Cryptocurrency Factor Portfolios: Performance, Decomposition and Pricing Models

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Abstract

We employ a non-parametric technique, almost stochastic dominance, and find that portfolios of cryptocurrencies based on nine factors dominate the S&P500, US 10-year T-bonds, US T-bills and a cryptocurrency index over longer investment horizons. After decomposing those nine long-short factor portfolios, we notice that their dominance relative to above four benchmarks and equity portfolios based on size, momentum and book-to-market, is mainly attributable to their long legs. A three-factor cryptocurrency model (market, size, and momentum) has insignificant alphas for five of the dominant cryptocurrency portfolios, indicating that their dominance is due to a risk premium. We then add the combinations of four mispricing factors and cryptocurrency fundamental factors to the three-factor model. The alphas of the other four dominant cryptocurrency portfolios remain significant, indicating that their dominance is due to mispricing.

Keywords: Asset Pricing, Cryptocurrencies, Almost Stochastic Dominance, Risk Premium, Mispricing

JEL Classification: G11, G12

1. Introduction

Cryptocurrencies are built on blockchain technology (Abadi and Brunnermeier, 2018; Biais et al., 2019) which permits transactions without central supervision, and the market has experienced a surge in the number of cryptocurrencies. Since the most famous, Bitcoin, appeared in 2009, more than 50 million investors have traded cryptocurrencies on more than 100 global exchanges, and over 100,000 companies worldwide accept payment in bitcoins and bitcoin debit cards (Easley et al., 2019; Makarov and Schoar, 2020). Companies at an early stage can raise money from initial coin offerings, rather than being financed through venture capital. As cryptocurrencies attract attention, whether they have investment value becomes an important issue, and both academics and practitioners are examining their properties for uses other than speculation. If we treat cryptocurrencies as a financial asset, it is vital to understand their characteristics in performance and pricing for at least three reasons. First, to find an appropriate performance metric for comparing cryptocurrencies with other financial classes. Second, to find factors that can be used to form outperforming cryptocurrency portfolios. Third, to determine whether any outperformance by cryptocurrency portfolios is caused by a risk premium or by mispricing.

An extensive academic finance literature on cryptocurrencies has been developed in recent years, especially in the areas of of ethics, initial coin offerings (ICOs) and analysis of several of the most popular coins (e.g. Ciaian et al., 2016; Foley et al., 2019; Gan et al., 2020). There is only limited literature that explores the factors that influence returns and even lessfocusing on the performance of cryptocurrency factor portfolios. For instance, Liu et al. (2020) and Borri (2019) study the relation between popular cryptocurrencies, finding only exposure to cryptocurrency-related factors. JUst a few of the most popular cryptocurrencies account for a vast majority of the capitalization of the whole cryptocurrency market. Their characteristics are well documented from the asset pricing side but further investigation is still needed to evaluate the performance, decomposition and pricing models of cryptocurrency anomalies. Hence, in this paper we examine questions associated with previous research: 1) Are cryptocurrency portfolios profitable compared to traditional financial asset classes? We evaluate the performance of portfolios of cryptocurrencies factors relative to conventional financial asset classes such as stocks, bonds, treasury bills, and a cryptocurrency index. 2) Is there a proper metric to compare the performances of different underlying assets? Because the empirical distributions of cryptocurrency returns are highly non-normal, this has limited the number of researchers who have examined the risk factors and analysed cryptocurrencies' performances. 3) If outperformance of cryptocurrency exists, do long leg or short leg of cryptocurrency factor portfolios contribute to outperformance? 4) Does any outperformance of cryptocurrency factor portfolios come from risk premium or mispricing? 5) Can outperforming cryptocurrency factor portfolios be accurately explained by adding mispriced factors and cryptocurrency fundamental factors to a coin market three-factor model?

To fill this gap, we examine the performance of cryptocurrency portfolios based on different risk factors by conducting almost stochastic dominance (ASD) proposed by Leshno and Levy (2002) on the 400 largest cryptocurrencies, which account for over 80% of total market capitalization. Almost stochastic dominance plays a vital role in comparing the performance of different asset classes that are highly skewed and leptokurtic, as the conventional mean-variance approach fails to measure the returns correctly (Bali et al., 2013). On the other hand, it would also eliminate the impact of investors' extreme preferences, where mean-variance cannot deliver an accurate measure. Furthermore, to form the factor portfolios, we rely on each cryptocurrency's open price, high price, low price, close price, volume and market capitalization, which comprise the only public information for each cryptocurrency. Inspired by Fama and French (1993), Carhart (1997), Liu et al. (2019) and Feng et al. (2020), we divide the available factors information into four categories: size, momentum, volume and volatility. We sub-divide the four large categories into 27 factor portfolios (see Table 3) to study whether cryptocurrencies share similarities with stocks regarding anomalies and examine each factor's relative performance against selected benchmarks. Subsequently, we decompose the long-short portfolios to detect which legs contribute to outperformance, and then we improve the existing coin market three-factor model developed by Liu et al. (2019) via incorporating mispriced factors and cryptocurrency fundamental factors (electricity and computing power).

This paper is the first to utilize the almost stochastic dominance (ASD) approach of Leshno and Levy (2002) to examine cryptocurrency factor portfolios' relative performance. ASD is a non-parametric method which compares two uncertain prospects by maximizing expected utility, and does not require any assumption about the return distribution. Due to cryptocurrencies' highly skewed returns distributions, standard performance metrics such as the mean-variance approach and Sharpe ratio cannot provide precise measure since these two approaches require the assumption of normality (Farinelli et al., 2008; Bali et al., 2013). Moreover, there exists an extreme utility function (pathological preference) of investors who are indifferent to a small amount of income and a large amount of income. Although this type of investor is a minority, standard metrics also fail to estimate accurately (Leshno and Levy, 2002; Bali et al., 2009). To avoid such problems, we employ almost first-order stochastic dominance (AFSD) and almost second-order stochastic dominance (ASSD) to compare the relative performance of each factor portfolio against S&P 500, US T-bonds, US T-bills and our cryptocurrency index at 4-week, 13-week, 26-week, 52-week and 78-week investment horizons. Our longest horizon is 1.5 years because cryptocurrencies have not existed for as long as equities and bonds, and because investors are unwilling to hold cryptocurrencies for relatively long horizons due to their high volatility. We obtain nine dominant portfolios against our four benchmarks in the sense of AFSD and ASSD.

Even though numerous studies (e.g. Stambaugh et al., 2012; Daniel and Moskowitz, 2016; Chu et al., 2020) argue that the importance of short legs is not as prominent as long legs, and their impacts are not symmetric as short legs face more frictions, we aim to clarify whether long leg or short leg or both legs contribute to outperformance among nine dominant factors for cost saving. For instance, a short sale may incur higher fees than buying an asset due to the frictions of short selling. Our paper is the first to decompose long-short portfolios into their long and short components in order to examine the individual contribution. Using AFSD and ASSD tests, we find that dominance is mostly attributable to the long-legs. For the long-only portfolios, unlike the long-short portfolios, there is no AFSD and ASSD dominance for horizons of 52-weeks and below. We conduct the same test against three equity benchmarks – equity portfolios based on size, momentum and BE/ME - since these factors have been widely used. We find that the dominant portfolios against equity portfolios based on size, momentum and BE/ME are to the same as those for the portfolios above. We conclude that the superior returns generated by long-short strategies are mainly contributed by their long legs. Although such portfolios could achieve AFSD and ASSD dominance via the long-only strategy, their violation areas are larger than those of the long-short portfolios, implying that the long-only strategy might not be optimal. Hence, it is likely that the long-short strategy is preferable to the long-only strategy and can boost performance, which is consistent with Stambaugh et al. (2012) and Edelen et al. (2016) for the case of equity factors.

Finally, we examine whether the variation in returns of the nine dominant factor portfolios can be captured by both the original and the improved coin market three-factor model to determine whether the outperformance comes from risk premium or mispricing. Even though hundreds of predictive cross-sectional asset pricing anomalies have been explored by finance academics, the debate on whether abnormal equity returns come from risk premium or mispricing never ends (Harvey et al., 2015; Chu et al., 2020). For instance, an inverse relation caused by risk premium between book-to-market portfolio and future growth rates have been documented by Fama and French (1995) and Penman (1996), whereas Lakonishok et al. (1994) and La Porta et al. (1997) propose that return on value/growth stocks is due to mispricing as investors have overly optimistic (pessimistic) expectations for future. The seminal literature focuses on stocks and hardly any research in this area explores cryptocurrencies, adding to our motivation. We find that a coin market three-factor model explains cross-sectional returns to a varying extent. Four dominant factor portfolios have positive and statistically significant alphas, and relatively small R^2 values, indicating their outperformance results from mispricing. A three-factor cryptocurrency model (market, size, and momentum) has insignificant alphas for the remaining five dominant cryptocurrency portfolios, indicating that their dominance is due to a risk premium. We then add four mispricing factors (subcategories of momentum, volume and volatility) and two cryptocurrency fundamental factors (electricity and computing power) to our three-factor model. The alphas of the four dominant cryptocurrency portfolios remain significant, while their R^2 remain low, indicating that their dominance is due to mispricing.

This paper is organized as follows. Section 2 discuss the related literature. Section 3 describes the data and summary statistics. Section 4 presents the methodology of the ASD approach. Section 5 describes the summary statistics of factor portfolios constructed in Section 4. Section 6 evaluates the empirical results of the ASD, decomposes long-short portfolios, and examines the cross-sectional return on dominant factor portfolios using a coin market three-factor model. Section 7 concludes the paper.

2. Related Literature

Although we are not aware of any other existing literature that focuses on cryptocurrency factor portfolios' performance, our paper is linked to various literature from the perspective of almost stochastic dominance, decomposition of long-short portfolios and pricing models.

2.1. Risk Factors Related to Traditional Assets

Financial economists have studied cross-sectional variations in stock and bond returns to find risk factors that can be used to create trading strategies. Fama and French (1993) document that the size factor (SMB) and the book-to-market factor (HML) can significantly explain the cross-sectional variation of stock returns. Subsequently, Carhart (1997) improved their model by adding the momentum factor (MOM), and found that it can explain cross-sectional returns on equity mutual funds. Bai et al. (2019) analyze the risk factors for corporate bonds by assuming that the downside risk is a strong indicator of future bond returns. Zhang (2005) and Lettau and Wachter (2007) evaluate the value premium of equities, suggesting that statistical models can capture portfolios' value premium. Stambaugh and Yuan (2017) argue that return anomalies can be captured by a model that incorporates mispricing factors, and risk factors such as the size factor have a risk premium twice the usual estimate. Neely et al. (2014) study the predictive power of technical indicators on the equity risk premium and find that technical indicators can provide in-sample and out-of-sample forecasts for equities. Likewise, Rapach et al. (2009) identifies the predictive power of combining individual forecasts of the equity premium, since combining forecasts generates economically and statistically significant gains both in and out-of-sample. The studies above emphasise the importance of studying risk factors which could explain the cross-sectional variation in asset returns and provide predictive power. However, few studies focus on cryptocurrencies, most of them evaluating the relation between several popular coins and different asset classes (equity, bond and commodity etc.). The relatively small sample size cannot detect cryptocurrencies' anomalies, and may incur sample bias. Hence, we are motivated to develop appropriate factors capturing the cross-sectional variation of cryptocurrency returns, taking into account the risk premium and mispricing of cryptocurrencies.

Our work relates to the literature that evaluates the factor anomalies, and a vast amount of literature documents whether an anomaly is caused by risk premium or mispricing. Keloharju et al. (2020) show that the seasonalities of stocks can be balanced out by seasonal reversal, demonstrating that seasonalities contribute to temporary mispricing. Ali et al. (2003) propose that book-to-market (B/M) has a greater effect on stocks with higher idiosyncratic volatility and higher transaction cost due to market-mispricing. Wang (2019) establish that zero-investment strategy that longs the portfolios with the lowest cash conversion cycle (CCC) and shorts portfolios with the highest CCC can generate 7% return annually due to mispricing. In this paper, we seek to diagnose 27 cryptocurrency factor portfolios to find whether anomalies can be generated in both long term and short term, and we use coin market pricing model to scrutinise which legs of factor portfolios contribute to outperformance. For robustness, we use the methos of Stambaugh and Yuan (2017) to test dominant portfolios with an adjusted three-factor model incorporating mispricing factors.

2.2. Almost Stochastic Dominance

Our paper is related to the literature that examines financial assets' performance by using almost stochastic dominance. Bali et al. (2009) analyze US stocks' performance versus bonds using almost stochastic dominance (ASD), and provide firm evidence that stocks dominate bonds by ASD at a long horizon after adjusting for pathological preferences. Similarly, Levy and Levy (2019) employ first-degree stochastic dominance with a riskless asset (FSDR) to evaluate the performance of stocks and bonds; finding that stocks tend to dominate bonds by FSDR for any investment horizon longer than three years. Similarly, Post (2003) evaluates the stochastic dominance of portfolios constructed from a list of assets and argues that benchmark portfolios based on market capitalization and book-to-market ratios are remarkably efficient compared to the Fama and French market portfolio. Second-degree stochastic dominance (SSD) is also applied by Board and Sutcliffe (1994) to rank a series of portfolios with or without short sales, and they provide robust results thorough the SSD approach at the 1% level. To examine the performance of hedge funds, Bali et al. (2013) employ almost stochastic dominance on hedge funds, and propose that long-short equity hedge and emerging markets hedge strategies dominate the US equity market. These two papers study the performance of common financial assets. The above literature evaluates stocks', bonds' and hedge funds' performance using a non-parametric approach, and underlying assets' superior performance has been detected. However, these studies do not mention how to build such dominant portfolios, even if investors knew that the performance of stocks, bonds and hedge funds is superior, investors are still left with the problem of assets selection. In contrast, we construct cryptocurrency factor portfolios and study their performance through almost stochastic dominance, to both avoid influence of special return distributions and clarify whether cryptocurrencies are worthy of investing.

2.3. Long/Short Legs of Zero-Investment Portfolios

Our research is also related to papers that evaluate whether cryptocurrency factor portfolios' outperformance is attributed to their long legs. Extensive research has employed the long-short strategy in studying the cross-section of factor portfolios. For instance, Israel and Moskowitz (2013) examine the effect of a long position and short position on overall stock portfolio performance. They find that outperformance of size factor, value factor, and momentum factor is attributed to a long position of portfolios. Similarly, Blitz et al. (2019) decompose Fama-French style equity portfolios into long- and short-leg portfolios, they find that most added return comes from long-leg portfolios and long-leg portfolios are more diversified than that of short-leg portfolios. A number of papers study long-short strategy (e.g. Frazzini and Pedersen, 2014; Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016). Nevertheless, most of previous literature concentrates on restricted asset classes such as equities, and the research on cryptocurrency regarding the decomposition of long-short portfolios is rare. For this reason, we examine the performance of long and short legs of each factor portfolio relative to four widely used benchmarks (S&P500, US 10-year T-bonds, US T-bills and a cryptocurrency index) and equity anomalies (size, momentum and book-to-market ratio), to gain a solid insight into cryptocurrencies.

2.4. Main Difference Between Current Literature on Cryptocurrency

Unlike equities and bonds that have been well evaluated, studies on cryptocurrencies are an emerging field that needs to be explored.Liu et al. (2019) as pioneers, study the cross-sectional returns of a large number of cryptocurrencies from the aspect of asset pricing. Specifically, they first form several effective risk factors with significant alphas, and they find such significant factors can be well explained by a coin three-factor model, where the model shares similarities with an equity pricing model. Similarly, Prior to Liu et al. (2019), Liu et al. (2020) examine the relationship between risk and returns for three mainstream cryptocurrencies (e.g. Bitcoin, Ripple and Ethereum). They demonstrate which exposures cryptocurrencies have, and narrow the scope of potential factors that may influence returns of cryptocurrencies to aid further studies. Particularly, they first test the exposures of cryptocurrencies to stocks (Fama-French factors), major currencies (Australian Dollar, Canadian Dollar, Euro etc.), precious metals (gold, silver and platinum) and macroeconomic factors (industrial production growth and personal income growth etc.), they claim that little or no evidence shows cryptocurrencies have exposures to the factors above. Thus, they evaluate the exposures of cryptocurrencies only associated with cryptocurrency market such as cryptocurrency momentum, proxy for investor attention, proxy for price-to-fundamental value and cost of mining, they conclude that factors have certain predictive power in certain horizons. This implies the direction of further study of cryptocurrencies.

Our research has some similarity to Liu et al. (2019) but with important differences. They find risk factors that capture variations in the cross-sectional returns of factor portfolios, and develop a cryptocurrency three-factor model. In contrast, our study focuses on factor portfolio performance. Because cryptocurrencies have non-normal returns distributions, we evaluate the investment value of cryptocurrencies by comparing their performance with those of different asset classes. Our paper also differs from Liu et al. (2020). They study the relationship between cryptocurrencies and a list of potential factors, aiming to exploit those with predictive power. In contrast, our paper focuses on which factors generate high excess returns. We also use a non-parametric approach, which allows for the highly non-normal distributions of cryptocurrency returns. We also disaggregate the long-short portfolios to examine whether outperformance comes from long or the short legs, and analyze whether the dominance of some factors is due to mispricing or a risk premium. Thus, we study cryptocurrencies mainly from a performance, rather than an asset pricing, perspective.

In summary, we test cryptocurrency portfolios using the non-parametric approach of almost stochastic dominance, and we then show that the dominance of some factor portfolios comes mainly from the long-leg portfolios due to either a risk premium or mispricing.

3. Data

The data of cryptocurrencies are collected from Coinmarketcap.com, which is a leading source of cryptocurrencies price, volume and market capitalization. Coinmarketcap.com aggregates information from over 200 major cryptocurrencies' exchanges data on opening price, high price, low price, close price, volume and market capitalization for most cryptocurrencies. Moreover, a cryptocurrency must meet certain criteria to be listed on exchange website, such as trading on a public exchange with an application programming interface which can show closing prices and non-zero trading volume during the previous 24 hours. Another reason for choosing Coinmarketcap.com is that it includes both defunct and active cryptocurrencies which might mitigate survivorship bias. Also some influential papers use this website as source of data (e.g. Detzel et al., 2020; Liu et al., 2020). We chose only cryptocurrencies with market capitalization larger than 1 million dollars. Because data on trading volume became available in the last week of 2013, we use cryptocurrencies date from the beginning of 2014. We select data for the top 400 cryptocurrencies based on their market capitalizations in USD over the period 1st January 2014 to 31st December 2019. The market capitalization of these 400 cryptocurrencies accounts for 82% percent of the whole market capitalization. We use the data of S&P 500, 10-year T-bond from CRSP and risk-free rate from Kenneth French's website.

To gain better insights into the investment value of cryptocurrencies, we calculate the market-capitalization-weighted return of all 400 cryptocurrencies. First, we calculate the log daily return across the sample period and allocate the weights to each asset every day, then get the summation of the value weighted return on each day to construct the daily market index return. The summary statistics of each asset are in Table 1. According to Table 1, it is clear that the coin market weekly return of 0.0103 is an order of magnitude higher than the return on the S&P 500 of 0.0019, return on T-bill of 0.0002 and proceeds of T-bond of 0.0007, but the risk of coin market is also much larger than those of stocks, bonds and the risk-free rate. The overall coin market return is positively skewed, similar to T-bills and T-bonds, whereas the skewness of returns on the S&P 500 is negative. The kurtosis of coin market and S&P 500 are both above the normal distribution of 3, which indicates the distributions of coin market and S&P 500 are leptokurtic. Although risk-adjusted returns could compare different asset classes such as Sharpe ratio (Sharpe, 1966), it might not be efficient with cryptocurrencies because of the high skewed distribution of returns. Thus, it is difficult to compare different asset classes due to their distinctive properties of returns by conducting the standard measure. This paper determines upon finding an appropriate mean to examine the investment value of cryptocurrencies.

Table 1 Descriptive Statistics

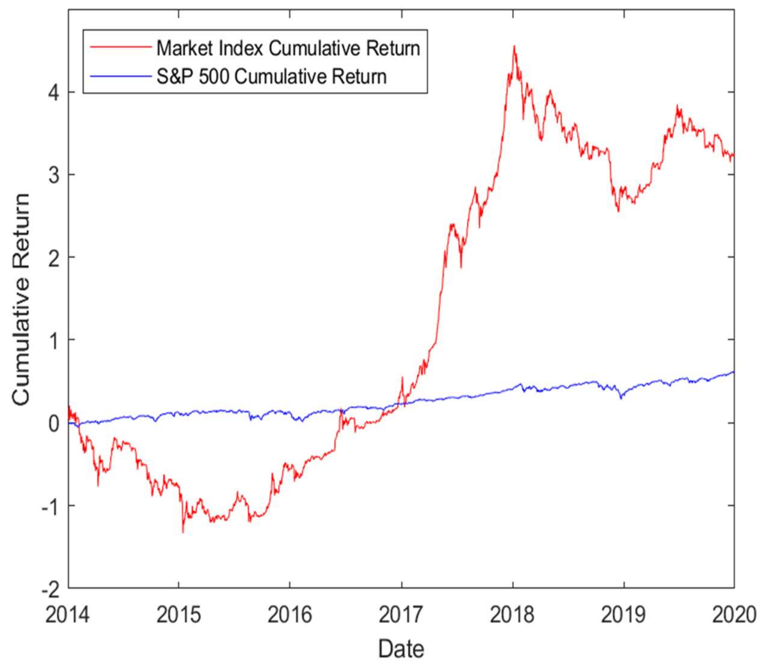
	Mean	Median	Std	Skewness	Kurtosis	J-B test	P-value
Coin Market (CMKT)	0.0103	0.0086	0.1054	0.1109	4.5026	2677	0.001
Bitcoin Return	0.0071	0.0040	0.1046	0.0299	4.0146	2761	0.001
Ripple Return	0.0063	-0.0067	0.1822	1.9627	11.1288	1479	0.001
Ethereum Return	0.0166	0.0100	0.1957	-0.4957	12.4147	3465	0.001
S&P 500	0.0019	0.0030	0.0174	-0.8320	5.1659	893.7	0.001
One-month T-bill	0.0002	0.0001	0.0002	0.6166	1.7923	97.81	0.001
Ten-year T-bond	0.0007	0.0000	0.0079	0.3104	3.4265	1872	0.001

Notes. This table presents descriptive statistics of weekly returns (not in percentage) on Coin market return including three popular cryptocurrencies such as Bitcoin, Ripple and Ethereum for data period 2014 to 2019. As well as the S&P 500 index, T-bill and T-bond are collected to be set as control groups. Specifically, coin market is the value-weighted average returns of 400 coins through sample period. This table reports the mean, median, standard deviation skewness and kurtosis to identify the distributions of corresponding assets. The Jarque-Bera (JB) test statistics and corresponding p-value indicate the shape is different from normal distribution.

Three popular cryptocurrencies are chosen to present a portrait of individual investors who invest in mainstream virtual currencies in the cryptocurrency market. Among the three popular cryptocurrencies, Ripple possesses the lowest weekly return of 0.0063 with a standard deviation of 0.1822, and Ethereum has the highest weekly return of 0.0166 with a standard deviation of 0.1957. Bitcoin, the most popular and famous cryptocurrency, has a weekly return of 0.0071, which is smaller than that of Ethereum, along with half its standard deviation. The kurtosis of Bitcoin is the most similar to that of a normal distribution, which is also the lowest kurtosis among the three coins. In contrast, comparing coin market return to three popular cryptocurrencies shows similar dispersion to Bitcoin but with higher weekly return of 0.0103 and the kurtosis of coin market return is slightly higher than that of Bitcoin but significantly lower than those of Ripple and Ethereum.

Compared with traditional assets, such as stocks, investors might gain larger returns by holding cryptocurrencies over long horizons. Figure 1 illustrates the cumulative returns on the Cryptocurrency market index and S&P 500 stock index, respectively. The red line is the cumulative return on coin market. Although it experienced the sharp drop over the period 2014 to 2016, it started to recover in 2016 and achieved exceptional return in the longer period. Conversely, the blue line represents the cumulative return on the stock market, which is steadily increasing over time but the growth rate of that is an order of magnitude lower than the coin market return. Thus, the attractive returns on coin market might provide an alternative investment opportunity for investors.

Figure 1 Cumulative return of Coin Market against S&P 500



Notes. This figure reports the cumulative return of Cryptocurrencies against S&P 500 over the period from 2014 to 2019. It is clear that the Cryptocurrencies is more profitable compared with the stock market.

4. Methodology

Because of the inapplicability of standard metrics such as mean-variance and normal stochastic dominance, we apply almost stochastic dominance to test the performance of cryptocurrencies against benchmarks: S&P 500, 10-year T-bond and 30-day T-bill. Since the distributions of cryptocurrencies are skewed, the usual performance metrics that are based on assumption of normal distribution are not appropriate to measure performance and capture the generic properties of returns on cryptocurrencies. Almost stochastic dominance does not require a parametric specification of investors' preferences and assumption of a normal distribution.

4.1. Inability of Mean Variance Approach

According to Bali et al. (2013), a classical mean-variance investment decision rule might be inefficient to identify the preference between two portfolios when all investors or almost all investors would choose one portfolio over another portfolio. To illustrate, consider two portfolios, H and L:

$$\text{H: } \mu_h = 100\%,\ \sigma_h = 5.1\%$$

$$\text{L: } \mu_L = 1\%,\ \sigma_L = 5.0\%$$

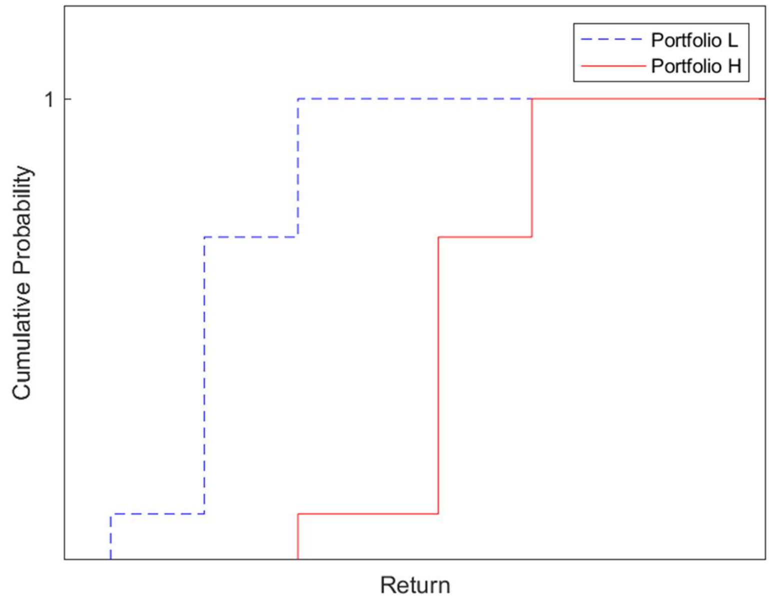
where H and L represents portfolios with high and low expected returns, respectively. The μ_h and μ_L are returns on portfolio H and L, respectively; the standard deviations of portfolios H and L are σ_h and σ_L, respectively. If portfolio H dominates portfolio L by the mean-variance approach, then the condition that $\mu_h > \mu_L$ and $\sigma_h < \sigma_L$ must be met. In this example, the expected return on portfolio H is dramatically higher than that of portfolio L (100 times) but with a slightly higher standard deviation (0.1 percent). However, in reality, most investors would choose portfolio H over portfolio L, because the decrease in expected utility of slightly higher risk is much less than the increase in expected utility of much higher expected return. Therefore, although most investors would choose portfolio H over L, yet the mean-variance approach fails to identify the outperforming portfolio.

4.2. Stochastic Dominance

In comparison with the mean-variance approach, stochastic dominance provides an alternative perspective to compare the performance of two assets. Recall the definition of first-order stochastic dominance (FSD) and second-order stochastic dominance (SSD) in the following (Leshno and Levy, 2002; Bali et al., 2013).

First-Order Stochastic Dominance. Suppose there are two hypothetical risky portfolios, H and L, and the cumulative distribution of H and L are denoted by F_H and F_L, respectively. Portfolio H dominates portfolio L by first-order stochastic dominance (H FSD L) if $F_H(r) \leq F_L(r)$ for all return values r and a strict inequality holds for at least some r. Specifically, H FSD L if and only if $E_H u(r) \geq E_L u(r)$ for all $u \in \mathcal{U}_1$, where $\mathcal{U}_1$ is the set of all nondecreasing differentiable real-valued functions. To get better understanding of FSD, Figure 2 might provide an intuitive insight into FSD through graphical explanation.

Figure 2 First-Order Stochastic Dominance

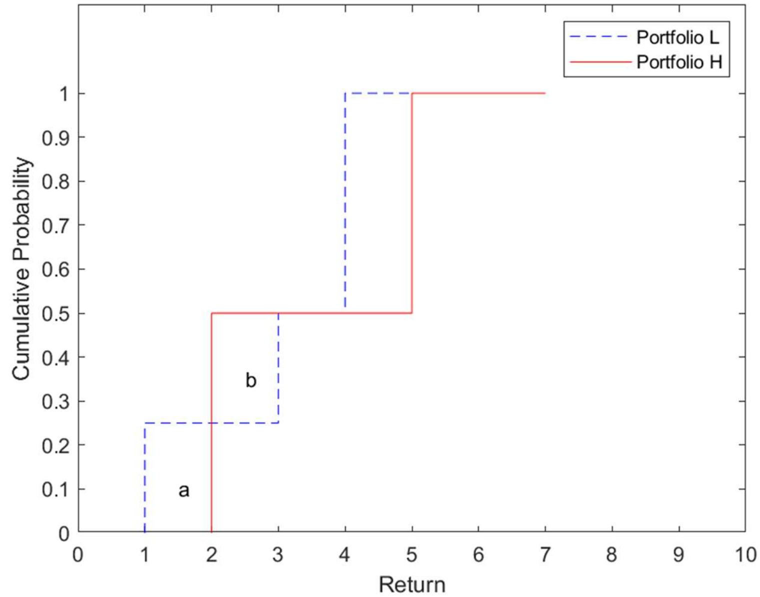


Notes. This figure reports the pattern that Portfolio H dominates Portfolio L by FSD.

According to Figure 2 which represents H FSD L, it is clear that portfolio H (red solid line) is plotted below the portfolio L (blue dashed line) for every point of return, which represents portfolio H would gain a higher return than that of portfolio L for any given level of probability. Hence, portfolio H reveals superiority over portfolio L since with portfolio H is always possible to achieve higher return that results in higher preference to portfolio L. However, FSD is difficult to achieve since the situation in reality is more complicated than at the theoretical level. Therefore, the birth of second-order stochastic dominance (SSD) is important, which enables the condition of domination less harsh than FSD and more effectively to use.

Second-Order Stochastic Dominance. Suppose there are two hypothetical risky portfolios, H and L, H represents high expected portfolio and L represents low expected return. The cumulative distribution of H and L are denoted by F_H and F_L, respectively. Portfolio H dominates portfolio L by second-order stochastic dominance (H SSD L) if $\int_{-\infty}^{r}[F_L(s) - F_H(s)]ds \geq 0$ for all return values r and a strict inequality holds for at least some r. Particularly, H SSD L if and only if $E_H u(r) \geq E_L u(r)$ for all $u \in \mathcal{U}_2$, where $\mathcal{U}_2$ is the set of all nondecreasing real-valued functions such that $u'' \leq 0$. To get better understanding of SSD, Figure 3 explains the second-order stochastic dominance by utilizing graphical explanation. Figure 3 illustrates the fact that H (red solid line) dominates L (blue dashed line) by SSD. To illustrate, there exist an area that portfolio H plots above portfolio L, which is denoted by b and falls into the range of [2,3].

Figure 3 Second-Order Stochastic Dominance



Notes. This figure reports the pattern that Portfolio H dominates Portfolio L by SSD.

Because this violation area that break the FSD rule that portfolio H dominates portfolio L if portfolio H plots below the portfolio L for every given return r, so FSD does not exist due to the reason above. Moreover, from the perspective of the FSD proposition, the $F_H(r)$ is larger than $F_L(r)$ in the interval of [2,3], which also indicates nonexistence of FSD in such a case. However, there might exist SSD according to the SSD proposition, because SSD examines the dominance regard to the area that enclosed by cumulative distributions of two portfolios, which is more tolerant than that of FSD that only compares the value of cumulative distributions. According to Figure 2, portfolio H dominates portfolio L when return is up to 2, which makes area **a** is larger than zero by SSD condition by SSD proposition $\int_{-\infty}^{r}[F_L(s) - F_H(s)]ds \geq 0$. Furthermore, portfolio H cannot dominate portfolio L when return falls into interval [2,3] since the area **b** enclosed by H and L is smaller than zero by SSD proposition $\int_{-\infty}^{r}[F_L(s) - F_H(s)]ds \geq 0$. The portfolio H would dominate L again after x larger than 4 since portfolio H plots portfolio L. In other words, if portfolio H SSD L, such condition $\boldsymbol{a} \geq \boldsymbol{b}$ must be held to ensure that $\int_{-\infty}^{r}[F_L(s) - F_H(s)]ds \geq 0$. Additionally, if the first point of portfolio H prior to that of portfolio L (the minimum value of portfolio H is smaller than that of portfolio L) that produces negative area by the SSD formula, then no matter how big the positive area after their first intersection, there would not be SSD because it violates the condition that $\int_{-\infty}^{r}[F_L(s) - F_H(s)]ds \geq 0$ in the interval. Nevertheless, portfolio H might fail to dominate L if area of **b** is slightly bigger than **a** no matter how big the positive area in the following part, and this is the reason why this paper conducts almost stochastic dominance, to avoid such an economically irrational selection.

The key difference between FSD and SSD is the assumption of an investor's utility function (Daskalaki et al., 2017). FSD allows that investors may be risk averters or risk lovers because it only requires investors prefer more to less (mathematically, $u' > 0$). SSD assumes investors are risk averters, which has a concave utility function and prefer certainty to gambling (mathematically, $u' > 0$ and $u'' < 0$). As most investors are risk averse, SSD plays a significant role in measuring performance of assets for risk averters. In following section, we discuss the almost stochastic dominance (ASD) for first-order and second-order respectively. Intuitively, ASD is also stochastic dominance but with a looser assumption, it assumes a part of utility function caused by extreme (unusual) utility function can be 'ignored' only if the violation area is small enough.

4.3. Almost Stochastic Dominance

Although most investors would prefer one asset to another asset in the real world, stochastic rules cannot explain such preference due to some extreme utility functions that only violate a small portion of these rules. Almost stochastic dominance (ASD) can provide a more realistic situation for solving this sort of problem. To illustrate the necessity of almost stochastic dominance, we begin with a hypothetical cash flow table as table 2 shows.

Table 2 demonstrates the returns on portfolio H and L with corresponding probabilities. Portfolio H dominates L by FSD, and the cumulative distribution of H should plot strictly below the cumulative distribution of L by FSD condition, which indicates that the return on portfolio H should always be higher than that of portfolio L.

Table 2 Cash Flow for Portfolio H and L

Statement	Probability (%)	L (£)	H (£)
Low	1	2	1
Medium	2	4	4
High	97	6	100k

Notes. This table presents the cash flows with probabilities for three statements (low, medium and high).

However, in this example, portfolio H plots below portfolio L for most possible regions except the statement of Low where portfolio L generates £2 and portfolio H earns £1. Hence, portfolio H fails to dominate portfolio L in such situation, although for most investors would choose portfolio H over L since H offers a greater amount of money than L at the same probability level. The inability of standard stochastic dominance also reveals a pathological utility function that only a few investors feel indifferently on receiving £6 or £100k, which is economically irrelevant or irrational (Bali et al., 2013).

4.3.1. Almost First-Order Stochastic Dominance (AFSD)

Almost First-Order Stochastic Dominance (AFSD) might solve the problem of a pathological utility function by excluding a few extreme utility functions and examining whether the small violation of FSD can be 'ignored' (Leshno and Levy, 2002). Additionally, to see whether AFSD exists, it is necessary that one distribution should be 'close to' to specific distribution that dominates another distribution in the traditional sense of FSD. In other words, if two cumulative distributions are close to FSD, then AFSD should be used rather than ASSD (Leshno and Levy, 2002).

To interpret the concept of almost stochastic dominance, we define the violation area that interfere the success of FSD. When considering whether portfolio H (red solid line) dominates L (blue dashed line) by AFSD, the area that cumulative distribution of H is above the cumulative distribution of L is called the violation area (denoted by M in Figure 4), which results in the failure of FSD.

According to (Bali et al., 2013), the violation area M could be defined as $\int_{r_1}^{r_2}[F_H(s) - F_L(s)]ds$, where the FSD violation range is given by

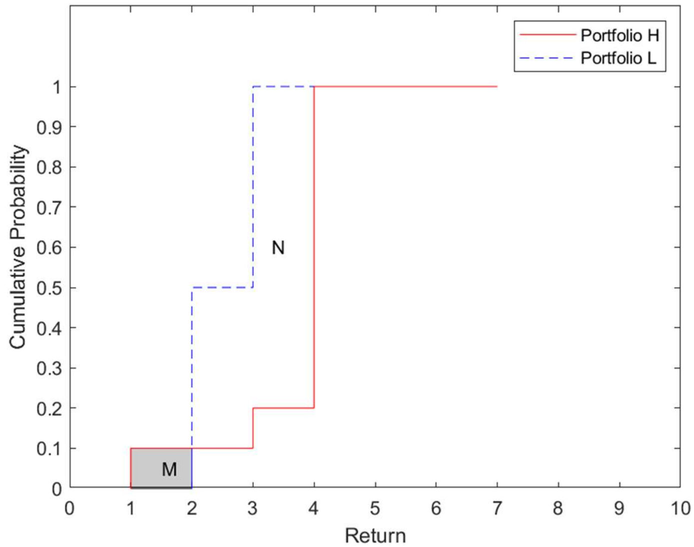
$$R_1(F_H, F_L) = \{s \in (r_1, r_2): F_L(s) < F_H(s)\} \tag{1}$$

The empirical violation area is defined as

$$\varepsilon_1 = \frac{\int_{R_1}[F_H(s) - F_L(s)]ds}{\int_{min}^{max}|F_H(s) - F_L(s)|ds} \tag{2}$$

where F_H and F_L have a finite support [min, max]. Equation (1) measures the violation range where the probability of H is larger than L (range [1,2] in Figure 4).

Figure 4 Almost First-Order Stochastic Dominance



Notes. This figure reports the cumulative distribution of high return portfolio (H) and low return portfolio (L). Because of the violation area M, H fails to dominate the by FSD, SSD or Mean-Variance approach. There are some extreme utility functions that assigns large weight to area M and a small or zero weight to area N. However, most of investors would choose H over L, which indicates the existence of AFSD if the violation area is small enough.

Moreover, according to Equation (2), ε_1 is defined as the area above [1,2] (area M in Figure 4) divided by the total absolute area enclosed between F_H and F_L (area $M + N$ in Figure4). It is clear that FSD may exist if $\varepsilon_1 = 0$, which implies no violation area at all. However, for $\varepsilon_1 > 0$, although H fails to dominate L by FSD, AFSD may exist if ε_1 is small enough to be 'ignored'. Levy et al. (2010) conducted the empirical test to find the minimum tolerance and suggests that the violation area could be 'ignored' if ε_1 is smaller or equal than 5.9%, which implies AFSD may exist if the violation area is smaller than the minimum accepted loss of investors.

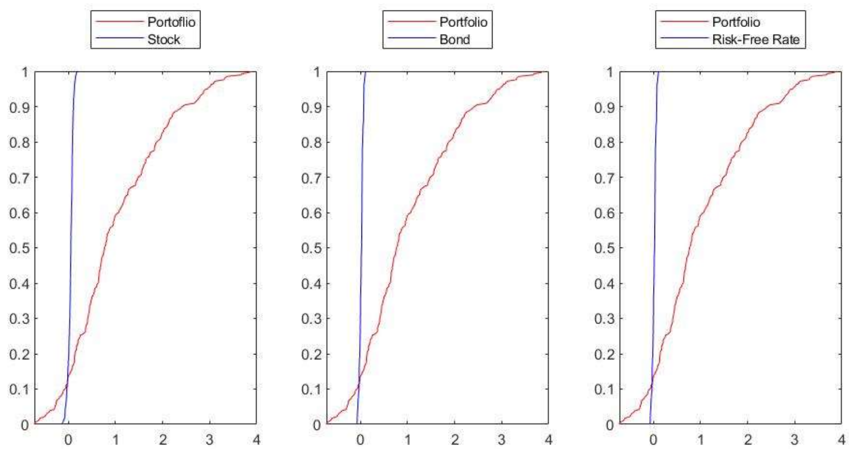
To examine whether AFSD is applicable, we evaluate cumulative distributions of cryptocurrency portfolios against benchmarks such as stock, bond and risk-free rate for short and long horizon. The minimum returns on cryptocurrency portfolios being always smaller than the benchmarks in the sample period, which indicates the CDF of portfolios always starts prior to benchmarks. As Leshno and Levy (2002) emphasize, the precondition to test AFSD is the cumulative distribution should be in traditional sense of FSD. In other words, firstly, ignoring the violation area and evaluating whether the rest part of CDF has a traditional sense of FSD; secondly, continue the test if the CDF meets the precondition.

Figure 5 gives details for understanding AFSD, which exhibits the empirical CDF distribution for a portfolio against three benchmarks. Specifically, the red lines represent the

CDF of the portfolio and blue lines are the benchmarks. According to Figure 5, the portfolio cannot dominate the benchmark by FSD due to the violation area that CDF of portfolio plots above that of benchmarks. However, the portfolio may dominate the benchmarks by AFSD if the violation area is small enough. Moreover, the set of preference $\mathcal{U}_1{}^*$ is defined as

$$\mathcal{U}_1{}^*(\varepsilon_1) = \{u \in \mathcal{U}_1; u'(s) \leq \text{Inf}\{u'(s)\}\left[\frac{1}{\varepsilon_1} - 1\right], \quad \forall\, s \in (\min, \max)\}, \tag{3}$$

Figure 5 Cumulative Distribution of Real Data



Notes. This figure reports the CDF of a portfolio against benchmarks. In this figure, red line represents the CDF of a portfolio and blue line represents stock, bond and risk-free rate. It is clear that H cannot dominate L by FSD, SSD or MV approach since there exist a violation area. L cannot dominate H due to the fact H has a higher expected return.

4.3.2. Almost Second-Order Stochastic Dominance (ASSD)

Similar to AFSD, there might exist almost second-order stochastic dominance (ASSD) when the cumulative distribution is close to traditional sense of SSD. In this paper, we first define the violation area in ASSD.

Figure 6 illustrates a case that H (red solid line) has a higher mean than L (blue dashed line) but due to the negative area C, H fail to dominate L by SSD. Specifically, because the integrated area between F_H and F_L become negative at the beginning of area C, which violates the SSD condition $\int_{-\infty}^{r}[F_L(s) - F_H(s)]ds \geq 0$ for all given s. The range of SSD violation area (C in this paper) could be defined as

$$R_2(F_H, F_L) = \{s \in R_1(F_H, F_L) \colon \int_0^r [\, F_L(s) - F_H(s)]ds < 0\} \tag{4}$$

Also, the empirical ASSD violation area ε_2 may be defined by

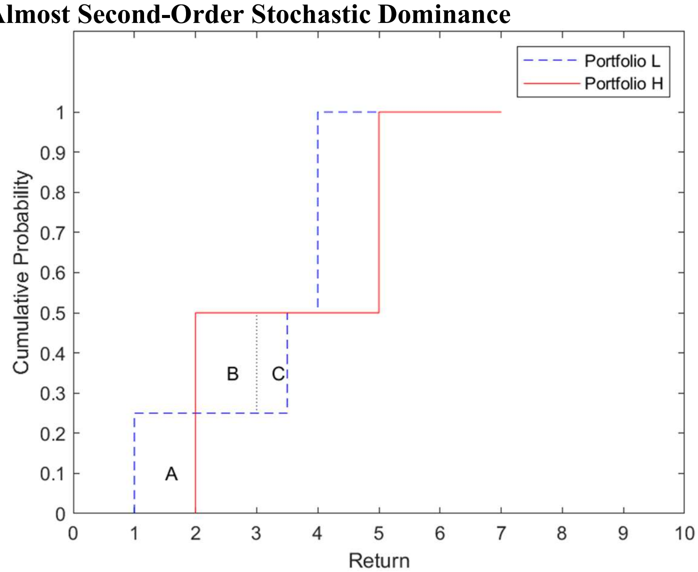
$$\varepsilon_2 = \frac{\int_{R_2} [F_H(s) - F_L(s)] ds}{\int_{min}^{max} |F_H(s) - F_L(s)| ds} \tag{5}$$

where ε_2 is defined as the violation area (area C in Figure 6) divided by the total absolute area enclosed between F_H and F_L. Similar to AFSD, Levy et al. (2010) suggests that the threshold value ${\varepsilon_2}^*$ of ASSD is 3.2%, which reveals the minimum tolerance for most investors. Hence, if ε_2 is smaller than or equal to ${\varepsilon_2}^*$ of 3.2%, ASSD may exist. Additionally, the set of preference ${\mathcal{U}_2}^*$ is defined by

$$\begin{aligned} {\mathcal{U}_2}^*(\varepsilon_2) = \{u \in \mathcal{U}_2; -u''(s) \leq \mathrm{Inf}\{-u''(s)\} \left[\frac{1}{\varepsilon_2} - 1\right], \\ \forall \text{ s} \in (\min, \max)\}, \end{aligned} \tag{6}$$

where $\mathcal{U}_2$ excludes the utility function of pathological preference and for all $u \in {\mathcal{U}_2}^*$, H dominates L by ASSD if and only if $\varepsilon_2 \leq {\varepsilon_2}^*$.

Figure 6 Almost Second-Order Stochastic Dominance



Notes. This figure demonstrates a case that portfolio H has a higher mean than that of L but there is no SSD of H over L due to there exist a negative area C, which makes the SSD condition failed. Nevertheless, if area C is relatively small, ASSD may exist.

Hence, in this paper, the violation area for ASSD would be same as that of AFSD but needs to be compared with a lower critical value of 3.2% because ASSD/SSD focuses on risk averters, which is developed by Levy et al (2010).

4.4. Portfolio Formation

To alleviate the anomalies of returns on cryptocurrencies and capture the generic properties of cryptocurrencies, we build zero-investment long-short based on a list of established factors complied with Liu et al. (2019) and Feng et al. (2020). We select factors that can be established by only using the available information such as opening price, closing price, high price, low price, trading volume and market capitalization.

The construction of Zero-Investment long-short portfolios

Category	Factor Used	Definition
Size	MARCAP	Log last day market capitalization in the portfolio formation week
Size	LPRC	Log last day price in the portfolio formation week
Size	MAXPRC	The maximum price of portfolio formation week
Size	Age	The number of existent weeks that listed on Coinmarketcap.com
Momentum	MOM1	One-week momentum
Momentum	MOM2	Two-week momentum
Momentum	MOM3	Three-week momentum
Momentum	MOM4	Four-week momentum
Momentum	MOM8	Eight-week momentum
Momentum	RMOM1	One-week risk-adjusted momentum based on Sharpe ratio
Momentum	RMOM2	Two-week risk-adjusted momentum based on Sharpe ratio
Momentum	RMOM3	Three-week risk-adjusted momentum based on Sharpe ratio
Momentum	RMOM4	Four-week risk-adjusted momentum based on Sharpe ratio
Momentum	RMOM8	Eight-week risk-adjusted momentum based on Sharpe ratio
Volume	VOL	Log average daily volume in the portfolio formation week
Volume	VOLPRC	Log average daily volume times price in the portfolio formation week
Volume	VOLSCALE	Log average daily volume times price then divided by market capitalization in the portfolio formation week
Volatility	RETVOL	The standard deviation of daily returns in the portfolio formation week
Volatility	RETSKEW	The skewness of daily returns in the portfolio formation week
Volatility	RETKURT	The kurtosis of daily returns in the portfolio formation week
Volatility	MAXRET	The maximum daily return of the portfolio formation week
Volatility	STDPRCVOL	Log standard deviation of dollar volume in the portfolio formation week
Volatility	MEANABS	The mean absolute daily return divided by dollar volume in the portfolio formation week
Volatility	BETA	The regression coefficient of β_{MKT}^{i} in $R_i - R_f = \alpha^i + \beta_{MKT}^{i} MKT + \varepsilon^i$. The model is estimated by using the daily return of previous 365 days before formation week
Volatility	BETA^2	Beta squared
Volatility	IDIOVOL	The idiosyncratic volatility is measured as the standard deviation of the residual after estimating $R_i - R_f = \alpha^i + \beta_{MKT}^{i} MKT + \varepsilon^i$. The model is estimated by using the daily return of previous 365 days before formation week.
Volatility	DELAY	The improvement of R^2 in $R_i - R_f = \alpha^i + \beta_{MKT}^{i} MKT + \beta_{MKT-1}^{i} MKT_{-1} + \beta_{MKT-2}^{i} MKT_{-2} + \varepsilon^i$ compared to regression that only uses MKT, where MKT_{-1} and MKT_{-2} are lagged one- and two-day market index return. The model is estimated by using the daily return of previous 365 days before formation week.

Notes. This table reports the construction of each portfolio based on specific factors. For instance, the procedure of establish a portfolio based on MARCAP is that sort each cryptocurrency by market cap into quintiles in formation week, then track the return of each portfolio in the week that follows. All portfolios are rebalanced weekly. MKT refers to coin market return that is value-weighted return of all selected cryptocurrencies.

Table 3 shows the constructions of different zero-investment long-short portfolios based on related factors. To grasp a comprehensive understanding of the investment value of cryptocurrencies, we identify four main aspects which are size, momentum, volume and volatility to form the corresponding portfolios to test. In addition, the main four aspects can be further divided into 18 meaningful factor-portfolios to be examined for stochastic dominance against different assets' benchmarks such as stock, bond and risk-free rate.

To form a portfolio, we sort individual cryptocurrency into quintiles in ascending order according to corresponding factors in each week, then track the return of each portfolio in the following week. Five quintile portfolios are acquired by repeating this procedure for each factor mentioned in Table 3. Subsequently, excess mean return over risk-free rate of each quintile portfolio is calculated for each factor portfolio, and we also compute the excess return of long-short portfolios based on the difference between fifth quintile and first quintile, which represents the long-short strategy. For instance, suppose there are N periodic returns (weekly in this paper) on cryptocurrencies for data period from 2014 to 2019 denoted as $C_{i,j}$, where i represents the i^{th} cryptocurrency and $i \in [1, N]$; j indicates the specific weekly time point and $j \in [2014{,}2019]$. $C_{i,j}$ is a matrix of j rows (number of weeks) and i columns (number of cryptocurrencies). Additionally, we sort $C_{i,j}$ in ascending order by a given factor in Table 3 at every time j to acquire a new return matrix denoted as $C^*_{i,j}$ based on the give factor. Then we divide $C^*_{i,j}$ into quintiles to form the five portfolios and denote the first quintile portfolio as $C^*_{[1,1st],j}$, the second quintile portfolio as $C^*_{[1st+1,2nd],j} \cdots$ and the fifth quintile portfolio $C^*_{[4th+1,5th],j}$, where the $1st, 2nd \cdots 5th$ represent quintiles. After five quintile return series are established, multiply their corresponding weight and sum them up to obtain five value-weighed quintile portfolios P_m, where m indicates the m^{th} portfolio. Moreover, the mean excess return of P_m is net of risk-free rate. The following paragraphs in this section will explain the detailed factor-portfolio and their mean excess returns.

4.4.1. Size-Related Portfolios

The size-factor-portfolios are constructed based on market capitalization, last price, maximum price and age factors. To illustrate, this paper sorts individual cryptocurrency into quintile portfolios based on given factors in each week, then tracks the return in the following week and repeats this procedure to establish quintile portfolios for each given size-related factor. Moreover, we estimate the excess return of each portfolio over risk-free rate and the excess return of zero-investment long-short investment which is represented by the difference between fifth quintile portfolio and first quintile portfolio (e.g. subtracting first quintile from fifth quintile).

Table 4 Portfolio Returns Based on Size

	Quintiles					
	1	2	3	4	5	5-1
MARCAP	Low				High	
Mean	0.0298	0.0121	-0.0049	-0.0033	-0.0018	-0.0316
LPRC	Low				High	
Mean	0.0323	0.0093	0.0324	0.0102	0.0095	-0.0228
MAXPRC	Low				High	
Mean	0.0176	0.0053	0.0149	-0.0051	-0.0057	-0.0233
Age	Low				High	
Mean	0.0080	0.0092	0.0038	-0.0014	0.0028	-0.0052

Note. This table presents the weekly mean excess returns on quintile portfolios for market capitalization, last price, maximum price and age factors. The mean excess returns are defined as the excess value-weighted expected returns, and '5-1' represents the long-short strategy.

Table 4 demonstrates the expected excess return for each quintile portfolio that is created on given factors. Fifth quintile portfolio minus first quintile portfolio represents the mimic long-short strategy - the negative sign before the value is not important because a positive return could be gained by conducting opposite action. For instance, the negative sign before the difference between the fifth and first quintile portfolios suggests that investors might loss return of 0.0316 per week if investors long the portfolio with the largest market capitalization and short the portfolio with the smallest market capitalization; however, an investor could gain a return of 0.0316 per week by taking an opposite action such as long the portfolio with the smallest market capitalization and short the portfolio with the largest market capitalization, which is similar to the size effect of stocks.

The portfolio of MARCAP generates the highest absolute return of 0.0316 on long-short strategy, the portfolio of AGE has an absolute return of 0.0052 on long-short strategy which is the worst performing of the portfolios in the size group. Moreover, the absolute returns on portfolios based on LPRC and MAXPRC are similar, they are 0.0228 and 0.0233, respectively. As noted above, the negative sign could be eliminated by conducting the opposite action which is to long first quintile portfolio and short fifth quintile portfolio. Moreover, compared to the mean return of summary statistics in Table 1, it is clear that the long-short portfolios have much higher expected returns than that of individual cryptocurrency and other benchmarks. Hence, these portfolios are used to test the investment value of cryptocurrencies.

4.4.2. Momentum-Related Portfolios

The momentum-factor-portfolios are formed based on one-, two-, three-, four-, eight-week momentum and risk-adjusted momentum (Sharpe ratio) factors. Specifically, we sort individual cryptocurrencies into quintile portfolios based on given factors in each week, then trace the return in the following week and repeat this procedure to form the quintile portfolios for each given momentum-related factor. In addition, we estimate the excess return of each portfolio over the risk-free rate and excess return of zero-investment long-short portfolio which is defined as the difference between fifth quintile portfolio and first quintile portfolio (e.g. subtracting first quintile portfolio from the fifth quintile portfolio). In terms of momentum portfolios, the low quintile portfolio indicates the badly performed portfolio (e.g. first quintile) and the high quintile portfolio represents the winning portfolios (e.g. fifth quintile).

Table 5 reports the expected excess return for each quintile portfolio that is created on given momentum factors. The fifth quintile portfolio minus the first quintile portfolio illustrates the procedure of going long the winning portfolio and short the losing portfolio. The highest expected excess return of 0.0367 on momentum-portfolio is established by using a three-week momentum factor, whereas the portfolio of eight-week momentum provides lowest expected return of 0.0149. Hence, expected excess return of portfolios shows an almost monotonically increasing pattern for one-week momentum factor to three-week momentum factor, and it starts to drop from three-week momentum factor to eight-week momentum factor. The long-short strategy for momentum-portfolio applied in this paper exhibits similar effect to that of stock.

Conversely, for risk-adjusted momentum portfolios, RMOM1 has the highest return of 0.0341 and the RMOM8 has the worst performance of 0.0202. In contrast to the almost monotonic increase pattern of momentum portfolios, the risk-adjusted momentum portfolios exhibit an almost monotonic decreasing pattern as the horizon becomes longer (one-week to eight-week horizon). The return on RMOM8 is 1 percent less than that of RMOM1 per week, which shows the risk-adjusted momentum strategy could best perform in relatively short period (one-week to four-week horizons).

Table 5 Portfolio Returns Based on Momentum

	Quintiles					
	1	2	3	4	5	5-1
MOM1	Low				High	
Mean	0.0019	-0.0084	0.0035	0.0197	0.0365	0.0346
MOM2	Low				High	
Mean	0.0054	-0.0065	0.0006	0.0284	0.0355	0.0300
MOM3	Low				High	
Mean	0.0031	-0.0016	0.0104	0.0128	0.0398	0.0367
MOM4	Low				High	
Mean	0.0047	-0.0073	0.0053	0.0146	0.0309	0.0262
MOM8	Low				High	
Mean	0.0060	0.0067	0.0093	0.0219	0.0209	0.0149
RMOM1	Low				High	
Mean	0.0012	0.0025	0.0069	0.0231	0.0353	0.0341
RMOM2	Low				High	
Mean	-0.0035	0.0088	0.0072	0.0157	0.0280	0.0315
RMOM3	Low				High	
Mean	0.0052	0.0006	0.0074	0.0083	0.0296	0.0244
RMOM4	Low				High	
Mean	0.0013	-0.0035	0.0127	0.0140	0.0288	0.0275
RMOM8	Low				High	
Mean	0.0009	0.0088	0.0161	0.0157	0.0211	0.0202

Note. This table presents the weekly mean excess returns on quintile portfolios for one-, two-, three-, four- and eight-week momentum (risk-adjusted momentum) factors. The mean excess returns are defined as the excess value-weighted expected returns, and '5-1' represents the long-short strategy.

4.4.3. Volume-Related Portfolios

The volume-factor-portfolios are constructed based on volume, volume times price and scaled volume times volume factors. We sort individual cryptocurrency into quintile portfolios based on given factors in each week, then track the return in the following week and repeats this procedure to establish quintile portfolios for each volume-related factor. We estimate the excess return of each portfolio over risk-free rate and the excess return of zero-investment long-short portfolio which is represented by the difference between fifth quintile portfolio and first quintile portfolio (e.g. subtracting first quintile from fifth quintile).

Table 6 Portfolio Returns Based on Volume						
	Quintiles					
	1	2	3	4	5	5-1
VOL	Low				High	
Mean	0.0398	0.0460	0.0281	0.0104	0.0117	-0.0281
VOLPRC	Low				High	
Mean	0.0390	0.0389	0.0258	0.0080	0.0100	-0.0291
VOLSCALE	Low				High	
Mean	0.0248	0.0245	0.0171	0.0150	0.0091	-0.0157

Note. This table presents the weekly mean excess returns on quintile portfolios for volume, volume times price and scaled volume times price factors. The mean excess returns are defined as the excess value-weighted expected returns, and '5-1' represents the long-short strategy.

Table 6 presents the expected excess return for each quintile portfolio that is created on given factors. Fifth quintile portfolio minus first quintile portfolio represents the mimic long-short strategy, the negative sign before the return on long-short portfolio could be turned into positive by conducting long first quintile portfolio and short fifth quintile portfolio. In respect of portfolios based on volume, the highest absolute excess return is 0.0291 which is generated by portfolio based on volume times price, whereas the portfolio of scaled volume times price delivers the lowest absolute return of 0.0157. It is clear that for every factor in volume portfolios, the first quintile portfolio always generates the highest return among all quintiles, which discloses the relationship between the volume and mean return.

4.4.4. Volatility-Related Portfolios

The volatility-factor-portfolios are constructed based on standard deviation of return, skewness of return, kurtosis of return, maximum return, log standard deviation of dollar volume and mean absolute daily return scaled by dollar volume factors. As an illustration, we sort individual cryptocurrencies into quintile portfolios based on given factors in each week, then track the return in the following week and repeat this procedure to establish quintile portfolios for given volatility-related factors. In addition, we estimate the excess return of each portfolio over risk-free rate, and the excess return of zero-investment long-short investment which is represented by the difference between the fifth quintile portfolio and the first quintile portfolio (e.g. subtracting first quintile from the fifth quintile).

Table 7 Portfolio Returns Based on Volatility

	Quintiles					
	1	2	3	4	5	5-1
RETVOL	Low				High	
Mean	0.0075	0.0025	0.0159	0.0121	0.0350	0.0275
RETSKEW	Low				High	
Mean	0.0060	-0.0003	0.0145	0.0039	0.0181	0.0121
RETKURT	Low				High	
Mean	0.0098	0.0046	0.0104	0.0046	0.0116	0.0018
MAXRET	Low				High	
Mean	0.0068	0.0099	0.0190	0.0231	0.0367	0.0299
STDPRCVOL	Low				High	
Mean	0.0414	0.0294	0.0266	0.0115	0.0080	-0.0334
MEANABS	Low				High	
Mean	0.0075	0.0181	0.0227	0.0408	0.0373	0.0298
BETA	Low				High	
Mean	0.0113	0.0230	0.0205	0.0206	0.0052	-0.0061
BETA2	Low				High	
Mean	0.0113	0.0231	0.0205	0.0206	0.0052	-0.0061
IDIOVOL	Low				High	
Mean	0.0120	0.0160	0.0148	0.0236	0.0371	0.0251
DELAY	Low				High	
Mean	0.0157	0.0036	0.0118	0.0205	0.0219	0.0062

Note. This table presents the weekly mean excess returns on quintile portfolios for RETVOL, RETSKEW, RETKURT, MAXRET, STDPRCVOL, MEANABS, BETA, BETA^2, IDIOVOL, DELAY. The mean excess returns are defined as the excess value-weighted expected returns, and '5-1' represents the long-short strategy.

Table 7 shows the expected return for each quintile portfolio that is created on given factors. The fifth quintile portfolio minus first quintile portfolio represents the mimic long-short strategy. Particularly, portfolio based on log standard deviation of dollar volume could achieve the highest absolute mean return of 0.0334, and portfolio based on BETA and BETA^2 deliver the lowest return of 0.0061. The low return on BETA and BETA^2 is counterintuitive since the portfolio with higher beta (systematic risk) should be compensated with higher return, yet this phenomenon cannot be found in our work. This might be because that we constructed the coin market index using the value-weighted average method, Bitcoin occupied the largest share of it among all the cryptocurrencies, so the coin market index is influenced by Bitcoin significantly; whereas other cryptocurrencies might not have such a property and have only a little relationship with market index, hence beta might not be an appropriate factor to rank the cryptocurrencies to form the portfolios. Moreover, the returns on quintile portfolios of maximum return shows conspicuous increasing pattern, and the returns on quintile portfolios for log standard deviation of return exhibits distinct decreasing trend from first quintile to fifth quintile.

5. Summary Statistics of Factor Portfolios

This section illustrates the summary statistics of factor portfolios based on the factors in table 3. The large skewness and kurtosis indicate that the distributions of factor portfolios heavily deviate from normality, which motivates us to find an alternative method to measure the performance of factor portfolios.

Table 8 Descriptive Statistics

	Mean	Median	Std	Skewness	Kurtosis	J-B test	P value
MARCAP	0.0316	0.0253	0.1517	2.0147	21.7848	4813.75	0.001
LPRC	0.0242	0.0138	0.1421	2.1506	16.3488	2565.19	0.001
MAXPRC	0.0233	0.0129	0.1435	2.0957	15.8456	2381.11	0.001
AGE	-0.0052	-0.0034	0.1438	-0.5203	8.4189	397.09	0.001
MOM1	0.0346	0.0093	0.2307	1.8286	12.9793	1468.51	0.001
MOM2	0.0300	0.0119	0.2348	0.7013	10.7627	808.95	0.001
MOM3	0.0367	0.0093	0.2363	0.3991	12.1101	1083.71	0.001
MOM4	0.0262	0.0151	0.2149	1.1057	8.9437	519.49	0.001
MOM8	0.0149	0.0014	0.2062	1.0367	10.5786	787.11	0.001
RMOM1	0.0341	0.0154	0.2000	1.6654	14.5713	1890.91	0.001
RMOM2	0.0315	0.0200	0.1875	1.4430	16.5212	2485.00	0.001
RMOM3	0.0244	0.0202	0.2166	-0.2546	14.7155	1781.94	0.001
RMOM4	0.0275	0.0197	0.1791	0.6379	9.3132	535.83	0.001
RMOM8	0.0202	0.0063	0.1762	1.5710	15.7319	2192.65	0.001
VOL	0.0281	0.0223	0.2161	0.8855	22.1340	4815.59	0.001
VOLPRC	0.0291	0.0077	0.1765	2.1719	15.2141	2191.69	0.001
VOLSCALE	0.0157	-0.0026	0.1580	2.5540	15.2384	2293.63	0.001
RETVOL	0.0275	-0.0032	0.2469	0.8554	14.0169	1621.08	0.001
RETSKEW	0.0121	0.0020	0.1707	0.1087	7.8823	311.49	0.001
RETKURT	0.0018	0.0025	0.1677	0.0427	7.7197	290.60	0.001
MAXRET	-0.0299	-0.0075	0.2615	0.1757	17.8606	2881.71	0.001
STDPRCVOL	0.0334	0.0054	0.1811	2.3954	15.0932	2206.61	0.001
MEANABS	0.0298	0.0107	0.1809	2.3847	15.6372	2379.40	0.001
BETA	-0.0061	-0.0031	0.1449	-0.4172	6.4648	138.12	0.001
BETA^2	-0.0061	-0.0031	0.1449	-0.4176	6.4635	138.05	0.001
IDIOVOL	0.0251	0.0053	0.1787	3.0674	23.8671	5144.64	0.001
DELAY	0.0062	-0.0013	0.1433	0.5956	7.6729	252.90	0.001

This table reports the summary statistics such as mean, median, stand deviation, skewness, kurtosis, J-B test and corresponding p values.

Table 8 shows the mean, median, standard deviation, skewness, kurtosis, J-B test and their p values for total 27 factor portfolios. For instance, the portfolio of MOM3 has the highest mean weekly return of 0.367, whereas the portfolio of MAXRET has the lowest average weekly return of -0.0299. Moreover, the portfolio of MAXRET is the most volatile portfolio with standard deviation of 0.2615, the portfolio of LPR is the steadiest portfolio with a standard deviation of 0.1421. Recalling the mean return of S&P is 0.0019 and the standard deviation is 0.0174 in Table 1, investors might compare the performance between factor portfolios and S&P 500 by using some simple risk-adjusted metrics. However, it is necessary to examine the return distribution before conducting performance comparison because the assumption of normality is vital. As demonstrated in Table 8, there are dramatic departures from normality in the return distribution of factor portfolios. To illustrate, the empirical return distributions are highly skewed and peaked around the mean. we conduct the Jarque-Bera (J-B) test to analyze whether factor portfolios are normally distributed, the extremely large J-B statistics for every factor portfolio reject the null hypothesis of normal distribution.

The considerable J-B statistics indicate the non-normality of factor portfolios, which does not allow us to study the factor portfolios via widely used methods based on an assumption of normal distribution. Hence, we are motivated to develop another methodology that not based on assumption of normality to investigate the factor portfolios in the aspect of performance.

6. Empirical Analysis

In this section, we analyze the empirical result of AFSD, ASSD and decomposition of zero-investment for 4-week, 13-week, 26-week, 52-week and 78-week horizon portfolios based on factors listed in Table 3. The formation for n-week long-horizon is as follows: sum the value from the first position of return series to $1+(n-1)^{th}$ position to get the first n-week value, then sum the value from the second position of return series to $2+(n-1)^{th}$ position to get the second n-week value, after that we can iteratively get a series of n-week return. We employ this method to construct different horizon portfolios for 4-week, 13-week, 26-week, 52-week and 78-week portfolio to examine the investment value of cryptocurrencies.

6.1. AFSD

To test whether AFSD and ASSD exist, we need to calculate the ratio of violation area (M in Figure 4) over total enclosed area (M + N in figure 4) for each portfolio and compare these ratios ε_i with critical value of AFSD (5.9%) and ASSD (3.2%). We define A_1 as the area between the cumulative distributions when the cumulative distribution of a portfolio plots above the cumulative distribution of benchmarks (e.g. S&P 500, T-Bill and T-Bond). Likewise, we define A_2 as the area between the cumulative distributions when the cumulative distribution of a benchmark plots above the portfolio. The measure of ε_i for AFSD is $\varepsilon_i = \frac{A_1}{A_1+A_2}$ by conducting empirical test. If a portfolio has a ε_i that is smaller than critical value of AFSD (ASSD), then we conclude that this portfolio dominates the AFSD (ASSD). The violation area is positively related to ε_i, so we can horizontally compare the violation area among the portfolios if they are against same benchmark (e.g. S&P 500, T-Bill and T-Bond) through the value of ε_i.

Table 9 demonstrates AFSD empirical results of ε_i values for each factor portfolio compared with S&P 500 index, T-Bill, T-Bonds and cryptocurrency index for 4-week to 78-week investment horizons. Among four panels, it is clear that almost every ε_i of portfolios is monotonically decreasing as investment horizon become longer (4-week to 78-week horizon) except portfolios based on age, kurtosis of returns, beta and beta squared. As ε_i is positively related to violation area, the increasing ε_i indicates the growing violation area, which reveals that these factors might not be efficient factors to construct profitable portfolios since these their factor portfolios neither dominate the benchmarks nor have long horizon investment value.

6.1.1. AFSD against S&P 500

Panel A of Table 9 reports the empirical ε_i values for each factor portfolio compared to S&P 500 index for 4-week to 78-week investment horizons. Among 4-week and 13-week horizons, no portfolios show dominance over the S&P 500 until the holding period is extended to a 26-week horizon. Specially, ε_i is directly determined by the size of violation area, the violation area is mainly determined by extreme negative values of two cumulative distribution functions (CDF). Hence, relatively large ε_i indicates that the negative returns of portfolio cannot be absorbed enough by positive returns after extending holding period from 4-week horizon to 13-week horizon. In this paper, 10 portfolios out of 27 portfolios exhibit AFSD at 26-week horizon as their ε_i values are less than 5.9%, they are portfolios of LPRC, MAXPRC, MOM1, MOM2, MOM3, ROMO1, RMOM2, RMOM3, RMOM4 and STDPRCVOL, respectively. Specifically, the portfolio of LPRC has the smallest empirical ε_i of 1.43%, which is the best of total six dominant portfolios. In contrast, the portfolio of RMOM1 has the largest empirical ε_i of 5.05%, which is the worst of the total ten dominant portfolios. All ten portfolios' empirical values are smaller than 5.9% of the AFSD critical value, which reveals that although portfolios of cryptocurrencies based on factors above have much higher volatility than S&P

500, yet their exceptional return could compensate the corresponding risk. Additionally, there are 17 portfolios out of 27 portfolios AFSD against benchmarks at 52-week horizon. To illustrate, apart from the ten portfolios that dominate the S&P 500 at both 26-week and 52-week horizon, seven new portfolios join the dominant group. They are Portfolios of MARCAP, VOLPRC, VOLSCALE, RETVOL, RETSKEW, STDPRCVOL, MEANABS and IDIOVOL, respectively. Among 17 dominant portfolios at 52-week horizon, 10 portfolios (portfolios of LPRC, MAXPRC, MOM1, MOM2, MOM3, RMOM1, RMOM2, RMOM3, RMOM4, STDPRCVOL) not only dominate S&P 500 at 26-week horizon but also dominate S&P 500 at 52-horizons, and the remaining dominant portfolios have no such properties. However, 7 new dominant portfolios emerged at 52-week horizon disclose that negative returns are absorbed by positive returns after extending the investment horizon, which might be a proof of investment value for cryptocurrencies. In this case, ε_i equals 0 for portfolio of MAXPRC and RMOM2 are the smallest violation among 17 outperformed portfolios, indicating FSD since there does not exist violation area. Nevertheless, Portfolio of RETVOL has the largest ε_i of 5.44%, which is very close to critical value of AFSD, revealing that this portfolio is the worst performed portfolio in 13 outperformed portfolios. The dominant portfolios at 52-week horizon behave better as the investment horizon extends to 78 weeks. The portfolio of VOL becomes a dominant portfolio against S&P 500 and be the member of the dominant portfolios group, which makes the total 18 portfolios dominate the stock index. Moreover, the portfolios with tiny ε_i values start to dominate the S&P 500 in the sense of FSD (see example such as LPRC, MOM1, RMOM1, RMOM2 and RMOM3), which reveals that the extreme negative return might be offset by significant positive return in long-term horizon.

6.1.2. AFSD against T-Bond

Panel B of Table 9 reports empirical ε_i values for each factor portfolio compared to ten-year T-Bond for 4-week to 78-week investment horizons. We find the same dominant portfolios as in Panel A at 26-week to 78-week horizon after conducting the empirical AFSD test. For instance, portfolio of LPRC still possesses the smallest ε_i value of 1.52%, indicating the best performance among six dominant portfolios at 26-week horizon. Moreover, portfolio of RMOM1 with a ε_i of 5.23% is the worst in ten dominant portfolios. As investment horizon extends to 52 weeks, we also get the same outperformed portfolio as in Panel A (17 out of 27 portfolios). The portfolio of RMOM2 remains the best performer with ε_i of 0, and the portfolio of RETVOL is the worst dominant portfolio with ε_i of 5.15%. Moreover, as the movement of returns on T-bond is steadier than stock index, portfolio of MAXPRC does not show FSD as in Panel A against S&P 500 index. As holding period lengthens to 78-week horizon, the dominant portfolios are the same as those in Panel A but with smaller ε_i value. In particular, portfolio base on MARCAP, MOM2, RMOM4, VOLPRC, STDPRCVOL becomes FSD against the T-bond. Hence, this phenomenon also provides the evidence that portfolios based on cryptocurrency factors tend to dominate more of the benchmark with less volatility (T-bond) compared to more volatile benchmark (S&P 500).

6.1.3. AFSD against T-Bill and Cryptocurrency Index

Panel C of Table 9 demonstrates empirical ε_i values for each factor portfolio compared to one-month T-Bill for 4-weel to 78-week investment horizons. For 26-week horizon, we get the same dominant portfolios as in Panel A, but the best performing portfolio is that based on MOM1 with ε_i equals 2.16% rather than the portfolio based on LPRC that is the best dominant portfolio in Panel A and B. However, the portfolio of RMOM1 with a ε_i of 4.98% remains the worst performer in Panel A and B. Hence, we might infer that portfolio of cryptocurrencies based on certain factors might behave similar compared to stock index and bond index. The outperformance of portfolio based on MOM1 in Panel C indicates that the extreme negative value of MOM1 might be small in order to dominate risk-free rate by smallest violation area at 26-week horizon. For 52-week horizon, the portfolio of RMOM2 with the smallest ε_i of 0 is the best performed among 17 outperformed same as in Panel A and Panel B, and portfolio on RETVOL with ε_i of 5.4% represents the worst performed dominant portfolio same as in Panel A and Panel B. In regard to 78-week horizon, the dominant portfolios in Panel A and B still show dominance against T-bill except portfolio based on STDPRCVOL deteriorates from ε_i from 0 to 0.06%. Additionally, we found the ε_i value of MAXRET is -1 for S&P 500, T-bond and T-bill, indicating that those benchmarks dominate the portfolio of MAXRET. However, given that such a portfolio dominated by benchmarks is in a minority, we can still conclude that the dominant 52-week and 78-week factor portfolios are behaving the same against S&P 500, T-bond and T-bill, which might confirm the investment value of cryptocurrencies.

Panel D of Table 9 illustrates the ε_i values of factor portfolios against cryptocurrency index (CMKT in Table 1). Unlike benchmarks of traditional assets, the AFSD first appears at 4-week horizon. Specifically, portfolios based on LPRC, MAXPRC and RMOM4 dominate the cryptocurrency index. Nevertheless, the persistence of the performance of such portfolios cannot last long, since none of the three portfolios above dominate cryptocurrency market in long horizons (52-week and 78-week horizon). We also find that the portfolios with a ε_i value of -1 or very large value (AGE, RETKURT, MAXRET, BETA and BTEA^2) that close to 1 do not dominate the traditional benchmarks either in any horizons, which performs cross validation to previous test. In addition, most portfolios based on momentum and risk-adjusted momentum dominate the cryptocurrency market in the sense of FSD, as they previously dominated other traditional benchmarks.

To sum up, we test the AFSD of 27 factor portfolios against four benchmarks such as S&P500, T-bond, T-bill and cryptocurrency index for 4-week to 78-week horizons. We find there are ten portfolios dominating every benchmark at 52-week and 78-week horizons, they are portfolios based on MOM1, MOM2, MOM3, RMOM1, RMOM2, RMOM3, VOLPRC, RETVOL, STDPRCVOL and MEANABS. The dominant portfolios are classified as momentum and volatility category, which proposes that portfolios constructed on such factors might generate high excess return compared to other factor portfolios.

6.2. ASSD

In addition to AFSD in Table 10, we conduct ASSD for each portfolio at 4-week to 78-week horizon in Table 10. The key difference between AFSD and ASSD is the critical value, ASSD has a lower critical value of 3.2% than that of AFSD 5.9%, which implies ASSD has less tolerance of loss than that of AFSD. Similar to AFSD, the ASSD first appears at 26-week horizon against stock, bond and risk-free rate, and the ASSD against cryptocurrency index first appears at 4-week horizon.

6.2.1. ASSD against S&P 500

Panel A of Table 10 documents empirical ε_i values for each factor portfolio compared to S&P 500 for 4-week to 52-week investment horizons. From 4-week to 13-week horizon, none of portfolios dominate S&P 500 index. For 26-week horizon, only 5 out of 27 portfolios dominate benchmark in the sense of ASSD. These are portfolios of LPRC, MAXPRC, MOM1, MOM3 and RMOM2, respectively. Among the dominant portfolios, the portfolio of LPRC is the best performing with ε_i 1.43% and the portfolio of ROMO2 performs worst with ε_i 2.95%. As the critical value decreases, the number of dominant portfolios in ASSD drops by five, yet the best performing portfolio is still the portfolio of LPRC which has the smallest violation area. As the investment horizon extends to 52 weeks, the number of dominant portfolios falls from 17 in AFSD to 14 in ASSD. The portfolios of MAXPRC and RMOM2 have ε_i of 0 which indicates ASD has no violation area, and is the best performed portfolio among 14 dominant portfolios. Among the remaining 12 dominant portfolios, two portfolios (MARCAP, LPRC) belong to size-related factor, seven portfolios (MOM-1,2,3 and RMOM-1,2,3,4) come from momentum-related factor, only one portfolio (VOLPRC) from volume-related factor and three portfolios come from volatility-related factor. Hence, we conclude that volume-related factor might not be an effective factor to construct portfolio of cryptocurrencies. As the investment horizon extends to 78-week horizon, 16 out of 27 portfolios exhibit ASSD against the S&P 500, showing similar outcome to AFSD. One interesting observation is that market risk factor (BETA and BETA^2) shows no impact on abnormal positive return since they cannot dominate the S&P 500 in terms of any investment horizon. This result apparently conflicts with both the CAPM model and the Fama-French three-factor model which assume a market factor is an important risk factor to explain returns. However, cryptocurrencies have existed for only a relatively short compared to traditional assets, the insufficient dataset might not provide a comprehensive insight into cryptocurrencies.

6.2.2. ASSD against T-Bond

Panel B in Table 10 documents empirical ε_i values for each factor portfolio compared to T-bond for 4-week to 52-week investment horizons. There are no portfolios that dominate the T-bond until 26-week, and the dominant portfolios are the same as those in Panel A except for portfolio of RMOM2. For a 26-week horizon, the portfolio of LPRC (last price) with the smallest ε_i value of 1.52% performs best among four dominant portfolios, whereas the portfolio of MOM3 (three-week momentum) performs badly with a ε_i of 2.81%. For a 52-week horizon, the portfolio of RMOM2 (risk-adjusted momentum) has the smallest ε_i value of 0 and the poorly performing portfolio of VOLPRC has the largest ε_i value of 0.98%. For a 78-week horizon, dominant portfolios are same as those in Panel A except the ε_i values are generally smaller than those in Panel A. This might be because T-bond is less variant than S&P 500 and results in a smaller violation area.

6.2.3. ASSD against T-Bill and Cryptocurrency Index

Panel C in table 10 reports the ε_i values for each factor portfolio compared to treasury bill for 4-week to 52-week investment horizons. The dominance first appears at 26-week horizon, but a difference is that only four portfolios (LPRC, MAXPRC, MOM1 and RMOM2) dominate the Treasure Bill compared to five dominant portfolios in Panel A. Another noteworthy point is that the portfolio of MOM1 with a ε_i of 2.16% becomes the best performing portfolio, and the portfolio of RMOM2 with a ε_i of 2.95% is the worst performing portfolio among the three outperforming portfolios. Moreover, the portfolios behave similarly to dominant portfolios in Panel A, B and C, providing evidence that portfolios will dominate three traditional benchmarks in long horizon if portfolios dominate one of three benchmarks.

Panel D in table 10 demonstrates the ε_i value for each portfolio against cryptocurrency index. Similar to Panel D in Table 9, ASSD of LPRC and MAXPRC first occurs at 4-week horizon. However, the first dominant portfolios fail to continue extraordinary performance as investment horizon becomes longer, which is identical with the result in AFSD. Since the dominant portfolios outperformed three benchmarks at same time, the investment value of cryptocurrencies based on certain factors might have been identified. There are several portfolios such as MOM1, MOM3, MOM4, VOLPRC, STDPRCVOL and MEANABS dominate cryptocurrency index for 13-week to 78-week horizon.

To conclude, we test the ASSD of 27 factor portfolios against four benchmarks such as S&P500, T-bond, T-bill and cryptocurrency index for 4-week to 78-week horizons. There are nine out of 27 portfolios dominate four benchmarks at the same time. They are portfolio based on MOM1, MOM2, MOM3, RMOM1, RMOM2, RMOM3, VOLPRC, STDPRCVOL and MEANABS. Compared to ten dominant portfolios in the sense of AFSD, portfolio based on RETVOL failed to ASSD benchmarks. Therefore, we have nine portfolios show AFSD and ASSD in total.

6.3. Decompose of Long-Short Portfolios

6.3.1 Decompose the Long/Short Portfolios against Four Indices

So far, this paper has considered the investment values of cryptocurrencies by conducting AFSD and ASSD on long-short factor portfolios. To investigate which counterpart (long/short) contributes most to ASD, we decompose the all the long-short portfolios into long only and short only parts and continue AFSD and ASSD. For instance, we list the mean return on quintile portfolios for each factor from Table 4 to Table 7, and we assume 5-1 as the normal action. If the 5-1(long fifth quintile and short first quintile) portfolio is negative, then we employ the opposite action that is 1-5 (long first quintile and short fifth quintile) to make our portfolio is profitable. We also conduct ASD against some stock benchmarks based on factors from Carhart four-factor model (Carhart, 1997) and Fama-French three-factor model (Fama and French, 1993) to examine the performance of cryptocurrency portfolios. The data of stock portfolios based on corresponding factors is collected from Kenneth French's website.

Table 9 Almost First-Order Stochastic Dominance

Portfolios	Panel A: Portfolios against S&P 500 Index					Panel B: Portfolios against Ten-year T-Bond					Panel C: Portfolios against One-month T-Bill					Panel D: Portfolios against Cryptocurrency Index				
	4-week	13-week	26-week	52-week	78-week	4-week	13-week	26-week	52-week	78-week	4-week	13-week	26-week	52-week	78-week	4-week	13-week	26-week	52-week	78-week
MARCAP	0.2283	0.1382	0.0648	0.0075*	0.0006*	0.2354	0.1349	0.0634	0.0079*	0.0000*	0.2416	0.1406	0.0678	0.0084*	0.0000*	0.0620	0.0835	0.0511*	0.0633	0.0299*
LPRC	0.2723	0.1307	0.0140*	0.0003*	0.0000*	0.2777	0.1339	0.0152*	0.0009*	0.0000*	0.2836	0.1429	0.0239*	0.0014*	0.0000*	0.0203*	0.0519*	0.1262	0.1304	0.1029
MAXPRC	0.2896	0.1363	0.0170*	0.0000*	0.0000*	0.2932	0.1378	0.0178*	0.0005*	0.0000*	0.2983	0.1481	0.0267*	0.0009*	0.0000*	0.0208*	0.0430*	0.1379	0.1571	0.1462
AGE	0.5706	0.5998	0.6374	0.6763	0.6955	0.5551	0.5770	0.6077	0.6263	0.6049	0.5483	0.5649	0.5905	0.6028	0.5823	0.9281	-1.0000	-1.0000	0.9777	-1.0000
MOM1	0.2740	0.1180	0.0160*	0.0033*	0.0000*	0.2771	0.1196	0.0170*	0.0037*	0.0000*	0.2810	0.1267	0.0216*	0.0042*	0.0000*	0.1121	0.0075*	0.0000*	0.0000*	0.0000*
MOM2	0.3224	0.1721	0.0370*	0.0005*	0.0001*	0.3230	0.1714	0.0370*	0.0008*	0.0000*	0.3252	0.1761	0.0425*	0.0011*	0.0000*	0.2425	0.0586*	0.0031*	0.0000*	0.0000*
MOM3	0.2522	0.0799	0.0280*	0.0024*	0.0014*	0.2565	0.0836	0.0280*	0.0029*	0.0009*	0.2608	0.0905	0.0330*	0.0041*	0.0015*	0.1043	0.0064*	0.0000*	0.0000*	0.0000*
MOM4	0.3127	0.1946	0.1522	0.0983	0.0848	0.3134	0.1913	0.1445	0.0883	0.0728	0.3162	0.1956	0.1487	0.0920	0.0756	0.1842	0.0076*	0.0251*	0.0106*	0.0754
MOM8	0.4176	0.3363	0.2924	0.2016	0.1267	0.4124	0.3262	0.2772	0.1850	0.1035	0.4119	0.3257	0.2771	0.1861	0.1074	0.4417	0.3390	0.4625	0.6606	0.8756
RMOM1	0.2655	0.1278	0.0505*	0.0028*	0.0000*	0.2736	0.1334	0.0520*	0.0038*	0.0000*	0.2695	0.1297	0.0498*	0.0033*	0.0000*	0.1398	0.1007	0.0210*	0.0000*	0.0000*
RMOM2	0.2860	0.1415	0.0295*	0.0000*	0.0000*	0.2923	0.1482	0.0340*	0.0000*	0.0000*	0.2887	0.1428	0.0295*	0.0000*	0.0000*	0.1567	0.0737	0.0001*	0.0053*	0.0000*
RMOM3	0.3071	0.1328	0.0372*	0.0023*	0.0000*	0.3116	0.1401	0.0400*	0.0028*	0.0000*	0.3088	0.1348	0.0369*	0.0026*	0.0000*	0.2199	0.0924	0.0189*	0.0085*	0.0000*
RMOM4	0.2713	0.1014	0.0374*	0.0025*	0.0001*	0.2802	0.1126	0.0440*	0.0035*	0.0000*	0.2754	0.1044	0.0364*	0.0029*	0.0000*	0.0527*	0.0000*	0.0000*	0.0959	0.1928
RMOM8	0.3616	0.2503	0.2381	0.1922	0.1791	0.3612	0.2484	0.2282	0.1787	0.1475	0.3598	0.2454	0.2263	0.1773	0.1501	0.2924	0.1318	0.2291	0.5353	0.9591
VOL	0.2694	0.1638	0.1176	0.0800	0.0501*	0.2733	0.1639	0.1130	0.0758	0.0443	0.2777	0.1691	0.1177	0.0781	0.0466*	0.1232	0.0410*	0.0039*	0.0000*	0.0195*
VOLPRC	0.2887	0.1449	0.0659	0.0093*	0.0004*	0.2907	0.1446	0.0634	0.0098*	0.0000*	0.2946	0.1514	0.0701	0.0110*	0.0000*	0.0846	0.0000*	0.0000*	0.0001*	0.0000*
VOLSCALE	0.3747	0.2982	0.2056	0.0505*	0.0461*	0.3708	0.2888	0.1896	0.0428*	0.0356*	0.3719	0.2898	0.1929	0.0481*	0.0395*	0.3311	0.2464	0.2665	0.1612	0.0298*
RETVOL	0.3739	0.2733	0.1649	0.0544*	0.0093*	0.3718	0.2681	0.1578	0.0515*	0.0076*	0.3725	0.2698	0.1615	0.0540*	0.0090*	0.3492	0.2066	0.0764*	0.0295*	0.0172*
RETSKEW	0.3785	0.2792	0.1393	0.0377*	0.0050*	0.3745	0.2699	0.1249	0.0343*	0.0029*	0.3756	0.2727	0.1341	0.0389*	0.0050*	0.2505	0.2968	0.4244	0.3926	0.4629
RETKURT	0.5031	0.5258	0.5789	0.5963	0.6017	0.4919	0.5061	0.5498	0.5490	0.5411	0.4880	0.4974	0.5353	0.5314	0.5276	0.7608	0.9802	-1.0000	-1.0000	-1.0000
MAXRET	0.6728	0.7898	0.9144	0.9903	-1.0000	0.6614	0.7786	0.9046	0.9867	-1.0000	0.6548	0.7702	0.8941	0.9818	-1.0000	0.8577	0.0000*	0.0000*	0.0001*	-1.0000
STDPRCVOL	0.2655	0.1453	0.0399*	0.0032*	0.0005*	0.2686	0.1449	0.0392*	0.0037*	0.0000*	0.2730	0.1507	0.0451*	0.0045*	0.0006*	0.0624	0.0055*	0.0000*	0.0000*	0.0000*
MEANABS	0.2812	0.1559	0.0676	0.0014*	0.0000*	0.2838	0.1554	0.0652	0.0019*	0.0000*	0.2800	0.1613	0.0714	0.0024*	0.0000*	0.0647	0.0063*	0.0000*	0.0000*	0.0000*
BETA	0.5991	0.6467	0.6718	0.7197	0.7956	0.5751	0.6121	0.6365	0.6654	0.7398	0.5830	0.6250	0.6483	0.6836	0.7216	0.9390	-1.0000	-1.0000	-1.0000	-1.0000
BETA^2	0.5988	0.6463	0.6713	0.7190	0.7947	0.5749	0.6117	0.6330	0.6646	0.7387	0.5827	0.6245	0.6478	0.6828	0.7206	0.9389	-1.0000	-1.0000	-1.0000	-1.0000
IDIOVOL	0.3113	0.1693	0.0730	0.0037*	0.0004*	0.3152	0.1740	0.0774	0.0058*	0.0000*	0.3117	0.1665	0.0683	0.0045*	0.0000*	0.1080	0.0053*	0.0194*	0.1641	0.1159
DELAY	0.4756	0.4498	0.4215	0.3445	0.2852	0.4633	0.4304	0.3954	0.3104	0.2350	0.4662	0.4351	0.4010	0.3147	0.2345	0.6746	0.8440	0.8893	0.9251	0.9902

Notes. This table presents the empirical estimates of ε_i for 4-week to 78-week investment horizon. To complete the stochastic dominance, this paper defines A_1 as the area between the cumulative distributions when the cumulative distribution of a portfolio plots above the cumulative distribution of benchmarks (e.g. S&P 500, T-Bond, T-Bill and Cryptocurrency Index). Likewise, this paper defines A_2 as the area between the cumulative distributions when the cumulative distribution of a benchmark plots above the long-short portfolio. The measure of ε_i for AFSD is $\varepsilon_i = \frac{M}{M+N}$ by conducting empirical test. Moreover, the critical value for AFSD is $\varepsilon^* = 5.9\%$, if the ε_i for any portfolio is less than the critical value, then the result indicates the outperformance of that portfolio. This paper uses * to label portfolios which is less than the critical value. The ε_i value of -1 indicates that benchmarks dominate corresponding portfolio.

Table 10 Almost Second-Order Stochastic Dominance

Portfolios	Panel A: Portfolios against S&P 500 Index					Panel B: Portfolios against Ten-year T-Bond					Panel C: Portfolios against One-month T-Bill					Panel D: Portfolios against Cryptocurrency Index				
	4-week	13-week	26-week	52-week	78-week	4-week	13-week	26-week	52-week	78-week	4-week	13-week	26-week	52-week	78-week	4-week	13-week	26-week	52-week	78-week
MARCAP	0.2283	0.1382	0.0648	0.0075*	0.0006*	0.2354	0.1349	0.0634	0.0079*	0.0000*	0.2416	0.1406	0.0678	0.0084*	0.0000*	0.0620	0.0835	0.0511	0.0633	0.0299*
LPRC	0.2723	0.1307	0.0140*	0.0003*	0.0000*	0.2777	0.1339	0.0152*	0.0009*	0.0000*	0.2836	0.1429	0.0239*	0.0014*	0.0000*	0.0203*	0.0519	0.1262	0.1304	0.1029
MAXPRC	0.2896	0.1363	0.0170*	0.0000*	0.0000*	0.2932	0.1378	0.0178*	0.0005*	0.0000*	0.2983	0.1481	0.0267*	0.0009*	0.0000*	0.0208*	0.0430	0.1379	0.1571	0.1462
AGE	0.5706	0.5998	0.6374	0.6763	0.6955	0.5551	0.5770	0.6077	0.6263	0.6049	0.5483	0.5649	0.5905	0.6028	0.5823	0.9281	-1.0000	-1.0000	0.9777	-1.0000
MOM1	0.2740	0.1180	0.0160*	0.0033*	0.0000*	0.2771	0.1196	0.0170*	0.0037*	0.0000*	0.2810	0.1267	0.0216*	0.0042*	0.0000*	0.1121	0.0075*	0.0000*	0.0000*	0.0000*
MOM2	0.3224	0.1721	0.0370	0.0005*	0.0001*	0.3230	0.1714	0.0370	0.0008*	0.0000*	0.3252	0.1761	0.0425	0.0011*	0.0000*	0.2425	0.0586	0.0031*	0.0000*	0.0000*
MOM3	0.2522	0.0799	0.0280*	0.0024*	0.0014*	0.2565	0.0836	0.0280*	0.0029*	0.0009*	0.2608	0.0905	0.0330	0.0041*	0.0015*	0.1043	0.0064*	0.0000*	0.0000*	0.0000*
MOM4	0.3127	0.1946	0.1522	0.0983	0.0848	0.3134	0.1913	0.1445	0.0883	0.0728	0.3162	0.1956	0.1487	0.0920	0.0756	0.1842	0.0076*	0.0251*	0.0106*	0.0754
MOM8	0.4176	0.3363	0.2924	0.2016	0.1267	0.4124	0.3262	0.2772	0.1850	0.1035	0.4119	0.3257	0.2771	0.1861	0.1074	0.4417	0.3390	0.4625	0.6606	0.8756
RMOM1	0.2655	0.1278	0.0505	0.0028*	0.0000*	0.2736	0.1334	0.0520	0.0038*	0.0000*	0.2695	0.1297	0.0498	0.0033*	0.0000*	0.1398	0.1007	0.0210*	0.0000*	0.0000*
RMOM2	0.2860	0.1415	0.0295*	0.0000*	0.0000*	0.2923	0.1482	0.0340	0.0000*	0.0000*	0.2887	0.1428	0.0295*	0.0000*	0.0000*	0.1567	0.0737	0.0001*	0.0053*	0.0000*
RMOM3	0.3071	0.1328	0.0372	0.0023*	0.0000*	0.3116	0.1401	0.0400	0.0028*	0.0000*	0.3088	0.1348	0.0369	0.0026*	0.0000*	0.2199	0.0924	0.0189*	0.0085*	0.0000*
RMOM4	0.2713	0.1014	0.0374	0.0025*	0.0001*	0.2802	0.1126	0.0440	0.0035*	0.0000*	0.2754	0.1044	0.0364	0.0029*	0.0000*	0.0527	0.0000*	0.0000*	0.0959	0.1928
RMOM8	0.3616	0.2503	0.2381	0.1922	0.1791	0.3612	0.2484	0.2282	0.1787	0.1475	0.3598	0.2454	0.2263	0.1773	0.1501	0.2924	0.1318	0.2291	0.5353	0.9591
VOL	0.2694	0.1638	0.1176	0.0800	0.0501	0.2733	0.1639	0.1130	0.0758	0.0443	0.2777	0.1691	0.1177	0.0781	0.0466	0.1232	0.0410	0.0039*	0.0000*	0.0195*
VOLPRC	0.2887	0.1449	0.0659	0.0093*	0.0004*	0.2907	0.1446	0.0634	0.0098*	0.0000*	0.2946	0.1514	0.0701	0.0110*	0.0000*	0.0846	0.0000*	0.0000*	0.0001*	0.0000*
VOLSCALE	0.3747	0.2982	0.2056	0.0505	0.0461	0.3708	0.2888	0.1896	0.0428	0.0356	0.3719	0.2898	0.1929	0.0481	0.0395	0.3311	0.2464	0.2665	0.1612	0.0298*
RETVOL	0.3739	0.2733	0.1649	0.0544	0.0093*	0.3718	0.2681	0.1578	0.0515	0.0076*	0.3725	0.2698	0.1615	0.0540	0.0090*	0.3492	0.2066	0.0764	0.0295*	0.0172*
RETSKEW	0.3785	0.2792	0.1393	0.0377	0.0050*	0.3745	0.2699	0.1249	0.0343	0.0029*	0.3756	0.2727	0.1341	0.0389	0.0050*	0.2505	0.2968	0.4244	0.3926	0.4629
RETKURT	0.5031	0.5258	0.5789	0.5963	0.6017	0.4919	0.5061	0.5498	0.5490	0.5411	0.4880	0.4974	0.5353	0.5314	0.5276	0.7608	0.9802	-1.0000	-1.0000	-1.0000
MAXRET	0.6728	0.7898	0.9144	0.9903	-1.0000	0.6614	0.7786	0.9046	0.9867	-1.0000	0.6548	0.7702	0.8941	0.9818	-1.0000	0.8577	0.0000*	0.0000*	0.0001*	-1.0000
STDPRCVOL	0.2655	0.1453	0.0399	0.0032*	0.0005*	0.2686	0.1449	0.0392	0.0037*	0.0000*	0.2730	0.1507	0.0451	0.0045*	0.0006*	0.0624	0.0055*	0.0000*	0.0000*	0.0000*
MEANABS	0.2812	0.1559	0.0676	0.0014*	0.0000*	0.2838	0.1554	0.0652	0.0019*	0.0000*	0.2800	0.1613	0.0714	0.0024*	0.0000*	0.0647	0.0063	0.0000*	0.0000*	0.0000*
BETA	0.5991	0.6467	0.6718	0.7197	0.7956	0.5751	0.6121	0.6365	0.6654	0.7398	0.5830	0.6250	0.6483	0.6836	0.7216	0.9390	-1.0000	-1.0000	-1.0000	-1.0000
BETA^2	0.5988	0.6463	0.6713	0.7190	0.7947	0.5749	0.6117	0.6330	0.6646	0.7387	0.5827	0.6245	0.6478	0.6828	0.7206	0.9389	-1.0000	-1.0000	-1.0000	-1.0000
IDIOVOL	0.3113	0.1693	0.0730	0.0037*	0.0004*	0.3152	0.1740	0.0774	0.0058*	0.0000*	0.3117	0.1665	0.0683	0.0045*	0.0000*	0.1080	0.0053*	0.0194*	0.1641	0.1159
DELAY	0.4756	0.4498	0.4215	0.3445	0.2852	0.4633	0.4304	0.3954	0.3104	0.2350	0.4662	0.4351	0.4010	0.3147	0.2345	0.6746	0.8440	0.8893	0.9251	0.9902

Notes. This table presents the empirical estimates of ε_i for 4-week to 78-week investment horizon. To complete the stochastic dominance, this paper defines A_1 as the area between the cumulative distributions when the cumulative distribution of a portfolio plots above the cumulative distribution of benchmarks (e.g. S&P 500, T-Bond, T-Bill and Cryptocurrency Index). Likewise, this paper defines A_2 as the area between the cumulative distributions when the cumulative distribution of a benchmark plots above the long-short portfolio. The measure of ε_i for ASD is $\varepsilon_i = \varepsilon_i = \frac{M}{M+N}$ by conducting empirical test. Moreover, the critical value for AFSD is $\varepsilon^* = 3.2\%$, if the ε_i for any portfolio is less than the critical value, then the result indicates the outperformance of that portfolio. This paper uses * to label portfolios which is less than the critical value. The ε_i value of -1 indicates that benchmarks dominate corresponding portfolio.

6.3.2 AFSD of Long-Leg Portfolios against S&P 500

Table 12 reports the empirical ε_i value of each long leg of portfolio in the sense of AFSD and ASSD against four benchmarks. We start with AFSD then ASSD. Panel A of Table 12 illustrate empirical ε_i for the long part of each portfolio against S&P 500. Unlike the dominance for the long-short portfolios in Table 9, none of any portfolios shows dominance against the S&P 500 at a 26-week horizon. As the investment horizon extends to 52 weeks, the phenomenon that total 13 portfolios out of 27 portfolios AFSD the S&P 500 appears. Among these 13 dominant portfolios, the portfolio of VOL has the smallest ε_i value of 0.92%, whereas the portfolio of RETVOL performs worst with an ε_i value of 5.08%. Although the best performed long-short portfolios are portfolio of MAXPRC and RMOM2 with ε_i values of 0 at 52-week horizon, none of each long leg portfolio dominate the stock index. Furthermore, long leg portfolios of MARCAP (ε_i equals 7.96%) and LPRC (ε_i equals 18.48%) are also absent from the dominant group without long-short strategy. Compared to the result in Table 9 of long-short strategy, we find that the dominance of portfolios based on size factor might be susceptible to the choice of trading strategy. For 78-week horizon, the number of dominant portfolios against all four benchmarks increased to 21, and the non-dominant portfolios are only LPRC, MAXPRC, AGE, RETKURT, BETA and BETA^2, respectively. This evidence shows that nearly 77.8% (21 out of 27 portfolios) of factor portfolios could dominate the S&P 500 in long term, which justifies the fact that cryptocurrencies can generate excess high return as long as long holding period.

6.3.3 AFSD of Long-Leg Portfolios against T-Bond

Panel B of Table 12 reports the empirical ε_i for the long leg of each portfolio against T-bond. The performance of portfolios is similar to Panel A of Table 12, none of the portfolios exhibiting dominance until a 52-week horizon. However, 15 portfolios out of 27 portfolios AFSD the T-bond at the 52-week horizon, which has two more dominant portfolios compared to dominant portfolios in Panel A. Moreover, the best performing portfolio is still VOL with ε_i 0.9% and the poorest portfolios 5.9%, which just meet the condition of AFSD. As the dominant portfolio is increased by two (MOM8 and RMOM2), we conclude that portfolios tend to behave relatively better when compared to a steadier benchmark and show more dominance. For a 78-week horizon, the same portfolios as in Panel A dominate the T-bond; all ε_i values of portfolios in Panel B are smaller than those in Panel A except for portfolios of RMOM1, RMOM3, VOL and STDPRCVOL that have zero ε_i values in both Panel A and Penal B.

6.3.4 AFSD of Long-Leg portfolios against T-Bill

Panel C of Table 12 reports the AFSD for long leg of portfolios against T-bill. There are no dominant portfolios for 4-week to 26-week horizon, which is the same as Panel A and Panel B. In Panel C of Table 12, 13 same portfolios as in Panel A dominate T-bill in the sense of AFSD. Among the dominant portfolios, portfolio of VOL performed best with a ε_i value equals 0.1%, whereas portfolio of RETVOL performed poorest with a ε_i value 5.07%. In contrast, recalling there are 17 dominant long-short portfolios at 52-week horizon against S&P 500 in Table 9, and 13 long-only portfolios dominate S&P 500 at 52-week horizon in Table 12, the number of dominant portfolios drops by four. This indicates that the excess return could be increased if investors conduct appropriate investment strategies. As investment horizon extends to 78 weeks, the dominant portfolios against T-bill are same as portfolios in Panel A and B despite the dominant portfolios are various at 52-week horizon for each panel.

6.3.5 AFSD of Long-Leg portfolios against Cryptocurrency Index

Panel D of Table 12 represents the AFSD for long-leg portfolios against cryptocurrency index. Unlike the other three panels, AFSD first appears in 13-week, and the dominant portfolios at 52-week and 78-week horizons are the same. The factor portfolios and cryptocurrency index are identical type of asset, which ensures their comparability. Therefore, on one hand, we conclude that the performance of factor portfolios is superior to every four selected indices, and even perform better when compare to cryptocurrency index. On the other hand, we assert that factor portfolios can alleviate the risk of high return since most long-leg factor portfolios dominate index of identical and different types of assets.

6.3.6 AFSD of Short-Leg Portfolios against Four Benchmarks

Table 13 reports the AFSD for short leg of portfolios against different benchmarks. Among Panel A, B and C in Table 13, there exist no dominant portfolio at any investment horizon. Moreover, the ε_i value for each portfolio increases as the investment horizon become longer, which illustrates that portfolios only perform poorly if investors long the portfolios labelled as short portfolio. We first examine the 52-week and 78-week investment horizon because there would exist no more dominance in shorter period if no significant dominance can be found in 52-week and 78-week horizon. Specifically, Panel A of Table 13 demonstrates the ε_i value for each portfolio labelled as short portfolio. At 52-week horizon, the portfolio of LPRC has the smallest ε_i value of 50%, which is almost 10 times of the critical value of 5.9%. Even the best performed portfolio cannot meet the condition, therefore no short portfolios dominate the S&P 500 in our case. At 78-week horizon, the extremely large ε_i value does not improve as time goes by, even portfolios of VOL and STDPRCVOL have a ε_i over 90%, indicating that the S&P 500 benchmark dominate the factor portfolios over 90% of the time. This phenomenon not only exist when against stock, bond and risk-free rate but also occurs in terms of cryptocurrency index.

Furthermore, Panel B of Table 13 reports the ε_i value of each portfolio labelled as short against T-bond. The best performed portfolio is still the portfolio of LPRC with a ε_i value of 46.8%, which cannot dominate the benchmark either. Therefore, no portfolios could dominate the T-bond as the best portfolio even fail to show dominance. Panel C of Table 13 shows the same performance as in Panel A and B, the portfolio of LPRC remains the best position with ε_i value of 45.9%, while the portfolio of IDIOVOL has the worst performance with ε_i value of 88.2%, which indicates nearly 90 percent of all the return cannot dominate benchmark. Moreover, there is no ASSD for short labelled portfolios since no portfolios in this case have ε_i values less than ASSD critical value of 3.2%. Panel D of Table 13 demonstrates ε_i values of the short-leg portfolios and most of factor portfolios are dominated by the cryptocurrency benchmarks, as most of their ε_i values are -1. For instance, there are eight portfolios are dominated by cryptocurrency index at 4-week horizon, and all of the portfolios are dominated by benchmark as investment horizon extends to 78 weeks. It is clear that Short-leg portfolios not only cannot gain excess return but also experience significant loss conversely. Therefore, we conclude that long the short leg of portfolio cannot gain excess return, and the short-leg portfolios should be used with long-leg portfolios to earn high return.

6.3.7 ASSD of Long-Leg Portfolios versus Four Benchmarks

On the other hand, some long leg of portfolios in Table 12 also dominate benchmarks at 52-week and 78-week horizon in the sense of ASSD. In Panel A of Table 12, there are six portfolios ASSD the S&P 500, the portfolio of VOL is the best portfolio with ε_i value of 0.9%, whereas portfolio of MEANABS performed worst with ε_i value equals 3.1%. In contrast to the 13 ASSD long-short portfolios in Table 10, the number of ASSD long-only portfolios falls significantly. This might prove that appropriate long-short strategy could enhance the performance of portfolios dramatically. Furthermore, the same phenomenon of dominance exists in Panel B and C with the same portfolios, and the best performed portfolio is still portfolio of VOL and the worst performed portfolio is portfolio of MEANABS. For 78-week horizon, the number of dominant portfolios raised to 16, which is the similar for Panel B and

C. In regard to ASSD, Panel D of Table 12 behaves differently from Panel A, B and C as their asset classes are variant. Although the criteria of ASSD is stricter than AFSD, the number of dominant portfolios of AFSD is consistent with that of ASSD, which reveals the investment value of factor portfolios again. Therefore, there are five long-leg portfolios out of nine dominant long-short portfolios dominate four benchmarks in the sense of AFSD and ASSD, respectively. Hence, we suggest the extraordinary performance of cryptocurrency portfolios results from risk premium as their long counterpart dominate the benchmarks, which share similarities with equities.

To summarize, the decomposition of long and short portfolio against four benchmarks illustrates that the power of dominance of long-short portfolios is mostly contributed by the long leg of the portfolios, since none of the short leg of portfolios dominate benchmarks at any investment horizons. Moreover, we document that the dominance is mainly from risk premium on each factor. However, the decreased number of dominant long-only portfolios compared to the amount of dominant long-short portfolio also indicates the necessity of conducting the long-short strategy as this grant investors more probability to gain the benefits.

6.3.8 Decompose the Long/Short Portfolios against Stock Factor Portfolios

We have so far provided evidence that cryptocurrency portfolios based on factors could dominate S&P 500, T-bond, T-bill and cryptocurrency index in long horizon, and the dominance is mainly contributed by long-leg portfolios. In this section, we examine the performance of long-leg portfolios against stock factor portfolios based on size, momentum and book-to-market equity (BE/ME) factors, because Fama and French (1992) document that size and BE/ME factors are two vital factors that could capture the variation in average stock returns. Meanwhile, Jegadeesh and Titman (1993) propose the strategy that long the winning stocks and short the losing stocks disclose momentum factor is also noteworthy for portfolio selection and construction. We select portfolios with highest top 20% return for each factor to ensure that selected stock benchmarks are profitable and attractive.

6.3.9 ASD for Long-Leg portfolios versus Stock Factor Portfolios

Panel A of Table 14 reports the ε_i values for each portfolio against stock portfolio based on size. We only focus on the portfolio dominating both in the sense of AFSD and ASSD as we want to compare them to nine dominant portfolios in last section. Hence, there are six portfolios dominate the benchmark at 52-week horizon. Among these portfolios, five portfolios of MOM2, RMOM1, RMOM3, STDPRCVOL and MEANABS belong to the group of nine

Table 12 AFSD and ASSD for Long Leg of Portfolios against S&P500, T-Bond, T-bill and Cryptocurrency Market

Portfolios	Panel A: Portfolios against S&P 500 Index					Panel B: Portfolios against Ten-year T-Bond					Panel C: Portfolios against One-month T-Bill					Panel D: Portfolios against Cryptocurrency Index				
	4-week	13-week	26-week	52-week	78-week	4-week	13-week	26-week	52-week	78-week	4-week	13-week	26-week	52-week	78-week	4-week	13-week	26-week	52-week	78-week
MARCAP	0.300	0.218	0.170	0.080	0.017**	0.301	0.216	0.164	0.075	0.014**	0.304	0.219	0.167	0.078	0.016**	0.183	0.123	0.095	0.010**	0.003**
LPRC	0.397	0.337	0.281	0.185	0.114	0.392	0.327	0.267	0.172	0.102	0.393	0.327	0.266	0.174	0.104	0.392	0.361	0.324	0.163	0.140
MAXPRC	0.402	0.346	0.291	0.197	0.123	0.397	0.336	0.278	0.185	0.111	0.397	0.335	0.277	0.186	0.113	0.404	0.381	0.350	0.188	0.164
AGE	0.464	0.432	0.375	0.268	0.163	0.457	0.421	0.359	0.246	0.139	0.455	0.417	0.356	0.245	0.141	0.535	0.583	0.603	0.713	0.949
MOM1	0.298	0.181	0.096	0.036*	0.005**	0.299	0.179	0.093	0.035*	0.003**	0.302	0.183	0.097	0.036*	0.005**	0.199	0.048*	0.007**	0.000**	0.000**
MOM2	0.302	0.162	0.083	0.030**	0.003**	0.303	0.161	0.080	0.029**	0.002**	0.306	0.166	0.085	0.031**	0.003**	0.207	0.039*	0.003**	0.000**	0.000**
MOM3	0.287	0.156	0.096	0.046*	0.016**	0.288	0.155	0.093	0.044*	0.013**	0.291	0.160	0.097	0.046*	0.015**	0.180	0.038*	0.026**	0.004**	0.000**
MOM4	0.323	0.189	0.114	0.065	0.033*	0.323	0.187	0.110	0.062	0.028**	0.325	0.190	0.114	0.064	0.030**	0.248	0.058*	0.027**	0.007**	0.001**
MOM8	0.368	0.240	0.149	0.062	0.032*	0.366	0.235	0.141	0.059*	0.026**	0.367	0.238	0.146	0.061	0.029**	0.326	0.087	0.013**	0.001**	0.000**
RMOM1	0.300	0.165	0.090	0.029**	0.000**	0.301	0.163	0.087	0.029**	0.000**	0.304	0.168	0.092	0.030**	0.000**	0.195	0.050*	0.003**	0.000**	0.000**
RMOM2	0.338	0.223	0.146	0.060	0.020**	0.337	0.219	0.141	0.058*	0.017**	0.339	0.222	0.144	0.060	0.019**	0.268	0.127	0.048*	0.001**	0.002**
RMOM3	0.302	0.176	0.086	0.028*	0.000**	0.303	0.175	0.083	0.027**	0.000**	0.306	0.179	0.088	0.028**	0.000**	0.189	0.050*	0.007**	0.000**	0.000**
RMOM4	0.303	0.152	0.093	0.048*	0.006**	0.304	0.152	0.090	0.046*	0.004**	0.308	0.158	0.095	0.048*	0.006**	0.174	0.019**	0.011**	0.000**	0.000**
RMOM8	0.356	0.239	0.150	0.080	0.020**	0.355	0.234	0.142	0.076	0.014**	0.356	0.237	0.147	0.078	0.018**	0.290	0.064	0.049*	0.010**	0.001**
VOL	0.267	0.146	0.087	0.009**	0.000**	0.270	0.146	0.084	0.009**	0.000**	0.274	0.150	0.088	0.010**	0.000**	0.160	0.025**	0.005**	0.000**	0.000**
VOLPRC	0.279	0.165	0.115	0.043*	0.003**	0.282	0.164	0.111	0.042*	0.002**	0.285	0.168	0.115	0.043*	0.003**	0.174	0.063	0.036*	0.002**	0.000**
VOLSCALE	0.342	0.251	0.185	0.094	0.043*	0.341	0.246	0.177	0.090	0.037*	0.343	0.248	0.180	0.092	0.039*	0.265	0.139	0.112	0.019**	0.003**
RETVOL	0.348	0.249	0.144	0.051*	0.001**	0.347	0.245	0.139	0.049*	0.000**	0.348	0.247	0.142	0.051*	0.000**	0.313	0.185	0.068	0.006**	0.000**
RETSKEW	0.362	0.269	0.200	0.096	0.044*	0.360	0.263	0.192	0.090	0.039*	0.361	0.265	0.194	0.093	0.041*	0.286	0.165	0.112	0.007**	0.005**
RETKURT	0.421	0.350	0.286	0.172	0.123	0.415	0.340	0.271	0.155	0.102	0.415	0.339	0.271	0.157	0.105	0.455	0.386	0.376	0.369	0.379
MAXRET	0.337	0.228	0.121	0.038*	0.003**	0.337	0.226	0.271	0.037*	0.002**	0.338	0.228	0.121	0.038*	0.003**	0.294	0.167	0.051*	0.003**	0.000**
STDPRCVOL	0.274	0.155	0.089	0.030**	0.000**	0.277	0.155	0.271	0.029**	0.000**	0.280	0.159	0.091	0.031**	0.000**	0.172	0.061	0.017**	0.000**	0.000**
MEANABS	0.289	0.165	0.096	0.031**	0.002**	0.291	0.164	0.271	0.030**	0.001**	0.294	0.168	0.097	0.031**	0.002**	0.187	0.055*	0.006**	0.000**	0.000**
BETA	0.403	0.335	0.272	0.180	0.105	0.396	0.323	0.271	0.163	0.085	0.396	0.322	0.255	0.165	0.087	0.447	0.400	0.353	0.315	0.260
BETA^2	0.404	0.335	0.272	0.180	0.105	0.397	0.323	0.271	0.163	0.085	0.397	0.322	0.255	0.165	0.088	0.448	0.401	0.354	0.317	0.262
IDIOVOL	0.269	0.147	0.081	0.034*	0.008**	0.272	0.147	0.271	0.033*	0.005**	0.276	0.152	0.083	0.034*	0.007**	0.130	0.018**	0.006**	0.000**	0.000**
DELAY	0.321	0.215	0.133	0.076	0.050*	0.322	0.211	0.271	0.070	0.040*	0.325	0.215	0.130	0.073	0.043*	0.119	0.049*	0.017**	0.007**	0.000**

Notes. This table reports the ε_i of AFSD and ASSD for each long portfolio against S&P 500, bond, T-bill and cryptocurrency index. The portfolio with * means AFSD against the benchmark and portfolio with ** represents both AFSD and ASSD. ε_i value equals -1 indicates that benchmark dominates corresponding portfolio.

Table 13 AFSD and ASSD for Short Leg of Portfolios against S&P500, T-Bond, T-bill and Cryptocurrency Market

Portfolios	Panel A: Portfolios against S&P 500 Index					Panel B: Portfolios against Ten-year T-Bond					Panel C: Portfolios against One-month T-Bill					Panel D: Portfolios against Cryptocurrency Index				
	4-week	13-week	26-week	52-week	78-week	4-week	13-week	26-week	52-week	78-week	4-week	13-week	26-week	52-week	78-week	4-week	13-week	26-week	52-week	78-week
MARCAP	0.509	0.531	0.565	0.625	0.699	0.497	0.512	0.541	0.595	0.664	0.492	0.503	0.530	0.583	0.654	0.854	0.952	-1.000	-1.000	-1.000
LPRC	0.464	0.465	0.471	0.500	0.554	0.455	0.449	0.448	0.468	0.512	0.452	0.443	0.440	0.459	0.504	0.658	0.845	0.990	-1.000	-1.000
MAXPRC	0.468	0.471	0.481	0.522	0.583	0.459	0.454	0.459	0.492	0.544	0.456	0.449	0.451	0.482	0.536	0.677	0.879	1.000	-1.000	-1.000
AGE	0.563	0.616	0.666	0.758	0.847	0.548	0.594	0.643	0.733	0.819	0.541	0.582	0.629	0.718	0.808	0.986	-1.000	-1.000	-1.000	-1.000
MOM1	0.540	0.571	0.614	0.684	0.734	0.528	0.553	0.590	0.642	0.682	0.523	0.544	0.577	0.622	0.667	0.781	0.986	-1.000	-1.000	-1.000
MOM2	0.568	0.599	0.615	0.676	0.769	0.555	0.582	0.596	0.649	0.735	0.549	0.573	0.585	0.636	0.724	0.863	0.960	0.998	-1.000	-1.000
MOM3	0.535	0.542	0.555	0.627	0.744	0.523	0.525	0.534	0.594	0.697	0.519	0.517	0.524	0.581	0.683	0.803	0.948	0.996	-1.000	-1.000
MOM4	0.568	0.620	0.675	0.813	0.897	0.554	0.603	0.655	0.789	0.872	0.548	0.593	0.642	0.773	0.861	0.868	1.000	-1.000	-1.000	-1.000
MOM8	0.589	0.661	0.717	0.813	0.917	0.575	0.642	0.697	0.793	0.898	0.569	0.631	0.683	0.779	0.890	0.886	-1.000	-1.000	-1.000	-1.000
RMOM1	0.538	0.581	0.596	0.639	0.743	0.525	0.560	0.571	0.601	0.690	0.520	0.549	0.558	0.585	0.674	0.853	0.958	-1.000	-1.000	-1.000
RMOM2	0.491	0.487	0.499	0.535	0.619	0.480	0.470	0.477	0.507	0.582	0.476	0.463	0.468	0.498	0.574	0.789	0.955	0.965	1.000	-1.000
RMOM3	0.559	0.556	0.559	0.591	0.683	0.544	0.538	0.535	0.560	0.641	0.538	0.529	0.524	0.548	0.630	0.916	0.961	-1.000	-1.000	-1.000
RMOM4	0.545	0.587	0.642	0.732	0.832	0.530	0.567	0.615	0.700	0.795	0.525	0.556	0.599	0.683	0.781	0.900	0.997	-1.000	-1.000	-1.000
RMOM8	0.548	0.590	0.628	0.700	0.814	0.535	0.573	0.611	0.680	0.791	0.529	0.564	0.600	0.669	0.783	0.877	0.956	0.992	-1.000	-1.000
VOL	0.648	0.716	0.757	0.824	0.910	0.628	0.695	0.738	0.806	0.891	0.618	0.681	0.724	0.794	0.884	-1.000	-1.000	-1.000	-1.000	-1.000
VOLPRC	0.632	0.694	0.732	0.800	0.895	0.612	0.673	0.713	0.781	0.873	0.603	0.660	0.699	0.769	0.865	-1.000	-1.000	-1.000	-1.000	-1.000
VOLSCALE	0.642	0.711	0.754	0.822	0.930	0.619	0.687	0.732	0.801	0.906	0.607	0.671	0.716	0.788	0.895	-1.000	-1.000	-1.000	-1.000	-1.000
RETVOL	0.627	0.697	0.750	0.805	0.924	0.605	0.672	0.726	0.782	0.904	0.594	0.657	0.709	0.767	0.894	-1.000	-1.000	-1.000	-1.000	-1.000
RETSKEW	0.589	0.650	0.722	0.813	0.882	0.573	0.629	0.701	0.793	0.857	0.565	0.617	0.687	0.778	0.847	0.964	-1.000	-1.000	-1.000	-1.000
RETKURT	0.601	0.683	0.792	0.906	0.957	0.587	0.666	0.774	0.889	0.944	0.581	0.655	0.759	0.873	0.936	0.879	0.981	-1.000	-1.000	-1.000
MAXRET	0.610	0.645	0.685	0.748	0.846	0.590	0.622	0.660	0.718	0.807	0.581	0.608	0.644	0.701	0.793	-1.000	-1.000	-1.000	-1.000	-1.000
STDPRCVOL	0.627	0.693	0.740	0.808	0.913	0.605	0.669	0.717	0.786	0.886	0.594	0.654	0.701	0.771	0.875	-1.000	-1.000	-1.000	-1.000	-1.000
MEANABS	0.629	0.700	0.752	0.816	0.932	0.606	0.674	0.727	0.793	0.903	0.594	0.658	0.709	0.777	0.890	-1.000	-1.000	-1.000	-1.000	-1.000
BETA	0.582	0.651	0.713	0.837	0.917	0.567	0.630	0.691	0.811	0.895	0.560	0.617	0.675	0.793	0.884	0.947	-1.000	-1.000	-1.000	-1.000
BETA^2	0.582	0.651	0.713	0.837	0.917	0.567	0.630	0.691	0.811	0.895	0.560	0.617	0.675	0.793	0.884	0.947	-1.000	-1.000	-1.000	-1.000
IDIOVOL	0.703	0.792	0.843	0.908	0.981	0.675	0.765	0.823	0.894	0.962	0.660	0.745	0.806	0.882	0.951	-1.000	-1.000	-1.000	-1.000	-1.000
DELAY	0.676	0.742	0.799	0.882	0.940	0.658	0.724	0.782	0.869	0.926	0.648	0.711	0.768	0.858	0.919	0.999	-1.000	-1.000	-1.000	-1.000

Notes. This table reports the ε_i of AFSD and ASSD for each short portfolio against S&P 500, bond, T-bill and cryptocurrency index. The portfolio with * means AFSD against the benchmark and portfolio with ** represents both AFSD and ASSD. ε_i value equals -1 indicates that benchmark dominates corresponding portfolio.

dominant portfolios. Moreover, portfolio based on RMOM3 is the best performed portfolio with the smallest ε_i value of 2.86%, whereas portfolio of MEANABS is the worst portfolio with ε_i value of 3.16%. For a 78-week horizon, there are 16 portfolios that outperform the benchmark, and each portfolio of dominant portfolios beats the benchmark. Among the nine dominant portfolios, portfolio based on STDPRCVOL has the best performance with ε_i value of 0.03%.

Panel B of Table 14 demonstrates the ε_i values for each portfolio against stock portfolio based on momentum, and the dominant portfolios are same as Panel A. Moreover, the best performing portfolios at 52-week and 78-week holding periods are still portfolios based on RMOM3 and STDPRCVOL, respectively. Panel C of Table 14 reports slightly different results from Panel A and B. Specifically, there are six out of nine dominant portfolios dominating the BE/ME portfolios. In addition to 5 dominant portfolios in Panel A and Panel B, portfolio based on MOM1 also dominate BE/ME benchmark at 52-week horizon. For 78-week horizon, every portfolio of nine dominant portfolio dominates the BE/ME benchmark, and the portfolio of RMOM3 and STDPRCVOL are best performed among nine dominant portfolios including MOM1-3, RMOM1-3, VOLPRC, STDPRCVOL and MEANABS.

In summary, the decomposition of long and short portfolio illustrates that the power of dominance of long-short portfolios is mostly contributed by the long leg of the portfolios, since none of the short leg of portfolios dominate benchmarks at any investment horizons. In the long run (52-week and 78-week holding periods), we find five long-leg portfolios that not only outperform the four benchmarks (S&P500, T-bond, T-bill and cryptocurrency index) but also dominate the three stock factor benchmarks (size, momentum and BE/ME), and they are portfolio based on MOM2, RMOM1, RMOM3, STDPRCVOL and MEANABS. However, the decreased number of dominant long-only portfolios at 52-week horizon compared to the amount of dominant long-short portfolio also indicates the necessity of conducting the long-short strategy as this grant investors more probability to gain the benefits.

6.4 Regression Analysis

We have discovered nine outperforming portfolios by conducting almost stochastic dominance. In this section, we decide to investigate whether cross-sectional return of nine dominant portfolios can be explained by applying the coin market three factor model of Liu et al. (2019).

We start with construction of three factors. The three-factor model is inspired by the Fama-French three factor model, and the three factors are cryptocurrency market, size and momentum. The formation of cryptocurrency market excess is discussed in Section 2. For size factor, we sort the coins into three size groups by market capitalization: bottom 30 percent (small group, S), middle 40 percent (middle group, M) and top 30 percent (big group, B). We then form value-weighted portfolios for each of three groups, and the cryptocurrency size factor (CSMB) is the return on small group minus that on big group. We construct the momentum factor by using three-week momentum as the return on long-short three-week momentum is the highest among the momentum factors (See Table 5). In particular, we sort the coins into three three-week momentum groups: bottom 30 percent, middle 40 percent and top 30 percent, then we form value-weighted portfolios for each of the three three-week momentum groups. The cryptocurrency momentum factor (CMOM) is the difference between return on top 30 percent portfolios and return on bottom 30 percent portfolios. The coin market three factor model is shown below.

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

where R_i is the return on factor portfolios, R_f is risk-free rate, CMKT is the cryptocurrency market excess return, CSMB is the cryptocurrency size factor and CMOM is the cryptocurrency momentum factor.

Table 15 reports regression results for nine dominant portfolios from previous section. We find that R-squared values of momentum portfolios are commonly higher than other types of portfolios, which provides more explanatory power. For instance, portfolio of MOM3 has the highest R^2 of 0.5544, whereas portfolio of MEANABS that is the most explained portfolio in other categories, only has the R^2 of 0.0954. The portfolio of MOM1 is an outlier with R^2 0.024, while the other momentum portfolios have a relatively high R^2 range from 0.2574 to 0.5544, indicating that portfolio based on momentum factors could be well explained by coin market three factor models. Furthermore, the values of α for MOM1, VOLPRC, STDPRCVOL and MEANABS are positive and significant at 1 percent level, suggesting that the four portfolios might be mispriced. Combined with relatively small R^2 that ranges from 0.0254 for portfolio of MOM1 to 0.0954 for portfolio of MEANABS, we suggest that the return anomalies on portfolio of MOM1, VOLPRC, STDPRCVOL and MEANABS might be caused by mispricing.

Table 14 Long Leg of Portfolios Against Momentum, Size and BE/ME Portfolios

	Panel A: Portfolios against Size Portfolios					Panel B: Portfolios against Momentum Portfolios					Panel C: Portfolios against BE/ME Portfolios				
Portfolios	4-week	13-week	26-week	52-week	78-week	4-week	13-week	26-week	52-week	78-week	4-week	13-week	26-week	52-week	78-week
MARCAP	0.3019	0.2209	0.1728	0.0821	0.0173**	0.2995	0.2176	0.1705	0.0822	0.0177**	0.2873	0.2054	0.1578	0.0681	0.0128**
LPRC	0.3998	0.3420	0.2860	0.1901	0.1181	0.3981	0.3390	0.2843	0.1900	0.1189	0.3875	0.3240	0.2630	0.1655	0.1004
MAXPRC	0.4045	0.3507	0.2963	0.2028	0.1271	0.4030	0.3479	0.2947	0.2026	0.1279	0.3926	0.3334	0.2745	0.1789	0.1104
AGE	0.4666	0.4367	0.3811	0.2766	0.1708	0.4660	0.4348	0.3802	0.2763	0.1721	0.4586	0.4240	0.3612	0.2432	0.1390
MOM1	0.3004	0.1838	0.0982	0.0370*	0.0057**	0.2982	0.1803	0.0954	0.0371*	0.0060**	0.2875	0.1671	0.0842	0.0297**	0.0018**
MOM2	0.3041	0.1650	0.0856	0.0312**	0.0034**	0.3019	0.1613	0.0827	0.0313**	0.0037**	0.2913	0.1483	0.0715	0.0246**	0.0010**
MOM3	0.2889	0.1583	0.0979	0.0468*	0.0171**	0.2866	0.1549	0.0953	0.0469*	0.0174**	0.2759	0.1429	0.0853	0.0397*	0.0113**
MOM4	0.3250	0.1920	0.1170	0.0670	0.0351*	0.3230	0.1887	0.1143	0.0670	0.0356*	0.3130	0.1761	0.1009	0.0549*	0.0251**
MOM8	0.3708	0.2444	0.1538	0.0644	0.0350*	0.3690	0.2406	0.1504	0.0645	0.0356*	0.3589	0.2249	0.1294	0.0513*	0.0222**
RMOM1	0.3017	0.1676	0.0926	0.0300**	0.0006**	0.2994	0.1636	0.0897	0.0301**	0.0007**	0.2885	0.1496	0.0781	0.0241**	0.0000**
RMOM2	0.3401	0.2259	0.1489	0.0623	0.0208**	0.3381	0.2224	0.1462	0.0624	0.0212**	0.3277	0.2088	0.1326	0.0513*	0.0157**
RMOM3	0.3041	0.1788	0.0886	0.0286**	0.0004**	0.3018	0.1751	0.0856	0.0288**	0.0005**	0.2902	0.1617	0.0742	0.0224**	0.0000**
RMOM4	0.3054	0.1552	0.0955	0.0495*	0.0073**	0.3029	0.1512	0.0923	0.0497*	0.0077**	0.2905	0.1376	0.0805	0.0408*	0.0017**
RMOM8	0.3590	0.2429	0.1539	0.0833	0.0224**	0.3570	0.2391	0.1503	0.0834	0.0231**	0.3459	0.2236	0.1323	0.0689	0.0103**
VOL	0.2692	0.1484	0.0894	0.0095**	0.0001**	0.2669	0.1449	0.0869	0.0097**	0.0002**	0.2563	0.1331	0.0749	0.0071**	0.0000**
VOLPRC	0.2811	0.1672	0.1168	0.0444*	0.0034**	0.2789	0.1639	0.1145	0.0444*	0.0036**	0.2684	0.1530	0.1041	0.0371*	0.0011**
VOLSCALE	0.3450	0.2546	0.1890	0.0969	0.0457*	0.3429	0.2514	0.1868	0.0970	0.0462*	0.3317	0.2379	0.1698	0.0830	0.0344*
RETVOL	0.3494	0.2515	0.1464	0.0523*	0.0014**	0.3481	0.2490	0.1441	0.0524*	0.0016**	0.3407	0.2389	0.1324	0.0436*	0.0004**
RETSKEW	0.3649	0.2729	0.2039	0.0994	0.0464*	0.3628	0.2693	0.2014	0.0994	0.0470*	0.3505	0.2543	0.1841	0.0819	0.0361*
RETKURT	0.4240	0.3548	0.2919	0.1796	0.1305	0.4226	0.3517	0.2899	0.1789	0.1315	0.4121	0.3370	0.2667	0.1447	0.0998
MAXRET	0.3388	0.2305	0.1228	0.0392*	0.0031**	0.3373	0.2280	0.1205	0.0393*	0.0034**	0.3296	0.2185	0.1104	0.0324*	0.0014**
STDPRCVOL	0.2759	0.1577	0.0912	0.0310**	0.0003**	0.2738	0.1545	0.0888	0.0310**	0.0004**	0.2635	0.1439	0.0798	0.0251**	0.0000**
MEANABS	0.2906	0.1672	0.0987	0.0316**	0.0020**	0.2885	0.1638	0.0960	0.0317**	0.0022**	0.2778	0.1523	0.0838	0.0252**	0.0004**
BETA	0.4076	0.3407	0.2781	0.1865	0.1120	0.4055	0.3372	0.2761	0.1860	0.1128	0.3909	0.3189	0.2505	0.1543	0.0814
BETA^2	0.4079	0.3410	0.2785	0.1869	0.1123	0.4058	0.3376	0.2765	0.1864	0.1131	0.3913	0.3193	0.2509	0.1547	0.0817
IDIOVOL	0.2708	0.1492	0.0834	0.0349*	0.0085**	0.2682	0.1454	0.0803	0.0350*	0.0088**	0.2560	0.1326	0.0692	0.0271**	0.0036**
DELAY	0.3245	0.2194	0.1373	0.0794	0.0540*	0.3215	0.2146	0.1334	0.0793	0.0547*	0.3062	0.1959	0.1108	0.0595	0.0363*

Notes. This table reports the ε_i of AFSD and ASSD for each long-leg portfolio against size, momentum and BE/ME portfolios. The portfolio with * means AFSD against the benchmark and portfolio with ** represents both AFSD and ASSD.

Table 15 Coin Market Three-Factor model					
	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	Adj R-squared
MOM1	0.0382***	0.2673**	0.0419	-0.1453**	0.0254
T-Statistics	2.8837	2.155	0.4079	-1.9837	
MOM2	0.0034	0.1396	0.1567*	0.7839***	0.3629
T-Statistics	0.3079	1.3641	1.846	12.9671	
MOM3	0.0015	0.1287	-0.2448***	0.9433***	0.5544
T-Statistics	0.1637	1.4957	-3.4327	18.5655	
RMOM1	0.0143	0.049	0.1367*	0.5544***	0.2574
T-Statistics	1.4547	0.5311	1.7874	10.1778	
RMOM2	0.0107	0.1624**	0.1799***	0.6055***	0.351
T-Statistics	1.2195	1.9701	2.6311	12.4335	
RMOM3	-0.0074	0.218***	-0.1754***	0.8369***	0.5266
T-Statistics	-0.8558	2.6825	-2.603	17.4358	
VOLPRC	0.033***	0.2943***	0.2829***	-0.1181**	0.0795
T-Statistics	3.3419	3.1836	3.6904	-2.1635	
STDPRCVOL	0.0352***	0.3454***	0.3069***	-0.0619	0.0817
T-Statistics	3.4765	3.6467	3.9077	-1.1059	
MEANABS	0.032***	0.341***	0.355***	-0.0594	0.0954
T-Statistics	3.1883	3.6307	4.5591	-1.0713	

Notes. This table reports the results of regression analysis for nine dominant portfolios. *, **, *** represent significance at 10%, 5%, 1% level, respectively.

In regard to cryptocurrency market factor, all non-momentum portfolios have significant exposures to cryptocurrency market factor, and only half of momentum-based portfolio (MOM1, RMOM2 and RMOM3) have significant relatively small exposures compared to non-momentum strategies. In other words, the cryptocurrency market factor can capture the cross-sectional return for non-momentum strategies. For the coin market size factor, nearly all dominant portfolios have statistically significant loadings but portfolio of MOM1. Moreover, size factor might have the reverse effect on portfolio of MOM3 and RMOM3 as their exposures are less than zero. For the coin market momentum factor, cross-sectional return of portfolios based on momentum strategies could be well captured as all their factor loadings are statistically significant, but other portfolios based on volatility (STDPRCVOL and MEANABS) cannot be explained appropriately as their momentum factor loadings are not significant.

To conclude, we test whether the dominant portfolio can be explained by a coin market three-factor model and find that the model could explain the cross-sectional return to a certain extent. The return anomalies for portfolio of MOM1, VOLPRC, STDPRCVOL and MEANABS are possibly associated with mispricing. Additionally, momentum factor provides stronger explanatory power concerning momentum strategy, market factor could capture the cross-sectional return of non-momentum strategy portfolios and size factor could explain both momentum and non-momentum strategy.

6.4.1 Enhance Performance of Model by Incorporating Mispricing Factors

The previous section illustrates the explanatory power of a coin market three-factor model when examining nine dominant portfolios, and there exist four factor portfolios that cannot be addressed well by coin market three-factor model. Moreover, inspired by Stambaugh and Yuan (2017) who claim that an asset pricing model might increase its explanatory power by incorporating mispricing factors, we decide to find factors that can explain the anomalies by incorporating unexplained portfolios in last section. Specifically, we add the potential combinations of four unexplained factor portfolios (MOM1, VOLPRC, STDPRCVOL and MEANABS) and two crypto fundamental factors (Electricity and computer power) to existing coin market three-factor model and examine the performance after incorporating mispricing factors. This procedure creates 28 adjusted models, which can be found in an appendix.

We construct mispricing factors based on their categories. For instance, four mispricing portfolios belong to three large categories: MOM1 of momentum factors, VOLPRC of volume factors, STDPRCVOL and MEANABS of volatility factors. Because there are two volatility factors, we apply equally weighted average rankings with respect to STDPRCVOL and MEANABS, in order to form a mispricing factor that captures the comprehensive effect of volatility. For MOM1 factor, we sort the coins into three one-week momentum groups: bottom 30 percent, middle 40 percent and top 30 percent, then we form value-weighted portfolios for each of the three three-week momentum groups. The mispricing cryptocurrency momentum factor (CMOM1) is the difference between return on top 30 percent portfolios and return on bottom 30 percent portfolios. Similarly, to construct VOLPRC, we sort the coins into three VOLPRC groups (We refer this to volume factor): bottom 30 percent, middle 40 percent and top 30 percent, then we form value-weighted portfolios for each of the three volume groups. The mispricing cryptocurrency volume factor (CVOL) is the difference between return on top 30 percent portfolios and return on bottom 30 percent portfolios. Moreover, to construct a composite mispricing factor for volatility, we apply equally weighted average to rankings with respect to two anomalies, then form the mispricing volatility factors based on averaged rankings. We sort the coins into three volatility groups, bottom 30 percent, middle 40 percent and top 30 percent, then we form value-weighted portfolios for each of the three volume groups. The mispricing cryptocurrency volatility factor (CSTD) is the difference between return on top 30 percent portfolios and return on bottom 30 percent portfolios.

We first try evaluating the performance of coin market three-factor model incorporating mispricing momentum (CMOM1). The adjusted coin market three-factor model is shown below after incorporating CMOM1.

$$R_i - R_f = \alpha^i + \beta^i_{CMKT} CMKT + \beta^i_{CSMB} CSMB + \beta^i_{CMOM} CMOM + \beta^i_{CMOM1} CMOM1 + \epsilon_i$$

where R_i, R_f, $CMKT$, $CSMB$, $CMOM$ have been illustrated above, $CMOM1$ is the mispricing momentum factor.

Table 16 reports the regression results of adjusted coin market three-factor model. We find that the R-squared for each portfolio does not improve significantly, indicating that CMOM1 cannot provide explanatory power to coin market three-factor model. For example, the values of alpha for mispriced portfolios are still significant and their R-squared are quite small, even the biggest R-squared of them is less than 0.1. We also find that the adjusted model could capture more cross-sectional variation for portfolios based on momentum (e.g. MOM2, MOM3, RMOM1, RMOM2) as their exposures are statistically significant at 1% level. However, we cannot suggest that the adjusted model improve the performance of coin market three factor model, since dominant portfolios based on other factors still failed to be explained by incorporating CMOM1 factor.

Next, we test the adjusted coin market three-factor model incorporating CVOL factor. The adjusted coin market three-factor model is shown below.

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

where R_i, R_f, $CMKT$, $CSMB$, $CMOM$ have been illustrated above, $CVOL$ is the mispricing volume factor.

Table 17 reports regression results for coin market three-factor model incorporating volume factor. We find that mispriced portfolios of VOLPRC, STDPRCVOL and MEANABS can be well explained by adjusted model under conditions of not decreasing other portfolios' explanatory power. To illustrate, compared to R-squared of coin market three-factor model for VOLPRC, STRPRCVOL and MEANABS which ranges from 0.0759 to 0.0954, the R-squared of adjusted model for them are 0.5553, 0.5963 and 0.6032, respectively. More importantly, their exposures to CVOL factor are all statistically significant at 1% level, their factor loadings of CSMB become insignificant, which might suggest that CSMB might not the most important factor to capture the variation among volume and volatility portfolios. In other words, we may argue that trading volume is an important factor driving the cryptocurrencies trading and development. On the other hand, Momentum factor still works well for portfolios based on momentum, and their R-squared does not exhibit considerable fluctuation.

Table 16 Three-Factor Model Incorporating CMOM1

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	β_{CMOM1}	R-squared
MOM1	0.0385***	0.2632***	0.0429	-0.1184	-0.0423	0.0262
T-Statistics	2.9007	2.1151	0.4165	-1.3009	-0.5001	
MOM2	0.0007	0.1736*	0.1488*	0.5586***	0.3537***	0.4164
T-Statistics	0.0684	1.7657	1.8291	7.7685	5.2927	
MOM3	0.0003	0.1435*	-0.2482***	0.8451***	0.1542***	0.5644
T-Statistics	0.0384	1.6808	-3.5141	13.5377	2.6570	
RMOM1	0.0095	0.1103	0.1226**	0.1481***	0.6380***	0.5069
T-Statistics	1.1868	1.4625	1.9637	2.6846	12.4442	
RMOM2	0.0094	0.1797***	0.1759***	0.4909***	0.1799***	0.3727
T-Statistics	1.0818	2.2090	2.6124	8.2503	3.2540	
RMOM3	-0.0078	0.2228***	-0.1765***	0.8049***	0.0503	0.5279
T-Statistics	-0.8979	2.7353	-2.6183	13.5117	0.9078	
VOLPRC	0.0333***	0.2898***	0.2839***	-0.0878	-0.0476	0.0812
T-Statistics	3.3718	3.1252	3.7009	-1.2955	-0.7552	
STDPRCVOL	0.0356***	0.3393***	0.3083***	-0.0211	-0.0640	0.0846
T-Statistics	3.5198	3.5739	3.9250	-0.3038	-0.9925	
MEANABS	0.0321***	0.3396***	0.3553***	-0.0507	-0.0136	0.0955
T-Statistics	3.1899	3.6034	4.5551	-0.7362	-0.2128	

Notes. This table reports the results of regression analysis for nine dominant portfolios. *, **, *** represent significance at 10%, 5%, 1% level, respectively.

However, alpha for portfolio of MOM1, VOLPRC, STDPRCVOL and MEANABS are still statistically significant at 1% level, indicating that there still exist anomalies that cannot be captured by adjusted model.

Finally, we test the adjusted coin market three-factor model by adding mispricing volatility factor (CSTD) to it. The adjusted model is shown below.

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

where R_i, R_f, $CMKT$, $CSMB$, $CMOM$ have been illustrated above, $CSTD$ is the mispricing volatility factor.

Table 17 Three-Factor Model Incorporating CVOL

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	β_{CVOL}	R-squared
MOM1	0.0380***	0.2388**	-0.0079	-0.1325**	-0.1683	0.0320
T-Statistics	2.8767	1.9046	-0.0732	-1.7993	-1.4404	
MOM2	0.0032	0.1186	0.1199	0.7934***	-0.1242	0.3664
T-Statistics	0.2976	1.1455	1.3397	13.0415	-1.2866	
MOM3	0.0016	0.1394	-0.2259***	0.9384***	0.0637	0.5553
T-Statistics	0.1700	1.5997	-3.0000	18.3244	0.7840	
RMOM1	0.0144	0.0580	0.1525**	0.5504***	0.0533	0.2583
T-Statistics	1.4582	0.6204	1.8874	10.0197	0.6119	
RMOM2	0.0107	0.1614*	0.1780**	0.6059***	-0.0061	0.3510
T-Statistics	1.2169	1.9299	2.4639	12.3325	-0.0787	
RMOM3	-0.0073	0.2425***	-0.1325	0.8259***	0.1446**	0.5321
T-Statistics	-0.8438	2.9587	-1.8715	17.1536	1.8936	
VOLPRC	0.0319***	0.1005	-0.0566	-0.0312	-1.1455***	0.5553
T-Statistics	4.8743	1.6179	-1.0551	-0.8543	-19.7913	
STDPRCVOL	0.0340***	0.1457**	-0.0430	0.0277	-1.1805***	0.5963
T-Statistics	5.1143	2.3064	-0.7870	0.7477	-20.0543	
MEANABS	0.0308***	0.1350**	-0.0057	0.0330	-1.2169***	0.6032
T-Statistics	4.9416	2.2817	-0.1114	0.9483	-22.0672	

Notes. This table reports the results of regression analysis for nine dominant portfolios. *, **,*** represent significance at 10%, 5%, 1% level, respectively.

Table 18 presents the regression results for coin market three-factor model incorporating mispricing volatility factor (CSTD). Compared to adjusted coin market three-factor model in Table 17, the degree of fitting deteriorates heavily as indicating by R-squared for portfolios of VOLPRC, STDPRCVOL and MEANABS. The R-squared for them drops significant from average 0.5 to average 0.1. Moreover, the alpha for portfolio of MOM3 becomes significant whereas the alpha for portfolio of

MEANABS turns into insignificant. Although the exposures to CSTD are statistically significant for VOLPRC, STDPRCVOL and MEANABS, yet it cannot prove the efficiency of this mispricing factor since the adjusted model lacks explanatory power for these three portfolios. Furthermore, the anomaly of MOM1 still cannot be captured by developed factor because its R-squared is always small (average 0.03) and its alpha is always statistically significant at 1% level. Therefore, further research needs to be done to discover such anomalies.

Table 18 Three-Factor Model Incorporating CSTD

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	β_{CSTD}	R-squared
MOM1	0.0463***	0.3351***	0.0581	-0.1449**	-0.0827	0.0319
T-Statistics	3.2194	2.5278	0.5628	-1.9810	-1.4314	
MOM2	-0.0144	-0.0080	0.1215	0.7830***	0.1799***	0.3924
T-Statistics	-1.2380	-0.0746	1.4545	13.2396	3.8513	
MOM3	-0.0162*	-0.0181	-0.2798***	0.9423***	0.1789***	0.5832
T-Statistics	-1.6694	-0.2031	-4.0258	19.1460	4.6016	
RMOM1	0.0164	0.0663	0.1408*	0.5545	-0.0211	0.2580
T-Statistics	1.5280	0.6705	1.8280	10.1672	-0.4898	
RMOM2	0.0031	0.0991	0.1648**	0.6051***	0.0772**	0.3595
T-Statistics	0.3257	1.1282	2.4079	12.4867	2.0161	
RMOM3	-0.0092	0.2033**	-0.1789***	0.8368***	0.0180	0.5270
T-Statistics	-0.9723	2.3329	-2.6358	17.4116	0.4731	
VOLPRC	0.0186*	0.1747*	0.2544***	-0.1189**	0.1458***	0.1137
T-Statistics	1.7584	1.7960	3.3563	-2.2159	3.4379	
STDPRCVOL	0.0224**	0.2393**	0.2816***	-0.0626	0.1294***	0.1073
T-Statistics	2.0564	2.3887	3.6090	-1.1324	2.9644	
MEANABS	0.0168	0.2151**	0.3250***	-0.0602	0.1533***	0.1315
T-Statistics	1.5685	2.1800	4.2274	-1.1067	3.5657	

Notes. This table reports the results of regression analysis for nine dominant portfolios. *, **, *** represent significance at 10%, 5%, 1% level, respectively.

In summary, apart from testing the explanatory power of coin market three factor model, we also evaluate adjusted three-factor model by incorporating anomalies of COMO1, CVOL and CSTD independently. We find that adjusted three-factor model incorporating CSTD could enhance the performance of coin market three-factor model, especially for portfolios based on volume factors and volatility factors. Such evidence illustrates that volume factor might drive the cryptocurrencies trading and development. The other adjusted models fail to improve the coin market three-factor model as no considerable improvement is observed. Moreover, the portfolio of MOM1 cannot be either explained by coin-market three-factor model or adjusted three-factor model, which needs further research.

7 Conclusions

This paper employs non-parametric almost stochastic dominance to identify portfolios of cryptocurrencies based on 27 different cryptocurrency factors to investigate whether they can generate superior returns benchmarked against US equities, US Treasury bills, US Treasury bonds and a cryptocurrency index over a relatively long horizon (52 and 78 weeks). We find nine dominant factor portfolios, in the sense of almost first degree stochastic dominance (AFSD) and almost second degree stochastic dominance (ASSD, which are based on momentum (1 to 3 weeks), risk momentum (1 to 3 weeks), daily turnover, the standard deviation of daily turnover, and the mean absolute return divided by daily turnover. Benchmarking these nine dominant factor portfolios against equity portfolios based on size, momentum and book-to-market, we find that the long-only strategy contributes more to performance than the short-only strategy. However, we suggest that the performance of long-short portfolios is generally preferable to that of long-only factor portfolios. We then test whether a coin market three-factor model can capture the variation of cross-sectional returns, and find that this model has limited success in explaining returns of the nine dominant factor portfolios. For five factor portfolios their alphas are statistically insignificant, and adjusted R^2 values reasonably high, so we conclude that the dominance of these five cryptocurrency factors can be explained by a risk premium. To investigate further, we added four mispricing factors (subdivision of momentum, volume and volatility**)** and two cryptocurrency fundamental factors (electricity and computing power) to our three factor model. Even with the addition of these mispricing factors, the alphas of the other four factor portfolios remained significant, and their adjusted R^2 values stayed low, indicating that their dominance may be due to mispricing, rather than a risk premium.

Our findings should improve investors' understanding of cryptocurrencies, and support a factor-based approach to analysing the cryptocurrency market. However, although we use 400 cryptocurrencies representing over 80% of cryptocurrency market capitalization, our empirical results might be changed by the inclusion of the remaining

20% of market capitalization. In addition, due to the high volatility of cryptocurrencies, different downside risk metrics might provide conflicting outcomes. Hence, further study is needed.

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Supplementary Appendix

A1. Simulation Test for ASD Critical Values

We discussed the critical values of ε_1 and ε_2 in Section 4.3, which are the maximum ratio of violation area to enclosed area of portfolio with high return (H) and portfolio with low return (L). According to Levy et al. (2010), they exploit experiments based on 400 subjects' choices to clarify the economically relevant set of preferences and quantify the critical epsilon values of ASD ($\varepsilon_1^* = 5.9\%, \varepsilon_2^* = 3.2\%$) that avoid the paradoxical choices. Moreover, the outcomes of Levy et al. (2010) are robust and not sensitive to both magnitude of asset returns and different asset classes. Therefore, we suggest that the critical values of ε_1 and ε_2 employed in our empirical analysis are robust criteria to reflect almost all investors' choices when investors are facing the similar scenarios. Nevertheless, one may be concerned about the reliability of critical values of Levy et al. (2010) because they completed the test ten years ago. To alleviate such potential concerns, we conduct analysis of critical values of ε_1 and ε_2 based on randomization techniques (Bali et al., 2013) to ensure the reliability of critical values for our study, and we focus on the p-values associated with critical values used in our paper.

We select monthly S&P 500 index return as a proxy for stock return over the time period from January 1926 to December 2019 and generate the distribution of ε_1 and ε_2 with repeated samples. Particularly, in each time of simulation, two series of 1000 monthly return observations are picked (with replacement) from the S&P 500 index, we further calculate and record the empirical ε_1 and ε_2 values. This procedure is repeated 3000 times, which generate 3000 pairs of ε_1 and ε_2 values. The null hypothesis is that two return series do not dominate each other in the sense of AFSD or ASSD. Mathematically, for AFSD, the null hypothesis is $H_0 : \varepsilon_1 \geq 5.9\%$; for ASSD, the null hypothesis is $H_0 : \varepsilon_2 \geq 3.2\%$.

Table A.1 reports the descriptive statistics for distribution of ε_1 and ε_2 based on randomization techniques. Specifically, the minimum, maximum, mean and 1, 3, 5, 10, 25, 50, 75, 90, 95, 99 percentiles of generated ε_1 and ε_2 values. We examine the p-values of each distribution to clarify whether the null hypothesis can be rejected. For ε_1, the third percentile of distribution of ε_1 is 6.99%, which is greater than 5.9%, indicating that estimated ε_1 values reported in Table A.1 have p-values lower than 3%. This result firmly rejected the null hypothesis of ε_1 at significance level of 3%. Similarly, from the perspective of ε_2, the 10^{th} percentile of distribution of ε_2 is 5.89%, we can reject the null hypothesis of ε_2 at significance level of 10%.

Table A.1: Distribution of ε_1 and ε_2 from Randomization													
	Min	1%	3%	5%	10%	25%	50%	75%	90%	95%	99%	Max	Mean
ε_1	0.0017	0.0326	0.0699	0.1047	0.1709	0.3791	0.6498	0.8513	0.9619	0.9880	1.0000	1.0000	0.6059
ε_2	0.0000	0.0010	0.0108	0.0256	0.0589	0.1813	0.3965	0.6650	0.8610	0.9374	0.9945	1.0000	0.4302

Notes. This table reports the statistics for distribution of ε_1 and ε_2 based on randomization techniques.

To sum up, we secure the results of Levy et al. (2010) by conducting ASD on randomly generated data, which provide robustness about our empirical results of cryptocurrency factors.

A2. Incorporating Mispricing and Fundamental Factors into Coin Market Model

In this section, we aim to construct every potential combination of mispricing factors and fundamental factors (electricity and computer power), we then incorporate these potential factors into coin market three factor model developed by Liu et al. (2019) to evaluate whether the performance of adjust model can be improved (Stambaugh and Yuan, 2017). We consider the two most important fundamental factors for cryptocurrencies: electricity and computer power, since these two factors are essential requirements to mine cryptocurrencies (Bianchi et al., 2020; Liu et al., 2020). We select two proxies for electricity, they are value-weighted stock return of US-listed electricity firms and value-weighted stock return of China-listed electricity firms, respectively. According to Li et al. (2019), We include China-listed electricity firms as China is assumed to have the vastest mining operations and electricity supply is location specific. Moreover, we choose one with the highest average correlation coefficients of each dominant factor. From the perspective of computer power, we consider the stock returns of primary GPU manufacturers such as Nvidia and TSMC as our two proxies for computer power (Liu et al., 2020). Likewise, we still choose one with the highest average correlation coefficients of each dominant factor as our proxy for computer power.

A2.1. Correlation between Fundamental Factors and Dominant Factors

The data for US-listed electricity firms, China-listed electricity firms, Nvidia and TSMC are collected from DataStream over the period from 2014 to 2019. We first examine the correlation between fundamental factors and nine dominant factors, choose one from each fundamental group with higher correlation to continue the combinations of potential models. The correlation coefficients between each fundamental factor and each dominant factor is reported in Table A.2.

Panel A of Table A.2 illustrates the correlation between US-listed electricity firms and nine dominant factors, MOM1 has the highest coefficient of 0.1520, whereas RMOM3 is almost not related to US-listed electricity as indicated by coefficient of 0.003, and the average correlation coefficient is 0.0580. Panel B of Table A.2 demonstrates the correlation between China-listed electricity firms and dominant factors. We can observe that none of dominant factors are strongly related to China-listed electricity firms and the average correlation coefficient is 0.0237. Therefore, we choose value-weighted returns of US-listed firms as our proxy for electricity.

Table A.2: Correlation between US, China Electricity Index and Nine Factors

Panel A: Correlation between 9 Factors and US Electricity Index										
Factor	MOM1	MOM2	MOM3	RMOM1	RMOM2	RMOM3	VOLPRC	STDPRCVOL	MEANABS	AVG
Corr	0.1520	-0.0614	-0.0319	-0.0792	-0.0533	0.0030	-0.0727	-0.0290	-0.0392	0.0580
Panel B: Correlation between 9 Factors and China Electricity Index										
Factor	MOM1	MOM2	MOM3	RMOM1	RMOM2	RMOM3	VOLPRC	STDPRCVOL	MEANABS	AVG
Corr	-0.0192	-0.0191	0.0325	0.0328	0.0078	0.0504	-0.0115	0.0270	-0.0129	0.0237

Notes. This table reports the correlation between US, China electricity and dominant factors.

We evaluate the suitability of two computer power in the same manner of electricity. Table A.3 reports the correlation between Nvidia, TSMC and nine dominant factors.

Table A.3: Correlation between AMD, TSMC and Nine Factors

Panel A: Correlation between 9 Factors and AMD										
Factor	MOM1	MOM2	MOM3	RMOM1	RMOM2	RMOM3	VOLPRC	STDPRCVOL	MEANABS	AVG
Corr	0.0102	-0.0350	0.0314	0.0161	-0.0254	-0.0237	0.0681	0.0860	0.0485	0.0383
Panel B: Correlation between 9 Factors and TSMC										
Factor	MOM1	MOM2	MOM3	RMOM1	RMOM2	RMOM3	VOLPRC	STDPRCVOL	MEANABS	AVG
Corr	-0.0712	0.0123	0.0600	0.0660	0.0365	0.0447	-0.0163	0.0441	-0.0178	0.0410

Notes. This table reports the correlation between AMD, TSMC and dominant factors.

Panel A of Table A.3 shows the correlation between nine factors and AMD, none of dominant factors heavily correlate to stock return of AMD, and the average correlation coefficient is 0.0383. Moreover, Panel B of Table A.3 indicates the similar results in Panel A but with a slightly higher average correlation coefficient of 0.041. Although the results are quite lower than what we expected, it is still consistent with Liu and Tsyvinski's finding (2020). Therefore, we choose TSMC as our proxy for computer power.

A2.2. Potential Combinations for Adjusted Models

After we determine to use stock returns of US-listed electricity firms as a proxy for electricity and consider stock return of TSMC as a proxy for computer power (Graphics in table), we list all adjusted models incorporating combinations of fundamental factors and mispricing factors, which are 28 models in total. Table A.4 lists all combination of these factors, where volatility category combines two volatility factors into one factor by using average technique. The first column represents the specific model number, and the first row illustrates coin market three-factor model, mispricing factors and selected fundamental factors. The value ‘Y’ means that corresponding model include this factor to form an adjusted model.

Table A.4: Models of Potential Combinations

	$Coin\ 3-Factor\ Model$	$CMOM1$	$CVOL$	$CSTD$	$Electricity$	$Graphics$
1	Y	Y				
2	Y		Y			
3	Y			Y		
4	Y	Y	Y			
5	Y	Y		Y		
6	Y		Y	Y		
7	Y	Y	Y	Y		
8	Y	Y			Y	
9	Y		Y		Y	
10	Y			Y	Y	
11	Y	Y	Y		Y	
12	Y	Y		Y	Y	
13	Y		Y	Y	Y	
14	Y	Y	Y	Y	Y	
15	Y	Y				Y
16	Y		Y			Y
17	Y			Y		Y
18	Y	Y	Y			Y
19	Y	Y		Y		Y
20	Y		Y	Y		Y
21	Y	Y	Y	Y		Y
22	Y	Y			Y	Y
23	Y		Y		Y	Y
24	Y			Y	Y	Y
25	Y	Y	Y		Y	Y
26	Y	Y		Y	Y	Y
27	Y		Y	Y	Y	Y
28	Y	Y	Y	Y	Y	Y

Notes. This table reports the 28 adjusted model based on mispricing factors and determined fundamental factors.

To get a better understanding of Table A.4, we explain the terms in this paragraph. Coin three-factor model represents a model consists of coin market ($CMKT$), size factor ($CSMB$) and momentum factor ($CMOM$), which is developed by Liu et al. (2019) and discussed in Section 6.4. Moreover, one-week momentum ($CMOM1$), volume factor ($CVOL$) and volatility factor ($CSTD$) are mispricing factors with significant alphas and relative low R-squared that cannot be explained by origin three factor model. We choose value-weighted returns of US-listed electricity firms as a proxy for electricity ($Electricity$ in Table A.4) and stock return of TSMC as a proxy for computer power ($Graphics$ in Table A.4).

The construction of each mispricing factor follows the Fama and French (1993) method. To illustrate, For $CMOM1$ factor, we sort the coins into three one-week momentum groups: bottom 30 percent, middle 40 percent and top 30 percent, then we form value-weighted portfolios for each of the three three-week momentum groups. The mispricing cryptocurrency momentum factor ($CMOM1$) is the difference between return on top 30 percent portfolios and return on bottom 30 percent portfolios. Similarly, to construct $CVOL$, we sort the coins into three volume groups (We refer this to volume factor): bottom 30 percent, middle 40 percent and top 30 percent, then we form value-weighted portfolios for each of the three volume groups. The mispricing cryptocurrency volume factor ($CVOL$) is the difference between return on top 30 percent portfolios and return on bottom 30 percent portfolios. Moreover, to construct a composite mispricing factor for volatility ($CSTD$), we apply equally weighted average to rankings with respect to two anomalies, then form the mispricing volatility factors based on averaged rankings. We sort the coins into three volatility groups, bottom 30 percent, middle 40 percent and top 30 percent, then we form value-weighted portfolios for each of the three volume groups. The mispricing cryptocurrency volatility factor ($CSTD$) is the difference between return on top 30 percent portfolios and return on bottom 30 percent portfolios.

Among 28 models, each model is formed by selected column(s) at each row, and the symbol 'Y' indicates that corresponding factor (column) is included in a model. For example, Model 1 is comprised of two parts: coin market three-factor model and one mispricing factor $CMOM1$, mathematical expression tends to provide a clearer picture:

$$R_i - R_f = \alpha^i + \beta^i_{CMKT} CMKT + \beta^i_{CSMB} CSMB + \beta^i_{CMOM} CMOM + \beta^i_{CMOM1} CMOM1 + \epsilon_i$$

where R_i, R_f, $CMKT$, $CSMB$, $CMOM$ have been illustrated above, $CMOM1$ is the mispricing momentum factor.

The rest models are constructed in the same manner.

A2.3. Empirical Results for 28 Models

In this section, we examine whether the returns of nine dominant factors can be explained better by 28 adjusted models, and we choose the best fit one as our improved model. The first row contains coefficients of regression analysis such as alpha, beta for each factor and adjusted R-squared. Moreover, the first column represents each one of nine dominant factors, and its t-statistics which is included in parenthesis.

Table A.5: Model 1						
	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	β_{CMOM1}	Adj R-squared
MOM1	0.0385***	0.2632***	0.0429	-0.1184	-0.0423	0.0262
T-Statistics	(2.9007)	(2.1151)	(0.4165)	(-1.3009)	(-0.5001)	
MOM2	0.0007	0.1736*	0.1488*	0.5586***	0.3537***	0.4164
T-Statistics	(0.0684)	(1.7657)	(1.8291)	(7.7685)	(5.2927)	
MOM3	0.0003	0.1435*	-0.2482***	0.8451***	0.1542***	0.5644
T-Statistics	(0.0384)	(1.6808)	(-3.5141)	(13.5377)	(2.657)	
RMOM1	0.0095	0.1103	0.1226**	0.1481***	0.6380***	0.5069
T-Statistics	(1.1868)	(1.4625)	(1.9637)	(2.6846)	(12.4442)	
RMOM2	0.0094	0.1797**	0.1759***	0.4909***	0.1799***	0.3727
T-Statistics	(1.0818)	(2.209)	(2.6124)	(8.2503)	(3.254)	
RMOM3	-0.0078	0.2228***	-0.1765***	0.8049***	0.0503	0.5279
T-Statistics	(-0.8979)	(2.7353)	(-2.6183)	(13.5117)	(0.9078)	
VOLPRC	0.0333***	0.2898***	0.2839***	-0.0878	-0.0476	0.0812
T-Statistics	(3.3718)	(3.1252)	(3.7009)	(-1.2955)	(-0.7552)	
STDPRCVOL	0.0356***	0.3393***	0.3083***	-0.0211	-0.064	0.0846
T-Statistics	(3.5198)	(3.5739)	(3.925)	(-0.3038)	(-0.9925)	
MEANABS	0.0321***	0.3396***	0.3553***	-0.0507	-0.0136	0.0955
T-Statistics	(3.1899)	(3.6034)	(4.5551)	(-0.7362)	(-0.2128)	
Average						0.2973

Notes. This table reports the empirical results of Model 1. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The average adjusted R-squared of Model 1 is 0.2973. Four mispricing factors still cannot be well explained due to their statistically significant alpha values.

Table A.6: Model 2

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	β_{CVOL}	Adj R-squared
MOM1	0.0380***	0.2388**	-0.0079	-0.1325**	-0.1683	0.032
T-Statistics	(2.8767)	(1.9046)	(-0.0732)	(-1.7993)	(-1.4404)	
MOM2	0.0032	0.1186	0.1199	0.7934***	-0.1242	0.3664
T-Statistics	(0.2976)	(1.1455)	(1.3397)	(13.0415)	(-1.2866)	
MOM3	0.0016	0.1394	-0.2259***	0.9384***	0.0637	0.5553
T-Statistics	(0.17)	(1.5997)	(-3)	(18.3244)	(0.784)	
RMOM1	0.0144	0.058	0.1525**	0.5504***	0.0533	0.2583
T-Statistics	(1.4582)	(0.6204)	(1.8874)	(10.0197)	(0.6119)	
RMOM2	0.0107	0.1614*	0.1780**	0.6059***	-0.0061	0.351
T-Statistics	(1.2169)	(1.9299)	(2.4639)	(12.3325)	(-0.0787)	
RMOM3	-0.0073	0.2425***	-0.1325	0.8259***	0.1446**	0.5321
T-Statistics	(-0.8438)	(2.9587)	(-1.8715)	(17.1536)	(1.8936)	
VOLPRC	0.0319***	0.1005	-0.0566	-0.0312	-1.1455***	0.5553
T-Statistics	(4.8743)	(1.6179)	(-1.0551)	(-0.8543)	(-19.7913)	
STDPRCVOL	0.0340***	0.1457**	-0.043	0.0277	-1.1805***	0.5963
T-Statistics	(5.1143)	(2.3064)	(-0.787)	(0.7477)	(-20.0543)	
MEANABS	0.0308***	0.1350**	-0.0057	0.033	-1.2169***	0.6032
T-Statistics	(4.9416)	(2.2817)	(-0.1114)	(0.9483)	(-22.0672)	
Average						0.4278

Notes. This table reports the empirical results of Model 2. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The average adjusted R-squared of Model 2 is 0.4278. Four mispricing factors still cannot be well explained due to their statistically significant alpha values.

Table A.7: Model 3

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	β_{CSTD}	Adj R-squared
MOM1	0.0463***	0.3351***	0.0581	-0.1449**	-0.0827	0.0319
T-Statistics	(3.2194)	(2.5278)	(0.5628)	(-1.981)	(-1.4314)	
MOM2	-0.0144	-0.008	0.1215	0.7830***	0.1799***	0.3924
T-Statistics	(-1.238)	(-0.0746)	(1.4545)	(13.2396)	(3.8513)	
MOM3	-0.0162*	-0.0181	-0.2798***	0.9423***	0.1789***	0.5832
T-Statistics	(-1.6694)	(-0.2031)	(-4.0258)	(19.146)	(4.6016)	
RMOM1	0.0164	0.0663	0.1408*	0.5545	-0.0211	0.258
T-Statistics	(1.528)	(0.6705)	(1.828)	(10.1672)	(-0.4898)	
RMOM2	0.0031	0.0991	0.1648**	0.6051***	0.0772**	0.3595
T-Statistics	(0.3257)	(1.1282)	(2.4079)	(12.4867)	(2.0161)	
RMOM3	-0.0092	0.2033**	-0.1789***	0.8368***	0.018	0.527
T-Statistics	(-0.9723)	(2.3329)	(-2.6358)	(17.4116)	(0.4731)	
VOLPRC	0.0186*	0.1747*	0.2544***	-0.1189**	0.1458***	0.1137
T-Statistics	(1.7584)	(1.796)	(3.3563)	(-2.2159)	(3.4379)	
STDPRCVOL	0.0224**	0.2393**	0.2816***	-0.0626	0.1294***	0.1073
T-Statistics	(2.0564)	(2.3887)	(3.609)	(-1.1324)	(2.9644)	
MEANABS	0.0168	0.2151**	0.3250***	-0.0602	0.1533***	0.1315
T-Statistics	(1.5685)	(2.18)	(4.2274)	(-1.1067)	(3.5657)	
Average						0.2783

Notes. This table reports the empirical results of Model 3. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The average adjusted R-squared of Model 3 is 0.2783. Three mispricing factors still cannot be well explained due to their statistically significant alpha values. However, MOM3 becomes statistically significant.

Table A.8: Model 4

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	β_{CMOM1}	β_{CVOL}	Adj R-squared
MOM1	0.0383***	0.2352*	-0.0067	-0.1073	-0.0398	-0.1672	0.0168
T-Statistics	(2.8923)	(1.8697)	(-0.0619)	(-1.1768)	(-0.471)	(-1.4284)	
MOM2	0.0006	0.1511	0.1089	0.5676***	0.3558***	-0.1345	0.4109
T-Statistics	(0.0551)	(1.5202)	(1.2708)	(7.8782)	(5.3316)	(-1.4542)	
MOM3	0.0004	0.1534*	-0.2307***	0.8412***	0.1533***	0.0592	0.5581
T-Statistics	(0.0452)	(1.7739)	(-3.0912)	(13.4158)	(2.6391)	(0.7362)	
RMOM1	0.0096	0.1162	0.1329**	0.1458***	0.6375***	0.0348	0.4993
T-Statistics	(1.1898)	(1.5193)	(2.0149)	(2.6298)	(12.4158)	(0.4898)	
RMOM2	0.0094	0.1778**	0.1725**	0.4916***	0.1801***	-0.0114	0.3625
T-Statistics	(1.0787)	(2.1553)	(2.4238)	(8.2199)	(3.2512)	(-0.1479)	
RMOM3	-0.0077	0.2469***	-0.134*	0.7954***	0.0481	0.1432*	0.5256
T-Statistics	(-0.8842)	(3.0054)	(-1.891)	(13.3583)	(0.8721)	(1.8743)	
VOLPRC	0.0321***	0.0977	-0.0557	-0.0119	-0.0303	-1.1446***	0.5904
T-Statistics	(4.8996)	(1.5692)	(-1.0367)	(-0.2643)	(-0.7251)	(-19.7564)	
STDPRCVOL	0.0344***	0.1415**	-0.0415	0.0571	-0.0462	-1.1791***	0.5983
T-Statistics	(5.1621)	(2.236)	(-0.761)	(1.2451)	(-1.0888)	(-20.0332)	
MEANABS	0.0308***	0.1354**	-0.0058	0.0300	0.0047	-1.217***	0.6452
T-Statistics	(4.9223)	(2.281)	(-0.114)	(0.6962)	(0.1186)	(-22.0293)	
Average							0.4674

Notes. This table reports the empirical results of Model 4. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The average adjusted R-squared of Model 4 is 0.4674. Four mispricing factors still cannot be well explained due to their statistically significant alpha values.

Table A.9: Model 5

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	β_{CMOM1}	β_{CSTD}	Adj R-squared
MOM1	0.0463***	0.3306**	0.0582	-0.1284	-0.0259	-0.0802	0.0163
T-Statistics	(3.2108)	(2.4743)	(0.5628)	(-1.4084)	(-0.3037)	(-1.3727)	
MOM2	-0.0138	0.0485	0.1204	0.5772***	0.3233***	0.1489***	0.4269
T-Statistics	(-1.2255)	(0.4662)	(1.4941)	(8.1271)	(4.8648)	(3.2707)	
MOM3	-0.0159*	0.0029	-0.2802***	0.866***	0.1199**	0.1674***	0.5825
T-Statistics	(-1.6537)	(0.0319)	(-4.054)	(14.2152)	(2.1041)	(4.287)	
RMOM1	0.0177**	0.1809**	0.1386**	0.1376**	0.6552***	-0.084**	0.5080
T-Statistics	(2.0392)	(2.247)	(2.2246)	(2.5056)	(12.7496)	(-2.3851)	
RMOM2	0.0034	0.1284	0.1642**	0.4985***	0.1674***	0.0611	0.3677
T-Statistics	(0.3655)	(1.4714)	(2.431)	(8.373)	(3.0059)	(1.6013)	
RMOM3	-0.0091	0.2116**	-0.1791***	0.8066***	0.0475	0.0134	0.5204
T-Statistics	(-0.9618)	(2.412)	(-2.637)	(13.477)	(0.8486)	(0.3494)	
VOLPRC	0.0184*	0.1609	0.2546***	-0.0687	-0.0789	0.1533***	0.1039
T-Statistics	(1.7451)	(1.6453)	(3.363)	(-1.0293)	(-1.2641)	(3.5844)	
STDPRCVOL	0.0222**	0.2231**	0.2819***	-0.0038	-0.0923	0.1382***	0.0988
T-Statistics	(2.0429)	(2.2175)	(3.6192)	(-0.0558)	(-1.4369)	(3.1415)	
MEANABS	0.0167	0.2071**	0.3251***	-0.0310	-0.0459	0.1577***	0.1187
T-Statistics	(1.5587)	(2.0839)	(4.2261)	(-0.4579)	(-0.7232)	(3.6291)	
Average							0.3048

Notes. This table reports the empirical results of Model 5. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The average adjusted R-squared of Model 5 is 0.3048. Three mispricing factors still cannot be well explained due to their statistically significant alpha values. Furthermore, alpha values of MOM3 and RMOM1 become statistically significant.

Table A.10: Model 6

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	β_{CVOL}	β_{CSTD}	Adj R-squared
MOM1	0.0478***	0.3147**	0.0015	-0.1294*	-0.2021*	-0.0995*	0.0254
T-Statistics	(3.3259)	(2.3714)	(0.0139)	(-1.7621)	(-1.7102)	(-1.7026)	
MOM2	-0.0139	-0.0146	0.1033	0.7879***	-0.0649	0.1745***	0.3834
T-Statistics	(-1.1943)	(-0.1352)	(1.1765)	(13.2107)	(-0.6763)	(3.6798)	
MOM3	-0.0171*	-0.0052	-0.2439***	0.9325***	0.1280	0.1895***	0.5800
T-Statistics	(-1.7668)	(-0.0579)	(-3.3499)	(18.8526)	(1.6093)	(4.8182)	
RMOM1	0.0161	0.0711	0.1541*	0.5509***	0.0475	-0.0172	0.2465
T-Statistics	(1.4915)	(0.7153)	(1.9025)	(10.0125)	(0.5365)	(-0.3922)	
RMOM2	0.0030	0.1012	0.1706**	0.6035***	0.0207	0.0789**	0.3491
T-Statistics	(0.309)	(1.1456)	(2.3692)	(12.341)	(0.2626)	(2.0286)	
RMOM3	-0.0103	0.219**	-0.1354*	0.825***	0.1551**	0.0308	0.5255
T-Statistics	(-1.0948)	(2.5149)	(-1.9092)	(17.1185)	(2.0008)	(0.8046)	
VOLPRC	0.0268***	0.0607	-0.0616	-0.0328	-1.1278***	0.0521*	0.5940
T-Statistics	(3.7617)	(0.9238)	(-1.15)	(-0.9019)	(-19.2793)	(1.8032)	
STDPRCVOL	0.0309***	0.121*	-0.0460	0.0267	-1.1695***	0.0323	0.5983
T-Statistics	(4.25)	(1.8051)	(-0.8424)	(0.7206)	(-19.5922)	(1.0954)	
MEANABS	0.0255***	0.0939	-0.0108	0.0313	-1.1986***	0.0539*	0.6496
T-Statistics	(3.7667)	(1.502)	(-0.212)	(0.9039)	(-21.5259)	(1.9562)	
Average							0.4391

Notes. This table reports the empirical results of Model 6. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The average adjusted R-squared of Model 6 is 0.4391. Four mispricing factors still cannot be well explained due to their statistically significant alpha values. Furthermore, alpha value of MOM3 becomes statistically significant.

Table A.11: Model 7

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	β_{CMOM1}	β_{CVOL}	β_{CSTD}	Adj R-squared
MOM1	0.0478***	0.3114**	0.0019	-0.1172	-0.0193	-0.2009*	-0.0975	0.0223
T-Statistics	(3.317)	(2.3297)	(0.0176)	(-1.2865)	(-0.2271)	(-1.6955)	(-1.6488)	
MOM2	-0.0131	0.0404	0.0964	0.582***	0.3261***	-0.0855	0.1415***	0.4266
T-Statistics	(-1.1673)	(0.3864)	(1.1387)	(8.1706)	(4.9007)	(-0.9237)	(3.0615)	
MOM3	-0.0168*	0.0144	-0.2464***	0.8593***	0.116**	0.1207	0.1778***	0.5843
T-Statistics	(-1.7462)	(0.1607)	(-3.4004)	(14.0987)	(2.0372)	(1.5232)	(4.4946)	
RMOM1	0.0177**	0.1814**	0.1403**	0.1373**	0.655***	0.0060	-0.0834**	0.5064
T-Statistics	(2.0272)	(2.2423)	(2.1397)	(2.4889)	(12.7118)	(0.0837)	(-2.3311)	
RMOM2	0.0034	0.1294	0.167**	0.4979***	0.1671***	0.0101	0.0620	0.3657
T-Statistics	(0.3564)	(1.4747)	(2.35)	(8.3283)	(2.992)	(0.1295)	(1.5971)	
RMOM3	-0.0102	0.2261***	-0.1363*	0.7981***	0.0425	0.1524**	0.0265	0.5248
T-Statistics	(-1.0829)	(2.5805)	(-1.9202)	(13.3627)	(0.7624)	(1.9626)	(0.6844)	
VOLPRC	0.0267***	0.0536	-0.0607	-0.0062	-0.0421	-1.1251***	0.0564*	0.5940
T-Statistics	(3.7468)	(0.811)	(-1.1333)	(-0.1372)	(-1.0017)	(-19.2138)	(1.9299)	
STDPRCVOL	0.0307***	0.1119*	-0.0449	0.0610	-0.0542	-1.166***	0.0378	0.5991
T-Statistics	(4.2354)	(1.661)	(-0.8222)	(1.3275)	(-1.2631)	(-19.5335)	(1.2688)	
MEANABS	0.0255***	0.0928	-0.0107	0.0355	-0.0067	-1.1982***	0.0545*	0.6485
T-Statistics	(3.7579)	(1.473)	(-0.2089)	(0.8273)	(-0.1672)	(-21.4617)	(1.9566)	
Average								0.4746

Notes. This table reports the empirical results of Model 7. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The average adjusted R-squared of Model 7 is 0.4746. Four mispricing factors still cannot be well explained due to their statistically significant alpha values. Furthermore, alpha values of MOM3 and RMOM1 become statistically significant.

Table A.12: Model 8

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	β_{CMOM1}	$\beta_{Electricity}$	Adj R-squared
MOM1	0.0344***	0.2863**	0.0405	-0.1241	-0.0233	1.9823***	0.0340
T-Statistics	(2.6044)	(2.3191)	(0.3976)	(-1.3782)	(-0.2773)	(2.7393)	
MOM2	0.0012	0.1712*	0.1491*	0.5593***	0.3517***	-0.2123	0.4071
T-Statistics	(0.1092)	(1.7341)	(1.8296)	(7.764)	(5.2368)	(-0.3669)	
MOM3	0.0001	0.145*	-0.2484***	0.8447***	0.1554***	0.1337	0.5574
T-Statistics	(0.0081)	(1.6925)	(-3.5109)	(13.5072)	(2.6659)	(0.266)	
RMOM1	0.0098	0.1087	0.1227**	0.1485***	0.6366***	-0.1425	0.4990
T-Statistics	(1.2137)	(1.4351)	(1.9635)	(2.6874)	(12.3569)	(-0.3211)	
RMOM2	0.0097	0.178**	0.1761***	0.4913***	0.1785***	-0.1476	0.3626
T-Statistics	(1.108)	(2.1796)	(2.6111)	(8.2431)	(3.2126)	(-0.3083)	
RMOM3	-0.0088	0.2287***	-0.1771***	0.8034***	0.0551	0.5077	0.5219
T-Statistics	(-1.0118)	(2.8018)	(-2.6277)	(13.486)	(0.9925)	(1.0608)	
VOLPRC	0.0349***	0.2809***	0.2848***	-0.0856	-0.0549	-0.7590	0.0721
T-Statistics	(3.5126)	(3.0277)	(3.7183)	(-1.2646)	(-0.8691)	(-1.3952)	
STDPRCVOL	0.0362***	0.3358***	0.3087***	-0.0202	-0.0669	-0.2975	0.0705
T-Statistics	(3.5533)	(3.5251)	(3.9248)	(-0.2909)	(-1.032)	(-0.5326)	
MEANABS	0.0328***	0.3353***	0.3557***	-0.0497	-0.0172	-0.3739	0.0820
T-Statistics	(3.2427)	(3.5459)	(4.5566)	(-0.7196)	(-0.2677)	(-0.6744)	
Average							0.2896

Notes. This table reports the empirical results of Model 8. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The average adjusted R-squared of Model 8 is 0.2896. Four mispricing factors still cannot be well explained due to their statistically significant alpha values. Only MOM1 has exposure to electricity.

Table A.13: Model 9

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	β_{CVOL}	$\beta_{Electricity}$	Adj R-squared
MOM1	0.034***	0.2599**	-0.0104	-0.126*	-0.1701	2.0046***	0.0406
T-Statistics	(2.5887)	(2.0922)	(-0.0973)	(-1.7282)	(-1.4715)	(2.7891)	
MOM2	0.0042	0.1138	0.1204	0.7919***	-0.1238	-0.4586	0.3572
T-Statistics	(0.3785)	(1.096)	(1.3451)	(13.0012)	(-1.2816)	(-0.7637)	
MOM3	0.0015	0.1397	-0.226***	0.9385***	0.0637	0.0208	0.5480
T-Statistics	(0.1643)	(1.5967)	(-2.9953)	(18.2863)	(0.7824)	(0.0411)	
RMOM1	0.0156	0.0517	0.1532*	0.5484***	0.0538	-0.5977	0.2492
T-Statistics	(1.5699)	(0.5521)	(1.8973)	(9.9825)	(0.6181)	(-1.1035)	
RMOM2	0.0113	0.1585*	0.1784**	0.605***	-0.0059	-0.2746	0.3411
T-Statistics	(1.2697)	(1.8896)	(2.4658)	(12.2941)	(-0.0756)	(-0.5659)	
RMOM3	-0.0082	0.2474***	-0.1331*	0.8274***	0.1442*	0.4636	0.5259
T-Statistics	(-0.9446)	(3.0125)	(-1.8794)	(17.1748)	(1.8881)	(0.976)	
VOLPRC	0.0333***	0.0933	-0.0558	-0.0334	-1.1449***	-0.6811*	0.5945
T-Statistics	(5.0723)	(1.5058)	(-1.0437)	(-0.9188)	(-19.8649)	(-1.9004)	
STDPRCVOL	0.0345***	0.1435**	-0.0427	0.0271	-1.1803***	-0.2099	0.5971
T-Statistics	(5.1406)	(2.2646)	(-0.7813)	(0.728)	(-20.0288)	(-0.5727)	
MEANABS	0.0315***	0.1316**	-0.0053	0.0319	-1.2166***	-0.3204	0.6462
T-Statistics	(5.0128)	(2.22)	(-0.1035)	(0.9175)	(-22.0572)	(-0.9341)	
Average							0.4333

Notes. This table reports the empirical results of Model 9. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The average adjusted R-squared of Model 9 is 0.4333. Four mispricing factors still cannot be well explained due to their statistically significant alpha values. Only MOM1 and VOLPRC have exposure to electricity.

Table A.14: Model 10

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	β_{CSTD}	$\beta_{Electricity}$	Adj R-squared
MOM1	0.0421***	0.3537***	0.0555	-0.1386*	-0.0795	1.9784***	0.0399
T-Statistics	(2.9386)	(2.6923)	(0.5435)	(-1.9139)	(-1.3899)	(2.751)	
MOM2	-0.0135	-0.0119	0.1220	0.7816***	0.1792***	-0.4165	0.3835
T-Statistics	(-1.1536)	(-0.1108)	(1.4598)	(13.1997)	(3.8329)	(-0.708)	
MOM3	-0.0163*	-0.0175	-0.2799***	0.9425***	0.179***	0.0692	0.5764
T-Statistics	(-1.6722)	(-0.1953)	(-4.0205)	(19.1102)	(4.5961)	(0.1412)	
RMOM1	0.0177	0.0607	0.1416*	0.5526***	-0.0221	-0.6016	0.2489
T-Statistics	(1.6393)	(0.613)	(1.8388)	(10.1307)	(-0.5127)	(-1.1103)	
RMOM2	0.0037	0.0967	0.1651**	0.6042***	0.0768**	-0.2550	0.3496
T-Statistics	(0.3804)	(1.0983)	(2.4098)	(12.4489)	(2.0025)	(-0.5288)	
RMOM3	-0.0102	0.2077**	-0.1795***	0.8383***	0.0187	0.4733	0.5208
T-Statistics	(-1.0733)	(2.3805)	(-2.6447)	(17.4337)	(0.4933)	(0.9909)	
VOLPRC	0.02*	0.1684*	0.2553***	-0.1211**	0.1446***	-0.6826	0.1040
T-Statistics	(1.888)	(1.7298)	(3.3714)	(-2.2577)	(3.4145)	(-1.281)	
STDPRCVOL	0.0228**	0.2373**	0.2819***	-0.0633	0.129***	-0.2165	0.0931
T-Statistics	(2.0841)	(2.3621)	(3.6074)	(-1.1428)	(2.9516)	(-0.3938)	
MEANABS	0.0175	0.2121**	0.3254***	-0.0613	0.1528***	-0.3222	0.1182
T-Statistics	(1.6218)	(2.1443)	(4.2282)	(-1.1239)	(3.549)	(-0.5948)	
Average							0.2705

Notes. This table reports the empirical results of Model 10. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The average adjusted R-squared of Model 10 is 0.2705. Three mispricing factors still cannot be well explained due to their statistically significant alpha values, MOM3 becomes significant as well. Only MOM1 has exposure to electricity.

Table A.15: Model 11

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	β_{CMOM1}	β_{CVOL}	$\beta_{Electricity}$	Adj R-squared
MOM1	0.0342***	0.2579**	-0.0098	-0.1129	-0.0207	-0.1695	1.9899***	0.0376
T-Statistics	(2.5945)	(2.068)	(-0.0911)	(-1.2515)	(-0.2464)	(-1.4636)	(2.7549)	
MOM2	0.0010	0.1487	0.1093	0.5681***	0.3538***	-0.1342	-0.2063	0.4092
T-Statistics	(0.0949)	(1.4911)	(1.2726)	(7.873)	(5.2761)	(-1.4495)	(-0.3571)	
MOM3	0.0001	0.1549*	-0.2309***	0.8408***	0.1545***	0.0591	0.1310	0.5567
T-Statistics	(0.0155)	(1.7846)	(-3.089)	(13.386)	(2.6476)	(0.7332)	(0.2605)	
RMOM1	0.0099	0.1145	0.1331**	0.1462***	0.6361***	0.0350	-0.1441	0.4978
T-Statistics	(1.217)	(1.4922)	(2.0152)	(2.6326)	(12.3281)	(0.4914)	(-0.3242)	
RMOM2	0.0097	0.1761**	0.1727**	0.492***	0.1787***	-0.0112	-0.1471	0.3606
T-Statistics	(1.1048)	(2.1271)	(2.4232)	(8.2125)	(3.2098)	(-0.1455)	(-0.3068)	
RMOM3	-0.0087	0.2526***	-0.1348*	0.794***	0.0529	0.1427*	0.5013	0.5258
T-Statistics	(-0.9972)	(3.069)	(-1.9021)	(13.3334)	(0.9563)	(1.867)	(1.0517)	
VOLPRC	0.0336***	0.0896	-0.0546	-0.0099	-0.0371	-1.1438***	-0.7076**	0.5942
T-Statistics	(5.1128)	(1.4429)	(-1.0211)	(-0.2209)	(-0.8889)	(-19.8344)	(-1.9668)	
STDPRCVOL	0.0349***	0.1387**	-0.0412	0.0578	-0.0486	-1.1788***	-0.2445	0.5975
T-Statistics	(5.1995)	(2.1851)	(-0.7534)	(1.2587)	(-1.1392)	(-20.0096)	(-0.6653)	
MEANABS	0.0314***	0.1318**	-0.0053	0.0309	0.0017	-1.2167***	-0.3192	0.6450
T-Statistics	(4.9942)	(2.2142)	(-0.1044)	(0.7168)	(0.0415)	(-22.0169)	(-0.9259)	
Average								0.4694

Notes. This table reports the empirical results of Model 11. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The average adjusted R-squared of Model 11 is 0.4694. Four mispricing factors still cannot be well explained due to their statistically significant alpha values. Only MOM1 and VOLPRC have exposures to electricity.

Table A.16: Model 12

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	β_{CMOM1}	β_{CSTD}	$\beta_{Electricity}$	Adj R-squared
MOM1	0.0421***	0.3523***	0.0556	-0.1339	-0.0073	-0.0788	1.9734***	0.0367
T-Statistics	(2.9335)	(2.6599)	(0.5429)	(-1.4844)	(-0.0858)	(-1.3623)	(2.7306)	
MOM2	-0.0134	0.0464	0.1207	0.5778***	0.3214***	0.1488***	-0.1954	0.4252
T-Statistics	(-1.18)	(0.4441)	(1.4951)	(8.121)	(4.8144)	(3.2628)	(-0.343)	
MOM3	-0.0163*	0.0045	-0.2804***	0.8656***	0.1214**	0.1675***	0.1527	0.5812
T-Statistics	(-1.6752)	(0.0506)	(-4.0508)	(14.1835)	(2.1193)	(4.2833)	(0.3124)	
RMOM1	0.018**	0.1792**	0.1388**	0.138**	0.6537***	-0.0841**	-0.1521	0.5066
T-Statistics	(2.0615)	(2.2189)	(2.2245)	(2.5091)	(12.662)	(-2.3847)	(-0.3452)	
RMOM2	0.0037	0.1268	0.1644**	0.4989***	0.1661***	0.0610	-0.1407	0.3658
T-Statistics	(0.3944)	(1.4488)	(2.43)	(8.365)	(2.9679)	(1.5962)	(-0.2946)	
RMOM3	-0.0102	0.2172**	-0.1797***	0.8051***	0.0523	0.0138	0.5093	0.5206
T-Statistics	(-1.0702)	(2.472)	(-2.6474)	(13.4524)	(0.9316)	(0.3591)	(1.0625)	
VOLPRC	0.02*	0.1528	0.2556***	-0.0666	-0.0859	0.1528***	-0.7417	0.1066
T-Statistics	(1.8865)	(1.5614)	(3.3811)	(-0.9993)	(-1.3739)	(3.5771)	(-1.3894)	
STDPRCVOL	0.0228**	0.22**	0.2823***	-0.0030	-0.0950	0.138***	-0.2818	0.0966
T-Statistics	(2.0835)	(2.1801)	(3.6195)	(-0.0442)	(-1.4717)	(3.133)	(-0.5118)	
MEANABS	0.0175	0.2032**	0.3256***	-0.0300	-0.0492	0.1575***	-0.3560	0.1171
T-Statistics	(1.6184)	(2.0389)	(4.2281)	(-0.4426)	(-0.7729)	(3.6196)	(-0.6548)	
Average								0.3063

Notes. This table reports the empirical results of Model 12. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The average adjusted R-squared of Model 12 is 0.3063. Four mispricing factors still cannot be well explained due to their statistically significant alpha values. Only MOM1 and VOLPRC have exposures to electricity.

Table A.17: Model 13

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	β_{CVOL}	β_{CSTD}	$\beta_{Electricity}$	Adj R-squared
MOM1	0.0436***	0.3332**	-0.0013	-0.1231*	-0.2027*	-0.0963*	1.9809***	0.0461
T-Statistics	(3.0457)	(2.5345)	(-0.0118)	(-1.6925)	(-1.7344)	(-1.6657)	(2.7635)	
MOM2	-0.0131	-0.0184	0.1039	0.7866***	-0.0647	0.1739***	-0.4157	0.3823
T-Statistics	(-1.1107)	(-0.1708)	(1.1821)	(13.1708)	(-0.6743)	(3.662)	(-0.706)	
MOM3	-0.0172*	-0.0045	-0.244***	0.9327***	0.1280	0.1896***	0.0676	0.5786
T-Statistics	(-1.7686)	(-0.0507)	(-3.3456)	(18.8172)	(1.6064)	(4.8122)	(0.1383)	
RMOM1	0.0174	0.0655	0.1549*	0.549***	0.0477	-0.0181	-0.6022	0.2471
T-Statistics	(1.6026)	(0.6582)	(1.9135)	(9.9761)	(0.539)	(-0.4144)	(-1.1101)	
RMOM2	0.0035	0.0988	0.1709**	0.6027***	0.0207	0.0785**	-0.2552	0.3476
T-Statistics	(0.3636)	(1.1158)	(2.3712)	(12.3034)	(0.2633)	(2.0153)	(-0.5285)	
RMOM3	-0.0113	0.2233**	-0.1361*	0.8265***	0.1549**	0.0316	0.4714	0.5254
T-Statistics	(-1.1949)	(2.5621)	(-1.9183)	(17.1409)	(1.9987)	(0.8241)	(0.9917)	
VOLPRC	0.0282***	0.0545	-0.0606	-0.0350	-1.1276***	0.0511*	-0.6685*	0.5973
T-Statistics	(3.9562)	(0.8312)	(-1.1372)	(-0.9645)	(-19.3544)	(1.773)	(-1.8714)	
STDPRCVOL	0.0313***	0.1191*	-0.0457	0.0261	-1.1694***	0.0320	-0.2020	0.5974
T-Statistics	(4.2798)	(1.7727)	(-0.8362)	(0.7019)	(-19.5687)	(1.083)	(-0.5512)	
MEANABS	0.0262***	0.0911	-0.0104	0.0303	-1.1985***	0.0534*	-0.3072	0.6494
T-Statistics	(3.8403)	(1.4538)	(-0.2035)	(0.8746)	(-21.5173)	(1.9373)	(-0.8995)	
Average								0.4413

Notes. This table reports the empirical results of Model 13. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The average adjusted R-squared of Model 13 is 0.4413. Four mispricing factors still cannot be well explained due to their statistically significant alpha values, MOM3 has a significant alpha as well. Only MOM1 and VOLPRC have exposures to electricity.

Table A.18: Model 14

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	β_{CMOM1}	β_{CVOL}	β_{CSTD}	$\beta_{Electricity}$	Adj R-squared
MOM1	0.0436***	0.3331**	-0.0012	-0.1227	-0.0006	-0.2027*	-0.0962	1.9805***	0.0430
T-Statistics	(3.0406)	(2.5138)	(-0.0116)	(-1.3607)	(-0.0068)	(-1.7294)	(-1.6445)	(2.7494)	
MOM2	-0.0127	0.0383	0.0967	0.5825***	0.3243***	-0.0854	0.1414***	-0.1924	0.4250
T-Statistics	(-1.123)	(0.3651)	(1.1406)	(8.1642)	(4.8503)	(-0.9204)	(3.0543)	(-0.3377)	
MOM3	-0.0171*	0.0160	-0.2466***	0.8589***	0.1174**	0.1206	0.1779***	0.1484	0.5830
T-Statistics	(-1.766)	(0.1782)	(-3.3984)	(14.0675)	(2.052)	(1.5192)	(4.4902)	(0.3043)	
RMOM1	0.018**	0.1798**	0.1405**	0.1377**	0.6535***	0.0061	-0.0835**	-0.1523	0.5050
T-Statistics	(2.0495)	(2.2147)	(2.1402)	(2.4923)	(12.6241)	(0.0856)	(-2.3304)	(-0.3451)	
RMOM2	0.0037	0.1278	0.1673**	0.4983***	0.1658***	0.0102	0.0619	-0.1411	0.3638
T-Statistics	(0.3853)	(1.4524)	(2.3495)	(8.3203)	(2.954)	(0.131)	(1.5923)	(-0.2949)	
RMOM3	-0.0113	0.2316***	-0.1371*	0.7967***	0.0473	0.1519*	0.0269	0.5040	0.5250
T-Statistics	(-1.1894)	(2.6392)	(-1.9318)	(13.3386)	(0.8453)	(1.9569)	(0.6929)	(1.0562)	
VOLPRC	0.0282***	0.0459	-0.0596	-0.0042	-0.0488	-1.1245***	0.056*	-0.7021**	0.5978
T-Statistics	(3.9517)	(0.6969)	(-1.1175)	(-0.0946)	(-1.1614)	(-19.2919)	(1.9233)	(-1.9602)	
STDPRCVOL	0.0312***	0.1093	-0.0445	0.0616	-0.0565	-1.1658***	0.0377	-0.2408	0.5983
T-Statistics	(4.2772)	(1.6175)	(-0.8143)	(1.3405)	(-1.3107)	(-19.5111)	(1.2623)	(-0.6559)	
MEANABS	0.0262***	0.0894	-0.0102	0.0364	-0.0097	-1.1979***	0.0543*	-0.3139	0.6483
T-Statistics	(3.8329)	(1.4157)	(-0.199)	(0.847)	(-0.2404)	(-21.4503)	(1.9487)	(-0.9146)	
Average									0.4766

Notes. This table reports the empirical results of Model 14. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The average adjusted R-squared of Model 14 is 0.4766. Four mispricing factors still cannot be well explained due to their statistically significant alpha values, MOM3 and RMOM1 have a significant alpha as well. Only MOM1 and VOLPRC have exposures to electricity.

Table A.19: Model 15

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	β_{CMOM1}	$\beta_{Graphcis}$	Adj R-squared
MOM1	0.0398***	0.262**	0.0408	-0.1114	-0.0434	-0.4057	0.0134
T-Statistics	(2.9819)	(2.1052)	(0.396)	(-1.2202)	(-0.5137)	(-0.9846)	
MOM2	0.0016	0.1728*	0.1474*	0.5634***	0.353***	-0.2743	0.4082
T-Statistics	(0.1491)	(1.7565)	(1.8105)	(7.8068)	(5.278)	(-0.8422)	
MOM3	0.0005	0.1434*	-0.2484***	0.8457***	0.1541***	-0.0377	0.5573
T-Statistics	(0.0509)	(1.6768)	(-3.5105)	(13.4853)	(2.6507)	(-0.133)	
RMOM1	0.0093	0.1106	0.1231**	0.1465***	0.6383***	0.0936	0.4991
T-Statistics	(1.1436)	(1.4641)	(1.9683)	(2.6436)	(12.4307)	(0.3741)	
RMOM2	0.0096	0.1795**	0.1755***	0.4921***	0.1797***	-0.0729	0.3626
T-Statistics	(1.1012)	(2.2029)	(2.6023)	(8.2339)	(3.245)	(-0.2703)	
RMOM3	-0.0074	0.2225***	-0.1772***	0.8071***	0.0499	-0.1277	0.5205
T-Statistics	(-0.8471)	(2.7271)	(-2.6242)	(13.4904)	(0.9)	(-0.4729)	
VOLPRC	0.0333***	0.2898***	0.2841***	-0.0883	-0.0475	0.0254	0.0662
T-Statistics	(3.3427)	(3.1208)	(3.6958)	(-1.2959)	(-0.7528)	(0.0825)	
STDPRCVOL	0.0346***	0.3403***	0.3101***	-0.0271	-0.0631	0.3469	0.0733
T-Statistics	(3.3985)	(3.5858)	(3.9483)	(-0.3889)	(-0.9775)	(1.1041)	
MEANABS	0.0321***	0.3396***	0.3552***	-0.0507	-0.0136	-0.0051	0.0807
T-Statistics	(3.1715)	(3.5972)	(4.5464)	(-0.7314)	(-0.2127)	(-0.0163)	
Average							0.2868

Notes. This table reports the empirical results of Model 15. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The average adjusted R-squared of Model 15 is 0.2868. Four mispricing factors still cannot be well explained due to their statistically significant alpha values. No factors have exposures to graphics.

Table A.20: Model 16

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	β_{CVOL}	$\beta_{Graphcis}$	Adj R-squared
MOM1	0.0393***	0.2375*	-0.0105	-0.1261*	-0.1697	-0.4096	0.0193
T-Statistics	(2.9588)	(1.8939)	(-0.0967)	(-1.7055)	(-1.4519)	(-0.9973)	
MOM2	0.0042	0.1176	0.1180	0.7981***	-0.1252	-0.3032	0.3577
T-Statistics	(0.3815)	(1.1356)	(1.3179)	(13.0654)	(-1.2965)	(-0.8935)	
MOM3	0.0017	0.1393	-0.2262***	0.9391***	0.0635	-0.0454	0.5480
T-Statistics	(0.1842)	(1.5954)	(-2.9981)	(18.2394)	(0.7808)	(-0.1589)	
RMOM1	0.0142	0.0582	0.1528*	0.5496***	0.0535	0.0527	0.2462
T-Statistics	(1.4328)	(0.6212)	(1.888)	(9.9508)	(0.6129)	(0.1719)	
RMOM2	0.0110	0.1611*	0.1775**	0.6073***	-0.0064	-0.0853	0.3406
T-Statistics	(1.2392)	(1.9236)	(2.4523)	(12.2945)	(-0.0822)	(-0.3109)	
RMOM3	-0.0069	0.2421***	-0.1333*	0.8279***	0.1442*	-0.1252	0.5248
T-Statistics	(-0.7943)	(2.9498)	(-1.8795)	(17.107)	(1.8857)	(-0.4656)	
VOLPRC	0.032***	0.1004	-0.0567	-0.0309	-1.1456***	-0.0181	0.5897
T-Statistics	(4.8526)	(1.6142)	(-1.0552)	(-0.842)	(-19.7589)	(-0.0888)	
STDPRCVOL	0.0331***	0.1467**	-0.0411	0.0230	-1.1795***	0.3031	0.5995
T-Statistics	(4.9602)	(2.3262)	(-0.7538)	(0.6184)	(-20.0737)	(1.4675)	
MEANABS	0.031***	0.1348**	-0.0060	0.0338	-1.2171***	-0.0538	0.6453
T-Statistics	(4.9381)	(2.2752)	(-0.1177)	(0.9674)	(-22.0357)	(-0.277)	
Average							0.4301

Notes. This table reports the empirical results of Model 16. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The average adjusted R-squared of Model 16 is 0.4301. Four mispricing factors still cannot be well explained due to their statistically significant alpha values. No factors have exposures to graphics.

Table A.21: Model 17

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	β_{CSTD}	$\beta_{Graphcis}$	Adj R-squared
MOM1	0.0478***	0.3354**	0.0562	-0.1384*	-0.0843	-0.4194	0.0194
T-Statistics	(3.3047)	(2.5296)	(0.5446)	(-1.8854)	(-1.4593)	(-1.0207)	
MOM2	-0.0135	-0.0079	0.1203	0.787***	0.1789***	-0.2628	0.3837
T-Statistics	(-1.1532)	(-0.0733)	(1.4394)	(13.2502)	(3.8256)	(-0.7903)	
MOM3	-0.0161*	-0.0181	-0.2799***	0.9425***	0.1788***	-0.0127	0.5764
T-Statistics	(-1.654)	(-0.2027)	(-4.0194)	(19.0471)	(4.591)	(-0.0459)	
RMOM1	0.0162	0.0663	0.141*	0.5538***	-0.0209	0.0464	0.2459
T-Statistics	(1.5032)	(0.6692)	(1.8275)	(10.0998)	(-0.4846)	(0.1513)	
RMOM2	0.0034	0.0991	0.1645**	0.6061***	0.0769**	-0.0699	0.3491
T-Statistics	(0.349)	(1.1269)	(2.3993)	(12.443)	(2.0052)	(-0.2562)	
RMOM3	-0.0088	0.2033**	-0.1795***	0.8388***	0.0175	-0.1276	0.5196
T-Statistics	(-0.9197)	(2.3307)	(-2.6405)	(17.3651)	(0.4592)	(-0.472)	
VOLPRC	0.0184*	0.1747*	0.2546***	-0.1198**	0.146***	0.0574	0.0993
T-Statistics	(1.7283)	(1.7928)	(3.3538)	(-2.2205)	(3.4365)	(0.19)	
STDPRCVOL	0.0211*	0.2391**	0.2833***	-0.0684	0.1309***	0.3770	0.0971
T-Statistics	(1.9279)	(2.3886)	(3.6328)	(-1.2342)	(2.9993)	(1.2152)	
MEANABS	0.0167	0.2151**	0.3251***	-0.0607	0.1534***	0.0261	0.1172
T-Statistics	(1.5499)	(2.1763)	(4.2214)	(-1.1082)	(3.5609)	(0.0852)	
Average							0.2675

Notes. This table reports the empirical results of Model 17. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The average adjusted R-squared of Model 17 is 0.2675. Three mispricing factors still cannot be well explained due to their statistically significant alpha values, MOM3 has a significant alpha value as well. No factors have exposures to graphics.

Table A.22: Model 18

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	β_{CMOM1}	β_{CVOL}	$\beta_{Graphcis}$	Adj R-squared
MOM1	0.0396***	0.2337*	-0.0092	-0.1001	-0.0409	-0.1685	-0.4124	0.0169
T-Statistics	(2.9753)	(1.8582)	(-0.0851)	(-1.0944)	(-0.4846)	(-1.4397)	(-1.0025)	
MOM2	0.0014	0.1501	0.1072	0.5724***	0.355***	-0.1354	-0.2797	0.4104
T-Statistics	(0.1375)	(1.5096)	(1.2499)	(7.9181)	(5.3171)	(-1.4632)	(-0.8602)	
MOM3	0.0005	0.1533*	-0.2309***	0.8418***	0.1532***	0.0591	-0.0353	0.5567
T-Statistics	(0.0568)	(1.7695)	(-3.0883)	(13.3626)	(2.6329)	(0.7336)	(-0.1246)	
RMOM1	0.0093	0.1165	0.1335**	0.1441***	0.6377***	0.0352	0.0950	0.4978
T-Statistics	(1.1462)	(1.5214)	(2.0203)	(2.5883)	(12.4023)	(0.4934)	(0.3792)	
RMOM2	0.0096	0.1776**	0.1721**	0.4929***	0.1799***	-0.0116	-0.0734	0.3605
T-Statistics	(1.0981)	(2.1488)	(2.4131)	(8.2034)	(3.2423)	(-0.1507)	(-0.2716)	
RMOM3	-0.0073	0.2464***	-0.1347*	0.7975***	0.0478	0.1428*	-0.1220	0.5244
T-Statistics	(-0.8354)	(2.9962)	(-1.8986)	(13.3353)	(0.8647)	(1.8666)	(-0.4537)	
VOLPRC	0.0322***	0.0976	-0.0558	-0.0116	-0.0304	-1.1447***	-0.0201	0.5890
T-Statistics	(4.8785)	(1.5654)	(-1.037)	(-0.2553)	(-0.7252)	(-19.7242)	(-0.0986)	
STDPRCVOL	0.0335***	0.1425**	-0.0397	0.0519	-0.0454	-1.1782***	0.3001	0.5997
T-Statistics	(5.0079)	(2.2566)	(-0.7285)	(1.1295)	(-1.0709)	(-20.052)	(1.4532)	
MEANABS	0.031***	0.1353**	-0.0062	0.0309	0.0046	-1.2172***	-0.0535	0.6441
T-Statistics	(4.9186)	(2.2743)	(-0.1201)	(0.7145)	(0.1146)	(-21.9976)	(-0.275)	
Average								0.4666

Notes. This table reports the empirical results of Model 18. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The average adjusted R-squared of Model 18 is 0.4666. Four mispricing factors still cannot be well explained due to their statistically significant alpha values. No factors have exposures to graphics.

Table A.23: Model 19

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	β_{CMOM1}	β_{CSTD}	$\beta_{Graphcis}$	Adj R-squared
MOM1	0.0478***	0.3307**	0.0563	-0.1213	-0.0268	-0.0818	-0.4207	0.0165
T-Statistics	(3.2962)	(2.475)	(0.5446)	(-1.3273)	(-0.3139)	(-1.399)	(-1.0223)	
MOM2	-0.0129	0.0486	0.1193	0.5814***	0.3228***	0.148***	-0.2471	0.4261
T-Statistics	(-1.1427)	(0.4663)	(1.4792)	(8.1566)	(4.8536)	(3.2474)	(-0.7703)	
MOM3	-0.0159	0.0029	-0.2802***	0.8661***	0.1199**	0.1674***	-0.0069	0.5811
T-Statistics	(-1.6405)	(0.0319)	(-4.0472)	(14.1532)	(2.1003)	(4.2778)	(-0.0251)	
RMOM1	0.0174**	0.1809**	0.139**	0.1363**	0.6553***	-0.0837**	0.0782	0.5066
T-Statistics	(1.9952)	(2.2435)	(2.2265)	(2.4709)	(12.7333)	(-2.3726)	(0.3149)	
RMOM2	0.0037	0.1284	0.1639**	0.4995***	0.1673***	0.0609	-0.0617	0.3658
T-Statistics	(0.3858)	(1.4692)	(2.4228)	(8.3534)	(2.9988)	(1.5923)	(-0.2294)	
RMOM3	-0.0087	0.2116**	-0.1796***	0.8087***	0.0473	0.0129	-0.1253	0.5191
T-Statistics	(-0.9101)	(2.4091)	(-2.6414)	(13.4561)	(0.8428)	(0.3367)	(-0.4632)	
VOLPRC	0.0182*	0.1609	0.2549***	-0.0696	-0.0788	0.1535***	0.0536	0.1010
T-Statistics	(1.7163)	(1.6426)	(3.3603)	(-1.0381)	(-1.2603)	(3.5822)	(0.1775)	
STDPRCVOL	0.0209*	0.2231**	0.2836***	-0.0101	-0.0915	0.1396***	0.3725	0.1001
T-Statistics	(1.9157)	(2.2185)	(3.6426)	(-0.1466)	(-1.4258)	(3.1741)	(1.2029)	
MEANABS	0.0166	0.2071**	0.3252***	-0.0314	-0.0458	0.1578***	0.0239	0.1159
T-Statistics	(1.5409)	(2.0805)	(4.2199)	(-0.4617)	(-0.7212)	(3.624)	(0.0779)	
Average								0.3036

Notes. This table reports the empirical results of Model 19. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The average adjusted R-squared of Model 19 is 0.3036. Three mispricing factors still cannot be well explained due to their statistically significant alpha values, RMOM1 has a significant alpha value as well. No factors have exposures to graphics.

Table A.24: Model 20

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	β_{CVOL}	β_{CSTD}	$\beta_{Graphcis}$	Adj R-squared
MOM1	0.0493***	0.3147**	-0.0010	-0.1226*	-0.2041*	-0.1013*	-0.4310	0.0257
T-Statistics	(3.4147)	(2.3719)	(-0.0092)	(-1.6631)	(-1.7277)	(-1.7339)	(-1.0524)	
MOM2	-0.0130	-0.0146	0.1018	0.7921***	-0.0662	0.1734***	-0.2666	0.3826
T-Statistics	(-1.1079)	(-0.135)	(1.1579)	(13.2223)	(-0.6891)	(3.6518)	(-0.8009)	
MOM3	-0.0171*	-0.0052	-0.244***	0.9326***	0.1280	0.1895***	-0.0054	0.5786
T-Statistics	(-1.7532)	(-0.0578)	(-3.344)	(18.7506)	(1.6061)	(4.8075)	(-0.0196)	
RMOM1	0.0159	0.0711	0.1544*	0.5501***	0.0477	-0.0170	0.0492	0.2441
T-Statistics	(1.4658)	(0.7141)	(1.9025)	(9.9438)	(0.5382)	(-0.3866)	(0.16)	
RMOM2	0.0032	0.1012	0.1702**	0.6046***	0.0203	0.0786**	-0.0687	0.3471
T-Statistics	(0.332)	(1.1438)	(2.3594)	(12.2965)	(0.258)	(2.017)	(-0.2515)	
RMOM3	-0.0099	0.219**	-0.1361*	0.8269***	0.1545**	0.0303	-0.1188	0.5242
T-Statistics	(-1.044)	(2.5117)	(-1.9159)	(17.0685)	(1.9906)	(0.7899)	(-0.4413)	
VOLPRC	0.0268***	0.0607	-0.0616	-0.0327	-1.1278***	0.0521*	-0.0071	0.5927
T-Statistics	(3.7403)	(0.9223)	(-1.1486)	(-0.8939)	(-19.2456)	(1.7984)	(-0.0349)	
STDPRCVOL	0.0298***	0.121*	-0.0442	0.0218	-1.168***	0.0337	0.3102	0.5999
T-Statistics	(4.088)	(1.8087)	(-0.8109)	(0.5873)	(-19.605)	(1.1424)	(1.502)	
MEANABS	0.0257***	0.0939	-0.0110	0.0320	-1.1988***	0.0537*	-0.0424	0.6485
T-Statistics	(3.764)	(1.4997)	(-0.2164)	(0.9182)	(-21.493)	(1.9456)	(-0.2195)	
Average								0.4382

Notes. This table reports the empirical results of Model 20. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The average adjusted R-squared of Model 20 is 0.4382. Four mispricing factors still cannot be well explained due to their statistically significant alpha values, MOM3 also has a significant alpha. No factors have exposures to graphics.

Table A.25: Model 21

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	β_{CMOM1}	β_{CVOL}	β_{CSTD}	$\beta_{Graphcis}$	Adj R-squared
MOM1	0.0493***	0.3113**	-0.0006	-0.1099	-0.0202	-0.2029*	-0.0993*	-0.4319	0.0227
T-Statistics	(3.4059)	(2.3292)	(-0.0053)	(-1.2025)	(-0.2369)	(-1.7125)	(-1.6784)	(-1.0529)	
MOM2	-0.0123	0.0403	0.0950	0.5863***	0.3256***	-0.0867	0.1405***	-0.2519	0.4259
T-Statistics	(-1.0827)	(0.3854)	(1.1206)	(8.2016)	(4.8901)	(-0.9356)	(3.036)	(-0.785)	
MOM3	-0.0168*	0.0144	-0.2464***	0.8593***	0.116**	0.1207	0.1778***	-0.0002	0.5829
T-Statistics	(-1.7346)	(0.1604)	(-3.394)	(14.0343)	(2.0337)	(1.5205)	(4.4854)	(-0.0007)	
RMOM1	0.0174**	0.1815**	0.1408**	0.1359**	0.6551***	0.0064	-0.0831**	0.0785	0.5050
T-Statistics	(1.9827)	(2.2393)	(2.1429)	(2.4538)	(12.6954)	(0.0886)	(-2.3177)	(0.3158)	
RMOM2	0.0036	0.1293	0.1667**	0.499***	0.167***	0.0098	0.0617	-0.0612	0.3637
T-Statistics	(0.3767)	(1.4722)	(2.3408)	(8.3083)	(2.9851)	(0.1257)	(1.5875)	(-0.227)	
RMOM3	-0.0098	0.2261**	-0.137*	0.8001***	0.0423	0.1519*	0.0261	-0.1169	0.5235
T-Statistics	(-1.0329)	(2.5767)	(-1.9266)	(13.3389)	(0.7573)	(1.9528)	(0.6709)	(-0.434)	
VOLPRC	0.0267***	0.0536	-0.0607	-0.0060	-0.0422	-1.1252***	0.0564*	-0.0090	0.5927
T-Statistics	(3.7265)	(0.8096)	(-1.1321)	(-0.1332)	(-1.0005)	(-19.1805)	(1.9247)	(-0.0442)	
STDPRCVOL	0.0297***	0.112*	-0.0431	0.0557	-0.0536	-1.1646***	0.0391	0.3078	0.6007
T-Statistics	(4.0745)	(1.6656)	(-0.7911)	(1.2122)	(-1.2517)	(-19.5464)	(1.3133)	(1.4917)	
MEANABS	0.0257***	0.0928	-0.0109	0.0363	-0.0068	-1.1984***	0.0544*	-0.0427	0.6474
T-Statistics	(3.7553)	(1.4705)	(-0.2133)	(0.8404)	(-0.169)	(-21.4288)	(1.9465)	(-0.2207)	
Average									0.4738

Notes. This table reports the empirical results of Model 21. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The average adjusted R-squared of Model 21 is 0.4738. Four mispricing factors still cannot be well explained due to their statistically significant alpha values, MOM3 and RMOM1 also has a significant alpha. No factors have exposures to graphics.

Table A.26: Model 22

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	β_{CMOM1}	$\beta_{Electricity}$	$\beta_{Graphcis}$	Adj R-squared
MOM1	0.0359***	0.2864**	0.0373	-0.1144	-0.0234	2.1431***	-0.5908	0.0374
T-Statistics	(2.7147)	(2.3241)	(0.3663)	(-1.2689)	(-0.2794)	(2.9315)	(-1.4345)	
MOM2	0.0018	0.1712*	0.1477*	0.5636***	0.3516***	-0.1410	-0.2621	0.4064
T-Statistics	(0.1719)	(1.7336)	(1.8104)	(7.797)	(5.2327)	(-0.2406)	(-0.794)	
MOM3	0.0002	0.1451*	-0.2487***	0.8455***	0.1554***	0.1474	-0.0504	0.5560
T-Statistics	(0.022)	(1.6899)	(-3.5083)	(13.4608)	(2.6615)	(0.2894)	(-0.1756)	
RMOM1	0.0096	0.1087	0.1233**	0.1467***	0.6367***	-0.1721	0.1084	0.4977
T-Statistics	(1.1742)	(1.4329)	(1.9699)	(2.6441)	(12.3408)	(-0.3825)	(0.4278)	
RMOM2	0.0098	0.178**	0.1757***	0.4923***	0.1785***	-0.1309	-0.0616	0.3606
T-Statistics	(1.1207)	(2.1763)	(2.6014)	(8.2239)	(3.2074)	(-0.2697)	(-0.2254)	
RMOM3	-0.0084	0.2288***	-0.1781***	0.8063***	0.0551	0.5556	-0.1757	0.5210
T-Statistics	(-0.9565)	(2.7996)	(-2.6389)	(13.4833)	(0.9908)	(1.1459)	(-0.6432)	
VOLPRC	0.0347***	0.2809***	0.2854***	-0.0872	-0.0548	-0.7844	0.0931	0.0693
T-Statistics	(3.4724)	(3.023)	(3.7185)	(-1.2816)	(-0.8675)	(-1.4227)	(0.2999)	
STDPRCVOL	0.0353***	0.3358***	0.3108***	-0.0265	-0.0668	-0.4014	0.3816	0.0718
T-Statistics	(3.4493)	(3.5268)	(3.9532)	(-0.3804)	(-1.0314)	(-0.7106)	(1.1992)	
MEANABS	0.0328***	0.3353***	0.3559***	-0.0501	-0.0172	-0.3815	0.0278	0.0791
T-Statistics	(3.2202)	(3.54)	(4.55)	(-0.723)	(-0.2671)	(-0.6789)	(0.088)	
Average								0.2888

Notes. This table reports the empirical results of Model 22. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The average adjusted R-squared of Model 22 is 0.2888. Four mispricing factors still cannot be well explained due to their statistically significant alpha values. Only MOM1 has exposure to electricity. No factors have exposures to graphics.

Table A.27: Model 23

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	β_{CVOL}	$\beta_{Electricity}$	$\beta_{Graphcis}$	Adj R-squared
MOM1	0.0356***	0.2597**	-0.0143	-0.1161	-0.1722	2.1677***	-0.5984	0.0441
T-Statistics	(2.701)	(2.0943)	(-0.134)	(-1.5882)	(-1.4924)	(2.9855)	(-1.4579)	
MOM2	0.0048	0.1137	0.1187	0.7963***	-0.1247	-0.3851	-0.2696	0.3564
T-Statistics	(0.4394)	(1.0944)	(1.3242)	(13.0096)	(-1.2905)	(-0.6333)	(-0.7844)	
MOM3	0.0016	0.1396	-0.2263***	0.9393***	0.0635	0.0340	-0.0484	0.5466
T-Statistics	(0.1768)	(1.5939)	(-2.9938)	(18.1934)	(0.779)	(0.0663)	(-0.1669)	
RMOM1	0.0153	0.0517	0.1539*	0.5466***	0.0542	-0.6270	0.1073	0.2470
T-Statistics	(1.5352)	(0.5517)	(1.9026)	(9.8926)	(0.6215)	(-1.1421)	(0.3459)	
RMOM2	0.0114	0.1585*	0.178**	0.6061***	-0.0061	-0.2574	-0.0629	0.3390
T-Statistics	(1.2817)	(1.8864)	(2.4555)	(12.2427)	(-0.0783)	(-0.5234)	(-0.2262)	
RMOM3	-0.0078	0.2473***	-0.1342*	0.8303***	0.1436*	0.5098	-0.1696	0.5250
T-Statistics	(-0.8912)	(3.0088)	(-1.8926)	(17.1411)	(1.8783)	(1.0594)	(-0.6234)	
VOLPRC	0.0332***	0.0933	-0.0555	-0.0341	-1.1448***	-0.6927*	0.0422	0.5932
T-Statistics	(5.032)	(1.5036)	(-1.0366)	(-0.9325)	(-19.8295)	(-1.9065)	(0.2055)	
STDPRCVOL	0.0336***	0.1436**	-0.0405	0.0216	-1.1791***	-0.2995	0.3292	0.5991
T-Statistics	(5.0118)	(2.272)	(-0.7435)	(0.5801)	(-20.0559)	(-0.8096)	(1.5739)	
MEANABS	0.0315***	0.1316**	-0.0055	0.0324	-1.2167***	-0.3132	-0.0265	0.6451
T-Statistics	(4.9996)	(2.2163)	(-0.1067)	(0.9246)	(-22.0217)	(-0.9007)	(-0.1349)	
Average								0.4328

Notes. This table reports the empirical results of Model 23. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The average adjusted R-squared of Model 23 is 0.4328. Four mispricing factors still cannot be well explained due to their statistically significant alpha values. Only MOM1 and VOLPRC has exposure to electricity No factors have exposures to graphics.

Table A.28: Model 24

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	β_{CSTD}	$\beta_{Electricity}$	$\beta_{Graphcis}$	Adj R-squared
MOM1	0.0439***	0.3555***	0.0526	-0.1287*	-0.0816	2.1427***	-0.6053	0.0435
T-Statistics	(3.0563)	(2.7115)	(0.5159)	(-1.7732)	(-1.4288)	(2.9498)	(-1.474)	
MOM2	-0.0128	-0.0112	0.1209	0.7854***	0.1784***	-0.3535	-0.2321	0.3824
T-Statistics	(-1.0915)	(-0.104)	(1.4449)	(13.1956)	(3.8112)	(-0.5933)	(-0.6891)	
MOM3	-0.0163*	-0.0174	-0.28***	0.9428***	0.1789***	0.0744	-0.0192	0.5750
T-Statistics	(-1.6581)	(-0.1943)	(-4.0145)	(19.0038)	(4.5855)	(0.1498)	(-0.0683)	
RMOM1	0.0174	0.0604	0.1421*	0.551***	-0.0217	-0.6290	0.1010	0.2467
T-Statistics	(1.6043)	(0.6089)	(1.8421)	(10.0425)	(-0.5037)	(-1.1454)	(0.3254)	
RMOM2	0.0038	0.0969	0.1649**	0.605***	0.0766**	-0.2417	-0.0489	0.3475
T-Statistics	(0.3932)	(1.0982)	(2.4021)	(12.3924)	(1.9943)	(-0.4945)	(-0.1769)	
RMOM3	-0.0097	0.2082**	-0.1803***	0.8411***	0.0181	0.5202	-0.1727	0.5198
T-Statistics	(-1.0162)	(2.3841)	(-2.6539)	(17.4004)	(0.477)	(1.0751)	(-0.6315)	
VOLPRC	0.0197*	0.168*	0.2558***	-0.1231**	0.1451***	-0.7150	0.1194	0.1015
T-Statistics	(1.8465)	(1.7236)	(3.3737)	(-2.2811)	(3.4185)	(-1.3241)	(0.3912)	
STDPRCVOL	0.0217**	0.236**	0.2838***	-0.0699	0.1304***	-0.3266	0.4053	0.0951
T-Statistics	(1.9723)	(2.3522)	(3.6357)	(-1.2583)	(2.986)	(-0.5874)	(1.2897)	
MEANABS	0.0173	0.212**	0.3257***	-0.0622	0.153***	-0.3372	0.0554	0.1154
T-Statistics	(1.5989)	(2.1391)	(4.2242)	(-1.1338)	(3.5467)	(-0.6142)	(0.1784)	
Average								0.2697

Notes. This table reports the empirical results of Model 24. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The average adjusted R-squared of Model 24 is 0.2697. Three mispricing factors still cannot be well explained due to their statistically significant alpha values, MOM3 has a significant alpha as well. Only MOM1 has a exposure to electricity. No factors have exposures to graphics.

Table A.29: Model 25

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	β_{CMOM1}	β_{CVOL}	$\beta_{Electricity}$	$\beta_{Graphcis}$	Adj R-squared
MOM1	0.0358***	0.2577**	-0.0137	-0.1029	-0.0208	-0.1716	2.1529***	-0.5985	0.0412
T-Statistics	(2.7066)	(2.07)	(-0.1277)	(-1.1396)	(-0.2481)	(-1.4845)	(2.9506)	(-1.4559)	
MOM2	0.0017	0.1486	0.1075	0.5726***	0.3537***	-0.1352	-0.1333	-0.2682	0.4085
T-Statistics	(0.1591)	(1.4892)	(1.2511)	(7.9077)	(5.2725)	(-1.4588)	(-0.2278)	(-0.8138)	
MOM3	0.0003	0.1549*	-0.2312***	0.8416***	0.1545***	0.0589	0.1440	-0.0477	0.5553
T-Statistics	(0.0286)	(1.7815)	(-3.0873)	(13.3386)	(2.6432)	(0.7299)	(0.2825)	(-0.1663)	
RMOM1	0.0096	0.1146	0.1339**	0.1444***	0.6361***	0.0354	-0.1741	0.1100	0.4964
T-Statistics	(1.1771)	(1.4908)	(2.0227)	(2.5886)	(12.312)	(0.4961)	(-0.3864)	(0.4335)	
RMOM2	0.0098	0.1761**	0.1723**	0.4931***	0.1787***	-0.0114	-0.1302	-0.0621	0.3586
T-Statistics	(1.1176)	(2.1235)	(2.413)	(8.1932)	(3.2046)	(-0.1481)	(-0.2679)	(-0.2269)	
RMOM3	-0.0082	0.2525***	-0.1359*	0.7968***	0.0529	0.1421*	0.5475	-0.1693	0.5248
T-Statistics	(-0.9437)	(3.0651)	(-1.9152)	(13.3287)	(0.9548)	(1.8571)	(1.1337)	(-0.6224)	
VOLPRC	0.0335***	0.0896	-0.0543	-0.0106	-0.0371	-1.1437***	-0.7191**	0.0421	0.5929
T-Statistics	(5.0724)	(1.4409)	(-1.014)	(-0.2355)	(-0.8873)	(-19.799)	(-1.9719)	(0.2047)	
STDPRCVOL	0.0341***	0.1388**	-0.0390	0.0523	-0.0485	-1.1777***	-0.3341	0.3290	0.5995
T-Statistics	(5.0708)	(2.1923)	(-0.7155)	(1.1386)	(-1.1406)	(-20.0368)	(-0.9004)	(1.5737)	
MEANABS	0.0315***	0.1318**	-0.0055	0.0313	0.0017	-1.2168***	-0.3120	-0.0265	0.6439
T-Statistics	(4.9811)	(2.2105)	(-0.1075)	(0.7238)	(0.0413)	(-21.9813)	(-0.8928)	(-0.1346)	
Average									0.4690

Notes. This table reports the empirical results of Model 25. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The average adjusted R-squared of Model 25 is 0.4690. Four mispricing factors still cannot be well explained due to their statistically significant alpha values. Only MOM1 and VOLPRC has exposure to electricity No factors have exposures to graphics.

Table A.30: Model 26

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	β_{CMOM1}	β_{CSTD}	$\beta_{Electricity}$	$\beta_{Graphcis}$	Adj R-squared
MOM1	0.0439***	0.3542***	0.0527	-0.1243	-0.0070	-0.0809	2.1379***	-0.6052	0.0404
T-Statistics	(3.051)	(2.6793)	(0.5153)	(-1.376)	(-0.0825)	(-1.4012)	(2.9289)	(-1.4714)	
MOM2	-0.0127	0.0471	0.1195	0.5816***	0.3216***	0.1479***	-0.1314	-0.2358	0.4243
T-Statistics	(-1.1149)	(0.4509)	(1.4796)	(8.1459)	(4.8123)	(3.2411)	(-0.2276)	(-0.7251)	
MOM3	-0.0162*	0.0046	-0.2805***	0.8659***	0.1214**	0.1674***	0.1583	-0.0206	0.5799
T-Statistics	(-1.6606)	(0.0512)	(-4.0448)	(14.1279)	(2.116)	(4.2731)	(0.3194)	(-0.0737)	
RMOM1	0.0178**	0.1789**	0.1393**	0.1365**	0.6537***	-0.0837**	-0.1775	0.0935	0.5052
T-Statistics	(2.0207)	(2.212)	(2.2281)	(2.4717)	(12.6431)	(-2.3713)	(-0.3975)	(0.3716)	
RMOM2	0.0039	0.1270	0.1642**	0.4997***	0.1661***	0.0608	-0.1269	-0.0508	0.3638
T-Statistics	(0.4078)	(1.4483)	(2.4221)	(8.343)	(2.9636)	(1.5885)	(-0.2622)	(-0.1862)	
RMOM3	-0.0097	0.2177**	-0.1806***	0.8079***	0.0524	0.0132	0.5564	-0.1733	0.5196
T-Statistics	(-1.013)	(2.4756)	(-2.6566)	(13.4496)	(0.9322)	(0.3428)	(1.146)	(-0.6335)	
VOLPRC	0.0196*	0.1524	0.2562***	-0.0685	-0.0860	0.1532***	-0.7744	0.1204	0.1041
T-Statistics	(1.8447)	(1.5553)	(3.3834)	(-1.0241)	(-1.3729)	(3.5809)	(-1.4316)	(0.395)	
STDPRCVOL	0.0216**	0.2188**	0.2842***	-0.0095	-0.0952	0.1395***	-0.3923	0.4064	0.0986
T-Statistics	(1.9713)	(2.1697)	(3.6479)	(-0.1387)	(-1.4764)	(3.1679)	(-0.7048)	(1.2956)	
MEANABS	0.0173	0.203**	0.3259***	-0.0309	-0.0493	0.1577***	-0.3712	0.0559	0.1143
T-Statistics	(1.5953)	(2.0338)	(4.2241)	(-0.4538)	(-0.7721)	(3.6172)	(-0.6736)	(0.1801)	
Average									0.3056

Notes. This table reports the empirical results of Model 26. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The average adjusted R-squared of Model 26 is 0.3056. Three mispricing factors still cannot be well explained due to their statistically significant alpha values, MOM3 and RMOM1 has a significant alpha as well. Only MOM1 has a exposure to electricity. No factors have exposures to graphics.

Table A.31: Model 27

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	β_{CVOL}	β_{CSTD}	$\beta_{Electricity}$	$\beta_{Graphcis}$	Adj R-squared
MOM1	0.0454***	0.3348**	-0.0051	-0.1128	-0.2057*	-0.0987*	2.1486***	-0.6175	0.0501
T-Statistics	(3.1677)	(2.5518)	(-0.0475)	(-1.5472)	(-1.7634)	(-1.7099)	(2.9681)	(-1.5088)	
MOM2	-0.0124	-0.0178	0.1024	0.7905***	-0.0659	0.1729***	-0.3516	-0.2360	0.3813
T-Statistics	(-1.0472)	(-0.165)	(1.1642)	(13.1674)	(-0.6856)	(3.6383)	(-0.5896)	(-0.7)	
MOM3	-0.0172*	-0.0045	-0.2441***	0.9329***	0.1280	0.1896***	0.0707	-0.0115	0.5772
T-Statistics	(-1.7561)	(-0.0503)	(-3.3402)	(18.7074)	(1.6028)	(4.8014)	(0.1428)	(-0.0412)	
RMOM1	0.0170	0.0652	0.1556*	0.5472***	0.0482	-0.0177	-0.6304	0.1039	0.2449
T-Statistics	(1.5667)	(0.6545)	(1.9181)	(9.8863)	(0.5438)	(-0.4045)	(-1.1466)	(0.3342)	
RMOM2	0.0036	0.0989	0.1706**	0.6035***	0.0205	0.0783**	-0.2423	-0.0477	0.3455
T-Statistics	(0.3762)	(1.1154)	(2.3627)	(12.2458)	(0.2599)	(2.0066)	(-0.495)	(-0.1722)	
RMOM3	-0.0109	0.2238**	-0.1371*	0.8292***	0.1542**	0.0310	0.5158	-0.1635	0.5244
T-Statistics	(-1.1392)	(2.5641)	(-1.93)	(17.1038)	(1.9861)	(0.8065)	(1.0711)	(-0.6007)	
VOLPRC	0.0281***	0.0543	-0.0603	-0.0358	-1.1273***	0.0513*	-0.6827*	0.0522	0.5960
T-Statistics	(3.9149)	(0.8278)	(-1.1291)	(-0.9827)	(-19.3174)	(1.7766)	(-1.8855)	(0.2549)	
STDPRCVOL	0.0303***	0.1183*	-0.0437	0.0205	-1.1678***	0.0333	-0.2931	0.3356	0.5994
T-Statistics	(4.1414)	(1.7644)	(-0.8002)	(0.5501)	(-19.5892)	(1.1293)	(-0.7924)	(1.6049)	
MEANABS	0.0262***	0.0911	-0.0105	0.0306	-1.1986***	0.0533*	-0.3028	-0.0162	0.6482
T-Statistics	(3.8275)	(1.4521)	(-0.2051)	(0.877)	(-21.4804)	(1.9311)	(-0.8747)	(-0.0825)	
Average									0.4408

Notes. This table reports the empirical results of Model 27. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The average adjusted R-squared of Model 27 is 0.4408. Four mispricing factors still cannot be well explained due to their statistically significant alpha values, MOM3 becomes significant. Only MOM1 and VOLPRC has exposure to electricity No factors have exposures to graphics.

Table A.32: Model 28

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	β_{CMOM1}	β_{CVOL}	β_{CSTD}	$\beta_{Electricity}$	$\beta_{Graphcis}$	Adj R-squared
MOM1	0.0454***	0.3347**	-0.0051	-0.1126	-0.0002	-0.2057*	-0.0987*	2.1484***	-0.6175	0.0470
T-Statistics	(3.1624)	(2.5315)	(-0.0474)	(-1.2484)	(-0.0021)	(-1.7586)	(-1.6889)	(2.9535)	(-1.5063)	
MOM2	-0.0120	0.0389	0.0952	0.5864***	0.3244***	-0.0865	0.1405***	-0.1269	-0.2410	0.4241
T-Statistics	(-1.0562)	(0.371)	(1.1219)	(8.1905)	(4.849)	(-0.9322)	(3.0304)	(-0.2199)	(-0.7408)	
MOM3	-0.0171*	0.0160	-0.2467***	0.8591***	0.1174**	0.1205	0.1778***	0.1520	-0.0133	0.5816
T-Statistics	(-1.7529)	(0.1783)	(-3.393)	(14.0093)	(2.0488)	(1.5156)	(4.4798)	(0.3076)	(-0.0479)	
RMOM1	0.0177**	0.1795**	0.1411**	0.1362**	0.6535***	0.0066	-0.0832**	-0.1778	0.0939	0.5036
T-Statistics	(2.0082)	(2.2083)	(2.1454)	(2.4544)	(12.6049)	(0.0918)	(-2.3159)	(-0.3976)	(0.3725)	
RMOM2	0.0038	0.1279	0.1669**	0.4991***	0.1658***	0.0100	0.0617	-0.1274	-0.0502	0.3617
T-Statistics	(0.3987)	(1.4515)	(2.3407)	(8.2978)	(2.9498)	(0.1276)	(1.5841)	(-0.2628)	(-0.1837)	
RMOM3	-0.0108	0.2321***	-0.1382*	0.7994***	0.0474	0.1511*	0.0262	0.5486	-0.1643	0.5240
T-Statistics	(-1.1335)	(2.6413)	(-1.9435)	(13.3327)	(0.8463)	(1.9442)	(0.6753)	(1.1351)	(-0.603)	
VOLPRC	0.028***	0.0458	-0.0592	-0.0051	-0.0488	-1.1242***	0.0562*	-0.7165**	0.0529	0.5965
T-Statistics	(3.9101)	(0.6937)	(-1.1093)	(-0.1133)	(-1.1604)	(-19.2549)	(1.9267)	(-1.9737)	(0.2587)	
STDPRCVOL	0.0303***	0.1083	-0.0424	0.0561	-0.0567	-1.1642***	0.0390	-0.3323	0.3365	0.6004
T-Statistics	(4.1385)	(1.6083)	(-0.778)	(1.2211)	(-1.3192)	(-19.5319)	(1.3096)	(-0.8967)	(1.611)	
MEANABS	0.0262***	0.0894	-0.0103	0.0367	-0.0097	-1.198***	0.0543*	-0.3095	-0.0160	0.6471
T-Statistics	(3.82)	(1.414)	(-0.2005)	(0.8494)	(-0.2398)	(-21.4134)	(1.9426)	(-0.8898)	(-0.0816)	
Average										0.4762

Notes. This table reports the empirical results of Model 28. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The average adjusted R-squared of Model 28 is 0.4762. Four mispricing factors still cannot be well explained due to their statistically significant alpha values, MOM3 and RMOM1 become significant. Only MOM1 and VOLPRC has exposure to electricity No factors have exposures to graphics.

Table A.33: Summary of 28 Models				
Model	Average Adj R-squared	Number of Significant α	Number of Significant exposures to $Electricity$	Number of Significant exposures to $Graphics$
1	0.2973	5	-	-
2	0.4278	4	-	-
3	0.2783	4	-	-
4	0.4674	4	-	-
5	0.3048	5	-	-
6	0.4391	5	-	-
7	0.4746	6	-	-
8	0.2896	4	1	-
9	0.4333	4	2	-
10	0.2705	4	1	-
11*	0.4694	4	2	-
12	0.3063	5	1	-
13	0.4413	5	2	-
14	0.4766	6	2	-
15	0.2868	4	-	0
16	0.4301	4	-	0
17	0.2675	4	-	0
18	0.4666	4	-	0
19	0.3036	4	-	0
20	0.4382	5	-	0
21	0.4738	6	-	0
22	0.2888	4	1	0
23	0.4328	4	2	0
24	0.2697	4	1	0
25	0.4690	4	2	0
26	0.3056	5	1	0
27	0.4408	5	2	0
28	0.4762	6	2	0

Notes. This table summarizes the average adjusted R-squared, number of significant α (out of 9), number of significant exposures to $Electricity$ and $Graphics$ (out of 9) for each of our 28 adjusted model, respectively. The – symbol indicates that no corresponding independent factor exists in this model. The model number with * symbol illustrates the best adjusted model among 28 models.

We test whether nine dominant factors can be better explained by conducting all the combinations of three different mispricing categories (momentum, volume and volatility) and two cryptocurrency fundamental factors (electricity and computer power) as additional independent factors that is added to origin three factor model of Liu et al. (2019), we establish that the explanatory power of new adjusted model No.11, which incorporates mispriced momentum and volume factor as well as electricity factor, provides the best explanatory power as it has the highest adjusted R-squared and minimum numbers of significant α values for nine dominant factors. To illustrate, we set the selection criteria as follow: we first determine the adjusted model with minimum numbers of significant α values, because increasing numbers of significant α values indicate deterioration as appearance of more abnormal returns which cannot be captured by model. Second, we pick the one with highest adjusted R-squared, since adjusted R-squared measures the proportion of the variation that can be captured by corresponding model, and adjusted R-squared also penalize for adding any uncorrelated independent factors that do not contribution to the fitness of the model, which mitigates the risk of overfitting the model when we construct the 28 models. According to Table A.33, Model No. 11 has the highest adjusted R-squared of 0.4694 and has four mispricing factors, we therefore assume this model is the best adjusted model in our case.

Table A.33 also demonstrate the numbers of significant exposures to $Electricity$ and $Graphics$ (proxy for computer power) as shown in the last two columns. We propose that cryptocurrencies may have no correlation with computer power, since none of 28 models have a significant exposure to this factor. Similarly, from the perspective of $Electricity$, there are only one to two dominant factors are exposed to $Electricity$, indicating a weekly relationship with cryptocurrencies. Although this finding is complied with Liu et al. (2020), further study is needed to dive deeper into this area.