On the (Almost) Stochastic Dominance of Cryptocurrency Factor Portfolios & Implications for Cryptocurrency Asset Pricing*

Weihao Han † David Newton ‡ Emmanouil Platanakis § Charles Sutcliffe ¶
Xiaoxia Ye ‖

European Financial Management, Forthcoming

Abstract

Cryptocurrency returns are highly non-normal, casting doubt on the standard performance metrics. We apply almost stochastic dominance (ASD), which does not require any assumption about the return distribution or degree of risk aversion. From 29 long-short cryptocurrency factor portfolios, we find eight that dominate our four benchmarks. Their returns cannot be fully explained by the three-factor coin model of Liu et al. (2022). So we develop a new three-factor model where momentum is replaced by a mispricing factor based on size and risk-adjusted momentum, which significantly improves pricing performance.

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

JEL Classification: G11, G12

*For helpful comments, we thank Adelphe Ekponon (Liverpool), Chris Florackis (Liverpool), Jayant Rao (Claremont), Richard T. Thakor (Minnesota & MIT), Yang Yang (Tsinghua), Peter Zimmerman (Fed), Victor DeMiguel (LBS), and conference and seminar participants at University of Bath, University of York, Aston University, University of Southampton, 2021 Southwestern Finance Association Annual Meeting, 28th Annual Global Finance Conference, 2021 Annual Meeting of the European Financial Management Association, 19th Annual Conference of the Hellenic Finance and Accounting Association, 2021 Annual Conference of the British Accounting and Finance Association, 2021 The Finance Symposium, 2021 Annual Conference of the Financial Engineering & Banking Society, and 2021 World Finance Conference, and 2022 Entrepreneurial Finance Association Annual Meeting. All errors are our own. The paper was previously circulated under the title 'Cryptocurrency Factor Portfolios: Performance, Decomposition and Pricing Models'.

†weihao.han@abdn.ac.uk, Business School, University of Aberdeen, Edward Wright Building, Aberdeen, AB24 3QY, UK; WH587@bath.ac.uk, School of Management, University of Bath, Claverton Down, Bath, BA2 7AY, UK.

‡D.P.Newton@bath.ac.uk, School of Management, University of Bath, Claverton Down, Bath, BA2 7AY, UK, Tel: +44(0) 1225 386890, *Corresponding Author*

§E.Platanakis@bath.ac.uk, School of Management, University of Bath, Claverton Down, Bath, BA2 7AY, UK. Tel: +44(0) 1274 235311

¶c.m.s.sutcliffe@rdg.ac.uk, ICMA Centre, Henley Business School, University of Reading, PO Box 242, Reading RG6 6BA, UK, Tel +44(0) 118 378 6117

‖x.ye@exeter.ac.uk, Streatham Court, University of Exeter, Rennes Drive, Exeter, EX4 4PU, UK

1 Introduction

Cryptocurrencies are built on blockchain technology (Abadi and Brunnermeier, 2018; Biais et al., 2019) which permits transactions without central supervision. Since Bitcoin, the most famous cryptocurrency, 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). As attention to cryptocurrencies rises, 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 financial assets, it is vital to understand their characteristics for several reasons. First, to find an appropriate performance metric for comparing cryptocurrencies with other financial classes. Second, to investigate whether factors can be used to form out-performing cryptocurrency portfolios. Third, to determine whether the cross-sectional variation in returns on out-performing cryptocurrency portfolios can be captured by a cryptocurrency pricing model.

A problem in this area is that the empirical distributions of cryptocurrency returns are highly non-normal, raising doubts about the metrics for pricing and performance measurement. Specifically, due to speculation and excessive active trading carried out by investors, the probability distribution of cryptocurrency returns is depicted by asymmetric and leptokurtic behaviour with fat tails induced by event risks, such as sudden price swing and hacks (Phillip et al., 2018; Borri, 2019). Consequently, investors may suffer from the overestimated risks and underestimated returns of cryptocurrencies if investors only rely on two moments — mean and variance — since the occurrence of events on right tails is more pronounced than that on their left tails (Nguyen et al., 2020). To circumvent this, we use almost stochastic dominance (ASD) (Leshno and Levy, 2002; Levy, 2006). ASD has several notable characteristics that are particularly appropriate for cryptocurrencies. First, unlike the mean-variance approach, ASD does not rely on the first two moments (e.g., mean and variance) and assumptions of return distributions when evaluating two uncertain prospects because it directly assesses the empirical cumulative distribution functions of these prospects, which also considers the higher moments. Thus, ASD has a natural advantage to tackle the assets with highly skewed and leptokurtic distributions in comparison to the potentially misleading mean-variance method (Farinelli et al., 2008; Bali et al., 2013), and produce unbiased decisions. Second, ASD is a non-parametric approach and does not require a specific form of utility functions of investors (e.g., quadratic utility function) (Holcblat et al., 2022). These properties relax the conditions of the mean-variance approach that a finite set of parameters must be pre-determined, and allows a more complex form of utility functions (with different risk preferences) rather than only relying on a combination of the first two moments and the coefficient of risk aversion. Third, ASD allows for the pathological utility function (i.e., investors with such utility functions are indifferent between a small and large amount of payoffs), which is superior to ordinary stochastic dominance and mean-variance approach (Bali et al., 2009). Meanwhile, ASD can also draw conclusions from the case that one asset has a higher expected return along with higher variance than those of another asset, whereas the mean-variance approach does not[1]. Therefore, ASD is a proper method to measure the performance of cryptocurrencies against benchmarks since cryptocurrencies are deemed as a highly fluctuated asset but with potentially high returns.

We examine cryptocurrency portfolios based on different risk factors for the 2,353 cryptocurrencies with a minimum market capitalization of $1 million, accounting for over 90% of the total market capitalization. In forming factor portfolios, we use each cryptocurrency's open price, close price, volume and market capitalization, which comprise the only public information for each cryptocurrency. Following Feng et al. (2020) and Liu et al. (2022), we classify these cryptocurrencies into four categories: size, momentum, volume and volatility, which we then sub-divide into 29 factor portfolios to study whether cryptocurrency returns respond to the same factors as shares, and examine each factor's relative performance against four benchmarks.

We employ almost first-order stochastic dominance (AFSD) and almost second-order stochastic dominance (ASSD) to compare relative performance over five different horizons for each factor portfolio against the S&P 500, US T-bonds, US T-bills and Bitcoin. Using AFSD, we find that eight of the 29 factors are dominant against our four benchmarks, demonstrating outperformance for investors, irrespective of their level of risk aversion. We then use the coin three factor model of Liu et al. (2022) to explain returns on our eight dominant factor portfolios. We find that seven of these dominant factor portfolios have positive alphas, indicating abnormal positive returns, which implies mispricing by the factor model.

Since portfolio managers use the capital asset pricing model (CAPM) and a range of multifactor models to compute expected returns (Fischer and Wermers, 2012; Ang, 2014; Ahmed et al., 2019), understanding which pricing model provides more the accurate estimates is im-

[1]We document a straightforward example with discussion in Section 4.

portant for both academics and practitioners. For equities, Stambaugh and Yuan (2017) note the proliferation of studies identifying anomalies that violate the standard (pre-cryptocurrency) three-factor model and how, with parsimony a virtue, these anomalies are only rarely included as additional factors. They press this conundrum in the following way: "given the proliferation of anomalies, however, the need for an alternative factor model that can accommodate more anomalies has become increasingly clear". To tackle this mispricing issue, Hou et al. (2015) constructed two factors from the set of eleven anomalies, and combined the market and size factors into a single factor in a four-factor model for equities.

Since cryptocurrencies lack pricing models that accommodate cryptocurrency anomalies, this motivated us to examine whether combining the returns of factor models that generate anomalies into a single extra factor – the mispricing factor – in the coin market three-factor pricing model for cryptocurrencies leads to superior performance. Inspired by Stambaugh and Yuan (2017), we form a mispricing factor by calculating the equally weighted average of the returns on those factor portfolios that generate anomalies, to approximate the average anomalous effect of these factor portfolios. When we do this, we find that the number of significant alphas drops substantially, and the R^2 values increase.

Liu and Tsyvinski (2020), among others, document the importance of network factors and investor attention in explaining and forecasting returns of the major cryptocurrencies. Thus, we also include cryptocurrency-related fundamental factors, such as network and investor attention, in the coin market three-factor model, along with our mispricing factor. Using seven performance metrics that are widely used in the empirical asset pricing literature (Fama and French, 1993, 2015, 2017; Stambaugh and Yuan, 2017; Ahmed et al., 2019) to evaluate the performance of the coin three-factor model plus the seven combinations of the mispricing, attention and network factors, we find that the best results are achieved when the mispricing and network factors are included. This gives us an augmented coin factor model with five factors. To check that all five factors are needed, we apply spanning regression to identify redundant factors, and conclude that the momentum and network factors can be removed from the augmented model.

Next, we investigate the composition of our mispricing factor. This is a combination of seven dominant factor portfolios based on size, momentum, risk-adjusted momentum and return volatility We again apply spanning regression, and discover that the momentum and volatility factors are redundant, leaving size and risk-adjusted momentum. This gives us our three-factor coin factor model which relies on the coin market index, coin size, and our mispricing factor based on the size and risk-adjusted momentum factors.

This paper is the first to use the ASD approach when examining the relative performance of cryptocurrency factor portfolios. This addresses the non-normality of cryptocurrency returns, and AFSD does not require any assumption about investor's risk aversion. We are unaware of any literature that focuses on cryptocurrency factor portfolio performance augmented pricing models. Liu et al. (2022) were the first to study the cross-sectional returns of a large number of cryptocurrencies from an asset pricing perspective. Our research has some similarities, but with important differences. Liu et al. (2022) find risk factors that capture variations in the cross-sectional returns of factor portfolios, and develop a cryptocurrency three-factor model. In contrast, we focus on factor portfolio performance. We evaluate the investment value of cryptocurrencies by comparing their performance with that of different asset classes using a non-parametric approach. Although influential studies have explored the performance of several popular asset pricing models (e.g., Fama and French, 2016; Hou et al., 2017), none accounts for sampling and model misspecification uncertainty due to the lack of a formal statistical procedure (Kan and Robotti, 2009; Harvey and Liu, 2021), and we rectify this omission by investigating the metrics related to alphas and model variations. We investigate the ability of a mispricing factor to explain returns on cryptocurrency factor portfolios by incorporating it into a new three-factor coin pricing model. Thus, we are the first to study the performance of cryptocurrency factors, along with constructing a model to capture the variation in returns of the dominant factor strategies.

For robustness and completeness, we present eight additional findings in Section A13 of the online appendix. First, we re-evaluate the empirical critical values for AFSD and ASSD proposed by Levy et al. (2010). Second, to eliminate the concern that shorting is expensive or unavailable for most of the coins, we evaluate the performance of our augmented model by regressing our eight dominant long-short factor portfolios shorting just Bitcoin, on our augmented model[2]. Third, we examine whether the coin market three factor model of Liu et al. (2022) and our augmented model (the coin market three-factor model incorporating a mispricing factor) capture the variation in returns of the 21 non-dominant factor portfolios. Fourth, we explore whether well-known equity pricing models can explain the cryptocurrency anomalies indicated

[2]Shorting Bitcoin can be effected by selling derivatives contracts. The Chicago Mercantile Exchange, Bakkt (part of ICE), Deribit, Binance, FTX, Quedex, Bitmex, and Bitfinex trade futures and options on Bitcoin; and Kraken and Poloniex trade futures on Bitcoin. Investors can also trade Bitcoin contracts for difference on IG Index, eToro and Plus500; or bet against Bitcoin on Predictious. Futures and options on other cryptocurrencies are also available

by our eight dominant factor portfolios. Fifth, we add the mispricing factor to coin market one and two-factor models. Sixth, we investigate the effect of electricity on the performance of our augmented pricing model. Seventh, using ASD we investigate whether the long and short legs have different effects on the performance of our eight dominant factor portfolios. Eighth, we test the long leg of our eight dominant factor portfolios against three equity benchmarks (i.e., equity portfolios based on size, momentum and BE/ME (book-to-market ratio).

This paper is organized as follows. Section 2 discusses the related literature. Section 3 describes our data and provides summary statistics. Section 4 presents the methodology of the ASD approach. Section 5 describes the formation of the factor portfolios, with their summary statistics. Section 6 evaluates the empirical results using ASD. In Section 6.3, using spanning regression, we develop a new three-factor model featuring a mispricing factor with better performance than existing models. Section 8 explores the driving force behind the pricing power of the proposed mispricing factor. Section 9 concludes the paper.

2 Related Literature

The academic finance literature on the application of blockchain has developed rapidly in recent years, especially in the areas of ethics, initial coin offerings (ICOs), token-weighted Crowdsourcing, and analysis of the most popular coins (Foley et al., 2019; Gan et al., 2020; Chod et al., 2020; Tsoukalas and Falk, 2020; Liu et al., 2021a; Cachon et al., 2021; Gan et al., 2021; Cachon et al., 2021; Gan et al., 2021; Benhaim et al., 2021). Although numerous papers have studied cryptocurrencies, most focus on the major cryptocurrencies, especially Bitcoin (e.g., Qiu et al., 2021; Atsalakis et al., 2019). Only a limited literature explores the factors that influence cryptocurrency returns, and even fewer focus on the performance of cryptocurrency factor portfolios. Borri (2019) and Liu and Tsyvinski (2020) study the relationship between popular cryptocurrencies, finding exposure to only cryptocurrency-related factors. A coin market three-factor pricing model for cryptocurrencies that captures much of the cross-sectional variation in a range of cryptocurrency factors is presented by Liu et al. (2022). Similarly, Liu et al. (2021b) find that information regarding the number of new addresses is valuable to the cryptocurrency market, where they find a negative relationship between price-to-new address ratios and future cryptocurrency returns.

Our paper is related to the literature that examines financial asset performance using ASD.

Levy and Levy (2019) apply stochastic dominance to compare the performance of different portfolios, and find that US stocks dominate US bonds. Other papers (Board and Sutcliffe, 1994; Post, 2003; Bali et al., 2013) apply stochastic dominance to examine the performance of hedge funds, relative to benchmarks. This literature evaluates equity, bond and hedge fund performance using a non-parametric approach. In addition, a series of studies have considered ASD from a methodological perspective (Post et al., 2018; Arvanitis et al., 2020; Liesiö et al., 2020; Lok and Tabri, 2021, among others). Our research is also related to the literature that explores asset pricing models and mispricing factors. There is a vast literature on equity asset pricing models, and a list of possible equity risk factors has been assembled by both academics and practitioners (Rapach et al., 2009; Zhou and Zhu, 2012; Kan et al., 2013; Han et al., 2013; Huang et al., 2014; Neely et al., 2014; Hou et al., 2015; Stambaugh and Yuan, 2017; Barillas and Shanken, 2018; Huang et al., 2020; Dong et al., 2022; Han et al., 2022).

Liu and Tsyvinski (2020) examine the relationship between risk and return for three mainstream cryptocurrencies (Bitcoin, Ripple and Ethereum). They find little or no evidence that cryptocurrencies have exposure to the Fama-French factors, major currencies, precious metal and macroeconomic factors. However, these three cryptocurrencies do have exposure to crypto-related factors such as cryptocurrency momentum, investor attention and the cost of mining. Their findings provide crucial information for selecting potential explanatory variables when constructing a cryptocurrency asset pricing model.

3 Data

We collected cryptocurrency data via a free application programming interface (API) from Coingecko.com, which is a source of cryptocurrency prices, volumes and market capitalizations. Coingecko.com aggregates information from over 400 major cryptocurrency exchanges on the opening price, closing price, volume and market capitalization. A cryptocurrency must meet certain criteria to be listed on this website, such as trading on a public exchange with an API which shows closing prices and non-zero trading volume during the previous 24 hours. Coingecko.com includes both defunct and active cryptocurrencies, which mitigates survivorship bias. We analyse all listed cryptocurrencies with a market capitalization larger than \$1 million on a daily basis during the sample period. Because data on trading volume first became available in the last week of 2013, we use cryptocurrency data from the beginning of 2014. After filtering, we analyse data for 2,353 cryptocurrencies over the period 1st January 2014 to 30th June 2021. The market capitalization of these cryptocurrencies accounts for over 90% of total cryptocurrency capitalization on 30th June 2021. We also use data for the S&P 500 and 10-year US T-bonds from CRSP, and the risk-free rate from Kenneth French's website[3].

To gain a better insight into cryptocurrency pricing models and factor portfolios, we construct a cryptocurrency market index using data on 2,353 cryptocurrencies. First, we calculate the daily log returns across the sample period for each cryptocurrency and allocate market capitalization weights to each asset every day. Then we sum these market capitalization weighted returns to obtain the daily returns on our coin market index (CMKT). The purpose of constructing CMKT is to help build a cryptocurrency pricing model. The summary statistics of the weekly returns of Bitcoin, CMKT, and the three other asset classes we use as benchmarks in our analysis, are in Table 1. The average weekly return on Bitcoin is 0.0101, which is an order of magnitude higher than the average return on the S&P 500 of 0.0025, 0.0001 for T-bills and 0.0008 for T-bonds. However, Bitcoin's risk is also much larger than for equities, bills and bonds. Bitcoin returns are negatively skewed, as are S&P 500 returns; whereas T-bill and T-bond returns are positively skewed. The kurtosis of Bitcoin, CMKT, S&P 500 and T-bond returns is higher than for the normal distribution, which indicates that these distributions are leptokurtic. The Jarque-Bera (J-B) test statistics and corresponding p-values indicate that these distributions are all highly non-normal. Therefore, comparisons of risk-adjusted returns across asset classes using standard performance measures such as the Sharpe ratio (Sharpe, 1966) are unreliable.

[Table 1 insert about here]

To construct cryptocurrency factor models, we seek additional explanatory variables. Numerous studies document network factors contributing to the valuation of cryptocurrencies (Pagnotta and Buraschi, 2018; Biais et al., 2020; Cong et al., 2021). Among network factors, the number of users plays a crucial role in explaining returns on cryptocurrencies since user adoption of cryptocurrencies provides a positive network externality. We use four metrics to proxy for network factors . They are the number of wallet users, the number of active addresses, the number of transactions and the number of payments. The data on wallet users was collected from Blockchain.info, and the numbers of active addresses, transactions, and payments

[3] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

were obtained from Coinmetrics.io. A growing literature on cryptocurrencies finds that investor attention (approximated by Tweet counts of a key word) predicts cryptocurrency returns (Liu and Tsyvinski, 2020; Sockin and Xiong, 2020; Cong et al., 2021). We use tweet counts for the key word 'blockchain' as a proxy for investor attention as it has been proved to have predictive power for returns.

4 Methodology

We test the performance of cryptocurrencies against four benchmarks: S&P 500, 10-year US T-bonds, 30-day US T-bills and Bitcoin. Since the distributions of cryptocurrencies are non-normal, the usual performance metrics based on the normal distribution are problematic, and we apply ASD, which does not require a parametric specification of investor preferences or the assumption of a normal distribution.

4.1 Unsuitability of the Mean-Variance Approach

Although the mean-variance (MV) approach, which is a cornerstone of modern portfolio theory, has been widely employed in both academia and industry, a number of studies document that stochastic dominance (SD) is superior to mean-variance (Malavasi et al., 2021; Gandhi and Saunders, 1981). MV analysis relies on returns following a normal distribution . However, there is a substantial literature indicating that this is not the case (Aharony and Loeb, 1977; Yitzhaki, 1982; Gotoh and Konno, 2000; Bali et al., 2009). First, SD does not assume returns have a normal distribution, and so does not require estimates of its parameters. Second, SD uses all the individual observations in the dataset, while MV uses only the first and second moments of returns. Finally, SD only assumes that investors prefer more to less when outcomes have the same probability (Gandhi and Saunders, 1981).

Leshno and Levy (2002) note that the classical MV decision rule can fail to show dominance between two portfolios when almost all investors would choose one portfolio over another. The few investors who fail to recognise dominance have extreme utility functions. To illustrate, consider two portfolios, H and L:

$$H : \mu_H = 1,000\%, \sigma_H = 5.1\%$$

$$L : \mu_L = 1\%, \sigma_L = 5\%$$

where H and L represent portfolios with high and low expected returns, respectively. The returns on portfolios H and L are μ_H and μ_L respectively, and the standard deviations are σ_H and σ_L. If portfolio H dominates portfolio L by MV, 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 (1,000 times) but with only a slightly higher standard deviation (0.1 percent). Most investors would surely choose portfolio H over portfolio L because the decrease in expected utility due to the slightly higher risk is much less than the increase in expected utility from the much higher expected return. Nonetheless, MV fails to identify any dominance.

4.2 Stochastic Dominance

Stochastic dominance provides an alternative perspective to MV when comparing the performance of two assets. Following Leshno and Levy (2002), first-order stochastic dominance (FSD) and second-order stochastic dominance (SSD) are defined as follows.

First-Order Stochastic Dominance. Suppose there are two risky portfolios, H and L, and the cumulative return distributions 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 one r.

Second-Order Stochastic Dominance. Suppose there are two risky portfolios, H and L. H represents a portfolio with a high expected return, and L represents a portfolio with a low expected return. The cumulative returns distributions 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 one r.

The key difference between FSD and SSD is what they assume about investors' utility functions (Daskalaki et al., 2017). FSD only requires that investors prefer more to less (mathematically, $\mu' > 0$, where μ is the utility function), and makes no assumption about their attitude towards risk. SSD also assumes that investors are risk averse, which implies a concave utility function (mathematically, $\mu' > 0$ and $\mu'' < 0$). Therefore, SSD finds more dominance relationships than FSD.

4.2.1 Almost First-Order Stochastic Dominance (AFSD)

Our numerical example above in Section 4.1 demonstrated a lack of MV dominance which requires investors to have an extreme or pathological utility function. Almost first-order stochastic dominance (AFSD) addresses the problem of pathological utility functions by excluding a few extreme utility functions, and examining whether a small violation of FSD can be 'ignored' (Leshno and Levy, 2002). AFSD exists when one distribution is 'close to' a distribution that dominates another distribution in the classical sense of FSD.

AFSD relies on the concept of a violation area. Figure 1 plots the cumulative distributions of portfolios H and L, where the plot for H lies below that for L, except for the shaded area denoted M. So there is no FSD in this case. When considering whether portfolio H (solid line) dominates L (dashed line) by AFSD, the area of the cumulative distribution of H that is above the cumulative distribution of L is called the violation area (denoted by M in Figure 1).

[Figure 1 insert about here]

According to Leshno and Levy (2002), the violation area M may be defined as $\int_{r_1}^{r_2}[F_H(s) - F_L(s)]ds$, where the FSD violation range is given by:

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

where r_1 and r_2 are the bounds of the range where portfolio H has a higher cumulative distribution function (CDF) value than portfolio L. The term ε_1 (the ratio of the violation area to the total area of difference) 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 1). According to Equation 2, ε_1 is defined as the area M in Figure 1 divided by the total absolute area enclosed between F_H and F_L (area M+N in Figure 1). It is clear that FSD exists if $\varepsilon_1 = 0$, which implies no violation area. 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 an empirical test to set the minimum tolerance, and propose that a violation can be ignored if ε_1 is smaller than, or equal to, the critical ε_1^* value of 5.9%. As the investment horizon lengthens, Leshno and Levy (2002) show that the value of ε_1 required for investors with pathological utility functions to recognise FSD becomes smaller.

4.2.2 Almost Second-Order Stochastic Dominance (ASSD)

Similar to AFSD, almost second-order stochastic dominance (ASSD) may exist when there is only a small violation of SSD. Provided the area under the CDF from minus infinity to r is the same or lower for H than for L for every value of r; and at some point is lower, then H SSD L. Therefore, unlike FSD, SSD permits the CDFs to cross several times. This is illustrated in Figure 2, where area A equals area B. If area C did not exist, H SSD L, but the presence of area C violates SSD. The range of the SSD violation area (area C in Figure 2) may be defined as:

$$R_2(F_H, F_L) = \{s \in R_1(F_H, F_L) : \int_0^r [F_L(s) - F_H(s)]\, ds < 0\} \tag{3}$$

The empirical ε_2 (the ratio of the violation area to total area difference) is defined as:

$$\varepsilon_2 = \frac{\int_{R_2} [F_H(s) - F_L(s)]\, ds}{\int_{min}^{max} |F_H(s) - F_L(s)|\, ds} \tag{4}$$

where ε_2 is the violation area (area C in Figure 2) divided by the total absolute area enclosed between F_H and F_L, i.e., $C/(A + B + C + D)$. Levy et al. (2010) suggest that the threshold value ε_2^* of ASSD is 3.2%, which is the minimum tolerance for most investors. Hence, if ε_2 is smaller than or equal to 3.2%, ASSD exists.

[Figure 2 insert about here]

5 Portfolio Formation

To investigate anomalies in cryptocurrency returns, we build zero-investment long-short portfolios based on the factors compiled by Liu et al. (2022) and Feng et al. (2020) that can be constructed using the available information. We identify four main factors — size, momentum, volume and volatility, which we divide into 29 the zero-investment long-short factor portfolios which are listed in Table 2.

To form the 29 factor portfolios, each week we sort the 2,353 individual cryptocurrencies into quintiles in ascending order of the factor under consideration, and then we track the return on each portfolio in the following week. The weekly portfolio returns are the market capitalization-weighted averages of the individual cryptocurrency returns, and we calculate the excess mean return over the risk-free rate of each quintile portfolio for each factor portfolio. We then compute the excess return on a long-short strategy based on the difference between the fifth and first quintiles (fifth quintile minus first quintile). For the long-short strategies that produce negative returns, we use the first quintile minus the fifth quintile. In the following sub-sections, we explain the factor portfolios and their mean excess returns in detail. (see Table 3).

[Table 2 insert about here]

5.1 Size Related Portfolios

The size factor portfolios are constructed based on market capitalization, closing price, and age factors. Panel A of Table 3 has the expected excess return for each quintile portfolio for each of the three size factors and the long-short strategy. The negative signs before the values of the long-short strategies are not important because a positive return could be achieved by reversing the long-short strategy.

The AGE long-short portfolio generates the highest absolute return of 0.0272, while the $LPRC$ portfolio has an absolute return of 0.0215 on the long-short strategy, and is the worst performing of the portfolios in the size group. Compared to the mean returns in Table 1, the long-short portfolios have much higher expected returns than $CMKT$, Bitcoin, and the other three benchmarks.

5.2 Momentum Related Portfolios

We formed the momentum factor portfolios based on 1, 2, 3, 4, 8 and 26 week momentum and risk-adjusted momentum (based on the Sharpe ratio) factors. We use risk-adjusted momentum strategies as our factors because portfolios based on risk-adjusted strategies can provide higher risk-adjusted returns, and have lower tail risks compared to portfolios based on ordinary momentum strategies (Rachev et al., 2007; Choi et al., 2015).

[Table 3 insert about here]

Panel A of Table 3 reports the expected excess return for each quintile portfolio created using each of the ten momentum factors. The highest expected excess return of 0.0359 on a long-short momentum portfolio ($MOM1$) uses a one-week momentum factor, and the portfolio of twenty-six-week momentum ($MOM26$) has the lowest expected return of -0.0177. The expected excess return on long-short portfolios monotonically decreases from $MOM1$ to $MOM26$, which is broadly similar to the pattern for equities (Jegadeesh and Titman, 1993). For the risk-adjusted long-short momentum portfolios, $RMOM3$ has the highest excess return of 0.0302, and $RMOM26$ has the lowest return of -0.0110. As for momentum, the risk-adjusted long-short momentum portfolios exhibit an almost monotonically decreasing pattern as the horizon is extended from one to 26 weeks. These results suggest that long-short momentum-based strategies with shorter horizons (one to three weeks) perform best.

5.3 Volume Related Portfolios

The volume factor portfolios are constructed based on volume, volume times price and scaled volume times price. Panel A of Table 3 reports the expected excess return for each quintile portfolio created using each of the three volume factors. For long-short portfolios based on volume, the highest absolute excess return of 0.0236 is generated by portfolios based on volume times price ($VOLPRC$), and the portfolio of scaled volume times price (VOL) delivers the lowest excess absolute return of 0.0016. For all three volume factors, the first quintile portfolio (low volume) generates the highest excess return, which is greater than the excess absolute return on the long-short portfolios.

5.4 Volatility Related Portfolios

The volatility factor portfolios are constructed based on the standard deviation of excess returns, skewness of excess returns, kurtosis of excess returns, maximum excess return, log of the standard deviation of dollar volume, the mean absolute daily excess return scaled by dollar volume, and liquidity. Panel A of Table 3 shows the expected excess return for each quintile portfolio created using these eleven factors. The long-short portfolio $STDPRCVOL$ has the highest excess absolute mean return of 0.0222, and $RETVOL$ has the lowest excess return of 0.0014. $BETA$ and $BETA^2$ have the second lowest excess return of around 0.0002, which is counterintuitive, as portfolios with a higher beta (systematic risk) should be compensated with a higher expected excess return. Hence, beta might not be an appropriate factor to rank cryptocurrencies to form portfolios. The excess returns on quintile portfolios of the maximum return ($MAXRET$) increase as $MAXRET$ increases, and excess returns on the quintile portfolios for the log standard deviation ($STDPRCVOL$) of excess returns, with one exception, decrease from the first to fifth quintiles, i.e., excess returns drop as risk increases, which is also unexpected.

5.5 Summary Statistics of the Factor Portfolios

Panel B of Table 3 shows the median, standard deviation, skewness, kurtosis, J-B test and their p values for the 29 factor portfolios. The $MOM1$ portfolio has the highest mean weekly return of 0.0359, and $RETVOL$ and $BETA^2$ have the lowest absolute weekly return of 0.0014. The VOL portfolio is the most volatile portfolio with a standard deviation of 0.2256, while the $MARCAP$ portfolio has the smallest standard deviation of 0.1046. As demonstrated by the J-B test in Panel B, there are dramatic departures from normality in the excess return distributions of all the factor portfolios, and our performance comparisons need to allow for this non-normality.

6 Empirical Analysis

In this section, we analyse the empirical results of MV, AFSD and ASSD for zero-investment 4, 13, 26, 52 and 78 week horizon portfolios based on the factors listed in Table 2. The n-week horizon portfolios are based on the rolling-window technique, where n is the window size. The 29 factors are now represented by their long-short portfolios.

6.1 MV Dominance for Factor Portfolios

We examine the MV dominances for our 29 factor portfolios for later comparison with those of ASD. First we consider the simplest case that compares the mean and standard deviation of returns with those of the four benchmarks. Tables 1 and 3 show the mean returns and standard deviations of our benchmarks and factor portfolios, respectively. We find that, although most of factor portfolios have higher absolute returns than our four benchmarks, there is no outperformance against the benchmarks under the MV framework. Even the long-short factor portfolio with the smallest standard deviation (namely $MARCAP$ with a standard deviation of 0.1046) is higher than the largest standard deviation of the four benchmarks, i.e., Bitcoin with a standard deviation of 0.1039.

Even though cryptocurrency factor portfolios have highly non-normal distributions, as a further illustration of the inadequacies of MV performance measures for cryptocurrency factor portfolios, we investigate the risk-adjusted returns for each factor portfolio using Sharpe ratios (SRs) and certainty equivalent returns (CERs) for 4 to 78 week horizons. CERs require a value for the risk aversion parameter (λ). We set $\lambda = 1,\ 3,\ 5$ as these values represent investors with different risk preferences with respect to risk-seeking, risk-neutral, and risk-averse investors, respectively (Tu and Zhou, 2010; Chen et al., 2022).

[Table 4 insert about here]

Table 4 contains the number of factor portfolios that dominate or outperform the S&P 500, T-Bond, and Bitcoin for horizons of 4 to 78 weeks, where each count has a maximum of 29. We exclude T-Bills from Table 4 because T-Bills are considered to be the risk-free asset, and it is pointless to evaluate its risk-adjusted return. Panel A reports the number of dominances by each factor portfolio evaluated using SRs, and Panel B has the results using CERs. The number of factor portfolios dominances using the SR is an order of magnitude greater than those for factor portfolios tested using the CER with λ values of 3 and 5. MV requires dominance for all levels of risk aversion, while CERs only require out-performance for a particular level of risk aversion. This leads to CERs finding more occasions of out-performance than does MV dominance.

6.2 AFSD

To test whether AFSD exists, we need to calculate the ratio of the violation area (M in Figure 1) to the total enclosed area for each portfolio, and compare these ratios (ε_1) with a critical value of 5.9%, as discussed in Section 4. We define M as the area between the cumulative distributions when the cumulative distribution of a factor portfolio plots above the cumulative distribution of a benchmark (e.g., S&P 500, T-Bills, T-Bonds and Bitcoin). Likewise, we define N as the area between the cumulative distributions. The value of ε_i for AFSD is $\varepsilon_i = \frac{M}{M+N}$. If a portfolio has a ε_i value that is smaller than the critical value for AFSD, we conclude there is AFSD domination.

Table 5 shows the AFSD values of ε_i for each factor portfolio compared with the S&P 500 index, T-Bills, T-Bonds and Bitcoin for 4 to 78 week investment horizons. For most factor portfolios as the investment horizon lengthens ε_i decreases monotonically. The generally decreasing ε_i values indicate that AFSD dominance by the factor portfolios of the four benchmarks tends to increase as the horizon lengthens, as predicted by Leshno and Levy (2002).

[Table 5 insert about here]

Panel A of Table 5 reports the empirical ε_i values for each factor portfolio compared to the S&P 500 index for 4 to 78 week investment horizons. No portfolios dominate the S&P 500 until the holding period is extended to 13 weeks. For a 13 week horizon, only $MARCAP$ dominates the S&P 500 by AFSD, as its ε_i value is less than 5.9%. As the holding period extends to 26 weeks, four out of the 29 portfolios exhibit AFSD. Similar to the results for a 13 week horizon, $MARCAP$ is the best performing portfolio with the smallest ε_i value of 0.44%, whereas $RMOM4$ has the largest ε_i value of 5.85%, which is the worst of the four dominant portfolios. These four factor portfolios have much higher volatility than the S&P 500, but their high returns compensate for their high risk. At a 52 week horizon, ten of the 29 factor portfolios dominate the S&P 500 benchmark by AFSD, as six new dominant factor portfolios ($MOM2, RMOM1-2, VOLPRC, RETSKEW$, and $MAXRET$) emerge. In this case portfolios such as $MARCAP$ and $MOM1$ perform well against the S&P 500 with zero ε_i values. $RETSKEW$ is the worst performing dominant portfolio with an ε_i value of 5.44%. When the investment horizon is extended to 78 weeks, the $LPRC$ and $STDPRCVOL$ factor portfolios now also dominate the S&P 500 by AFSD, resulting in 12 dominant factor portfolios.

Panel B of Table 5 reports ε_i values for each factor portfolio compared to 10 year T-Bonds for 4 to 78 week investment horizons. One more dominant portfolio (AGE) appears compared to Panel A at 26 to 78 week horizons. At a 26 week horizon, $MARCAP$ still has the smallest ε_i value of 0.74%, and $RMOM4$ is the worst of the 13 dominant portfolios with an ε_i of 5.62%. As the investment horizon extends to 52 weeks, the same factor portfolios as in Panel A (10 out of 29 portfolios) and $STDPRCVOL$ are dominant. As the holding period lengthens to 78 weeks, the number of dominant portfolios increases by one compared to Panel A.

Panel C of Table 5 has ε_i values for each factor portfolio compared to one-month T-Bills for 4 to 78 week investment horizons. Unlike Panels A and B, dominance appears at the 4 week horizon, and nine factor portfolios dominate 1-month T-Bills using FSD, rather than just AFSD. An important reason for this is that T-Bills have a small weekly return of 0.0001. As the investment horizon extends to 13, 26, 52 and 78 weeks, the number of factor portfolios that are dominant according to AFSD are 15, 15, 10, 13 respectively.

Panel D of Table 5 contains the ε_i values of factor portfolios against Bitcoin. Unlike the S&P 500 and T-Bond benchmarks, AFSD first appears at the 4 week horizon. As the horizon increases from 4 to 78 weeks the number of AFSD dominances also increases (5, 6, 6, 9 and

10). At 78 weeks it has fewer AFSD dominances than in Panels A, B and C. We also find that Bitcoin FSD dominates five factor portfolios ($MOM8, MOM26, RMOM8, RMOM26$, and $RETSKEW$ at 78 weeks).

To sum up, the same eight factor portfolios AFSD dominate all four of our benchmarks at 52 and 78 week horizons. They are factor portfolios based on $MARCAP$, $MOM1$ and 2, $RMOM1$ to 4, and $MAXRET$. This suggests that portfolios based on these factors may generate excess returns, irrespective of investor risk preferences.

6.3 ASSD

The results from applying ASSD to each factor portfolio, relative to our four benchmarks at 4 to 78 week horizons, are in Table 6. The key difference between AFSD and ASSD is the critical value, as ASSD has a lower critical value of 3.2%, as opposed to the value of 5.9% for AFSD. This reveals that ASSD permits smaller violations of SD than AFSD. Panel A of Table 6 documents ε_i values for each factor portfolio compared to the S&P 500 for 4 to 78 week investment horizons. For 4 and 13 week horizons, none of portfolios dominate the S&P 500 index. As the investment horizon extends to 26 weeks, two out of 29 factor portfolios dominate this benchmark. $MARCAP$ is the best performing portfolio with an ε_i value of 0.44%. For a 52 week horizon, eight factor portfolios dominate the benchmark in the sense of ASSD. $MARCAP$ and $MOM1$ are the best performing portfolios with ε_i values of zero. As the investment horizon extends to 78 weeks, the number of ASSD dominant portfolios increases to ten, and five of these factor portfolios exhibit SSD dominance.

Panel B in Table 6 has ε_i values for each factor portfolio compared to T-bonds for 4 to 78 week investment horizons. There is no dominance at 4 and 13 weeks. For a 26 week horizon, the number dominant portfolios (three) is the same as for Panel A. The best performing factor portfolio is still $MARCAP$, with an ε_i value of 0.74%. As the investment horizon extends to 52 and 78 weeks, the number of dominant portfolios increases to 9 and 11, respectively – slightly more than the number of dominant portfolios in Panel A.

Panel C in Table 6 reports the ε_i values for each factor portfolio compared to T-Bills for 4 to 78 week investment horizons. All the dominances are SSD, rather than just ASSD. Unlike Panels A and B, dominance first appears at a 4 week horizon, with 9 factor portfolios exhibiting SSD dominance. As the investment horizon extends to 13, 26, 52 and 78 weeks the number of SSD dominant portfolios increases to 15, 15, 10 and 10, respectively.

Panel D in Table 6 shows the ε_i value for each portfolio against Bitcoin. Similar to Panel D in Table 5, ASSD of three portfolios occurs at a 4 week horizon. As the investment horizon becomes longer (13, 26, 52, 78 weeks), the number of ASSD factor portfolios increases to 8, 8, 14 and 11, respectively. As for AFSD, when the horizon is 78 weeks Bitcoin SSD dominates the same five factor portfolios.

We have tested the 29 factor portfolios for AFSD and ASSD against four benchmarks — the S&P500, T-bonds, T-bills and Bitcoin for 4 to 78 week horizons. For 52 and 78 week horizons, eight of the 29 factor portfolios dominate the four benchmarks by both AFSD and ASSD. They are factor portfolios based on $MARCAP$, $MOM1$ and 2, $RMOM1$ to 4, and $MAXRET$. Therefore no additional factor portfolios exhibit dominance when investors are assumed to be risk averse, and the following sections focus on these eight factors.

[Table 6 insert about here]

7 Cryptocurrency Asset Pricing and Factor Models

After identifying eight ASD dominant factor portfolios, we now turn to regression analysis. Specifically, we aim to examine whether the excess cross-sectional returns of these eight dominant factor portfolios can be explained by the existing coin market three-factor model of Liu et al. (2022), and how the existing model can be improved. The performance of the existing coin market three-factor model may be unsatisfactory for at least two reasons. First, the dominant factors established by ASD may behave differently, compared to factors determined by regression. So we evaluate whether the coin market three-factor model can account for the dominant factor portfolios we identify. Second, if the coin market three-factor model does not have adequate explanatory power, it is important to find a more comprehensive model to better explain the dominant factor portfolios.

7.1 Coin Market Three-Factor Model

We start with the construction of three cryptocurrency market factors: market, size and momentum. The cryptocurrency market excess return ($CMKT$) was discussed in Section 2. For the size factor, we follow the Fama and French three-factor model procedure. We sort the 2,353 coins into three size groups by market capitalization: the bottom 30 percent (Small group), the middle 40 percent (Middle group) and the top 30 percent (Big group). We then form value-weighted portfolios of each of three groups. The cryptocurrency size factor ($CSMB$) is the return on the small group minus that on the big group. As the return on the long-short one-week momentum portfolio is the highest among the momentum factors (see Table 3), we construct the momentum factor ($CMOM$) using the intersection of one-week momentum and coin size factor under dependent sorting. Specifically, we first sort the coins into two groups, namely Small and Big. We then establish three momentum portfolios (Low, Medium, and High which correspond to the bottom 30 percent, the middle 40 percent, and the top 30 percent) based on one week returns for each size group. Finally we compute weekly value-weighted returns on these six groups. $CMOM$ is formed by longing the High portfolios and shorting the Low portfolios across the Big and Small size groups. The mathematical formulation is:

$$CMOM = \frac{1}{2}(Small\ High + Big\ High) - \frac{1}{2}(Small\ Low + Big\ Low) \tag{5}$$

Therefore. the coin market three-factor model (Liu et al., 2022) is:

$$R_i - R_f = \alpha_i + \beta_{i,CMKT}CMKT + \beta_{i,CSMB}CSMB + \beta_{i,CMOM}CMOM + \varepsilon_i \tag{6}$$

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

Table 7 reports the regression results for our eight dominant factor portfolios. We find that the coin market three-factor model only accounts for one of the eight dominant factors. With the exception of $MAXRET$, all the dominant factor portfolios have statistically significant alphas. Seven of the eight dominant factor portfolios have positive exposure to the momentum factor ($CMOM$), including the non-momentum factor portfolios based on size and volatility. The market and size factors have fewer significant loadings than the momentum factor. Both the non-momentum dominant factor portfolios ($MARCAP$and $MAXRET$) have statistically significant loadings on $CMKT$ and $CSMB$, whereas the six momentum factor portfolios have less significant exposure to these two risk factors. The alpha values for seven of the factor portfolios are positive and significant at the 1% to 5% levels, and so the three-factor model suggests these dominant factor portfolios offer abnormal returns.

[Table 7 insert about here]

To conclude, we find that the coin market three-factor model cannot explain 75% to 99% of the variation in excess returns for these eight factor portfolios. The three-factor coin model also finds that seven factor portfolios have significantly positive alphas, indicating there are abnormal returns. The three-factor model does have significant explanatory power for the 21 non-dominant portfolios. As shown in Table A.18 in Appendix A5, the three-factor model provides a good explanation for 15 of the 21 non-dominant factor portfolios. These results indicate that Liu et al.'s (2022) model explains factor portfolios which do not dominate our four benchmarks, but cannot fully explain our eight dominant factor portfolios. Therefore, to better understand the coin market and its performance, it is important to develop a cryptocurrency asset pricing model that can explain the dominant factor portfolios we have identified.

7.2 Augmented Coin Factor Models

The previous section found that the coin market three-factor model can provide some explanatory power, but seven of the eight dominant factor portfolios have significant alphas. In this section, we propose an augmented coin factor model that provides a better explanation of returns on the dominant factor portfolios. Stambaugh and Yuan (2017) propose that an asset pricing model might increase its explanatory power by incorporating a mispricing factor. They constructed a mispricing factor by computing the equally weighted average of returns on the anomalous assets. We draw on the idea of incorporating a mispricing factor, but use a different approach to evaluate the performance of the augmented model. We use the unweighted average of returns on the mispriced factor portfolios because we cannot determine which factor portfolios are more important; and the unweighted average is considered to be an effective and easily interpretable way of aggregating returns on the seven mispriced factor portfolios (Opitz and Maclin, 1999; Kotsiantis et al., 2006). Our mispricing factor can be easily replicated by $\frac{1}{N}$ investing in the anomalous factor portfolios, and the correlations between these factor portfolios are relatively low.

We now augment the three-factor model with two additional factors, in addition to a mispricing factor. Since cryptocurrency is an application of blockchain, we use Twitter counts of the keyword 'blockchain' (normalised to zero mean and unit standard deviation) as a proxy for investor attention (*Attention*). We also collected four measures to create a proxy for network effects, complying with Liu and Tsyvinski (2020). These are the number of wallet users for

Bitcoin, the number of active addresses for Bitcoin, the number of transactions for Bitcoin, and the number of payments for Bitcoin. We calculate the growth rate for each of these four network proxies, and use their first principal component ($PC1$), which accounts for 88.2% of total variation in four network proxies, as the network proxy ($Network$). These additional variables create seven augmented coin market models, which are listed in Table 8.

[Table 8 insert about here]

The value 'Y' in Table 8 means that the corresponding coin market model includes this factor. For example, Model 1 is comprises the coin market three-factor model and the mispricing factor Mispricing, as in the equation below. The rest of the models are constructed in the same manner.

$$R_i - R_f = \alpha_i + \beta_{i,CMKT}CMKT + \beta_{i,CSMB}CSMB + \beta_{i,CMOM}CMOM + \beta_{i,Mispricing}Mispricing + \varepsilon_i \quad (7)$$

Table 9 presents the regression results for Model 6 of Table 8. The number of strategies with a significant exposure to size and momentum is slightly lower than for the original model in Table 7, while the number of significant coefficients for the coin market factor remains unchanged. In addition, only three of the alphas are significant. Since all the mispricing factor coefficients are significant, the mispricing factor appears to be absorbing part of the size and momentum effects, as well as some of the mispricings. The network factor included in Model 6 is significant for only one dominant factor portfolio ($MARCAP$). We archive the complete regression results for seven augmented models in section A2 of Appendix.

[Table 9 insert about here]

In Table 10 we compare the performance of the coin market three-factor model in Table 7, and the seven augmented five-factor coin market models in Table 8. We apply seven formal asset pricing metrics (Fama and French, 2015; Ahmed et al., 2019). The first metric is $A|R^2|$, representing the average R^2 for each augmented model - the higher is $A|R^2|$ the higher is the explanatory power. Second, the number of significant alphas indicates how many of the dominant factor portfolios appear to have anomalous returns according to the model. Our third metric is the GRS statistic, which has the null hypothesis that all alphas are jointly indistinguishable from zero (Gibbons et al., 1989). Hence, a small GRS statistic is preferable.

Our fourth metric is the average absolute value of the eight alphas, denoted as $A|\alpha_i|$. As significant alphas are viewed as a measure of model mispricing, a model with a smaller value of this metric performs better. Our fifth metric is the ratio of the average absolute value of the alphas to the average absolute value of $\bar{r}_i$, denoted by $A|\alpha_i|/A|\bar{r}_i|$, where $\bar{r}_i$ is the average excess return on a dominant factor portfolio, minus the average excess return on the market portfolio. Our sixth metric is the ratio of the average squared alpha to the average squared value of $\bar{r}_i$, denoted by $A\alpha_i^2/A\bar{r}_i^2$. Both $A|\alpha_i|/A|\bar{r}_i|$ and $A\alpha_i^2/A\bar{r}_i^2$ evaluate the variation of the alphas, relative to the variation of the average excess returns on each dominant factor portfolio; with low values of these ratios representing a good performance of the model. Our final metric is $As^2(\alpha_i)/A\alpha_i^2$, which is the ratio of the average variance of the sampling errors of the estimated alphas to $A\alpha_i^2$. This final metric measures the proportion of the variance of the alphas due to sampling errors, rather than the dispersion of the true alphas. Therefore, a higher value of this ratio indicates a better model. The right hand column (*Score*) is the number of metrics on which the factor model is the best.

[Table 10 insert about here]

Panels A and B show that Model 6 is the best performing of the three-factor model and the seven models in Table 8 for four reasons. First, the number of significant alphas decreases to three, instead of seven for the original coin market three-factor model. Second, the R^2 values for the dominant factor portfolios are significantly improved, especially for the momentum factor portfolios. For instance, compared to the results for the original model in Table 7, the R^2 value for $MOM2$ increases from 5.3% to 49.8%. Third, Model 6 has the highest score for the performance comparison among the seven models. Finally, in Model 6 all eight dominant factor portfolios have a significant exposure to the mispricing factor, indicating that the average effect of the seven anomalous factor portfolios helps to capture variation in the excess returns of the eight dominant factor portfolios. The models including the mispricing factor (Models 1, 4, and 7) outperform those without the mispricing factor (Models 2, 3, and 5), highlighting the importance of the mispricing factor.

7.3 Identifying Redundant Independent Variables and Revising the Augmented Model

In this section, we examine whether Model 6 has redundant risk factors, and whether we can simplify the mispricing factor. Our empirical test is largely similar to Fama and French (2015, 2018), e.g., by applying spanning regression. Spanning regression is a right-hand-side (RHS) approach to determine whether an independent variable contributes to an asset pricing model's explanatory power. We regress each independent variable on the model's other independent variables in turn. If the intercept of these spanning regressions is statistically different from zero, this individual factor is necessary to the model.

First we investigate Model 6 that includes the coin market, size, momentum, mispricing, and network factors. Table 11 shows the results of spanning regressions for Model 6. We find that the coin market ($CMKT$), size ($CSMB$), and mispricing factors ($Mispricing$) have statistically significant intercepts, which reveals that these three factors contribute to the explanatory power of Model 6. In contrast, the momentum ($CMOM$) and network ($Network$) factor spanning regressions have insignificant intercepts, and so these factors make only a limited contribution to our augmented coin market factor model, and will be dropped from further consideration. For the momentum factor, the probable reason is that the mispricing factor contains six types of momentum-based portfolio, and the effect of $CMOM$ is subsumed by the mispricing factor. Although the network factor has some predictive power in explaining returns for several mainstream coins (Liu and Tsyvinski, 2020), it cannot account for the variation in returns of our eight dominant factor portfolios. Therefore, we use the remaining three factors – the market, size, and mispricing factors – to form a new three-factor model (NTFM), and its performance is shown in panel C of Table 10.

[Table 11 insert about here]

Next we evaluate whether we can reduce the components of the mispricing factor. The mispricing factor is based on six momentum-based components, and so incorporates similar information up to six times. To address this issue, we disaggregate the mispricing factor, and replace it in the NTFM model with its components. In other words, the independent variables to be investigated are the coin market and size factors, and the seven anomalous factor portfolios in Table 7. We apply spanning regression to these risk factors, and the results are in section A11 of the Appendix. We find that the coin market and size factors still have significant intercepts. The mispricing components $MARCAP$, $RMOM1-2$, and $RMOM4$ also have non-zero intercepts, but the momentum-based portfolios (MOM 1 and 2) do not contribute to improving model performance. This indicates that the risk-adjusted momentum factor portfolios are superior to the momentum factor portfolios in capturing mispricings. Therefore, we use only the four remaining components – $MARCAP, RMOM1, RMOM2$, and $RMOM4$ – to compute a simplified mispricing factor ($Mispricing2$). We refer to the model (see Equation 8) which includes $Mispricing2$ as the new three-factor model with the simplified mispricing factor (NTFM-SM).

$$R_i - R_f = \alpha_i + \beta_{i,CMKT}CMKT + \beta_{i,CSMB}CSMB + \beta_{i,Mispricing2}Mispricing2 + \varepsilon_i \quad (8)$$

Table 12 displays the results of using our NTFM-SM three factor model with $Mispricing2$ to explain returns on our eight dominant factor portfolios, and find that this model outperforms all the other models. The number of significant alphas drops from the three of Model 6 in Table 9 to one, and all of the dominant factors except $MAXRET$ have exposure to the new mispricing factor.

[Table 12 insert about here]

The performance of the NTFM-SM is the best across panels A, B and C in Table 10, with a score of 6. Although its R^2 is 0.21, which is only the sixth best, it accounts for most of the variation in average excess returns on the dominant factor portfolios, since the values of the four metrics evaluating this property (e.g., GRS, $A|\alpha_i|$, $A|\alpha_i|/A|\bar{r}_i|$, and $A\alpha_i^2/A\bar{r}_i^2$) are minimum in all panels.

8 Dissecting the Driving Force and Mechanism of Pricing Models

In this section, we first study whether the explanatory power of the $Mispricing2$ factor is due to the inclusion of size ($MARCAP$), risk-adjusted momentum ($RMOM1-2, RMOM4$) or both. Then we investigate the how size, momentum and the investment horizon interact. This analysis is important for two reasons. First, we aim to design a tradable mispricing factor which will allow both academics and practitioners to replicate the mispricing factor for their research or investing. Second, it will show stylized facts for cryptocurrencies, which are comparable to traditional asset classes like equities and bonds.

8.1 Assessing the Inherent Driving Force within the Mispricing Factor

To evaluate their separate contribution to the NTFM-SM model, we decompose the simplified mispricing factor ($Mispricing2$) into two new factors - a size mispricing factor ($MispricingS$, based on $MARCAP$) and a risk-adjusted momentum mispricing factor ($MispricingM$, based on $RMOM1-2, RMOM4$). We replace $Mispricing2$ in the NTFM-SM model and create two new models, which we refer to as NTFM-SIZE and NTFM-RMOM, where the terms $SIZE$ and $RMOM$ specify the factors used to replace $Mispricing2$. $MispricingM$ is the simple average of returns on the risk-adjusted momentum portfolios $RMOM1-2$ and $RMOM4$. $MispricingS$ is the returns on $MARCAP$, and so the $MispricingS$ factor is just $MARCAP$. We detail the results for these two models in Table 13 and 14. We exclude $MARCAP$ from the dominant portfolios when examining the NTFM-SIZE model because it is not sensible to include the same variable on both sides of the regression. The NTFM-SIZE model cannot explain the cross-sectional variation because all the dominant factor portfolios have significant alphas, along with small R^2 values. In contrast, the NTFM-RMOM model captures much more of the variation, as only one dominant factor portfolio ($MARCAP$) has a significant alpha, and the R^2 values are much higher than for NTFM-SIZE, ranging from 5.8% for $MAXRET$ to 36.7% for $RMOM1$. All the dominant factor portfolios, except for $MARCAP$, have significant coefficients for the $MispricingM$ factor.

[Table 13 insert about here]

Although the NTFM-RMOM model provides a good explanation for the dominant factor portfolios, it is inferior to the NTFM-SM model. Panels C and D of Table 10 shows that on five of the tests NTFM-SM is superior to NTFM-RMOM, and inferior on only one – the average R^2. Thus we conclude that there is a combined effect between the $MispricingS$ and $MispricingM$ factors, which improves the model's performance.

[Table 14 insert about here]

8.2 The Mechanism between the Effects of Size and Risk-Adjusted Momentum

We investigate the interactive effects of the $MispricingS$ and $MispricingM$ factors. Most previous studies treat size and momentum effects separately, and do not investigate their combined effects. The influential studies of Chordia and Shivakumar (2002); Stivers and Sun (2010) emphasize that momentum effects become stronger in bull markets, and are pro-cyclical. Similarly, the literature documents that the size effect accounts for cross-sectional variation in returns (e.g., Fama and French, 1992, 1993, 2017). In contrast, recent papers (Hur et al., 2014; hyun Ahn et al., 2019) find that the size effect is counter-cyclical, and more pronounced in bear markets. To investigate the interactive effect of the $MispricingS$ and $MispricingM$ factors, we disaggregate the $Mispricing2$ factor into the $MispricingS$ and $MispricingM$ factors to create a new model (*New Mispricing Model*) that regresses our seven dominant factor portfolios (excluding $MARCAP$ as a dependent variable) on $CMKT, CSMB, MispricingS$, and $MispricingM$. We then divide our data in half, as have other papers (Stivers and Sun, 2010; Avramov et al., 2016), into January 2014 to September 2016 (3.75 years), and October 2016 to June 2021 (3.75 years), where Bitcoin experienced mild growth during the first period, and rapid growth during the second period.

Table 15 contains the regression results for the seven dominant factor portfolios using the new model (*New Mispricing Model*). Table 15 only displays the coefficients for $MispricingS$ and $MispricingM$ as these are the variables of interest (we document the complete table in section A9 of Appendix). The number of significant $MispricingS$ coefficients is three in first period, increasing to five in the second period. Likewise, the number of significant $MispricingM$ coefficients rises from three to six. Our results are consistent with the literature documenting that the momentum effect is larger in bull markets (e.g., Chordia and Shivakumar, 2002; Stivers and Sun, 2010). Our finding is also consistent with Liu et al. (2022) who find that outperforming cryptocurrency portfolios tend to be based on momentum. Nevertheless, our findings are in contrast to the studies proposing that the equity market size effect is counter-cyclical, as more significant coefficients appear for $MispricingS$ in the second period.

[Table 15 insert about here]

We also evaluate the interactive effect of the $MispricingS$ and $MispricingM$ factors by exploring the excess returns on risk-adjusted momentum portfolios while controlling for size;

and then the excess returns for portfolios of coins of a different size, while controlling for risk-adjusted momentum. Numerous studies (e.g., Fama and French, 2008, 2012) have found that the momentum effect is strong for large-size equity portfolios, and weak for small-size equity portfolios in the US and most international markets. To form size and risk-adjusted momentum portfolios, we rely on the double sorting technique. First, we sort the cryptocurrencies into two groups (small and big) using their median value as the division point. Then we sort each of these size groups into three groups (high, medium, and low) based on risk-adjusted momentum at the 30th and 70th percentiles. Finally we sort each of these six groups by their horizon period of 1, 2 and 4 weeks, which are corresponding to the statistically significant components of a simplified mispricing factor — $Mispricing2$. Therefore, after dropping the medium size momentum group, we form 12 portfolios using size, risk-adjusted momentum and horizon.

Table 16 displays the excess returns on these 12 portfolios. All of the small size portfolios generate statistically significant returns. In contrast, only the big size and high risk-adjusted momentum portfolios have statistically significant returns, as the big size and low risk-adjusted momentum portfolios produce small returns that are insignificantly different from zero. Returns on the nine significant portfolios decrease as the horizon increases. For the same size of portfolio, all the high risk-adjusted momentum portfolios have greater returns than the low risk-adjusted momentum portfolios. For the same risk-adjusted momentum, all the big size portfolios have lower returns than the small size portfolios. These results suggest that portfolios of small market capitalization coins with high risk-adjusted momentum outperform, particularly over a one week horizon. Thus, our findings are inconsistent with the papers of Fama and French (2008, 2012), and are in line with Hong et al. (2000) who emphasize that the momentum effect is more pronounced in small size portfolios. We also find support for a small coin, short horizon, effect.

[Table 16 insert about here]

We summarize the above findings related to the interactive effects of the $MispricingS$ and $MispricingM$ factors. Forming a mispricing factor that combines both size and risk-adjusted momentum is superior to using either alone. Both $MispricingS$ and $MispricingM$ capture more variation in the returns of our dominant factor portfolios during bull than bear markets. Portfolios of big coins (large market capitalization) deliver lower returns than portfolios of small coins, and small coins generate statistically positive excess returns. Similarly, cryptocurrencies with a high risk-adjusted momentum tend to have larger returns. Since the cryptocurrency market includes coins with large and small market capitalization, and high and low risk-adjusted momentum, it is important to take the size and momentum effects into account when constructing pricing models.

9 Conclusions

We explore the factors that influence the returns and performance of cryptocurrency factor portfolios. A problem in this area is that the empirical distributions of cryptocurrency returns are highly non-normal, undermining the usual metrics for measuring performance. To circumvent this we use almost stochastic dominance (ASD), a non-parametric method which does not require any assumptions about the return distribution. This paper is the first to use the ASD approach when examining the relative performance of cryptocurrency factor portfolios.

To investigate anomalies in cryptocurrency returns, we build zero-investment long-short portfolios using factors that can be constructed using the available information: opening price, closing price, trading volume and market capitalization. We identify four main factors - size, momentum, volume and volatility, which we use to create 29 factor portfolios. Using portfolios based on these 29 cryptocurrency factors, we investigate whether they generate superior returns over horizons of 4, 13, 26, 52 and 78 weeks, benchmarked against US equities, US Treasury bills, US Treasury bonds and Bitcoin. We find eight dominant factor portfolios, in the sense of almost first-degree stochastic dominance (AFSD) and almost second-degree stochastic dominance (ASSD). These dominant factor portfolios are based on market capitalization, momentum (1 and 2 weeks), risk momentum (1, 2, 3, and 4 weeks), and maximum return, Benchmarking these eight dominant factor portfolios against our four benchmarks and equity portfolios based on size, momentum and book-to-market, we find that the long-only strategies contribute more to performance than the short-only strategies.

We test whether the eight dominant factor portfolios can be explained by a coin market three-factor model, and find that this model has limited success in explaining their returns. For these eight dominant portfolios, the alphas are statistically significant, implying that their dominance is due to mispricing. We then test the explanatory power of the coin market three-factor model versus an augmented three-factor model which incorporates a mispricing factor (the combined average effect of the eight dominant factors), investor attention and network factors. We find that the momentum factor in our augmented model is redundant, and that the mispricing factor can be refined to include just the size and risk-adjusted momentum dominant factor portfolios. We call the result the three factor NTFM-SM coin model, and the number of non-zero alphas drops from seven to one, and almost all the coefficients of the refined mispricing factor are statistically significant. Since short selling is unavailable for most coins, we also test whether our augmented model can explain returns on our eight dominant factor portfolios, but shorting only Bitcoin. We find it captures variations in returns better than the coin market three-factor model. To address the possibility that equity asset pricing models might have explanatory power in explaining the returns on our eight dominant strategies, we test the performance of nine widely used equity asset pricing models. None of these equity asset pricing models can explain returns on the eight dominant factor portfolios.

Our work supports an augmented three factor model (NTFM-SM) for cryptocurrencies. To highlight the importance of the mispricing factor, we test the performance of a coin market one-factor model with only a cryptocurrency market factor, and two versions of a coin market two-factor model versus the performance of these models augmented with a mispricing factor based on the size and risk-adjusted momentum dominant factor portfolios. The two two-factor models comprise first, a cryptocurrency market factor and a cryptocurrency size factor; and second a cryptocurrency market factor and a momentum factor. We find that the mispricing factor always improves the performance of the original model. Hence, our work establishes a collection of stylized facts on cryptocurrency factor portfolios which may promote further studies in evaluating cryptocurrencies and developing theoretical models.

References

Abadi, J. and Brunnermeier, M. (2018). Blockchain Economics. *NBER Working Paper 25407*. DOI 10.3386/w25407.

Aharony, J. and Loeb, M. (1977). Mean-variance vs. stochastic dominance some empirical findings on efficient sets. *Journal of Banking and Finance*, 1(1):95–102.

Ahmed, S., Bu, Z., and Tsvetanov, D. (2019). Best of the Best: A Comparison of Factor Models. *Journal of Financial and Quantitative Analysis*, 54(4):1713–1758.

Ang, A. (2014). Asset management: A systematic approach to factor investing. *Oxford University Press*. ISBN-10: 0199959323; ISBN-13: 978-0199959327.

Arvanitis, S., Scaillet, O., and Topaloglou, N. (2020). Spanning tests for Markowitz stochastic dominance. *Journal of Econometrics*, 217(2):291–311.

Atsalakis, G. S., Atsalaki, I. G., Pasiouras, F., and Zopounidis, C. (2019). Bitcoin Price Forecasting with Neuro-fuzzy Techniques. *European Journal of Operational Research*, 276(2):770–780.

Avramov, D., Cheng, S., and Hameed, A. (2016). Time-varying liquidity and momentum profits. *Journal of Financial and Quantitative Analysis*, 51(6):1897–1923.

Bali, T. G., Brown, S. J., and Demirtas, K. O. (2013). Do Hedge Funds Outperform Stocks and Bonds? *Management Science*, 59(8):1887–1903.

Bali, T. G., Demirtas, K. O., Levy, H., and Wolf, A. (2009). Bonds versus stocks: Investors' age and risk taking. *Journal of Monetary Economics*, 56(6):817–830.

Barillas, F. and Shanken, J. (2018). Comparing Asset Pricing Models. *Journal of Finance*, 73(2):715–754.

Benhaim, A., Hemenway Falk, B., and Tsoukalas, G. (2021). Scaling blockchains: Can elected committees help?

Biais, B., Bisiere, C., Bouvard, M., Casamatta, C., and Menkveld, A. J. (2020). Equilibrium bitcoin pricing. Available at SSRN: https://ssrn.com/abstract=3261063 or http://dx.doi.org/10.2139/ssrn.3261063.

Biais, B., Bisière, C., Bouvard, M., and Casamatta, C. (2019). The Blockchain Folk Theorem. *Review of Financial Studies*, 32(5):1662–1715.

Board, J. L. G. and Sutcliffe, C. M. S. (1994). Estimation Methods in Portfolio Selection and the Effectiveness of Short Sales Restrictions: Uk Evidence. *Management Science*, 40(4):516–534.

Borri, N. (2019). Conditional tail-risk in cryptocurrency markets. *Journal of Empirical Finance*, 50:1–19.

Cachon, G. P., Dizdarer, T., and Tsoukalas, G. (2021). Decentralized or centralized control of online service platforms: Who should set prices? Available at SSRN: https://ssrn.com/abstract=3957209 or http://dx.doi.org/10.2139/ssrn.3957209.

Chen, J., Tang, G., Yao, J., and Zhou, G. (2022). Investor attention and stock returns. *Journal of Financial and Quantitative Analysis*, 57(2):455–484.

Chod, J., Trichakis, N., Tsoukalas, G., Aspegren, H., and Weber, M. (2020). On the Financing Benefits of Supply Chain Transparency and Blockchain Adoption. *Management Science*, 66(10):4378–4396.

Choi, J., Kim, Y. S., and Mitov, I. (2015). Reward-risk Momentum Strategies Using Classical Tempered Stable Distribution. *Journal of Banking and Finance*, 58:194–213.

Chordia, T. and Shivakumar, L. (2002). Momentum, business cycle, and time-varying expected returns. *The Journal of Finance*, 57(2):985–1019.

Cong, L. W., Li, Y., and Wang, N. (2021). Tokenomics: Dynamic Adoption and Valuation. *Review of Financial Studies*, 34(3):1105–1155.

Daskalaki, C., Skiadopoulos, G., and Topaloglou, N. (2017). Diversification Benefits of Commodities: A Stochastic Dominance Efficiency Approach. *Journal of Empirical Finance*, 44:250–269.

Dong, X., Li, Y., Rapach, D. E., and Zhou, G. (2022). Anomalies and the expected market return. *Journal of Finance*, 77(1):639–681.

Easley, D., O'Hara, M., and Basu, S. (2019). From Mining to Markets: The Evolution of Bitcoin Transaction Fees. *Journal of Financial Economics*, 134(1):91–109.

Fama, E. F. and French, K. R. (1992). The cross-section of expected stock returns. *Journal of Finance*, 47(2):427–465.

Fama, E. F. and French, K. R. (1993). Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics*, 33(1):3–56.

Fama, E. F. and French, K. R. (2008). Dissecting anomalies. *Journal of Finance*, 63(4):1653–1678.

Fama, E. F. and French, K. R. (2012). Size, value, and momentum in international stock returns. *Journal of Financial Economics*, 105(3):457–472.

Fama, E. F. and French, K. R. (2015). A Five-factor Asset Pricing Model. *Journal of Financial Economics*, 116(1):1–22.

Fama, E. F. and French, K. R. (2016). Dissecting Anomalies with a Five-Factor Model. *Review of Financial Studies*, 29(1):69–103.

Fama, E. F. and French, K. R. (2017). International Tests of a Five-factor Asset Pricing Model. *Journal of Financial Economics*, 123(3):441–463.

Fama, E. F. and French, K. R. (2018). Choosing factors. *Journal of Financial Economics*, 128(2):234–252.

Farinelli, S., Ferreira, M., Rossello, D., Thoeny, M., and Tibiletti, L. (2008). Beyond Sharpe Ratio: Optimal Asset Allocation Using Different Performance Ratios. *Journal of Banking and Finance*, 32(10):2057–2063.

Feng, G., Giglio, S., and Xiu, D. (2020). Taming the Factor Zoo: A Test of New Factors. *Journal of Finance*, 75(3):1327–1370.

Fischer, B. R. and Wermers, R. (2012). *Performance Evaluation and Attribution of Security Portfolios*. Elsevier, 1 edition.

Foley, S., Karlsen, J. R., and Putniņš, T. J. (2019). Sex, Drugs, and Bitcoin: How Much Illegal Activity Is Financed through Cryptocurrencies? *Review of Financial Studies*, 32(5):1798–1853.

Gan, J. R., Tsoukalas, G., and Netessine, S. (2020). Initial Coin Offerings, Speculation, and Asset Tokenization. *Management Science*, 67(2):914–931.

Gan, R., Tsoukalas, G., and Netessine, S. (2021). To infinity and beyond: Financing platforms with uncapped crypto tokens. Available at SSRN: https://ssrn.com/abstract=3776411 or http://dx.doi.org/10.2139/ssrn.3776411.

Gandhi, D. K. and Saunders, A. (1981). The Superiority of Stochastic Dominance Over Mean Variance Efficiency Criteria: Some Clarifications: The Superiority of Stochastic Dominance Over Mean Variance Efficiency Criteria. *Journal of Business Finance & Accounting*, 8(1):51–59.

Gibbons, M. R., Ross, S. A., and Shanken, J. (1989). A Test of the Efficiency of a Given Portfolio. *Econometrica*, 57(5):1121–1152.

Gotoh, J.-y. and Konno, H. (2000). Third degree stochastic dominance and mean-risk analysis. *Management Science*, 46(2):289–301.

Han, Y., Huang, D., Huang, D., and Zhou, G. (2022). Expected return, volume, and mispricing. *Journal of Financial Economics*, 143(3):1295–1315.

Han, Y., Yang, K., and Zhou, G. (2013). A new anomaly: The cross-sectional profitability of technical analysis. *Journal of Financial and Quantitative Analysis*, 48(5):1433–1461.

Harvey, C. R. and Liu, Y. (2021). Lucky Factors. *Journal of Financial Economics*. Corrected Proff. DOI: https://doi.org/10.1016/j.jfineco.2021.04.014.

Holcblat, B., Lioui, A., and Weber, M. (2022). Anomaly or possible risk factor? simple-to-use tests. (22-11). Simple-To-Use Tests (March 22, 2022). Chicago Booth Research Paper. Available at SSRN: https://ssrn.com/abstract=4064159 or http://dx.doi.org/10.2139/ssrn.4064159.

Hong, H., Lim, T., and Stein, J. C. (2000). Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. *Journal of Finance*, 55(1):265–295.

Hou, K., Xue, C., and Zhang, L. (2015). Digesting Anomalies: An Investment Approach. *Review of Financial Studies*, 28(3):650–705.

Hou, K., Xue, C., and Zhang, L. (2017). A Comparison of New Factor Models. (2015-03):05. NBER Working Paper 20682.

Huang, D., Jiang, F., Tu, J., and Zhou, G. (2014). Investor Sentiment Aligned: A Powerful Predictor of Stock Returns. *Review of Financial Studies*, 28(3):791–837.

Huang, D., Li, J., Wang, L., and Zhou, G. (2020). Time series momentum: Is it there? *Journal of Financial Economics*, 135(3):774–794.

Hur, J., Pettengill, G., and Singh, V. (2014). Market states and the risk-based explanation of the size premium. *Journal of Empirical Finance*, 28(C):139–150.

hyun Ahn, D., kyu Min, B., and Yoon, B. (2019). Why has the size effect disappeared? *Journal of Banking and Finance*, 102:256–276.

Jegadeesh, N. and Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *Journal of Finance*, 48(1):65–91.

Kan, R. and Robotti, C. (2009). Model Comparison Using the Hansen-Jagannathan Distance. *Review of Financial Studies*, 22(9):3449–3490.

Kan, R., Robotti, C., and Shanken, J. (2013). Pricing Model Performance and the Two-pass Cross-sectional Regression Methodology. *Journal of Finance*, 68(6):2617–2649.

Kotsiantis, S. B., Zaharakis, I. D., and Pintelas, P. E. (2006). Machine learning: A review of classification and combining techniques. *Artificial Intelligence Review*, 26(3):159–190.

Leshno, M. and Levy, H. (2002). Preferred by “All” and Preferred by “Most” Decision Makers: Almost Stochastic Dominance. *Management Science*, 48(8):1074–1085.

Levy, H. (2006). *Stochastic Dominance: Investment Decision Making under Uncertainty*, volume 34. Springer, second edition.

Levy, H., Leshno, M., and Leibovitch, B. (2010). Economically Relevant Preferences for All Observed Epsilon. *Annals of Operations Research*, 176(1):153–178.

Levy, H. and Levy, M. (2019). Stocks versus Bonds and the Investment Horizon. Available at SSRN: https://ssrn.com/abstract=3458828 or http://dx.doi.org/10.2139/ssrn.3458828.

Liesiö, J., Xu, P., and Kuosmanen, T. (2020). Portfolio Diversification Based on Stochastic Dominance under Incomplete Probability Information. *European Journal of Operational Research*, 286(2):755–768.

Liu, Y., Sheng, J., and Wang, W. (2021a). Technology and Cryptocurrency Valuation: Evidence from Machine Learning. Available at SSRN: https://ssrn.com/abstract=3577208 or http://dx.doi.org/10.2139/ssrn.3577208.

Liu, Y. and Tsyvinski, A. (2020). Risks and Returns of Cryptocurrency. *Review of Financial Studies*, 34(6):2689–2727.

Liu, Y., Tsyvinski, A., and Wu, X. (2021b). Accounting for Cryptocurrency Value. Available at SSRN: https://ssrn.com/abstract=3951514 or http://dx.doi.org/10.2139/ssrn.3951514.

Liu, Y., Tsyvinski, A., and Wu, X. (2022). Common risk factors in cryptocurrency. *Journal of Finance*, 77(2):1133–1177.

Lok, T. M. and Tabri, R. V. (2021). An Improved Bootstrap Test for Restricted Stochastic Dominance. *Journal of Econometrics*.

Makarov, I. and Schoar, A. (2020). Trading and Arbitrage in Cryptocurrency Markets. *Journal of Financial Economics*, 135(2):293–319.

Malavasi, M., Ortobelli Lozza, S., and Trück, S. (2021). Second order of stochastic dominance efficiency vs mean variance efficiency. *European Journal of Operational Research*, 290(3):1192–1206.

Neely, C. J., Rapach, D. E., Tu, J., and Zhou, G. (2014). Forecasting the equity risk premium: The role of technical indicators. *Management Science*, 60(7):1772–1791.

Nguyen, L. H., Chevapatrakul, T., and Yao, K. (2020). Investigating tail-risk dependence in the cryptocurrency markets: A lasso quantile regression approach. *Journal of Empirical Finance*, 58:333–355.

Opitz, D. and Maclin, R. (1999). Popular ensemble methods: An empirical study. *Journal of Artificial Intelligence Research*, 11:169–198.

Pagnotta, E. and Buraschi, A. (2018). An Equilibrium Valuation of Bitcoin and Decentralized Network Assets. Available at SSRN: https://ssrn.com/abstract=3142022 or http://dx.doi.org/10.2139/ssrn.3142022.

Phillip, A., Chan, J. S., and Peiris, S. (2018). A new look at cryptocurrencies. *Economics Letters*, 163:6–9.

Post, T. (2003). Empirical Tests for Stochastic Dominance Efficiency. *Journal of Finance*, 58(5):1905–1931.

Post, T., Karabatı, S., and Arvanitis, S. (2018). Portfolio Optimization Based on Stochastic Dominance and Empirical Likelihood. *Journal of Econometrics*, 206(1):167–186.

Qiu, Y., Wang, Z., Xie, T., and Zhang, X. (2021). Forecasting Bitcoin realized volatility by exploiting measurement error under model uncertainty. *Journal of Empirical Finance*, 62:179–201.

Rachev, S., Jašić, T., Stoyanov, S., and Fabozzi, F. J. (2007). Momentum Strategies Based on Reward–risk Stock Selection Criteria. *Journal of Banking and Finance*, 31(8):2325–2346.

Rapach, D. E., Strauss, J. K., and Zhou, G. (2009). Out-of-Sample Equity Premium Prediction: Combination Forecasts and Links to the Real Economy. *Review of Financial Studies*, 23(2):821–862.

Sharpe, W. F. (1966). Mutual Fund Performance. *Journal of Business*, 39(1):119–138.

Sockin, M. and Xiong, W. (2020). A model of cryptocurrencies. *NBER Working Paper 26816.*

Stambaugh, R. F. and Yuan, Y. (2017). Mispricing Factors. *Review of Financial Studies*, 30(4):1270–1315.

Stivers, C. and Sun, L. (2010). Cross-sectional return dispersion and time variation in value and momentum premiums. *Journal of Financial and Quantitative Analysis*, 45(4):987–1014.

Tsoukalas, G. and Falk, B. H. (2020). Token-weighted crowdsourcing. *Management Science*, 66(9):3843–3859.

Tu, J. and Zhou, G. (2010). Incorporating economic objectives into bayesian priors: Portfolio choice under parameter uncertainty. *Journal of Financial and Quantitative Analysis*, 45(4):959–986.

Yitzhaki, S. (1982). Stochastic dominance, mean variance, and gini's mean difference. *American Economic Review*, 72(1):178–85.

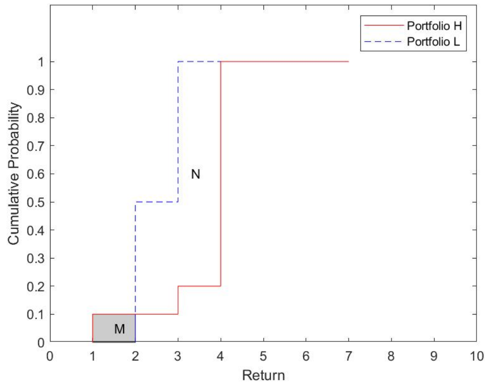
Zhou, G. and Zhu, Y. (2012). Volatility trading: What is the role of the long-run volatility component? *Journal of Financial and Quantitative Analysis*, 47(2):273–307.

Table 1: Descriptive Statistics

	Mean	Median	Std	Skewness	Kurtosis	J-B test	P-value
Bitcoin Return	0.0101	0.0104	0.1039	-0.2402	4.9013	62.8161	0.001
CMKT	0.0145	0.0140	0.1069	-0.0381	6.0799	155.0315	0.001
S&P 500	0.0025	0.0042	0.0236	-0.644	13.7708	1921.937	0.001
One-month T-bill	0.0001	0.0001	0.0002	0.8154	2.1456	55.3662	0.001
Ten-year T-bond	0.0008	0.0009	0.0082	0.5974	8.6441	543.6354	0.001

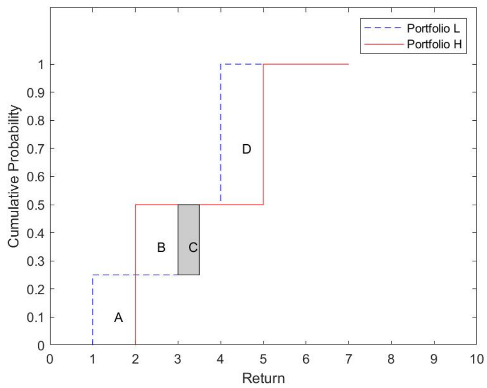
This table presents descriptive statistics of weekly returns (not percentages) on Bitcoin, CMKT, S&P 500 index, T-bills and T-bonds for 2014 to the first half of 2021.

Figure 1: Almost First-Order Stochastic Dominance



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

Figure 2: Almost First-Order Stochastic Dominance



This figure demonstrates a case where portfolio H has a higher mean than portfolio L, but there is no SSD of H over L due to the presence of the shaded area C, which makes the SSD condition fail. If area C is relatively small, ASSD may exist.

Table 2: The Zero-Investment Long-Short Factor 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	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	MOM26	Twenty-six-week momentum
Momentum	RMOM1	One-week risk-adjusted momentum based on the Sharpe ratio
Momentum	RMOM2	Two-week risk-adjusted momentum based on the Sharpe ratio
Momentum	RMOM3	Three-week risk-adjusted momentum based on the Sharpe ratio
Momentum	RMOM4	Four-week risk-adjusted momentum based on the Sharpe ratio
Momentum	RMOM8	Eight-week risk-adjusted momentum based on the Sharpe ratio
Momentum	RMOM26	Twenty-six-week risk-adjusted momentum based on the 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 $\beta_{MKT,i}$ in $R_i - R_f = \alpha^i + \beta_{MKT,i}MKT + \epsilon_i$.The model is estimated using the daily returns of the previous 365 days before formation week
Volatility	BETA^2	Beta squared
Volatility	IDIOVOL	The IDIOVOL volatility is measured as the standard deviation of the residuals after estimating $R_i - R_f = \alpha^i + \beta_{MKT,i}MKT + \epsilon_i$. The model is estimated using the daily returns of the previous 365 days before the formation week.
Volatility	DELAY	The improvement of R^2 in $R_i - R_f = \alpha^i + \beta_{MKT,i}MKT + \beta_{MKT_{-1},i}MKT_{-1} + \beta_{MKT_{-2},i}MKT_{-2} + \epsilon_i$compared to a regression that only uses MKT, where MKT_{-1} and MKT_{-2} are lagged one- and two-day market index returns. The model is estimated using the daily returns of the previous 365 days before formation week.
Volatility	LIQ	The average absolute daily return divided by price volume in the portfolio formation week.

This table reports the construction of each factor portfolio based on a specific factor. For instance, the procedure for creating a portfolio based on MARCAP is that each week the 2,353 cryptocurrencies were sorted into quintiles using market capitalization. All the portfolios were rebalanced weekly. CMKT refers to our coin market index (CMKT), which is the value-weighted return of the full sample of cryptocurrencies.

Table 3: Descriptive Statistics for Each Factor Portfolio

	Panel A: Quintiles						Panel B: Statistics for '5-1' Portfolios					
	1 (Low)	2	3	4	5 (High)	5-1 (Mean)	Median	Std	Skewness	Kurtosis	J-B test	p-value
MARCAP	0.0203	0.0026	-0.0127	-0.0100	-0.0066	-0.0269	0.0213	0.1046	0.8481	6.3198	226.43	0.001
LPRC	0.0264	0.0273	0.0091	0.0115	0.0049	-0.0215	-0.0016	0.1675	3.3295	23.5690	7615.15	0.001
AGE	0.0333	0.0123	0.0025	0.0092	0.0060	-0.0272	0.0008	0.2193	-2.6346	16.8386	3572.28	0.001
MOM1	-0.0045	-0.0017	0.0084	0.0150	0.0314	0.0359	0.0226	0.1876	1.6170	15.5703	2744.66	0.001
MOM2	-0.0052	-0.0018	0.0017	0.0145	0.0296	0.0349	0.0246	0.1790	1.3031	13.8838	2035.29	0.001
MOM3	-0.0016	-0.0081	0.0079	0.0171	0.0246	0.0262	0.0143	0.2063	1.1433	18.3854	3921.41	0.001
MOM4	0.0024	-0.0016	0.0035	0.0237	0.0161	0.0137	0.0067	0.1477	0.8768	7.3223	351.75	0.001
MOM8	0.0098	0.0047	0.0083	0.0186	0.0025	-0.0072	-0.0060	0.1628	1.7656	17.9600	3780.36	0.001
MOM26	0.0194	0.0112	0.0029	0.0116	0.0017	-0.0177	-0.0069	0.1768	-1.7661	18.7137	3955.79	0.001
RMOM1	-0.0020	0.0009	0.0106	0.0090	0.0247	0.0268	0.0133	0.1521	1.8871	20.4177	5174.58	0.001
RMOM2	-0.0056	-0.0010	0.0135	0.0116	0.0207	0.0264	0.0254	0.1667	0.8223	22.7316	6337.96	0.001
RMOM3	-0.0032	0.0021	0.0078	0.0081	0.0270	0.0302	0.0273	0.1780	2.8670	27.9396	10614.22	0.001
RMOM4	-0.0038	0.0052	0.0119	0.0087	0.0190	0.0228	0.0158	0.1424	0.4663	7.4890	339.83	0.001
RMOM8	0.0065	0.0132	0.0140	0.0127	0.0100	0.0035	0.0096	0.1425	0.4462	7.6440	357.82	0.001
RMOM26	0.0151	0.0138	0.0104	0.0099	0.0040	-0.0110	-0.0036	0.1530	-0.4496	9.7310	703.26	0.001
VOL	0.0155	0.0266	0.0233	0.0059	0.0139	-0.0016	0.0040	0.2256	-9.5698	154.7759	381261.46	0.001
VOLPRC	0.0344	0.0228	0.0177	0.0139	0.0108	-0.0236	0.0063	0.1605	3.7847	28.7442	11731.03	0.001
VOLSCALE	0.0223	0.0226	0.0093	0.0078	0.0106	-0.0117	-0.0025	0.1412	2.7424	18.8200	4567.44	0.001
RETVOL	0.0092	0.0090	0.0129	0.0128	0.0106	0.0014	-0.0107	0.2007	1.6729	18.0143	3854.99	0.001
RETSKEW	0.0051	0.0089	0.0075	0.0097	0.0172	0.0121	0.0050	0.1527	1.7954	20.9129	5437.60	0.001
RETKURT	0.0057	0.0142	0.0128	0.0092	0.0093	0.0036	0.0044	0.1270	0.2689	7.1715	288.21	0.001
MAXRET	0.0003	0.0109	0.0119	0.0156	0.0204	0.0201	0.0078	0.1464	0.9446	5.8347	189.06	0.001
STDPRCVOL	0.0325	0.0223	0.0157	0.0210	0.0103	-0.0222	0.0049	0.1587	3.7806	29.2807	12183.67	0.001
MEANABS	0.0107	0.0083	0.0222	0.0231	0.0281	0.0174	-0.0055	0.1845	4.2588	30.2452	13275.29	0.001
BETA	0.0062	0.0119	0.0050	0.0127	0.0034	-0.0029	0.0013	0.1492	0.1955	13.8392	1661.68	0.001
BETA$\hat{2}$	0.0048	0.0104	0.0092	0.0101	0.0034	-0.0014	0.0019	0.1296	-0.3705	20.3684	4268.71	0.001
IDIOVOL	0.0071	0.0150	0.0193	0.0184	0.0034	-0.0037	0.0123	0.1298	-0.8429	21.3632	4803.19	0.001
DELAY	0.0162	0.0160	0.0187	0.0221	0.0047	-0.0115	0.0169	0.1239	0.2481	8.3735	411.33	0.001
LIQ	0.0107	0.0083	0.0222	0.0231	0.0281	0.0174	-0.0055	0.1845	4.2588	30.2452	13275.29	0.001

Panel A reports weekly mean excess returns on the 29 quintile factor portfolios. The mean excess returns are defined as the excess value-weighted expected returns, and '5-1' represents the long-short strategy. Panel B illustrates the summary statistics of (5-1) mean (where any negative (5-1) mean return can be converted to positive by reversing the differencing), median, standard deviation, skewness, kurtosis, J-B test and corresponding p values.

Table 4: Sharpe Ratio and Certainty Equivalent Return

	Panel A: Counts of Dominance by Factor Portfolios using SR					Panel B: Counts of Outperformance by Factor Portfolios using CER ($\lambda = 1,\ 3,\ 5$)				
	Panel A1: Portfolios against S&P 500 Index					Panel B1: Portfolios against S&P 500 Index				
	4-week	13-week	26-week	52-week	78-week	4-week	13-week	26-week	52-week	78-week
Counts	5	6	3	4	2	7/1/0	7/1/1	10/1/1	11/2/1	11/3/1
	Panel A2: Portfolios against Ten-year T-Bond					Panel B2: Portfolios against Ten-year T-Bond				
	4-week	13-week	26-week	52-week	78-week	4-week	13-week	26-week	52-week	78-week
Counts	7	9	12	11	11	7/1/0	11/1/1	11/2/1	11/2/1	11/3/1
	Panel A3: Portfolios against Bitcoin					Panel B3: Portfolios against Bitcoin				
	4-week	13-week	26-week	52-week	78-week	4-week	13-week	26-week	52-week	78-week
Counts	7	8	10	11	9	7/1/1	8/4/2	9/4/3	10/5/4	11/4/4

This table reports the counts of outperformance by factor portfolios against S&P 500, T-Bonds, and Bitcoin for different horizons. The entries in Panel B represent CER values with $\lambda = 1,\ 3\ ,5$, respectively. For brevity, the values of these tests are in the Appendix. See section A12 in Appendix.

Table 5: Almost First-Order Stochastic Dominance

Portfolios	Panel A: Portfolios against S&P 500 Index 4-week	13-week	26-week	52-week	78-week	Panel B: Portfolios against Ten-year T-Bond 4-week	13-week	26-week	52-week	78-week	Panel C: Portfolios against One-month T-Bill 4-week	13-week	26-week	52-week	78-week	Panel D: AFSD for Portfolios against Bitcoin 4-week	13-week	26-week	52-week	78-week
MARCAP	0.1643	0.04*	0.0044*	0*	0*	0.1834	0.0549*	0.0074*	0.0006*	0*	0*	0*	0*	0*	0*	0.003*	0.0355*	0.0592	0.032*	0.0068*
LPRC	0.3313	0.2538	0.1777	0.0786	0.0545*	0.3284	0.2412	0.1594	0.0644	0.038*	0.3320	0.2465	0*	0.0707	0.0415*	0.2175	0.1522	0.1300	0.1363	0.0907
AGE	0.3389	0.2167	0.1560	0.0885	0.0609	0.3361	0.2099	0.1428	0.0761	0.048*	0.3384	0*	0*	0.0811	0.051*	0.2863	0.0825	0.0582*	0.0144*	0.0263*
MOM1	0.2193	0.0601	0.0227*	0*	0*	0.2273	0.0683	0.0238*	0.0003*	0*	0*	0*	0*	0*	0*	0.0344*	0*	0*	0*	0*
MOM2	0.2451	0.1383	0.1013	0.0124*	0.0087*	0.2507	0.1405	0.0978	0.0123*	0.0081*	0*	0*	0*	0*	0*	0.1164	0.0933	0.0643	0*	0.0009*
MOM3	0.3308	0.2567	0.2136	0.1485	0.1457	0.3296	0.2495	0.1996	0.1364	0.1294	0*	0*	0*	0.1383	0.1291	0.2342	0.2071	0.1694	0.0780	0.1945
MOM4	0.3808	0.3018	0.2580	0.2013	0.1058	0.3742	0.2844	0.2284	0.1664	0.0767	0.3755	0*	0*	0.1686	0.0798	0.3152	0.1422	0.6432	0.7763	0.8692
MOM8	0.6003	0.6562	0.7537	0.8515	0.9278	0.5797	0.6255	0.7186	0.8258	0.9133	0.5706	0.6116	0.6982	0.8040	0.8924	0.8472	0.9220	0.9739	0.9858	1.0000
MOM26	0.6669	0.7863	0.8547	0.9648	1.0000	0.6464	0.7573	0.8259	0.9515	1.0000	0.6358	0.7397	0.8051	0.9381	0.9992	0.9328	1.0000	1.0000	1.0000	1.0000
RMOM1	0.2306	0.1058	0.0652	0.005*	0*	0.2401	0.1117	0.0620	0.0053*	0*	0*	0*	0*	0*	0*	0.0071*	0.0052*	0.0019*	0*	0*
RMOM2	0.2647	0.1636	0.1181	0.0166*	0*	0.2704	0.1642	0.1137	0.0164*	0*	0*	0*	0*	0*	0*	0.1187	0.0959	0.1010	0*	0*
RMOM3	0.2268	0.1051	0.0381*	0.0013*	0.0003*	0.2367	0.1115	0.0379*	0.0019*	0.0007*	0*	0*	0*	0*	0*	0.0315*	0.0033*	0*	0*	0*
RMOM4	0.2691	0.1167	0.0585*	0.0088*	0*	0.2741	0.1219	0.0562*	0.0088*	0*	0*	0*	0*	0*	0*	0.0204*	0*	0.0038*	0.0101*	0.0031*
RMOM8	0.4959	0.4940	0.5011	0.5667	0.6488	0.4810	0.4664	0.4600	0.5140	0.5882	0.4766	0*	0.4495	0.4923	0.5566	0.7399	0.9426	0.9996	1.0000	1.0000
RMOM26	0.6329	0.7173	0.7823	0.8631	0.8929	0.6111	0.6833	0.7441	0.8315	0.8702	0.6009	0.6664	0.7213	0.8051	0.8474	0.9243	0.9923	1.0000	1.0000	1.0000
VOL	0.5189	0.4960	0.4830	0.4399	0.4073	0.5030	0.4730	0.4562	0.4114	0.3739	0.4977	0.4671	0.4492	0.4025	0.3631	0.7311	0.7506	0.7294	0.6782	0.6934
VOLPRC	0.2973	0.1944	0.0986	0.016*	0.0071*	0.2971	0.1846	0.0876	0.0145*	0.0053*	0.3025	0*	0*	0*	0*	0.1592	0.1110	0.1552	0.0965	0.0528*
VOLSCALE	0.4131	0.3710	0.3169	0.2032	0.1794	0.4032	0.3483	0.2840	0.1670	0.1455	0.4028	0.3473	0.2831	0.1684	0.1433	0.4667	0.5028	0.5319	0.4486	0.4705
RETVOL	0.5227	0.5425	0.5347	0.4824	0.4456	0.5098	0.5195	0.5039	0.4413	0.3949	0.5052	0.5119	0.4938	0.4271	0.3765	0.6468	0.7998	0.8983	0.9450	0.9143
RETSKEW	0.3954	0.2703	0.1527	0.0544*	0.0167*	0.3875	0.2542	0.1328	0.0458*	0.0141*	0.3881	0*	0*	0*	0*	0.3748	0.1453	0.3166	0.1591	0.0945
RETKURT	0.4884	0.4838	0.4557	0.4512	0.4987	0.4700	0.4473	0.4050	0.3954	0.4321	0.4652	0.4397	0.3962	0.3802	0.4067	0.9125	0.9986	0.9604	1.0000	1.0000
MAXRET	0.3333	0.2196	0.1307	0.0069*	0.0064*	0.3312	0.2114	0.1187	0.007*	0.005*	0.3347	0*	0*	0*	0*	0.1935	0.0309*	0.0133*	0*	0*
STDPRCVOL	0.3130	0.2192	0.1449	0.0704	0.0452*	0.3115	0.2077	0.1263	0.055*	0.0279*	0.3160	0.2151	0.1366	0.0619	0.0319*	0.2004	0.1521	0.1931	0.1724	0.1542
MEANABS	0.3774	0.3142	0.2502	0.1555	0.1416	0.3702	0.2979	0.2286	0.1345	0.1226	0.3714	0.2994	0.2307	0.1369	0.1222	0.3904	0.3519	0.3157	0.2228	0.2249
BETA	0.5059	0.4928	0.4706	0.4309	0.3753	0.4901	0.4666	0.4373	0.3919	0.3354	0.4851	0.4602	0.4294	0.3810	0.3238	0.6839	0.7346	0.7832	0.7809	0.8213
BETA$\hat{2}$	0.5218	0.5151	0.5011	0.4758	0.4258	0.5024	0.4853	0.4661	0.4333	0.3788	0.4960	0.4772	0.4565	0.4193	0.3632	0.8738	0.9476	0.8776	0.8469	0.9368
IDIOVOL	0.4936	0.4711	0.4477	0.3844	0.2831	0.4763	0.4424	0.4131	0.3412	0.2243	0.4715	0.4366	0.4063	0.3321	0.2153	0.8974	0.9541	0.8873	0.8380	0.9788
DELAY	0.3911	0.3171	0.2368	0.1833	0.1388	0.3835	0.2965	0.2117	0.1603	0.1149	0*	0*	0*	0.1617	0.1153	0.3377	0.5211	0.5572	0.4618	0.4016
LIQ	0.3774	0.3142	0.2502	0.1555	0.1416	0.3702	0.2979	0.2286	0.1345	0.1226	0.3714	0.2994	0.2307	0.1369	0.1222	0.3904	0.3519	0.3157	0.2228	0.2249

This table presents the empirical estimates of ε_i for 4 to 78 week investment horizons. M is the area between the cumulative distributions when the cumulative distribution of a factor portfolio plots above the cumulative distribution of our benchmarks (i.e., S&P 500, T-Bonds, T-Bills and Bitcoin). Likewise, N is the area between the cumulative distributions. The measure of ε_i for AFSD is $\varepsilon_i = \frac{M}{M+N}$. The critical value for AFSD is $\varepsilon^* = 5.9\%$. If the ε_i value for any portfolio is less than the critical value, this indicates the out-performance by that portfolio. * denotes portfolios where ε_i is less than the critical value. The ε_i value of 1 indicates that the benchmark dominates the corresponding portfolio by AFSD.

Table 6: Almost Second-Order Stochastic Dominance

	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: AFSD for Portfolios against Bitcoin				
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	4-week	13-week	26-week	52-week	78-week
MARCAP	0.1976	0.0417	0.0044**	0**	0**	0.2245	0.0580	0.0074**	0.0006**	0**	0**	0**	0**	0**	0**	0**	0**	0**	0**	0**
LPRC	0.4955	0.3402	0.2161	0.0853	0.0577	0.4890	0.3179	0.1897	0.0689	0.0395	0.4970	0.3272	0**	0.0761	0.0433	0.4034	0.3132	0.0460	0**	0.0760
AGE	0.5127	0.2766	0.1848	0.0971	0.0648	0.5062	0.2657	0.1666	0.0824	0.0504	0.5114	0**	0**	0.0882	0.0537	0.5725	0.1649	0.1583	0**	0**
MOM1	0.2809	0.0639	0.0232**	0**	0**	0.2942	0.0733	0.0244**	0.0003**	0**	0**	0**	0**	0**	0**	0.0776	0**	0**	0**	0**
MOM2	0.3247	0.1606	0.1127	0.0125**	0.0088**	0.3346	0.1635	0.1083	0.0124**	0.0081**	0**	0**	0**	0**	0**	0.1317	0.1030	0.0687	0**	0.0009**
MOM3	0.4944	0.3453	0.2716	0.1744	0.1705	0.4916	0.3324	0.2494	0.1580	0.1486	0**	0**	0**	0.1605	0.1483	0.5683	0.2612	0.2039	0.0845	0.2415
MOM4	0.6150	0.4322	0.3478	0.2520	0.1184	0.5978	0.3975	0.2961	0.1996	0.0831	0.6012	0**	0**	0.2028	0.0867	0.6257	0.3779	0.7207	0.7763	0.5003
MOM8	0.7495	0.6775	0.5977	0.5477	0.5202	0.7843	0.7137	0.6217	0.5590	0.5249	0.8017	0.7326	0.6378	0.5694	0.5321	0.7844	0.6859	0.5068	0.5036	1.0000
MOM26	0.6664	0.5786	0.5465	0.5093	1.0000	0.6883	0.5954	0.5589	0.5131	0.5000	0.7007	0.6067	0.5688	0.5171	0.5002	0.7594	1.0000	1.0000	1.0000	1.0000
RMOM1	0.2997	0.1183	0.0698	0.005**	0**	0.3160	0.1258	0.0661	0.0054**	0**	0**	0**	0**	0**	0**	0.003**	0.005**	0.0019**	0**	0**
RMOM2	0.3599	0.1955	0.1339	0.0169**	0**	0.3705	0.1965	0.1283	0.0167**	0**	0**	0**	0**	0**	0**	0.2370	0.1060	0.1124	0**	0**
RMOM3	0.2934	0.1174	0.0396	0.0013**	0.0003**	0.3102	0.1255	0.0394	0.002**	0.0007**	0**	0**	0**	0**	0**	0.0867	0.0021**	0**	0**	0**
RMOM4	0.3682	0.1321	0.0621	0.0089**	0**	0.3775	0.1388	0.0595	0.0089**	0**	0**	0**	0**	0**	0**	0.0151**	0**	0**	0**	0**
RMOM8	0.9838	0.9763	0.9955	0.8094	0.6856	0.9266	0.8741	0.8517	0.9482	0.7693	0.9105	0**	0.8164	0.9698	0.8311	0.9119	0.7314	0.6667	1.0000	1.0000
RMOM26	0.7042	0.6227	0.5808	0.5431	0.5319	0.7333	0.6508	0.6038	0.5564	0.5403	0.7486	0.6670	0.6197	0.5689	0.5495	0.6834	0.6682	1.0000	1.0000	1.0000
VOL	0.9320	0.9842	0.9342	0.7855	0.6871	0.9883	0.8976	0.8387	0.6989	0.5972	0.9907	0.8764	0.8154	0.6736	0.5702	0.8804	0.5996	0.6138	0.6555	0.6419
VOLPRC	0.4230	0.2413	0.1094	0.0320	0.0072**	0.4227	0.2263	0.0960	0.0147**	0.0053**	0.4336	0**	0**	0**	0**	0.1382	0**	0.0027**	0**	0**
VOLSCALE	0.7038	0.5897	0.4640	0.2549	0.2186	0.6756	0.5343	0.3966	0.2005	0.1703	0.6745	0.5322	0.3949	0.2025	0.1673	0.8741	0.9963	0.9078	0.7707	0.9410
RETVOL	0.9200	0.8646	0.8851	0.9321	0.8036	0.9629	0.9303	0.9846	0.7900	0.6527	0.9798	0.9557	0.9757	0.7456	0.6039	0.6878	0.5715	0.7715	0.6787	0.5246
RETSKEW	0.6540	0.3704	0.1803	0.0575	0.0169**	0.6325	0.3408	0.1532	0.0480	0.0143**	0.6341	0**	0**	0**	0**	0.8152	0.0252**	0**	0**	0**
RETKURT	0.9548	0.9374	0.8372	0.8222	0.9949	0.8870	0.8091	0.6805	0.6539	0.7608	0.8700	0.7848	0.6562	0.6134	0.6856	0.7941	0.9986	0.6292	1.0000	1.0000
MAXRET	0.5000	0.2814	0.1504	0.007**	0.0064**	0.4953	0.2681	0.1347	0.0071**	0.005**	0.5031	0**	0**	0**	0**	0.3512	0.0319**	0.0015**	0**	0**
STDPRCVOL	0.4556	0.2808	0.1694	0.0757	0.0473	0.4524	0.2621	0.1446	0.0582	0.0287**	0.4620	0.2740	0.1582	0.0660	0.0329	0.2657	0.0874	0.1008	0.0145**	0.1454
MEANABS	0.6061	0.4582	0.3337	0.1841	0.1649	0.5879	0.4242	0.2963	0.1554	0.1398	0.5908	0.4273	0.2999	0.1586	0.1393	0.6341	0.5429	0.6313	0.2756	0.2901
BETA	0.9771	0.9715	0.8890	0.7572	0.6007	0.9610	0.8749	0.7771	0.6445	0.5047	0.9421	0.8524	0.7526	0.6155	0.4789	0.6502	0.6102	0.5803	0.5814	0.5611
BETA$\hat{2}$	0.9228	0.9447	0.9977	0.9515	0.7415	0.9906	0.9429	0.8731	0.7646	0.6098	0.9842	0.9129	0.8400	0.7220	0.5704	0.6844	0.8392	0.5375	0.5495	0.5175
IDIOVOL	0.9746	0.8906	0.8105	0.6245	0.3948	0.9095	0.7936	0.7039	0.5180	0.2892	0.8922	0.7750	0.6845	0.4973	0.2744	0.9346	0.7786	0.5339	0.5535	0.6705
DELAY	0.6422	0.4644	0.3102	0.2245	0.1611	0.6220	0.4214	0.2685	0.1908	0.1298	0**	0**	0**	0.1928	0.1303	0.8584	0.8090	0.6850	0**	0.5925
LIQ	0.6061	0.4582	0.3337	0.1841	0.1649	0.5879	0.4242	0.2963	0.1554	0.1398	0.5908	0.4273	0.2999	0.1586	0.1393	0.6341	0.5429	0.6313	0.2756	0.2901

This table presents the empirical estimates of ε_i for 4 to 78 week investment horizons. A_1 is the area between the cumulative distributions when the cumulative distribution of a portfolio plots above the cumulative distribution of a benchmark (i.e. S&P 500, T-Bonds, T-Bills and Bitcoin), and the aggregate area becomes positive. A_2 is the absolute value of the area enclosed between the CDFs of the two assets. The measure of ε_i for ASSD is $\varepsilon_i = \frac{A_1}{A_2}$. The critical value for ASSD is $\varepsilon^* = 3.2\%$. If the ε_i for any portfolio is less than the critical value, then the result indicates outperformance by that portfolio. ** denotes portfolios where ε_i is less than the critical value. The ε_i value of 1 indicates that benchmark dominates the corresponding portfolio.

Table 7: Coin Market Three-Factor Model

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	$AdjR^2$
MARCAP	0.0189***	-0.386***	0.2233***	0.0373***	0.2523
	(3.8616)	(-8.9708)	(7.8978)	(2.6239)	
MOM1	0.0234**	0.0458	0.0854	0.2357***	0.1617
	(2.5164)	(0.5601)	(1.5909)	(8.7357)	
MOM2	0.025***	0.0206	0.1036*	0.1285***	0.0530
	(2.6457)	(0.2484)	(1.8966)	(4.6911)	
RMOM1	0.0201***	0.1257*	-0.0081	0.1761***	0.1448
	(2.6408)	(1.8793)	(-0.1849)	(7.9663)	
RMOM2	0.033***	-0.0504	-0.0775	-0.0564**	0.0106
	(3.6661)	(-0.6378)	(-1.4899)	(-2.1435)	
RMOM3	0.0223**	0.1407*	0.0303	0.1419***	0.0686
	(2.3975)	(1.7196)	(0.5622)	(5.2470)	
RMOM4	0.0247***	0.2027***	-0.089**	0.0051	0.0240
	(3.2328)	(3.0230)	(-2.0144)	(0.2305)	
MAXRET	0.0087	0.2938***	0.0739*	0.1***	0.0988
	(1.1612)	(4.4429)	(1.7014)	(4.5794)	

This table reports the results of regression analysis for the coin market three-factor model and our eight dominant factor portfolios. The dependent variables are the long-short factor portfolios constructed in Section 5. *, **, *** represent significance at 10%, 5%, 1% levels, respectively. The t-statistics are reported in parentheses.

Table 8: Potential Combinations

	Coin Market 3-Factor Model	*Mispricing*	*Attention*	Network
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

This table reports the seven augmented models based on the mispricing and two non-financial factors. A 'Y' means that the corresponding model incorporates the factor.

Table 9: Augmented Coin Market Model (Model 6)

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	$\beta_{Mispricing}$	$\beta_{Network}$	$Adj R^2$
MARCAP	0.0162***	-0.3813***	0.2212***	0.0252*	0.1072*	0.0156*	0.2620
	(3.2120)	(-8.8870)	(7.8422)	(1.6684)	(1.8911)	(1.7361)	
MOM1	-0.0134**	0.0299	0.0272	0.0874***	1.5405***	0.0150	0.6050
	(-2.0234)	(0.5314)	(0.7353)	(4.4056)	(20.7143)	(1.2665)	
MOM2	-0.0102	-0.0013	0.0456	-0.0122	1.4811***	-0.0023	0.4980
	(-1.4355)	(-0.0216)	(1.1409)	(-0.5710)	(18.5189)	(-0.1786)	
RMOM1	-0.0072	0.1069**	-0.0540	0.0674***	1.1501***	-0.0067	0.5140
	(-1.2085)	(2.1108)	(-1.6224)	(3.7786)	(17.1946)	(-0.6271)	
RMOM2	0.0211**	-0.0581	-0.0976*	-0.1035***	0.5022***	-0.0012	0.0652
	(2.3268)	(-0.7532)	(-1.9209)	(-3.7836)	(4.9349)	(-0.0766)	
RMOM3	-0.0094	0.1144*	-0.0254	0.0166	1.3407***	-0.0217	0.4362
	(-1.2515)	(1.7900)	(-0.6019)	(0.7374)	(15.8978)	(-1.6148)	
RMOM4	0.0038	0.19***	-0.124***	-0.0777***	0.8821***	-0.0003	0.2717
	(0.5555)	(3.2667)	(-3.2338)	(-3.7672)	(11.4881)	(-0.0286)	
MAXRET	0.0038	0.2921***	0.0663	0.0799***	0.2069**	0.0033	0.1075
	(0.4870)	(4.4234)	(1.5264)	(3.4335)	(2.3711)	(0.2381)	

This table reports the results of regression analysis of our eight dominant factor portfolios using Model 6 in Table 8. *, **, *** represent significance at the 10%, 5%, 1% levels, respectively. The t-statistics are reported in parentheses.

Table 10: Comparison of Model Performance

Panel A: Coin market three-factor model								
Model	$A\|R^2\|$	Significant Alphas	GRS	$A\|\alpha_i\|$	$A\|\alpha_i\|/A\|\bar{r}_i\|$	$A\alpha_i^2/A\bar{r}_i^2$	$As^2(\alpha_i)/A\alpha_i^2$	Score
3-factor	0.10	7	8.3486	0.0220	1.6188	0.0149	0.1284	0
Panel B: Performance metrics for potential models								
1	0.35	3	3.3648	0.0106	0.3803	0.1793	0.3454	2
2	0.10	7	7.3838	0.0213	0.7621	0.6281	0.1465	0
3	0.10	7	8.2794	0.0219	0.7827	0.6434	0.1296	0
4	0.34	2	3.5880	0.0113	0.4031	0.2161	0.3132	1
5	0.10	7	7.3828	0.0213	0.7603	0.6254	0.1472	0
6	0.34	3	3.3678	0.0106	0.3801	0.1792	0.3458	4
7	0.34	2	3.6111	0.0113	0.4042	0.2171	0.3120	1
Panel C: Performance metrics for reduced model								
NTFM	0.33	3	3.4828	0.0107	0.3821	0.1810	0.3503	0
NTFM-SM	0.21	1	1.2127	0.0051	0.3754	0.0012	1.5940	6
Panel D: Performance metrics for the augmented model with MispricingM								
NTFM-RMOM	0.24	1	3.1132	0.0066	0.4878	0.0025	0.7038	1

This table reports the performance measures for the coin market three-factor model, the seven augmented coin market five-factor models, and the coin market three-factor NTFM and NTFM-SM models. The last row contains results for the NTFM-RMOM model analysed in Section 8. Columns two to the penultimate column are measures of model performance, and the last column illustrates the overall scores for each model, the higher the better. * and ** demonstrate the highest score within the panel, and the highest score across the panels.

Table 11: Spanning Regressions for Model 6

	Intercept	*CMKT*	*CSMB*	*CMOM*	*Mispricing*	*Network*	*Ajd* R^2
CMKT	0.0101*	-	0.0512	0.015	0.0322	-0.0177*	0.006
	(1.6905)	-	(1.5346)	(0.8363)	(0.4793)	(-1.6611)	
CSMB	0.0507***	0.1185	-	-0.0536**	0.1639	-0.0156	0.011
	(5.8222)	(1.5346)	-	(-1.9735)	(1.6079)	(-0.9606)	
CMOM	0.0008	0.1207	-0.1864**	-	1.3179***	0.0274	0.127
	(0.0456)	(0.8363)	(-1.9735)	-	(7.3799)	(0.9064)	
Mispricing	0.0236***	0.0185	0.0406	0.0938***	-	0.011	0.125
	(5.4235)	(0.4793)	(1.6079)	(7.3799)	-	(1.3596)	
Network	-0.001	-0.4017*	-0.1531	0.0775	0.4349	-	0.010
	(-0.0367)	(-1.6611)	(-0.9606)	(0.9064)	(1.3596)	-	

This table reports the results of spanning regression analysis of each individual factor on the other factors of Model 6 in Table 8. *, **, *** represent significance at the 10%, 5%, 1% levels, respectively. The t-statistics are reported in parentheses.

Table 12: Three-Factor Model with a New Mispricing Factor (NTFM-SM)

	α	β_{CMKT}	β_{CSMB}	$\beta_{Mispricing2}$	*Adj* R^2
MARCAP	0.0106**	-0.3725***	0.2149***	0.3797***	0.2990
	(2.1128)	(-8.9465)	(7.8760)	(5.7573)	
MOM1	-0.0006	0.1075	0.0397	1.2799***	0.2085
	(-0.0624)	(1.3548)	(0.7643)	(10.1842)	
MOM2	0.0079	0.0572	0.0784	0.851***	0.1023
	(0.8137)	(0.7093)	(1.4783)	(6.6656)	
RMOM1	-0.0049	0.1777***	-0.0440	1.2334***	0.3042
	(-0.6777)	(2.9463)	(-1.1130)	(12.9109)	
RMOM2	-0.0012	-0.0315	-0.0773*	1.2575***	0.2598
	(-0.1421)	(-0.4607)	(-1.7217)	(11.6365)	
RMOM3	-0.0008	0.1858**	0.0013	1.1032***	0.1779
	(-0.0898)	(2.4180)	(0.0259)	(9.0769)	
RMOM4	-0.0043	0.2287***	-0.0967***	1.133***	0.3139
	(-0.6301)	(4.0712)	(-2.6180)	(12.7401)	
MAXRET	0.0106	0.31***	0.0575	0.0716	0.0511
	(1.3029)	(4.5720)	(1.2950)	(0.6664)	

This table reports the results of regression analysis of the eight dominant portfolios using the NTFM-SM model. *, **, *** represent significance at the 10%, 5%, 1% levels, respectively. The t-statistics are reported in parentheses.

Table 13: NTFM-SIZE

	α	β_{CMKT}	β_{CSMB}	$\beta_{MispricingS}$	$Adj\ R^2$
MOM1	0.032***	0.0818	0.0472	0.0034	-0.0036
	(3.1052)	(0.8364)	(0.7511)	(0.0320)	
MOM2	0.029***	0.0502	0.0778	0.0292	-0.0008
	(2.9436)	(0.5389)	(1.2950)	(0.2929)	
RMOM1	0.0297***	0.0935	-0.0029	-0.153*	0.0130
	(3.5807)	(1.1893)	(-0.0572)	(-1.8169)	
RMOM2	0.0336***	-0.1071	-0.0419	-0.1256	0.0035
	(3.6660)	(-1.2354)	(-0.7483)	(-1.3511)	
RMOM3	0.0258***	0.1903**	-0.0074	0.0744	0.0034
	(2.6389)	(2.0559)	(-0.1245)	(0.7512)	
RMOM4	0.0226***	0.2466***	-0.1147**	0.1134	0.0291
	(2.9244)	(3.3727)	(-2.4293)	(1.4468)	
MAXRET	0.0173**	0.2173***	0.1101**	-0.2397***	0.0723
	(2.2332)	(2.9616)	(2.3358)	(-3.0512)	

This table reports the results of regression analysis of the eight dominant portfolios using the NTFM-SIZE model. *, **, *** represent significance at the 10%, 5%, 1% levels, respectively. The t-statistics are reported in parentheses.

Table 14: NTFM-RMOM

	α	β_{CMKT}	β_{CSMB}	$\beta_{MispricingM}$	$Adj\ R^2$
MARCAP	0.022***	-0.3743***	0.2133***	-0.0626	0.2416
	(4.3012)	(-8.5850)	(7.4635)	(-1.1691)	
MOM1	0.0038	-0.0219	0.1142**	1.0372***	0.2253
	(0.4079)	(-0.2768)	(2.2046)	(10.6941)	
MOM2	0.0110	-0.0280	0.1276**	0.6796***	0.1073
	(1.1610)	(-0.3453)	(2.3948)	(6.8428)	
RMOM1	-0.0023	0.0473	0.0315	1.0575***	0.3665
	(-0.3352)	(0.8166)	(0.8287)	(14.8706)	
RMOM2	0.0015	-0.1631**	0.0002	1.0697***	0.3083
	(0.1910)	(-2.4546)	(0.0036)	(13.1083)	
RMOM3	0.0036	0.0767	0.0642	0.8675***	0.2309
	(0.3987)	(0.9935)	(1.2640)	(9.1656)	
RMOM4	0.0005	0.1183**	-0.0324	0.8799***	0.3105
	(0.0687)	(2.0866)	(-0.8685)	(12.6348)	
MAXRET	0.0084	0.294***	0.0674	0.1469*	0.0575
	(1.0565)	(4.3210)	(1.5110)	(1.7595)	

This table reports the results of regression analysis of the eight dominant portfolios using the NTFM-RMOM model. *, **, *** represent significance at the 10%, 5%, 1% levels, respectively. The t-statistics are reported in parentheses.

Table 15: Betas for Two Sample Periods using the $NewMispricing$ Model

	Panel A: First Period (2014.01-2016.09)			Panel B: Second Period (2016.10-2021-06)		
	$\beta_{MispricingS}$	$\beta_{MispricingM}$	$Adj\ R^2$	$\beta_{MispricingS}$	$\beta_{MispricingM}$	$Adj\ R^2$
MOM1	0.1001	1.1131***	0.2148	0.0167	0.8764***	0.2421
	(0.7045)	(7.3710)		(0.1562)	(7.9835)	
MOM2	-0.413***	-0.0442	0.0448	0.3979***	0.4359***	0.1497
	(-2.8510)	(-0.2869)		(3.3065)	(3.5282)	
RMOM1	-0.1474	1.0906***	0.3625	0.0457	0.9359***	0.3688
	(-1.4597)	(10.1612)		(0.5286)	(10.5269)	
RMOM2	-0.3891***	-0.1012	0.0214	-0.1959*	0.7242***	0.2108
	(-2.8168)	(-0.6890)		(-1.8701)	(6.7881)	
RMOM3	0.1888	-0.2809*	0.0246	0.326***	1.0578***	0.4700
	(1.2537)	(-1.7550)		(3.8425)	(12.2424)	
RMOM4	0.0770	-0.0456	-0.0160	0.1559**	1.3387***	0.6010
	(0.7061)	(-0.3932)		(1.9626)	(16.5407)	
MAXRET	-0.1865*	0.1259	0.0433	-0.3047***	0.1419	0.1242
	(-1.6836)	(1.0696)		(-2.6233)	(1.1879)	

This table reports partial results for the regression of seven dominant factor portfolio using the $NewMispricing$ model. Only the results for $MispricingS$ and $MispricingM$ are displayed as they are the variables of interest. $R_i - R_f = \alpha_i + \beta_{i,CMKT}CMKT + \beta_{i,CSMB}CSMB + \beta_{i,MispricingS}MispricingS + \beta_{i,MispricingM}MispricingM + \epsilon_i$. *, **, *** represent significance at the 10%, 5%, 1% levels, respectively. The t-statistics are reported in parentheses.

Table 16: Interactive Effect of Size, RMOM and Horizon

	RMOM1	RMOM2	RMOM4
Small & Low	0.0449***	0.0320***	0.0211***
	(5.0294)	(4.0404)	(2.6680)
Small & High	0.0535***	0.0509***	0.0417***
	(4.8883)	(4.7636)	(3.3019)
Big & Low	-0.0043	-0.0044	0.0007
	(-0.7056)	(-0.7313)	(0.1098)
Big & High	0.0276***	0.0250***	0.0198***
	(3.6521)	(3.2836)	(2.9973)

This table reports the excess return on each size and momentum portfolio for different risk-adjusted portfolios over three horizons that were used to construct $MispricingM$. *, **, *** represent significance at the 10%, 5%, 1% levels, respectively. The t-statistics are reported in parentheses.

Online Appendix for

On the (Almost) Stochastic Dominance of Cryptocurrency Factor Portfolios & Implications for Cryptocurrency Asset Pricing

Contents

A1 Simulation Test for ASD Critical Values

We discussed the critical values of ε_1 and ε_2 in Section 4.2, which are the maximum ratios of the violation area to the enclosed area between the CDFs of the high return (H) and low return (L) portfolios. Levy et al. (2010) exploit experiments based on 400 subjects' choices to quantify the critical epsilon values of ASD ($\varepsilon_1^* = 5.9\%, \varepsilon_2^* = 3.2\%$) that avoid paradoxical choices. The outcomes of Levy et al. (2010) are robust and insensitive to both the 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 reflect almost all investors' choices when investors are facing similar scenarios. Nevertheless, one may be concerned about the reliability of the critical values of Levy et al. (2010) because they completed the test over a decade ago. To alleviate such concerns, we conduct an analysis of critical values of ε_1 and ε_2 based on randomization techniques (Bali et al., 2013) to ensure the reliability of the critical values for our study.

We select monthly S&P 500 index return as a proxy for stock return over the time period from January 1926 to June 2021 and generate the distribution of ε_1 and ε_2 with repeated samples. Particularly, in each simulation, two series of 1000 monthly return observations are picked (with replacement) from the S&P 500 index and we calculate and record the empirical ε_1 and ε_2 values. This procedure is repeated 3000 times, generating

3000 pairs of ε_1 and ε_2 values. The null hypothesis is that neither return series dominates 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 A1 reports descriptive statistics for distributions 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 10th percentile of distribution of ε_1 is 8.55%, which is greater than 5.9%, indicating that estimated ε_1 values reported in Table A.1 have p-values lower than 10% (between 5% and 10%). This result rejects the null hypothesis of ε_1 at significance level of 10%. Similarly, from the perspective of ε_2, the fifth percentile of distribution of ε_2 is 3.23%, we can reject the null hypothesis of ε_2 at significance level of 5%.

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

Table A1: 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	0.0056	0.0245	0.0412	0.0855	0.2252	0.4928	0.7543	0.9060	0.9562	0.9951	1	0.4939
ε_2	0.0006	0.0053	0.0158	0.0323	0.0816	0.5345	0.7969	0.9039	0.9537	0.9730	0.9971	1	0.6712

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

A2 Incorporating Mispricing and Fundamental Factors into Coin Market Model

Next, we aim to construct every potential combination of mispricing factors and fundamental factors (electricity and computer power), then incorporate these potential factors into a coin market three-factor model developed by Liu et al. (2022) to evaluate whether the performance of an adjusted model can be improved (Stambaugh and Yuan, 2017). We consider the two most important cryptocurrency related factors: investor sentiment and network factor, since these two factors are essential requirements in mining cryptocurrencies (Bianchi et al., 2020; Liu and Tsyvinski, 2020).

Table A2: Potential Combinations

	Coin Market 3-Factor Model	*Mispricing*	*Attention*	Network
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

This table reports the seven augmented models based on the mispricing and two non-financial factors. A 'Y' means that the corresponding model incorporates the factor.

A2.1 Potential Combinations for Adjusted Models

For a better understanding of Table A2, we explain the terms next. The coin three-factor model consists of coin market ($CMKT$), size factor ($CSMB$) and momentum factor ($CMOM$), as developed by Liu et al. (2022) and discussed in Section 6.4. Moreover, a mispricing factor ($Mispricing$), investor sentiment factor ($Sentiment$) and first principal component ($PC1$) are added to original coin three-factor model to examine whether the performance of adjusted models is an improvement.

Among seven models, each is formed via 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 Mispricing, mathematical expression tends to provide a clearer picture:

$$R_i - R_f = \alpha^i + \beta^i_{CMKT} CMKT + \beta^i_{CSMB} CSMB + \beta^i_{CMOM} CMOM + \beta^i_{Mispricing} Mispricing + \epsilon_i \quad (1)$$

where R_i, R_f, $CMKT$, $CSMB$, $CMOM$ have been illustrated above, Mispricing is the mispricing factor. The other models are constructed in the same manner.

A2.2 Empirical Results for 7 Models

In this section, we examine whether the returns of eight dominant factors can be explained better by seven adjusted models, choosing the best fitting 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 eight dominant factors, and its t-statistics which is included in parentheses.

Table A3: Adjusted Coin Market Model 1

	α	β_{CMKT}	β_{CSMB}	β_{COM}	$\beta_{Mispricing}$	$Adj\ R^2$
MARCAP	0.0162***	-0.3876***	0.2188***	0.0264*	0.114**	0.2581
	(3.2004)	(-9.0419)	(7.7465)	(1.7457)	(2.0106)	
MOM1	-0.0134**	0.0239	0.0249	0.0886***	1.547***	0.6044
	(-2.0242)	(0.4259)	(0.6737)	(4.4652)	(20.8352)	
MOM2	-0.0102	-0.0004	0.0460	-0.0124	1.4801***	0.4992
	(-1.4378)	(-0.0068)	(1.1538)	(-0.5811)	(18.5741)	
RMOM1	-0.0072	0.1095**	-0.0530	0.0669***	1.1472***	0.5147
	(-1.2082)	(2.1730)	(-1.5950)	(3.7566)	(17.2059)	
RMOM2	0.0211**	-0.0576	-0.0974*	-0.1036***	0.5017***	0.0676
	(2.3294)	(-0.7504)	(-1.9221)	(-3.7982)	(4.9480)	
RMOM3	-0.0095	0.1231*	-0.0217	0.0148	1.3315***	0.4338
	(-1.2557)	(1.9290)	(-0.5139)	(0.6554)	(15.7915)	
RMOM4	0.0038	0.1901***	-0.1239***	-0.0777***	0.8819***	0.2736
	(0.5561)	(3.2854)	(-3.2414)	(-3.7791)	(11.5291)	
MAXRET	0.0038	0.2908***	0.0658	0.0802***	0.2083**	0.1097
	(0.4872)	(4.4244)	(1.5185)	(3.4523)	(2.3962)	

This table reports the empirical results of Model 1. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The t-statistics are reported in parentheses and are Newey-West adjusted with $n-1$ lags.

Table A4: Adjusted Coin Market Model 2

	α	β_{CMKT}	β_{CSMB}	β_{COM}	$\beta_{Sentiment}$	$Adj\ R^2$
MARCAP	0.0185***	-0.385***	0.2236***	0.0371***	0.0010	0.2505
	(3.6206)	(-8.9006)	(7.8899)	(2.6036)	(0.2462)	
MOM1	0.0247**	0.0421	0.0840	0.2365***	-0.0037	0.1601
	(2.5484)	(0.5127)	(1.5603)	(8.7409)	(-0.4908)	
MOM2	0.0224**	0.0273	0.1063*	0.1271***	0.0069	0.0525
	(2.2724)	(0.3286)	(1.9425)	(4.6343)	(0.8974)	
RMOM1	0.0198**	0.1263*	-0.0079	0.1759***	0.0006	0.1426
	(2.4960)	(1.8781)	(-0.1790)	(7.9392)	(0.0983)	
RMOM2	0.0369***	-0.0580	-0.0823	-0.0557**	-0.0119	0.0121
	(3.8784)	(-0.7322)	(-1.5795)	(-2.1192)	(-1.2575)	
RMOM3	0.0173*	0.1507*	0.0366	0.1405***	0.0151	0.0719
	(1.7525)	(1.8396)	(0.6791)	(5.2007)	(1.5461)	
RMOM4	0.0216***	0.2086***	-0.0852*	0.0046	0.0093	0.0249
	(2.6738)	(3.1038)	(-1.9246)	(0.2071)	(1.1576)	
MAXRET	0.0092	0.2924***	0.0734*	0.1003***	-0.0014	0.0966
	(1.1771)	(4.3981)	(1.6842)	(4.5796)	(-0.2314)	

This table reports the empirical results of Model 2. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The t-statistics are reported in parentheses and are Newey-West adjusted with $n-1$ lags.

Table A5: Adjusted Coin Market Model 3

	α	β_{CMKT}	β_{CSMB}	β_{COM}	$\beta_{Network}$	$Adj\ R^2$
MARCAP	0.0187***	-0.3793***	0.2255***	0.0353**	0.0168*	0.2570
	(3.8414)	(-8.8142)	(7.9966)	(2.4843)	(1.8649)	
MOM1	0.0231**	0.0584	0.0897*	0.232***	0.0318*	0.1670
	(2.4921)	(0.7140)	(1.6753)	(8.5984)	(1.8612)	
MOM2	0.0248***	0.0260	0.1058*	0.1267***	0.0140	0.0521
	(2.6264)	(0.3127)	(1.9329)	(4.6117)	(0.8013)	
RMOM1	0.02***	0.1281*	-0.0073	0.1753***	0.0059	0.1430
	(2.6304)	(1.9059)	(-0.1662)	(7.9034)	(0.4227)	
RMOM2	0.0329***	-0.0486	-0.0768	-0.057**	0.0043	0.0082
	(3.6541)	(-0.6129)	(-1.4732)	(-2.1551)	(0.2599)	
RMOM3	0.0224**	0.1379*	0.0292	0.1428***	-0.0071	0.0666
	(2.4039)	(1.6775)	(0.5406)	(5.2576)	(-0.4140)	
RMOM4	0.0246***	0.2065***	-0.0875**	0.0039	0.0094	0.0226
	(3.2129)	(3.0662)	(-1.9772)	(0.1740)	(0.6675)	
MAXRET	0.0087	0.296***	0.0747*	0.0993***	0.0056	0.0968
	(1.1529)	(4.4559)	(1.7153)	(4.5313)	(0.4004)	

This table reports the empirical results of Model 3. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The t-statistics are reported in parentheses and are Newey-West adjusted with $n-1$ lags.

Table A6: Adjusted Coin Market Model 4

	α	β_{CMKT}	β_{CSMB}	β_{COM}	$\beta_{Mispricing}$	$\beta_{Sentiment}$	$Adj\ R^2$
MARCAP	0.0159***	-0.3868***	0.2191***	0.0263*	0.1137**	0.0008	0.2563
	(3.0167)	(-8.9744)	(7.7363)	(1.7331)	(2.0034)	(0.2057)	
MOM1	-0.0112	0.0180	0.0225	0.0896***	1.5488***	-0.0059	0.6047
	(-1.6317)	(0.3199)	(0.6088)	(4.5123)	(20.8628)	(-1.1461)	
MOM2	-0.0120	0.0043	0.0479	-0.0132	1.4787***	0.0047	0.4989
	(-1.6158)	(0.0706)	(1.1995)	(-0.6173)	(18.5460)	(0.8512)	
RMOM1	-0.0068	0.1085**	-0.0534	0.0671***	1.1475***	-0.0010	0.5135
	(-1.0985)	(2.1409)	(-1.6031)	(3.7582)	(17.1856)	(-0.2243)	
RMOM2	0.0256***	-0.0665	-0.1033**	-0.1034***	0.5085***	-0.0139	0.0708
	(2.6879)	(-0.8665)	(-2.0366)	(-3.7994)	(5.0190)	(-1.5184)	
RMOM3	-0.0124	0.1293**	-0.0176	0.0144	1.3265***	0.0092	0.4345
	(-1.5706)	(2.0209)	(-0.4160)	(0.6383)	(15.7233)	(1.2119)	
RMOM4	0.0020	0.1938***	-0.1214***	-0.0778***	0.8791***	0.0058	0.2730
	(0.2730)	(3.3382)	(-3.1667)	(-3.7804)	(11.4761)	(0.8291)	
MAXRET	0.0044	0.2891***	0.0651	0.0805***	0.2088**	-0.0017	0.1076
	(0.5455)	(4.3751)	(1.4985)	(3.4572)	(2.3987)	(-0.2823)	

This table reports the empirical results of Model 4. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The t-statistics are reported in parentheses and are Newey-West adjusted with $n-1$ lags.

Table A7: Adjusted Coin Market Model 5

	α	β_{CMKT}	β_{CSMB}	β_{COM}	$\beta_{Sentiment}$	$\beta_{Network}$	$Adj\ R^2$
MARCAP	0.0184***	-0.3786***	0.2258***	0.0351**	0.0008	0.0167*	0.2552
	(3.6159)	(-8.7515)	(7.9857)	(2.4677)	(0.1965)	(1.8566)	
MOM1	0.0246**	0.0544	0.0882	0.2327***	-0.0041	0.0321*	0.1655
	(2.5405)	(0.6626)	(1.6425)	(8.6071)	(-0.5431)	(1.8736)	
MOM2	0.0223**	0.0325	0.1084**	0.1255***	0.0067	0.0136	0.0515
	(2.2609)	(0.3886)	(1.9764)	(4.5586)	(0.8758)	(0.7774)	
RMOM1	0.0198**	0.1286*	-0.0071	0.1752***	0.0005	0.0059	0.1408
	(2.4897)	(1.9037)	(-0.1611)	(7.8782)	(0.0868)	(0.4197)	
RMOM2	0.0369***	-0.0558	-0.0815	-0.0565**	-0.0121	0.0057	0.0098
	(3.8732)	(-0.7020)	(-1.5607)	(-2.1378)	(-1.2758)	(0.3431)	
RMOM3	0.0173*	0.1475*	0.0354	0.1415***	0.0154	-0.0088	0.0701
	(1.7515)	(1.7923)	(0.6551)	(5.2198)	(1.5733)	(-0.5112)	
RMOM4	0.0216***	0.2118***	-0.084*	0.0035	0.0090	0.0084	0.0232
	(2.6703)	(3.1383)	(-1.8943)	(0.1575)	(1.1153)	(0.5933)	
MAXRET	0.0092	0.2945***	0.0741*	0.0996***	-0.0015	0.0057	0.0946
	(1.1723)	(4.4118)	(1.6979)	(4.5322)	(-0.2421)	(0.4063)	

This table reports the empirical results of Model 5. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The t-statistics are reported in parentheses and are Newey-West adjusted with $n-1$ lags.

Table A8: Adjusted Coin Market Model 6

	α	β_{CMKT}	β_{CSMB}	β_{COM}	$\beta_{Mispricing}$	$\beta_{Network}$	$Adj\ R^2$
MARCAP	0.0162***	-0.3813***	0.2212***	0.0252*	0.1072*	0.0156*	0.2620
	(3.2120)	(-8.8870)	(7.8422)	(1.6684)	(1.8911)	(1.7361)	
MOM1	-0.0134**	0.0299	0.0272	0.0874***	1.5405***	0.0150	0.6050
	(-2.0234)	(0.5314)	(0.7353)	(4.4056)	(20.7143)	(1.2665)	
MOM2	-0.0102	-0.0013	0.0456	-0.0122	1.4811***	-0.0023	0.4980
	(-1.4355)	(-0.0216)	(1.1409)	(-0.5710)	(18.5189)	(-0.1786)	
RMOM1	-0.0072	0.1069**	-0.0540	0.0674***	1.1501***	-0.0067	0.5140
	(-1.2085)	(2.1108)	(-1.6224)	(3.7786)	(17.1946)	(-0.6271)	
RMOM2	0.0211**	-0.0581	-0.0976*	-0.1035***	0.5022***	-0.0012	0.0652
	(2.3268)	(-0.7532)	(-1.9209)	(-3.7836)	(4.9349)	(-0.0766)	
RMOM3	-0.0094	0.1144*	-0.0254	0.0166	1.3407***	-0.0217	0.4362
	(-1.2515)	(1.7900)	(-0.6019)	(0.7374)	(15.8978)	(-1.6148)	
RMOM4	0.0038	0.19***	-0.124***	-0.0777***	0.8821***	-0.0003	0.2717
	(0.5555)	(3.2667)	(-3.2338)	(-3.7672)	(11.4881)	(-0.0286)	
MAXRET	0.0038	0.2921***	0.0663	0.0799***	0.2069**	0.0033	0.1075
	(0.4870)	(4.4234)	(1.5264)	(3.4335)	(2.3711)	(0.2381)	

This table reports the empirical results of Model 6. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The t-statistics are reported in parentheses and are Newey-West adjusted with $n-1$ lags.

Table A9: Adjusted Coin Market Model 7

	α	β_{CMKT}	β_{CSMB}	β_{COM}	$\beta_{Mispricing}$	$\beta_{Sentiment}$	$\beta_{Network}$	*Adj* R^2
MARCAP	0.0159***	-0.3807***	0.2214***	0.0251*	0.107*	0.0006	0.0156*	0.2601
	(3.0397)	(-8.8265)	(7.8294)	(1.6581)	(1.8854)	(0.1616)	(1.7292)	
MOM1	-0.0111	0.0240	0.0248	0.0884***	1.5422***	-0.0061	0.0153	0.6054
	(-1.6216)	(0.4250)	(0.6701)	(4.4534)	(20.7434)	(-1.1801)	(1.2971)	
MOM2	-0.0120	0.0033	0.0475	-0.0130	1.4798***	0.0048	-0.0025	0.4976
	(-1.6147)	(0.0542)	(1.1857)	(-0.6062)	(18.4930)	(0.8549)	(-0.2002)	
RMOM1	-0.0068	0.1059**	-0.0544	0.0676***	1.1504***	-0.0010	-0.0066	0.5128
	(-1.1031)	(2.0814)	(-1.6294)	(3.7793)	(17.1741)	(-0.2080)	(-0.6207)	
RMOM2	0.0256***	-0.0664	-0.1033**	-0.1035***	0.5084***	-0.0139	0.0003	0.0683
	(2.6844)	(-0.8611)	(-2.0304)	(-3.7899)	(5.0000)	(-1.5146)	(0.0182)	
RMOM3	-0.0126	0.1207*	-0.0211	0.0163	1.3358***	0.0100	-0.0227*	0.4372
	(-1.5982)	(1.8850)	(-0.5003)	(0.7230)	(15.8381)	(1.3120)	(-1.6905)	
RMOM4	0.0020	0.1934***	-0.1216***	-0.0777***	0.8795***	0.0058	-0.0010	0.2711
	(0.2715)	(3.3165)	(-3.1626)	(-3.7657)	(11.4409)	(0.8315)	(-0.0805)	
MAXRET	0.0044	0.2904***	0.0656	0.0802***	0.2074**	-0.0017	0.0034	0.1054
	(0.5469)	(4.3752)	(1.5066)	(3.4384)	(2.3733)	(-0.2881)	(0.2452)	

This table reports the empirical results of Model 7. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The t-statistics are reported in parentheses and are Newey-West adjusted with $n-1$ lags.

Table A10: Comparison of Model Performance

Model	$A\lvert R^2\rvert$	Significant Alphas	GRS	$A\lvert\alpha_i\rvert$	$A\lvert\alpha_i\rvert/A\lvert\bar{r}_i\rvert$	$A\alpha_i^2/A\bar{r}_i^2$	$As^2(\alpha_i)/A\alpha_i^2$	Score
1	0.35	3	3.3648	0.0106	0.3803	0.1793	0.3454	2
2	0.10	7	7.3838	0.0213	0.7621	0.6281	0.1465	0
3	0.10	7	8.2794	0.0219	0.7827	0.6434	0.1296	0
4	0.34	2	3.5880	0.0113	0.4031	0.2161	0.3132	1
5	0.10	7	7.3828	0.0213	0.7603	0.6254	0.1472	0
6	0.34	3	3.3678	0.0106	0.3801	0.1792	0.3458	4
7	0.34	2	3.6111	0.0113	0.4042	0.2171	0.3120	1

This table reports the performance measures for 7 adjusted models. Each column represents one measure of model performance, and the last column illustrates the overall scores for each model. Columns from second column to second last column report seven different performance metrics for each model.

Table A10 reports the performance measures for seven models. The first metric is $A|R^2|$, representing the average R^2 for each augmented model - the higher is $A|R^2|$ the higher is the explanatory power. Second, the number of significant alphas indicates how many of the dominant factor portfolios appear to have anomalous returns according to the model. Our third metric is the GRS statistic, which has the null hypothesis that all alphas are jointly indistinguishable from zero. Hence, a small GRS statistic is preferable. Our fourth metric is the average absolute value of the eight alphas, denoted as $A|\alpha_i|$. As significant alphas are viewed as a measure of model mispricing, a model with a smaller value of this metric performs better. Our fifth metric is the ratio of the average absolute value of the alphas to the average absolute value of $\bar{r}_i$, denoted by $A|\alpha_i|/A|\bar{r}_i|$, where $\bar{r}_i$ is the average excess return on a dominant factor portfolio, minus the average excess return on the market portfolio. Our sixth metric is the ratio of the average squared alpha to the average squared value of $\bar{r}_i$, denoted by $A\alpha_i^2/A\bar{r}_i^2$. Both $A|\alpha_i|/A|\bar{r}_i|$ and $A\alpha_i^2/A\bar{r}_i^2$ evaluate the variation of the alphas, relative to the variation of the average excess returns on each dominant factor portfolio; with low values of these ratios representing a good performance of the model. Our final metric is $As^2(\alpha_i)/A\alpha_i^2$, which is the ratio of the average variance of the sampling errors of the estimated alphas to $A\alpha_i^2$. This final metric measures the proportion of the variance of the alphas due to sampling errors, rather than the dispersion of the true alphas. Therefore, a higher value of this ratio indicates a better model. The right hand column (*Score*) is the number of metrics on which the factor model is the best.

A3 Decomposition of the Long-Short Portfolios Against Equity Factor Portfolios

In this section, we examine the performance of long leg portfolios against equity factor portfolios based on size, momentum and book-to-market equity (BE/ME) factors. Fama and French (1992) document that size and BE/ME are vital factors in capturing variations in average equity returns. In addition, Jegadeesh and Titman (1993) find that a long position in winning stocks and a short position in losing stocks benefits from a momentum factor. We create factor portfolios of US equities, and analyze the performance of the quintile with the highest returns for each factor to ensure that our equity benchmarks are profitable and attractive. Panel A of A11 reports the ε_i values for each long only factor portfolio against equity portfolios based on size. We focus on long only portfolios dominating in terms of AFSD. Almost all of the eight factor portfolios (with exception of $MAXRET$) are ASSD dominant when the horizon is 78 weeks. Panel B of Table A11 has the ε_i values for each factor portfolio against equity portfolios based on momentum, and the dominance results are similar to those for Panel A, where all long legs of dominant portfolios outperform the momentum portfolios. Panel C of Table A11 shows that, compared to Panels A and B, the 13 dominant momentum and volume factor portfolios have smaller violation areas against the BE/ME benchmark.

Table A11: 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	0.2767	0.1552	0.1100	0.0502*	0.015*	0.2644	0.1391	0.0960	0.0397*	0.0095*	0.2734	0.1520	0.1063	0.0477*	0.0128*
LPRC	0.3471	0.2736	0.2257	0.1562	0.1105	0.3397	0.2614	0.2122	0.1410	0.0974	0.3445	0.2691	0.2203	0.1502	0.1042
AGE	0.3156	0.2057	0.1707	0.1215	0.0949	0.3089	0.1940	0.1596	0.1088	0.0830	0.3133	0.2021	0.1667	0.1170	0.0894
MOM1	0.3008	0.1795	0.1185	0.0659	0.0441*	0.2937	0.1676	0.1081	0.0569*	0.0355*	0.2987	0.1764	0.1154	0.0633	0.0404*
MOM2	0.3180	0.2313	0.1976	0.0965	0.0655	0.3108	0.2205	0.1876	0.0878	0.0568*	0.3156	0.2281	0.1941	0.0940	0.0616
MOM3	0.3576	0.2598	0.2032	0.1102	0.0820	0.3498	0.2468	0.1897	0.0973	0.0685	0.3547	0.2559	0.1985	0.1061	0.0759
MOM4	0.3877	0.2997	0.2487	0.1934	0.1187	0.3788	0.2835	0.2297	0.1731	0.0983	0.3842	0.2939	0.2410	0.1858	0.1091
MOM8	0.4244	0.3534	0.3018	0.2217	0.1423	0.4139	0.3355	0.2815	0.1988	0.1198	0.4202	0.3469	0.2937	0.2131	0.1317
MOM26	0.5006	0.4606	0.4444	0.4463	0.4504	0.4873	0.4405	0.4187	0.3984	0.3675	0.4945	0.4521	0.4328	0.4266	0.4096
RMOM1	0.3168	0.2150	0.1718	0.0962	0.0359*	0.3083	0.2011	0.1592	0.0849	0.0271*	0.3141	0.2110	0.1675	0.0928	0.0321*
RMOM2	0.3599	0.2706	0.2119	0.0972	0.0438*	0.3519	0.2579	0.1997	0.0870	0.0342*	0.3571	0.2667	0.2077	0.0943	0.0396*
RMOM3	0.3115	0.2002	0.1430	0.0806	0.0394*	0.3024	0.1857	0.1292	0.0692	0.0272*	0.3086	0.1964	0.1386	0.0774	0.0339*
RMOM4	0.3516	0.2375	0.1671	0.0781	0.0395*	0.3422	0.2204	0.1488	0.0647	0.0228*	0.3482	0.2324	0.1608	0.0745	0.0318*
RMOM8	0.4110	0.3286	0.2889	0.2370	0.1733	0.3997	0.3083	0.2662	0.2086	0.1355	0.4065	0.3213	0.2798	0.2266	0.1550
RMOM26	0.4773	0.4329	0.4219	0.4191	0.4006	0.4669	0.4141	0.3984	0.3849	0.3560	0.4727	0.4253	0.4115	0.4050	0.3787
VOL	0.4061	0.3430	0.3049	0.2124	0.1562	0.3984	0.3313	0.2922	0.1957	0.1390	0.4031	0.3388	0.2997	0.2058	0.1480
VOLPRC	0.2775	0.1639	0.1089	0.0435*	0.0246*	0.2698	0.1509	0.0970	0.0351*	0.0179*	0.2752	0.1605	0.1051	0.0414*	0.0218*
VOLSCALE	0.3437	0.2553	0.1935	0.1074	0.0786	0.3350	0.2408	0.1788	0.0926	0.0653	0.3406	0.2505	0.1881	0.1023	0.0725
RETVOL	0.4499	0.4093	0.3563	0.2850	0.2296	0.4431	0.3975	0.3414	0.2662	0.2097	0.4470	0.4045	0.3499	0.2774	0.2199
RETSKEW	0.3581	0.2327	0.1617	0.0759	0.0096*	0.3485	0.2152	0.1453	0.0646	0.0036*	0.3547	0.2277	0.1564	0.0730	0.007*
RETKURT	0.4265	0.3413	0.2535	0.1567	0.1004	0.4166	0.3225	0.2307	0.1342	0.0755	0.4225	0.3346	0.2448	0.1490	0.0887
MAXRET	0.3726	0.2719	0.2069	0.0837	0.0491*	0.3649	0.2586	0.1930	0.0733	0.0382*	0.3697	0.2674	0.2017	0.0807	0.0442*
STDPRCVOL	0.2912	0.1816	0.1235	0.0632	0.044*	0.2835	0.1682	0.1101	0.0502*	0.0334*	0.2887	0.1778	0.1189	0.0587*	0.0392*
MEANABS	0.3275	0.2226	0.1628	0.0967	0.0698	0.3199	0.2095	0.1506	0.0858	0.0608	0.3249	0.2181	0.1583	0.0930	0.0658
BETA	0.4468	0.4013	0.3444	0.2776	0.2025	0.4342	0.3796	0.3150	0.2473	0.1720	0.4414	0.3923	0.3315	0.2656	0.1876
BETA$\hat{2}$	0.4510	0.4114	0.3694	0.3085	0.2255	0.4362	0.3868	0.3383	0.2751	0.1911	0.4447	0.4013	0.3557	0.2951	0.2087
IDIOVOL	0.4224	0.3596	0.3081	0.2201	0.1094	0.4080	0.3335	0.2784	0.1903	0.0739	0.4166	0.3494	0.2957	0.2091	0.0917
DELAY	0.3205	0.2107	0.1567	0.0922	0.0281*	0.3080	0.1896	0.1377	0.0777	0.0143*	0.3167	0.2051	0.1507	0.0881	0.022*
LIQ	0.3275	0.2226	0.1628	0.0967	0.0698	0.3199	0.2095	0.1506	0.0858	0.0608	0.3249	0.2181	0.1583	0.0930	0.0658

This table reports the ε_i values of AFSD for each long-leg portfolio against the size, momentum and BE/ME portfolios. * denotes AFSD against the benchmark. Panel A, B and C report the results against equity anomalies based on size, momentum and BE/ME portfolios. The data equity anomalies are retrieved from Kenneth French website.

A4 Shorting Bitcoin for Dominant Factor Portfolios

We also examine whether these dominant strategies shorting Bitcoin can be explained by coin market three-factor model and our adjusted model (NTFM-SM). Table A12 and A13 reports the results for coin market three-factor model and NTFM-SM, respectively. Moreover, Table A14 exhibits the comparison of performance for two models above. We find that our adjusted Model, NTFM-SM, can provide stronger explanatory power than that of coin market three-factor model in explaining the performance of strategies shorting Bitcoin.

Table A12: Coin Market Three-Factor model for Strategies Shorting Bitcoin

	α	β_{CMKT}	β_{CSMB}	β_{Cmom}	$Adj\ R^2$
MARCAP	-0.0060	-0.3753***	0.3622***	0.1078***	0.4056
	(-1.3296)	(-9.4550)	(13.8879)	(4.1117)	
MOM1	0.0082	0.1077	0.1281***	0.3074***	0.1109
	(1.0187)	(1.5109)	(2.7368)	(6.5310)	
MOM2	0.0080	-0.0114	0.1557***	0.2238***	0.0579
	(0.9143)	(-0.1486)	(3.0666)	(4.3957)	
RMOM1	0.0031	0.0891	0.1266***	0.2298***	0.0891
	(0.4310)	(1.4167)	(3.0628)	(5.5324)	
RMOM2	0.0199*	-0.7868***	0.0418	-0.0106	0.1568
	(1.9197)	(-8.6353)	(0.6961)	(-0.1753)	
RMOM3	0.0053	0.0493	0.1187***	0.2994***	0.1078
	(0.6847)	(0.7204)	(2.6329)	(6.6168)	
RMOM4	0.0056	0.0898*	0.0190	0.0678*	0.0108
	(0.9327)	(1.6955)	(0.5447)	(1.9211)	
MAXRET	-0.0031	0.168**	0.1513***	0.1848***	0.0801
	(-0.4115)	(2.5415)	(3.4841)	(4.2326)	

This table reports the empirical results of coin market three-factor model. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The t-statistics are reported in parentheses and are Newey-West adjusted with n-1 lags.

Table A13: NTFM-SM for Strategies Shorting Bitcoin

	α	β_{CMKT}	β_{CSMB}	$\beta_{Mispricing2}$	$Adj\ R^2$
MARCAP	-0.0016	-0.3694***	0.3542***	-0.0951	0.3831
	(-0.3229)	(-9.1402)	(13.3742)	(-1.4855)	
MOM1	0.0021	0.1401*	0.1007**	0.4622***	0.0515
	(0.2425)	(1.9042)	(2.0896)	(3.9674)	
MOM2	0.0054	0.0102	0.137***	0.2618**	0.0220
	(0.5693)	(0.1306)	(2.6559)	(2.1085)	
RMOM1	-0.0083	0.1189*	0.1044**	0.6106***	0.1056
	(-1.1045)	(1.9093)	(2.5573)	(6.1898)	
RMOM2	-0.0050	-0.7662***	0.0366	0.9645***	0.2551
	(-0.4891)	(-8.9542)	(0.6498)	(7.1206)	
RMOM3	0.0007	0.0801	0.0934**	0.3877***	0.0360
	(0.0830)	(1.1267)	(1.9989)	(3.4460)	
RMOM4	-0.0012	0.102*	0.0123	0.3069***	0.0359
	(-0.1853)	(1.9531)	(0.3578)	(3.7115)	
MAXRET	0.0044	0.1782***	0.1376***	-0.1594	0.0430
	(0.5453)	(2.6456)	(3.1167)	(-1.4935)	

This table reports the empirical results of NTFM-SM. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The t-statistics are reported in parentheses and are Newey-West adjusted with n-1 lags.

Table A14: Comparison of Two Models for Strategies Shorting Bitcoin

Model	$A\|R^2\|$	Significant Alphas	GRS	$A\|\alpha_i\|$	$A\|\alpha_i\|/A\|\bar{r}_i\|$	$A\alpha_i^2/A\bar{r}_i^2$	$As^2(\alpha_i)/A\alpha_i^2$	Score
3-factor	0.13	1	1.3865	0.0052	0.4628	0.0012	1.2315	2
NTFM-SM	0.12	0	0.6369	0.0036	0.8703	0.0005	3.5213	5

This table reports the performance measures for coin market three-factor model and the best adjusted model (NTFM-SM) in explaining non-dominant strategies. Each column represents one measure of model performance, and the last column illustrates the overall scores for each model.

A5 Tests for Non-Dominant Factors

To address the concern that our adjusted model (NTFM-SM) cannot accommodate each factor portfolio, we examine whether NTFM-SM can capture the variation in returns on non-dominant factors, and we set the performance of coin market three-factor model as a control group. For completeness of our study, we also conduct a series of tests to verify whether equity asset pricing models can generate explanatory power in explaining our eight dominant strategies.

The 21 non-dominant factor portfolios are portfolios based on *LPRC, AGE, MOM3, MOM4, MOM8, MOM26, RMOM8, RMOM26, VOL, VOLPRC, VOLSCALE, RETVOL, RETSKEW, RETKURT, STDPRCVOL, MEANABS, BETA, BETA²*, *IDIOVOL, DELAY*, and *LIQ*, respectively. Since our mispricing factor is constructed via dominant factors, the tests on non-dominant factors by our NTFM-SM can be considered as out-of-sample tests. Table A15 illustrates the empirical findings of non-dominant strategies for coin market three-factor model.

Table A15: Coin Market Three-Factor model for Non-Dominant Factors

	Panel A: Factor Loadings				Panel B: t-statistics for Factor Loadings				
	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	*Adj* R^2
LPRC	0.0085	0.309***	0.1283**	0.0967*	0.9702	3.9996	2.5277	1.8959	0.0598
AGE	0.0095	-0.0458	0.2769***	0.2006***	0.8212	-0.4512	4.1495	2.9897	0.0519
MOM3	0.0237**	-0.0404	-0.0677	0.477***	2.2872	-0.4427	-1.1269	7.9179	0.1392
MOM4	0.0132*	-0.0593	-0.0093	0.1435***	1.6610	-0.8506	-0.2033	3.0873	0.0184
MOM8	-0.0008	-0.2534***	-0.0697	0.1071**	-0.0957	-3.3064	-1.3884	2.1037	0.0376
MOM26	-0.006	-0.2724***	-0.1321**	0.0259	-0.6142	-3.2002	-2.2576	0.4428	0.0370
RMOM8	0.0087	0.0652	-0.1155***	0.0279	1.1226	0.9593	-2.5958	0.6177	0.0129
RMOM26	-0.0109	0.0461	-0.0341	0.0829	-1.2727	0.6144	-0.6617	1.6072	0.0017
VOL	-0.0211*	0.012	0.2766***	0.467***	-1.8581	0.1200	4.2190	7.0863	0.1357
VOLPRC	0.0016	0.111	0.316***	0.1933***	0.1933	1.5638	6.7783	4.1241	0.1355
VOLSCALED	-0.0033	0.1973***	0.2021***	0.0603	-0.4516	3.0590	4.7697	1.4163	0.0785
RETVOL	-0.0081	0.1579*	0.0603	0.2563***	-0.7601	1.6932	0.9835	4.1596	0.0454
RETSKEW	0.0033	0.1116	0.0579	0.2594***	0.4227	1.6002	1.2644	5.6309	0.0784
RETKURT	0.006	0.0489	-0.0596	0.015	0.8718	0.8090	-1.5005	0.3750	0.0000
STDPRCVOL	-0.0007	0.0982	0.3343***	0.1912***	-0.0871	1.4100	7.3073	4.1554	0.1485
MEANABS	-0.015*	0.2428***	0.5233***	-0.0129	-1.7211	3.1720	10.4059	-0.2546	0.2392
BETA	-0.0008	-0.0253	0.0707	0.0045	-0.0960	-0.3380	1.3588	0.0850	-0.0033
BETA2	-0.0007	-0.0716	0.0627	-0.0102	-0.0971	-1.1023	1.3894	-0.2238	0.0001
IDIOSYN	0.0009	-0.0468	0.06	0.0155	0.1186	-0.7176	1.3261	0.3409	-0.0025
DELAY	0.0123*	0.2303***	-0.0791*	-0.0578	1.7231	3.7874	-1.8755	-1.3616	0.0421
LIQ	-0.015*	0.2428***	0.5233***	-0.0129	-1.7211	3.1720	10.4059	-0.2546	0.2392

This table reports the empirical results of coin market three-factor model for 21 non-dominant factors. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The t-statistics are reported in parentheses and are Newey-West adjusted with n-1 lags.

Unlike the results for dominant strategies, the coin market three-factor model have certain explanatory power in explaining non-dominant strategies, as only six out of 21 strategies have significant alphas (see Table A15). Table A16 reports the empirical results of our adjusted model (NTFM-SM) for non-dominant strategies, and Table A17 shows the comparison of performance for these two models. We find that NTFM-SM also provides more explanatory power than that of coin market three-factor model in examining the non-dominant strategies.

Table A16: NTFM-SM for Non-Dominant Factors

	Panel A: Factor Loadings				Panel B: t-statistics for Factor Loadings				
	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	$Adj\ R^2$
LPRC	0.018*	0.3097***	0.1225**	-0.3028**	1.9535	4.0250	2.4296	-2.4838	0.0659
AGE	0.0158	-0.0332	0.2616***	-0.1029	1.2849	-0.3238	3.8898	-0.6334	0.0310
MOM3	0.0112	0.0131	-0.1093*	0.819***	0.9862	0.1380	-1.7579	5.4710	0.0712
MOM4	-0.0031	-0.0318	-0.024	0.723***	-0.3824	-0.4774	-0.5479	6.8591	0.1038
MOM8	-0.0143	-0.2339***	-0.0809*	0.5934***	-1.5852	-3.1368	-1.6599	5.0442	0.0875
MOM26	-0.0093	-0.2649***	-0.1353**	0.14	-0.8930	-3.1118	-2.3226	1.0105	0.0392
RMOM8	-0.0053	0.0783	-0.1207***	0.5634***	-0.6766	1.1961	-2.8224	5.4572	0.0838
RMOM26	-0.0105	0.0531	-0.0413	0.033	-1.1409	0.7053	-0.8011	0.2691	-0.0052
VOL	-0.0066	0.0416	0.2409***	-0.2287	-0.5163	0.3931	3.4762	-1.3656	0.0282
VOLPRC	0.012	0.1195*	0.3024***	-0.2696**	1.3932	1.6615	6.4129	-2.3654	0.1104
VOLSCALED	0.0054	0.1955***	0.1992***	-0.2961***	0.7006	3.0584	4.7550	-2.9246	0.0937
RETVOL	-0.0086	0.1811*	0.0386	0.2061	-0.7507	1.9060	0.6192	1.3691	0.0076
RETSKEW	0.0024	0.1355*	0.0359	0.2252**	0.2781	1.8779	0.7587	1.9711	0.0128
RETKURT	0.0088	0.0479	-0.0601	-0.0977	1.2098	0.7946	-1.5212	-1.0233	0.0023
STDPRCVOL	0.0095	0.1068	0.3208***	-0.2614**	1.1247	1.5115	6.9297	-2.3364	0.1229
MEANABS	-0.0109	0.2383***	0.5254***	-0.1679	-1.1916	3.1228	10.5051	-1.3890	0.2429
BETA	-0.0008	-0.025	0.0703	0.0015	-0.0864	-0.3330	1.3556	0.0119	-0.0033
BETA2	-0.0022	-0.0706	0.063	0.0458	-0.2636	-1.0848	1.4020	0.4129	0.0005
IDIOSYN	-0.0005	-0.0435	0.0581	0.0601	-0.0588	-0.6665	1.2883	0.5400	-0.0020
DELAY	-0.0024	0.2456***	-0.0796*	0.503***	-0.3185	4.1715	-1.9566	5.0085	0.1039
LIQ	-0.0109	0.2383***	0.5254***	-0.1679	-1.1916	3.1228	10.5051	-1.3890	0.2429

This table reports the empirical results of NTFM-SM for 21 non-dominant factors. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The t-statistics are reported in parentheses and are Newey-West

Table A17: Comparison of Two Models for Non-Dominant Strategies

Model	$A\|R^2\|$	Significant Alphas	GRS	$A\|\alpha_i\|$	$A\|\alpha_i\|/A\|\bar{r}_i\|$	$A\alpha_i^2/A\bar{r}_i^2$	$As^2(\alpha_i)/A\alpha_i^2$	Score
3-Factor	0.07	6	1.2617	0.0081	0.7546	0.0030	0.7012	1
NTFM-SM	0.07	1	1.0724	0.0080	0.7467	0.0024	0.9911	7

This table reports the performance measures for coin market three-factor model and the best adjusted model (NTFM-SM) in explaining non-dominant strategies. From second column to the second last column, each column represents one measure of model performance, and the last column illustrates the overall scores for each model.

A6 Tests for Different Coin Market Factor Models

Although the findings in our paper show that our adjusted model effectively captures the variation in cryptocurrency anomalies, we examine whether our mispricing factor can enhance performance of the coin market one-factor model (that is the coin market CAPM model) and coin market two-factor model (adding size factor or momentum factor based on coin market one factor model).

The following equations illustrate the coin market factor models. Equation 2 shows the coin market one-factor model (1F); Equation 3 and Equation 4 show different versions of coin market two-factor models (2F-CSMB and 2F-CMOM).

$$R_i - R_f = \alpha_i + \beta_{i,CMKT} CMKT + \varepsilon_i \tag{2}$$

$$R_i - R_f = \alpha_i + \beta_{i,CMKT} CMKT + \beta_{i,CSMB} CSMB + \varepsilon_i \tag{3}$$

$$R_i - R_f = \alpha_i + \beta_{i,CMKT} CMKT + \beta_{i,CMOM} CMOM + \varepsilon_i \tag{4}$$

where R_i is the return on the factor portfolio, R_f is the risk-free rate, $CMKT$ is the cryptocurrency market index excess return, $CSMB$ is the cryptocurrency size factor and $CMOM$ is the cryptocurrency momentum factor. We test the performance of three models above and their augmented models by incorporating a mispricing factor ($Mispricing2$) to the three original models. The corresponding augmented models are shown as below:

$$R_i - R_f = \alpha_i + \beta_{i,CMKT} CMKT + \beta_{i,Mispricing2} Mispricing2 + \varepsilon_i \tag{5}$$

$$R_i - R_f = \alpha_i + \beta_{i,CMKT}CMKT + \beta_{i,CSMB}CSMB + \beta_{i,Mispricing2}Mispricing2 + \varepsilon_i \quad (6)$$

$$R_i - R_f = \alpha_i + \beta_{i,CMKT}CMKT + \beta_{i,CMOM}CMOM + \beta_{i,Mispricing2}Mispricing2 + \varepsilon_i \quad (7)$$

where $R_i, CMKT, CSMB$ and $CMOM$ are same as above, Mispricing is the mispricing factor. We refer equation 5, 6 and 7 as 1FM, 2F-CSMBM and 2F-CMOMM, respectively.

Table A18 to Table A.26 reports the regression results for equation 2 to equation 7. Table A.27 shows the comparison of original model and augmented model, indicating that a mispricing factor can significantly improve the original model regardless for all three models.

Table A18: Coin Market One-Factor Model (1F)

	α	β_{CMKT}	*Adj* R^2
MARCAP	0.0319***	-0.3538***	0.1285
	(6.4119)	(-7.6502)	
MOM1	0.0347***	0.0864	-0.0001
	(3.6219)	(0.9723)	
MOM2	0.0342***	0.0496	-0.0017
	(3.7343)	(0.5852)	
RMOM1	0.0247***	0.1473**	0.0082
	(3.1897)	(2.0527)	
RMOM2	0.0274***	-0.0680	-0.0007
	(3.2019)	(-0.8603)	
RMOM3	0.0278***	0.1631*	0.0071
	(3.0638)	(1.9395)	
RMOM4	0.0199***	0.1924***	0.0184
	(2.7580)	(2.8749)	
MAXRET	0.0156**	0.3156***	0.0507
	(2.1363)	(4.6717)	

This table reports the empirical results for coin market one-factor model (1F). *, **, *** represent significance at 10%, 5%, 1% level, respectively. The t-statistics are reported in parentheses and are Newey-West adjusted with n-1 lags.

Table A19: Coin Market Two-Factor Model incorporating Size Factor (2F-CSMB)

	α	β_{CMKT}	β_{CSMB}	$Adj\ R^2$
MARCAP	0.0203***	-0.3805***	0.2173***	0.2409
	(4.1378)	(-8.7872)	(7.6548)	
MOM1	0.0321***	0.0805	0.0479	-0.0010
	(3.1838)	(0.9027)	(0.8193)	
MOM2	0.0296***	0.0391	0.0842	0.0016
	(3.0709)	(0.4599)	(1.5056)	
RMOM1	0.0266***	0.1517**	-0.0361	0.0071
	(3.2675)	(2.1066)	(-0.7652)	
RMOM2	0.0312***	-0.0594	-0.0695	0.0013
	(3.4627)	(-0.7495)	(-1.3333)	
RMOM3	0.0273***	0.162*	0.0088	0.0046
	(2.8526)	(1.9173)	(0.1591)	
RMOM4	0.0249***	0.2035***	-0.0897**	0.0264
	(3.2734)	(3.0434)	(-2.0387)	
MAXRET	0.0124	0.3085***	0.0580	0.0524
	(1.6237)	(4.5555)	(1.3063)	

This table reports the empirical results for coin market two-factor model (2F-CSMB). *, **, *** represent significance at 10%, 5%, 1% level, respectively. The t-statistics are reported in parentheses and are Newey-West adjusted with n-1 lags.

Table A20: Coin Market Two-Factor Model Incorporating Momentum Factor (2F-CMOM)

	α	β_{CMKT}	β_{CMOM}	$Adj\ R^2$
MARCAP	0.0311***	-0.3574***	0.0566*	0.1340
	(6.2455)	(-7.7458)	(1.8573)	
MOM1	0.028***	0.0567	0.4646***	0.1584
	(3.1813)	(0.6950)	(8.6192)	
MOM2	0.0307***	0.0341	0.2491***	0.0466
	(3.4283)	(0.4113)	(4.5453)	
RMOM1	0.0196***	0.1247*	0.3528***	0.1469
	(2.7267)	(1.8727)	(8.0168)	
RMOM2	0.0287***	-0.0604	-0.1072**	0.0074
	(3.3603)	(-0.7661)	(-2.0386)	
RMOM3	0.024***	0.1447*	0.2815***	0.0702
	(2.7250)	(1.7761)	(5.2240)	
RMOM4	0.0197***	0.1912***	0.0168	0.0162
	(2.7186)	(2.8507)	(0.3745)	
MAXRET	0.0128*	0.3032***	0.1941***	0.0944
	(1.7909)	(4.5911)	(4.4468)	

This table reports the empirical results for coin market two-factor model (2F-CMOM). *, **, *** represent significance at 10%, 5%, 1% level, respectively. The t-statistics are reported in parentheses and are Newey-West adjusted with n-1 lags.

Table A21: Coin Market One-Factor Model with Mispricing Factor (1FM)

	α	β_{CMKT}	$\beta_{Mispricing2}$	$Adj\ R^2$
MARCAP	0.0219***	-0.3459***	0.3877***	0.1887
	(4.2582)	(-7.7485)	(5.4653)	
MOM1	0.0015	0.1124	1.2814***	0.2094
	(0.1653)	(1.4222)	(10.2026)	
MOM2	0.0121	0.0671	0.8541***	0.0996
	(1.3018)	(0.8336)	(6.6805)	
RMOM1	-0.0072	0.1723***	1.2318***	0.3038
	(-1.0430)	(2.8647)	(12.8913)	
RMOM2	-0.0053	-0.0411	1.2547***	0.2560
	(-0.6764)	(-0.6025)	(11.5827)	
RMOM3	-0.0008	0.1859**	1.1033***	0.1800
	(-0.0861)	(2.4317)	(9.0904)	
RMOM4	-0.0095	0.2167***	1.1295***	0.3034
	(-1.4533)	(3.8404)	(12.6071)	
MAXRET	0.0136*	0.3171***	0.0737	0.0494
	(1.7496)	(4.6883)	(0.6859)	

This table reports the empirical results for coin market one-factor model with a mispricing factor (1FM). *, **, *** represent significance at 10%, 5%, 1% level, respectively. The t-statistics are reported in parentheses and are Newey-West adjusted with n-1 lags.

Table A22: Coin Market Two-Factor (Size Factor) Model with Mispricing Factor (2F-CSMBM)

	α	β_{CMKT}	β_{CSMB}	$\beta_{Mispricing2}$	$Adj\ R^2$
MARCAP	0.0106**	-0.3725***	0.2149***	0.3797***	0.2990
	(2.1128)	(-8.9465)	(7.8760)	(5.7573)	
MOM1	-0.0006	0.1075	0.0397	1.2799***	0.2085
	(-0.0624)	(1.3548)	(0.7643)	(10.1842)	
MOM2	0.0079	0.0572	0.0784	0.851***	0.1023
	(0.8137)	(0.7093)	(1.4783)	(6.6656)	
RMOM1	-0.0049	0.1777***	-0.0440	1.2334***	0.3042
	(-0.6777)	(2.9463)	(-1.1130)	(12.9109)	
RMOM2	-0.0012	-0.0315	-0.0773*	1.2575***	0.2598
	(-0.1421)	(-0.4607)	(-1.7217)	(11.6365)	
RMOM3	-0.0008	0.1858**	0.0013	1.1032***	0.1779
	(-0.0898)	(2.4180)	(0.0259)	(9.0769)	
RMOM4	-0.0043	0.2287***	-0.0967***	1.133***	0.3139
	(-0.6301)	(4.0712)	(-2.6180)	(12.7401)	
MAXRET	0.0106	0.31***	0.0575	0.0716	0.0511
	(1.3029)	(4.5720)	(1.2950)	(0.6664)	

This table reports the empirical results for coin market two-factor model (added size factor) with a mispricing factor (2F-CSMBM). *, **, *** represent significance at 10%, 5%, 1% level, respectively. The t-statistics are reported in parentheses and are Newey-West adjusted with n-1 lags.

Table A23: Coin Market Two-Factor Model (Momentum Factor) with Mispricing Factor (2F-CMOMM)

	α	β_{CMKT}	β_{CMOM}	$\beta_{Mispricing2}$	$Adj\ R^2$
MARCAP	0.0219***	-0.3478***	0.0268	0.3754***	0.1883
	(4.2443)	(-7.7810)	(0.8912)	(5.1930)	
MOM1	0.0006	0.0848	0.3765***	1.1085***	0.3096
	(0.0715)	(1.1471)	(7.5700)	(9.2708)	
MOM2	0.0117	0.0536	0.188***	0.768***	0.1253
	(1.2790)	(0.6745)	(3.5168)	(5.9825)	
RMOM1	-0.0079	0.1529***	0.2645***	1.1103***	0.3788
	(-1.2003)	(2.6882)	(6.9149)	(12.0747)	
RMOM2	-0.0053	-0.0231	-0.2209***	1.3594***	0.2979
	(-0.6976)	(-0.3485)	(-4.8956)	(12.6591)	
RMOM3	-0.0011	0.1709**	0.2008***	1.0111***	0.2102
	(-0.1245)	(2.2742)	(3.9686)	(8.3316)	
RMOM4	-0.0095	0.2232***	-0.081**	1.1678***	0.3097
	(-1.4604)	(3.9688)	(-2.1165)	(12.8318)	
MAXRET	0.0132*	0.3028***	0.1953***	-0.0160	0.0921
	(1.7291)	(4.5753)	(4.3879)	(-0.1493)	

This table reports the empirical results for coin market two-factor model (added momentum factor) with a mispricing factor (2F-CMOMM). *, **, *** represent significance at 10%, 5%, 1% level, respectively. The t-statistics are reported in parentheses and are Newey-West adjusted with n-1 lags.

Table A24: Comparison of Model Performance for Coin Market factor models and Models with a Mispricing Factor

Panel A: Coin Market One-Factor Model (1F) and Coin Market One-Factor Model with Mispricing Factor (1FM)

Model	$A\|R^2\|$	Significant Alphas	GRS	$A\|\alpha_i\|$	$A\|\alpha_i\|/A\|\bar{r}_i\|$	$A\alpha_i^2/A\bar{r}_i^2$	$As^2(\alpha_i)/A\alpha_i^2$	Score
1F	0.0263	8	12.6801	0.027	1.9878	0.0218	0.0845	0
1FM	0.1988	2	3.9897	0.009	0.6619	0.0035	0.4942	7

Panel B: Coin Market Two-Factor Model (2F-CSMB) and Coin Market Two-Factor Model with Mispricing Factor (2F-CSMBM)

Model	$A\|R^2\|$	Significant Alphas	GRS	$A\|\alpha_i\|$	$A\|\alpha_i\|/A\|\bar{r}_i\|$	$A\alpha_i^2/A\bar{r}_i^2$	$As^2(\alpha_i)/A\alpha_i^2$	Score
2F-CSMB	0.0417	7	9.4186	0.0255	1.8793	0.0195	0.1041	0
2F-CSMBM	0.2146	1	1.2127	0.0051	0.3754	0.0012	1.594	7

Panel C: Coin Market Two-Factor Model (2F-CMOM) and Coin Market Two-Factor Model with Mispricing Factor (2F-CMOMM)

Model	$A\|R^2\|$	Significant Alphas	GRS	$A\|\alpha_i\|$	$A\|\alpha_i\|/A\|\bar{r}_i\|$	$A\alpha_i^2/A\bar{r}_i^2$	$As^2(\alpha_i)/A\alpha_i^2$	Score
2F-CMOM	0.0843	8	11.747	0.0243	1.7912	0.0178	0.097	0
2F-CMOMM	0.239	2	4.1434	0.0089	0.6541	0.0034	0.4739	7

This table reports the comparison of three coin market factor models and corresponding augmented models in explaining eight dominant strategies. Panel A reports the results for coin market one-factor model (1F) and its augmented model 1FM. Panel B demonstrates the results for coin market two-factor model (2F-CSMB) and its augmented model 2F-CSMBM. Penal C exhibits the results for coin market two-factor model (2F-CMOM) and its augmented model 2F-CMOMM. From second column to the second last column, each column represents one measure of model performance, and the last column illustrates the overall scores for each model.

A7 Tests for Different Equity Asset Pricing Models

For robustness in our study, we assess whether famous equity asset pricing models can explain the dominant strategies in our paper. These models are:

1. the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965) that only uses a market factor (see equation 8);
2. the Fama-French three-factor model (FF3) of Fama and French (1993), which expands the CAPM model by adding size and value factors (see equation 9);
3. the Carhart (1997) four-factor model (FFC), which includes a momentum factor to the FF3 model (see equation 10);
4. the Fama and French (1993) and Pástor and Stambaugh (2003) four-factor model (FFPS), which incorporates a liquidity factor into FF3 model (see equation 11);
5. the Asness and Frazzini (2013) three-factor model (FFAF), which replaced the value factor in FF3 with a latest version of value factor (see equation 12);
6. the Hou et al. (2015) q-factor model (HXZ), which consists of market, size, investment, and profitability factors (see equation 13);
7. the Fama and French (2015) five-factor model (FF5), comprising market, size, value, profitability and investment factors (see equation 14);
8. the Fama and French four-factor model (FF4), which discards the value factor of FF5 (see equation15);
9. the Barillas and Shanken (2018) six-factor (BS6), which incorporates the value factor of FFAF model, the market ,size, and momentum factors of FF5 model, the profitability and investment factors of HXZ model (see equation 16).

The equations for nine models above are shown as follows:

$$R_{i,t} - R_{f,t} = \alpha_{i,CAPM} + \beta_{i,MKT} MKT_t + \varepsilon_{i,t} \tag{8}$$

$$R_{i,t} - R_{f,t} = \alpha_{i,FF3} + \beta_{i,MKT}MKT_t + \beta_{i,SMB^*}SMB_t^* + \beta_{i,HML}HML_t + \varepsilon_{i,t} \quad (9)$$

$$R_{i,t} - R_{f,t} = \alpha_{i,FFC} + \beta_{i,MKT}MKT_t + \beta_{i,SMB^*}SMB_t^* + \beta_{i,HML}HML_t + \beta_{i,UMD}UMD_t + \varepsilon_{i,t} \quad (10)$$

$$R_{i,t} - R_{f,t} = \alpha_{i,FFPS} + \beta_{i,MKT}MKT_t + \beta_{i,SMB^*}SMB_t^* + \beta_{i,HML}HML_t + \beta_{i,LIQ}LIQ_t + \varepsilon_{i,t} \quad (11)$$

$$R_{i,t} - R_{f,t} = \alpha_{i,FFAF} + \beta_{i,MKT}MKT_t + \beta_{i,SMB^*}SMB_t^* + \beta_{i,HML^m}HML_t^m + \varepsilon_{i,t} \quad (12)$$

$$R_{i,t} - R_{f,t} = \alpha_{i,HXZ} + \beta_{i,MKT}MKT_t + \beta_{i,ME}ME_t + \beta_{i,IA}IA_t + \beta_{i,ROE}ROE_t + \varepsilon_{i,t} \quad (13)$$

$$R_{i,t} - R_{f,t} = \alpha_{i,FF5} + \beta_{i,MKT}MKT_t + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \beta_{i,RMW}RMW_t + \beta_{i,CMA}CMA_t + \varepsilon_{i,t} \quad (14)$$

$$R_{i,t} - R_{f,t} = \alpha_{i,FF4} + \beta_{i,MKT}MKT_t + \beta_{i,SMB}SMB_t + \beta_{i,RMW}RMW_t + \beta_{i,CMA}CMA_t + \varepsilon_{i,t} \quad (15)$$

$$R_{i,t} - R_{f,t} = \alpha_{i,BS6} + \beta_{i,MKT}MKT_t + \beta_{i,SMB}SMB_t + \beta_{i,IA}IA_t + \beta_{i,ROE}ROE_t + \beta_{i,HML^m}HML_t^m + \beta_{i,UMD}UMD_t + \varepsilon_{i,t} \quad (16)$$

where $R_{i,t} - R_{f,t}$ is the excess return on dominant strategy i at period t; MKT_t, SMB_t^*, and HML_t are the market, size, and value factors of Fama and French (1993); SMB_t, RMW_t, CMA_t, and UMD_t are size, profitability, investment, and momentum factors of Fama and French (2015) and Carhart (1997); ME, IA, and ROE are Hou et al. (2015) size, investment and profitability factors, respectively; HML_t^m is the value factor of Asness and Frazzini (2013); LIQ_t is the liquidity factor of Pástor and Stambaugh (2003).

We collect the data of $MKT_t, SMB^*_t,\ HML_t, SMB_t, RMW_t, CMA_t, UMD_t,$ and $R_{f,t}$ from Kenneth French's Website[1]. The data of HML^m_t are retrieved from AQR Data Library[2], and LIQ_t factor is gathered from Lubos Pastor's website[3]. The data for ME, IA, and ROE are collected from Lu Zhang's website[4].

Table A25 to A33 exhibit the regression results for equation 8 to 16. We find that none of the equity asset pricing models can explain our eight dominant strategies, since the value of average adjusted R^2 for each model is exceedingly close to zero, and each model produces eight significant alphas.

Table A25: The CAPM Model

	α	β_{MKT}	*Adj* R^2
MARCAP	0.0283***	-0.5146**	0.0106
	(5.3425)	(-2.2742)	
MOM1	0.0361***	-0.0605	-0.0025
	(3.7710)	(-0.1480)	
MOM2	0.0358***	-0.3215	-0.0008
	(3.9170)	(-0.8257)	
RMOM1	0.025***	0.6242*	0.0066
	(3.2423)	(1.8933)	
RMOM2	0.0264***	-0.0262	-0.0026
	(3.0971)	(-0.0720)	
RMOM3	0.0298***	0.1163	-0.0024
	(3.2793)	(0.3001)	
RMOM4	0.023***	-0.0794	-0.0024
	(3.1503)	(-0.2553)	
MAXRET	0.0193***	0.2919	-0.0004
	(2.5820)	(0.9164)	

This table reports the empirical results of eight dominant strategies for the CAPM model of Sharpe (1964) and Lintner (1965), which includes a market factor as an explanatory variable. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The t-statistics are reported in parentheses and are Newey-West adjusted with n-1 lags.

[1] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[2] https://www.aqr.com/Insights/Datasets/The-Devil-in-HMLs-Details-Factors-Monthly
[3] https://faculty.chicagobooth.edu/lubos-pastor/research
[4] http://global-q.org/index.html

Table A26: The FF3 Model

	α	β_{MKT}	β_{SMB^*}	β_{HML}	*Adj* R^2
MARCAP	0.0282***	-0.4209*	-0.8813**	0.1046	0.0174
	(5.3226)	(-1.7975)	(-2.1463)	(0.3625)	
MOM1	0.0371***	-0.0980	-0.6714	0.8717*	0.0014
	(3.8749)	(-0.2315)	(-0.9043)	(1.6713)	
MOM2	0.0355***	-0.2228	-0.8406	0.0319	-0.0024
	(3.8785)	(-0.5508)	(-1.1845)	(0.0639)	
RMOM1	0.0262***	0.4872	0.2620	0.7629*	0.0105
	(3.3886)	(1.4258)	(0.4373)	(1.8124)	
RMOM2	0.0272***	-0.1635	0.6271	0.4313	-0.0030
	(3.1823)	(-0.4328)	(0.9478)	(0.9281)	
RMOM3	0.0306***	0.0364	0.0517	0.5340	-0.0045
	(3.3478)	(0.0904)	(0.0731)	(1.0750)	
RMOM4	0.0229***	-0.0486	-0.2893	0.0367	-0.0069
	(3.1264)	(-0.1501)	(-0.5106)	(0.0923)	
MAXRET	0.0194***	0.3072	-0.2835	0.1412	-0.0047
	(2.5839)	(0.9271)	(-0.4877)	(0.3458)	

This table reports the empirical results of eight dominant strategies for the FF3 model of Fama and French (1993), which includes market, size, and value factors. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The t-statistics are reported in parentheses and are Newey-West adjusted with n-1 lags.

Table A27: The FFC Model

	α	β_{MKT}	β_{SMB^*}	β_{HML}	β_{UMD}	*Adj* R^2
MARCAP	0.0279***	-0.4235*	-0.8571**	0.0865	-0.5297	0.0170
	(5.2481)	(-1.8082)	(-2.0827)	(0.2991)	(-0.9162)	
MOM1	0.0371***	-0.0979	-0.6720	0.8721*	0.0119	-0.0012
	(3.8619)	(-0.2310)	(-0.9020)	(1.6660)	(0.0113)	
MOM2	0.0354***	-0.2236	-0.8329	0.0262	-0.1669	-0.0049
	(3.8539)	(-0.5520)	(-1.1698)	(0.0523)	(-0.1669)	
RMOM1	0.0264***	0.4884	0.2501	0.7718*	0.2617	0.0082
	(3.3978)	(1.4278)	(0.4161)	(1.8272)	(0.3099)	
RMOM2	0.0275***	-0.1609	0.6081	0.4450	0.4042	-0.0052
	(3.2000)	(-0.4255)	(0.9160)	(0.9545)	(0.4333)	
RMOM3	0.0301***	0.0327	0.0861	0.5082	-0.7532	-0.0056
	(3.2882)	(0.0812)	(0.1215)	(1.0201)	(-0.7569)	
RMOM4	0.0224***	-0.0543	-0.2475	0.0065	-0.8877	-0.0063
	(3.0507)	(-0.1678)	(-0.4359)	(0.0163)	(-1.1127)	
MAXRET	0.0185**	0.3002	-0.2182	0.0924	-1.4299*	0.0007
	(2.4674)	(0.9082)	(-0.3757)	(0.2264)	(-1.7523)	

This table reports the empirical results of eight dominant strategies for the FFC model of Fama French (1993) and Carhart (1997), which comprises market, size, value, and momentum factors. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The t-statistics are reported in parentheses and are Newey-West adjusted with n-1 lags.

Table A28: The FFPS Model

	α	β_{MKT}	β_{SMB}	β_{HML}	β_{LIQ}	$Adj\ R^2$
MARCAP	0.0258***	-0.1022	-0.5277	-0.1325	0.0240	-0.0025
	(4.8846)	(-0.4411)	(-1.2539)	(-0.4339)	(0.8348)	
MOM1	0.0342***	0.6847*	0.4065	0.2050	0.0007	0.0014
	(3.7722)	(1.7237)	(0.5632)	(0.3915)	(0.0146)	
MOM2	0.0359***	0.4894	-0.5226	-0.0429	-0.0418	-0.0037
	(3.9212)	(1.2206)	(-0.7172)	(-0.0811)	(-0.8405)	
RMOM1	0.0279***	0.4338	0.4409	-0.0899	0.0124	-0.0037
	(3.5531)	(1.2620)	(0.7058)	(-0.1984)	(0.2911)	
RMOM2	0.0315***	-0.4288	-1.1621*	0.6308	0.0181	0.0065
	(3.7918)	(-1.1800)	(-1.7596)	(1.3165)	(0.4020)	
RMOM3	0.027***	0.2947	-0.0332	-0.8387*	0.0203	-0.0018
	(3.1997)	(0.7974)	(-0.0494)	(-1.7209)	(0.4434)	
RMOM4	0.0178**	0.1482	0.2935	-0.3779	0.0348	-0.0057
	(2.4152)	(0.4603)	(0.5014)	(-0.8899)	(0.8707)	
MAXRET	0.0219***	0.3499	0.5225	-0.1023	-0.0130	-0.0045
	(2.8797)	(1.0494)	(0.8623)	(-0.2326)	(-0.3154)	

This table reports the empirical results of eight dominant strategies for the FFPS model of Fama and French (1993) and Pástor and Stambaugh (2003), which combines market, size, value, and liquidity factors. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The t-statistics are reported in parentheses and are Newey-West adjusted with n-1 lags.

Table A29: The FFAF Model

	α	β_{MKT}	β_{SMB^*}	β_{HML^m}	$Adj\ R^2$
MARCAP	0.0289***	-0.4231*	-0.9436**	0.162*	0.0244
	(5.4612)	(-1.8363)	(-2.2972)	(1.7135)	
MOM1	0.0368***	-0.0005	-0.6983	0.1716	-0.0033
	(3.8234)	(-0.0012)	(-0.9346)	(0.9983)	
MOM2	0.0354***	-0.2156	-0.8262	-0.0304	-0.0023
	(3.8529)	(-0.5397)	(-1.1596)	(-0.1855)	
RMOM1	0.0256***	0.5771*	0.2583	0.1029	0.0035
	(3.3011)	(1.7043)	(0.4278)	(0.7408)	
RMOM2	0.0267***	-0.1068	0.6498	0.0003	-0.0053
	(3.1069)	(-0.2858)	(0.9770)	(0.0020)	
RMOM3	0.0304***	0.0963	0.0365	0.1039	-0.0065
	(3.3177)	(0.2417)	(0.0514)	(0.6359)	
RMOM4	0.023***	-0.0453	-0.2940	0.0157	-0.0069
	(3.1267)	(-0.1416)	(-0.5167)	(0.1201)	
MAXRET	0.0194***	0.3213	-0.2954	0.0458	-0.0047
	(2.5851)	(0.9815)	(-0.5062)	(0.3414)	

This table reports the empirical results of eight dominant strategies for the FFAF model of Asness and Frazzini (2013), which consists of market, size, and a timely version of value factors. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The t-statistics are reported in parentheses and are Newey-West adjusted with n-1 lags.

Table A30: The HXZ Model

	α	β_{MKT}	β_{ME}	β_{IA}	β_{ROE}	$Adj\ R^2$
MARCAP	0.0282***	-0.3487	-1.0202**	0.5513	-0.6229	0.0209
	(5.3353)	(-1.4118)	(-2.4631)	(0.9360)	(-1.3082)	
MOM1	0.0369***	-0.0440	-0.7962	0.8154	-1.5852*	0.0007
	(3.8523)	(-0.0984)	(-1.0608)	(0.7640)	(-1.8374)	
MOM2	0.0357***	-0.2305	-1.1721	0.0489	-1.1285	0.0005
	(3.9052)	(-0.5399)	(-1.6369)	(0.0481)	(-1.3702)	
RMOM1	0.0258***	0.4933	0.2829	0.1728	-0.6748	0.0031
	(3.3216)	(1.3612)	(0.4654)	(0.2000)	(-0.9658)	
RMOM2	0.0271***	-0.3268	0.8282	-0.8826	-0.4883	-0.0018
	(3.1689)	(-0.8183)	(1.2404)	(-0.9290)	(-0.6352)	
RMOM3	0.0302***	0.0056	-0.2869	-0.5016	-0.9857	-0.0058
	(3.2996)	(0.0132)	(-0.4015)	(-0.4936)	(-1.1986)	
RMOM4	0.0223***	-0.0334	-0.1053	-0.5315	0.5100	-0.0069
	(3.0436)	(-0.0977)	(-0.1840)	(-0.6529)	(0.7742)	
MAXRET	0.0195***	0.2377	-0.4101	-0.2863	-0.8708	-0.0033
	(2.5973)	(0.6791)	(-0.6987)	(-0.3431)	(-1.2906)	

This table reports the empirical results of eight dominant strategies for the HXZ model of Hou, Xue and Zhang (2015), which includes market, size, investment, and profitability factors. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The t-statistics are reported in parentheses and are Newey-West adjusted with n-1 lags.

Table A31: The FF5 Model

	α	β_{MKT}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	$Adj\ R^2$
MARCAP	0.0289***	-0.3358	-1.1439***	0.3712	-1.2313*	0.9235	0.0253
	(5.4619)	(-1.3771)	(-2.6367)	(0.9410)	(-1.8726)	(1.1265)	
MOM1	0.0375***	-0.1322	-0.7481	1.2266*	-0.5255	-0.4430	-0.0035
	(3.8891)	(-0.2979)	(-0.9476)	(1.7087)	(-0.4391)	(-0.2969)	
MOM2	0.0363***	-0.2162	-1.1153	0.4934	-1.1445	-0.0386	-0.0048
	(3.9386)	(-0.5104)	(-1.4799)	(0.7199)	(-0.9986)	(-0.0271)	
RMOM1	0.0268***	0.3826	-0.0718	1.2473**	-0.9563	-1.1983	0.0104
	(3.4557)	(1.0706)	(-0.1129)	(2.1582)	(-0.9926)	(-0.9975)	
RMOM2	0.0269***	-0.2848	0.8280	0.4072	0.6585	-1.2075	-0.0041
	(3.1339)	(-0.7197)	(1.1797)	(0.6382)	(0.6169)	(-0.9087)	
RMOM3	0.0313***	-0.1264	-0.3573	1.2744*	-1.0015	-2.0384	-0.0022
	(3.4167)	(-0.3003)	(-0.4772)	(1.8718)	(-0.8791)	(-1.4396)	
RMOM4	0.0222***	-0.1809	-0.0128	0.1836	1.2931	-1.7820	-0.0009
	(3.0263)	(-0.5358)	(-0.0214)	(0.3371)	(1.4194)	(-1.5714)	
MAXRET	0.0194**	0.2597	-0.2439	0.3113	0.0618	-0.5935	-0.0094
	(2.5684)	(0.7476)	(-0.3946)	(0.5541)	(0.0660)	(-0.5082)	

This table reports the empirical results of eight dominant strategies for the FF5 model of Fama and French (2015), which comprises market, size, value, profitability, and investment factors. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The t-statistics are reported in parentheses and are Newey-West adjusted with n-1 lags.

Table A32: The FF4 Model

	α	β_{MKT}	β_{SMB}	β_{RMW}	β_{CMA}	*Adj* R^2
MARCAP	0.0285***	-0.2888	-0.9748**	-0.9782	1.3045*	0.0256
	(5.4030)	(-1.2102)	(-2.4690)	(-1.6306)	(1.8302)	
MOM1	0.0361***	0.0230	-0.1893	0.3110	0.8160	-0.0085
	(3.7503)	(0.0529)	(-0.2628)	(0.2842)	(0.6274)	
MOM2	0.0357***	-0.1538	-0.8905	-0.8068	0.4684	-0.0036
	(3.8941)	(-0.3711)	(-1.2991)	(-0.7720)	(0.3783)	
RMOM1	0.0254***	0.5404	0.4965	-0.1056	0.0820	0.0010
	(3.2716)	(1.5380)	(0.8541)	(-0.1196)	(0.0782)	
RMOM2	0.0265***	-0.2327	1.0131	0.9369	-0.7880	-0.0025
	(3.0930)	(-0.6016)	(1.5865)	(0.9624)	(-0.6829)	
RMOM3	0.0298***	0.0349	0.2234	-0.1295	-0.7287	-0.0088
	(3.2603)	(0.0844)	(0.3268)	(-0.1242)	(-0.5900)	
RMOM4	0.022***	-0.1575	0.0706	1.4186*	-1.5929	0.0014
	(3.0120)	(-0.4771)	(0.1296)	(1.7081)	(-1.6181)	
MAXRET	0.019**	0.2991	-0.1021	0.2742	-0.2739	-0.0076
	(2.5333)	(0.8805)	(-0.1816)	(0.3210)	(-0.2700)	

This table reports the empirical results of eight dominant strategies for the FF4 model of Fama and French (2015), which consists of market, size, profitability, and investment factors. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The t-statistics are reported in parentheses and are Newey-West adjusted with n-1 lags.

Table A33: The BS6 Model

	α	β_{MKT}	β_{SMB}	β_{IA}	β_{ROE}	β_{HML}	β_{UMD}	*Adj* R^2
MARCAP	0.0284***	-0.4138*	-1.2128***	0.3546	-0.8743*	0.1675	-0.3723	0.0209
	(5.3401)	(-1.6499)	(-2.6367)	(0.4842)	(-1.6818)	(0.4455)	(-0.6370)	
MOM1	0.0383***	-0.2657	-1.4199*	-0.5224	-1.9276**	1.1757*	0.3543	0.0044
	(3.9842)	(-0.5857)	(-1.7069)	(-0.3944)	(-2.0502)	(1.7289)	(0.3351)	
MOM2	0.0363***	-0.3231	-1.4594*	-0.2804	-1.4838*	0.2982	0.1020	-0.0028
	(3.9455)	(-0.7441)	(-1.8325)	(-0.2211)	(-1.6478)	(0.4575)	(0.1008)	
RMOM1	0.0268***	0.3326	-0.1565	-1.0343	-0.7206	1.0558*	0.4018	0.0075
	(3.4468)	(0.9057)	(-0.2324)	(-0.9647)	(-0.9468)	(1.9179)	(0.4696)	
RMOM2	0.0279***	-0.4236	0.4041	-1.8715	-0.4507	0.8737	0.4843	-0.0021
	(3.2440)	(-1.0441)	(0.5450)	(-1.5833)	(-0.5373)	(1.4395)	(0.5135)	
RMOM3	0.0307***	-0.2058	-0.4691	-1.7506	-0.9157	1.0487	-0.5694	-0.0033
	(3.3487)	(-0.4762)	(-0.5920)	(-1.3872)	(-1.0214)	(1.6170)	(-0.5655)	
RMOM4	0.022***	-0.1195	0.0503	-0.9585	0.7187	0.3201	-1.0133	-0.0067
	(2.9906)	(-0.3438)	(0.0792)	(-0.9466)	(1.0001)	(0.6156)	(-1.2540)	
MAXRET	0.019**	0.1644	-0.5624	-0.7438	-0.8608	0.3607	-1.2750	0.0001
	(2.5322)	(0.4634)	(-0.8643)	(-0.7180)	(-1.1705)	(0.6782)	(-1.5422)	

This table reports the empirical results of eight dominant strategies for the BS6 model of Barillas and Shanken (2018), which incorporates value factor of the FFAF model, market, size, and momentum factors of FF5 model, the profitability and investment factors of the HXZ model. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The t-statistics are reported in parentheses and are Newey-West adjusted with n-1 lags.

A8 Tests the Effect of Electricity Factor on explaining the Dominant Strategies

Although the study of Liu and Tsyvinski (2020) documents cryptocurrencies having no exposure to electricity-related factors (aggregated stock returns on electricity sector), we nevertheless consider the possible effect of electricity in explaining the dominant strategies. We use the aggregated returns on all stocks of electricity sector (SIC 4911) listed in CRSP as a proxy for electricity factor (Ele).

We first examine the correlation coefficients between each dominant strategies and electricity factor. Table A34 indicates that electricity has limited correlation with cryptocurrency factor portfolios as the average absolute correlation coefficient is small.

Table A34: Correlation Coefficients between Each Dominant Strategy and Electricity

Portfolios	Correlation
MARCAP	-0.1033
MOM1	0.0122
MOM2	-0.0277
RMOM1	0.0600
RMOM2	-0.0350
RMOM3	0.0108
RMOM4	-0.0074
MAXRET	0.0107
Average	0.0334

This table reports the Pearson correlation coefficients between each dominant strategy and electricity factor. The last row demonstrates the simple average of absolute value of eight correlation coefficients.

Table A35 illustrates the new combinations after incorporating the electricity factors. Moreover, Table A36 to A44 demonstrate the regression results for each model after combining ElE factor.

Table A35: Potential Combinations for Electricity

	Coin Market 3-Factor Model	*Mispricing2*	*Sentiment*	*Network*	*Electricity*
1	Y	-	-	-	Y
2	Y	Y	-	-	Y
3	Y	-	Y	-	Y
4	Y	-	-	Y	Y
5	Y	Y	Y	-	Y
6	Y	Y	-	Y	Y
7	Y	-	Y	Y	Y
8	Y	Y	Y	Y	Y

This table reports the 7 adjusted model based on mispricing factors and determined fundamental factors. The 'Y' means that corresponding model incorporates the factors within these columns. For example, model 1 indicates the following model: $R_i - R_f = \alpha_i + \beta_{i,CMKT}CMKT + \beta_{i,CSMB}CSMB + \beta_{i,CMOM}CMOM + \beta_{i,Mispricing2}Mispricing2 + \beta_{i,Ele}Ele + \epsilon_i$. The rest of the models are constructed following the same manner.

Table A36: Adjusted Model 1 with Electricity

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	β_{ELE}	*Adj* R^2
MARCAP	0.0193***	-0.3816***	0.2209***	0.075***	-0.2216	0.2531
	(3.9364)	(-8.8411)	(7.8001)	(2.6392)	(-1.1890)	
MOM1	0.0233**	0.0448	0.0859	0.4714***	0.0491	0.1596
	(2.4977)	(0.5455)	(1.5947)	(8.7224)	(0.1384)	
MOM2	0.0253***	0.0245	0.1016*	0.2573***	-0.2000	0.0513
	(2.6747)	(0.2945)	(1.8531)	(4.6926)	(-0.5564)	
RMOM1	0.0196**	0.1203*	-0.0052	0.3516***	0.2779	0.1446
	(2.5683)	(1.7904)	(-0.1178)	(7.9536)	(0.9579)	
RMOM2	0.0334***	-0.0458	-0.0800	-0.1122**	-0.2351	0.0092
	(3.7023)	(-0.5777)	(-1.5323)	(-2.1308)	(-0.6866)	
RMOM3	0.0223**	0.1406*	0.0304	0.2838***	0.0055	0.0662
	(2.3879)	(1.7099)	(0.5612)	(5.2397)	(0.0154)	
RMOM4	0.025***	0.2057***	-0.0906**	0.0107	-0.1521	0.0221
	(3.2582)	(3.0533)	(-2.0436)	(0.2386)	(-0.5231)	
MAXRET	0.0088	0.2945***	0.0735*	0.2001***	-0.0354	0.0965
	(1.1655)	(4.4315)	(1.6865)	(4.5747)	(-0.1235)	

This table reports the empirical results of Model 1 with electricity factor. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The t-statistics are reported in parentheses and are Newey-West adjusted with n-1 lags.

Table A37: Adjusted Model 2 with Electricity

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	$\beta_{Mispricing2}$	β_{ELE}	*Adj* R^2
MARCAP	0.0106**	-0.3725***	0.2167***	0.0462*	0.3563***	-0.1920	0.3023
	(2.1287)	(-8.9233)	(7.9121)	(1.6523)	(5.3117)	(-1.0652)	
MOM1	-0.0035	0.0728	0.0728	0.3823***	1.1046***	0.1409	0.3102
	(-0.3888)	(0.9780)	(1.4903)	(7.6609)	(9.2335)	(0.4384)	
MOM2	0.0069	0.0438	0.0924*	0.1961***	0.7592***	-0.1367	0.1283
	(0.7247)	(0.5487)	(1.7587)	(3.6614)	(5.9186)	(-0.3965)	
RMOM1	-0.0074	0.1486***	-0.0185	0.2616***	1.1163***	0.3707	0.3797
	(-1.0861)	(2.5957)	(-0.4920)	(6.8177)	(12.1376)	(1.5000)	
RMOM2	0.0000	-0.0087	-0.0953**	-0.228***	1.3648***	-0.1107	0.3029
	(-0.0044)	(-0.1303)	(-2.1764)	(-5.0535)	(12.7433)	(-0.3854)	
RMOM3	-0.0022	0.1669**	0.0182	0.202***	1.0108***	0.0898	0.2065
	(-0.2401)	(2.1993)	(0.3639)	(3.9693)	(8.3015)	(0.2743)	
RMOM4	-0.0038	0.2376***	-0.1038***	-0.0889**	1.1748***	-0.0451	0.3201
	(-0.5650)	(4.2270)	(-2.8069)	(-2.3353)	(12.9937)	(-0.1858)	
MAXRET	0.0093	0.2939***	0.0738*	0.2019***	-0.0221	-0.0373	0.0943
	(1.1681)	(4.4139)	(1.6897)	(4.5228)	(-0.2067)	(-0.1297)	

This table reports the empirical results of Model 2 with electricity factor. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The t-statistics are reported in parentheses and are Newey-West adjusted with n-1 lags.

Table A38: Adjusted Model 3 with Electricity

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	$\beta_{Sentiment}$	β_{ELE}	*Adj* R^2
MARCAP	0.019***	-0.3808***	0.2212***	0.0746***	0.0008	-0.2205	0.2512
	(3.6998)	(-8.7771)	(7.7901)	(2.6204)	(0.2136)	(-1.1812)	
MOM1	0.0246**	0.0413	0.0844	0.4728***	-0.0037	0.0443	0.1579
	(2.5289)	(0.5000)	(1.5632)	(8.7274)	(-0.4866)	(0.1248)	
MOM2	0.0228**	0.0310	0.1043*	0.2546***	0.0067	-0.1913	0.0507
	(2.3028)	(0.3708)	(1.8995)	(4.6362)	(0.8816)	(-0.5318)	
RMOM1	0.0193**	0.121*	-0.0049	0.3513***	0.0008	0.2789	0.1424
	(2.4180)	(1.7922)	(-0.1104)	(7.9250)	(0.1247)	(0.9597)	
RMOM2	0.0374***	-0.0533	-0.0850	-0.1108**	-0.0121	-0.2488	0.0109
	(3.9198)	(-0.6704)	(-1.6260)	(-2.1055)	(-1.2789)	(-0.7270)	
RMOM3	0.0172*	0.1503*	0.0369	0.2809***	0.0151	0.0249	0.0695
	(1.7400)	(1.8253)	(0.6815)	(5.1928)	(1.5456)	(0.0702)	
RMOM4	0.0219***	0.2113***	-0.0867*	0.0096	0.0092	-0.1416	0.0229
	(2.7003)	(3.1299)	(-1.9523)	(0.2150)	(1.1405)	(-0.4871)	
MAXRET	0.0093	0.2931***	0.073*	0.2006***	-0.0014	-0.0373	0.0943
	(1.1820)	(4.3882)	(1.6686)	(4.5751)	(-0.2346)	(-0.1297)	

This table reports the empirical results of Model 3 with electricity factor. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The t-statistics are reported in parentheses and are Newey-West adjusted with n-1 lags.

Table A39: Adjusted Model 4 with Electricity

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	$\beta_{Network}$	β_{ELE}	$Adj\ R^2$
MARCAP	0.0191***	-0.3756***	0.2233***	0.0711**	0.0162*	-0.2005	0.2573
	(3.9082)	(-8.7014)	(7.8993)	(2.5023)	(1.7935)	(-1.0767)	
MOM1	0.0229**	0.0567	0.0907*	0.4637***	0.0321*	0.0910	0.1650
	(2.4649)	(0.6903)	(1.6875)	(8.5825)	(1.8715)	(0.2568)	
MOM2	0.0251***	0.0294	0.1038*	0.2539***	0.0134	-0.1829	0.0503
	(2.6526)	(0.3519)	(1.8904)	(4.6147)	(0.7676)	(-0.5075)	
RMOM1	0.0195**	0.1228*	-0.0042	0.35***	0.0068	0.2868	0.1429
	(2.5547)	(1.8207)	(-0.0944)	(7.8857)	(0.4841)	(0.9856)	
RMOM2	0.0334***	-0.0445	-0.0793	-0.1132**	0.0036	-0.2304	0.0067
	(3.6898)	(-0.5582)	(-1.5164)	(-2.1388)	(0.2168)	(-0.6706)	
RMOM3	0.0224**	0.138*	0.0292	0.2856***	-0.0071	-0.0036	0.0641
	(2.3958)	(1.6708)	(0.5379)	(5.2503)	(-0.4133)	(-0.0102)	
RMOM4	0.0248***	0.209***	-0.089**	0.0083	0.0090	-0.1404	0.0206
	(3.2357)	(3.0914)	(-2.0046)	(0.1840)	(0.6351)	(-0.4814)	
MAXRET	0.0087	0.2965***	0.0744*	0.1988***	0.0055	-0.0283	0.0945
	(1.1555)	(4.4438)	(1.7015)	(4.5265)	(0.3928)	(-0.0983)	

This table reports the empirical results of Model 4 with electricity factor. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The t-statistics are reported in parentheses and are Newey-West adjusted with n-1 lags.

Table A40: Adjusted Model 5 with Electricity

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	$\beta_{Mispricing2}$	$\beta_{Sentiment}$	β_{ELE}	$Adj\ R^2$
MARCAP	0.0103**	-0.3716***	0.217***	0.0459	0.3564***	0.0009	-0.1908	0.3006
	(1.9766)	(-8.8566)	(7.9034)	(1.6350)	(5.3060)	(0.2389)	(-1.0569)	
MOM1	-0.0022	0.0695	0.0714	0.3837***	1.1044***	-0.0035	0.1364	0.3088
	(-0.2330)	(0.9287)	(1.4581)	(7.6697)	(9.2228)	(-0.5060)	(0.4239)	
MOM2	0.0044	0.0504	0.0952*	0.1934***	0.7596***	0.0069	-0.1278	0.1281
	(0.4361)	(0.6292)	(1.8087)	(3.6046)	(5.9208)	(0.9397)	(-0.3704)	
RMOM1	-0.0078	0.1495***	-0.0181	0.2612***	1.1164***	0.0010	0.3720	0.3782
	(-1.0942)	(2.5988)	(-0.4801)	(6.7892)	(12.1229)	(0.1873)	(1.5027)	
RMOM2	0.0045	-0.0172	-0.1012**	-0.2266***	1.3684***	-0.014*	-0.1263	0.3068
	(0.5408)	(-0.2583)	(-2.3106)	(-5.0375)	(12.8094)	(-1.7662)	(-0.4407)	
RMOM3	-0.0070	0.1759**	0.0244	0.1994***	1.0087***	0.0142	0.1079	0.2096
	(-0.7260)	(2.3167)	(0.4879)	(3.9250)	(8.2995)	(1.5838)	(0.3302)	
RMOM4	-0.0063	0.2422***	-0.1006***	-0.0896**	1.1729***	0.0075	-0.0366	0.3206
	(-0.8849)	(4.2989)	(-2.7141)	(-2.3545)	(12.9750)	(1.1257)	(-0.1511)	
MAXRET	0.0099	0.2925***	0.0732*	0.2024***	-0.0222	-0.0014	-0.0391	0.0920
	(1.1861)	(4.3706)	(1.6718)	(4.5234)	(-0.2072)	(-0.2350)	(-0.1359)	

This table reports the empirical results of Model 5 with electricity factor. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The t-statistics are reported in parentheses and are Newey-West adjusted with n-1 lags.

Table A41: Adjusted Model 6 with Electricity

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	$\beta_{Mispricing2}$	$\beta_{Network}$	β_{ELE}	Adj R^2
MARCAP	0.0107**	-0.3679***	0.2187***	0.0437	0.3494***	0.0130	-0.1756	0.3045
	(2.1352)	(-8.8015)	(7.9890)	(1.5601)	(5.2039)	(1.4875)	(-0.9739)	
MOM1	-0.0034	0.0807	0.0763	0.3779***	1.0928***	0.0222	0.1689	0.3120
	(-0.3862)	(1.0828)	(1.5615)	(7.5688)	(9.1247)	(1.4232)	(0.5253)	
MOM2	0.0069	0.0461	0.0936*	0.1948***	0.7557***	0.0065	-0.1287	0.1264
	(0.7232)	(0.5751)	(1.7756)	(3.6247)	(5.8704)	(0.3885)	(-0.3721)	
RMOM1	-0.0075	0.1474**	-0.0190	0.2622***	1.1181***	-0.0033	0.3665	0.3782
	(-1.0854)	(2.5649)	(-0.5045)	(6.8135)	(12.1128)	(-0.2740)	(1.4786)	
RMOM2	0.0000	-0.0117	-0.0968**	-0.2261***	1.3691***	-0.0084	-0.1212	0.3018
	(-0.0010)	(-0.1749)	(-2.2046)	(-4.9957)	(12.7439)	(-0.5963)	(-0.4208)	
RMOM3	-0.0022	0.161**	0.0153	0.2054***	1.0195***	-0.0164	0.0696	0.2066
	(-0.2365)	(2.1165)	(0.3066)	(4.0285)	(8.3532)	(-1.0263)	(0.2124)	
RMOM4	-0.0038	0.2372***	-0.104***	-0.0886**	1.1755***	-0.0013	-0.0467	0.3183
	(-0.5636)	(4.2011)	(-2.8050)	(-2.3191)	(12.9550)	(-0.1089)	(-0.1918)	
MAXRET	0.0093	0.2959***	0.0747*	0.2007***	-0.0252	0.0057	-0.0301	0.0923
	(1.1677)	(4.4273)	(1.7062)	(4.4842)	(-0.2343)	(0.4077)	(-0.1043)	

This table reports the empirical results of Model 6 with electricity factor. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The t-statistics are reported in parentheses and are Newey-West adjusted with n-1 lags.

Table A42: Adjusted Model 7 with Electricity

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	$\beta_{Sentiment}$	$\beta_{Network}$	β_{ELE}	Adj R^2
MARCAP	0.0188***	-0.375***	0.2236***	0.0708**	0.0007	0.0161*	-0.1997	0.2555
	(3.6864)	(-8.6437)	(7.8866)	(2.4869)	(0.1687)	(1.7864)	(-1.0706)	
MOM1	0.0244**	0.0529	0.0891*	0.4652***	-0.0040	0.0324*	0.0860	0.1635
	(2.5122)	(0.6410)	(1.6539)	(8.5909)	(-0.5359)	(1.8828)	(0.2426)	
MOM2	0.0226**	0.0356	0.1064*	0.2514***	0.0066	0.0131	-0.1749	0.0496
	(2.2880)	(0.4245)	(1.9345)	(4.5616)	(0.8621)	(0.7455)	(-0.4849)	
RMOM1	0.0192**	0.1234*	-0.0039	0.3497***	0.0007	0.0068	0.2876	0.1407
	(2.4091)	(1.8213)	(-0.0879)	(7.8590)	(0.1124)	(0.4805)	(0.9869)	
RMOM2	0.0374***	-0.0515	-0.0842	-0.1122**	-0.0123	0.0050	-0.2425	0.0085
	(3.9131)	(-0.6457)	(-1.6073)	(-2.1206)	(-1.2938)	(0.2989)	(-0.7064)	
RMOM3	0.0173*	0.1472*	0.0356	0.2831***	0.0154	-0.0088	0.0141	0.0677
	(1.7413)	(1.7816)	(0.6554)	(5.2116)	(1.5717)	(-0.5073)	(0.0396)	
RMOM4	0.0219***	0.2141***	-0.0855*	0.0075	0.0089	0.0080	-0.1316	0.0212
	(2.6941)	(3.1602)	(-1.9203)	(0.1671)	(1.1013)	(0.5639)	(-0.4512)	
MAXRET	0.0093	0.2951***	0.0738*	0.1993***	-0.0015	0.0056	-0.0301	0.0923
	(1.1753)	(4.4009)	(1.6834)	(4.5275)	(-0.2444)	(0.3984)	(-0.1044)	

This table reports the empirical results of Model 7 with electricity factor. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The t-statistics are reported in parentheses and are Newey-West adjusted with n-1 lags.

Table A43: Adjusted Model 8 with Electricity

	α	β_{CMKT}	β_{CSMB}	β_{CMOM}	$\beta_{Mispricing2}$	$\beta_{Sentiment}$	$\beta_{Network}$	β_{ELE}	*Adj* R^2
MARCAP	0.0104**	-0.3672***	0.219***	0.0434	0.3495***	0.0008	0.0130	-0.1746	0.3027
	(1.9932)	(-8.7406)	(7.9780)	(1.5455)	(5.1984)	(0.2011)	(1.4799)	(-0.9671)	
MOM1	-0.0020	0.0772	0.0748	0.3794***	1.0924***	-0.0037	0.0224	0.1644	0.3107
	(-0.2201)	(1.0310)	(1.5279)	(7.5800)	(9.1134)	(-0.5435)	(1.4354)	(0.5105)	
MOM2	0.0044	0.0525	0.0963*	0.1921***	0.7563***	0.0068	0.0061	-0.1203	0.1261
	(0.4375)	(0.6528)	(1.8237)	(3.5704)	(5.8741)	(0.9290)	(0.3647)	(-0.3478)	
RMOM1	-0.0078	0.1484**	-0.0186	0.2618***	1.1182***	0.0010	-0.0034	0.3678	0.3767
	(-1.0954)	(2.5689)	(-0.4924)	(6.7855)	(12.0984)	(0.1942)	(-0.2786)	(1.4813)	
RMOM2	0.0045	-0.0195	-0.1023**	-0.2251***	1.3718***	-0.0138*	-0.0068	-0.1347	0.3054
	(0.5334)	(-0.2921)	(-2.3303)	(-4.9872)	(12.8009)	(-1.7304)	(-0.4885)	(-0.4684)	
RMOM3	-0.0071	0.1699**	0.0215	0.2031***	1.0181***	0.0148*	-0.0179	0.0866	0.2102
	(-0.7433)	(2.2327)	(0.4305)	(3.9903)	(8.3600)	(1.6480)	(-1.1242)	(0.2647)	
RMOM4	-0.0063	0.2415***	-0.1009***	-0.0892**	1.174***	0.0076	-0.0021	-0.0392	0.3188
	(-0.8862)	(4.2698)	(-2.7163)	(-2.3337)	(12.9421)	(1.1333)	(-0.1796)	(-0.1613)	
MAXRET	0.0099	0.2945***	0.0741*	0.2013***	-0.0253	-0.0015	0.0058	-0.0319	0.0901
	(1.1886)	(4.3843)	(1.6881)	(4.4854)	(-0.2353)	(-0.2453)	(0.4133)	(-0.1106)	

This table reports the empirical results of Model 8 with electricity factor. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The t-statistics are reported in parentheses and are Newey-West adjusted with n-1 lags.

Table A44: Comparison of Model Performance Incorporating Electricity

Model	$A\|R^2\|$	Significant Alphas	GRS	$A\|\alpha_i\|$	$A\|\alpha_i\|/A\|\bar{r}_i\|$	$A\alpha_i^2/A\bar{r}_i^2$	$As^2(\alpha_i)/A\alpha_i^2$	Score
1	0.10	7	8.4497	0.0221	1.6272	0.0151	0.1276	0
2	0.26	1	1.1953	0.0055	0.4036	0.0012	1.4910	3
3	0.10	7	7.5017	0.0214	1.5781	0.0146	0.1455	0
4	0.10	7	8.3671	0.0220	1.6182	0.0149	0.1291	0
5	0.26	1	1.1777	0.0065	0.4810	0.0014	1.3765	3
6	0.26	1	1.2067	0.0055	0.4029	0.0012	1.4918	6
7	0.10	7	7.4850	0.0214	1.5725	0.0145	0.1465	0
8	0.26	1	1.2103	0.0066	0.4823	0.0014	1.3637	2

This table reports the performance measures for 8 adjusted models comprising electricity factor. From second column to the second last column, each column represents one measure of model performance, and the last column illustrates the overall scores for each model.

A9 Test the Model Performance on Short Sample

We split the sample into two halves, to address the concern that our sample period is short. Then, we test of best model's (NTFM-SM) performance on two sub-samples (2014 January to the 2016 September and the 2016 October to 2021 June).

Table A45: Adjusted Coin Market Model on Subsamples

	Panel A: Previous Period (2014.01-2016.09)						**Panel B: Post Period (2016.10-2021-06)**					
	α	β_{CMKT}	β_{CSMB}	$\beta_{MispricingS}$	$\beta_{MispricingM}$	*Adj* R^2	α	β_{CMKT}	β_{CSMB}	$\beta_{MispricingS}$	$\beta_{MispricingM}$	*Adj* R^2
MOM1	0.0055	0.1306	0.0872	0.1001	1.1131***	0.2148	0.0002	-0.0751	0.1169**	0.0167	0.8764***	0.2421
	(0.3320)	(0.7611)	(0.8710)	(0.7045)	(7.3710)		(0.0194)	(-0.9861)	(2.3051)	(0.1562)	(7.9835)	
MOM2	0.0325*	-0.0347	0.3061***	-0.413***	-0.0442	0.0448	0.0044	0.0491	0.154***	0.3979***	0.4359***	0.1497
	(1.9390)	(-0.1984)	(2.9979)	(-2.8510)	(-0.2869)		(0.4322)	(0.5734)	(2.6986)	(3.3065)	(3.5282)	
RMOM1	0.0028	0.0047	0.0675	-0.1474	1.0906***	0.3625	-0.0049	0.0639	0.0282	0.0457	0.9359***	0.3688
	(0.2368)	(0.0385)	(0.9485)	(-1.4597)	(10.1612)		(-0.6695)	(1.0359)	(0.6860)	(0.5286)	(10.5269)	
RMOM2	0.0368**	-0.1129	0.1375	-0.3891***	-0.1012	0.0214	0.0228***	-0.1613**	-0.0416	-0.1959*	0.7242***	0.2108
	(2.2971)	(-0.6768)	(1.4122)	(-2.8168)	(-0.6890)		(2.5779)	(-2.1625)	(-0.8413)	(-1.8701)	(6.7881)	
RMOM3	0.0495***	0.2229	-0.2464**	0.1888	-0.2809*	0.0246	-0.0129*	0.1374**	0.0423	0.326***	1.0578***	0.4700
	(2.8382)	(1.2257)	(-2.3210)	(1.2537)	(-1.7550)		(-1.8022)	(2.2746)	(1.0553)	(3.8425)	(12.2424)	
RMOM4	0.0292**	0.0903	-0.0154	0.0770	-0.0456	-0.0160	-0.0161**	0.1081*	0.0033	0.1559**	1.3387***	0.6010
	(2.3151)	(0.6855)	(-0.2005)	(0.7061)	(-0.3932)		(-2.4024)	(1.9102)	(0.0887)	(1.9626)	(16.5407)	
MAXRET	0.0214*	0.2749**	0.0606	-0.1865*	0.1259	0.0433	0.0045	0.1491*	0.1831***	-0.3047***	0.1419	0.1242
	(1.6649)	(2.0550)	(0.7760)	(-1.6836)	(1.0696)		(0.4579)	(1.7978)	(3.3173)	(-2.6233)	(1.1879)	

This table reports the empirical results of NTFM-SM 1 on two sub-samples. Panel A represents the data of the first half of the sample period, and Panel B demonstrates the second half of the sample. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The t-statistics are reported in parentheses and are Newey-West adjusted with n-1 lags.

A10 Decomposition of the Long-Short Portfolios

To investigate which leg of the zero-cost spreads (long or short) contributes most to ASD, we decompose the eight dominant long-short portfolios into their long only and short only legs, and repeat the AFSD and ASSD tests against our four benchmarks. If a 5-1 (long fifth quintile and short first quintile) factor portfolio in Table 3 has a negative value, we long the first quintile, and short the fifth quintile.

Tables A46 and A47 report the ε_i values of each long leg of the factor portfolios for both AFSD and ASSD against our four benchmarks. Panel A of Tables A46 and A47 show the empirical ε_i values against the S&P 500. Similar to AFSD in Table 5 for long-short portfolios, no factor portfolios dominate the S&P 500 benchmark at a 4 week horizon. As the investment horizon extends to 52 and 78 weeks, the number of AFSD dominances increases to 2 and 11, respectively. Three ASSD dominant factor portfolios appear at 78 weeks. The number of dominant factor portfolios sharply declines from ten long-short portfolios to three long-only portfolios, showing the effect of the short legs on diversifying the risks of long-short portfolios. Over 78 weeks, 11 of the 29 long-only portfolios dominate the S&P 500 by AFSD, suggesting that almost half the cryptocurrency long-only portfolios outperform the equity market.

Table A46: Almost First-Order Stochastic Dominance for Long Legs

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: AFSD for Portfolios against Bitcoin				
	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	0.2734	0.1536	0.1148	0.0566*	0.018*	0.2783	0.1544	0.1073	0.0508*	0.0147*	0*	0*	0*	0*	0*	0.0245*	0.0245*	0.0282*	0.0006*	0.0005*
LPRC	0.3512	0.2840	0.2387	0.1715	0.1232	0.3483	0.2738	0.2248	0.1569	0.1112	0.3501	0.2759	0.2271	0.1583	0.1115	0.3062	0.2639	0.2406	0.1823	0.1554
AGE	0.3181	0.2117	0.1792	0.1326	0.1050	0.3166	0.2053	0.1693	0.1218	0.0953	0.3192	0.2098	0.1733	0.1242	0.0959	0.2572	0.1219	0.1249	0.0848	0.1127
MOM1	0.3009	0.1825	0.1233	0.0719	0.05*	0.3018	0.1789	0.1164	0.0661	0.044*	0*	0*	0*	0*	0.0456*	0.2106	0.0611	0.0551*	0.0224*	0.0307*
MOM2	0.3198	0.2364	0.2054	0.1028	0.0718	0.3191	0.2310	0.1965	0.0970	0.0656	0*	0*	0*	0*	0.0666	0.2438	0.1732	0.1795	0.0524*	0.0643
MOM3	0.3624	0.2673	0.2139	0.1211	0.0932	0.3589	0.2597	0.2018	0.1109	0.0824	0.3604	0*	0*	0.1134	0.0835	0.3202	0.2117	0.1801	0.0549*	0.0948
MOM4	0.3955	0.3142	0.2687	0.2151	0.1389	0.3892	0.3000	0.2478	0.1947	0.1198	0.3895	0.3020	0.2501	0.1952	0.1199	0.3897	0.2989	0.3035	0.2606	0.2298
MOM8	0.4366	0.3729	0.3252	0.2466	0.1645	0.4263	0.3544	0.3016	0.2237	0.1438	0.4249	0.3539	0.3017	0.2227	0.1429	0.5240	0.5042	0.5031	0.3699	0.3080
MOM26	0.5237	0.4919	0.4833	0.5148	0.5625	0.5033	0.4630	0.4473	0.4554	0.4667	0.4965	0.4560	0.4383	0.4352	0.4292	0.7633	0.8157	0.8715	0.9162	1.0000
RMOM1	0.3184	0.2214	0.1808	0.1046	0.042*	0.3180	0.2146	0.1701	0.0967	0.0357*	0*	0*	0*	0*	0.0377*	0.2116	0.0968	0.1216	0.0318*	0.0136*
RMOM2	0.3641	0.2788	0.2217	0.1047	0.0508*	0.3611	0.2706	0.2107	0.0979	0.0436*	0*	0*	0*	0*	0.0456*	0.3261	0.2365	0.2105	0.0563*	0.0249*
RMOM3	0.3126	0.2049	0.1511	0.0885	0.0487*	0.3128	0.1997	0.1407	0.0811	0.0393*	0*	0*	0*	0*	0.0417*	0.1763	0.0643	0.0493*	0.0162*	0.0147*
RMOM4	0.3568	0.2469	0.1805	0.0878	0.0528*	0.3531	0.2372	0.1645	0.0791	0.0393*	0.3552	0*	0*	0*	0.0428*	0.2790	0.0906	0.0367*	0.0218*	0.0041*
RMOM8	0.4233	0.3490	0.3147	0.2699	0.2157	0.4130	0.3294	0.2884	0.2400	0.1768	0.4121	0.3302	0.2892	0.2375	0.1732	0.4951	0.4571	0.5729	0.7793	0.9904
RMOM26	0.4936	0.4603	0.4562	0.4652	0.4571	0.4794	0.4349	0.4240	0.4251	0.4087	0.4752	0.4299	0.4172	0.4123	0.3911	0.6572	0.7892	0.9054	0.9902	1.0000
VOL	0.4136	0.3550	0.3194	0.2309	0.1741	0.4075	0.3436	0.3048	0.2137	0.1577	0*	0.3436	0.3048	0.2134	0.1566	0.4286	0.3808	0.3699	0.2914	0.2481
VOLPRC	0.2768	0.1666	0.1149	0.0486*	0.0288*	0.2785	0.1631	0.1065	0.0437*	0.0243*	0*	0*	0*	0*	0.0262*	0.1444	0.0276*	0.0249*	0.0025*	0.0036*
VOLSCALE	0.3481	0.2658	0.2059	0.1207	0.0893	0.3450	0.2552	0.1920	0.1077	0.0789	0.3473	0.2587	0.1962	0.1110	0.0801	0.2778	0.2085	0.1631	0.0792	0.0947
RETVOL	0.4590	0.4249	0.3752	0.3072	0.2523	0.4512	0.4103	0.3568	0.2871	0.2321	0.4494	0.4080	0.3548	0.2842	0.2285	0.5041	0.5125	0.4869	0.4257	0.3895
RETSKEW	0.3637	0.2416	0.1720	0.0834	0.0133*	0.3597	0.2324	0.1592	0.0766	0.0091*	0*	0*	0*	0*	0.012*	0.2932	0.0548*	0.0594	0.0004*	0*
RETKURT	0.4380	0.3608	0.2774	0.1798	0.1237	0.4283	0.3422	0.2523	0.1586	0.1014	0.4268	0.3423	0*	0.1600	0.1024	0.5113	0.4803	0.4364	0.2754	0.2697
MAXRET	0.3783	0.2816	0.2190	0.0913	0.0569*	0.3738	0.2719	0.2056	0.0843	0.049*	0.3747	0.2746	0.2091	0*	0.0509*	0.3565	0.2355	0.1808	0.0291*	0.0327*
STDPRCVOL	0.2918	0.1865	0.1327	0.0735	0.0519*	0.2923	0.1809	0.1212	0.0630	0.044*	0.2964	0*	0.1278	0.0674	0.0459*	0.1757	0.0419*	0.0351*	0.0281*	0.0286*
MEANABS	0.3307	0.2312	0.1725	0.1056	0.0772	0.3287	0.2224	0.1612	0.0969	0.0700	0.3313	0.2264	0.1657	0.0996	0.0710	0.2648	0.1662	0.1164	0.0455*	0.0707
BETA	0.4643	0.4306	0.3822	0.3143	0.2397	0.4492	0.4032	0.3457	0.2808	0.2060	0.4460	0.3993	0.3418	0.2766	0.2016	0.6232	0.6567	0.7199	0.6388	0.5608
BETA$\hat{2}$	0.4723	0.4456	0.4110	0.3506	0.2675	0.4539	0.4137	0.3712	0.3126	0.2297	0.4498	0.4087	0.3656	0.3061	0.2237	0.8419	0.9168	0.8770	0.7690	0.7022
IDIOVOL	0.4395	0.3903	0.3442	0.2542	0.1488	0.4250	0.3611	0.3081	0.2229	0.1123	0.4231	0.3597	0.3075	0.2215	0.1123	0.9459	0.8948	0.9018	0.7065	0.5981
DELAY	0.3226	0.2194	0.1689	0.1031	0.0394*	0.3223	0.2100	0.1537	0.0933	0.0275*	0*	0*	0*	0*	0.0315*	0.0582*	0.0135*	0.0189*	0.016*	0*
LIQ	0.3307	0.2312	0.1725	0.1056	0.0772	0.3287	0.2224	0.1612	0.0969	0.0700	0.3313	0.2264	0.1657	0.0996	0.0710	0.2648	0.1662	0.1164	0.0455*	0.0707

This table presents the ε_i of AFSD for each long portfolio against S&P 500, T-bonds, T-bills and Bitcoin at different investment horizons. * denotes AFSD against the benchmark, and 1 indicates that the benchmark dominates the corresponding factor portfolio

Table A47: Almost Second-Order Stochastic Dominance for Long Legs

	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: AFSD for Portfolios against Bitcoin				
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	4-week	13-week	26-week	52-week	78-week
MARCAP	0.3763	0.1815	0.1297	0.0600	0.0184**	0.3857	0.1826	0.1202	0.0535	0.0149**	0**	0**	0**	0**	0**	0.0219**	0.0251**	0.029**	0.0006**	0.0005**
LPRC	0.5412	0.3967	0.3136	0.2070	0.1404	0.5344	0.3770	0.2900	0.1860	0.1251	0.5387	0.3810	0.2939	0.1880	0.1254	0.7579	0.3585	0.3168	0.2229	0.1840
AGE	0.4665	0.2686	0.2183	0.1529	0.1173	0.4632	0.2584	0.2039	0.1388	0.1053	0.4689	0.2655	0.2096	0.1418	0.1061	0.3462	0.1388	0.1427	0.1352	0.1271
MOM1	0.4303	0.2232	0.1406	0.0775	0.0526	0.4323	0.2178	0.1318	0.0708	0.0460	0**	0**	0**	0**	0.0478	0.4212	0.0871	0.0583	0.0229**	0.0317**
MOM2	0.4701	0.3096	0.2584	0.1146	0.0773	0.4686	0.3004	0.2445	0.1074	0.0702	0**	0**	0**	0**	0.0714	0.3225	0.2095	0.2188	0.0553	0.0687
MOM3	0.5684	0.3649	0.2720	0.1378	0.1027	0.5598	0.3509	0.2528	0.1247	0.0898	0.5635	0**	0**	0.1279	0.0911	0.4710	0.2685	0.2196	0.1097	0.1048
MOM4	0.6544	0.4580	0.3674	0.2740	0.1613	0.6371	0.4286	0.3295	0.2418	0.1361	0.6381	0.4326	0.3335	0.2426	0.1362	0.6387	0.5970	0.4358	0.3525	0.5600
MOM8	0.7749	0.5946	0.4819	0.3273	0.1969	0.7432	0.5488	0.4319	0.2882	0.1680	0.7387	0.5477	0.4321	0.2866	0.1667	0.9775	0.9945	0.9877	0.5870	0.4451
MOM26	0.9170	0.9681	0.9353	0.9458	0.8182	0.9869	0.8623	0.8092	0.8363	0.8752	0.9860	0.8381	0.7803	0.7706	0.7519	0.7386	0.5637	0.5398	0.5239	1.0000
RMOM1	0.4672	0.2843	0.2207	0.1168	0.0438	0.4663	0.2732	0.2050	0.1070	0.0370	0**	0**	0**	0**	0.0392	0.5238	0.1927	0.1385	0.0329	0.0523
RMOM2	0.5726	0.3866	0.2848	0.1170	0.0535	0.5653	0.3710	0.2670	0.1086	0.0456	0**	0**	0**	0**	0.0478	0.6522	0.4729	0.2666	0.0597	0.0417
RMOM3	0.4548	0.2576	0.1780	0.0971	0.0512	0.4551	0.2495	0.1637	0.0883	0.0409	0**	0**	0**	0**	0.0435	0.4481	0.0687	0.1405	0.0165**	0.0133**
RMOM4	0.5548	0.3278	0.2202	0.0963	0.0558	0.5459	0.3110	0.1970	0.0858	0.0409	0.5510	0**	0**	0**	0.0447	0.6550	0.1785	0.1496	0.0223**	0.0003**
RMOM8	0.7339	0.5360	0.4593	0.3697	0.2750	0.7036	0.4911	0.4052	0.3158	0.2147	0.7011	0.4930	0.4069	0.3115	0.2095	0.9897	0.8403	0.8906	0.7788	0.6465
RMOM26	0.9748	0.8527	0.8391	0.8700	0.8421	0.9207	0.7695	0.7361	0.7396	0.6913	0.9053	0.7542	0.7158	0.7015	0.6423	0.7920	0.8036	0.6726	0.8520	1.0000
VOL	0.7054	0.5503	0.4693	0.3002	0.2108	0.6878	0.5234	0.4385	0.2717	0.1872	0**	0.5235	0.4384	0.2712	0.1857	0.7501	0.7616	0.7397	0.4113	0.3300
VOLPRC	0.3827	0.1999	0.1298	0.0511	0.0296**	0.3860	0.1949	0.1191	0.0457	0.025**	0**	0**	0**	0**	0.027**	0.3778	0.0970	0.0255**	0.0025**	0.0031**
VOLSCALE	0.5341	0.3621	0.2592	0.1373	0.0980	0.5267	0.3427	0.2376	0.1207	0.0856	0.5320	0.3490	0.2441	0.1248	0.0870	0.3847	0.2634	0.5084	0.0975	0.1616
RETVOL	0.8486	0.7389	0.6005	0.4434	0.3374	0.8222	0.6959	0.5548	0.4028	0.3023	0.8161	0.6893	0.5499	0.3971	0.2962	0.9839	0.9535	0.9490	0.7412	0.7789
RETSKEW	0.5716	0.3185	0.2078	0.0910	0.0135**	0.5617	0.3027	0.1893	0.0830	0.0092**	0**	0**	0**	0**	0.0121**	0.4146	0.2483	0.0609	0**	0**
RETKURT	0.7793	0.5646	0.3838	0.2192	0.1412	0.7492	0.5201	0.3374	0.1884	0.1128	0.7446	0.5205	0**	0.1905	0.1141	0.9855	0.9731	0.9317	0.3520	0.3694
MAXRET	0.6085	0.3920	0.2803	0.1004	0.0603	0.5970	0.3735	0.2588	0.0921	0.0515	0.5992	0.3786	0.2644	0**	0.0537	0.7883	0.3080	0.4490	0.0299**	0.0338
STDPRCVOL	0.4120	0.2292	0.1530	0.0794	0.0548	0.4130	0.2209	0.1379	0.0672	0.0460	0.4213	0**	0.1465	0.0723	0.0481	0.2124	0.0769	0.0486	0.0004**	0.0294**
MEANABS	0.4942	0.3006	0.2084	0.1181	0.0837	0.4896	0.2860	0.1922	0.1073	0.0752	0.4954	0.2927	0.1986	0.1106	0.0764	0.3602	0.1993	0.2176	0.0477	0.0761
BETA	0.8667	0.7563	0.6187	0.4583	0.3153	0.8156	0.6756	0.5284	0.3905	0.2594	0.8049	0.6646	0.5194	0.3823	0.2525	0.7343	0.6875	0.8308	0.6965	0.8218
BETA2̂	0.8949	0.8039	0.6977	0.5398	0.3652	0.8310	0.7056	0.5904	0.4548	0.2983	0.8175	0.6912	0.5762	0.4411	0.2881	0.8614	0.8076	0.5368	0.5867	0.6346
IDIOVOL	0.7840	0.6402	0.5248	0.3408	0.1748	0.7392	0.5652	0.4453	0.2869	0.1265	0.7334	0.5618	0.4440	0.2845	0.1265	0.8762	0.7125	0.5280	0.6311	0.7530
DELAY	0.4763	0.2811	0.2032	0.1150	0.0410	0.4757	0.2659	0.1816	0.1029	0.0283**	0**	0**	0**	0**	0.0325	0.0971	0.0137**	0.0167**	0.0157**	0**
LIQ	0.4942	0.3006	0.2084	0.1181	0.0837	0.4896	0.2860	0.1922	0.1073	0.0752	0.4954	0.2927	0.1986	0.1106	0.0764	0.3602	0.1993	0.2176	0.0477	0.0761

This table presents the ε_i of ASSD for each long portfolio against S&P 500, T-bonds, T-bills and Bitcoin at different investment horizons. ** denotes ASSD against the benchmark, and 1 indicates that the benchmark dominates the corresponding factor portfolio

Panel B of Tables A46 and A47 report the ε_i values of the long leg factor portfolios against T-bonds for AFSD and ASSD. The AFSD performance of these long-only portfolios is similar to Panel A of Tables A46 and A47, with exactly the same numbers (2 and 11) of AFSD dominant portfolios for 52 to 78 weeks, while the number of ASSD dominant portfolios against T-Bonds is four. Panel C of Tables A46 and A47 reports AFSD and ASSD for long leg factor portfolios against T-Bills. An even greater number of factors are dominant at each horizon than in Panels A and B, except for ASSD at a 78 week horizon. For instance, the numbers of AFSD dominant long-only portfolios against T-Bills are 10, 12, 12, 11, and 11, respectively; whereas the numbers of AFSD dominant long leg portfolios are merely 0, 0, 0, 2, and 11, respectively. Moreover, the numbers of ASSD dominant long-leg portfolios are 10, 12, 12, 11, and 3; which are much larger than those in Panels A and B. This indicates that almost half of the long leg factor portfolios dominate T-Bills, with the number of dominances almost reaching that for long-short portfolios in Tables 4 and 5 for T-Bills. Panel D of Tables A46 and A47 displays AFSD for long leg portfolios against Bitcoin. For each of the five horizons, similar to the performance of long-short portfolios, the numbers of AFSD dominant long leg portfolios are 2, 5, 7, 15, and 11, respectively. Likewise, the numbers of ASSD dominances are 1, 2, 3, 9, and 8, respectively. This reinforces the view that the dominant performance of cryptocurrency long-short factor portfolios is due to their long legs.

Tables A48 and A49 report the AFSD and ASSD for the short leg factor portfolios against our four benchmarks. In Panels A, B and C of Tables A48 and A49, there is no dominance by the short legs at any investment horizon. The ε_i values for each factor portfolio generally increase as the investment horizon lengthens. In Panel D of Tables A48 and A49, the short leg factor portfolios are increasing dominated by Bitcoin as the horizon increases from 4 to 78 weeks. These results support our previous finding, that the good performance of long-short factor portfolios is due to their long legs. We also exhibit the Share ratio for each long-short portfolio in Table A50.

To summarize, the decomposition of the long-short portfolios illustrates that the dominance of the long-short portfolios against the four benchmarks is mostly due to the long legs of the factor portfolios. In addition, a few long-short and long only factor portfolios dominate the S&P 500, T-Bonds, T-Bills and Bitcoin. In the long run (52 and 78 week holding periods).

Table A48: Almost First-Order Stochastic Dominance for Short Legs

	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: AFSD for Portfolios against Bitcoin				
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	4-week	13-week	26-week	52-week	78-week
MARCAP	0.4706	0.4879	0.4992	0.5049	0.5149	0.4581	0.4640	0.4658	0.4697	0.4784	0.4551	0.4640	0.4568	0.4565	0.4626	0.6199	0.8568	0.9844	0.9773	0.9963
LPRC	0.5853	0.6483	0.6882	0.7349	0.7984	0.5639	0.6165	0.6531	0.6979	0.7613	0.5550	0.6031	0.6357	0.6745	0.7347	0.9541	1.0000	1.0000	1.0000	1.0000
AGE	0.5959	0.6548	0.6901	0.7577	0.7944	0.5738	0.6246	0.6586	0.7267	0.7677	0.5645	0.6112	0.6425	0.7049	0.7463	0.9321	1.0000	1.0000	1.0000	1.0000
MOM1	0.4896	0.5048	0.5472	0.5728	0.5826	0.4759	0.4788	0.5086	0.5206	0.5275	0.4719	0.4719	0.4960	0.4981	0.5009	0.6609	0.8600	0.9988	0.9992	1.0000
MOM2	0.4711	0.4709	0.4746	0.4437	0.4268	0.4572	0.4413	0.4320	0.3943	0.3743	0.4539	0.4353	0.4228	0.3807	0.3574	0.6705	0.9963	1.0000	1.0000	1.0000
MOM3	0.5159	0.5617	0.6203	0.6850	0.7496	0.5007	0.5310	0.5750	0.6287	0.6899	0.4956	0.5208	0.5570	0.5970	0.6520	0.7293	0.9493	1.0000	1.0000	1.0000
MOM4	0.5515	0.6118	0.6769	0.7583	0.8240	0.5336	0.5809	0.6378	0.7197	0.7897	0.5268	0.5688	0.6191	0.6924	0.7598	0.8224	0.9829	1.0000	1.0000	1.0000
MOM8	0.5650	0.6208	0.6166	0.6187	0.6195	0.5431	0.5833	0.5697	0.5525	0.5128	0.5347	0.5687	0.5512	0.5223	0.4658	0.9370	1.0000	1.0000	1.0000	1.0000
MOM26	0.6763	0.8333	0.9076	0.9785	1.0000	0.6559	0.8058	0.8834	0.9683	0.9998	0.6453	0.7875	0.8625	0.9571	0.9968	0.9286	1.0000	1.0000	1.0000	1.0000
RMOM1	0.5134	0.5334	0.5529	0.5534	0.5542	0.4957	0.5027	0.5147	0.5093	0.5097	0.4901	0.4937	0.5021	0.4907	0.4892	0.8982	1.0000	1.0000	1.0000	1.0000
RMOM2	0.4724	0.4761	0.4681	0.4249	0.4038	0.4571	0.4471	0.4306	0.3838	0.3582	0.4535	0.4410	0.4225	0.3727	0.3441	0.7981	0.9704	0.9962	1.0000	0.9992
RMOM3	0.4986	0.5262	0.5379	0.5259	0.5204	0.4821	0.4950	0.4972	0.4738	0.4604	0.4772	0.4862	0.4845	0.4545	0.4359	0.8469	0.9936	1.0000	1.0000	1.0000
RMOM4	0.4877	0.5079	0.5193	0.5252	0.5424	0.4721	0.4798	0.4836	0.4802	0.4913	0.4678	0.4723	0.4731	0.4631	0.4691	0.7807	0.9964	0.9986	1.0000	1.0000
RMOM8	0.6063	0.6847	0.7220	0.7996	0.8712	0.5817	0.6500	0.6868	0.7660	0.8455	0.5713	0.6337	0.6679	0.7404	0.8182	0.9760	1.0000	1.0000	1.0000	1.0000
RMOM26	0.6776	0.7708	0.8175	0.8986	0.9419	0.6515	0.7407	0.7890	0.8733	0.9274	0.6389	0.7232	0.7696	0.8492	0.9058	0.9826	1.0000	1.0000	1.0000	1.0000
VOL	0.6944	0.8013	0.8685	0.9224	0.9608	0.6634	0.7660	0.8372	0.8999	0.9460	0.6478	0.7445	0.8130	0.8752	0.9211	0.9976	1.0000	1.0000	1.0000	1.0000
VOLPRC	0.6618	0.7578	0.8217	0.8877	0.9363	0.6325	0.7198	0.7850	0.8584	0.9158	0.6186	0.6996	0.7608	0.8313	0.8868	0.9945	1.0000	1.0000	1.0000	1.0000
VOLSCALE	0.6629	0.7521	0.8158	0.8782	0.9464	0.6331	0.7165	0.7802	0.8491	0.9231	0.6190	0.6972	0.7568	0.8224	0.8944	1.0000	1.0000	1.0000	1.0000	1.0000
RETVOL	0.6531	0.7342	0.7833	0.8214	0.9159	0.6245	0.6977	0.7488	0.7933	0.8943	0.6107	0.6788	0.7275	0.7710	0.8659	1.0000	1.0000	1.0000	1.0000	1.0000
RETSKEW	0.5810	0.6384	0.6823	0.7503	0.7843	0.5601	0.6074	0.6476	0.7109	0.7454	0.5516	0.5944	0.6303	0.6847	0.7169	0.9602	1.0000	1.0000	1.0000	1.0000
RETKURT	0.5812	0.6387	0.6730	0.7321	0.8112	0.5628	0.6123	0.6445	0.7033	0.7844	0.5551	0.6009	0.6305	0.6841	0.7626	0.8476	0.9893	1.0000	1.0000	1.0000
MAXRET	0.5468	0.6025	0.6466	0.6954	0.7686	0.5243	0.5680	0.6053	0.6519	0.7233	0.5163	0.5551	0.5873	0.6263	0.6904	0.9540	0.9965	1.0000	1.0000	1.0000
STDPRCVOL	0.6554	0.7491	0.8091	0.8777	0.9329	0.6265	0.7112	0.7723	0.8464	0.9078	0.6131	0.6914	0.7487	0.8182	0.8773	0.9937	1.0000	1.0000	1.0000	1.0000
MEANABS	0.6758	0.7804	0.8278	0.8792	0.9609	0.6445	0.7408	0.7913	0.8523	0.9435	0.6291	0.7185	0.7672	0.8288	0.9153	0.9981	1.0000	1.0000	1.0000	1.0000
BETA	0.7334	0.8163	0.8943	0.9729	0.9833	0.6611	0.7272	0.7888	0.8682	0.9487	0.6273	0.6755	0.7196	0.7776	0.8675	0.7168	0.8405	0.9247	0.9995	1.0000
BETA$\hat{2}$	0.7332	0.8161	0.8940	0.9727	0.9833	0.6609	0.7267	0.7886	0.8681	0.9487	0.6272	0.6753	0.7194	0.7776	0.8674	0.7168	0.8402	0.9246	0.9995	1.0000
IDIOVOL	0.7331	0.8158	0.8940	0.9722	0.9833	0.6608	0.7264	0.7884	0.8674	0.9484	0.6269	0.6746	0.7187	0.7768	0.8672	0.7167	0.8401	0.9245	0.9994	1.0000
DELAY	0.5849	0.6674	0.7221	0.7635	0.7525	0.5635	0.6313	0.6789	0.7126	0.7003	0.5544	0.6149	0.6559	0.6781	0.6640	0.8777	1.0000	1.0000	1.0000	1.0000
LIQ	0.6758	0.7804	0.8278	0.8792	0.9609	0.6445	0.7408	0.7913	0.8523	0.9435	0.6291	0.7185	0.7672	0.8288	0.9153	0.9981	1.0000	1.0000	1.0000	1.0000

This table presents the ε_i of AFSD for each short portfolio against S&P 500, T-bonds, T-bills and Bitcoin at different investment horizons. * denotes AFSD against the benchmark, and 1 indicates that the benchmark dominates the corresponding factor portfolio

Table A49: Almost Second-Order Stochastic Dominance for Short Legs

Portfolios	Panel A: Portfolios against S&P 500 Index 4-week	13-week	26-week	52-week	78-week	Panel B: Portfolios against Ten-year T-Bond 4-week	13-week	26-week	52-week	78-week	Panel C: Portfolios against One-month T-Bill 4-week	13-week	26-week	52-week	78-week	Panel D: AFSD for Portfolios against Bitcoin 4-week	13-week	26-week	52-week	78-week
MARCAP	0.8888	0.9526	0.9967	0.9808	0.9454	0.8455	0.8656	0.8721	0.8858	0.9172	0.8352	0.8656	0.8409	0.8401	0.8607	0.9184	0.9026	0.8745	0.6637	0.6644
LPRC	0.7743	0.6861	0.6465	0.6100	0.5722	0.8153	0.7257	0.6808	0.6381	0.5930	0.8345	0.7452	0.7008	0.6590	0.6102	0.8361	1.0000	1.0000	1.0000	1.0000
AGE	0.7565	0.6790	0.6448	0.5951	0.5743	0.7955	0.7149	0.6749	0.6158	0.5892	0.8140	0.7332	0.6927	0.6323	0.6024	0.6748	1.0000	1.0000	1.0000	1.0000
MOM1	0.9592	0.9813	0.8528	0.7974	0.7792	0.9079	0.9188	0.9673	0.9268	0.9057	0.8937	0.8937	0.9841	0.9923	0.9963	0.9110	0.8557	0.6666	0.7499	1.0000
MOM2	0.8908	0.8899	0.9033	0.7974	0.7445	0.8424	0.7899	0.7604	0.6511	0.5982	0.8313	0.7709	0.7324	0.6146	0.5562	0.9041	0.7997	1.0000	1.0000	1.0000
MOM3	0.9420	0.8199	0.7206	0.6493	0.6003	0.9974	0.8953	0.7931	0.7095	0.6449	0.9825	0.9260	0.8302	0.7547	0.6820	0.7602	0.5137	1.0000	1.0000	1.0000
MOM4	0.8426	0.7323	0.6567	0.5948	0.5598	0.8880	0.7821	0.6983	0.6209	0.5768	0.9076	0.8053	0.7221	0.6428	0.5939	0.8356	0.5044	1.0000	1.0000	1.0000
MOM8	0.8129	0.7198	0.7256	0.7228	0.8383	0.9264	0.7778	0.8035	0.8404	0.9525	0.8852	0.8054	0.8433	0.9213	0.8718	0.6738	1.0000	1.0000	1.0000	1.0000
MOM26	0.6573	0.5556	0.5268	0.5056	0.5000	0.6778	0.5685	0.5353	0.5083	0.5001	0.6895	0.5780	0.5433	0.5115	0.5008	0.6753	1.0000	1.0000	1.0000	1.0000
RMOM1	0.9504	0.8888	0.8393	0.8382	0.8363	0.9830	0.9893	0.9458	0.9649	0.9634	0.9613	0.9752	0.9918	0.9636	0.9576	0.8842	1.0000	1.0000	1.0000	1.0000
RMOM2	0.8952	0.9086	0.8801	0.7389	0.6773	0.8421	0.8087	0.7564	0.6229	0.5581	0.8300	0.7888	0.7316	0.5943	0.5246	0.8948	0.8222	0.8229	1.0000	0.7544
RMOM3	0.9944	0.9095	0.8765	0.9104	0.9272	0.9307	0.9802	0.9888	0.9003	0.8534	0.9129	0.9462	0.9397	0.8332	0.7729	0.9209	0.6618	1.0000	1.0000	1.0000
RMOM4	0.9520	0.9698	0.9310	0.9125	0.8649	0.8942	0.9222	0.9364	0.9237	0.9660	0.8791	0.8952	0.8981	0.8625	0.8838	0.9015	0.8505	0.7817	1.0000	1.0000
RMOM8	0.7403	0.6496	0.6192	0.5716	0.5399	0.7806	0.6842	0.6477	0.5901	0.5503	0.8003	0.7033	0.6655	0.6063	0.5625	0.7516	1.0000	1.0000	1.0000	1.0000
RMOM26	0.6561	0.5873	0.5628	0.5299	0.5159	0.6825	0.6061	0.5772	0.5391	0.6845	0.6969	0.6183	0.5880	0.5487	0.5274	0.7510	1.0000	1.0000	1.0000	1.0000
VOL	0.6411	0.5708	0.5409	0.5219	0.5104	0.6700	0.5901	0.5539	0.5295	0.5147	0.6866	0.6036	0.5650	0.5384	0.5224	0.6655	1.0000	1.0000	1.0000	1.0000
VOLPRC	0.6716	0.5951	0.5608	0.5338	0.5176	0.7048	0.6209	0.5794	0.5449	0.5241	0.7228	0.6367	0.5933	0.5565	0.5341	0.6662	1.0000	1.0000	1.0000	1.0000
VOLSCALE	0.6705	0.5987	0.5636	0.5373	0.5146	0.7040	0.6233	0.5820	0.5488	0.5217	0.7223	0.6387	0.5957	0.5605	0.5314	1.0000	1.0000	1.0000	1.0000	1.0000
RETVOL	0.6808	0.6105	0.5803	0.5610	0.5241	0.7150	0.6383	0.6007	0.5749	0.5314	0.7339	0.6549	0.6153	0.5872	0.5420	1.0000	1.0000	1.0000	1.0000	1.0000
RETSKEW	0.7819	0.6975	0.6517	0.5998	0.5797	0.8232	0.7387	0.6869	0.6276	0.6030	0.8423	0.7590	0.7074	0.6495	0.6230	0.8889	1.0000	1.0000	1.0000	1.0000
RETKURT	0.7815	0.6971	0.6605	0.6120	0.5658	0.8176	0.7317	0.6904	0.6337	0.5797	0.8345	0.7486	0.7073	0.6501	0.5922	0.8214	0.8518	1.0000	1.0000	1.0000
MAXRET	0.8539	0.7461	0.6881	0.6402	0.5886	0.9151	0.8068	0.7419	0.6821	0.6183	0.9406	0.8345	0.7709	0.7126	0.6445	0.8613	0.6671	0.5000	1.0000	1.0000
STDPRCVOL	0.6784	0.6006	0.5669	0.5374	0.5187	0.7123	0.6273	0.5864	0.5499	0.5267	0.7306	0.6436	0.6008	0.5625	0.5376	0.6663	1.0000	1.0000	1.0000	1.0000
MEANABS	0.6578	0.5819	0.5580	0.5369	0.5104	0.6904	0.6060	0.5760	0.5474	0.5154	0.7090	0.6218	0.5894	0.5576	0.5243	0.6651	1.0000	1.0000	1.0000	1.0000
BETA	0.8659	0.5634	0.5314	0.6692	0.5043	0.7989	0.8606	0.5773	0.5411	0.6778	0.7114	0.6580	0.6210	0.5834	0.5413	0.5481	0.5366	0.5349	0.9995	1.0000
BETA$\hat{2}$	0.8659	0.5635	0.5315	0.6692	0.5043	0.7989	0.8608	0.5774	0.5411	0.6779	0.7114	0.6583	0.6212	0.5835	0.5414	0.5481	0.5366	0.5349	0.9995	1.0000
IDIOVOL	0.8660	0.5636	0.5315	0.6693	0.5043	0.7991	0.8612	0.5775	0.5414	0.6779	0.7118	0.6589	0.6217	0.5839	0.5415	0.5482	0.5367	0.5349	0.9994	1.0000
DELAY	0.7751	0.6659	0.6191	0.5916	0.5984	0.8162	0.7063	0.6549	0.6263	0.6361	0.8359	0.7280	0.6778	0.6556	0.6694	0.8047	1.0000	1.0000	1.0000	1.0000
LIQ	0.6578	0.5819	0.5580	0.5369	0.5104	0.6904	0.6060	0.5760	0.5474	0.5154	0.7090	0.6218	0.5894	0.5576	0.5243	0.6651	1.0000	1.0000	1.0000	1.0000

This table presents the ε_i of ASSD for each short portfolio against S&P 500, T-bonds, T-bills and Bitcoin at different investment horizons. ** denotes ASSD against the benchmark, and 1 indicates that the benchmark dominates the corresponding factor portfolio

A11 Spanning Regression for the Mispricing Factor

Table A50: Spanning Regression for Expanded Pricing Models

	Int	CMKT	CSMB	MARCAP	MOM1	MOM2	RMOM1	RMOM2	RMOM3	RMOM4	R_squared
CMKT	0.0155***		0.1467***	-0.4332***	0.0027	-0.0171	0.0273	-0.0263	0.0089	0.1082***	0.1819
	(2.8250)		(4.5935)	(-8.6624)	(0.0684)	(-0.4991)	(0.5720)	(-0.8781)	(0.2573)	(2.7137)	
CSMB	0.0367***	0.3568***		0.5811***	0.0451	0.0686	-0.0870	-0.0432	0.0525	-0.1782***	0.1444
	(4.3404)	(4.5935)		(7.2672)	(0.7235)	(1.2867)	(-1.1712)	(-0.9257)	(0.9775)	(-2.8696)	
MARCAP	0.0213***	-0.379***	0.209***		0.0579	0.0050	-0.1261***	-0.0401	0.0296	0.0278	0.2521
	(4.1985)	(-8.6624)	(7.2672)		(1.5542)	(0.1564)	(-2.8545)	(-1.4333)	(0.9183)	(0.7386)	
MOM1	-0.0007	0.0045	0.0304	0.1085		0.3519***	0.7077***	0.0645*	-0.0731*	0.0584	0.5646
	(-0.1051)	(0.0684)	(0.7235)	(1.5542)		(8.8043)	(14.3795)	(1.6875)	(-1.6607)	(1.1347)	
MOM2	0.0085	-0.0381	0.0629	0.0128	0.4793***		0.0436	-0.0327	0.1292**	0.0684	0.3466
	(1.0301)	(-0.4991)	(1.2867)	(0.1564)	(8.8043)		(0.6113)	(-0.7322)	(2.5286)	(1.1392)	
RMOM1	0.0115*	0.0314	-0.0411	-0.1656***	0.4963***	0.0224		-0.0486	0.2244***	-0.1116***	0.5356
	(1.9401)	(0.5720)	(-1.1712)	(-2.8545)	(14.3795)	(0.6113)		(-1.5170)	(6.3841)	(-2.6103)	
RMOM2	0.0372***	-0.0766	-0.0518	-0.1335	0.1148*	-0.0428	-0.1233		-0.0350	-0.0795	0.0103
	(4.0026)	(-0.8781)	(-0.9257)	(-1.4333)	(1.6875)	(-0.7322)	(-1.5170)		(-0.5937)	(-1.1592)	
RMOM3	0.0015	0.0195	0.0475	0.0744	-0.0981*	0.1274**	0.4296***	-0.0264		0.5261***	0.3476
	(0.1814)	(0.2573)	(0.9775)	(0.9183)	(-1.6607)	(2.5286)	(6.3841)	(-0.5937)		(9.8756)	
RMOM4	0.0152**	0.1748***	-0.1184***	0.0513	0.0576	0.0495	-0.157***	-0.0441	0.3866***		0.2494
	(2.1697)	(2.7137)	(-2.8696)	(0.7386)	(1.1347)	(1.1392)	(-2.6103)	(-1.1592)	(9.8756)		

This table reports the spanning regression results for the components of the mispricing factor. *, **, *** represent significance at 10%, 5%, 1% level, respectively. The t-statistics are reported in parentheses and are Newey-West adjusted with n-1 lags

A12 Risk-Adjusted Returns

Table A51: Sharpe Ratio for Long-Short Factor Portfolios

	Panel A: Portfolios against S&P 500 Index					Panel B: Portfolios against Ten-year T-Bond					Panel C: Portfolios against Bitcoin				
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
Benchmark	0.2095	0.4663	0.7844	1.1097	1.6470	0.1541	0.2333	0.3162	0.4934	0.6031	0.1735	0.3217	0.4689	0.6201	0.9137
MARCAP	0.5174***	1.0782***	1.6518***	2.4213***	2.9574***	0.5174***	1.0782***	1.6518***	2.4213***	2.9574***	0.5174***	1.0782***	1.6518***	2.4213***	2.9574***
LPRC	0.2030	0.3295	0.4879	0.6916	0.8243	0.2030	0.3295	0.4879	0.6916	0.8243	0.2030	0.3295	0.4879	0.6916	0.8243
AGE	0.2232	0.3928	0.4810	0.6749	0.8146	0.2232	0.3928	0.4810	0.6749	0.8146	0.2232	0.3928	0.4810	0.6749	0.8146
MOM1	0.4067**	0.7283***	0.9934**	1.2864	1.4692	0.4067***	0.7283***	0.9934***	1.2864***	1.4692***	0.4067***	0.7283***	0.9934***	1.2864***	1.4692***
MOM2	0.3752**	0.6228*	0.8739	1.3863**	1.6581	0.3752***	0.6228***	0.8739***	1.3863***	1.6581***	0.3752***	0.6228***	0.8739***	1.3863***	1.6581***
MOM3	0.2501	0.4063	0.5503	0.7577	0.7841	0.2501	0.4063*	0.5503**	0.7577*	0.7841	0.2501	0.4063	0.5503	0.7577	0.7841
MOM4	0.1930	0.3473	0.4634	0.6471	0.9261	0.1930	0.3473	0.4634	0.6471	0.9261**	0.1930	0.3473	0.4634	0.6471	0.9261
MOM8	-0.0819	-0.1440	-0.2905	-0.5207	-0.8006	-0.0819	-0.1440	-0.2905	-0.5207	-0.8006	-0.0819	-0.1440	-0.2905	-0.5207	-0.8006
MOM26	-0.1887	-0.3953	-0.5745	-1.1660	-1.8767	-0.1887	-0.3953	-0.5745	-1.1660	-1.8767	-0.1887	-0.3953	-0.5745	-1.1660	-1.8767
RMOM1	0.3877**	0.7246***	0.9561	1.2576	1.5351	0.3877***	0.7246***	0.9561***	1.2576***	1.5351***	0.3877***	0.7246***	0.9561***	1.2576***	1.5351***
RMOM2	0.3316	0.5588	0.7416	1.3786**	1.7400	0.3316**	0.5588***	0.7416***	1.3786***	1.74***	0.3316**	0.5588***	0.7416***	1.3786***	1.74***
RMOM3	0.3907**	0.7033***	0.8810	1.1513	1.4108	0.3907***	0.7033***	0.881***	1.1513***	1.4108***	0.3907***	0.7033***	0.881***	1.1513***	1.4108***
RMOM4	0.3411	0.7072***	1.0167**	1.4574***	1.9892*	0.3411**	0.7072***	1.0167***	1.4574***	1.9892***	0.3411**	0.7072***	1.0167***	1.4574***	1.9892***
RMOM8	0.0441	0.0682	0.0866	0.0195	-0.0880	0.0441	0.0682	0.0866	0.0195	-0.0880	0.0441	0.0682	0.0866	0.0195	-0.0880
RMOM26	-0.1257	-0.2042	-0.3147	-0.4982	-0.6332	-0.1257	-0.2042	-0.3147	-0.4982	-0.6332	-0.1257	-0.2042	-0.3147	-0.4982	-0.6332
VOL	0.0170	0.0496	0.0741	0.1419	0.1946	0.0170	0.0496	0.0741	0.1419	0.1946	0.0170	0.0496	0.0741	0.1419	0.1946
VOLPRC	0.2266	0.3675	0.5482	0.7564	0.9039	0.2266	0.3675	0.5482*	0.7564	0.9039	0.2266	0.3675	0.5482	0.7564**	0.9039
VOLSCALE	0.1236	0.1929	0.2996	0.4677	0.5509	0.1236	0.1929	0.2996	0.4677	0.5509	0.1236	0.1929	0.2996	0.4677	0.5509
RETVOL	0.0042	-0.0102	0.0164	0.1224	0.1926	0.0042	-0.0102	0.0164	0.1224	0.1926	0.0042	-0.0102	0.0164	0.1224	0.1926
RETSKEW	0.1725	0.3973	0.6092	1.1303	1.6494	0.1725	0.3973	0.6092***	1.1303***	1.6494***	0.1725	0.3973	0.6092*	1.1303***	1.6494***
RETKURT	0.0605	0.1038	0.1714	0.2126	0.1724	0.0605	0.1038	0.1714	0.2126	0.1724	0.0605	0.1038	0.1714	0.2126	0.1724
MAXRET	0.2488	0.4326	0.6235	1.0564	1.3709	0.2488	0.4326**	0.6235***	1.0564***	1.3709***	0.2488	0.4326	0.6235**	1.0564***	1.3709***
STDPRCVOL	0.2150	0.3458	0.4969	0.6595	0.7707	0.2150	0.3458	0.4969	0.6595	0.7707	0.2150	0.3458	0.4969	0.6595	0.7707
MEANABS	0.1459	0.2321	0.3481	0.4886	0.5930	0.1459	0.2321	0.3481	0.4886	0.5930	0.1459	0.2321	0.3481	0.4886	0.5930
BETA	0.0322	0.0627	0.1076	0.1811	0.2919	0.0322	0.0627	0.1076	0.1811	0.2919	0.0322	0.0627	0.1076	0.1811	0.2919
$\mathrm{BETA}\hat{2}$	0.0180	0.0422	0.0734	0.1265	0.2262	0.0180	0.0422	0.0734	0.1265	0.2262	0.0180	0.0422	0.0734	0.1265	0.2262
IDIOVOL	0.0508	0.1017	0.1545	0.2586	0.4477	0.0508	0.1017	0.1545	0.2586	0.4477	0.0508	0.1017	0.1545	0.2586	0.4477
DELAY	0.1869	0.3378	0.5475	0.7472	0.9114	0.1869	0.3378	0.5475***	0.7472**	0.9114**	0.1869	0.3378*	0.5475*	0.7472**	0.9114
LIQ	0.1459	0.2321	0.3481	0.4886	0.5930	0.1459	0.2321	0.3481	0.4886	0.5930	0.1459	0.2321	0.3481	0.4886	0.5930

This table documents the Sharpe ratio for 29 factor portfolios for different horizons against S&P 500, T-Bond, and Bitcoin. The Benchmark in the first column represents S&P 500, T-Bond, and Bitcoin across Panel A, B, and C. *, **, *** denotes the significance at 10%, 5%, and 1% level, respectively.

Table A52: CER Ratio ($\boldsymbol{\lambda = 1}$)

Portfolios	Panel A: Portfolios against S&P 500 Index 4-week	13-week	26-week	52-week	78-week	Panel B: Portfolios against Ten-year T-Bond 4-week	13-week	26-week	52-week	78-week	Panel C: Portfolios against Bitcoin 4-week	13-week	26-week	52-week	78-week
Benchmark	0.0092	0.0312	0.0619	0.1162	0.1647	0.0030	0.0091	0.0182	0.0402	0.0605	0.0142	0.0456	0.0945	0.1392	0.4226
MARCAP	0.0858***	0.2942***	0.5824***	1.1275***	1.661***	0.0858***	0.2942***	0.5824***	1.1275***	1.661***	0.0858***	0.2942***	0.5824***	1.1275***	1.661***
LPRC	0.0019	-0.0323	0.0022	0.0007	-0.0961	0.0019	-0.0323	0.0022	0.0007	-0.0961	0.0019	-0.0323	0.0022	0.0007	-0.0961
AGE	-0.0057	-0.0358	-0.2880	-0.1340	-0.0162	-0.0057	-0.0358	-0.2880	-0.1340	-0.0162	-0.0057	-0.0358	-0.2880	-0.1340	-0.0162
MOM1	0.0818***	0.2642***	0.4931***	0.8279***	1.0266***	0.0818***	0.2642***	0.4931***	0.8279***	1.0266***	0.0818***	0.2642***	0.4931***	0.8279***	1.0266***
MOM2	0.0707***	0.1855***	0.3633***	0.964***	1.3611***	0.0707***	0.1855***	0.3633***	0.964***	1.3611***	0.0707***	0.1855***	0.3633***	0.964***	1.3611***
MOM3	0.0239	0.0358	0.0514	0.0221	-0.4700	0.0239	0.0358	0.0514	0.0221	-0.4700	0.0239	0.0358	0.0514	0.0221	-0.4700
MOM4	0.0148	0.0531	0.0977	0.2117**	0.422***	0.0148	0.0531*	0.0977**	0.2117***	0.422***	0.0148	0.0531	0.0977	0.2117	0.4220
MOM8	-0.0881	-0.3380	-0.7001	-1.5545	-2.3364	-0.0881	-0.3380	-0.7001	-1.5545	-2.3364	-0.0881	-0.3380	-0.7001	-1.5545	-2.3364
MOM26	-0.1388	-0.4110	-0.7971	-1.3671	-1.8883	-0.1388	-0.4110	-0.7971	-1.3671	-1.8883	-0.1388	-0.4110	-0.7971	-1.3671	-1.8883
RMOM1	0.0697***	0.2382***	0.4397***	0.7945***	1.1873***	0.0697***	0.2382***	0.4397***	0.7945***	1.1873***	0.0697***	0.2382***	0.4397***	0.7945***	1.1873***
RMOM2	0.0553***	0.1549***	0.2476***	0.9303***	1.4625***	0.0553***	0.1549***	0.2476***	0.9303***	1.4625***	0.0553**	0.1549**	0.2476**	0.9303***	1.4625***
RMOM3	0.0708***	0.2287***	0.388***	0.6649***	0.9966***	0.0708***	0.2287***	0.388***	0.6649***	0.9966***	0.0708***	0.2287***	0.388***	0.6649***	0.9966***
RMOM4	0.0561***	0.2088***	0.4113***	0.7913***	1.1954***	0.0561***	0.2088***	0.4113***	0.7913***	1.1954***	0.0561**	0.2088***	0.4113***	0.7913***	1.1954***
RMOM8	-0.0332	-0.1319	-0.2091	-0.5255	-0.7553	-0.0332	-0.1319	-0.2091	-0.5255	-0.7553	-0.0332	-0.1319	-0.2091	-0.5255	-0.7553
RMOM26	-0.1081	-0.3997	-0.7419	-1.6625	-2.8465	-0.1081	-0.3997	-0.7419	-1.6625	-2.8465	-0.1081	-0.3997	-0.7419	-1.6625	-2.8465
VOL	-0.0970	-0.3252	-0.7534	-1.7107	-2.3371	-0.0970	-0.3252	-0.7534	-1.7107	-2.3371	-0.0970	-0.3252	-0.7534	-1.7107	-2.3371
VOLPRC	0.0095	-0.0103	0.0566	0.0453	-0.0392	0.0095	-0.0103	0.0566	0.0453	-0.0392	0.0095	-0.0103	0.0566	0.0453	-0.0392
VOLSCALE	-0.0233	-0.1351	-0.1847	-0.3151	-0.5928	-0.0233	-0.1351	-0.1847	-0.3151	-0.5928	-0.0233	-0.1351	-0.1847	-0.3151	-0.5928
RETVOL	-0.0854	-0.2703	-0.4820	-0.6305	-0.7733	-0.0854	-0.2703	-0.4820	-0.6305	-0.7733	-0.0854	-0.2703	-0.4820	-0.6305	-0.7733
RETSKEW	0.0086	0.08**	0.1886***	0.5483***	0.985***	0.0086	0.08***	0.1886***	0.5483***	0.985***	0.0086	0.0800	0.1886*	0.5483***	0.985***
RETKURT	-0.0141	-0.0405	-0.0642	-0.1758	-0.2777	-0.0141	-0.0405	-0.0642	-0.1758	-0.2777	-0.0141	-0.0405	-0.0642	-0.1758	-0.2777
MAXRET	0.0289	0.0788	0.1693**	0.5645***	0.9329***	0.0289	0.0788**	0.1693***	0.5645***	0.9329***	0.0289	0.0788	0.1693	0.5645***	0.9329***
STDPRCVOL	0.0057	-0.0250	-0.0005	-0.1323	-0.4122	0.0057	-0.0250	-0.0005	-0.1323	-0.4122	0.0057	-0.0250	-0.0005	-0.1323	-0.4122
MEANABS	-0.0394	-0.2607	-0.5174	-1.4668	-2.5023	-0.0394	-0.2607	-0.5174	-1.4668	-2.5023	-0.0394	-0.2607	-0.5174	-1.4668	-2.5023
BETA	-0.0487	-0.1984	-0.3831	-0.7357	-0.8291	-0.0487	-0.1984	-0.3831	-0.7357	-0.8291	-0.0487	-0.1984	-0.3831	-0.7357	-0.8291
BETA$\hat{2}$	-0.0366	-0.1343	-0.3288	-0.6862	-0.6930	-0.0366	-0.1343	-0.3288	-0.6862	-0.6930	-0.0366	-0.1343	-0.3288	-0.6862	-0.6930
IDIOVOL	-0.0270	-0.0957	-0.2187	-0.3892	-0.1133	-0.0270	-0.0957	-0.2187	-0.3892	-0.1133	-0.0270	-0.0957	-0.2187	-0.3892	-0.1133
DELAY	0.0158	0.0553	0.1531***	0.2836***	0.4116***	0.0158	0.0553**	0.1531***	0.2836***	0.4116***	0.0158	0.0553*	0.1531*	0.2836**	0.4116
LIQ	-0.0394	-0.2607	-0.5174	-1.4668	-2.5023	-0.0394	-0.2607	-0.5174	-1.4668	-2.5023	-0.0394	-0.2607	-0.5174	-1.4668	-2.5023

This table reports the CER ($\lambda = 1$) of 29 factors against S&P 500, T-Bond, and Bitcoin. *, **, *** represent significant outperformance at 10%, 5%, 1% level, respectively.

Table A53: CER Ratio ($\boldsymbol{\lambda = 3}$)

Portfolios	Panel A: Portfolios against S&P 500 Index 4-week	13-week	26-week	52-week	78-week	Panel B: Portfolios against Ten-year T-Bond 4-week	13-week	26-week	52-week	78-week	Panel C: Portfolios against Bitcoin 4-week	13-week	26-week	52-week	78-week
Benchmark	0.0070	0.0265	0.0558	0.1057	0.1557	0.0027	0.0079	0.0157	0.0353	0.0533	-0.0365	-0.1535	-0.3445	-0.7964	-0.6334
MARCAP	0.0433***	0.1926***	0.4231***	0.8586***	1.2716***	0.0433***	0.1926***	0.4231***	0.8586***	1.2716***	0.0433***	0.1926***	0.4231***	0.8586***	1.2716***
LPRC	-0.1571	-0.5938	-0.9537	-1.9361	-3.2273	-0.1571	-0.5938	-0.9537	-1.9361	-3.2273	-0.1571	-0.5938	-0.9537	-1.9361	-3.2273
AGE	-0.2288	-0.7941	-2.2000	-2.4848	-2.7775	-0.2288	-0.7941	-2.2000	-2.4848	-2.7775	-0.2288	-0.7941	-2.2000	-2.4848	-2.7775
MOM1	-0.0454	-0.1743	-0.3489	-1.0939	-2.2849	-0.0454	-0.1743	-0.3489	-1.0939	-2.2849	-0.0454	-0.1743	-0.3489	-1.0939	-2.2849
MOM2	-0.0720	-0.3940	-0.8007	-1.1388	-2.1209	-0.0720	-0.3940	-0.8007	-1.1388	-2.1209	-0.0720	-0.3940	-0.8007	-1.1388	-2.1209
MOM3	-0.1166	-0.4777	-0.9566	-2.2110	-4.6291	-0.1166	-0.4777	-0.9566	-2.2110	-4.6291	-0.1166	-0.4777	-0.9566	-2.2110	-4.6291
MOM4	-0.0669	-0.1773	-0.2927	-0.3460	-0.1140	-0.0669	-0.1773	-0.2927	-0.3460	-0.1140	-0.0669	-0.1773	-0.2927	-0.346***	-0.114***
MOM8	-0.2085	-0.8183	-1.5675	-3.3042	-4.6198	-0.2085	-0.8183	-1.5675	-3.3042	-4.6198	-0.2085	-0.8183	-1.5675	-3.3042	-4.6198
MOM26	-0.2772	-0.7662	-1.4627	-2.1104	-2.5784	-0.2772	-0.7662	-1.4627	-2.1104	-2.5784	-0.2772	-0.7662	-1.4627	-2.1104	-2.5784
RMOM1	-0.0084	-0.0100	-0.1308	-0.6263	-1.0900	-0.0084	-0.0100	-0.1308	-0.6263	-1.0900	-0.0084	-0.01***	-0.1308**	-0.6263	-1.0900
RMOM2	-0.0455	-0.2425	-0.7269	-0.3965	-0.4758	-0.0455	-0.2425	-0.7269	-0.3965	-0.4758	-0.0455	-0.2425	-0.7269	-0.3965*	-0.4758
RMOM3	-0.0087	-0.0250	-0.2602	-0.8692	-1.3723	-0.0087	-0.0250	-0.2602	-0.8692	-1.3723	-0.0087	-0.025**	-0.2602	-0.8692	-1.3723
RMOM4	-0.0168	0.0365	0.1079	0.2833**	0.6637***	-0.0168	0.0365	0.1079**	0.2833***	0.6637***	-0.0168	0.0365***	0.1079***	0.2833***	0.6637***
RMOM8	-0.1277	-0.4797	-0.7636	-1.6335	-2.0891	-0.1277	-0.4797	-0.7636	-1.6335	-2.0891	-0.1277	-0.4797	-0.7636	-1.6335	-2.0891
RMOM26	-0.2357	-0.9110	-1.6382	-3.6139	-6.2378	-0.2357	-0.9110	-1.6382	-3.6139	-6.2378	-0.2357	-0.9110	-1.6382	-3.6139	-6.2378
VOL	-0.3076	-1.0645	-2.4609	-5.7154	-7.9589	-0.3076	-1.0645	-2.4609	-5.7154	-7.9589	-0.3076	-1.0645	-2.4609	-5.7154	-7.9589
VOLPRC	-0.1574	-0.5965	-0.9198	-2.0846	-3.5031	-0.1574	-0.5965	-0.9198	-2.0846	-3.5031	-0.1574	-0.5965	-0.9198	-2.0846	-3.5031
VOLSCALE	-0.1633	-0.6979	-1.1494	-2.2662	-3.7632	-0.1633	-0.6979	-1.1494	-2.2662	-3.7632	-0.1633	-0.6979	-1.1494	-2.2662	-3.7632
RETVOL	-0.2607	-0.7998	-1.4863	-2.2155	-2.9080	-0.2607	-0.7998	-1.4863	-2.2155	-2.9080	-0.2607	-0.7998	-1.4863	-2.2155	-2.9080
RETSKEW	-0.0749	-0.1030	-0.1558	0.0738	0.3915***	-0.0749	-0.1030	-0.1558	0.0738	0.3915***	-0.0749	-0.1030	-0.1558**	0.0738***	0.3915***
RETKURT	-0.0725	-0.2106	-0.3978	-0.9066	-1.1878	-0.0725	-0.2106	-0.3978	-0.9066	-1.1878	-0.0725	-0.2106	-0.3978	-0.9066	-1.1878
MAXRET	-0.0732	-0.2968	-0.5710	-0.5578	-0.4718	-0.0732	-0.2968	-0.5710	-0.5578	-0.4718	-0.0732	-0.2968	-0.5710	-0.5578	-0.4718
STDPRCVOL	-0.1575	-0.6047	-1.0026	-2.3935	-4.2955	-0.1575	-0.6047	-1.0026	-2.3935	-4.2955	-0.1575	-0.6047	-1.0026	-2.3935	-4.2955
MEANABS	-0.2545	-1.2460	-2.5511	-6.6346	-10.9810	-0.2545	-1.2460	-2.5511	-6.6346	-10.9810	-0.2545	-1.2460	-2.5511	-6.6346	-10.9810
BETA	-0.1695	-0.6862	-1.3701	-2.7345	-3.4584	-0.1695	-0.6862	-1.3701	-2.7345	-3.4584	-0.1695	-0.6862	-1.3701	-2.7345	-3.4584
BETA$\hat{2}$	-0.1213	-0.4542	-1.1246	-2.4058	-2.7530	-0.1213	-0.4542	-1.1246	-2.4058	-2.7530	-0.1213	-0.4542	-1.1246	-2.4058	-2.7530
IDIOVOL	-0.1115	-0.4032	-0.9226	-1.7960	-1.3663	-0.1115	-0.4032	-0.9226	-1.7960	-1.3663	-0.1115	-0.4032	-0.9226	-1.7960	-1.3663
DELAY	-0.0478	-0.1213	-0.1342	-0.3872	-0.7650	-0.0478	-0.1213	-0.1342	-0.3872	-0.7650	-0.0478	-0.1213	-0.1342	-0.3872	-0.7650
LIQ	-0.2545	-1.2460	-2.5511	-6.6346	-10.9810	-0.2545	-1.2460	-2.5511	-6.6346	-10.9810	-0.2545	-1.2460	-2.5511	-6.6346	-10.9810

This table reports the CER ($\lambda =$ 3) of 29 factors against S&P 500, T-Bond, and Bitcoin. *, **, *** represent significant outperformance at 10%, 5%, 1% level, respectively.

Table A54: CER Ratio ($\boldsymbol{\lambda} = 5$)

Portfolios	Panel A: Portfolios against S&P 500 Index					Panel B: Portfolios against Ten-year T-Bond					Panel C: Portfolios against Bitcoin				
	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
Benchmark	0.0049	0.0219	0.0497	0.0953	0.1467	0.0024	0.0068	0.0133	0.0304	0.0461	-0.0873	-0.3527	-0.7835	-1.7320	-1.6894
MARCAP	0.0008	0.0911***	0.2639***	0.5896***	0.8821***	0.0008	0.0911***	0.2639***	0.5896***	0.8821***	0.0008***	0.0911***	0.2639***	0.5896***	0.8821***
LPRC	-0.3161	-1.1552	-1.9096	-3.8728	-6.3584	-0.3161	-1.1552	-1.9096	-3.8728	-6.3584	-0.3161	-1.1552	-1.9096	-3.8728	-6.3584
AGE	-0.4519	-1.5524	-4.1119	-4.8355	-5.5388	-0.4519	-1.5524	-4.1119	-4.8355	-5.5388	-0.4519	-1.5524	-4.1119	-4.8355	-5.5388
MOM1	-0.1727	-0.6128	-1.1909	-3.0158	-5.5963	-0.1727	-0.6128	-1.1909	-3.0158	-5.5963	-0.1727	-0.6128	-1.1909	-3.0158	-5.5963
MOM2	-0.2147	-0.9736	-1.9646	-3.2416	-5.6029	-0.2147	-0.9736	-1.9646	-3.2416	-5.6029	-0.2147	-0.9736	-1.9646	-3.2416	-5.6029
MOM3	-0.2571	-0.9912	-1.9647	-4.4440	-8.7881	-0.2571	-0.9912	-1.9647	-4.4440	-8.7881	-0.2571	-0.9912	-1.9647	-4.4440	-8.7881
MOM4	-0.1487	-0.4076	-0.6831	-0.9038	-0.6500	-0.1487	-0.4076	-0.6831	-0.9038	-0.6500	-0.1487	-0.4076	-0.6831	-0.9038***	-0.65***
MOM8	-0.3290	-1.2986	-2.4350	-5.0540	-6.9032	-0.3290	-1.2986	-2.4350	-5.0540	-6.9032	-0.3290	-1.2986	-2.4350	-5.0540	-6.9032
MOM26	-0.4157	-1.1214	-2.1283	-2.8536	-3.2686	-0.4157	-1.1214	-2.1283	-2.8536	-3.2686	-0.4157	-1.1214	-2.1283	-2.8536	-3.2686
RMOM1	-0.0865	-0.2583	-0.7013	-2.0470	-3.3673	-0.0865	-0.2583	-0.7013	-2.0470	-3.3673	-0.0865	-0.2583	-0.7013	-2.0470	-3.3673
RMOM2	-0.1462	-0.6400	-1.7013	-1.7233	-2.4141	-0.1462	-0.6400	-1.7013	-1.7233	-2.4141	-0.1462	-0.6400	-1.7013	-1.7233	-2.4141
RMOM3	-0.0883	-0.2787	-0.9083	-2.4034	-3.7411	-0.0883	-0.2787	-0.9083	-2.4034	-3.7411	-0.0883	-0.2787	-0.9083	-2.4034	-3.7411
RMOM4	-0.0898	-0.1357	-0.1954	-0.2246	0.1320	-0.0898	-0.1357	-0.1954	-0.2246	0.1320	-0.0898	-0.1357***	-0.1954***	-0.2246***	0.132***
RMOM8	-0.2222	-0.8274	-1.3181	-2.7416	-3.4229	-0.2222	-0.8274	-1.3181	-2.7416	-3.4229	-0.2222	-0.8274	-1.3181	-2.7416	-3.4229
RMOM26	-0.3633	-1.4223	-2.5345	-5.5654	-9.6290	-0.3633	-1.4223	-2.5345	-5.5654	-9.6290	-0.3633	-1.4223	-2.5345	-5.5654	-9.6290
VOL	-0.5182	-1.8038	-4.1684	-9.7202	-13.5807	-0.5182	-1.8038	-4.1684	-9.7202	-13.5807	-0.5182	-1.8038	-4.1684	-9.7202	-13.5807
VOLPRC	-0.3244	-1.1827	-1.8961	-4.2146	-6.9670	-0.3244	-1.1827	-1.8961	-4.2146	-6.9670	-0.3244	-1.1827	-1.8961	-4.2146	-6.9670
VOLSCALE	-0.3033	-1.2607	-2.1140	-4.2172	-6.9336	-0.3033	-1.2607	-2.1140	-4.2172	-6.9336	-0.3033	-1.2607	-2.1140	-4.2172	-6.9336
RETVOL	-0.4361	-1.3293	-2.4906	-3.8005	-5.0427	-0.4361	-1.3293	-2.4906	-3.8005	-5.0427	-0.4361	-1.3293	-2.4906	-3.8005	-5.0427
RETSKEW	-0.1585	-0.2861	-0.5001	-0.4006	-0.2021	-0.1585	-0.2861	-0.5001	-0.4006	-0.2021	-0.1585	-0.2861	-0.5001**	-0.4006***	-0.2021***
RETKURT	-0.1310	-0.3807	-0.7314	-1.6374	-2.0978	-0.1310	-0.3807	-0.7314	-1.6374	-2.0978	-0.1310	-0.3807	-0.7314	-1.6374	-2.0978
MAXRET	-0.1752	-0.6725	-1.3113	-1.6801	-1.8765	-0.1752	-0.6725	-1.3113	-1.6801	-1.8765	-0.1752	-0.6725	-1.3113	-1.6801	-1.8765
STDPRCVOL	-0.3207	-1.1843	-2.0047	-4.6547	-8.1788	-0.3207	-1.1843	-2.0047	-4.6547	-8.1788	-0.3207	-1.1843	-2.0047	-4.6547	-8.1788
MEANABS	-0.4696	-2.2312	-4.5849	-11.8024	-19.4597	-0.4696	-2.2312	-4.5849	-11.8024	-19.4597	-0.4696	-2.2312	-4.5849	-11.8024	-19.4597
BETA	-0.2904	-1.1740	-2.3571	-4.7333	-6.0878	-0.2904	-1.1740	-2.3571	-4.7333	-6.0878	-0.2904	-1.1740	-2.3571	-4.7333	-6.0878
BETA$\hat{2}$	-0.2061	-0.7741	-1.9204	-4.1255	-4.8131	-0.2061	-0.7741	-1.9204	-4.1255	-4.8131	-0.2061	-0.7741	-1.9204	-4.1255	-4.8131
IDIOVOL	-0.1961	-0.7107	-1.6264	-3.2028	-2.6194	-0.1961	-0.7107	-1.6264	-3.2028	-2.6194	-0.1961	-0.7107	-1.6264	-3.2028	-2.6194
DELAY	-0.1113	-0.2979	-0.4216	-1.0579	-1.9415	-0.1113	-0.2979	-0.4216	-1.0579	-1.9415	-0.1113	-0.2979	-0.4216	-1.0579	-1.9415
LIQ	-0.4696	-2.2312	-4.5849	-11.8024	-19.4597	-0.4696	-2.2312	-4.5849	-11.8024	-19.4597	-0.4696	-2.2312	-4.5849	-11.8024	-19.4597

This table reports the CER ($\lambda = 5$) of 29 factors against S&P 500, T-Bond, and Bitcoin. *, **, *** represent significant outperformance at 10%, 5%, 1% level, respectively.

A13 Summary of Additional Results

For robustness we conduct eight additional tests on our dominant and non-dominant factor portfolios. The results are summarised below, and the details are documented in the Supplementary Appendix.

First, due to a concern that the empirical critical values used in our AFSD and ASSD tests may need updating, we validate the empirical critical values of Levy et al. (2010) by running simulations. We rely on randomization techniques with replacement, and select monthly S&P 500 index returns as a proxy for stock returns over the period from January 1926 to June 2021 to generate the distribution of ε_1 and ε_2 with repeated samples. We find the empirical critical values, ε_1 and ε_2, of Levy et al. (2010) are significant at the 10 and 3 percent levels, respectively. We document the results in section A1 of Appendix.

Second and third, we study whether non-dominant and dominant factor portfolios that short Bitcoin can be explained by the coin market three-factor model, and our augmented model (NTFM-SM). We find that the coin market three-factor model has better explanatory power for the non-dominant than for the dominant factor portfolios. Our augmented model can accommodate more strategies (even shorting Bitcoin) than the coin market three-factor model. Thus, we find our NTFM-SM model is robust to this out-of-sample test. We depict the results in sections A4 and A5 of Appendix.

Fourth, to alleviate the concern that equity asset pricing models have explanatory power in explaining our eight dominant factor portfolios, we test the performance of nine widely used equity asset pricing models for these eight dominant factor portfolios. The empirical results for the nine equity asset pricing models show that all of the equity asset pricing models have statistically significant alphas, indicting abnormal returns, and R^2 values close to zero. We archive the results in section A7 of Appendix.

Fifth, to emphasize the importance of the mispricing factors, we test the performance of the coin market one-factor model with just the $CMKT$ factor, and two versions of the coin market two-factor model with $CMKT$ and $CSMB$; or $CMKT$ and $CMOM$. These one and two factor models cannot explain most of the variation of the returns of the eight dominant factor portfolios. However, adding the $Mispricing2$ factor significantly increases the explanatory power of these two models (see section A6 of Appendix).

Sixth, we investigate whether the electricity factor plays a significant role in explaining our eight dominant factor portfolios. Although electricity (Aggregated returns of SIC 4911 stocks) has been found to have no explanatory power for the major cryptocurrencies (Liu and Tsyvinski, 2020), we investigate the effect of electricity in capturing variation in the returns of our dominant factor portfolios. We use aggregate returns on all US stocks in the electricity sector (SIC 4911) listed in CRSP as a proxy for the electricity factor. We form models incorporating the electricity factor by constructing all possible combinations of the coin market three-factor model, and the mispricing, investor attention, network and electricity factors. We find no evidence supporting the ability of the electricity factor to explain returns on our eight dominant factor cryptocurrency factor portfolios. The results are detailed in section A8 of Appendix.

Seventh, we investigate whether the long and short legs have different effects on the outperformance of our eight dominant factor portfolios using ASD, because influential studies (Stambaugh et al., 2012; Daniel and Moskowitz, 2016; Chu et al., 2020) argue that the importance of short legs is less than for long legs. Equity short sales incur higher fees than buying due to the frictions of short selling, or investors may be unable to short an overvalued asset (Stambaugh et al., 2015). We find that dominance by the eight factor portfolios is mostly attributable to their long legs, as 87.5% dominant strategies continue to dominate our four benchmarks by AFSD, while none of the short legs dominate the benchmarks. We report the results in section A10 of Appendix.

Eighth, we test the long legs of the eight dominant factor portfolios against three equity benchmarks - equity portfolios based on size, momentum and BE/ME (book-to-market ratio) - because these factors have been widely used, and relate to our factor categories (e.g., size, value, profitability, investment style and momentum). We note that the long legs of our eight dominant factor (except for $MOM2$) portfolios that are dominant against our four benchmarks (the S&P 500, US T-bonds, US T-bills and Bitcoin) are also dominant against equity portfolios based on size, momentum and BE/ME. This strengthens the view that the out-performance of our eight factor portfolios comes mainly from their long legs, consistent with Stambaugh et al. (2012), Edelen et al. (2016), Chen et al. (2018), and Freyberger et al. (2020) for equity factors. We record the findings in section A3 of Appendix.

References

Asness, C. and Frazzini, A. (2013). The devil in hml's details. *Journal of Portfolio Management*, 39(4):49–68.

Bali, T. G., Brown, S. J., and Demirtas, K. O. (2013). Do Hedge Funds Outperform Stocks and Bonds? *Management Science*, 59(8):1887–1903.

Barillas, F. and Shanken, J. (2018). Comparing Asset Pricing Models. *Journal of Finance*, 73(2):715–754.

Bianchi, D., Guidolin, M., and Pedio, M. (2020). Dissecting time-varying risk exposures in cryptocurrency markets. *BAFFI CAREFIN Centre Research Paper*, (2020-143).

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

Chen, Y., Da, Z., and Huang, D. (2018). Arbitrage Trading: The Long and the Short of It. *Review of Financial Studies*, 32(4):1608–1646.

Chu, Y., Hirshleifer, D., and Ma, L. (2020). The Causal Effect of Limits to Arbitrage on Asset Pricing Anomalies. *Journal of Finance*, 75(5):2631–2672.

Daniel, K. and Moskowitz, T. J. (2016). Momentum Crashes. *Journal of Financial Economics*, 122(2):221–247.

Edelen, R. M., Ince, O. S., and Kadlec, G. B. (2016). Institutional Investors and Stock Return Anomalies. *Journal of Financial Economics*, 119(3):472–488.

Fama, E. F. and French, K. R. (1992). The cross-section of expected stock returns. *Journal of Finance*, 47(2):427–465.

Fama, E. F. and French, K. R. (1993). Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics*, 33(1):3–56.

Fama, E. F. and French, K. R. (2015). A Five-factor Asset Pricing Model. *Journal of Financial Economics*, 116(1):1–22.

Freyberger, J., Neuhierl, A., and Weber, M. (2020). Dissecting Characteristics Nonparametrically. *Review of Financial Studies*, 33(5):2326–2377.

Hou, K., Xue, C., and Zhang, L. (2015). Digesting Anomalies: An Investment Approach. *Review of Financial Studies*, 28(3):650–705.

Jegadeesh, N. and Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *Journal of Finance*, 48(1):65–91.

Levy, H., Leshno, M., and Leibovitch, B. (2010). Economically Relevant Preferences for All Observed Epsilon. *Annals of Operations Research*, 176(1):153–178.

Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *Review of Economics and Statistics*, 47(1):13–37.

Liu, Y. and Tsyvinski, A. (2020). Risks and Returns of Cryptocurrency. *Review of Financial Studies*, 34(6):2689–2727.

Liu, Y., Tsyvinski, A., and Wu, X. (2022). Common risk factors in cryptocurrency. *Journal of Finance*, 77(2):1133–1177.

Pástor, L. and Stambaugh, R. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy*, 111(3):642–685.

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

Stambaugh, R. F., Yu, J., and Yuan, Y. (2012). The Short of It: Investor Sentiment and Anomalies. *Journal of Financial Economics*, 104(2):288–302.

Stambaugh, R. F., Yu, J., and Yuan, Y. (2015). Arbitrage Asymmetry and the Idiosyncratic Volatility Puzzle. *The Journal of Finance*, 70(5):1903–1948.

Stambaugh, R. F. and Yuan, Y. (2017). Mispricing Factors. *Review of Financial Studies*, 30(4):1270–1315.