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Keywords: Cryptocurrency, Asset Pricing, Multi-Factor Pricing Model, Behavioral Finance

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Abstract

Based on classic stock pricing factors and unique cryptocurrency characteristics, we propose a five-factor pricing model for cryptocurrencies. The factors are *Market*, *Size*, and *Liquidity*, *Momentum* and *Attention* . We find that although the market factor does not have much explanatory power, the other four factors can explain 84.2% of excess returns' variations of cryptocurrency portfolios. In particular, there are significant positive size effect and reversal effect of the momentum factor in the cryptocurrency market. In addition, liquidity is positively related with excess returns of cryptocurrency portfolios. Finally, attention negatively correlates with the overall excess return.

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1 Introduction

Since the launch of Bitcoin peer-to-peer network in 2009, cryptocurrencies have experienced an explosive growth. The price of Bitcoin reached a peak of $19,783 on December 17, 2017 from $100 in early 2013. There is also a rapid increase in the number of cryptocurrencies. There are nearly 1,900 cryptocurrencies with a total market capitalization of $233 billion by the end of August, 2018[1]. The fast development of the cryptocurrency market may be due to two reasons. On the one hand, cryptocurrencies other than Bitcoin, also called altcoins, can be easily created by modifying the open-source code, algorithms or mechanisms of major cryptocurrencies such as Bitcoin or Ethereum with limited costs. On the other hand, although many governments have banned the cryptocurrency trading or fundraising activities, cryptocurrencies' decentralization characteristic has made the implementation of regulations rather difficult. For example, there have been institutions and individuals that take the opportunity to speculate on cryptocurrencies. In short, the cryptocurrency market has drawn an increasing number of participants and funds. However, there is a lack of valuation and pricing models for cryptocurrencies.

Understanding the pricing factors for the cryptocurrency market is important for both investors and regulators. Given the unique characteristics of cryptocurrency, traditional valuation methods such as discounted cash flow are not applicable because most of the underlying blockchain projects do not generate a net cash inflow. Moreover, cryptocurrencies are generally used to exchange for goods or services on certain platforms, which do not have any tangible flow to derive the intrinsic values. Besides, the cryptocurrency entitles its holders different rights from equity, so it does not represent legal ownership or residual right of the firm value. However, other than to exchange for future products or services, most investors are driven by similar motivations when they buy cryptocurrencies, either investment or speculation. That is to say, investors buy more tokens if they

[1] Based on data from https://www.coingecko.com/ as of 31 August, 2018.

are confident about the project or the blockchain startup and they expect the token price to increase, similar to the investors in the stock market. Therefore, the variation of cryptocurrency returns, to some extent, are likely to be captured the pricing factors used in the stock market. Scholars have examined hundreds of anomalies and proposed various pricing models for the equity market, but little research has been done for the cryptocurrency market. Therefore, we hope to fill this guy and provide insights and inspirations on the valuation of cryptocurrency as an emerging asset type.

We construct a five-factor pricing model for cryptocurrencies. The model includes factors based on traditional finance theories such as *Market* factor, *Size* factor, and *Liquidity* factor. We also include *Momentum* factor, and *Attention* factor based on behavioral finance. The results suggest that the *market* factor does not have much explanatory power in the cryptocurrency market. It may be due to that the cryptocurrency market index is dominated by Bitcoin, but the equity market index is well diversified. In addition, there is a significant positive size effect in the cryptocurrency market, indicating that dominating cryptocurrencies with large market capitalisation such as Bitcoin and Ethereum provide higher returns than small-size cryptocurrencies. *Liquidity* is another significant factor in explaining cryptocurrencies' excess returns. As the level of liquidity increases, the portfolio excess return increases. Moreover, the effect becomes more pronounced at high liquidity levels. *Momentum* factor, however, only improves the explanatory power of the model when using *Size-Momentum* sorts, which are consistent with findings in Fama and French (2016). Also, it is a reversal factor for portfolio returns, indicating that the cryptocurrency market is overreacting to the price. Finally, excess return of cryptocurrency portfolios is negatively associated with *Attention* factor, suggesting that investing in cryptocurrencies based on popularity is not a good strategy.

Previous studies on cryptocurrency either focus on a single cryptocurrency or several popular cryptocurrencies with large market value. Our paper contributes to the literature by examining the cryptocurrency market as a whole. We fill the gap by covering cryptocurrencies that account for 99.9% of the market capitalization. By doing so, our study sheds light on the controversy over the intrinsic value of cryptocurrency and the risks of investing in cryptocurrencies. The in-depth analysis is of great importance for the development of the cryptocurrency market, the rational allocation of investments, and the regulatory policies.

Moreover, this paper applies the multi-factor pricing model to the emerging cryptocurrency market for the first time and simulates the real-time investment by periodically adjusting the portfolios. For the cryptocurrency market, many researchers have discovered the presence of possible speculative bubbles and the high Sharpe ratio (e.g. Cheah & Fry, 2015; Bouoiyour, Selmi, Tiwari, & Olayeni, 2016; Dyhrberg, 2016). However, there is no systematic analysis on the risk-return profile of cryptocurrencies. Therefore, we conduct a thorough study on the risk factors in the cryptocurrency market and examine the risk exposure of cryptocurrencies.

This paper consists of four sections. Section 1 is introduction. In Section 2, we summarize the institutional background, review the literature on cryptocurrencies and asset pricing theories, and introduce the pricing factors. Section 3 includes the description of the sample construction and empirical results. Finally, Section 4 concludes the paper by offering some explanations of the empirical results and suggests areas for future research.

2 Institutional background, literature review and pricing factors of cryptocurrency

2.1 Institutional background

The cryptocurrency market has been growing fast for the past a few years. Most participants consider the cryptocurrency as an emerging class of alternative investments, while critics view the cryptocurrency as a speculative bubble. The unique features of cryptocurrency such as decentralized, open-source and distributed, and more importantly, the underlying technology, blockchain, are what makes it appealing to investors. Blockchain is a distributed ledger using cryptography to ‘chain’ the encrypted and time-stamped data (or blocks) together. It solves the two major problems in digital transactions, the Byzantine Generals’ problem and the double-spending problem, which enables cryptocurrencies to thrive. But innovative technology as blockchain is, it has many other applications. There are mainly three types of blockchains - public chain, consortium chain and private chain. On top of the main chain, secondary chains such as side chain and lightning network have been developed as supplements.

The majority of blockchain projects use public chains. In a public chain, transaction data is accessible to everyone that runs a node or initiates transactions with final confirmations recorded on the chain. Miners participate in the consensus process and verify the transactions. Public chains are usually associated with crypto-tokens as a reward for miners to facilitate the transactions and as a means for participants to buy goods or services in the ecosystem. There are various cryptocurrencies with different designs in terms of algorithm, consensus, token rights, and other mechanisms.

2.2 Literature review

As the most representative cryptocurrency, Bitcoin has drawn much academic attention. Previous Bitcoin studies have examined its monetary functions, valuation, and roles in risk hedging and portfolio diversification.

One of the most debated controversies is whether Bitcoin behaves as a currency. After comparing similarities and differences between the historical trading performance of Bitcoin and fiat currencies, Yermack (2014) concludes that the volatility of Bitcoin is too high to be used as a unit of account. Also, correlations between Bitcoin and other currencies are close to zero, so it is not a good hedging tool. Moreover, Bitcoin is not part of the financial banking system and thus cannot serve as collateral assets to increase the creditability record of its holder. Valstad and Vagstad (2014) calculate the IVaR of Bitcoin based on the Monte Carlo simulation and analyze the volatility characteristics of Bitcoin. They question the role of Bitcoin as a medium of exchange because Bitcoin is riskier than gold and euro.

In terms of the relationship between the Bitcoin price and fundamentals, Wijk (2013) argues that global financial factors, including stock markets, exchange rates, and oil prices, have a significant impact on the long-term price of Bitcoin. Kristoufek (2013) finds that the increase in the circulating supply of Bitcoin tends to decrease its prices in the long run. Ciaian, Rajcaniova, and Kancs (2016) and Bouoiyour et al. (2016) find that the role of Bitcoin as a medium of exchange has made it more attractive, leading to an increase in its long-term price. In the long run, its price is also affected by its own supply and demand, as well as the monetary policies. Nevertheless, some studies conclude that there is a bubble in the price of Bitcoin and fundamentals have little explanatory power. Baek and Elbeck (2015) compare the volatility of Bitcoin with that of the S&P 500 and select a variety of fundamental variables such as productivity, monthly consumption expenditure per capita, 10-year bond yield, euro exchange rate, and unemployment rate to explain the return of Bitcoin. They find that the price of Bitcoin, mainly driven by the transactions of buyers and sellers, is highly speculative. By constructing an econometric model, Cheah and Fry (2015) conclude that there is a speculative bubble in Bitcoin and the intrinsic value of Bitcoin is zero. Based on the Barro

(1979)'s model, Ciaian et al. (2016) find that the market forces of Bitcoin's supply and demand, as well as the attractiveness of Bitcoin to its investors and users, have significant influences on the price of Bitcoin. Their findings also suggest that macro-financial developments are not driving the Bitcoin price in the long run. Balcilar, Bouri, Gupta, and Roubaud (2017) adopt the non-parametric causality test to predict the price and volatility with the historical trading volume data of Bitcoin.

Another popular research topic is whether Bitcoin can expand the effective frontier of a portfolio or as a hedging instrument. Instead of the traditional mean-variance model, Eisl, Gasser, and Weinmayer (2015) use the CVaR model to analyze the risk-return characteristics of Bitcoin and conclude that Bitcoin should be included in the optimal portfolio. Although adding Bitcoin increases the CVaR of the portfolio, its high returns lead to a better risk-return profile. Dyhrberg (2016) use the GARCH model to study the hedging function of Bitcoin and find that Bitcoin has a hedging effect on stocks in the FTSE 100 index. Also, Bitcoin can be used to hedge against risks associated with US dollar in the short term, so it has similar risk hedging function as gold. Bouri, Molnár, Azzi, Roubaud, and Hagfors (2017) use dynamic correlation models to test whether Bitcoin has a hedging effect on stocks, bonds, oil, gold, commodities, and the US dollar index. The study concludes that Bitcoin's hedging effect is weak and only suitable for the diversification of investment portfolio, but in the Asian market, Bitcoin can be used as a safe-haven asset especially in a bear market. Similarly, from the perspective of US investors, Brière, Oosterlinck, and Szafarz (2015) add Bitcoin into a diversified portfolio consisting of traditional asset classes such as stocks, bonds, currencies, hedge funds, and real estate. They discover that the high volatility of Bitcoin is associated with high returns, and even adding a small portion of Bitcoin to the portfolio will effectively increase the overall risk-return profile.

Apart from Bitcoin, there are few reseach on the cryptocurrency market as a whole. These papers focus mainly on the summary statistics of cryptocurrency, portfolio diversification, and price determinants. Hayes (2015) uses data of 66 cryptocurrencies to analyze factors driving the value of cryptocurrency, and find that there are three significant factors: mining difficulty, cryptocurrency efficiency, and encryption algorithm. Hubrich (2017) applies the factor analysis method to the cryptocurrency market and constructs a three-factor model using data of 11 cryptocurrencies. Results suggest that the value of cryptocurrencies is mainly driven by mining difficulty, productivity of its creation, and algorithm. Elendner, Trimborn, Ong, and Lee (2017) select ten cryptocurrencies with largest market capitalization to construct three portfolios, an equal-weighted portfolio, a capitalization-weighted portfolio, and a portfolio based on the CRyptocurrency IndeX (CRIX)[2]. They analyze the risk-return characteristics and find that the CRIX-based portfolio is less risky than a single cryptocurrency. In addition, given the low liquidity of cryptocurrency, Trimborn, Li, and Härdle (2018) use 39 cryptocurrencies to construct a liquidity bounded risk-return optimization model under the Markowitz's liquidity constraints and suggest that cryptocurrency can increase the return and decrease the risk of the portfolio. The analysis of the factors affecting the overall risk and return of cryptocurrencies mainly involves market momentum and market beta. Sovbetov (2018) constructs the Crypto 50 index based on market beta, trading volume, volatility, attractiveness, and S&P 500 index and studies its short-term and long-term effects on the prices of five cryptocurrencies. Kość, Sakowski, and Ślepaczuk (2018) dynamically select the top 100 cryptocurrency according to the market value and conclude that there is a significant reversal effect in the cryptocurrency market in the short term. Using the CRIX index, Guo, Lee, and Wang (2018) conclude that the cryptocurrency provides a good

[2] http://thecrix.de/

diversification effect and including CRIX index in the portfolio that consists of mainstream assets will generate higher risk-adjusted return. They also document that investor attention, proxied by average returns over past 10 days, drives the prices of cryptocurrencies.

For the pricing of traditional assets, there are plenty of seminal studies (Markowitz, 1952; Sharpe, 1964; Ross, 1976; Banz, 1981; Fama & French, 1993; Carhart, 1997; Fama & French, 2015). After relaxing the rational assumptions, behavioral finance further contributes to the asset pricing literature (De Bondt & Thaler, 1985; Jegadeesh & Titman, 1993; Barberis, Shleifer, & Vishny, 1998; Hong & Stein, 2007; Daniel, Hirshleifer & Subrahmanyam, 2010). Other than the common market, size, momentum and liquidity factors, another widely accepted factor is attention which is a belief about future cash flows and investment risks that is not justified by the facts. According to Baker and Wurgler (2007), real investors and financial markets are too complicated to be simply generalized as a few selected biases and trading frictions. They propose a top-down approach based on investor attention and arbitrage constraints and find that stocks with low market capitalization, no profits, high volatility or no dividends, stocks at an initial stage, and growth stocks are more likely to be affected by large fluctuations in investor attention. With the widespread of the Internet, instead of proxies such as closed-end fund discount rate, IPO quantity, and consumer confidence index, new progress has been made in measuring investor attention and quantifying its impact on asset prices. For instance, Fang and Peress (2009) find that stocks not reported by the news are more profitable than stocks that are frequently reported by the news, especially for stocks with small market capitalization, high concentration of individual investors, low analyst tracking and high volatility. Weiss, Irresberger, and König (2014) use the Google Trends as an estimator and find that market-level crisis attention is a highly significant predictor of stock returns. In addition, media news and social media also provide the ground for the development of attention proxies.

McGurk and Nowak (2014) use textual analysis to analyze the messages on Twitter and find that investor attention has a significant positive impact on stock returns.

2.3 Pricing factors of cryptocurrency

It is difficult to determine the intrinsic value of cryptocurrencies. Different from traditional asset classes, valuation models such as discounted cash flow are not applicable for cryptocurrencies because most projects are still at an early stage and can barely generate a net inflow of cash. In addition, cryptocurrency is also different from precious metals such as gold. Gold has attributes as a currency and its limited storage results in scarcity. Although the number of issues may be limited for an individual cryptocurrency, such as the maximum supply of 21 million Bitcoins, there is no scarcity for the cryptocurrency market as a whole because it is easy to issue new cryptocurrencies through replications. One possible method is to use the acquisition cost of cryptocurrency as book value. For instance, the costs of obtaining Bitcoins are mainly the labor costs, cost of the mining machine, and electricity fees, of which electricity costs account for about 40%. However, the mining difficulty increases with the computing power, requiring a continuous upgrading of the mining machines. Also, the success rate and electricity fees vary a lot. Therefore, the estimated value is very sensitive to the inputs.

Currently, the trading of cryptocurrencies is largely driven by speculation. As “fuels” to pay for the transactions and facilitate the blockchain platform, the value of cryptocurrencies stems from investors' prospects about blockchain platforms or projects. As the number of potential users increases and the supply is limited, the demand for the cryptocurrency inevitably increases, resulting in a higher price. It is, to some extent, similar to the equity market - when investors are optimistic about the company's future prospects, the value of stocks will increase accordingly.

Therefore, it is likely that cryptocurrencies and stocks share common pricing factors. Appendix A lists the pricing factors for stocks. For example, the well-stablished Fama-French five-factor asset pricing model includes market risk, value, size, profitability, and investment factors (Fama & French, 2015). Given that value, profitability and investment are not applicable to cryptocurrency market, we start with the market and size factors.[3] In addition, Liu (2006) finds that liquidity is an important source of priced risk and has significant explanatory powers on stock returns. Momentum factor and attention factor are among the most widely used factors in behavioral finance and thus included. In conclusion, we select five pricing factors in this paper, namely market risk factor, size factor, liquidity factor, momentum factor, and attention factor.

3 Empirical results

3.1 Data and sample

We obtain the data for cryptocurrencies from the *CoinMarketCap* website and the data for mainstream asset classes from Wind and Bloomberg from August 3, 2014 to August 26, 2018. Following the literature on cryptocurrencies, we use market value to screen the sample. But additional screening conditions such as the trading volume are not necessary because we need to study the influence of liquidity factors. We are left with the 110 largest cryptocurrencies after requiring their aggregated market value accounts for 99.9% of the total market value at the beginning of the sample. As of August 26, 2018, when the sample period ends, there are 1,801 cryptocurrencies, of which 1,407 are active. The smallest market value is $4,000 and the market

[3] Hubrich (2017) uses the cryptocurrency market value divided by the last 7 days of trading volume as the proxy variable of the value, which is similar to the reciprocal of the turnover rate. However, it is not as widely adopted as the BM (Book-to-Market) value indicator in the stock market and its feasibility is yet to be proved. Therefore, we do not include the pricing factor of value.

value of 110th is \$51.75 million. The top 110 cryptocurrencies accounted for 97.51% of the total market value. Considering that the market values of the top 110 cryptocurrencies are constantly changing, we update the top 110 cryptocurrencies monthly. The final sample covers 506 cryptocurrencies.

If the closing price of a certain day is missing, we replace it with the data of latest date following earlier literature. If the trading volume of a day is missing, we assume the trading volume to be 0 on that day. Cryptocurrencies may be delisted due to technical problems or lack of market recognition. We do not exclude the sample of cryptocurrencies prior to the delisting because it is difficult for investors to foresee the risk of delisting in reality.

3.2 Descriptive statistics of cryptocurrency

We first compare multiple equity market indices with CRIX index and Bitcoin using the daily return from August 3, 2014 to August 26, 2018. CRIX index is a market index for the cryptocurrency market (Trimborn et al., 2018). Table 1 reports the summary statistics. The standard deviation of CRIX index is about three times larger than that of the S&P 500. In spite of the high volatility, the Sharpe ratio of CRIX is as twice as that of the S&P 500 because the average daily return of CRIX is as high as 0.288%.

[Insert Table 1 here.]

Table 2 summarizes the correlations between cryptocurrencies and mainstream assets. While the CRIX index has weak positive correlations with S&P 500, gold and commodities, there is a weak negative correlation with the Chinese equity market. The results confirm that cryptocurrencies could bring a good diversification effect to a portfolio.

[Insert Table 2 here.]

Table 3 reports the summary statistics of top 10 (Panel A) and bottom 10 (Panel B) cryptocurrencies based on the market value. The largest 10 cryptocurrencies consistently have positive average returns for the sample period. However, the average returns of eight out of ten bottom cryptocurrencies are negative. In addition, for most cryptocurrencies in Panel A, the larger the market value, the higher the Sharpe ratio. According to the standard deviation, cryptocurrencies with small market caps are much riskier than large-cap cryptocurrencies. Negative returns of small-cap cryptocurrencies suggest that contrary to the equity market, there is no risk premium for the small-cap cryptocurrencies. But this may result from the extreme cases selected.

[Insert Table 3 here.]

3.3 Construction of measures

Based on previous analyses of the characteristics of cryptocurrencies and the stock market in Section 2.3, we construct five factors including *Market*, *Size*, *Liquidity*, *Momentum* and *Attention* based on the approach of Fama-French five factor model.

a. *Market (RM)*

Unlike the stock market, there are few indices for the whole cryptocurrency market. CRIX is one of the most widely used (e.g. Elendner et al., 2017; Guo et al., 2018).[4] Established in 2016, CRIX index covers most influential cryptocurrencies. It is a real-time index balanced monthly using formulas based on market value and trading volume. Other indices are either introduced very

[4] http://thecrix.de/references

recently or consist of limited number of cryptocurrencies. Appendix B summarizes the common cryptocurrency indices. We define the *Market* factor as the weekly return of the CRIX index minus the risk-free rate of US one-month government bond yield as follows.

$$RM = RM_{CRIX} - R_f \tag{1}$$

b. *Size* (*SMB*)

We follow Fama and French (2015) and calculate the *Size* (*SMB*) factor as the weekly average return of the small market value portfolio (*Small*) minus the big market value portfolio (*Big*).

c. *Liquidity* (*HML*)

Regarding transaction characteristics, liquidity is commonly measured by turnover rate. We calculate the measure of liquidity as the seven-day turnover rate scaled by market value as follows.

$$\frac{Vol_{7m}}{MV_{7m}} \tag{2}$$

where *Vol* and *MV* are the moving averages of the daily transaction volume and market value over the previous seven days. On the adjustment day, portfolios are ranked based on the previous day's liquidity measure, with high (low) turnover rate indicating good (poor) liquidity. The *Liquidity* (*HML*) factor is then calculated as the mean returns of high liquidity (*High*) portfolio minus the low liquidity (*Low*) one.

d. *Momentum* (*WMF*)

When constructing the momentum portfolio, we sort cryptocurrencies according to the cumulative yields of the past seven days prior to the adjustment date *t*. Portfolios with high returns are the winners (*Win*) and those with low returns are the losers (*Fail*). We construct the *Momentum* (*WMF*) factor by subtracting mean return of losers from that of winners.

e. *Attention* (*GMB*)

We use global search volumes from Google Trends as a proxy for the *Attention* of cryptocurrencies.[5] We then sort portfolios by the Google Trends, and obtain the *Attention* (*GMB*) factor by subtracting the weekly mean return of portfolio with small search volume (*Bad*) from that of portfolio with large search volume (*Good*).

3.4 Portfolio analysis

We group the cryptocurrencies using a seven-day adjustment frequency. The total adjustment is 212 times. Fama and French (2015) use several grouping methods to perform the tests, including 5×5 sorts (25 portfolios), 2×4×4 sorts (32 portfolios), and 2×2×2×2 (16 portfolios). Considering the relatively small sample size, we adopt the 4×4 sort to form 16 portfolios and 5×5 to form 25 portfolios.

[Insert Table 4 here.]

Table 4 shows average weekly returns of 16 value-weighted portfolios from 4×4 cross-grouping according to *Size-Liquidity* (Panel A), *Size-Momentum* (Panel B) and *Size-Attention* (Panel C). Regarding the results on *Size*, negative returns occur more often in portfolios with small market capitalization (6 times) than those with large market capitalization (1 time). In addition, the returns tend to increase with the market value. In Panel A, the average return generally increases with the

[5] It is worth noting that the search volume reflects the overall attention on cryptocurrencies. It does not, however, differentiate attentions drawn due to good news and bad news, which is beyond the research of this study.

liquidity. For the *Size-Momentum* sorts in Panel B, portfolios with high momentum on average generate lower returns, indicating a reversal effect. Moreover, returns are positively correlated with *Attention*.

[Insert Table 5 here.]

The three panels of Table 5 report the results for 25 value-weighted portfolios from 5×5 cross-grouping according to *Size-Liquidity, Size-Momentum* and *Size-Attention,* respectively. The results are similar with Table 4.

3.5 A Five-Factor model

In this section, we follow Fama and French (2015) to conduct analyses on the factor model. First, the factor pricing model for the cryptocurrency market can be presented as follows:

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + w_i WMF_t + g_i GMB_t + e_{it} \tag{3}$$

where R_{it}, R_{Ft}, R_{mt}, *SMB*, *HML*, *WMF*, and *GMB* stand for the return of the cryptocurrency portfolio, the risk-free rate, the return of CRIX, *Size*, *Liquidity*, *Momentum*, and *Attention*, respectively. The intercept term a_i is the excess return that cannot be explained by the factors. e_{it} is the residual term.

To calculate the factor returns of *Size*, *Liquidity*, *Momentum*, and *Attention,* we use the classic 2×3 and 2×2 sorts. In the 2×3 sort, cryptocurrencies in the sample are first divided into the small market value group (*S*) and the big market value group (*B*) based on the median value of the whole sample, and then into three groups of high (*H*), medium (*N*), and low (*L*) for *Liquidity* using the 30% and 70% thresholds. Thus six portfolios of *SH*, *SN*, *SL*, *BH*, *BN*, and *BL* are formed. Similarly, we obtain the 2×3 sort for *Size-Momentum* and *Size-Attention*. As for the 2×2 sorts, instead of the 30% and 70% percentiles, we use the median values of *Liquidity*, *Momentum*, and *Attention*. The factors are computed as shown in Appendix C. Once the grouping is complete, we use the differences of the average returns to construct respective portfolios.

[Insert Table 6 here.]

Table 6 reports summary statistics and correlations for returns of factor portfolios. According to Panel A, we can see that *RM* factor is significant at the 10% significance level, and the *Momentum* factor and the *Attention* factor are significant at the 1% significance level. While we cannot reject the null hypothesis that the returns for *Size* and *Liquidity* portfolios are zero, we cannot conclude that they are not significant when interpreting the excess return of cryptocurrencies. We will further examine the effects in the regression analysis. As shown in Panel B of Table 6, correlations of *SMB*, *HML* and *WMF* from 2×3 and 2×2 sorts are over 0.9. While the correlation of *GMB* factor from 2×3 and 2×2 sort is slightly lower, it is still as high as 0.76. The results suggest that the choice of grouping methods has little effect on the characteristics of the factors.

According to Panel C, the correlations of various pairs of factor portfolios are not significant except that between *HML* and *GMB*, which is -0.68 and -0.64 in 2×3 and 2×2 sort, respectively. It may be due to that the cryptocurrencies with large market value are more likely to have higher search volume, but the transaction volumes may not increase in the same degree. As a result, after scaling the transaction volume with the market value, the liquidity of the cryptocurrencies with large market value tends to negatively correlate with search volume.

In addition, we examine whether any of the five factors is a redundant factor by regressing individual factor portfolio returns on the other four. The intercept term in the regression represents the risk premium of the factor after accounting for the other four factors. If the regression intercept cannot reject the null hypothesis that it is zero, the examined factor is considered as a "redundant" factor. According to Table 7, the intercept coefficients of *RM* and *Size* regressions are not significantly different from zero, suggesting that they may be redundant factors. However, when using *RM* as the dependent variable, *SMB* is significant at 5% significance level, and similarly *RM* is significant at 5% significance level as well when *SMB* is used as the dependent variable. Further analysis is needed before we can safely conclude whether these factors are redundant for the pricing model.

[Insert Table 7 here.]

Next, we examine the explanatory power of the five-factor model. There are two common approaches. The first one is the GRS test (Gibbons, Ross, & Shanken, 1989), which allows examining whether all intercept terms are zero at the same time. The second is to calculate indicators, including $A|a_i|$, $A|a_i|/A|\overline{r_i}|$, and $A(\widehat{a_i^2})/A(\widehat{r_i^2})$, to test whether the regression intercept term is zero, which indicates that the factors included in the model have a good explanatory power on the portfolio's excess return. $A|a_i|$ is the average absolute value of the intercepts in the time-series regressions of 16 portfolios with a_i standing for the intercept of the *i*th cryptocurrency portfolio. r_i is the return of portfolio i minus the average of all portfolio returns. $A|a_i|/A|\overline{r_i}|$, indicates the average absolute value of the intercept a_i over the absolute value of r_i. $A(\widehat{a_i^2})/A(\widehat{r_i^2})$ represents the proportion of the cryptocurrency portfolio excess return that cannot be explained by the factor model in the second order. The smaller the four indicators, the closer the intercept term in the regression is to zero. In other words, the factor model is more effective.

[Insert Table 8 here.]

According to the GRS test results in Table 8, the explanatory power of *Size-Momentum* factor is relatively poor. One possible reason is that the ability of *Size-Momentum* factor to explain the excess return is weakened when the sample is divided into different sorts. Nevertheless, the average absolute intercepts, $A|a_i|$, are relatively small and very close to zero for all factors (0.002 to 0.004). In addition, estimates for $A|a_i|/A|\overline{r_i}|$ range from 7.3% to 15.8%, suggesting that the five-factor model can explain as high as 84.2% to 92.7% of the variations of average excess returns. Similarly, the proportion of the unexplained variances of expected returns is merely 0.5% to 2.5%. Therefore, the five-factor model is generally effective.

[Insert Table 9 here.]

Then, we test whether the intercept terms in the time-series regressions are significantly different from zero for various portfolios. We first examine the 16 *Size-Liquidity* portfolios. The regression results are shown in Table 9. We cannot reject the null hypothesis of intercept = 0 for 14 out of 16 portfolios, indicating a good performance of the five-factor model in explaining the excess return of cryptocurrency portfolios. Except for two small size portfolios, R^2s for the rest are rather high, especially for the portfolios with high liquidity and large size (as high as 77%). This may be due to that cryptocurrencies with high liquidity and larger market capitalization have longer and more complete trading sample.

The coefficient estimates and the t-statistics for *RM* factor are significant for only 4 portfolios, so *RM* has a relatively low explanatory power for the variations of cryptocurrency portfolios excess return, which is consistent with our findings in Table 7. While *Size* is also considered as a redundant factor in Table 7, the coefficient estimates and the t-statistics of the *Size* factor for 12 out of the 16 portfolios are significant in Table 9. Regression results show that *s* estimates for portfolios with smaller market value are positive. By contrast, coefficients for the portfolios with larger market value are all negative. For the *Liquidity* factor, 11 out of 16 portfolios are significant at the 1% significance level, indicating a good explanatory power. As for the *Momentum* factor, *w* estimates for only two portfolios are significant at the 5% and 10% significance levels, respectively, which indicates that changes in excess return of cryptocurrencies cannot be well explained by *Momentum*.[6] Estimates for *Attention* factor, *g*, show that other than the portfolios with small *Size*, *GMB* has a good explanatory power for the rest. The reason why its performance in cryptocurrencies with small market value is not strong may be that small-cap cryptocurrencies usually are the ones not known to the general public, and thus the search volume and attention drawn are low.

[Insert Table 10 here.]

Second, we perform similar tests using 16 *Size-Momentum* portfolios. Results are reported in Table 10. From estimates of the intercept term, α, we can see that half of the portfolios cannot reject the null hypothesis of α = 0, but all coefficients are relatively small and close to zero, and thus making the five-factor model a good fit to explain the excess return of the cryptocurrency portfolios. Similar to *Size-Liquidity* portfolios, coefficients for *RM* factor show no pattern and are not significant for most portfolios. Coefficients of the *Liquidity* factor, *h*, are all significant at 1% significance level, suggesting a good explanatory effect of *HML*. In addition, there is no obvious trend in the value of coefficients among the loser and the winner portfolios, indicating that the effect of *Liquidity* factor on the excess return of cryptocurrencies is consistent in spite of different

[6] Fama and French (2016) find that when controlling other variables, it is difficult to provide sufficient momentum variances for different portfolios. Therefore, adding *Momentum* to the five-factor model has little effect on improving the model, unless we group using *Size-Momentum* combination.

liquidity levels. Results show that *Momentum* factor has a significant effect on portfolio returns. As for the *Attention* factor, coefficients for almost all portfolios (15 out of 16) are negative, which is consistent with the findings of the *Size-Liquidity* group.

[Insert Table 11 here.]

Lastly, Table 11 presents the results for the 16 *Size-Attention* portfolios. Based on estimates of the intercept term, α, all cryptocurrency portfolios cannot reject the null hypothesis (α = 0) except for one with α = -0.003 (t = -1.76). Therefore, the five-factor model can well explain the excess return of cryptocurrencies in our sample. Results of the *RM*, *HML*, *WMF* and *GMB* factors are consistent with previous analysis for *Size-Liquidity* and *Size-Momentum* sorts. However, given the same *Size*, regression coefficients tend to decrease as the *Attention* level increases. The estimate for the small-cap *GMB* portfolio, for example, is 0.476 (t = 4.8) for the *Bad* one and -0.727 (t = -4.9) for the *Good* one. Thus, consistent with previous analyses, investing in cryptocurrencies based solely on the popularity is not a good strategy, in fact, may lead to the decrease in the portfolio's overall return.

4. Conclusion

The boom and bust of the cryptocurrency market were undoubtedly one of the most eye-catching phenomena in the past couple of years. However, it is still unclear how to systematically price cryptocurrencies. In this paper, we construct a five-factor pricing model for cryptocurrencies based on traditional asset pricing theories, aiming to provide insights and inspiration on the valuation of cryptocurrency as an emerging asset type. The model includes *Market* factor (*RM*), *Size* factor (*SMB*), *Liquidity* factor (*HML*), *Momentum* factor (*WMF*), and *Attention* factor (*GMB*).

In general, while the five-factor model well explains the excess return of cryptocurrency portfolios, there are several prominent differences between cryptocurrencies and stocks. We find that different from the stock market, the market factor in the cryptocurrency market does not have much explanatory power. This is possibly due to that the cryptocurrency market is dominated by one single cryptocurrency, Bitcoin. Furthermore, the cryptocurrency market exhibits a positive size effect, that is to say, cryptocurrencies with large market capitalization generate higher returns compared to the ones with small size. On top of that, cryptocurrencies with high liquidity have higher returns. Nevertheless, the *Momentum* factor only has explanatory power under the *Size-Momentum* sorts, and there is a significant reversal effect in the cryptocurrency market, which suggests that investors are overreacting to the price. Last but not least, for the *Attention* factor, results show that cryptocurrency portfolios with high attention have lower excess returns. Therefore, it is not a good strategy to invest in cryptocurrencies solely based on popularity.

Considering the difference between cryptocurrencies and stocks, it will be interesting for future research to use Bitcoin rather than fiat currency as the benchmark for valuation. This is because the cryptocurrency network derives income from two sources, namely, transaction fees and newly mined cryptocurrency. While the latter is predictable and pre-programmed, the former is related to the scope of the utility and intensity of usage of the network. Rather than measuring the cash flow in fiat currency, it may be appropriate to measure the income flow from cryptocurrency networks in Bitcoin.

Also, given the recent development in cross chain and multi-layer technology such as state channel, lightning, atomic transfer and other techniques, it will be interesting to analyze and value the cryptocurrency network using Bitcoin as a benchmark as these networks scale technically in terms of transactions per seconds and scale socially in terms of reaching out to more users via cross chain technology and smart contract. This direction of research may be important as we progress towards security tokens that have the characteristics of a security, possess the risk of blockchain technology, with the corresponding increased returns from additional income flow measured in cryptocurrency such as Bitcoin.

Reference

Baek, C., & Elbeck, M. (2015). Bitcoins as an investment or speculative vehicle? A first look. *Applied Economics Letters*, 22(1), 30-34.

Baker, M., & Wurgler, J. (2007). Investor attention in the stock market. *Journal of Economic Perspectives*, 21(2), 129-151.

Balcilar, M., Bouri, E., Gupta, R., & Roubaud, D. (2017). Can volume predict Bitcoin returns and volatility? A quantiles-based approach. *Economic Modelling*, 64, 74-81.

Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics*, 9(1), 3-18.

Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor attention. *Journal of Financial Economics*, 49(3), 307-343.

Barro, R. J. (1979). Money and the price level under the gold standard. *Economic Journal*, 89(353), 13-33.

Brière, M., Oosterlinck, K., & Szafarz, A. (2015). Virtual currency, tangible return: Portfolio diversification with Bitcoin. *Journal of Asset Management*, 16(6), 365-373.

Bouoiyour, J., Selmi, R., Tiwari, A. K., & Olayeni, O. R. (2016). What drives Bitcoin price. *Economics Bulletin*, 36(2), 843-850.

Bouri, E., Molnár, P., Azzi, G., Roubaud, D., & Hagfors, L. I. (2017). On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier? *Finance Research Letters*, 20, 192-198.

Carhart, M. M. (1997). On Persistence in Mutual Fund Performance. *Journal of Finance*, 52(1), 57-82.

Cheah, E. T., & Fry, J. (2015). Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. *Economics Letters*, 130, 32-36.

Ciaian, P., Rajcaniova, M., & Kancs, D. A. (2016). The economics of Bitcoin price formation. *Applied Economics*, 48(19), 1799-1815.

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (2010). Overconfidence, arbitrage, and equilibrium asset pricing. *Journal of Finance*, 56(3), 921-965.

De Bondt, W. F., & Thaler, R. (1985). Does the stock market overreact?. *Journal of Finance*, 40(3), 793-805.

Dyhrberg, A. H. (2016). Hedging capabilities of Bitcoin; Is it the virtual gold?. *Finance Research Letters*, 16, 139-144.

Eisl, A., Gasser, S., & Weinmayer, K. (2015). Caveat emptor: does Bitcoin improve portfolio diversification?. Working paper.

Elendner, H., Trimborn, S., Ong, B., & Lee, T. M. (2017). The cross-section of crypto-currencies as financial assets: investing in crypto-currencies beyond Bitcoin. In *Handbook of Blockchain, Digital Finance, and Inclusion, Volume 1* (pp. 145-173).

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 3-56.

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1), 1-22.

Fama, E. F., & French, K. R. (2016). Dissecting anomalies with a five-factor model. *Review of Financial Studies*, 29(1), 69-103.

Fang, L., & Peress, J. (2009). Media coverage and the cross-section of stock returns. *Journal of Finance*, 64(5), 2023-2052.

Gibbons, M. R., Ross, S. A., & Shanken, J. (1989). A test of the efficiency of a given portfolio. *Econometrica: Journal of the Econometric Society*, 1121-1152.

Guo, L., Lee, D. K. C., & Wang, Y. (2018). Cryptocurrency: A new investment opportunity?. *Journal of Alternative Investments*, 20 (3), 16-40.

Hayes, A. (2015). What factors give cryptocurrencies their value: an empirical analysis. Working papers.

Hong, H., & Stein, J. C. (2007). Disagreement and the stock market. *Journal of Economic Perspectives*, 21(2), 109-128.

Hubrich, S. (2017). 'Know When to Hodl ‘Em, Know When to Fodl ‘Em': An Investigation of Factor Based Investing in the Cryptocurrency Space. Working paper.

Jegadeesh, N. & Titman, S. (1993). Returns to buying winners and selling losers: implications for stock market efficiency. *Journal of Finance*, 48(1), 65-91.

Kość, K., Sakowski, P., & Ślepaczuk, R. (2018). Momentum and contrarian effects on the cryptocurrency market. Working Papers, 2018.

Kristoufek, L. (2013) Bitcoin meets Google Trends and Wikipedia: quantifying the relationship between phenomena of the Internet era. *Scientific Reports*, 3 (3415), 1–7.

Liu, W. (2006). A liquidity-augmented capital asset pricing model. *Journal of Financial Economics*, 82(3), 631-671.

Markowitz, H. (1952). Portfolio selection. *The Journal of Finance*, 7(1), 77-91.

McGurk, Z., & Nowak, A. (2014). The relationship between stock returns and investor attention: evidence from social media. West Virginia University working paper, No. 14-38.

Ross, S. A. (1976). The Arbitrage Theory of Capital Asset Pricing. In *HANDBOOK OF THE FUNDAMENTALS OF FINANCIAL DECISION MAKING: Part I* (pp. 11-30).

Sovbetov, Y. (2018). Factors influencing cryptocurrency prices: evidence from Bitcoin, Ethereum, Dash, Litcoin, and Monero. *Social Science Electronic Publishing*.

Stattman, D. (1980). Book Values and Stock Returns. *The Chicago MBA: A journal of selected papers*, 4(1)：25-45.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *Journal of Finance*, 19(3), 425-442.

Trimborn, S., Li, M., & Härdle, W. K. (2018). Investing with cryptocurrencies - a liquidity constrained investment approach. *Social Science Electronic Publishing*.

Valstad, O. C. A., & Vagstad, K. (2014). A bit risky? A comparison between Bitcoin and other assets using an intraday Value at Risk approach. Institutt for Industriell Økonomi Og Teknologiledelse.

Weiss, G. N., Irresberger, F., & König, F. E. (2014). Crisis attention and insurer performance. SSRN working paper, No. 2364365.

Wijk, D. V. (2013). What can be expected from the Bitcoin. Working paper No. 345986.

Yermack, D. (2014). Is Bitcoin a real currency? An economic appraisal. NBER working paper No. 19747.

Appendix A: Common pricing factors in the stock market

Factor	Indicator	Remark
Market	β	CAPM model
Value	PE ratio, PB ratio	Fama-French five-factor model
Momentum	Historical cumulative return	Carhart four-factor model
Size	Market capitalization	Fama-French five-factor model
Profitability	PE ratio, ROA, ROE, net profit, EPS	Fama-French five-factor model
Growth	Net asset growth rate, revenue growth rate	Fama-French five-factor model
Liquidity	Turnover rate, trading volume, Bid-ask spread	Liu(2006)
Attention	Number of new account, trading volume, media attention	Behavioral finance

Appendix B: Overview of cryptocurrency indices

Index	Year launched	Methodology	Remark
CRyptocurrency IndeX (CRIX)	2014	Market capitalization weighted & liquidity rules	It covers a wide spectrum of cryptocurrencies.
Coinbase Index (CBI)	2015	Market capitalization weighted	It covers only the ones listed on Coinbase's exchange, GDAX.
BB Index	2017	Market capitalization smoothened	Top 7, 20, 30, and 50 by market capitalization with ranking by different types available.
Huobi 10 Index (HB10)	2018	Trading volume weighted	Top 10 and sample covers only the Huobi platform
Bloomberg Galaxy Crypto Index (BGCI)	2018	Market capitalization weighted	Top 10 based on market capitalization with at least $2M of trading volume for the past 30 days

Appendix C: Construction of factors

Independent sorts are used to classify cryptocurrencies into two *Size* groups, and two or three *Liquidity*, *Momentum* and *Attention* groups. These portfolios are denoted using letters. Specifically, *Small* (*S*) and *Big* (B) are the *Size* group sorted by the median value of the market capitalization on day *t*. For, *High* (*H*) or *Low* (*L*) *Liquidity*, we sort cryptocurrencies based on the seven-day moving average of turnover rate at day *t-1*. *Momentum*, *Win* (*W*) or *Fail* (*F*), is based on seven-day moving average of returns at day *t-1*. *Attention*, *Good* (*G*) or *Bad* (*B*), is based on seven-day moving average of the Google Trends search volume. The factors are *SMB* (*Small* minus *Big*), *HML* (*High* minus *Low*), *WMF* (*Win* n minus *Fail*), and *GMB* (*Good* minus *Bad*).

Sort	Breakpoints	Factor calculation formula
2×3 sorts on *Size* and *Liquidity*, or *Size* and M*omentum*, or *Size* and *Attention*	30^{th} & 70^{th}	SMB_{VOL} = (SH + SN + SL) / 3 - (BH + BN + BL) / 3 SMB_{mom}= (SW + SN + SF) / 3 - (BW + BN + BF) / 3 SMB_{attr}= (SG + SN + SB) / 3 - (BG + BN + BB) / 3 SMB = ($SMB_{VOL} + SMB_{mom} + SMB_{attr}$) / 3 HML = (SH + BH) / 2 – (SL + BL) / 2 = [(SH – SL) + (BH +BL)] / 2 WMF = (SW + BW) / 2 – (SF + BF) / 2 = [(SW – SF) + (BW +BF)] / 2 GMB = (SG + BG) / 2 – (SG + BB) / 2 = [(SG – SB) + (BG+BB)] / 2
2×2 sorts on *Size* and *Liquidity*, or *Size* and M*omentum*, or *Size* and *Attention*	50^{th}	SMB = (SH + SL + SW + SF + SG + SB) / 6 – (BH + BL + BW + BF + BG + BB) / 6 HML = (SH + BH) / 2– (SL + BL) / 2 = [(SH – SL) + (BH –BL)] / 2 WMF = (SW + BW) / 2 – (SF + BF) / 2 = [(SW – SF) + (BW–BF] / 2 GMB = (SG + BG) / 2 – (SB + BB) / 2 = [(SG – SB) + (BG –BB)] / 2

Table 1 Summary statistics of cryptocurrencies and other assets

CRIX is a market index (benchmark) for the cryptocurrency market. CSI 300 (500, 1000) stands for the stock market index designed to represent the performance of top 300 (500, 1000) stocks traded in the Shanghai and Shenzhen stock exchanges in China. Hang Seng Index is an index that includes the largest and most liquid stocks listed on the Main Board of the Stock Exchange of Hong Kong. Data are obtained from *CoinMarketCap*, Bloomberg and Wind. The sample period is from August 3, 2014 to August 26, 2018. Returns are calculated based on daily closing price.

Asset Class	Mean	Std Dev	Skewness	Kurtosis	Min	Max	Sharpe Ratio
CRIX	0. 288	0.034	-0.6	6.6	-0.22	0.13	8.5
Bitcoin	0.216	0.036	-0.5	6.1	-0.22	0.14	6.0
S&P 500	0.035	0.008	-0.6	6.4	-0.04	0.04	4.3
CSI 300	0.033	0.016	-1.1	9.5	-0.09	0.06	2.1
CSI 500	0.014	0.019	-1.2	7.5	-0.09	0.06	0.8
CSI 1000	0.002	0.020	-1.1	6.6	-0.09	0.06	0.1
Hang Seng Index	0.014	0.011	-0.4	5.6	-0.06	0.04	1.3
GSCI	-0.061	0.013	0.0	4.6	-0.07	0.05	-4.7
Gold	-0.007	0.009	-0.1	8.2	-0.07	0.05	-0.8
U.S. Dollar Index	0.012	0.005	-0.1	4.9	-0.02	0.02	2.6

Table 2 Correlations between cryptocurrencies and other assets

CRIX is a market index (benchmark) for the cryptocurrency market. CSI 300 (500, 1000) stands for the stock market index designed to represent the performance of top 300 (500, 1000) stocks traded in the Shanghai and Shenzhen stock exchanges in China. Hang Seng Index is an index that includes the largest and most liquid stocks listed on the Main Board of the Stock Exchange of Hong Kong. Data are obtained from *CoinMarketCap*, Bloomberg and Wind. The sample period is from August 3, 2014 to August 26, 2018. Returns are calculated based on daily closing price.

	CSI 300	CSI 500	CSI 1000	Hang Seng Index	GSCI	Gold	U.S. Dollar Index	S&P 500	CRIX	Bitcoin
CSI 300	1.00									
CSI 500	0.83	1.00								
CSI 1000	0.74	0.97	1.00							
Hang Seng Index	0.03	0.01	0.01	1.00						
GSCI	-0.04	-0.01	-0.01	0.02	1.00					
Gold	0.01	0.00	0.01	0.01	0.05	1.00				
U.S. Dollar Index	-0.01	-0.01	-0.01	0.02	0.05	-0.02	1.00			
S&P 500	-0.01	0.00	0.00	0.01	0.01	0.02	-0.01	1.00		
CRIX	-0.04	-0.07	-0.07	-0.03	0.00	0.01	-0.06	0.05	1.00	
Bitcoin	-0.04	-0.07	-0.07	-0.01	-0.01	0.02	-0.07	0.05	0.97	1.00

Table 3 Summary statistics of top 10 and bottom 10 cryptocurrencies

The sample period is from August 3, 2014 to August 26, 2018. Cryptocurrencies with available price, market value, and transaction volume data are ranked according to the market value. Panel A and Panel B report summary statistics for the top 10 and bottom 10 cryptocurrencies, respectively.

Name	Market Value	Mean	Std Dev	Skewness	Kurtosis	Min	Max	Sharpe Ratio
Panel A								
Bitcoin	116,387,236,698	0.16	0.04	-0.35	8.47	-0.24	0.23	4.0
XRP	12,970,457,793	0.28	0.07	2.98	44.45	-0.62	1.03	4.0
Stellar	4,202,536,839	0.30	0.08	1.95	17.49	-0.37	0.72	3.6
Monero	1,517,266,238	0.26	0.07	0.87	9.47	-0.33	0.58	3.6
Bytecoin	321,568,822	0.32	0.12	3.28	45.35	-0.91	1.60	2.6
BitShares	285,511,071	0.16	0.08	1.01	9.90	-0.39	0.52	2.0
DigiByte	279,892,778	0.32	0.10	2.33	23.72	-0.43	1.17	3.1
Dogecoin	274,339,095	0.17	0.07	0.85	13.98	-0.49	0.52	2.6
MaidSafeCoin	111,022,305	0.16	0.07	-0.05	6.17	-0.38	0.35	2.2
Nxt	68,994,760	0.03	0.08	0.59	13.49	-0.60	0.59	0.4
Panel B								
AsiaCoin	3,183,055	0.09	0.29	0.30	27.61	-3.10	2.76	0.3
Digitalcoin	293,901	-0.02	0.15	-0.55	46.27	-1.98	1.46	-0.1
TagCoin	261,043	-0.03	0.13	0.30	16.91	-1.07	1.11	-0.2
HoboNickels	238,593	-0.15	0.11	0.18	19.99	-1.04	0.96	-1.3
UltraCoin	177,692	-0.04	0.14	0.77	11.75	-0.83	1.24	-0.3
NetCoin	159,682	-0.02	0.14	0.72	19.59	-1.27	1.38	-0.1
Freicoin	154,887	0.03	0.24	-0.15	19.23	-1.75	1.95	0.1
TEKcoin	95,621	-0.49	0.27	0.15	10.46	-1.81	1.84	-1.8
SecureCoin	73,103	-0.12	0.17	0.00	32.16	-1.83	1.38	-0.7
Quatloo	70,466	-0.09	0.13	0.4142	8.8235	-0.6324	0.8274	-0.67

Table 4 Excess returns of 4×4 portfolios

This table shows the average weekly excess returns for portfolios formed on *Size* and *Liquidity*, *Size* and *Momentum*, *Size* and *Attention*. Sample period is from August 3, 2014 to August 26, 2018. We adjust the cryptocurrency portfolios every seven days and denote the adjustment day as *t*. Cryptocurrencies are classified into four *Size* groups from Small to Big according to the market capitalization on day *t-1*, and then further divided into four groups based on the ranking of *Liquidity*, *Momentum* and *Attention*, respectively. The intersections of any two sorts produce 16 (4×4) portfolios. The ranking of *Liquidity*, *Momentum* and *Attention* are calculated based on the seven-day moving average of turnover rate, return, and Google Trends at day *t-1*, respectively. The total number of adjustments is 212. Excess returns are calculated as portfolio returns in excess of the one-month U.S. Treasury bill rate.

	Small	2	3	Big
Panel A: *Size-Liquidity* portfolios				
Low	-0.16	0.29	0.04	0.16
2	0.28	0.16	0.06	0.25
3	-0.19	0.13	0.13	0.48
High	0.33	0.67	0.59	0.44
Panel B: *Size-Momentum* portfolios				
Low	1.20	1.63	1.03	0.17
2	-0.08	0.26	0.10	0.37
3	0.41	0.74	0.49	0.55
High	-1.26	-1.45	-0.87	0.20
Panel C: *Size-Attention* portfolios				
Low	-0.33	0.09	-0.53	-0.27
2	-0.06	0.18	0.09	0.13
3	0.13	0.44	0.56	0.43
High	0.55	0.54	0.69	1.06

Table 5 Excess returns of 5×5 portfolios

This table shows the average weekly excess returns for portfolios formed on *Size* and *Liquidity*, *Size* and *Momentum*, *Size* and *Attention*. Sample period is from August 3, 2014 to August 26, 2018. We adjust the cryptocurrency portfolios every seven days and denote the adjustment day as *t*. Cryptocurrencies are classified into five *Size* groups from *Small* to *Big* according to the market capitalization on day *t-1*, and then further divided into five groups based on the ranking of *Liquidity*, *Momentum* and *Attention*, respectively. The intersections of any two sorts produce 25 (5×5) portfolios. The ranking of *Liquidity*, *Momentum* and *Attention* are calculated based on the seven-day moving average of turnover rate, return, and Google Trends at day *t-1*, respectively. The total number of adjustments is 212. Excess returns are calculated as portfolio returns in excess of the one-month U.S. Treasury bill rate.

	Small	2	3	4	Big
Panel A: *Size-Liquidity* portfolios					
Low	-0.24	0.41	0.11	-0.19	-0.02
2	0.15	-0.04	0.02	0.46	0.47
3	0.12	0.01	0.04	0.41	0.27
4	-0.03	0.03	0.35	0.19	0.67
High	0.53	0.70	0.50	0.44	0.34
Panel B: *Size-Momentum* portfolios					
Low	1.81	2.09	1.24	0.99	0.28
2	-0.32	0.33	0.22	-0.04	0.26
3	-0.03	0.23	0.33	0.41	0.72
4	0.46	0.65	0.69	0.62	0.36
High	-1.39	-2.22	-1.45	-0.66	0.04
Panel C: *Size-Attention* portfolios					
Low	-0.16	0.14	-0.41	-0.25	-0.31
2	-0.09	-0.13	-0.15	0.16	0.05
3	-0.35	0.48	0.11	0.38	0.31
4	0.33	0.23	0.31	0.05	0.56
High	0.83	0.37	1.13	0.99	1.04

Table 6 Factor portfolio returns

Independent sorts are used to classify cryptocurrencies into two *Size* groups, and two or three *Liquidity*, *Momentum* and *Attention* groups. These portfolios are denoted using letters. Specifically, *Small* (*S*) and *Big* (B) for the *Size* group sorted by the median value of the market capitalization on day *t-1*. For, *High* (*H*) or *Low* (*L*) *Liquidity*, we sort cryptocurrencies based on the seven-day moving average of turnover rate at day *t-1*. *Momentum*, *Win* (*W*) or *Fail* (*F*), is based on seven-day moving average of returns at day *t-1*. *Attention*, *Good* (*G*) or *Bad* (*B*), is based on seven-day moving average of the Google Trends search volume. The factors are *SMB* (*Small* minus *Big*), *HML* (*High* minus *Low*), *WMF* (*Win* minus *Fail*), and *GMB* (*Good* minus *Bad*). *RM* is calculated using the seven-day accumulated return of CRIX index in excess of the one-month U.S. Treasury bill rate on adjustment day *t*. Panel A of the table shows the average weekly returns (Mean), the standard deviations of weekly returns (Std Dev) and the t-statistics for the average returns. Panel B shows the correlations of the same factor from different sorts. Panel C shows the correlations between different factors.

Panel A: Average, standard deviations, and t-statistics for weekly returns

	2×3 factors					**2×2 factors**				
	RM	*SMB*	*HML*	*WMF*	*GMB*	*RM*	*SMB*	*HML*	*WMF*	*GMB*
Mean	0.56	-0.07	0.29	1.37	-0.93	0.56	-0.07	0.21	0.74	-0.37
Std Dev	4.55	1.99	4.9	3.99	3.78	4.55	1.97	3.91	3.17	1.52
t-statistics	1.79	-0.48	0.87	4.99	-3.58	1.79	-0.54	0.80	3.39	-3.52

Panel B: Correlations between different version of the same factor

	SMB		**HML**		**WMF**		**GMB**	
	2×3	2×2	2×3	2×2	2×3	2×2	2×3	2×2
2×3	1.00	1.00	1.00	0.97	1.00	0.93	1.00	0.76
2×2	1.00	1.00	0.97	1.00	0.93	1.00	0.76	1.00

Panel C: Correlations between different factors

	2×3					**2×2**				
	RM	*SMB*	*HML*	*WMF*	*GMB*	*RM*	*SMB*	*HML*	*WMF*	*GMB*
RM	1.00	-0.19	0.10	0.11	-0.13	1.00	-0.19	0.08	0.03	-0.13
SMB	-0.19	1.00	-0.03	-0.13	0.13	-0.19	1.00	-0.06	-0.09	0.20
HML	0.10	-0.03	1.00	0.07	-0.68	0.08	-0.06	1.00	0.00	-0.64
WMF	0.11	-0.13	0.07	1.00	-0.10	0.03	-0.09	0.00	1.00	-0.08
GMB	-0.13	0.13	-0.68	-0.10	1.00	-0.13	0.20	-0.64	-0.08	1.00

Table 7 Tests on redundant factors

This table shows the regression results of redundant factors. *Small* (*S*) and *Big* (B) for the *Size* group are sorted by the median value of the market capitalization on day *t-1*. For, *High* (*H*) or *Low* (*L*) *Liquidity*, we sort cryptocurrencies based on the seven-day moving average of turnover rate at day *t-1*. *Momentum*, *Win* (*W*) or *Fail* (*F*), is based on seven-day moving average of returns at day *t-1*. *Attention*, *Good* (*G*) or *Bad* (*B*), is based on seven-day moving average of the Google Trends search volume. The factors are *SMB* (*Small* minus *Big*), *HML* (*High* minus *Low*), *WMF* (*Win* minus *Fail*), and *GMB* (*Good* minus *Bad*). *RM* is calculated using the seven-day accumulated log-return rate of CRIX index in excess of the one-month U.S. Treasury bill rate on adjustment day *t*. *, **, and *** denote significant at significance level of 10%, 5%, and 1%, respectively.

	Intercept	***RM***	***SMB***	***HML***	***WMF***	***GMB***
RM						
Coef	0.00		-0.381**	0.05	0.10	-0.08
t-statistics	-0.96		-2.41	0.53	1.23	-0.67
SMB						
Coef	0.00	-0.0719**		0.05	-0.05	0.0954**
t-statistics	0.81	-2.41		1.31	-1.46	1.97
HML						
Coef	-0.00550**	0.03	0.17		0.01	-0.884***
t-statistics	-2.05	0.53	1.31		0.18	-13.19
WMF						
Coef	0.0125***	0.08	-0.21	0.01		-0.07
t-statistics	4.38	1.23	-1.46	0.18		-0.66
GMB						
Coef	-0.00705***	-0.03	0.194**	-0.517***	-0.03	
t-statistics	-3.50	-0.67	1.97	-13.19	-0.66	

Table 8 Tests of the five-factor model

$A|a_i|$is the average absolute value of the intercepts in the time-series regressions of 16 portfolios with $a_i$standing for the intercept of the ith cryptocurrency portfolio. r_i is the return of portfolio i minus the average of all portfolio returns. $A|a_i|/A|\overline{r_i}|$ indicates the average absolute value of the intercept a_i over the absolute value of r_i . $A(\widehat{a_i^2})/A(\widehat{r_i^2})$ represents the proportion of the cryptocurrency portfolio excess return that cannot be explained by the factor model in the second order. Values in parentheses for the GRS column are p-values.

	GRS	$A\|a_i\|$	$A\|a_i\|/A\|\overline{r_i}\|$	$A(\widehat{a_i^2})/A(\widehat{r_i^2})$
Size-Liquidity	0.96 (0.49)	0.002	0.073	0.005
Size-Momentum	4.89(0.00)	0.004	0.158	0.025
Size-Attention	1.06 (0.39)	0.002	0.083	0.007

Table 9 Regression results for *Size-Liquidity* portfolios

Table 9 shows the regression results for 16 *Size-Liquidity* portfolios, including the intercepts, coefficients and corresponding t-statistics for the five-factor model. Sample period is from August 3, 2014 to August 26, 2018. There are 212 weeks in total. We adjust the cryptocurrency portfolios every seven days and denote the adjustment day as *t*. Cryptocurrencies are classified into four *Size* groups from *Small* to *Big* according to the market capitalization on day *t-1*, and then independently sorted into four *Liquidity* groups (*Low* to *High*) according to the seven-day moving average of turnover rate at day *t-1*. The intersections of the two sorts result in 16 *Size-Liquidity* portfolios. The explanatory variables are the market excess return, $R_{Mt} - R_{Ft}$, the *Size* factor, *SMB*, the *Liquidity* factor, *HML*, the *Momentum* factor, *WMF*, and the *Attention* factor, *GMB*. *, **, and *** denote significant at significance level of 10%, 5%, and 1%, respectively. The five-factor regression equation is as follows:

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + w_i WMF_t + g_i GMB_t + e_{it}$$

Table 9 (continued) Regression results for *Size-Liquidity* portfolios

Size→		Small	2	3	Big	Small	2	3	Big
				α			**t(α)**		
Intercept	Low	-0.002	0.002	0.000	-0.001	-0.9	0.87	-0.26	-0.4
	2	0.001	-0.003	-0.005**	-0.003	0.59	-1.06	-2.12	-1.36
	3	-0.005	-0.005**	0.000	0.000	-1.39	-2.05	-0.08	-0.1
	High	0.002	0.000	0.000	0.000	0.7	0.14	-0.07	-0.05
				r			**t(r)**		
RM	Low	0.013	-0.042	-0.078**	-0.117***	0.34	-0.86	-1.98	-2.72
	2	0.013	-0.03	-0.100**	-0.023	0.33	-0.55	-2.06	-0.47
	3	-0.176***	-0.092	-0.072	-0.06	-2.62	-1.57	-1.13	-0.83
	High	-0.083	-0.063	0.009	-0.003	-1.14	-0.74	0.17	-0.06
				s			**t(s)**		
Size	Low	0.450***	-0.317***	-0.336***	-0.904***	4.37	-2.88	-3.14	-2.69
	2	0.127	-0.085	-0.886***	-1.058***	0.97	-0.45	-6.12	-6.27
	3	0.258	-0.151	-0.958***	-1.038***	1	-1.03	-6.93	-6.71
	High	0.405**	0.458**	-0.865***	-0.693***	2.24	2.54	-5.72	-5.86
				h			**t(h)**		
Liquidity	Low	0.032	0.019	0.085	-0.115	0.46	0.32	1.55	-0.85
	2	0.084	0.280***	0.278***	0.584***	1.02	2.78	3.83	7.33
	3	0.818***	0.578***	0.759***	0.700***	7.73	7.05	10.78	11.18
	High	1.276***	0.890***	0.984***	0.789***	12.51	9.39	10.13	14.54
				w			**t(w)**		
Momentum	Low	0.011	-0.043	-0.090*	-0.081	0.21	-0.76	-1.79	-0.83
	2	0.031	-0.086	0.098	0.021	0.46	-0.98	1.57	0.32
	3	-0.05	-0.079	-0.156**	0.007	-0.61	-1.15	-2.15	0.11
	High	-0.033	0.042	-0.016	-0.001	-0.45	0.54	-0.21	-0.02
				g			**t(g)**		
Attention	Low	-0.03	-0.189**	-0.124	-0.434***	-0.29	-2.21	-1.63	-3.11
	2	-0.08	-0.534***	-0.361***	-0.349***	-0.63	-3.75	-3.76	-2.98
	3	-0.251	-0.694***	-0.124	-0.274***	-1.57	-6.12	-1.31	-2.81
	High	0.114	-0.488***	-0.299**	-0.193**	0.82	-2.77	-2.19	-2.36
R^2	Low	0.09	0.12	0.15	0.27				
	2	0.04	0.38	0.46	0.67				
	3	0.52	0.64	0.66	0.69				
	High	0.70	0.67	0.75	0.77				

Table 10 Regression results for *Size-Momentum* portfolios

Table 10 shows the regression results for 16 *Size-Momentum* portfolios with weekly ranking window, including the intercepts, coefficients and corresponding t-statistics for the five-factor model. Sample period is from August 3, 2014 to August 26, 2018. There are 212 weeks in total. We adjust the cryptocurrency portfolios every seven days and denote the adjustment day as *t*. Cryptocurrencies are classified into four *Size* groups from *Small* to *Big* according to the market capitalization on day *t-1*, and then independently sorted into four *Momentum* groups (*Low* to *High*) according to the seven-day moving average of log-return at day *t-1*. The intersections of the two sorts result in 16 *Size-Momentum* portfolios. The explanatory variables are the market excess return, $R_{Mt} – R_{Ft}$, the *Size* factor, *SMB*, the *Liquidity* factor, *HML*, the *Momentum* factor, *WMF*, and the *Attention* factor, *GMB*. *, **, and *** denote significant at significance level of 10%, 5%, and 1%, respectively. The five-factor regression equation is as follows:

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} – R_{Ft}) + s_i SMB_t + h_i HML_t + w_i WMF_t + g_i GMB_t + e_{it}$$

Table 10 (continued) Regression results for *Size-Momentum* portfolios

Size→		Small	2	3	Big	Small	2	3	Big
				α				**t(α)**	
Intercept	Low	0.002	-0.001	0.000	-0.007***	0.53	-0.4	0.05	-2.72
	2	-0.004*	-0.002	-0.003	-0.001	-1.86	-0.81	-1.47	-0.76
	3	0.006***	0.008***	0.004*	0.003	2.92	3.55	1.91	1.21
	High	-0.006*	-0.012***	-0.006**	0.001	-1.84	-4.59	-2.49	0.38
				r				**t(r)**	
RM	Low	-0.129*	-0.029	-0.047	-0.107*	-1.97	-0.44	-0.85	-1.85
	2	0.007	-0.089	-0.123**	-0.120**	0.1	-1.3	-1.99	-2.1
	3	0.023	0.042	0.043	0.051	0.46	0.8	0.79	1.01
	High	-0.138	-0.157***	-0.126**	-0.025	-1.33	-3.05	-2.57	-0.56
				s				**t(s)**	
Size	Low	0.378*	0.434**	-1.068***	-1.014***	1.81	2.5	-7.08	-5.77
	2	0.318**	-0.350**	-0.719***	-0.747***	2.08	-2.56	-4.29	-5.37
	3	0.019	-0.2	-0.504***	-0.966***	0.16	-1.46	-4.25	-5.32
	High	0.539**	-0.006	-0.744***	-0.978***	2.27	-0.04	-6.16	-4.24
				h				**t(h)**	
Liquidity	Low	0.792***	0.453***	0.674***	0.593***	7.83	5.02	7.6	6.64
	2	0.247***	0.314***	0.378***	0.450***	3.11	4.34	4.76	6.94
	3	0.346***	0.382***	0.451***	0.472***	5.28	5.25	7.08	6.19
	High	0.799***	0.619***	0.586***	0.436***	6.93	7.09	7.4	4.46
				w				**t(w)**	
Momentum	Low	0.594***	0.665***	0.365***	0.342***	8.35	8.25	5.71	4.76
	2	0.199**	0.153*	0.185**	0.110*	2.28	1.82	2.23	1.83
	3	-0.196***	-0.381***	-0.218***	-0.142*	-3.79	-5.67	-3.22	-1.92
	High	-0.655***	-0.624***	-0.503***	-0.369***	-5.49	-8.71	-7.47	-4.44
				g				**t(g)**	
Attention	Low	-0.083	-0.792***	-0.323***	-0.232*	-0.61	-5.41	-2.88	-1.88
	2	-0.028	-0.210**	-0.101	-0.277***	-0.27	-1.97	-0.88	-3.28
	3	0.014	-0.325***	-0.206**	-0.273***	0.16	-3.54	-2.3	-2.72
	High	-0.155	-0.545***	-0.259**	-0.467***	-0.95	-4.91	-2.43	-3.99
R^2	Low	0.56	0.66	0.68	0.63				
	2	0.21	0.36	0.46	0.61				
	3	0.27	0.49	0.52	0.61				
	High	0.53	0.65	0.61	0.59				

Table 11 Regression results for *Size-Attention* portfolios

Table 11 shows the regression results for 16 *Size-Attention* portfolios, including the intercepts, coefficients and corresponding t-statistics for the five-factor model. Sample period is from August 3, 2014 to August 26, 2018. There are 212 weeks in total. We adjust the cryptocurrency portfolios every seven days and denote the adjustment day as *t*. Cryptocurrencies are classified into four *Size* groups from *Small* to *Big* according to the market capitalization on day *t-1*, and then independently sorted into four *Attention* groups (*Low* to *High*) according to the seven-day moving average of Google Trends search volume at day *t-1*. The intersections of the two sorts result in 16 *Size-Attention* portfolios. The explanatory variables are the market excess return, $R_{Mt}– R_{Ft}$, the *Size* factor, *SMB*, the *Liquidity* factor, *HML*, the *Momentum* factor, *WMF*, and the *Attention* factor, *GMB*. *, **, and *** denote significant at significance level of 10%, 5%, and 1%, respectively. The five-factor regression equation is as follows:

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt}– R_{Ft}) + s_iSMB_t + h_iHML_t + w_iWMF_t + g_iGMB_t + e_{it}$$

Table 11 (continued) Regression results for *Size-Attention* portfolios

Size→		Small	2	3	Big	Small	2	3	Big
				α			**t(α)**		
Intercept	Low	0	-0.001	-0.003*	-0.003	0.08	-0.44	-1.76	-1.53
	2	0.001	-0.001	-0.002	-0.003	0.39	-0.49	-0.88	-1.23
	3	-0.003	-0.002	0.003	-0.001	-1.11	-0.78	1	-0.65
	High	-0.001	-0.002	-0.002	0.003	-0.28	-0.96	-1.04	1.35
				r			**t(r)**		
RM	Low	-0.013	-0.079	-0.097**	-0.053	-0.26	-1.37	-2.27	-1.21
	2	-0.054	-0.096*	-0.089*	-0.01	-1.04	-1.74	-1.78	-0.21
	3	-0.062	0.024	-0.04	-0.118**	-0.89	0.3	-0.65	-2.13
	High	-0.106	-0.079	-0.025	-0.02	-1.38	-1.44	-0.58	-0.35
				s			**t(s)**		
Size	Low	0.508***	0.083	-0.695***	-0.937***	3.96	0.64	-4.37	-3.85
	2	0.2	-0.172	-0.592***	-0.865***	1.09	-1.12	-5	-6.35
	3	0.094	-0.209	-1.065***	-0.977***	0.53	-1.13	-7.49	-6.97
	High	0.445***	0.18	-0.700***	-0.921***	2.97	0.97	-5.75	-5.31
				h			**t(h)**		
Liquidity	Low	0.481***	0.394***	0.377***	0.256***	7.4	5.96	5.03	2.64
	2	0.599***	0.518***	0.537***	0.592***	6.63	6.34	8.32	9.82
	3	0.625***	0.480***	0.644***	0.618***	6.02	5.49	7.87	8.12
	High	0.491***	0.368***	0.528***	0.485***	5.61	4.25	8.75	6.57
				w			**t(w)**		
Momentum	Low	0	0.029	-0.048	-0.089	0	0.39	-0.79	-1.14
	2	-0.045	-0.05	-0.007	0.034	-0.62	-0.73	-0.11	0.6
	3	0.076	-0.045	-0.129	0.05	1.07	-0.51	-1.47	0.96
	High	-0.073	-0.111	0.02	-0.044	-1	-1.51	0.38	-0.67
				g			**t(g)**		
Attention	Low	0.476***	-0.084	0.234**	-0.092	4.8	-0.81	2.58	-0.83
	2	0.232*	-0.279**	-0.143	-0.127	1.85	-2.11	-1.44	-1.2
	3	-0.239*	-0.593***	-0.254**	-0.338***	-1.72	-3.76	-2.16	-2.94
	High	-0.727***	-0.934***	-0.763***	-0.711***	-4.9	-8.69	-9.31	-6.52
R^2	Low	0.31	0.30	0.29	0.36				
	2	0.35	0.45	0.55	0.64				
	3	0.45	0.52	0.63	0.68				
	High	0.58	0.66	0.73	0.72				