end) to the two-week momentum strategy based on the coin market return adjusted alpha is $1.8/(1.8 + 1.1) = 62\%$ (38%). Similarly, the long-end of the three-week momentum strategy has a coin market return adjusted alpha of 2.4 and the short-end of the three-week momentum strategy has a coin market return adjusted alpha of -0.6. The contribution of the long-end (short-end) to the three-week momentum strategy based on the coin market return adjusted alpha is $2.4/(2.4 + 0.6) = 80\%$ (20%).

6.2.1 Using Bitcoin for Short Portfolios

Table IA.12 in the Internet Appendix presents the analysis of the strategies that short Bitcoin rather than shorting the relevant strategy quintiles. The results are qualitatively similar to those of Section 4. The reason is that most of the relevant factor quintiles behave similarly to Bitcoin. The exceptions are the momentum factors for which the lowest quintiles behave differently from Bitcoin. As a result, the mean returns of the one-, four-, and one-to-four-week momentum strategies are no longer statistically significant, and the returns to the Bitcoin zero-investment strategies are somewhat different. We also report the results adjusting for the one- and three-factor cryptocurrency models. Consistent with the findings in Section 4, none of the alphas remain statistically significant controlling for the cryptocurrency three-factor model.

6.2.2 Top 20 Coins Only

The portfolio sorting results based on size show that the size premium is mainly driven by the smallest quintile portfolio, suggesting that the size effect is non-linear and concentrated among the smallest coins. We further investigate the behavior of the size effect by restricting our sample to the largest and most liquid coins in the market and test the performances of the successful long-short strategies. Each period, we restrict our sample to the largest 20 coins at the time based on the market capitalizations of the cryptocurrencies. We form tercile portfolios based on each of the ten significant factors. The results are reported in Table IA.13 of the Internet Appendix. The directions of the long-short portfolios are the same as those based on the whole sample. Among the top 20 coins, buying the smallest tercile of coins and shorting the largest tercile of coins generate positive excess returns based on market capitalization (0.2 percent per week), price (1.0 percent), and maximum day price (0.9 percent). However, these long-short strategies are not statistically significant. The large coins are in general much more liquid than the small coins, and thus the cryptocurrency size premia decrease among these largest cryptocurrencies. For the momentum strategies, the average long-short strategy returns are highly statistically significant. The sizes of the premia are larger than those of the baseline results, consistent with the above findings that the cryptocurrency momentum effects are stronger among large coins. Additionally, in Table IA.14 of the Internet Appendix, we show that using the top 100 coins with quintile portfolios also generates qualitatively similar results.

6.2.3 Crypto-to-USD Pair Only and Reputable Exchanges

Another concern about the results is that many of the cryptocurrencies are not directly traded against fiat money in small exchanges, where the price and volume information may be inaccurate. The information of Coinmarketcap.com is aggregated from many exchange platforms and is denominated in the U.S. Dollar. The data collection process by Coinmarketcap.com may also lead to spurious findings.

To mitigate these concerns, we test the sensitivity of our results using cryptocurrencies that are traded against USD in at least one of the following three large and reputable cryptocurrency exchanges: Kraken, Coinbase Pro, and Bitfinex. To mitigate concerns of aggregation, we use price and volume data from the cryptocurrency exchanges directly. If the cryptocurrency is traded on Kraken, the data is from Kraken. If the cryptocurrency is traded on Coinbase Pro but not on Kraken, the data is from Coinbase Pro. If the cryptocurrency is only traded on Bitfinex, the data is from Bitfinex.

We report the results for the ten significant factors in Table IA.15 of the Internet Appendix. The directions of the long-short strategy returns are consistent with the baseline results. Buying the smallest quintile of coins and shorting the largest quintile of coins generate positive excess returns based on market capitalization (2.4 percent), price (2.1 percent), and maximum day price (2.1 percent). However, the long-short strategy based on market capitalization is insignificant. In general, the strategies based on the momentum effect stay large and significant.

6.2.4 Accounting for Trading Costs

We also address concerns about trading costs and test the extent to which the trading profits remain after incorporating trading costs. We consider three kinds of transaction costs: trading fees, bid-ask spreads, and shorting fees. To be conservative, we focus on the strategies using the largest 20 coins. These coins are the most liquid coins in the market, and it is relatively easy to evaluate the trading costs of these coins. We focus on long-only strategies and long-short strategies that short Bitcoin, because shorting the small coins are difficult to implement.

Static Trading Cost

To evaluate the impact of trading fees on the cross-section of portfolio returns, we collect the trading fees for the major cryptocurrency exchanges in our sample. The trading fees range from 0.1 percent to 0.2 percent. Therefore, we test the impact of trading fees on the strategy returns based on both the lower bound (0.1 percent) and the upper bound (0.2 percent). To evaluate the impact of bid-ask spread on the strategy returns, we first collect the bid-ask spreads of Bitcoin from Bitcoinity.org. The bid-ask spreads were relatively high in early 2014, reaching 0.3 percent at one point. The spreads quickly declined in 2015 and stayed at a low level (less than 0.1 percent) ever since. The bid-ask spread for Bitcoin is close to 0.001 percent recently. Second, we collect the current bid-ask spreads of several top cryptocurrency-USD pairs from Tokenspread.com.[22] The bid-ask spreads of Bitcoin (1st largest) and Ripple (3rd) are 0.001 percent. The bid-ask spread of Ethereum (2nd) is 0.01 percent. The bid-ask spreads of Bitcoin Cash (5th) and Litecoin (6th) are 0.05 percent. The bid-ask spreads of Dash (17th) and Monero (13th) are 0.27 percent and 0.34 percent, respectively. Therefore, we make a conservative assumption and set the bid-ask spreads of the top 20 coins to be 0.5 percent. We further assume that the price is halfway in between the bid and ask prices. Lastly, we set the margin fee required to maintain a short position for one week for Bitcoin to be 0.35 percent.

Table IA.16 in the Internet Appendix reports the results for the long-only strategies and the long-short strategies that short Bitcoin. The results are based on the largest 20 coins and tercile portfolios. For the long-only strategies, we long the first portfolios of the non-momentum strategies and long the third portfolios of the momentum strategies. The two costs associated with the long-only strategies are the trading fees and the bid-ask spreads. We report the average raw excess returns, the trading cost adjusted excess returns, and the

[22] The bid-ask spread data is based on Sep 27th, 2019, which is the date we collected the data. The date does not hold any special significance.

ratios between the adjusted excess returns and the raw excess returns. The ratios between the adjusted returns and the raw returns are around 90 percent. The exception is the one-week momentum strategy, where the ratio is about 80 percent, because the turnover rate of this strategy is high at about 70 percent per week.

For the long-short strategies, we also take the cost of shorting Bitcoin into consideration. Again, we report the average raw excess returns, trading cost adjusted excess returns, and the ratios between the adjusted excess returns and the raw excess returns in the table. As discussed in the top 20 coins only section, the excess returns for the non-momentum strategies are generally lower than the full sample results, because the cryptocurrency size effects are concentrated among the small coins. However, the directions of the raw excess returns are all in line with the main results. Adjusted for the transaction costs, the strategy based on market capitalization is no longer profitable, while the other nine strategies remain profitable.

Dynamic Trading Cost

Alternatively, we calculate the effective bid-ask spread measure proposed in Hasbrouck (2009). The estimation of the effective bid-ask spread measure only uses price information so that we can estimate the bid-ask spread of each coin at any given year. The effective bid-ask spreads are estimated using a Bayesian Gibbs sampler on a generalized Roll (1984) of stock price dynamics.[23] As discussed in Novy-Marx and Velikov (2015) and Frazzini, Israel, and Moskowitz (2018), the effective bid-ask spread is a relatively conservative measure. The average effective bid-ask spread for the top 20 coins is around 0.5 percent since 2018. The number is higher for the earlier part of the sample at around 1.5 percent. We make the same assumptions for the fee and shorting cost as in the static trading cost section. The results are presented in Table IA.17 of the Internet Appendix. For the long-only strategies, the ratios between the adjusted excess returns and the raw excess returns are generally around 90 percent. The exception is the one-week momentum strategy, where the ratio is about 80 percent, because the turnover rate of the one-week momentum strategy is high. For the long-short strategy, the ratios between the adjusted excess returns and the raw excess returns are around 60 percent. Similar to the static adjustment, the strategy based on

[23] Hasbrouck provides code for estimating the effective bid-ask spread measure at http://people.stern.nyu.edu/jhasbrou/Research/GibbsCurrent/gibbsCurrentIndex.html.

market capitalization is no longer profitable after adjusted for transaction costs, while the other nine strategies remain profitable.

6.3 Comparing Cryptocurrency and Currency Markets

We motivate the analyses in the paper using the equity market since the equity market is perhaps the most studied market and many trading strategies in other asset markets can find their counterparts in the equity market. However, the market capitalization of Bitcoin is by far the largest in the current cryptocurrency system, making its excess returns highly correlate with the coin market excess returns. This is an important distinction between the equity market and the cryptocurrency market. In this subsection, we compare the cryptocurrency market with the currency market as there are several similarities between the two.

First, both the cryptocurrency market and the currency market have clear level factors: Bitcoin and the U.S. dollar. We conduct tests using an alternative coin market return measured as the value-weighted return of all coins excluding Bitcoin and document the results in Table IA.18 of the Internet Appendix. We denote this alternative cryptocurrency market factor as $CMKT^2$. The correlation between $CMKT$ and $CMKT^2$ is 0.82. For each of the ten successful strategies, we regress the level portfolio returns and the long-short strategy spread on $CMKT^2$ and compare the R^2s with those from using $CMKT$. Similar to $CMKT$, $CMKT^2$ does not account for much of the long-short strategy spreads of the ten successful strategies. We then focus on the average R^2 of the level portfolios for each strategy. The average R^2s range from 0.468 for the size strategy using MCAP to 0.559 for the past four-week strategy. The average R^2s are lower than those based on $CMKT$. The cryptocurrency market factor with Bitcoin performs well in explaining portfolios that contain Bitcoin. For example, the R^2 for the highest price portfolio is 0.583 based on $CMKT^2$ but is 0.976 based on $CMKT$. The results suggest that Bitcoin accounts for an important portion of the cryptocurrency market factor in explaining the level portfolios of the strategies.

Second, as documented in Menkhoff, Sarno, Schmeling, and Schrimpf (2012), there is a strong momentum effect in the international currency markets. Moreover, Menkhoff, Sarno, Schmeling, and Schrimpf (2012) show that there is a long-run reversal effect in the currency market and that the currency momentum effect is more pronounced among currencies with high idiosyncratic volatility – we find a consistent phenomenon in the cryptocurrency market. We note that the momentum effect in other markets is at the monthly horizons, whereas the cryptocurrency momentum effect is at the weekly horizon.

Additionally, we note that cryptocurrency competition is a possible explanation of the cryptocurrency size effect. There have not been any theoretical papers on convenience yield in the cryptocurrency literature (e.g., Cong, Li, and Wang 2018; Sockin and Xiong 2018) that involves this element of cryptocurrency competition.[24] Therefore, we discuss a plausible mechanism of competition in the cryptocurrency market that can potentially generate the size effect. The small and young coins compete with each other. Only the winners of the competition become stable and long-lasting, while the losers of the competition are short-lived. Therefore, the risks associated with the small and young coins, especially the smallest ones, may be significantly higher than the large and mature coins, leading to higher average returns for the small coins and lower average returns for the large coins. This mechanism of cryptocurrency competition is thus plausibly consistent with the cryptocurrency size effect we document.

6.4 Relationship to Initial Coin Offering

There is a boom of initial coin offerings (ICOs) in recent years. Benedetti and Kostovetsky (2018) document a substantial amount of underpricing for the ICOs, with average returns of over 100 percent in the first month. The ICO boom may potentially account for the cryptocurrency size and momentum effects we show in this paper. We test the channel by investigating whether the long-short strategies can be accounted for by the returns of the ICOs.

We use a one-month horizon and a one-week horizon to construct the initial ICO returns. Then, we test the exposures of the returns of the long-short strategies to the ICO return index. Table IA.19 of the Internet Appendix shows the results. Panel A is based on ICO returns calculated over the first month. For all the strategies, the alphas adjusting for the cryptocurrency market and ICO returns remain statistically significant. For the strategies

[24] Benigno, Schilling, and Uhlig (2019) analyze a model where currency competes with cryptocurrency. Fernández-Villaverde and Sanches (2019) build a model of competition among privately issued fiat currencies and study its effect on price stability. However, neither studies the effect of cryptocurrency competition on asset valuation.

based on past returns, controlling for ICO returns barely changes the average long-short strategy returns. For the other strategies, controlling for ICO returns reduces the average long-short strategy returns by about 10 to 20 percent. Results are similar if we calculate ICO returns over the first week in Panel B. We conclude that, although controlling for ICO returns reduces the magnitudes of the excess returns of non-momentum strategies, the average excess returns remain statistically significant and large.

6.5 Additional Cross-Sectional Results

We test the robustness of the results from the cross-sectional regressions using the Fama-MacBeth method. Table 12 shows the results. We first sort each coin into one of five portfolios based on the corresponding characteristics. Then, we use the portfolio rank number as the explanatory variable. Panel A shows the results for the size-related predictors. All of them are individually statistically significant but not jointly significant. This is consistent with the fact that these predictors are correlated. Panel B and Panel C show the results for the price volume predictor and the volatility predictor, respectively. Both are statistically significant. Panel D shows that the past return predictors are not statistically significant in the Fama-MacBeth regressions. This is different from what we find in the previous section using the value-weighted portfolio strategies. A potential reason for this discrepancy is that, in essence, the Fama-MacBeth regressions consider each observation equally and thus are close to strategies formed on equally weighted portfolios. In Panel E, we show that the momentum strategies perform strongly for the large coins, defined as coins with more than 10 million dollar market capitalization.

We also report the results based on market cap weighted least squares (WLS) regressions. The results are presented in Table IA.20 of the Internet Appendix. The results based on the WLS regressions are consistent with the portfolio results and the standard Fama-MacBeth OLS cross-sectional regression results. The non-momentum characteristics negatively correlate with subsequent coin returns, and the momentum characteristics positively predict future coin returns. In the multivariate regression, we include market beta, market cap, and past three-week return as the independent variables. We show that market cap negatively predicts future coin returns, past three-week return positively predicts future coin returns, and market beta does not significantly predict future coin returns. Again, the results are consistent with the portfolio results.

Table 12: Fama-MacBeth Cross-Sectional Regression

This table reports the Fama-MacBeth regression results. Each characteristic is first sorted into five portfolios at the end of each week, and the portfolio rank numbers are used as the explanatory variables. Panel A, B, C, and D are based on the sample of coins with market capitalizations of more than 1 million dollars. Panel E is based on the sample of coins with market capitalizations of more than 10 million dollars. The t-statistics of the coefficient estimates are reported in the parentheses.*, **, *** denote significance levels at the 10%, 5%, and 1%.

			ret_{t+1}				
> 1 mil	Panel A	**MCAP**	-0.004**			-0.001	
			(-2.14)			(-0.85)	
		PRC		-0.007***		-0.030	
				(-3.58)		(-1.63)	
		MAXDPRC			-0.007***	0.023	
					(-3.64)	(1.29)	
	Panel B	**PRCVOL**	-0.006***				
			(-2.97)				
	Panel C	**STDPRCVOL**	-0.007***				
			(-3.34)				
	Panel D	**r 1,0**	-0.004				-0.004*
			(-1.63)				(-1.93)
		r 2,0		-0.002			0.003
				(-1.04)			(0.93)
		r 3,0			-0.003		-0.004
					(-1.46)		(-1.28)
		r 4,0				-0.002	0.001
						(-1.34)	(0.28)
> 10 mil	Panel E	**r 1,0**	0.005*				-0.005
			(1.93)				(-1.64)
		r 2,0		0.006***			0.006
				(2.68)			(1.57)
		r 3,0			0.007***		0.001
					(2.66)		(0.16)
		r 4,0				0.004*	0.004
						(1.86)	(1.20)

6.6 Stock Market Factors

We next investigate whether the stock market risk factors can explain the ten successful long-short strategies in the cryptocurrency market. Previous research (e.g., Asness, Moskowitz, and Pedersen 2013) finds that value and momentum strategies comove strongly across different asset classes. Hence, the cryptocurrency strategies may also comove with their corresponding counterparts in the equity market. In the Internet Appendix (Table IA.21 – Table IA.25), we present results based on the CAPM, Fama-French three-factor, Carhart four-factor, Fama-French five-factor, and the Daniel-Hirshleifer-Sun behavioral-factor models. We compute weekly returns for each of the equity factors from daily factor returns following the timing of the cryptocurrency portfolios as described in Section 3.[25] The results are qualitatively similar using any of the stock market factor models.

We briefly discuss the results based on the Fama-French three-factor model. Overall, the Fama-French three-factor model adjusted alphas of the cryptocurrency strategies are quantitatively similar to the unadjusted excess returns. For example, the adjusted alpha for the market capitalization long-short strategy is -6.3 percent per week with a t-statistic of -2.63. The unadjusted average excess return of the long-short strategy is -5.8 percent per week with a t-statistic of -2.45. The adjusted alpha for the three-week momentum long-short strategy is 3.3 percent per week with a t-statistic of 2.77. The unadjusted average excess return of the long-short strategy is 3.1 percent per week with a t-statistic of 2.65.

6.7 Hedged Strategies

Recent empirical asset pricing literature found that the common practice to create factor-portfolios by sorting on characteristics associated with average returns captures both priced and unpriced risks. Daniel, Mota, Rottke, and Santos (2018) develop a method to hedge the unpriced risks in the stock market using covariance information estimated from past returns. In this section, we apply their method to our factors and evaluate whether we can further strengthen the performance of our cryptocurrency factors.

We follow the procedure in Daniel, Mota, Rottke, and Santos (2018) and provide an

[25]Constructing weekly returns from daily returns implicitly rebalance the factor daily not at the signal level but in the blend and leverage dimensions. However, given the observed low exposures to equity factors, we do not expect this would be quantitatively important.

example based on the cryptocurrency size factor. Detailed descriptions of the theoretical motivation and empirical account can be found in Daniel, Mota, Rottke, and Santos (2018). We first rank all cryptocurrencies by their previous week's market capitalization. Breakpoints are selected at the 30 percent and 70 percent marks. Then, all cryptocurrencies are assigned to one of the three bins. Next, each of the three bins is further sorted into three equal bins based on the coins' expected covariances with the cryptocurrency size factor. We estimate the expected covariance between coin returns and the size factor using the rolling past 365 days of data. Finally, the hedge-portfolio for the cryptocurrency size factor is constructed as going long on an equal-weighted portfolio of the low size-factor-loading portfolios and short on an equal-weighted portfolio of the high size-factor-loading portfolios. We find that the hedge-portfolio does not carry statistically significant return spreads for either the cryptocurrency size strategy or momentum strategy, similar to findings in the stock market (See Daniel and Titman 1997). We build the cryptocurrency momentum hedge-portfolio in the same way.

We use the squared Sharpe-ratio to evaluate the performance of the strategies. For the cryptocurrency size factor, we find considerable gains from hedging the unpriced risks. The gains are economically large. However, for the cryptocurrency momentum factor, the adjustment does not increase the squared Sharpe-ratio of the momentum strategy. One possibility for the lack of improvement of the cryptocurrency momentum strategy is that the expected loadings on the momentum factors change faster and are more transient than those on the size factors.

7 Conclusion

This paper shows that the cross-section of cryptocurrencies can be meaningfully analyzed using standard asset pricing tools. We document that, similar to other asset classes (see, e.g., Asness, Moskowitz, and Pedersen 2013), size and momentum factors are important in capturing the cross-section of cryptocurrency returns. Moreover, a parsimonious three-factor model that can be constructed using the market information is successful in pricing the strategies in the cryptocurrency market.

Furthermore, we analyze a number of theoretical explanations for our factors. For the cryptocurrency size premium, our findings are potentially consistent with two mechanisms.

First, the cryptocurrency size factor relates to the liquidity effect. We provide three sets of evidence to support the liquidity view of the size premium: (1) the small coins have lower price and higher Amihud illiquidity measure relative to the large coins; (2) in the cross-section, the cryptocurrency size premium is more pronounced among coins that have high arbitrage costs; and (3) in the time-series, the cryptocurrency size premium is larger at times of high cryptocurrency market volatility. Second, we find some evidence that the size premium is consistent with a mechanism proposed by the recent cryptocurrency theories: the trade-off between capital gain and convenience yield (e.g., Cong, Li, and Wang 2018; Sockin and Xiong 2018; Prat, Danos, and Marcassa 2019). For the cryptocurrency momentum premium, we show that it is in line with the investor overreaction channel (e.g., Daniel, Hirshleifer, and Subrahmanyam 1998; Sockin and Xiong 2018). In particular, the findings are in line with the recent theories on attention-driven overreaction-induced momentum (Peng and Xiong 2006; Hou, Xiong, and Peng 2009). We note that although we provide evidence to support some plausible mechanisms behind the cryptocurrency size and momentum effects, the channels are only possible explanations.

The cryptocurrency market is a nascent and emerging market where many changes are taking place. The current state of the market is relatively underdeveloped, and it is possible that our results apply to an immature market where a lot of speculations and even frauds are present. When the cryptocurrency market becomes mature, the pricing dynamics of the market can also change. The cryptocurrency market is still in an early stage, and the sample period may have been unusual. The premia we documented in the paper are an order of magnitude larger than those in the equity market. It is unrealistic to expect the magnitudes of the premia to continue in the long run. However, in a broader point, our results may apply to other new asset classes that may come into existence in the future, and therefore studying cryptocurrencies help us learn more about new asset classes beyond just cryptocurrencies.

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