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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.

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: first, to establish a set of empirical regularities that can be used as stylized facts to assess and develop theoretical models, and second, to understand and differentiate the theoretical

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

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explanations of the asset pricing factors in both the traditional asset pricing and the newly developed cryptocurrency literature.

We consider all coins with market capitalization above 1 million dollars and their returns from the beginning of 2014 to July 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 has established a number of factors that explain the cross section of stock returns. Among the return predictors compiled by Feng, Giglio, and Xiu (2020) and Chen and Zimmermann (2020), we select those based only on price and market information and construct their cryptocurrency counterparts.[2] Of the 24 cryptocurrency characteristics we consider, 10 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 literature and the newly developed cryptocurrency literature have proposed theoretical explanations to account for the size and momentum phenomena. With respect to the cryptocurrency size premium, the findings are potentially consistent with two mechanisms. First, the cryptocurrency size factor may capture the liquidity effect. Second, the size premium is consistent with the trade-off between capital gains and the convenience yield proposed by recent cryptocurrency theories (e.g., Sockin and Xiong (2018), Prat, Danos, and Marcassa (2019), Cong, Li, and Wang (2021))—in equilibrium, the convenience yield of larger and more mature cryptocurrencies is higher, and thus their capital gains should be lower. With respect to 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)).

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

We next analyze the performance 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 each portfolio's average excess return over the risk-free rate. We then form a 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 of the 24 characteristics, namely, market capitalization, price, and maximum price; past one-, two-, three-, four-, and one-to-four-week

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

return; price volume; and standard deviation of price volume. We now turn to a 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% excess weekly returns (5.8% for market capitalization, 3.2% for end-of-week price, and 3.3% for 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% excess weekly returns (2.5% for one-week momentum, 3.1% for two-week momentum, 3.1% for three-week momentum, 2.2% for four-week momentum, and 1.7% for one-to-four-week momentum strategies). For the volume-related strategies, a zero-investment strategy that longs coins with the lowest volume and shorts coins with the highest volume generates about 3% excess weekly returns (3.3% for price volume). For the volatility strategy, a zero-investment strategy that longs coins with the lowest price volume volatility and shorts coins with the highest price volume volatility generates 3.2% excess weekly returns. For all of these strategies, returns on individual quintile portfolios change almost monotonically 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 10 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 Capital Asset Pricing Model (CAPM) model. The results are similar to those for 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 10 successful zero-investment strategies. Adjusted for the cryptocurrency three-factor model, none of the alphas of the 10 strategies remains statistically significant. The CSMB factor accounts for the following strategies: market capitalization, price, maximum day price, price volume, and 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.

Motivated by the Arbitrage Pricing Theory of Ross (1976), we also conduct principal component analysis on the 24 long-short strategies. We show that the first two principal components account for more than 45% of the variation in the 24 long-short strategies. In particular, the first and second principal components strongly correlate with the cryptocurrency size and momentum factors, respectively, while the cryptocurrency market factor captures the level instead of the long-short strategy premia. Results based on the 10 successful long-short strategies show a similar pattern. When we examine the level of the portfolios for the 24 strategies, we find that the first three principal components account for 73% of the variation 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 well captures the cross section of cryptocurrencies' expected returns.

We next examine plausible mechanisms behind the cryptocurrency size and momentum effects. With respect to the cryptocurrency size effect, the findings are potentially consistent with two mechanisms. First, part of the size premium may capture the illiquidity premium of the market. We find three sets of evidence that are in line with this liquidity view of size premium: (i) small coins have lower prices and higher Amihud illiquidity measures relative to large coins, (ii) in the cross section, the cryptocurrency size premium is more pronounced among coins that have high arbitrage costs, and (iii) in the time series, the cryptocurrency size premium is larger at times of high cryptocurrency market volatility. Second, consistent with recent theories emphasizing the trade-off between capital gains and the 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 over 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 weekly returns of 3.2%. 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 (i) the cryptocurrency momentum effect is more pronounced among coins that receive high investor attention, and (ii) the momentum factor is stronger at times of high investor attention.

We document several additional results. First, we investigate the multiple hypothesis testing problem and test the joint significance of the 10 successful strategies. Using the k-familywise error rate (k-FWER) 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. Second, 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 are almost unchanged. We next focus on the 20 largest and most liquid cryptocurrencies and test the trading strategies. We show that using the top 20 coins yields qualitatively similar results. When we restrict our sample to those cryptocurrencies that are traded against the U.S. dollar on reputable exchange platforms, we continue to find consistent results. We further account for three different trading costs—trading fees, bid-ask spreads, and shorting fees—and find that although transaction costs are substantial in the cryptocurrency market, about 90% of the long-only strategy returns and 60% of the long-short strategy returns remain after the adjustments.

Third, we examine 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), and both markets exhibit momentum effects. Fourth, we show that the cryptocurrency size and momentum effects are not driven by the surge of ICOs. Fifth, we show consistent results using Fama-MacBeth cross-sectional regressions. Sixth, we show that the stock market factor models, such as the Fama-French three-factor, Carhart four-factor, and the Fama-French five-factor models, do not account for the cross section of cryptocurrency returns. Finally, we show that removing the unpriced risks similar to Daniel et al. (2020) strengthens the cryptocurrency size factor but not the cryptocurrency momentum factor. One possible explanation for this result is that loadings on the cryptocurrency momentum factor are more transient than loadings on the cryptocurrency size factor.

Turning to the relationship between our paper and 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 interpretation of the size effect, suggesting that the size effect may be the result of data mining. Our 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), and Hong and Stein (1999)). Risk-based explanations of the momentum effect consider companies' organization and cash-flow timing (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 the size premium (e.g., Amihud (2002), Bali et al. (2005), Bali and Cakici (2008)), while 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 (2021) model dynamic user adoption. Their main prediction is on the endogenous adoption of cryptocurrency and on prices at different stages of cryptocurrencies' life cycles. Other studies focusing on the network effects of cryptocurrencies include Pagnotta (2018), Pagnotta and Buraschi (2018), and Biais et al. (2018). Sockin and Xiong (2018) consider the possibility

[3] The use of factor models to analyze asset returns dates back to Fama and French (1993, 1996). Lustig, Roussanov, and Verdelhan (2011), Szymanowska et al. (2014), and Bai, Bali, and Wen (2019) develop factor models for the currency, commodity, and corporate bond markets, respectively.

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 effects can arise in some specifications of sentiment because users have incorrect expectations about future prices. The mechanism is similar to that in De Long et al. (1990), where irrational noise traders with erroneous stochastic beliefs affect prices so that prices can diverge significantly from fundamental values. Athey et al. (2016) model bitcoin prices as a function of its usage as a payment vehicle. Schilling and Uhlig (2019) consider an economy in which 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 to Cong, Li, and Wang (2021), Sockin and Xiong (2018), and Prat, Danos, and Marcassa (2019) on the tradeoff between capital gains and the convenience yield.

Several recent papers document empirical facts related to cryptocurrency investments. Liu and Tsyvinski (2021) are the first to comprehensively study valuations of the cryptocurrency market in the aggregate time series. They show that 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 cryptocurrency market, size, and momentum factors well captures the cross-sectional variation in cryptocurrency returns. Borri (2019) shows that cryptocurrency returns are exposed to tail risks within cryptocurrencies but are not exposed to tail risks concerning other global assets. Makarov and Schoar (2018) and Borri and Shakhnov (2021) show that there are dispersions in Bitcoin prices across different exchange platforms. Hu, Parlour, and Rajan (2019) show that most cryptocurrency returns have positive correlations with Bitcoin returns.

The paper is organized as follows. Section I describes the data. Section II examines the cross-sectional return predictors. Section III builds the cryptocurrency factor models. Section IV investigates potential mechanisms behind the cryptocurrency size and momentum effects. Section V provides additional results. Finally, Section VI concludes.

I. Data

We collect trading data on 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, and low prices as well as volume and market capitalization (in dollars) for most of the cryptocurrencies.[4]

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

For each cryptocurrency on the website, its price is calculated by taking the volume-weighted average of all prices reported on each market. A cryptocurrency needs to meet a list of criteria to be listed, such as being traded on a public exchange with an application programming interface (API) that reports the last traded price and the last 24-hour trading volume, and having nonzero 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 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 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 capitalization of less than $1,000,000.

Summary statistics are presented in Panel A of Table I. The number of coins in our sample that satisfy all of our filters increases from 109 in 2014 to 1,559 in 2018, but then decreases to 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 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. Summary statistics are presented in Panel B of Table I. During the sample period, the average coin market index return is 1.3% per week, which is similar to the average Bitcoin return (1.3% per week) but is lower than the average Ripple return (2.6% per week) or Ethereum return (3.6% 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 U.S. dollar value of

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

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

[7] Bitcoin, Ripple, and Ethereum are 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%, 0.7%, 0.7%, and 1.8%, respectively.

Table I
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 32nd week of 2015.

Panel A. Characteristics by Year

		Market Cap (mil)		Volume (thous)	
Year	Number	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. Return Characteristics

	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

investing one dollar from the inception of the given cryptocurrency to facilitate comparison. The figure shows strong correlations between the cryptocurrency market index and the values of the major coins.

We obtain the stock market factors for the Fama-French three-factor, Carhart four-factor, and Fama-French five-factor models from Kenneth French's website.

II. 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 for analyzing equity risk factors to the cryptocurrency market, we establish a set of empirical regularities for

[8] Menkhoff et al. (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.

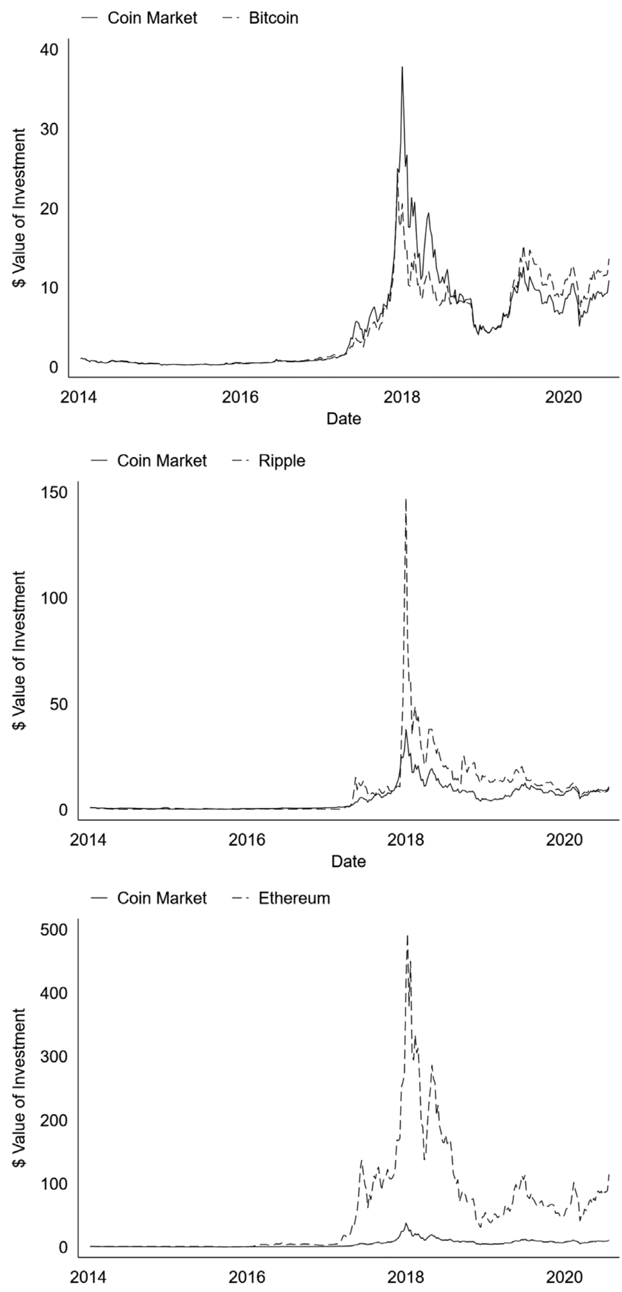


Figure 1. Cryptocurrency market and major coins. This figure plots the aggregate cryptocurrency market against Bitcoin, Ripple, and Ethereum.

cryptocurrencies that can be used as stylized facts to develop and assess theoretical models.

We begin by considering a comprehensive list of the established return predictors for the cross section of stock returns compiled by Feng, Giglio, and Xiu (2020) and Chen and Zimmermann (2020). Among these, we select all characteristics that can be directly constructed using information only on price, volume, and market capitalization.[9] The reason we focus on 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 therefore investigate 24 characteristics that we present in Table II. We further group them into four broad categories: size, momentum, volume, and volatility. Using the equity factors provides discipline against the critique of picking and choosing factors that suit the paper—by using the equity factors, we have a comprehensive, well-established list of factors to examine.

A. Size Characteristics

We analyze the performance of the zero-investment long-short strategies based on the size-related characteristics of market capitalization, price, maximum day price, and age. Each week, we sort 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. We then calculate the average excess return 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 III presents the results. For the first three characteristics, the average mean excess return decreases from the top to the bottom quintiles. The differences in the average returns of the highest and lowest quintiles are −5.8% for market capitalization, −3.2% for the end-of-week price, and −3.3% for the highest price of the week. All of these differences are statistically significant at the 5% level. In other words, a zero-investment strategy that longs the smallest coins and shorts the largest coins generates more than 3% 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 V. In Table IA.II, we also present results based on tercile instead of quintile portfolios.[10] The results based on tercile portfolios are qualitatively similar.

[9] Several 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.

[10] The same robustness results are presented for all other successful strategies in Table IA.II.

Table II
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)	Maximum price of the portfolio formation week.
Size	AGE	Barry and Brown (1984)	Number of days 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 16-week return.
Mom	r 50,0	De Bondt and Thaler (1985)	Past 50-week return.
Mom	r 100,0	De Bondt and Thaler (1985)	Past 100-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 et al. (2006)	Idiosyncratic volatility, 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.

(Continued)

Table II—*Continued*

Category	Predictor	Reference	Definition
Vol	RETVOL	Ang et al. (2006)	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)	Average absolute daily return divided by price volume in the portfolio formation week.

Table III

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. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	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)

B. Momentum Characteristics

We analyze the performance of the zero-investment long-short strategies based on past one-, two-, three-, four-, one-to-four-, eight-, 16-, 50-, and 100-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-, 16-, 50-, and 100-week returns are not statistically significant and are summarized in the last part of the section.

Table IV presents results of the successful return predictors for the portfolios sorted into quintiles. For the one-, two-, three-, four-, and one-to-four-week momentum strategies, the average mean excess return increases in the portfolio quintiles. The patterns are almost universally monotonic. The difference in the average returns of the highest and lowest quintiles is about 3% 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% excess weekly returns. The differences in the average returns of the highest and lowest quintiles are 2.5% for the one-week momentum strategy, 3.1% for the two-week momentum strategy, 3.1% for the three-week momentum strategy, 2.2% for the four-week momentum strategy, and 1.7% for the one-to-four-week momentum strategy.

C. Volume Characteristics

We analyze the performance of the volume-related return predictors of volume, price volume, and scaled volume. Each week, we sort individual

Table IV

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. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	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)

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 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 from the reputable cryptocurrency exchanges. We also use alternative measures that do not involve volume information when feasible.

Table V presents results for the portfolios sorted into quintiles based on price volume. The average mean excess returns decrease with the portfolio 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% for price volume. The difference is statistically significant at the 5% 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% excess weekly returns.

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

Table V
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. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	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)

Table VI
Volatility Strategy Returns

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

	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)

D. Volatility Characteristics

We analyze the performance of the volatility-related return predictors of beta, beta squared, idiosyncratic volatility, the standard deviation of returns, maximum day return, delay, the standard deviation of price volume, and the Amihud illiquidity measure.[12] Each week, we sort individual cryptocurrencies into quintile portfolios based on the value of a given characteristic. All strategies are rebalanced weekly. The standard deviation of the price volume measure generates statistically significant long-short strategy returns, while the other characteristics do not. We summarize the insignificant volatility characteristics in the last part of the section.

Table VI presents results for the portfolios sorted into 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 portfolio returns 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%. In other words, a

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

zero-investment strategy that longs coins with the lowest price volume volatility and shorts coins with the highest price volume volatility generates 3.2% excess weekly returns.[13]

E. Insignificant Strategies

In this subsection, we turn to results for the zero-investment strategies of the characteristics that do not generate statistically significant returns. There are 14 such characteristics: age; past eight-, 16-, 50-, and 100-week returns; volume and scaled volume; and beta, beta squared, idiosyncratic volatility, the standard deviation of returns, maximum day return, delay, and the Amihud illiquidity measure.

Table VII presents results on 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 16-week momentum strategy generates statistically insignificant excess returns of 0.3% per week on the long-short strategy.

F. Discussion of 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 significant nonmomentum 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: (i) small coins have higher average returns than large coins, (ii) low-price coins have higher average returns than high-price coins, and (iii) low-maximum-price coins have higher average returns than high-maximum-price coins. Consistent with Chordia, Subrahmanyam, and Anshuman (2001), we find that (i) low-price-volume coins have higher average returns than high-price-volume coins, and (ii) coins with a low standard deviation of price volume have higher average returns than coins with a high standard deviation of price volume. Jegadeesh and Titman (1993) find that the momentum effect in the equity market concentrates between the past second and 12$^{\text{th}}$ months, while a reversal effect obtains in the past first month. In the cryptocurrency market, we find that the momentum effect holds at a shorter horizon. In particular, the momentum effect in the cryptocurrency market exists for one to four weeks, horizons over which reversal effects obtain in the equity market. At the horizon in which

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

Table VII

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. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

		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)

momentum is observed in the equity market, there is no evidence of a cryptocurrency momentum effect.

III. Cryptocurrency Factors

A. Cryptocurrency Factor Model

In this section, we investigate whether a small number of factors can span the 10 cross-sectional cryptocurrency return predictors that we identify above. To do so, 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 10 strategies. We then analyze 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 10 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 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 10 strategies.

The construction of the cryptocurrency market excess returns is discussed in Section I. 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% (small, S), middle 40% (middle, M), and top 30% (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 three-week momentum and form the momentum factor portfolio based on the intersection of 2×3 portfolios.[15] In particular, for each week, we first sort coins into two portfolios based on coin size. We then form three momentum portfolios within each size portfolio based on past three-week returns. The first, second, and third momentum portfolios are the bottom 30%, middle 40%, and top 30% of the coins based on past three-week returns. The momentum factor is constructed as

$$CMOM = 1/2(Small\ High + Big\ High) - 1/2(Small\ Low + Big\ Low).$$

We first consider a one-factor model with only the CMKT or the cryptocurrency CAPM. The assumption for the cryptocurrency CAPM is that investors predominantly invested in cryptocurrencies.[16] Table VIII presents results for all 10 significant zero-investment strategies that we identify above. 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 in the zero-investment strategy excess returns for the statistically significant strategies is only 9.50%.

[14] We use market capitalization as our main size measure because of the convention 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.

[16] We formally test for 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 return on the global Fama-French factors (market, size, value, investment, and profitability factors) and the major currency returns (Canadian dollar, Singapore dollar, Australian dollar, euro, and British pound). The results are reported in Table IA.III. We find that the equity and currency factors account for a small amount of the cross-sectional variation in cryptocurrency returns. Based on the interpretation of the international finance literature, this result implies strong market segmentation.

Table VIII

Cryptocurrency One-Factor Model

This table reports results for the cryptocurrency one-factor model adjustment of the 10 successful long-short strategies. The pricing model is

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

where *CMKT* is the cryptocurrency excess market return. Quintile portfolio formation for the 10 significant strategies is discussed in Section II. t-Statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels. m.a.e and $\bar{R}^2$ are the mean absolute pricing error 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

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 return. 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 return. The only exception is the two-week momentum strategy, which is positively exposed to the coin market return. 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 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 0% for the one-week momentum strategy to 5.2% for the price and the maximum day price strategies.

We next consider a two-factor model with the CMKT and the cryptocurrency size factor. Model (1) of Table IX presents results for all 10 zero-investment long-short strategies adjusting for the two-factor model. The long-short alphas for most strategies, 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% under the one-factor model to an insignificant 0.7% 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 nonmomentum strategies, the absolute values of their size factor

Table IX
Cryptocurrency Factor Models

This table reports results on the cryptocurrency factor adjustments of the 10 successful long-short strategies. *CMKT* is the cryptocurrency excess market return, *CSMB* is the cryptocurrency size factor, and *CMOM* is the cryptocurrency momentum factor. *t*-Statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels. m.a.e and $\bar{R}^2$ are the mean absolute pricing error and the average R^2 of the five portfolios, respectively.

		Cons	t	CMKT	t	CSMB	t	CMOM	t	R^2	m.a.e	$\bar{R}^2$
MCAP	(1)	−0.000	(−0.05)	−0.025	(−0.54)	−1.611***	(−82.15)			0.953	0.003	0.719
	(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
PRC	(1)	−0.015	(−1.28)	−0.387***	(−3.75)	−0.342***	(−7.76)			0.195	0.007	0.567
	(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
MAXDPRC	(1)	−0.016	(−1.32)	−0.393***	(−3.76)	−0.339***	(−7.63)			0.191	0.007	0.560
	(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
r 1,0	(1)	0.020*	(1.78)	−0.034	(−0.35)	0.144***	(3.41)			0.033	0.012	0.465
	(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
r 2,0	(1)	0.028**	(2.57)	0.154	(1.61)	0.035	(0.85)			0.011	0.009	0.507
	(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
r 3,0	(1)	0.033***	(2.77)	0.095	(0.91)	−0.084*	(−1.89)			0.012	0.010	0.491
	(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
r 4,0	(1)	0.019*	(1.85)	0.109	(1.23)	0.068*	(1.80)			0.015	0.007	0.540
	(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
r 4,1	(1)	0.020**	(2.15)	0.165**	(1.98)	−0.140***	(−3.94)			0.051	0.007	0.539
	(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
PRCVOL	(1)	−0.007	(−0.73)	−0.150*	(−1.78)	−0.688***	(−19.14)			0.530	0.003	0.601
	(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
STDPRCVOL	(1)	−0.008	(−1.04)	−0.076	(−1.07)	−0.631***	(−20.91)			0.570	0.004	0.605
	(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

loadings range from 0.339 for the maximum 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 for 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, and the one-, two-, three-, and four-week momentum factors. For all nonmomentum strategies, the model explains a substantial part of the return variation beyond what the coin market factor explains. Among the nonmomentum strategies, the zero-investment long-short strategy R^2s range from 19.1% for the strategy based on the maximum day price factor to 95.3% 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 mean absolute pricing errors decrease dramatically for the nonmomentum strategies. For example, the m.a.e of the price volume strategy decreases from 0.8% in the one-factor model to 0.3% in the two-factor model controlling for the cryptocurrency market and size factors—a 63% decrease. The mean absolute pricing error does 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 IX presents the results for all 10 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% under the one-factor model to 0.7% 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 strategy. All nonmomentum strategies have significant exposures to the market. On the other hand, none of the momentum strategies is significantly exposed to the CMKT. For the momentum strategies, this alternative two-factor model explains a substantial fraction of the return variation 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% for the one-week momentum to 57.1% for the three-week momentum strategy. However, the model underperforms in explaining the return variation of the nonmomentum strategies compared to the two-factor model with the cryptocurrency market and the cryptocurrency size factors. The alphas of the nonmomentum strategies remain statistically significant. Compared to the one-factor model, the mean absolute pricing error largely decreases for the momentum factors. For example, the m.a.e of the two-week momentum strategy falls from 0.9% in the one-factor model to 0.4% 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 IX presents results for all 10 strategies. Adjusted for the cryptocurrency three-factor model, none of the alphas for the 10 strategies remains statistically significant. 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 eight other long-short strategies are significantly exposed to both the size and the 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 cryptocurrencies' expected returns. Compared to the one-factor model, the mean absolute pricing error largely decreases for all of the 10 strategies.

B. Principal Component Analysis

The Arbitrage Pricing Theory of Ross (1976) suggests that a small number of risk factors can capture substantial common variation 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 variation in the strategies' returns. We show that two components explain substantial variation in 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, while the second principal component is significantly exposed to the cryptocurrency momentum factor.

Table X presents results of the principal component analysis for the 24 long-short strategies. Panel A of Table X reports the eigenvalues and the explanatory power of the first 15 principal components. We omit the remaining components because the first 15 components already explain the majority of the variation 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 those of the remaining principal components. The first two principals combined already explain approximately 45% of the variation in the 24 long-short strategies.

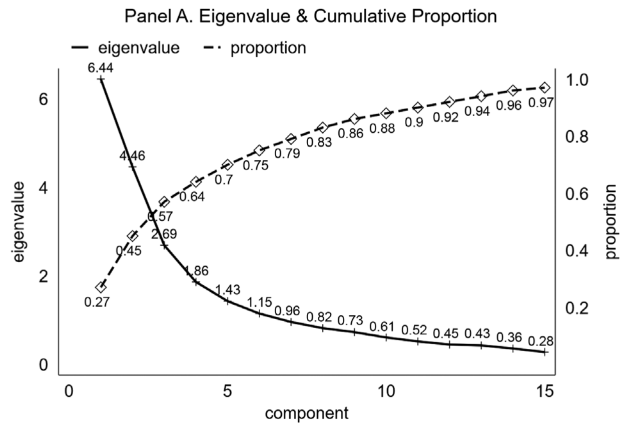
Panel B of Table X reports the correlation matrix of the first three principal components and the three cryptocurrency factors. The first principal component strongly correlates with the cryptocurrency size factor. The absolute value of the correlation is 0.826. The first principal component also negatively 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, with the correlation between them equal to 0.662. The second

Table X

Principal Component Analysis

This table reports results of principal component analysis of the full set of long-short strategies. Panel A plots the eigenvalues and the cumulative shares of total variation explained for the first 15 principal components. Panel B reports the correlation matrix of the first two principal components, the cryptocurrency excess market return, the cryptocurrency size factor, and the cryptocurrency momentum factor.

Panel A. Eigenvalue & Cumalative Proportion



Panel B. Correlation

	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

component negatively correlates with the cryptocurrency size factor and has a relatively low correlation with the CMKT. The third principal component has moderate correlation with any of the cryptocurrency factors.

We further apply principal component analysis at the portfolio level for all 24 strategies. We present the results in Table IA.IV. We find that the first three principal components account for 72.9% of the variation of the portfolios. Consistent with the evidence in Table X, the first principal component strongly correlates with the cryptocurrency market factor (correlation of 94.7%), the second principal component strongly correlates with the cryptocurrency size factor (correlation of 87.3%), and the third principal component strongly correlates with the cryptocurrency momentum factor (correlation of 57.7%). The results show that the cryptocurrency market factor is crucial in explaining the portfolio returns of the quintile portfolios.

IV. Investigating Mechanism

In this section, we explore 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 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, prior studies show 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, size may proxy for an illiquidity premium. We report three sets of evidence that are potentially consistent with the liquidity view: (i) small coins have lower prices and higher Amihud illiquidity relative to large coins, (ii) in the cross section, the cryptocurrency size premium is more pronounced among coins that have high arbitrage costs, and (iii) in the time series, the cryptocurrency size premium is larger at times of high cryptocurrency market volatility. Second, the size premium is consistent with a mechanism proposed by recent cryptocurrency theories: the trade-off between capital gains and the convenience yield (e.g., Sockin and Xiong (2018), Prat, Danos, and Marcassa (2019), Cong, Li, and Wang (2021))—in equilibrium, the convenience yield of larger and more mature cryptocurrencies is higher, and thus their capital gain should be lower. Consistent with the prediction that the cryptocurrency size premium should be relatively large at times of high demand for transactions, we show that the size premium is larger at times of relatively high Bitcoin transactions.

Theories of the 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. Investor over- and underreaction are both 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 the cryptocurrency momentum effect is more pronounced among coins that receive high investor attention and at times of high investor attention.

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

A. Cryptocurrency Size Effect

A.1. Portfolio Characteristics

We first explore 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, seven-day return standard deviation, 30-day return standard deviation, and idiosyncratic volatility measures. The results are reported in Table IA.V.

For the quintile portfolios based on market capitalization, the first quintile portfolio, which consists 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, small coins have lower prices and are less liquid compared to big coins. These 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 market capitalization quintile portfolios are consistent with the view 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 indicate that the high momentum portfolio contains larger and more liquid coins.

A.2. Costs of Arbitrage

We next 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 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 et al. (2020). To construct the composite index, we use five underlying measures: idiosyncratic volatility, coin age, Amihud illiquidity, coin price, and volume-volatility. The first four measures are cost of arbitrage measures proposed in the literature. We use the volume-volatility measure, constructed as the ratio between cryptocurrency volume and return volatility, to proxy for the dispersion in 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 among agreeing agents. We sort cryptocurrencies into quintiles based on their volatility, Amihud illiquidity, volume-volatility ratio, price, and age, with a higher quintile indicating higher costs of arbitrage. We then 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, with higher values indicating higher costs of arbitrage.

In a next step, we double-sort cryptocurrencies based on their cost of arbitrage and market capitalization. We report the results in Table IA.VI. 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 costs generates a spread of 8.7%. 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 risk among the small size coins.

Table IA.VI also presents results double-sorted based on the cost of arbitrage and the cryptocurrency three-week momentum factor. 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.

A.3. Time-Series Analysis

We also study the exposures of the cryptocurrency size and momentum factors to time-series variables. Specifically, we test the exposures of the cryptocurrency size and momentum factors to the Daniel, Hirshleifer, and Sun (2020) behavioral factor model, the Fama-French three-factor model, the Carhart four-factor model, the Fama-French five-factor model, the standard deviation of cryptocurrency market returns, and the logged Bitcoin transaction amount. The results are summarized in Table IA.VII. The time-series tests are performed at the weekly frequency.

The cryptocurrency size and momentum factors are not significantly exposed to any of the stock market factors in the time series. However, the cryptocurrency size factor is significantly and positively exposed to the standard deviation of cryptocurrency market returns, suggesting that the cryptocurrency size factor performs well when the cryptocurrency market is more volatile. This result further supports the liquidity view of the size premium. In contrast, the momentum factor is not significantly exposed to the standard deviation of cryptocurrency market returns.

We further test the implications of the trade-off theory between capital gains and the convenience yield as proposed by recent cryptocurrency models (e.g., Sockin and Xiong (2018), Prat, Danos, and Marcassa (2019), Cong, Li, and Wang (2021)). 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 logged Bitcoin transaction amount. Consistent with the theory, we find that the cryptocurrency size factor is positively exposed to the logged transaction amount, suggesting that the cryptocurrency size effect is larger when the convenience yield is higher. Unlike the size factor, however, the momentum factor is not exposed to the logged Bitcoin transaction amount.

A.4. Lottery and Skewness Effect

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

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

Recent theories also provide some risk-based explanations for momentum, such as Li (2017), who relies on riskiness of firms' cash flows to obtain momentum effects. Li (2017) finds 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 explaining the cryptocurrency momentum effect because the channel relies on the cash flow risk of winner firms making greater commitments to future capital investment than loser firms. We find that the cryptocurrency momentum effect is strong at relatively short horizons (less than a month), which is unlikely to match the investment adjustment horizons. Indeed, the momentum

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

effect in the equity market that the cash flow explanation is based on has a much longer horizon of one year. In addition, the mechanism in Li (2017) relies on the differential exposures of winner firms and loser firms to shocks to the price of investment goods. We test whether the cryptocurrency momentum factor is exposed to fluctuations in the price of investment goods. Following Li (2017), we measure relative price shocks as 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 is not significantly exposed to the relative price shocks with a t-statistic of only 0.85.

B.1. Relationship between Cryptocurrency Size and Momentum

A key implication of the behavioral 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 coins, which provides a sound setting for 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 sort first on market capitalization into two groups based on the median. Then, within each size group, we sort cryptocurrencies into five groups based on past three-week returns. The results are reported in Table IA.X. 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% 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 underreaction-based explanations of the momentum effect. In the next subsection, we further investigate possible mechanisms underlying the cryptocurrency momentum effect.

B.2. Attention and Momentum

The finding that the momentum effect is concentrated among large coins is most consistent with recent theories of investor overreaction (Peng and Xiong (2006), Andrei and Hasler (2015)), whereby an overreaction-induced momentum effect is predicted to be more pronounced among high-attention assets. The Peng and Xiong (2006) model applied to the cryptocurrency market suggests that each coin has fundamental factors that are not directly observable, and that are subject to positive and negative shocks at different times. Investors have limited attention, and thus 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 information (Daniel, Hirshleifer, and Subrahmanyam (1998), Peng and Xiong (2006)). Taken together, limited attention and overconfidence lead to an 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)). Specifically, we test the hypothesis that the overreaction-driven momentum effect is stronger among high-attention cryptocurrencies. To proxy for investor attention, we first follow Hou, Xiong, and Peng (2009) and use a volume-based measure of investor attention. However, as noted above, volume data may be subject to misreporting. We therefore also use Google searches as an alternative proxy for investor attention. We summarize the results in Table IA.XI.

Panel A of the table reports 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 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 is a statistically insignificant −0.6% per week. For the high-volume group, the long-short strategy return based on the past three-week return is a statistically significant 3.4% per week. The excess returns are monotonically increasing across quintile portfolios for the high-volume subgroup. These 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 searches that week. The first portfolio has coins with below-median Google searches, and the second portfolio has coins with above-median Google searches. 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 searches. For the low-search group, the long-short strategy return is a statistically insignificant 1.6% per week. For the high-search group, the long-short strategy return

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

is a statistically significant 3.6% per week. The excess returns are monotonically increasing across the quintile portfolios for the high-search subgroup.

In addition, 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 (2021), we use Google searches to capture aggregate investor attention in the time series. Specifically, we use the number of Google searches for the word "blockchain" as our measure of investor attention and denote the variable *Google*.[19] To examine whether the momentum effect is stronger at times of high investor attention, we regress the momentum factor on lagged *Google*. The results are reported in Panel C of the table. Column (1) regresses the momentum factor on *Google* only. The coefficient estimate on *Google* is positive and statistically significant at the 1% level, suggesting that the momentum effect is larger at times of high investor attention as measured by Google searches. 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 that in the stand-alone 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) to (6) report the results based on $Google^{rank}$. The coefficient estimates on $Google^{rank}$ are all statistically significant at the 5% level. The magnitudes of the coefficient estimates are large. Based on the estimates, the average momentum factor returns of the top tercile, or high attention, periods, is about 4% higher than the average momentum factor returns of the bottom tercile, or low attention, periods. We also use Twitter posting data as an alternative aggregate attention measure: the results are summarized in columns (7) to (9).[20] Although the economic magnitudes are smaller, the results using Twitter posting data are consistent with those based on 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.

V. Additional Results

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

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

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

Table XI

Multiple Hypothesis Testing

This table presents results of multiple hypothesis testing. Panel A reports results adjusting the p-value for the 10 successful long-short strategies using the k-familywise error rate (k-FWER) of 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 Actual	Adj 5% 0.021	Adj 10% 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

Joint Test	(1) Mean	(2) FF 6Fac	(3) Cryto 3Fac
p-Value	0.001	0.033	0.194

A. Multiple Hypothesis Testing

Among the 24 predictors we investigate, 10 form successful long-short zero-investment strategies. However, the strategies are not independent of each other. In this subsection, we investigate the multiple hypothesis testing problem and test the joint significance of the set of strategies that we study. Using both the k-FWER of 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-FWER method in Lehmann and Romano (2005). Our main results show that 10 of the 24 characteristics that we consider generate significant long-short strategy returns. We set $k = 10$, which corresponds to the probability under the null of falsely rejecting 10 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% p-value threshold from 0.05 to $0.05 \times 10/24 = 0.021$ and the 10% p-value threshold from 0.10 to $0.10 \times 10/24 = 0.042$.

Panel A of Table XI 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% level (10% level) under the k-FWER threshold. All nonmomentum strategies are significant at the 5% level under the k-FWER threshold. The two- and three-week momentum strategies are significant at the 5% level under the k-FWER threshold, and the one- and four-week momentum strategies are significant at the 10% level under the k-FWER threshold. The only strategy that is not significant at the 10% level under the k-FWER threshold is the one-to-four-week momentum strategy.

In addition, we conduct a joint test considering both the significant and the insignificant strategies to examine 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 XI. Column (1) reports the result of the F-test, which checks 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% level. Columns (2) and (3) report F-test results following Gibbons, Ross, and Shanken (1989), where the factor models used are the Fama-French six-factor model and the cryptocurrency three-factor model, respectively. The p-value based on the Fama-French six-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 six-factor model are jointly zero at the 5% level. The p-value based on the cryptocurrency three-factor model is 0.194, suggesting that we cannot reject the null hypothesis that the 24 alphas adjusted for the cryptocurrency three-factor model are jointly zero. These results are consistent with our main finding that the cryptocurrency three-factor model is successful in pricing the 24 strategies we consider.

B. Implementability and Robustness of the Strategies

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

We partially address these concerns by splitting the sample period into two halves and checking whether our results are stable in these subsamples. During the first half of the sample, there was considerably more uncertainty and learning about cryptocurrency as an asset class. We find that the directions of all results hold in both halves of the sample. A high level of uncertainty and learning about cryptocurrencies potentially remain today, but the assumption we need for the subsample tests is relatively mild: uncertainty has decreased from the first half to the second half of the sample period.

One concern with constructing zero-investment strategies in cryptocurrencies is that shorting is not readily available for most coins. Based on the cryptocurrency one-factor adjusted alphas in Table VIII, we calculate the

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

contributions of the long end and the short end to the strategies, relative to the average coin market return. For the nonmomentum 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 nonmomentum strategies because they only require 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 IV, the fifth quintile or the long end of the two-week momentum strategy has an average excess return of 3.1% per week and the first quintile or the short end of the two-week momentum strategy has an average excess return of 0.0% per week. However, the level of the excess returns includes exposures to the average coin market excess return, 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 return as the benchmark. Relative to the average coin market return, as shown in Table VIII, 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%).

B.1. Using Bitcoin for Short Portfolios

Table IA.XII 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 III. 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 III, none of the alphas remain statistically significant controlling for the cryptocurrency three-factor model.

B.2. Top 20 Coins Only

The portfolio sort results based on size show that the size premium is driven mainly by the smallest quintile portfolio, suggesting that the size effect is nonlinear and concentrated among the smallest coins. Here, 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 performance of the successful long-short strategies. Each period, we restrict our sample to the largest 20 coins at the time based on the market capitalization of the cryptocurrencies. We form tercile portfolios based on each of the 10 significant factors. The results are reported in Table IA.XIII. The directions of the long-short portfolios are the same as those based on the full sample. Among the top 20 coins, buying the smallest tercile of coins and shorting the largest tercile of coins generates positive excess returns based on market capitalization (0.2% per week), price (1.0%), and maximum day price (0.9%). 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 findings above that cryptocurrency momentum effects are stronger among large coins. In addition, in Table IA.XIV, we show that using the top 100 coins with quintile portfolios generates qualitatively similar results.

B.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 the U.S. dollar 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 are from Kraken. If the cryptocurrency is traded on Coinbase Pro but not on Kraken, the data are from Coinbase Pro. If the cryptocurrency is traded only on Bitfinex, the data are from Bitfinex.

We report the results for the 10 significant factors in Table IA.XV. 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 generates positive excess returns based on market capitalization (2.4%), price (2.1%), and maximum day price (2.1%). However, the long-short strategy based on market capitalization is insignificant. In general, the strategies based on the momentum effect remain large and significant.

B.4. Accounting for Trading Costs

We next address concerns about trading costs by testing the extent to which 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 hence 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 small coins is difficult to implement.

Static Trading Cost: To evaluate the impact of trading fees on the cross section of portfolio returns, we collect trading fees for the major cryptocurrency exchanges in our sample. Trading fees range from 0.1% to 0.2%. Therefore, we test the impact of trading fees on the strategy returns based on both the lower bound (0.1%) and the upper bound (0.2%). To evaluate the impact of the bid-ask spread on strategy returns, we first collect the bid-ask spread of Bitcoin from Bitcoinity.org. The bid-ask spread was relatively high in early 2014, reaching 0.3% at one point. The spread quickly declined in 2015 and has stayed at a low level (less than 0.1%) since. The bid-ask spread for Bitcoin regresses close to 0.001% in recent months. Second, we collect the current bid-ask spreads of several top cryptocurrency-USD pairs from Tokenspread.com.[22] The bid-ask spreads of Bitcoin (first largest) and Ripple (third) are 0.001%. The bid-ask spread of Ethereum (second) is 0.01%. The bid-ask spreads of Bitcoin Cash (fifth) and Litecoin (sixth) are 0.05%. The bid-ask spreads of Dash (17$^{\text{th}}$) and Monero (13$^{\text{th}}$) are 0.27% and 0.34%, respectively. Accordingly, we make a conservative assumption and set the bid-ask spread of the top 20 coins to 0.5%. We further assume that the price is halfway between the bid and ask prices. Finally, we set the margin fee required to maintain a short position in Bitcoin for one week to 0.35%.

Table IA.XVI 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 nonmomentum strategies and we long the third portfolios of the momentum strategies. The two costs associated with the long-only strategies are trading fees and the bid-ask spread. We report the average raw excess returns, the trading cost-adjusted excess returns, and the ratios between the adjusted excess returns and the raw excess returns. The ratios between the adjusted returns and the raw returns are around 90%. The exception is the one-week momentum strategy, where the ratio is about 80%, because the turnover rate of this strategy is high at about 70% 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. As discussed for the top 20 coins only, the excess returns for the nonmomentum strategies are generally lower than for the full-sample results because the cryptocurrency size effects concentrate among the small coins. However, the directions of the raw excess returns are all in

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

line with the main results. Adjusted for 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). Estimation of the effective bid-ask spread measure only uses price information, so we can estimate the bid-ask spread of each coin in any given year. The effective bid-ask spreads are estimated using a Bayesian Gibbs sampler on a generalized Roll (1984) measure.[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% since 2018. The number is higher for the earlier part of the sample at around 1.5%. We make the same assumptions about fees and shorting costs as in the static trading cost section above. The results are presented in Table IA.XVII. For the long-only strategies, the ratios between the adjusted excess returns and the raw excess returns are generally around 90%. The exception is the one-week momentum strategy, where the ratio is about 80% 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%. Similar to the static adjustment, the strategy based on market capitalization is no longer profitable after adjusting for transaction costs, while the other nine strategies remain profitable.

C. 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 correlated 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, namely, the value-weighted return of all coins excluding Bitcoin and report the results in Table IA.XVIII. We denote the alternative cryptocurrency market factor as $CMKT^2$. The correlation between $CMKT$ and $CMKT^2$ is 0.82. For each of the 10 successful strategies, we regress the level portfolio return and the long-short strategy spread on $CMKT^2$ and compare the R^2 with that based on $CMKT$. Similar to $CMKT$, $CMKT^2$ does not account

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

for much of the long-short strategy spreads of the 10 successful strategies. We next focus on the average R^2 of the level portfolios for each strategy. The average R^2 ranges 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 et al. (2012), there is a strong momentum effect in the international currency markets. Moreover, Menkhoff et al. (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 similar phenomenon in the cryptocurrency market. We note that the momentum effect in other markets is at the monthly horizon, whereas the cryptocurrency momentum effect is at the weekly horizon.

In addition, we note that cryptocurrency competition is a possible explanation for the cryptocurrency size effect. To date, no theoretical papers on the convenience yield in the cryptocurrency literature (e.g., Sockin and Xiong (2018), Cong, Li, and Wang (2021)) take cryptocurrency competition into account.[24] Accordingly, we discuss a plausible competition mechanism in the cryptocurrency market that may generate the size effect. 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 that small and young coins face, especially the smallest ones, may be significantly higher than those of the large and mature coins, leading to higher average returns for small coins and lower average returns for large coins. This mechanism of cryptocurrency competition is thus plausibly consistent with the cryptocurrency size effect we document.

D. Relationship to ICO

There has been a boom of ICOs in recent years. Benedetti and Kostovetsky (2021) document a substantial amount of ICO underpricing, with average returns of over 100% in the first month. The ICO boom may potentially account for the cryptocurrency size and momentum effects that we document in this paper. We test this 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 initial ICO returns. We then test the exposures of long-short strategy returns to the ICO

[24] Benigno, Schilling, and Uhlig (2019) analyze a model in which 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 paper studies the effect of cryptocurrency competition on asset valuation.

return index. Table IA.XIX reports the results. Panel A is based on ICO returns calculated over the first month. For all strategies, the alphas adjusting for the cryptocurrency market and ICO returns remain statistically significant. For the strategies based on past returns, controlling for ICO returns changes average long-short strategy returns little. For the other strategies, controlling for ICO returns reduces average long-short strategy returns by about 10% to 20%. 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 nonmomentum strategies' excess returns, the average excess returns remain statistically significant and large.

E. Additional Cross-Sectional Results

We test the robustness of the cross-sectional regression results using the Fama-MacBeth method. Table XII reports the results. We first sort each coin into one of five portfolios based on the corresponding characteristics. We then use the portfolio rank number as the explanatory variable. Panel A reports the results for the size-related predictors. All of them are individually statistically significant but not jointly significant. This result is consistent with the fact that these predictors are correlated. Panels B and C report 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 market capitalization greater than 10 million dollars.

We also report results based on market cap weighted least squares (WLS) regressions. The results presented in Table IA.XX are consistent with the portfolio results and the standard Fama-MacBeth ordinary least squares (OLS) cross-sectional regression results. The nonmomentum 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 independent variables. We show that market cap negatively predicts future coin returns, the 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.

F. Stock Market Factors

We next investigate whether the stock market risk factors can explain the 10 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,

Table XII

Fama-MacBeth Cross-Sectional Regression

This table reports 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 explanatory variables. Panels A, B, C, and D are based on the sample of coins with market capitalization greater than 1 million dollars. Panel E is based on the sample of coins with market capitalization greater than 10 million dollars. t-Statistics of the coefficient estimates are reported in parentheses.*, **, and *** denote significance at the 10%, 5%, and 1% levels.

			Market Cap > 1 Million		
			Panel A. Size		
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. Volume		
PRCVOL	−0.006***				
	(−2.97)				
			Panel C. Volatility		
STDPRCVOL	−0.007***				
	(−3.34)				
			Panel D. Momentum		
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)
			Market Cap > 10 Million		
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)

the cryptocurrency strategies may also comove with their corresponding counterparts in the equity market. In the Internet Appendix (Tables IA.XXI to IA.XXV), we present results based on the CAPM, Fama-French three-factor, Carhart four-factor, Fama-French five-factor, and 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 II.[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% per week with a t-statistic of −2.63. The unadjusted average excess return of the long-short strategy is −5.8% per week with a t-statistic of −2.45. The adjusted alpha for the three-week momentum long-short strategy is 3.3% per week with a t-statistic of 2.77. The unadjusted average excess return of the long-short strategy is 3.1% per week with a t-statistic of 2.65.

G. Hedged Strategies

Recent empirical asset pricing literature finds that the common practice of creating factor portfolios by sorting on characteristics associated with average returns captures both priced and unpriced risks. Daniel et al. (2020) 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 et al. (2020) and provide an example based on the cryptocurrency size factor. Detailed descriptions of the theoretical motivation and empirical account can be found in Daniel et al. (2020). We first rank all cryptocurrencies by their previous week's market capitalization. Break-points are selected at the 30% and 70% marks. Cryptocurrencies are then 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 by 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 the momentum strategy,

[25] Constructing weekly returns from daily returns implicitly rebalances the factor daily. However, given the observed low exposures to equity factors, we do not expect this to be quantitatively important.

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 economically considerable gains from hedging the unpriced risks. However, for the cryptocurrency momentum factor, the adjustment does not increase the squared Sharpe ratio of the momentum strategy. One possible reason 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.

VI. Conclusion

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

We further 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: (i) small coins have lower price and higher Amihud illiquidity relative to the large coins, (ii) in the cross section, the cryptocurrency size premium is more pronounced among coins that have high arbitrage costs, and (iii) 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 recent cryptocurrency theories: the trade-off between capital gains and the convenience yield (e.g., Sockin and Xiong (2018), Prat, Danos, and Marcassa (2019), Cong, Li, and Wang (2021)). 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 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 fraud are present. As the cryptocurrency market matures, the pricing dynamics of the market may change. In addition, the cryptocurrency market is still in an early stage, and the sample period may be unusual. The premia we document in the paper are an order of magnitude larger than those in the equity market, and it is unrealistic to expect the magnitudes of the premia to continue in the long run. However, more broadly, our results may apply to other new asset classes that may come into existence in the future, and therefore studying early-stage cryptocurrencies can help us understand the dynamics of new asset classes beyond just cryptocurrencies.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication Code.