# Value Premium, Network Adoption, and Factor Pricing of Crypto Assets[1]

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**Abstract**

We document characteristics-based return anomalies in a large cross-section (>4,000) of crypto assets. Cryptocurrency returns exhibit momentum in the largest-cap group, reversals in other size groups, and strong crypto value and network adoption premia, from which we derive two novel factors to add to the cryptocurrency versions of market, size, and momentum factors. The resulting C-5 model outperforms extant models in pricing the cross-section of crypto assets and test portfolios in-sample and out-of-sample. We also provide the first comprehensive classification of all major cryptocurrencies based on their economic functionality. We then adopt methodologies from international finance to demonstrate significant market segmentation across token categories, underscoring the importance of considering token categories in investment and regulatory policymaking.

**Keywords:** Blockchain, Cryptocurrency, DeFi, Factor Models, Network Effect, Market Segmentation.

**JEL Codes**: F30, G10, G11, G15

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## 1. Introduction.

The aggregate market capitalization of crypto assets has grown to $3 trillion as of November 2021. Yet, cryptocurrencies lack a systematic classification scheme and their risk and return tradeoffs still are not well understood. Using 4,007 crypto assets, we document a comprehensive list of return anomalies, including the novel crypto "value" and "network adoption" premia. We then build upon the foundational work of Liu, Tsyvinski, and Wu (2022, henceforth referred to as LTW) to develop a new factor-pricing framework based on observable factors that significantly improves our explanation of the cross-section of cryptocurrency returns. More importantly, we provide the first empirical categorization of all major cryptocurrencies to study token pricing within and across categories. From this, we identify significant market segmentation in the crypto market, which not only validates the categorization proposed in Cong and Xiao (2021) based on economic functionality but also informs the pricing and regulation of crypto assets.[2]

Theory suggests that fundamental characteristics of cryptocurrencies, such as network scale or user adoption, constitute key determinants of token valuation (e.g., Cong, Li, and Wang, 2021a), which empirical studies corroborate (e.g., Liu and Tsyvinski, 2021; Shams, 2020). Many cryptocurrencies are also hybrid assets (Cong, Li, and Wang, 2021a; Cong, He, and Tang, 2022), thereby potentially exhibiting "value" premium as seen in commodity and currency markets (Asness, Moskowitz, and Pedersen, 2013).[3] Indeed, we find that long-short portfolios sorted based on network- or value-related characteristics generate significant excess returns. We also show that the momentum effect documented in LTW applies to cryptocurrencies with

[2] Extant categorizations such as the one on CoinMarketCap tend to be ad hoc, too granular, and not based on economic functionality of tokens. A proper categorization is needed for financial disclosure, accounting, and regulation too (e.g., Cong, Landsman, Maydew, and Rabetti, 2022).

[3] Most cryptocurrencies do not have cash flows or tangible book values, which precludes the use of conventional concept of value from equity markets. Asness, Moskowitz and Pedersen (2013) use prices or exchange rates 5 years ago over the current prices or exchange rates as the value measure of a commodity or currency, because "these long-term past return measures of value are motivated by DeBondt and Thaler (1985), who use similar measures for individual stocks to identify 'cheap' and 'expensive' firms." Moreover "Fama and French (1996) show that the negative of the past 5-year return generates portfolios that are highly correlated with portfolios formed on BE/ME, and Gerakos and Linnainmaa (2012) document a direct link between past returns and BE/ME ratios."

the largest market capitalizations; by contrast, smaller tokens--not previously examined--exhibit short-term reversals.

Importantly, we find that a new parsimonious crypto five-factor model (referred to as "C-5") comprised of market, size, momentum, value, and network factors, outperforms extant factor models based on GRS, constrained R-Squared, cross-sectional R squared, and Max-squared tests and on common sets of test asset portfolios. We also show that different token categories exhibit different return structures that can be analyzed using the framework of local versus global factor construction (Hou, Karolyi and Kho, 2011), and partial segmentation (Karolyi and Wu, 2018). Models using what we refer to as "local" (constructed within the category) or a hybrid of local and "foreign" (constructed from other categories) factors tend to price cryptocurrencies better than those using global factors (built regardless of token category), indicating significant market segmentations among crypto asset categories.

Specifically, we assemble a rich dataset of almost 8,000 cryptocurrencies from which we construct a "Full Sample" containing information on 4,007 cryptocurrencies, including information on market capitalization, trading volume, and price, as well as on fundamental characteristics of a subset of 616 cryptocurrencies (referred to as our "Core Sample") for which we have the number of total addresses, the number of total addresses with non-zero balances, and the trading volume on-chain.[4] Overall, we consider 13 available cryptocurrency characteristics that largely fall into 4 broad categories: size, momentum, value, and network. While some of them have analogs in other asset classes, many are specific to blockchains, capturing safety and value of the network (e.g., Biais, Bisiere, Bouvard, Casamatta, 2021). We then use a few more recently discovered or discussed characteristics to generate test portfolios and demonstrate robustness of the C-5 model---they are "out-of-sample" since they are not used in constructing the factors.

We first sort cryptocurrencies according to these characteristics into deciles, then

[4] The definition of total addresses with a balance subtracts those addresses that have no balance from the total number of addresses in the network.

construct portfolios by buying top and shorting bottom deciles. We find that 4 out of 13 characteristics-based long-short portfolios generate significant excess returns. For example, a crypto value portfolio constructed as the negative of the past 1-year (52-week) return generates a significant average excess return of 5.7% per week with a significant t-statistic (2.7). The long-short portfolio based on the market capitalization of cryptos generates significantly negative excess returns of -47.1%. However, the momentum portfolio based on cumulative returns with a construction window of only one to four weeks generates *negative* excess returns of -4.1%, -2.4%, -2.5%, and -1.2%, respectively, indicating strong patterns of reversal. Network portfolios based on sorting along the growth in the total numbers of addresses with and without positive balances generate average returns of 4.0% (t-statistic=2.8) and 2.8% (t-statistic=2.0), respectively. Note that these network-related characteristics are only available in the Core Sample and, given the relatively smaller number of available coins, based on the sorts of the Core Sample into quintiles.

We examine whether these findings hold across cryptocurrency test portfolios with different market capitalization through double-sorting ($5 \times 5$ portfolios) that anchors on size as one sort. The long-short momentum portfolios in the four smaller quintiles are all negative and the return of the biggest quintile is significantly positive. In fact, the long-short portfolio returns increase from -19.5 percent in the first size quintile (small) to 4.1 percent in the fifth (big) size quintile almost monotonically. The weekly excess returns decrease from the lowest momentum to the highest for the four smaller quintiles and increase for the fifth (biggest) quintile. The results show that momentum only exists in large cryptocurrencies but not in small ones, reconciling the apparent difference of our paper with LTW concerning the crypto momentum effect. In fact, when we restrict our sample to cryptocurrencies with a market cap greater than $1 million, we recover the patterns in LTW. We note that the finding is in stark contrast to the results in equity markets that momentum premiums are larger for small stocks (Hong, Lim, and Stein 2000; Fama and French 2012). Our long-short value portfolio returns, in contrast, decrease from 15.1 percent in the first size quintile (small) to 0.8 percent in the fifth (big) monotonically, consistent with observations in the equity market.

We next construct the value ("VAL" instead of the more familiar "HML"), network ("NET"), size ("SMB"), momentum ("MOM"), reversal ("REV"), and market ("MKT") factors from various characteristic-based anomalies following the procedures in Fama and French (1993, 1996, 2018).[5] Similar to Cong, George, and Wang (2018), we use both the left-hand-side (LHS) and right-hand-side (RHS) approaches (Barillas and Shanken, 2017; Maio, 2019; Fama and French, 2012, 2017, 2018) to test the explanatory power of various factor models, including the 3-factor model proposed by LTW (hereafter, LTW-3 model) and models combining SMB, VAL, MOM, REV, and NET factors.[6] The 5-factor model with MKT, SMB, MOM, VAL, and NET (what we call the "C-5 model") factors performs the best with the low Gibbons-Ross-Shanken (GRS) F-statistics, smallest mean absolute errors, relatively large adjusted R-squared, and large and positive constrained-R squared (Maio, 2019) and cross-sectional R squared (Kelly, Palhares, and Pruitt, 2020; Feng, Polson, and Xu, 2021; Cong, Feng, He, and He, 2021) under the LHS approach.[7] Using the RHS approach for C-5, the contribution of MKT, SMB, MOM, VAL and NET is 1.37%, 6.69%, 3.74%, 8.93% and 1.87%, respectively. As such, we advocate for this C-5 factor model for pricing crypto assets and for future empirical research.

Furthermore, we manually collect information on cryptocurrencies in the Core Sample and classify them into four primary categories - General Payment Token, Platform Token, Product/Ownership Token, and Security Token - according to Cong and Xiao (2021). Following Hou, Karolyi and Kho (2011), we use 16 sets of characteristic-sorted decile portfolios as test assets (4 characteristics of size, momentum, value, and network × 4 categories) and compare

[5] We use the largest 20% cryptocurrencies to construct the momentum factor, and the smallest 80% to construct the reversal factor. Details follow in Section 4.1 below.
[6] LTW propose a 3-factor model of market factor (referred to as MKT_LTW to distinguish it from the market factor constructed in this paper), size factor (SMB_LTW), and momentum factor (MOM_LTW) to capture cross-sectional returns in the cryptocurrency market. We refer the 3-factor model as "LTW-3" model henceforth.
[7] According to Barillas and Shanken (2017), the left-hand-side (LHS) approach allows the factors that are *not* included as right-hand-side explanatory variables for a given model to play the role of left-hand-side dependent returns whose pricing must be explained by the model's factors. Details follow in Section 4.2 below.

the relative performance of what we call global (factors built regardless of token category), local (within token category only), and international (separately within and outside category) versions of cryptocurrency factor models. In an efficient and fully integrated crypto asset market, there should be only one set of risk or statistical factors that describe the expected returns of crypto-tokens from all four categories. However, just as whether markets are locally segmented or globally integrated has been one of the most enduring issues in international asset pricing (Karolyi and Stulz, 2003), whether different categories are segmented remain an open question. This is intuitive because implicit barriers, such as differences in information quality and market regulation, may cause a local model rather a global model to substantially affect expected returns. To this end, we evaluate a CAPM-style model (hereafter, Crypto-CAPM), the LTW-3 model from LTW, and our C-5 model to test the explanatory power of different categories driven by local within-category components or across-category, non-local components, or both. We observe significant and robust market segmentations in crypto assets, such that the local version of the C-5 model performs best with low average pricing errors and much higher average adjusted- and constrained- R squared.

We also examine the dynamics of different factor models' performance and the importance of each factor over time. Over our sample period, the cryptocurrency market matured gradually and experienced huge fluctuation. Using the test assets containing 150 portfolios and a rolling window of 104 weeks, the results show that the explanatory power of the C-5 model is always larger than the Crypto-CAPM and LTW-3 models. The trend of factor importance changed sharply at the end of 2017 and early 2020, which may indicate a change in market style at these two points. To explore whether the market is getting more integrated or not, we use the omnibus set of 16 sets of decile portfolios (4 characteristics×4 categories) as test assets, and find that the differences in the adjusted average R squared are converging. And the importance trends of factors constructed by the market trading data, such as the SMB and VAL fator, are similar across different categories, but that of the NET factor, which is constructed by fundamental data, has a persistent and clear divergency in different categories.

Our study adds to emerging empirical studies on crypto asset pricing. Liu and Tsyvinski (2021) show that returns of the index of cryptocurrencies they construct are significantly predicted by momentum and investor attention, not valuation ratios, while being exposed to a network growth factor, but not common factors, from other asset markets. Shams (2020) is among the earliest to indirectly measure the network effect using comments posted on "SubReddit" pages and shows that cryptocurrency characteristics, especially exposure to similar investor bases, explain a sizable variation in the return correlations. Schwenkler and Zheng (2020) use news data to construct peer linkages and analyze price co-movements in crypto markets. Liu and Tsyvinski (2021) and Bhambhwani, Delikouras and Korniotis (2022) use the growth of fundamental indicators, such as the number of addresses of Bitcoin and of ten cryptocurrencies, to measure the network effect directly. More recently, Fracassi and Kogan (2022) find a "pure momentum" effect in high-frequency cryptocurrency data---a positive association between average hourly return and lagged 24-hour return. A related trading strategy requires turning over the portfolio twice every hour and becomes unprofitable once commissions and price impact are taken into consideration.

We add by documenting a value premium widely observed in various asset classes (Asness, Moskowitz and Pedersen, 2013) and demonstrating that the crypto value factor matters for pricing the cross-section of cryptocurrencies. The strategies thus derived do not require high-frequency trading or high turnover and are thus easily implementable. We also highlight the importance of network effect on the valuation of cryptocurrencies (e.g., Cong, Li and Wang, 2021a), and incorporate network metrics into a factor pricing model for comparisons with other models. The interaction patterns between momentum and size add nuances to the momentum effect documented in LTW. Our study complements Liu, Tsyvinski and Wu (2021) and Liebi (2022) in underscoring how value metrics can help predict crypto asset returns. Borri, Massacci, Rubin, and Ruzzi (2022) subsequently confirm a number of our findings and in addition, examine factor candidates using macroeconomic information and link cryptocurrencies to other asset classes, focusing on latent factors instead of observable factors. Finally, our study is the most comprehensive study on factor pricing of crypto assets up to date, with a data sample size multiple times of that used in other studies.

This research stream obviously belongs more broadly to the empirical asset pricing literature, especially that on characteristic-based anomalies such as momentum and competing factor models (e.g., Carhart, 1997; Barillas and Shanken, 2017; Maio, 2019; Fama and French, 2012, 2015, 2017, 2018). We specifically contribute to the studies proposing factor pricing models for cryptocurrencies (LTW; Bhambhwani, Delikouras and Korniotis, 2022). We use a more comprehensive and up-to-date dataset for documenting characteristic-based crypto anomalies and for constructing both the factors and test assets, in order to capture information about long-term sources of risk and offer a pricing model for a larger cross-section of assets. Our discussion of token classification also provides insights into segmentation in the crypto markets, tying our study to the literature on international asset pricing (e.g., Hou, Karolyi, and Kho, 2011; Fama and French, 2012; Fama and French, 2017).

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 examines the cross-sectional returns of cryptocurrencies. Section 4 constructs cryptocurrency factors and compares various crypto asset pricing models. Section 5 introduces token classification and shows the relative performance of global, local, and international models in each token category. Section 6 concludes.

## 2. Data Description.

We collect data on all crypto assets available on *CoinMarketCap.com* which include daily prices, trading volume, and market capitalization of most cryptocurrencies traded on around 300 exchanges. *CoinMarketCap.com* is the world's most-referenced price tracking website for crypto assets, and a cryptocurrency is included in the *CoinMarketCap.com* list only when meeting criteria such as being actively traded on at least one exchange. *CoinMarketCap.com*'s stated mission is "to make crypto discoverable and efficient globally by empowering retail users with unbiased, high quality, and accurate information."

In total, there are 8,378 cryptocurrencies in the sample. We exclude stable coins, coins with zero prices, zero market capitalization, or zero trading volumes in all periods. The cleaned sample (which we call the "Full Sample") contains 4,007 tokens with weekly observations from 2014/01/01 to 2021/01/04 (366 weeks in total). We truncate all non-return variables at the 1st and 99th percentiles.[8] For robustness and to facilitate comparison of our study with LTW, which restricts the sample to cryptocurrencies with market values larger than $1 million, we also construct a sample with the same restriction (what we call the "Large Cap Sample").

In addition to the information provided by *CoinMarketCap.com*, we make use of a few features related to network adoption. The important indicators of interest are the number of addresses and transaction volumes on-chain (Cong, Li, and Wang, 2021a, 2021b). For example, an increase in the number of addresses with positive balances indicates a growing user base. Moreover, the total number of addresses (all addresses that once held the specific crypto-asset, even currently without a balance) is also informative. The third measure of successful adoption is the total on-chain transaction volume (the aggregate transaction volume recorded on-chain on a given day). Finally, total on-chain transaction volume in USD measures the aggregate on-chain volume in dollars. We collect data on these four indicators of network adoption from *intotheblock*, a data science company that applies research in AI to the crypto-market, including blockchain analytics, price predictions, DeFi analytics, and off-chain analytics. After matching our samples with the data from *CoinMarketCap.com*, we identify 745 crypto assets. As of 2021, there were 834 cryptocurrencies on *intotheblock*. We note that it is important to use on-chain data, given manipulations such as wash trading and pump-and-dump schemes which plague crypto exchanges (e.g., Cong et al., 2020; Li, Shin, and Wang,

[8] The market cap of one coin, Innovative-Bioresearch-Classic, reaches $29,328 trillion, which is abnormal. We removed this coin from the sample.

2021). Applying the same filtering as before, there are 616 cryptocurrencies left with data from 2014/01/22 to 2021/01/04 covering 363 weeks (the "Core Sample"). This sample is much larger than the one-coin sample used for network metrics in Liu and Tsyvinski (2021) (one cryptocurrency) and the ten-coin sample in Bhambhwani, Delikouras and Korniotis (2022).[9]

Table 1 reports the summary statistics. Panel A displays the number of cryptocurrencies, the average value-weighted daily market returns, and the market capitalization on the last day of each year for both the Full Sample and Core Sample. The number of cryptocurrencies increases from 713 in 2014 to 2,585 in 2020 for the Full Sample and from 4 to 613 for the Core Sample. The only year in which the value-weighted daily returns in the Full and Core Samples are notably different from each other is 2014, in which there are only 4 cryptocurrencies in the Core Sample compared with 713 in the Full Sample. Large differences in daily value-weighted average returns between the two samples appear in 2017 and 2020. Figure 1 shows the total weekly number of cryptocurrencies and their market capitalizations of both samples during the sample period. 2018 saw a total market capitalization exceeding \$800 billion for the Full Sample; after that the markets collapsed and soared again after 2020. The market capitalization of the Full Sample rises from \$10.7 billion in 2014/01/01 to \$866.2 billion in 2021/01/04. Although the Core Sample is small in terms of the number of crypto assets, they are well representative of the Full Sample in terms of the total market cap, making up 65% to 97% of the Full Sample (shown in Figure 1.C).

We split all cryptocurrencies in the Full Sample into quintiles according to their market capitalization. Panel B of Table 1 shows the cross-sectional averages of different features in each quintile. We find that the trading volume increases monotonically with size rising from \$17,992 traded on average per week among the smallest quintile to \$5.7 billion traded among the largest quintile. The return volatility (measured as the standard deviation of the daily

[9] At the beginning of 2014, only three cryptocurrencies survived in the Core Sample. Due to the limitation of sample size, the rapid increase in the price of DOGE coin during the third week (2014/01/15-2014/01/21) introduced an outlier to the dataset, which has a great impact on the analysis. Therefore, we removed the data of the third week of the Core Sample.

returns per week) decreases with the size quintile monotonically from 0.27% per day (Quintile 1) to 0.04% per day (Quintile 5) revealing that large cryptocurrencies have dramatically higher liquidity and low volatility relative to small cryptocurrencies. Panel C reports some characteristics averages for the Core Sample, which are comparable to those of the largest quintile of the Full Sample in Panel B.

### 3. Portfolio Returns.

We consider 13 cryptocurrency characteristics (shown in the Internet Appendix in Table A1) grouped into 4 categories: size, momentum, value, and network. The size category is associated with the market capitalization of the cryptocurrency on the last day of a given week (MarketCap). There are four different momentum measures ranging from the past 1- to 4-weeks of past returns. One of the characteristics in the value category is based on a longer-horizon reversal based on the negative of the past 52-week returns (NPast52), while the other three rely on ratios relative to market marketcapitalization drawing from the number of transactions recorded on-chain (T/M ratio), the cumulative number of addresses to date created on the chain (A/M ratio), and finally the number of addresses with balance (U/M ratio).[10] Finally, the four network characteristics are based on weekly first differences in the number of total addresses with balance (BAgrowth), in the total addresses overall (TAgrowth), in the total transaction volume on the chain (Volgrowth), and in the total transaction volume in US dollars on the chain (VolUSDgrowth). Note that the four network and three of the value characteristics (T/M, A/M and U/M ratios) are only available for the Core Sample, and all other characteristics are available for the Full Sample.

We first construct single-sorted or double-sorted portfolios at the end of each week and

[10] Following *intotheblock*, we denote addresses that currently hold the particular cryptocurrency as "addresses with balance," a metric that could approximates the user base of the crypto asset. In revising the paper, we further tested other value proxies such as the active address-to-market cap ratio, the new address-to-market cap ratio, the price-to-active address ratio, and the price-to-new address ratio which is used as the value proxy in Liu, Tsyvinski and Wu (2021b). Though unreported here, they do not generate significant excess returns either, likely due to the fact that our time series starts earlier than 2018, which is the start year for the sample in Liu, Tsyvinski and Wu (2021b).

track the returns of each portfolio in the following week. A cryptocurrency added to a portfolio at week's end must have non-zero market capitalization, non-zero trading volume and a non-missing return at the end of the formation week. All portfolio returns are value-weighted.

*3.1. Size Sorted Portfolio Returns.*

At the end of each week, we divide cryptocurrencies of the Full Sample and the Large Cap Sample into 10 deciles according to the weekend market cap. The portfolio returns are value-weighted of constituent cryptocurrencies for the week that follows. We then construct a long/short portfolio by longing $10^{th}$ portfolio and shorting the $1^{st}$ portfolio. Each portfolio is rebalanced weekly.

The results of portfolios grouped by market capitalization are shown in Table 2. The smallest capitalization (Decile 1) portfolio has an average return of 48.6% per week (*t*-statistic of 3.09), the average returns decline nearly monotonically to the average return of the largest capitalization (Decile 10) portfolio of 1.5% per week, insignificantly different from zero. We find that market capitalization 10-1 spread portfolio generates significant returns, but only in the Full Sample with -47.1% weekly returns (*t*-statistic of -3.02). Note that in the Large Cap Sample there is almost no monotonic decline across its ten decile portfolios. For the Large Cap Sample, the average weekly portfolio 10-1 spread portfolio return is about -1.0% (*t*-statistic of -0.87). In the Large Cap Sample, the excess returns of Deciles 6 to 8 are the lowest.

*3.2. Momentum Sorted Portfolio Returns and Reversals.*

We construct momentum single sorted (10 deciles), and size-momentum $5 \times 5$ double sorted portfolios to analyze the performance of the long-short strategies. We analyze the (short-term) momentum sorted portfolio with a construction window of one, two, three, and four weeks, respectively. For the independent double sorted portfolios, the 25 size and momentum portfolios are the intersections of quintiles sorted by market capitalization and by past two-week cumulative returns. To construct the dependent double sorted portfolios, we first split cryptocurrencies into quintile portfolios based on their week-end market capitalization, then further split the cryptocurrencies into quintile portfolios according to the momentum characteristics.

Table 3 presents the results of 2-week momentum. The results of one-, three-, and four-weeks momentum are shown in Table A2. Panel A of Table 3 shows that all sorting on past returns cannot generate significant positive long-short (10 – 1 spread) portfolio excess returns. The spread portfolio average return is, in fact, *negative* at -2.40% per week (*t*-statistic of -0.82). For the Full Sample, the excess return presents a U-shape pattern with the highest average returns for the Lowest Momentum (Decile 1) portfolio, the Highest Momentum (Decile 10) portfolio, and then the Decile 8 Momentum portfolio, in that order. In the Large Sample - which is similar in attributes to the large decile by market capitalization of the Full Sample - there arises a clear monotonic pattern from an average return of -1.80% (*t*-statistic of -1.70) for the Lowest Momentum (Decile 1) portfolio to 3.60% (*t*-statistic of 2.30) for the Highest Momentum (Decile 10) portfolio. The Momentum long-short spread (10 – 1) portfolio has an average return of 5.4% (*t*-statistic of 4.07). These findings imply that there are important interactions between size and momentum that required further study.

Panel B presents the results of the independently double sorted portfolios with two-week returns momentum window for the Full Sample. The Momentum spread (5 – 1) portfolio returns of the four smallest-size quintiles are all reliably negative, consistent with the single sorted results. However, the return for the biggest quintile is significantly positive with a weekly return of 4.1% (t-statistic of 3.20) as we saw for the Large Cap Sample. In fact, long-short momentum returns increase from the smallest-size quintile to the largest-size quintile almost monotonically, from -19.5% in the first quintile to 4.1% in the fifth quintile. Focusing on the size pattern in each momentum quintile, the weekly excess returns decrease from the smallest to the biggest group in the lower momentum quintiles, but present a U-shape pattern in the highest momentum quintile, just as we saw for the Large Cap Sample in Panel A. Panel C shows that this size-based pattern is not an artifact of the portfolio sorting methodology;

the results of the sequentially double sorted portfolios are very similar to results in Panel B.

Overall, short-term momentum only manifests itself in the returns of large-cap cryptocurrencies (Panel A). This is consistent with Liu, Tsyvinski and Wu (2022) that examines the equivalent of our Large Cap Sample and it implies that this momentum effect in cryptocurrencies may not be as robust as previously thought.

*3.3. Value Sorted Portfolio Returns.*

As noted above, we use two proxies to measure the value effect of cryptocurrencies: The negative of the past long-term return (Asness, Moskowitz and Pedersen 2013) and the fundamental-to-market value (only available for the Core Sample) motivated by the equity market (Liu and Tsyvinski, 2021).[11] The fundamental value of cryptocurrencies is user-related and should be reflected in the number of users, the number of addresses, and on-chain transaction volume.

We first split cryptocurrencies into deciles according to the negative of the past 52-week return (NPast52). Panel A in Table 4 shows that the long-short value-based spread portfolio has a 5.7% weekly return (*t*-statistic of 2.71). The Highest Value (Decile 10) portfolio return is 6.8% per week (*t*-statistic of 3.00) and the average returns decline almost monotonically for four deciles to an average return of 1.7% per week for Decile 7, and it remains flat to 1.1% per week for the Lowest Value portfolio (Decile 1). Note that the value-based spread portfolio also generates a much smaller 1.7% weekly return (*t*-statistic of 1.44) in the Large Cap Sample, but there is much less clearly a monotonic pattern.[12] Again, these findings imply an important interaction between value and market capitalization among cryptocurrencies.

To further test the robustness of the performance of value sorted portfolios across

[11] In a recent study, Liu, Tsyvinski and Wu (2021b) find that the price-to-new address ratio negatively predict future cryptocurrency returns using a sample from 2018.

[12] To the negative of the past long-term return meature, we test different horizons from 3- to 24- months, and find that the long=short portfolio constructed by the Full Sample can generate significant positive excess return from 7- to 24-months.

different market cap groups, we construct size-value independent and dependent double sorted portfolios using the same method as those in the size-momentum portfolios (shown in Panel B and C). Panel B shows that the long-short value-sorted portfolios have almost monotonic decreasing returns from the first size quintile (small) to the fifth (big): from 15.1% to 0.8% in weekly excess returns, respectively. Focusing on size, the weekly excess return decreases from the smallest to the biggest group in the high-value quintiles, but presents a similar U-shape pattern in the lowest value quintile, similar to the result in Section 3.2. The results of sequentially double sorted portfolios in Panel C are very similar to the independently double sorted portfolios. These double-sorted portfolios are only built for the Full Sample.

We also construct single sorted portfolios into 5 quintiles according to the fundamental to market ratios: the user-to-market ratio, the address-to-market ratio, and the volume-to-market ratio, using the Core Sample. These are presented in the Internet Appendix in Table A3 where they show that none of the three proxies can generate long-short portfolios with significant excess returns.[13]

Overall, we find that the value effect constructed from the negative of the past 52-week returns does exist in the crypto markets, in a way that is persistent across groups with various coin market capitalizations.

### *3.4. Network Sorted Portfolio Returns.*

We next construct weekly growth rates by taking log differences in total addresses, total addresses with balance, total on-chain transaction volume, and total USD transaction volume on-chain to measure the network effect of cryptocurrencies. Due to the smaller size of the Core Sample in the early years, we only construct single sorted portfolios and only in quintiles when using the Core Sample.

[13] As mentioned in footnote 10, we test the price-to-new address ratio used in Liu, Tsyvinski and Wu (2021b) and some other value proxies. Using the Core Sample after 2018, we find that the active address-to-market cap ratio can generate significant positive weekly long-short portfolio return of 1.35% (t-statistic of 2.21).

Table 5 shows that both the weekly growth in total addresses (TAgrowth) and total addresses with balance (BAgrowth) do generate statistically significant long-short strategy (5 – 1) spread portfolio returns in the Core Sample. The excess returns of these two characteristics are from 2.8% to 4.0% per week with *t*-statistics from 2.03 to 2.85. The patterns in mean returns across the quintiles are not monotonic for either of the network portfolios: it is the highest growth quintiles (Quintile 5) that has the most positive and statistically significant mean returns that are distinctly different from each of the first four quintile mean returns (Quintiles 1 to 4). Note that the results of the weekly growth in total transaction volume and total USD transaction volume on-chain are not statistically significant, as shown in Table A4.

## 4. Factor Pricing for Crypto Assets.

Section 3 naturally suggests six candidate characteristics for constructing factors to price the cross-section of cryptocurrencies: Market, Size, Momentum, Reversal, Value, and Network.[14] In this section, we formally construct crypto asset pricing factors from them and compare factor pricing models for crypto assets, similar to how Cong, George, and Wang (2018) recover a value premium based on the residual-income model (RIM) and propose new factor models using value-price divergences.

### *4.1. Factor Construction.*

Following LTW, we first construct the crypto market index using the value-weighted price of all available cryptocurrencies. The market factor (MKT) is the difference between the weekly market index return and the risk-free interest rate proxied by the 1-month Treasury bill rate available at a weekly frequency. We then construct the cryptocurrency size, value and network factor following the portfolio approach of Fama and French (1993, 1996). Specifically,

[14] LTW propose a 3-factor model of Market, Size and Momentum factor, while Shen, Urquhart and Wang (2020) document that it's reversal rather that momentum in the short term, and propose a 3-factor model of Market, Size and Reversal factor. We find (short term) momentum in the largest crypto coins and (short term) reversal in the small coins. To capture the variation better, we construct the Momentum and Reversal factors at the same time.

the size (SMB) and value (VAL) factors are constructed as follows: each week, all cryptocurrencies in the Full Sample are independently sorted into three unequal-sized groups [30% lowest, 40% middle, 30% highest] value portfolios by the negative of the past 52-week returns, and two equal-sized [50% smallest, 50% largest] size portfolios of the ranked market capitalization. This independent $2 \times 3$ sorting on size and value produces six portfolios for which the returns within each portfolio are value-weighted. SMB is the equal-weighted average of the returns on the three small portfolios minus the equal-weighted returns on the three big portfolios. VAL is the difference between an equal-weighted average of the returns of the smallest and largest high price-ratio portfolios and an equal-weighted average of the same for the low price-ratio portfolios. The network factor (NET) is constructed by splitting the coins of the Core Sample into 3 groups due to the limitation of available coins. That is, each week we split the cryptocurrencies into three unequal-sized [30% lowest, 40% middle, 30% highest] groups by the growth rate in total addresses with balances.[15] The network factor (NET) is the return difference between the top and the bottom network portfolios.

In section 3.2, we find that momentum only exists in the biggest quintile, while the four small quintiles exhibit reversal rather than momentum. Fama and French (2018) compare factor models that just use the big or small component of those factors which are constructed by double sorts on size and other characteristics. Following them, we construct the momentum factor (MOM) and reversal factor (REV) as follows: each week, we split all cryptocurrencies in the Full Sample into two unequal-sized [80% smallest, 20% largest] size portfolios of the ranked market capitalization, and three unequal-sized groups [30% lowest, 40% middle, 30% highest] momentum portfolios by the past 2-week returns. This independent $2 \times 3$ sorting on size and momentum produces six portfolios for which the returns within each portfolio are value-weighted. MOM is the return difference between the highest and the lowest past 2-week return portfolios in the largest size group, and REV is the return difference

[15] The network factor constructed by total addresses can be spanned by total addresses with balance.

in the smallest group.

Panel A of Table 6 presents the summary statistics of weekly returns for all the six factors considered. The mean of MKT, SMB, MOM, REV, VAL and NET factors are 1.55%, 5.18%, 3.34%, -6.23%, 4.00% and 3.76% with t-statistics of 2.39, 4.57, 3.29, -2.73, 5.63 and 2.82, respectively. These are economically large returns and not unexpected given the preliminary findings in the previous section. As seen in Panel B of Table 6, the SMB factor is positively correlated with MKT with a correlation of 0.03. The MOM factor is positively correlated with MKT and negatively correlated with SMB with 0.06 and -0.03, respectively. The REV factor is positively correlated with MKT, SMB, and MOM with 0.04, 0.15 and 0.08, respectively. The VAL factor is negatively correlated with MKT, MOM, and REV with -0.04, -0.08 and -0.11, and positively correlated with SMB with 0.07, respectively. The NET factor is positively correlated with MKT, SMB, MOM, REV, and VAL, and the correlation is 0.06, 0.04, 0.06, 0.02 and 0.03, respectively.

To compare with the 3-factor model proposed by LTW, we construct an alternative market, size, and momentum factor, which we denote with an "LTW" suffix, MKT_LTW, SMB_LTW, and MOM_LTW. We construct a Large Cap market index using the value-weighted price of the cryptocurrencies in the Large Cap Sample. The MKT_LTW is the difference between the returns of Large Cap market index and the 1-month US Treasury bill rate available at a weekly frequency. The SMB_LTW factor is constructed as follows: each week the cryptocurrencies of the Large Cap Sample are split into three size groups by market capitalization: bottom 30 percent (Small), middle 40 percent, and top 30 percent (Big). The SMB_LTW factor is the value-weighted return difference between the portfolios of Small and the Big portfolios. The MOM_LTW factor is constructed similarly to the VAL factor: each week, all cryptocurrencies in the LargeCap Sample are independently sorted into three unequal-sized groups [30% lowest, 40% middle, 30% highest] momentum portfolios by the past 2-week returns, and two equal-sized [50% smallest, 50% largest] size portfolios of the ranked market capitalization. MOM_LTW is the difference between an equal-weighted average of the returns of the smallest and largest high past 2-week return portfolios and an equal-weighted average of the same for the low past 2-week return portfolios. The summary of these three LTW factors is shown in Table A6. The mean of MKT_LTW, SMB_LTW and MOM_LTW factors are 1.54%, 0.64% and 3.32% with t-statistics of 2.37, 0.77, and 4.07, respectively.

*4.2. Selecting Factors.*

Fama and French (2018) divide their methods of model selection into two approaches: the left-hand-side (LHS) approach and the right-hand-side (RHS) approach. Normally, the LHS approach selects models by the intercepts (alphas) of the time series regressions of test asset returns on model factors.[16] The alternative, the so-called right-hand-side (RHS) approach, focuses on RHS factors of competing models.

*4.2.1. LHS Method.*

In the LHS approach, we use both the In-Sample and Out-of-Sample portfolios as test assets, and the definition and construction process are shown in the Internet Appendix. Specifically, there are six different single and double-characteristic sets of the In-Sample test asset portfolios: two 10-decile single sorts on MarketCap and NPast52 of the Full Sample, one 10-decile single sorts on ret-2 week of the Large Cap Sample, one 5-quintile sorts on BAgrowth of the Core Sample, and two 5×5 double sorts on size-momentum and size-value of the Full Sample. All these portfolios are constructed by those factor-related characteristics and have been tested in Section 3, and therefore referred to as the In-Sample portfolios.

Besides the characteristics tested in this paper, previous studies have documented many other return predictors in the crypto market. LTW finds that the long-short portfolios based on the weekend price and maximum price in the portfolio formation week can generate significant excess returns. Zhang, Li, Xiong and Wang (2021) suggest that the downside risk can positively predict the expected returns in cryptocurrency market. Zhang and Li (2020) demonstrate a positive relationship between idiosyncratic volatility and future returns. Some

[16] An important limitation of LHS approach is that th the largest e model selection results are dependent on the test assets chosen.

papers focus on the liquidity in the crypto market (Zhang and Li, 2021; LTW). Therefore, we compare the explanatory power of different factor models in capturing these ``out-of-sample'' characteristics. There are six different sets of Out-of-Sample test portfolios: five 10-decile single sorts on price (PRC), maximum price in the portfolio formation week (MAXPRC), value at risk (VaR), idiosyncratic volatility (IVOL), and illiquidity (ILLIQ), and one Core Sample portfolio test assets (named "CoreSet") containing three 5-quintile portfolios sorted on MarketCap, ret-2 week, and NPast52 of the Core Sample, respectively.[17] We also include an omnibus set that pools together all test asset portfolios mentioned above, which includes a total of 150 portfolios of cryptocurrencies.

We then test 13 competing models: the Crypto-CAPM model, [MKT], five 3-factor models, [MKT, SMB, MOM], [MKT, SMB, REV], [MKT SMB VAL], [MKT SMB NET], as well as [MKT_LTW SMB_LTW MOM_LTW] proposed by LTW, three 4-factor models, [MKT SMB VAL MOM], [MKT SMB VAL REV] and [MKT SMB VAL NET], three 5-factor models, [MKT SMB VAL MOM NET], [MKT SMB VAL MOM REV], [MKT SMB VAL REV NET], and one 6-factor model [MKT SMB VAL MOM REV NET].[18]

Following Fama and French (2012, 2015), we regress LHS test assets on RHS factors to compare these models. A good model should have returns intercepts across test asset portfolios jointly indistinguishable from zero. We use the GRS statistic of Gibbons, Ross, and Shanken (1989) to jointly test the significance of alphas of the regressions of portfolio excess returns (LHS) on model factors (RHS). Besides GRS, other diagnostic statistics we use to evaluate different models include: mean absolute alphas across test asset portfolios, A$|\alpha|$, and average adjusted R squared for a given set of test asset portfolios, A$R^2$. In addition, we calculate the constrained R squared, $R_C^2$, and its *p*-value, denoted $p(R_C^2)$, a measure recently

[17] Table A5 reports the mean weekly excess returns of the 5-quintile and the long-short portfolios constructed by the Core Sample according to MarketCap, ret-2 week, and NPast52, which have been tested in the Full Sample.
[18] From Table 7, we can observe that the factor model of [MKT SMB VAL] performs best among the five 3-factor models, so we only present results of the three 4-factor models and three 5-factor models adding another factors to the [MKT SMB VAL] model.

proposed by Maio (2019).[19] We also calculate the cross-section R squared, $Cross\ Section\ R^2$, which evaluates the performance of different factor models in the cross-sectional dimension (Kelly, Palhares, and Pruitt, 2020; Feng, Polson, and Xu, 2021; Cong, Feng, He, and He, 2021). The results are shown in Table 7 and Table A.7.

Table 7 presents four different performance metrics, the GRS statistics, A$|\alpha|$, A$R^2$, and $R_C^2$, of the 13 factor models on 13 different sets of test assets, which contains six In-Sample sets, six Out-of-Sample sets, and one omnibus set that pools together all In-Sample and Out-of-Sample test asset portfolios. We also report the p-value of GRS and $R_C^2$, and the $Cross\ Section\ R^2$ in Table A.7. We refer to the given set of test assets as our 13 experiments. Each panel is organized by the given set of performance metrics denoted in each heading. The results show that a basic Crypto-CAPM model fares poorly in our tests (Row 1 for each panel). This simple, single-factor model has a larger GRS *F*-statistics (the largest half in 10 out of 13 experiments), a larger average pricing error (the largest half in 11 out of 13 experiments), the smallest average adjusted R squared (12 out of 13 experiments), a smaller constrained R squared and cross-sectional R squared. Consider, for example, the experiment with 10 NPast52 portfolios (Column 3 for each panel), the Crypto-CAPM model has the largest GRS *F*-statistic at 2.646 (associated *p*-value of 0.004) in the 13 factor models evaluated, the highest average absolute alphas of 0.016, the smallest average R-squared at 0.150, the second lowest Constrained R squared at 0.143 (associated *p*-value of 0.028), and the smallest cross-sectional R squared at 0.470. The weakest performance of the single-factor Crypto-CAPM model is best noted in the omnibus experiment in the last column in each panel, the Crypto-CAPM model produces the largest GRS *F*-statistic, the largest average absolute alphas of 3.6% per week, the lowest R squared (0.127), a negative constrained R squared (-0.029), and a small cross-sectional R squared (0.098, the largest is 0.610).

Switching to multi-factor models, we note performance improvement in terms of their

[19] See details of the "Constrained R squared Test" in the "Bootstrap Simulation" section of Miao (2019).

explanatory power for different sets of test asset portfolios. Not surprisingly, the relative performance of the multi-factor models varies with the test asset experiments, but several general patterns arise. Focusing on the 3-factor models, the model of [MKT_LTW SMB_LTW MOM_LTW] proposed by LTW (reported in the second row of each panel) performs worse. The LTW-3 model has the largest half GRS statistics and A$|\alpha|$ in 9 out of 13 experiments, respectively. The experiments with BAgrowth (in Column 4) and CoreSet (in Column 12) suggest that the excess returns of test asset portfolios constructed only from the Core Sample can be well explained by all these models and arguably the three-factor model, [MKT SMB NET].

Of special interest, the last column in each panel presents the results of the omnibus experiment with the largest set of 150 test asset portfolios. For the LTW-3 factor models, the GRS statistic is 3.700, which is larger than any of the other 11 multifactor model (though all are able to reject the overidentifying restriction that the alphas are jointly zero), the mean average alpha is 3.4%, which is the largest among the multifactor models, and the average adjusted R square is 0.161, notably lower than that for the other 11 multifactor models. The constrained R squared is -0.075, which is not the lowest, but is negative. The cross-sectional R square is positive but small (the largest is 0.610).

The three-factor LTW model underperforms relative to the other 11 multifactor models, but it is equally interesting to see which of the other 11 delivers the relatively stronger performance in terms of test asset spanning power. Firstly, we focus our attention on the omnibus experiment with 150 test asset portfolios in the last column in each panel. Among the four other 3-factor models considered (always in Rows 3 to 6 in each panel), the model with MKT, SMB and VAL performs relatively better with the largest and positive $R_C^2$, 0.412 (the only positive $R_C^2$ among the four 3-factor models), and it has the smallest GRS F-statistic of 3.102 and the smallest A$|\alpha|$ of 0.025. We consider three 4-factor models (always in Rows 7 to 9 in each panel), which add the MOM, REV, or the NET factor to the 3-factor model with MKT, SMB and VAL to further improve the pricing performance. We further construct three 5-factor models (always in Rows 10 to 12 in each panel), which add two out of MOM, REV, and NET to the 3-factor model with MKT, SMB, and VAL, and one 6-factor model of [MKT SMB VAL MOM REV NET] (always Row 13 of each panel). Compared to the model of [MKT SMB VAL MOM NET], the other two 5-factor models and the one 6-factor model produce a larger average R squared, but the constrained R squared and cross-sectional R squared are all negative, which means these three-factor models cannot explain the cross-sectional variation well. In fact, there are only four-factor models, [MKT SMB VAL], [MKT SMB VAL MOM], [MKT SMB VAL NET] and [MKT SMB VAL MOM NET] can generate positive constrained R squared as Panel D of Table 7 shows. Overall, the 5-factor model of [MKT SMB VAL MOM NET] leads to a lower GRS F-statistic to 2.880 (only larger than the 6-factor model with 2.784 and the 5-factor model of [MKT SMB VAL MOM REV] with 2.817), the smallest average absolute alpha of 2.3%, whose $AR^2$ increases to 19.2% (smaller than the 4-, 5-, and 6-factor models containing the REV factor, but $R_C^2$ and $Cross\ Section\ R^2$ of them are negative), and the constrained R squared ($R_C^2$) and cross-sectional R squared ($Cross\ Section\ R^2$) increases to 0.425 and 0.588 (only smaller than [MKT SMB VAL NET]).

Among all the 13 factor models, the 5-factor model (“C-5”), [MKT SMB VAL MOM NET] performs the best across different performance metrics, followed by the 4-factor model of [MKT SMB VAL NET] and [MKT SMB VAL MOM]. The C-5 model typically produces the third smallest GRS F-statistics, the smallest pricing errors, a large average adjusted R squared, a relatively large and positive constrained R squared and cross-sectional R squared.

*4.2.2. RHS methods.*

We use two RHS approaches. The first one entails spanning regressions that are most common in previous studies. Each factor is regressed on the other factors to see if this factor could be spanned by others. Barillas and Shanken (2016) argue that models should be compared in terms of their ability to price all returns that include both test assets and pricing factors. In our second RHS approach, we use their newly proposed test, the maximum squared Sharpe ratio test, that only considers the factors. Define $f$ as a model's factors, $\bar{r}$ as the vector of the sample mean excess return, $\hat{V}$ as the variance-covariance matrix of assets, the squared Sharpe ratio is:

$$Sh^2(f) = \bar{r}'\hat{V}^{-1}\bar{r}.$$

Table 8 displays our findings using the first RHS approach. The columns represent the univariate regressions by the factor on the five-factor C-5 model. We see that the intercept of each regression is significant and the $t$-statistics range from a low of 1.82 for the NET factor to a high of 5.50 for the VAL factor. We interpret, from these regressions, all the five factors, MKT, SMB, VAL, NET and MOM cannot be reliably explained by the others.

Table 9 presents the max squared Sharpe ratio of different factor models and the marginal contribution of each factor to the max squared Sharpe ratio. Besides the $Sh^2(f)$ from the observed sample, we follow Fama and French (2018) to run 10,000 bootstrap simulations and calculate the mean and median of $Sh^2(f)$. The marginal contribution of a factor to the max squared Sharpe ratio is computed as the square of the ratio of the intercept in the spanning regression of the factor on the model's other factors to the standard error of its regression residuals. From Table 9, the max squared Sharpe ratio of the LTW-3 factor model is only 0.0327. Among the five 3-factor models, the model of [MKT SMB VAL] (Row 4 of the table) generates the largest max squared Sharpe ratio at 0.1807. Among all 12 models, the three five-factor models (including the C-5 model) and the one six-factor model have the highest max squared Sharpe ratios. The six-factor model has the largest max squared sharp ratio. The C-5 model (Row 9 of the table) has the max squared Sharpe ratio at 0.2402. For that model, the VAL contributes the most at 8.93%, followed by SMB at 6.69%, and MOM at 3.74%. The NET and MKT factors contribute the least at 1.87% and 1.37%, respectively.

*4.3. Performance of C-5 Model.*

In summary, when using the LHS approach, the best factor model varies with the composition of the test asset portfolios. But, when combining all of the test asset portfolios in one omnibus experiment and when considering all test diagnostics in a holistic manner, the performance of C-5 dominates that of all the other factor models. Using the RHS approach, none of the five factors in MKT, SMB, VAL, MOM and NET, can be spanned by others. From the largest max squared Sharpe ratio test, all five factors contribute to the pricing performance. We, therefore, advocate the C-5 model for the pricing of the cross-section of crypto assets for future empirical research.

To further test the usefulness of the C-5 model, Table A8 shows the relative alpha of the 10-decile and the long-short zero investment portfolios constructed by the Out-of-Sample characteristics of the main factor models, including the Crypto-CAPM, LTW-3, and our C-5 model. The C-5 model can explain all the long-short portfolios constructed by the Out-of-Sample characteristics and generate a lower relative alpha among these factor models in most characteristics. For example, the zero-investment portfolio based on PRC can generate a significant weekly excess return with -8.9% (t-statistic of -2.39), which cannot be explained by the Crypto-CAPM model with the alpha of -8.1% (t-statistic of -2.16) and the LTW-3 model with an alpha of -7.5% (t-statistic of -1.79). The relative alpha of the C-5 model is -2.6% (t-statistic of -0.97).

Table A9 shows the explanation power of individual cryptocurrencies. As of 2021/01/04, the top 5 cryptocurrencies in market capitalization (excluding stable coins) are Bitcoin, Ethereum, Litecoin, Xrp, and Polkadot. We examine whether these individual cryptocurrencies can be well priced by the factor models mentioned before. From Table A9, we can observe that all the cryptocurrencies can be well priced by the Crypto-CAPM factor model, except for Ethereum. For the Ethereum, the intercepts of Crypto-CAPM and LTW-3 factor model are 0.028 (t-statistic of 2.05) and 0.023 (t-statistic of 2.13), respectively, while that of the C-5 model is 0.013 (t-statistic of 1.14), which means that only the C-5 model can price the Ethereum well. The factor loadings on MKT, VAL, and NET are significant, at 0.432 (t-statistic of 5.02), 0.134 (t-statistic of 1.83), and 0.536 (t-statistic of 4.14), respectively.

## 5. Token Classification and Factor Pricing in Segmented Markets.

### *5.1. Token Categorization based on Economic Functions.*

The Securities and Exchange Commission (SEC) broadly labels cryptocurrencies as security tokens or utility tokens, but no consensus has been reached on the proper classification of tokens.[20] Any classification should be based on commonalities on how cryptocurrencies derive value and function economically, which might then matter for how we regulate their issuance and trading. To this end, Cong and Xiao (2021) propose four non-mutually exclusive token categories: general payment, platform token, product token and security token. General payment tokens are perceived as substitutes for fiat money or other liquid instruments such as Treasury bills and are used as monies, such as Bitcoin, Tether, Libra, etc. Platform Tokens are used as local means of payment on platforms that provide certain services or functions. Ownership/product tokens include corporate coupons, which enable holders to redeem from the issuer (or a service provider) a pre-determined quantity of product/service, as well as non-fungible tokens (NFTs) that signifies ownership of collectibles. Finally, security tokens, the fourth category, entitle the holder to future cash flows from a business and essentially represent a form of tokenization of security contracts.

We implement the four-category classification manually with the 616 cryptocurrencies in the Core Sample based on information obtained from public articles, cryptocurrency information service websites, and the tokens' official websites/whitepapers. The information was collected up until May of 2021.[21] Note that we focus on the Core Sample due to the need

[20] Entities such as Coinbase use hundreds of industry categories, which do not admit a parsimonious factor pricing model..

[21] Frequently sourced websites for further information includes *Coinmarketcap.com*, *Coincentral.com*, and *Coincheckup.com*, which provide summaries of tokens' intended purposes, corporate background, and technology.

to construct local factors which require more detailed cryptocurrency characteristics. In the event that a token belongs to multiple categories, we assign it to one based on its primary economic function.

Table 10 contains the summary statistics. The four categories, General Payment, Platform Token, Product Token, and Security Token, contain 28, 483, 72 and 26 cryptocurrencies, respectively.[22] The General Payment category has the longest history and the largest market value: it starts on 2014/01/01 and the average market capitalization is above $5 billion. The start dates of the Platform, Product and Security tokens are 2016/05/11, 2017/06/07 and 2016/12/28, respectively. General payment tokens and platform tokens have more addresses and more activities on average. The number of addresses with non-zero balances in each category are 2.004 million, 105,200, 19,400, and 16,100, respectively. While general payment tokens include the ones with the largest market cap, platform tokens are the most common. In a sense, general payment tokens are also platform tokens where the platform is the entire economy.

For each category, we split cryptocurrencies into quintiles according to their characteristics. Table 11 presents the excess returns for four categories; the left panels report the mean returns and the right panels, the respective *t*-statistics for those mean returns. The long-short (5-1) spread portfolios in all categories generate negative returns across size quintiles and positive returns in value quintiles. More importantly, Platform Tokens generate significantly larger network spread returns, which is consistent with the notion that the network effect is important to the Platform Token (Cong, Li, and Wang, 2021a, and Cong and Xiao, 2021). The network effects also generate positive returns for General Payment Token, although they are not statistically significant. As for the momentum (2-week returns) characteristics, the signs of long-short spread portfolio returns of different categories are all

[22] There are 11 cryptocurrencies that can't be classified due to the lack of information, which means 605 cryptocurrencies are classified successfully. And there are 4 cryptocurrencies divided into both product token and security token.

negative. The most important takeaway from this table is that the spread in returns along cryptocurrency attributes depends on the token category.

*5.2. Local versus Global Pricing Models and Segmentation in Crypto Markets.*

Following Hou, Karolyi, and Kho (2011), we compare the performance of the global, local, and "international" versions of cryptocurrency CAPM model (Crypto-CAPM), LTW-3 model, and our C-5 model to test for potential market segmentation and better understand the "global" factor structures that we have pursued and successfully uncovered so far in Sections 3 and 4. To that end, we propose three versions of each of the Crypto-CAPM model (Models 1a to 1c), LTW-3 model (Models 2a to 2c), and C-5 model (Models 3a to 3c) where the global versions (1a, 2a, 3a) are contrasted with the local versions (1b, 2b, 3b) and international versions (1c, 2c, 3c). They are:

1a. Crypto-CAPM. $r_{it} - r_{ft} = \alpha_i + \beta_i^G MKT_t^G + \epsilon_i$

1b. Crypto-CAPM. $r_{it} - r_{ft} = \alpha_i + \beta_i^L MKT_t^L + \epsilon_i$

1c. Crypto-CAPM. $r_{it} - r_{ft} = \alpha_i + \beta_i^L MKT_t^L + \beta_i^F MKT_t^F + \epsilon_i$

2a. LTW-3. $r_{it} - r_{ft} = \alpha_i + \beta_i^G MKT_t^G + s_i^G SMB_t^G + w_i^G MOM_t^G + \epsilon_i$

2b. LTW-3. $r_{it} - r_{ft} = \alpha_i + \beta_i^L MKT_t^L + s_i^L SMB_t^L + w_i^L MOM_t^L + \epsilon_i$

2c. LTW-3. $r_{it} - r_{ft} = \alpha_i + \beta_i^L MKT_t^L + s_i^L SMB_t^L + w_i^L MOM_t^L + \beta_i^F MKT_t^F + s_i^F SMB_t^F + w_i^F MOM_t^F + \epsilon_i$

3a. C-5. $r_{it} - r_{ft} = \alpha_i + \beta_i^G MKT_t^G + s_i^G SMB_t^G + w_i^G MOM_t^G + h_i^G VAL_t^G + n_i^G NET_t^G + \epsilon_i$

3b. C-5. $r_{it} - r_{ft} = \alpha_i + \beta_i^L MKT_t^L + s_i^L SMB_t^L + w_i^L MOM_t^L + h_i^L VAL_t^L + n_i^L NET_t^L + \epsilon_i$

3c. C-5. $r_{it} - r_{ft} = \alpha_i + \beta_i^L MKT_t^L + s_i^L SMB_t^L + w_i^L MOM_t^L + +h_i^L VAL_t^L + n_i^L NET_t^L +$

$\beta_i^F MKT_t^F + s_i^F SMB_t^F + w_i^F MOM_t^F + h_i^F VAL_t^F + n_i^F NET_t^F + \epsilon_i.$

The subscript "G" denotes a global factor constructed from all the 605 cryptocurrencies in all these categories, the subscript "L" denotes a local factor constructed from the cryptocurrencies in a certain category, and the subscript "F" denotes a foreign factor constructed from all the cryptocurrencies excluding those form the category of interest.[23] For local, global, and international versions of a given model, we use 16 sets of characteristic-sorted decile portfolios as test assets (4 characteristics × 4 categories) to compare the performance of Models 1 through 3.

Table A10 and Table 12 shows horserace among these models using various test diagnostic statistics as in Section 3, including GRS *F*-statistic, the average absolute alpha, the average adjusted R squared and constrained R squared. The results are reported separately for each characteristic in each category. At the bottom of each of the three panels of the table, there are total counts to summarize the findings: Total for *p*-value (GRS) indicates how many of the 16 experiments reject the model; Total for average absolute alpha ($A|a|$), average adjusted R square ($AR^2$), and constrained R square ($R_C^2$) denote the average of the respective values across the 16 experiments; Total for *p*-value ($R_C^2$) indicates how many tests have positive constrained R square with *p*-values less than or equal to 0.05, i.e., p value is positive at the 5% level. For Total *p*-value ($R_C^2$), a larger value indicates better performance; it is the opposite of the Total *p*-value (GRS).

Panel A in Table A10 reports the results for the global, local, and international versions of the Crypto-CAPM model and separately for each of the four categories. The international model performs best overall with the lowest rejection rate and pricing error, as well as the highest average adjusted and constrained R squared. This is not an unexpected finding in international asset pricing tests with partial-segmentation versions (Karolyi and Wu, 2018). Out of the 16 test portfolios, 4 reject the global version, and 3 reject the local version and the international versions, respectively. The Crypto-CAPM model produces a much higher average pricing error (3.1% versus 1.3% for the local model and 1.5% for the international model) and much lower average R squared (0.128 versus 0.198 for the local model and 0.295 for the

[23] Due to the limitation of sample size, all the factors are constructed as follows: the currencies are split into three groups: bottom 30%, middle 40%, and top 30%. Then, we form value-weighted portfolios for each of the three groups and the characteristic-sorted factor is the return difference between the top and the bottom portfolios.

international model). The constrained R squared of the global model performs better than the local model (0.063 vs 0.038 for the local factor model and 0.116 for the international factor model), and the *p*-value of the constrained R squared also shows that the global model performs better. There are 10 significantly positive constrained R squared at the 5% level, and there are 8 for the local and international models, respectively.

Panel B in Table A10 reports the results for the global, local, and international versions of the LTW-3 factor model. Although the global factor model performs worse than the corresponding Crypto-CAPM model, the local and international LTW-3 model significantly increases the explanatory power of the corresponding Crypto-CAPM model. Among the three versions, the local version of LTW-3 model performs better than the international model with a smaller GRS *F*-statistics (1.244 for local vs 1.509 for international), a lower rejection rate in GRS tests (5 reject the global version, 3 reject the local version, and 5 reject the international version), a lower average pricing error (1.7% for the local factor model vs 2.5% for the global factor model and 1.9% for the international factor model) and higher constrained R squared (0.472 for local and 0.365 for international). There are 8, 13, 13 experiments having positive and significant values for constrained R squared, respectively.

Finally, Table 12 reports the results concerning the global, local, and international versions of the C-5 model. All C-5 models improve upon the local and international versions of LTW-3 model. Out of the 16 test portfolios, 5 reject the global version, 6 reject the international version, and 3 reject the local version. The average R squared value, especially for the constrained R squared value, improves by a large margin. Comparing different versions of the C-5 model, we note the global version performs worse and the local version performs best just like the LTW-3 models. The global C-5 model produces a much higher average pricing error (2.5% vs 1.7% for the local model and 2.1% for the international model), a much lower average R squared (0.256 vs 0.326 for the local model and 0.425 for the international model) and constrained R squared (-0.487 vs 0.548 for the local model and 0.468 for the international model). Based on the p values, the global model performs worse with 8 significantly positive constrained R squared at the 5% level, and there are 13 and 12 for the local and international models, respectively.

Focusing on the global version of different factor models, we observe that the global factor model rejections arise when they are challenged to explain the test asset portfolios constructed by the Security Token category. For example, the constrained R squared are all negative for the global LTW-3 factor model and the global C-5 factor model when testing the excess returns of security categories. Among the 605 crypto coins, 511 tokens belong to General Payment Tokens or Platform Tokens, so the global factor models are dominated by them. The rejections indirectly reveal the category segmentation.

In summary, the local C-5 model is the best performing one with low average pricing errors and much higher average adjusted and constrained R squared. We also observe evidence of robust market segmentation in the crypto markets across the token categories. The findings not only validate the categorization proposed in Cong and Xiao (2021), but also inform researchers and policy-makers to carefully consider the categories when it comes to understanding pricing patterns and regulating crypto asset markets.

**6. Time Variation in Factors' Performance and Market Segmentation.**

Figure 1 shows that the cryptocurrency market continued to mature and the market experienced significant volatility over our sample period. Panel A of Figure 1 reports that the number of cryptocurrencis grown rapidly from the mid-2017 and stabilized after early 2018. From Panel B of Figure 1, we can observe that the total market capitalization of cryptocurrencies grown rapidly from mid-2017 to early 2018, driven by a combination of rising prices and climbing number of cryptocurrencies. Then the market fell rapidly. Until early 2020, the market cap picked up again, while the number of cryptocurrencies remained stable. Amid the development and fluctuation of the cryptocurrency market, do the explanatory power of the factor pricing models and the importance of each factor change over time? Are the four categories of crypto assets getting more integrated? In this section, we explore the dynamics of factor models' performance and market segmentation.

*6.1 Dynamics in Fitness of Different Factor Models and Importance of Each Factor.*

Using the omnibus set in section 4.2.1 as the set of test assets, we assess the fitness of Crypto-CAPM, LTW-3, and C-5 models over time. Panel A of Figure 2 reports the average adjusted R squared for 150 rolling-regressions with the rolling window of 104 weeks. We can see that before 2018, the explanatory power of all the three factor models fluctuated; after 2018, the explanatory power improved as a whole. And the C-5 model always has higher adjusted R-squared than Crypto-CAPM and LTW-3 models.

To explore the importance of each factor in the C-5 model over time, we also examine the dynamics of marginal contribution of each factor to the max squared Sharpe ratio. Panel B of Figure 2 shows that before mid-2017, the VAL factor played the most important role in the C-5 factor model, and the importance of SMB and MKT increased gradually. After the mid-2017, the market style changed sharply: the marginal contribution of the VAL factor dropped from more than 30% to less than 5%; the marginal contribution of the SMB factor dominated at around 35%, but gradually declined from January 2018. In the end of 2019, the marginal contribution of all the factors jumped up except the MKT factor, indicating that the market style changed again. The marginal contribution of the VAL factor rebounded to the highest, and the NET factor remained in second or third place after 2020. The marginal contribution of the MKT factor is the lowest, which is close to zero and picked up slightly at the end of 2020.

*6.2 Dynamics in Market Segmentation.*

Similarly, we examine the explanatory power of the local and global factor models over time, to explore whether the four categories are getting more integrated or not. If the relative explanatory power of the global factor model is getting better over time, it suggests that the market segmentation is diminishing.

Using the omnibus set of 16 sets of characteristic-sorted decile portfolios as test assets (4 characteristics × 4 categories), we regress all the 160 test portfolios on the global C-5 model and 40 test portfolios of each category on the corresponding category local C-5 model with the rolling window of 104 weeks to examine the dynamics of explanatory power of the global C-5 factor model and the local C-5 factor models, respectively. Panel A of Figure 3 shows that the average adjusted R squared of the local C-5 model decreased continuously, while that of the global C-5 model increased before 2020, and the difference between them is converging, which indicates that different categories may get more integrated as the market matures.

To test the time variation in importance of different factors in the overall market, we report the marginal contributions of each factor of the global C-5 model in Panel B of Figure 3. The dynamics of each factor of the global C-5 model constructed by the Core Sample is similar with that of the C-5 model constructed by the Full Sample. Panel B of Figure 3 shows that for the global C-5 model, the marginal contribution of the NET factor increased rapidly after 2020, growing to the largest of all the five factors within few months. We further explore factor contributions of local factor models based on each category and report the results in Panel C of Figure 3. The SMB factor plays an important role in all the four categories. In addition, the dynamic track of the marginal contributions of the SMB, VAL, and MOM factors, which are constructed by market trading data, shows some degree of consistency across all categories. However, the importance of the NET factors has a clear and persistent divergence across different categories. In the category of General Payment Token, the marginal contribution of the NET factor remained 2% before 2019 and rebounded to 2% again at the end of 2020. For Platform Token, the marginal contribution of the NET factor jumped to around 9% after 2020 and has remained high since then. But for the Product Token and Security Token, the marginal contribution of the NET factor is close to zero consistently. The importance of the NET factor in the Product Token increased slightly from October 2020.

Considering the number of tokens in the platform category (483) is much larger than the number of tokens in the other three categories (26-72), we further conduct 100 random subsamplings of 50 tokens from the platform category to exclude the influence of the dominant sample size of the Platform Token. Using the random subsamplings of Platform Token, we redo the tests of average adjusted R squared of global and local factor models and marginal contributions of different factors for 100 times, taking the average of the 100 results, and show the average results in the Internet Appendix in Figure A1. Panel A of Figure A1 shows that the difference in average adjusted R squared between the global and local model decreased gradually, and the global model even surpassed the local model from the end of September 2020 to the midterm of November 2020. Panel B and C show the factors' marginal contributions in the global model and four category local models. The NET factor still plays an important role in Platform Token with a relative large marinal contribution. Overall, the bootstrap test shows that the persistent differentiation of the importance of the NET factor across different categories and the gradual intergration of the whole market are robust.

**7. Conclusion.**

We examine characteristics-based return patterns in the cross-section of over 4,000 cryptocurrencies and tokens, including recent ones used in DeFi projects. To the best of our understanding, this study adds to the foundational work on the topic (e.g., Liu, Tsyvinski, and Wu, 2022 and Liu and Tsyvinski, 2021) and provides the most comprehensive analysis of the cross-section of crypto asset returns to date. We document crypto value and network adoption premia and propose a five-factor model (C-5) for pricing crypto assets, adding the novel value and network factors to the cryptocurrency version of the market, size, and momentum factors. The C-5 model performs better than alternative factor pricing models when tested on various portfolios and when using various criteria for asset pricing model selection. In addition, we provide the first systematic categorization of cryptocurrencies based on their economic functionality and find robust market segmentation across categories, which has implications for cryptocurrency investment and regulation. We believe that the factors and token categories we dynamically and frequently update will facilitate future empirical studies on crypto assets.

There lacks consensus on re-evaluating asset pricing with illiquidity in general, and one needs some state variables to capture market illiquidity in crypto assets. Intuitively, a crypto asset's required return depends on its expected liquidity as well as on the covariances of its own return and liquidity with the market return and liquidity. It, therefore, constitutes interesting future research to extend our model to incorporate transaction costs and illiquidity in the spirit of Pastor and Stambaugh (2003) and Acharya and Pedersen (2005).

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**Figure 1. Aggregate Statistics of the Full Sample and the Core Sample**

This figure shows the aggregate statistics of both the Full Sample containing 4007 cryptocurrencies and the Core Sample containing 616 cryptocurrencies after applying the filters described in Section 2. Panel A shows the weekly number of cryptocurrencies of both samples. Panel B shows the daily market capitalization of both samples. Panel C presents the market capitalization ratio of the Core Sample to the Full Sample.

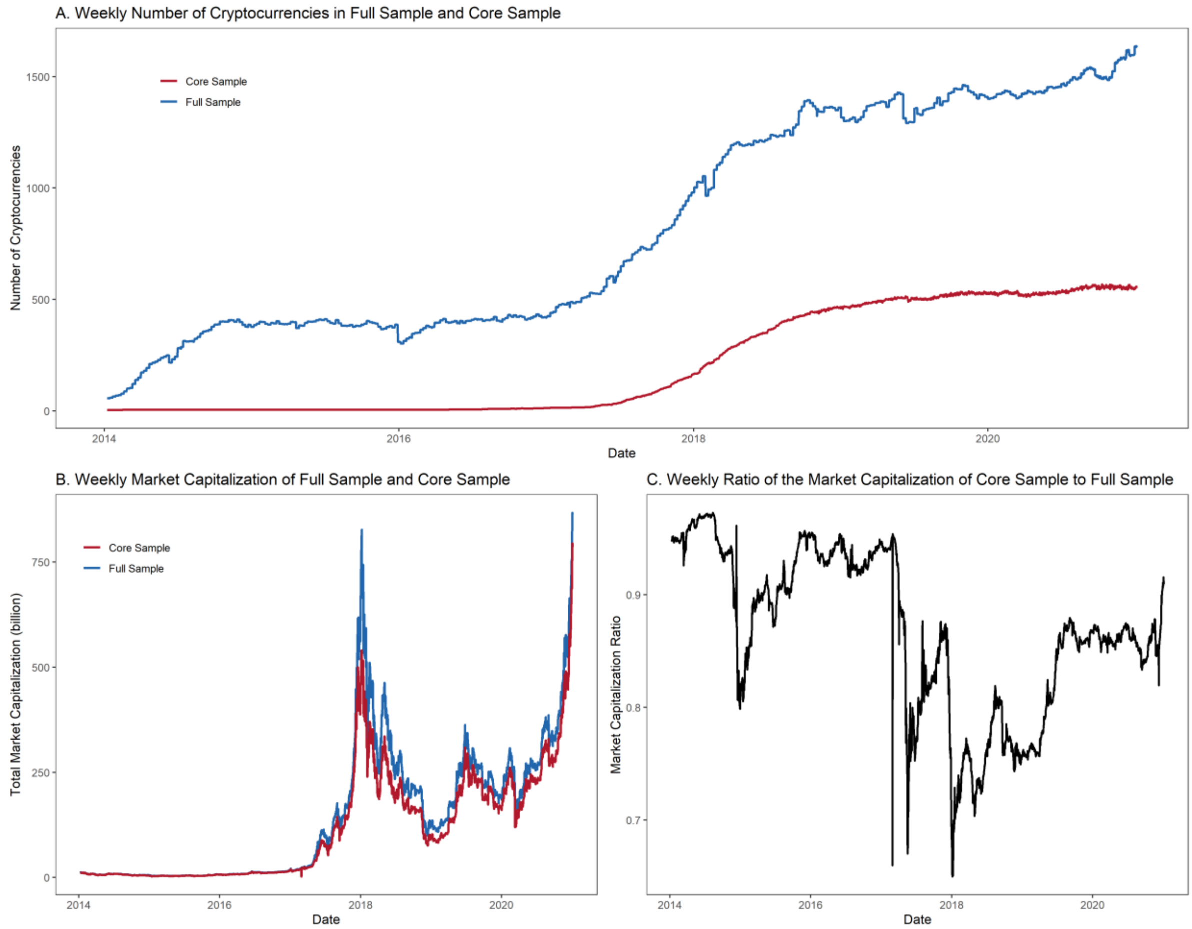
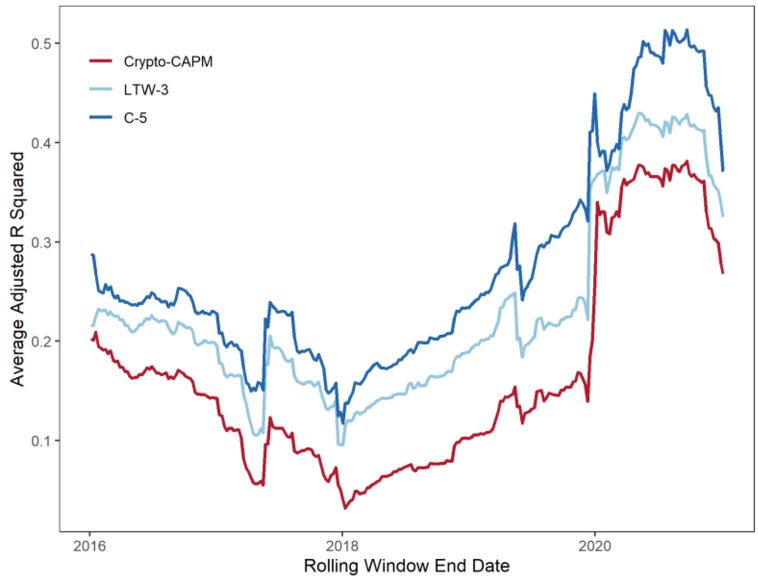


**Figure 2. Dynamics of Factor Models' Explanatory Power and Importance of Each Factor**

This figure reports the dynamics of explanatory power of three different factor models and the importance of each factor in the C-5 model. Panel A plots the average adjusted R squared for the 150 rolling regressions of the omnibus set of test assets on three different factor models, Crypto-CAPM, LTW-3, and C-5, respectively. Panel B plots factor marginal contributions to maximum squared sharpe ratios of C-5 model over time. The rolling window is 104 weeks.

A. Time Series of Average Adjusted R Squared for Different Factor Models




B. Time Series of the C-5 Model's Factor Marginal Contributions

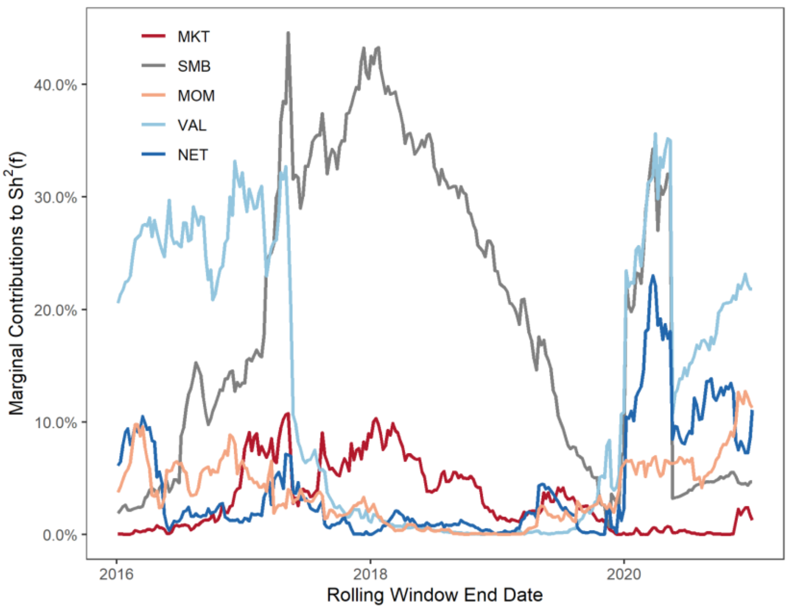
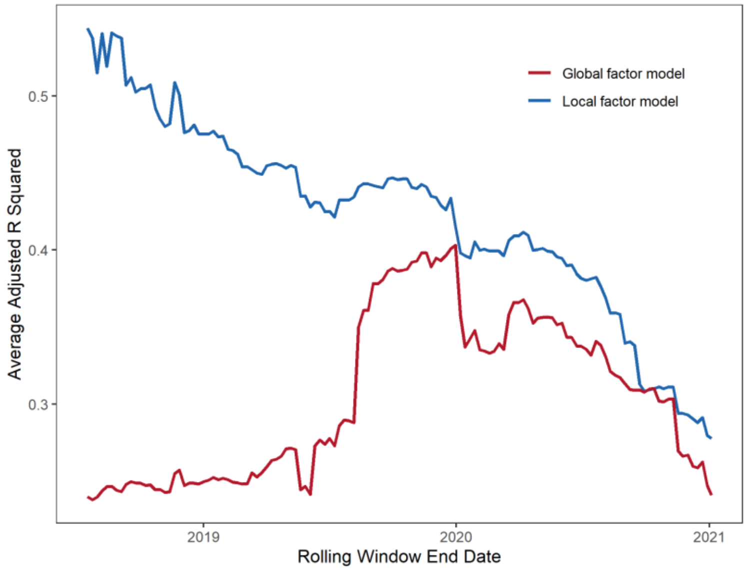


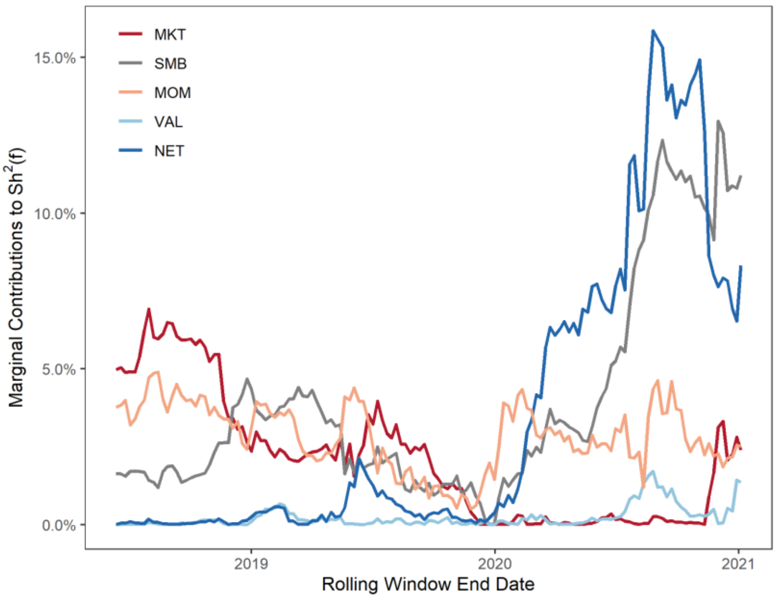
**Figure 3. Dynamics in Market Segmentation**

This figure shows the dynamics of the market segmentation. Panel A plots the average adjusted R squared for the 160 rolling regressions on global and local C-5 factor models. The set of test assets contains 16 groups of decile portfolios formed on size, value, momentum and network in General Payment, Platform Token, Product Token and Security Token. Panel B plots factor marginal contributions to maximum squared sharpe ratios of the global C-5 model over time. Panel C plots factor marginal contributions to maximum squared sharpe ratios of the local C-5 model for each category.

A. Time Series of Average Adjusted R Squared for Global and Local C-5 Factor Models




B. Time Series of the Global C-5 Model's Factor Marginal Contributions



C. Time Series of the Local C-5 Model's Factor Marginal Contributions

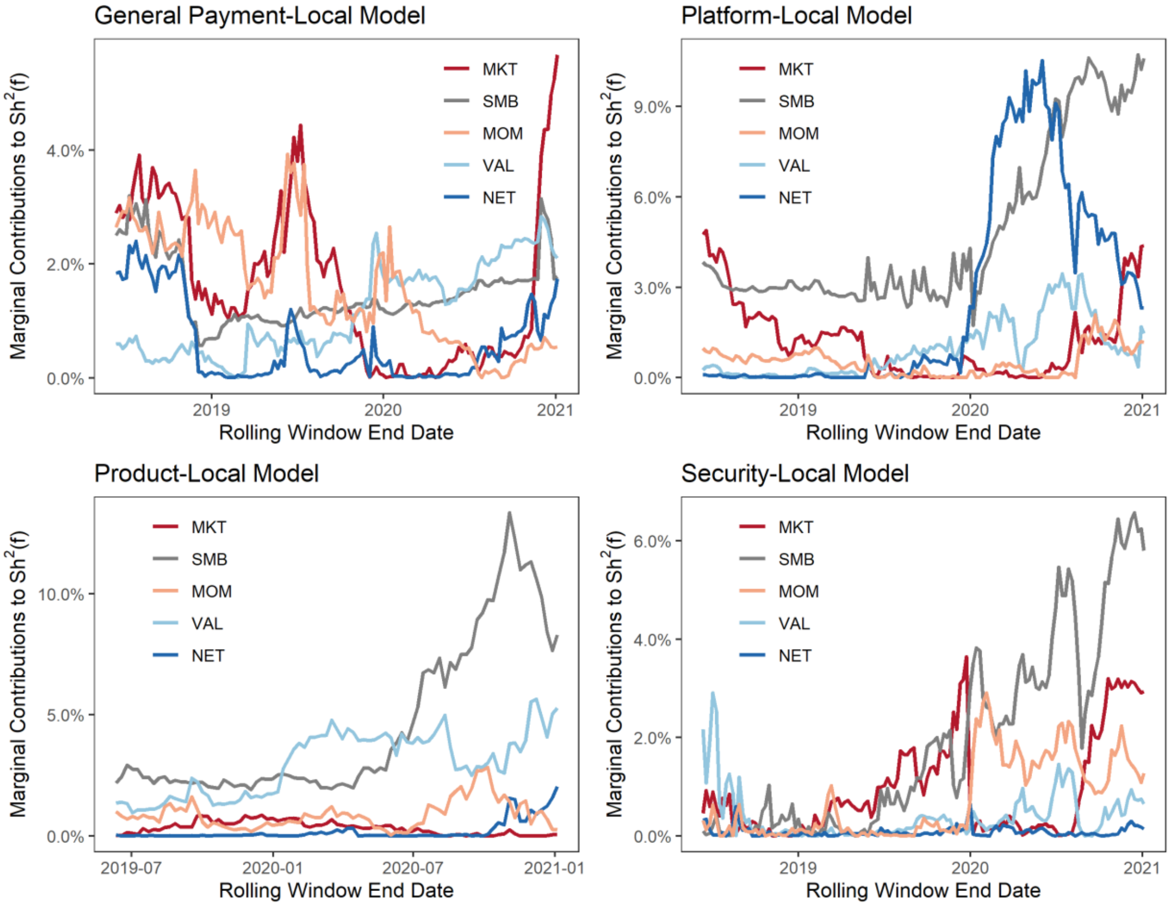


**Table 1. Summary Statistics of Full Sample and Core Sample**

This table summarizes the two datasets used in this paper. Full Sample refers to the 4007 cryptocurrencies sample and Core Sample refers to the 616 cryptocurrencies sample described in Section 2. Panel A reports the number of cryptocurrencies, the time series average of value-weighted daily returns and the year-end total market capitalization of all cryptocurrencies in each sample by year. Also, we present the ratio of the total market capitalization of the Core Sample to that of the Full Sample. At the end of each week, coins in Full Sample are split into five quintiles according to week-end market capitalization. Panel B reports the time-series averages of cross-sectional value-weighted averages of various coin characteristics for cryptocurrencies in five size quintiles sorted by market capitalization and constructed by the Full Sample at the end of each week. **Min**, **Max**, **Skewness** and **Kurtosis** are the minimum, maximum, skewness and kurtosis of daily market capitalization in the portfolio formation week, respectively. **Volume** is the trading volume at the end of each week. **Volatility** is the standard deviation of daily returns in the portfolio formation week in percentages. Panel C reports the time-series averages of cross-sectional averages of various coin characteristics for cryptocurrencies in the Core Sample. The sample period is from 2014/01/01 to 2021/01/04 for the Full Sample, and from 2014/01/22 to 2021/01/04 for the Core Sample.

Panel A: Number of Cryptocurrencies in the Sample Over Time

| | Full Sample | | | Core Sample | | | Ratio |
|---|---|---|---|---|---|---|---|
| | Number | VW Daily Returns | Market Capitalization | Number | VW Daily Returns | Market Capitalization | |
| 2014 | 713 | 0.0272 | 5,590,775,513.86 | 4 | -0.0016 | 4,501,213,557.62 | 80.51% |
| 2015 | 798 | 0.0017 | 7,071,231,742.81 | 5 | 0.0016 | 6,730,120,499.22 | 95.18% |
| 2016 | 819 | 0.0038 | 17,679,151,572.41 | 13 | 0.0035 | 16,685,064,386.58 | 94.38% |
| 2017 | 1217 | 0.0175 | 613,829,894,279.19 | 164 | 0.0116 | 420,271,935,036.29 | 68.47% |
| 2018 | 2055 | -0.0019 | 123,266,270,405.90 | 473 | -0.0018 | 93,148,343,463.62 | 75.57% |
| 2019 | 2290 | 0.0029 | 190,527,053,662.33 | 558 | 0.0027 | 164,677,505,319.75 | 86.43% |
| 2020 | 2585 | 0.0082 | 759,675,660,931.37 | 613 | 0.0053 | 686,635,739,073.18 | 90.39% |
| Total | 4007 | | | 616 | | | |

Panel B: Cryptocurrency Characteristics of Size Portfolios Constructed by the Full Sample

| Size Quintile | Min | Max | Skewness | Kurtosis | Volume | Volatility |
|---|---|---|---|---|---|---|
| Small | 1,438.87 | 129,088.50 | 0.399 | 2.051 | 17,992.11 | 0.274 |
| 2 | 130,598.11 | 636,696.50 | 0.456 | 2.080 | 41,050.52 | 0.241 |
| 3 | 641,492.94 | 2,460,081.00 | 0.431 | 2.027 | 123,619.40 | 0.175 |
| 4 | 2,478,359.24 | 10,085,580.00 | 0.659 | 2.341 | 555,128.10 | 0.148 |
| Big | 10,210,124.00 | 79,132,000,000.00 | 11.150 | 143.442 | 5,716,679,000.00 | 0.040 |

Panel C: Cryptocurrency Characteristics of Core Sample

| | Min | Max | Skewness | Kurtosis | Volume | Volatility |
|---|---|---|---|---|---|---|
| Core Sample | 6,491,659.00 | 78,940,900,000.00 | 9.977 | 187.902 | 6,621,632,000.00 | 0.037 |

**Table 2. Summary Statistics of Returns of Size-based Cryptocurrency Portfolios (2014/01/01-2021/01/04, 366 weeks)**

This table reports the mean weekly excess returns of ten deciles sorted by the size characteristic, the week-end market capitalization. Decile 1 (10) includes the 10% cryptocurrencies with the lowest (highest) market capitalization (MarketCap) and a long-short portfolio High-Low that buys cryptocurrencies in decile 10 and shorts cryptocurrencies in decile 1 is also constructed at the same time. Each portfolio is then held for 1 week. We both test the cross-sectional size excess returns of the Full Sample and the Large Cap Sample. Mean is the average weekly value-weighted returns of each portfolio, and t(Mean) is the ratio of Mean to its standard error, which is adjusted for heteroskedasticity and autocorrelations. The sample period is from 2014/01/01 to 2021/01/04.

| | (1) Full sample | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 10-1 |
| **MarketCap** | **Low** | | | | | | | | | **High** | |
| Mean | 0.486 | 0.135 | 0.100 | 0.263 | 0.062 | 0.046 | 0.034 | 0.026 | 0.011 | 0.015 | -0.471 |
| t(Mean) | 3.086 | 9.465 | 5.575 | 1.729 | 4.532 | 3.531 | 2.548 | 2.282 | 1.108 | 1.591 | -3.016 |
| | (2) Large Cap Sample | | | | | | | | | | |
| **MarketCap** | **Low** | | | | | | | | | **High** | |
| Mean | 0.026 | 0.026 | 0.018 | 0.021 | 0.015 | 0.005 | 0.011 | 0.005 | 0.027 | 0.017 | -0.010 |
| t(Mean) | 1.898 | 1.755 | 1.159 | 1.367 | 1.428 | 0.384 | 1.030 | 0.483 | 1.827 | 1.576 | -0.872 |

**Table 3. Excess Returns for Momentum Single Sorted and Size-Momentum Double Sorted Portfolios (2014/01/01-2021/01/04, 366 weeks)**

Each week, we construct 10 momentum single sorted portfolios and 25 size-momentum double sorted portfolios. In a single sort, we split cryptocurrencies into deciles according to 2-week momentum. Decile 1 (10) includes the 10% cryptocurrencies with the lowest (highest) 2-week momentum. In double sort, at the end of each week, we break cryptocurrencies into five size groups using the breakpoints for the quintiles of the ranked Market Cap and form 25 size-momentum portfolios by independently and dependently splitting cryptocurrencies into five momentum quintiles according to the ranking of ret-2 week. Quintile 1 (5) includes the 20% cryptocurrencies with the lowest (highest) ret-2 week, and a long-short portfolio momentum 5-1 that buys cryptocurrencies in momentum quintile 5 and shorts cryptocurrencies in momentum quintile 1 is also constructed within each size quintile at the same time. Each portfolio is then held for 1 week and all the portfolio returns are value-weighted. Panel A reports mean excess return and their t-statistics for single sorted portfolios constructed by both the Full Sample and the Large Cap Sample. Panel B reports mean excess return and their t-statistics for 25 independently size-momentum portfolios and 5 long-short portfolios. Panel C reports mean excess return and their t-statistics for 25 dependently size-momentum portfolios and 5 long-short portfolios. Mean is the average weekly value-weighted returns of each portfolio, and t(Mean) is the ratio of Mean to its standard error, which is adjusted for heteroskedasticity and autocorrelations. The sample period is from 2014/01/01 to 2021/01/04.

Panel A: Independent Single Sort

(1) Full sample

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 10-1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Momentum** | **Low** | | | | | | | | | **High** | |
| Mean | 0.054 | 0.012 | 0.012 | 0.005 | 0.006 | 0.027 | 0.013 | 0.031 | 0.028 | 0.031 | -0.024 |
| t(Mean) | 1.953 | 1.111 | 1.195 | 0.411 | 0.640 | 1.928 | 1.496 | 2.560 | 2.278 | 1.983 | -0.815 |

(2) Large Cap Sample

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 10-1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Momentum** | **Low** | | | | | | | | | **High** | |
| Mean | -0.018 | 0.002 | 0.008 | 0.006 | 0.014 | 0.022 | 0.007 | 0.019 | 0.022 | 0.036 | 0.054 |
| t(Mean) | -1.703 | 0.269 | 0.793 | 0.482 | 1.449 | 1.873 | 0.807 | 1.849 | 2.063 | 2.298 | 4.074 |

Panel B: Independent Double Sorts

| | Mean | | | | | | t-statistic | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Low** | 2 | 3 | 4 | **High** | H-L | **Low** | 2 | 3 | 4 | **High** | H-L |
| Small | 0.265 | 0.106 | 0.099 | 0.086 | 0.070 | -0.195 | 10.024 | 6.070 | 5.988 | 4.713 | 2.865 | -5.658 |
| 2 | 0.460 | 0.088 | 0.047 | 0.050 | 0.118 | -0.343 | 1.467 | 4.223 | 3.182 | 3.016 | 1.565 | -1.065 |
| 3 | 0.101 | 0.053 | 0.067 | 0.030 | 0.005 | -0.096 | 6.721 | 2.829 | 2.900 | 2.470 | 0.432 | -8.100 |
| 4 | 0.055 | 0.027 | 0.021 | 0.023 | 0.010 | -0.045 | 4.865 | 2.408 | 1.552 | 1.894 | 0.641 | -3.342 |
| Big | -0.007 | 0.004 | 0.014 | 0.022 | 0.034 | 0.041 | -0.592 | 0.442 | 1.783 | 2.261 | 2.575 | 3.200 |

**Table 3. Excess Returns for Momentum Single Sorted and Size-Momentum Double Sorted Portfolios (2014/01/01-2021/01/04, 366 weeks)** (continued)

| Panel C: Sequential Double Sorts | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | | | | | | t-statistic | | | | | |
| | **Low** | 2 | 3 | 4 | **High** | H-L | **Low** | 2 | 3 | 4 | **High** | H-L |
| Small | 0.330 | 0.145 | 0.092 | 0.090 | 0.074 | -0.257 | 9.771 | 7.587 | 6.528 | 5.213 | 2.880 | -6.173 |
| 2 | 0.650 | 0.104 | 0.047 | 0.057 | 0.113 | -0.537 | 1.310 | 4.281 | 3.623 | 3.231 | 1.325 | -1.065 |
| 3 | 0.100 | 0.057 | 0.062 | 0.024 | 0.008 | -0.092 | 6.260 | 2.997 | 2.698 | 2.085 | 0.646 | -7.080 |
| 4 | 0.046 | 0.031 | 0.027 | 0.019 | 0.010 | -0.036 | 4.365 | 2.677 | 1.849 | 1.676 | 0.643 | -3.200 |
| Big | -0.005 | 0.002 | 0.010 | 0.020 | 0.033 | 0.038 | -0.503 | 0.183 | 1.210 | 2.167 | 2.712 | 3.929 |

**Table 4. Excess Returns for Value Single Sorted and Size-Value Double Sorted Portfolios (2014/01/01-2021/01/04, 366 weeks)**

This table presents the results of the first type proxy of value, which is the long-term past performance measure: the negative of the past 52-week return. For this type, each week, we construct 10 value single sorted portfolios and 25 size-value double sorted portfolios. In a single sort, we split cryptocurrencies into deciles according to the value indicator, the negative of the past 52-week return ("NPast52"). Decile 1 (10) includes the 10% cryptocurrencies with the highest(lowest) NPast52. In double sort, at the end of each week, we break cryptocurrencies into five size groups using the breakpoints for the quintiles of the ranked Market Capitalization and form 25 size-value portfolios by independently and dependently splitting cryptocurrencies into five value quintiles according to the ranking of NPast52. Quintile 1 (5) includes the 20% cryptocurrencies with the lowest (highest) NPast52, and a long-short portfolio value 5-1 that buys cryptocurrencies in value quintile 5 and shorts cryptocurrencies in value quintile 1 is also constructed within each size quintile at the same time. Each portfolio is then held for 1 week and all the portfolio returns are value-weighted. Panel A reports mean excess return and their t-statistics for single sorted portfolios constructed by both the Full Sample and the Large Cap Sample. Panel B reports mean excess return and their t-statistics for 25 independently size-value portfolios and 5 long-short portfolios. Panel C reports mean excess return and their t-statistics for 25 dependently size-value portfolios and 5 long-short portfolios. Mean is the average weekly value-weighted returns of each portfolio, and t(Mean) or t-statistic is adjusted for heteroskedasticity and autocorrelations. The sample period is from 2014/01/01 to 2021/01/04.

Panel A: Independent Single Sort

| | (1) Full sample | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 10-1 |
| **Value** | **Low** | | | | | | | | | **High** | |
| Mean | 0.011 | 0.024 | 0.009 | 0.021 | 0.030 | 0.016 | 0.017 | 0.037 | 0.036 | 0.068 | 0.057 |
| t(Mean) | 1.206 | 2.137 | 1.178 | 1.723 | 2.581 | 1.330 | 1.688 | 2.747 | 2.973 | 2.997 | 2.712 |
| | (2) Large Cap Sample | | | | | | | | | | |
| **Value** | **Low** | | | | | | | | | **High** | |
| Mean | 0.012 | 0.015 | 0.010 | 0.019 | 0.007 | 0.019 | 0.025 | 0.023 | 0.011 | 0.030 | 0.017 |
| t(Mean) | 1.083 | 1.649 | 0.867 | 1.841 | 0.705 | 1.609 | 2.696 | 1.868 | 1.246 | 2.415 | 1.437 |

Panel B: Independent Double Sorts

| | Mean | | | | | | t-statistic | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Low** | 2 | 3 | 4 | **High** | H-L | **Low** | 2 | 3 | 4 | **High** | H-L |
| Small | 0.039 | 0.058 | 0.073 | 0.175 | 0.190 | 0.151 | 2.496 | 3.894 | 4.286 | 3.894 | 4.197 | 3.892 |
| 2 | 0.019 | 0.062 | 0.175 | 0.071 | 0.111 | 0.092 | 1.376 | 3.302 | 1.634 | 4.655 | 6.148 | 5.233 |
| 3 | 0.052 | 0.036 | 0.078 | 0.050 | 0.078 | 0.026 | 3.219 | 2.758 | 2.775 | 3.352 | 5.009 | 1.679 |
| 4 | 0.014 | 0.024 | 0.025 | 0.033 | 0.041 | 0.027 | 1.221 | 2.413 | 1.906 | 2.191 | 3.064 | 2.768 |
| Big | 0.018 | 0.013 | 0.022 | 0.017 | 0.026 | 0.008 | 1.941 | 1.464 | 2.193 | 1.761 | 2.252 | 0.904 |

**Table 4. Excess Returns for Value Single Sorted and Size-Value Double Sorted Portfolios (2014/01/01-2021/01/04, 366 weeks)** (continued)

| Panel C: Sequential Double Sorts | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | | | | | | t-statistic | | | | | |
| | **Low** | 2 | 3 | 4 | **High** | H-L | **Low** | 2 | 3 | 4 | **High** | H-L |
| Small | 0.047 | 0.079 | 0.154 | 0.142 | 0.248 | 0.201 | 3.301 | 5.141 | 3.871 | 6.976 | 3.551 | 3.176 |
| 2 | 0.030 | 0.060 | 0.185 | 0.095 | 0.110 | 0.081 | 1.825 | 3.085 | 1.480 | 4.601 | 5.485 | 4.275 |
| 3 | 0.051 | 0.036 | 0.077 | 0.048 | 0.075 | 0.024 | 3.188 | 2.636 | 2.954 | 3.198 | 4.783 | 1.727 |
| 4 | 0.010 | 0.019 | 0.021 | 0.025 | 0.041 | 0.031 | 0.840 | 1.634 | 1.858 | 1.845 | 2.457 | 2.396 |
| Big | 0.013 | 0.021 | 0.019 | 0.021 | 0.018 | 0.004 | 1.513 | 1.973 | 1.998 | 2.041 | 1.860 | 0.540 |

**Table 5. Excess Returns for Network Portfolios (2014/01/22-2021/01/04, 363 weeks)**

Each week, we construct 5 network single sorted portfolios based on the Core Sample containing 616 cryptocurrencies. Due to the limitation of sample size, we split cryptocurrencies into quintiles according to the weekly growth rate of total addresses with balance, BAgrowth, and of total addresses, TAgrowth. Quintile 1 (5) includes the 20% cryptocurrencies with the lowest(highest) BAgrowth or TAgrowth. And a long-short portfolio network 5-1 that buys cryptocurrencies in network quintile 5 and shorts cryptocurrencies in network quintile 1 is also constructed at the same time. Each portfolio is then held for 1 week and all the portfolio returns are value-weighted. Mean is the average weekly value-weighted returns of each portfolio, and t(Mean) or t-statistic is adjusted for heteroskedasticity and autocorrelations. The sample period is from 2014/01/22 to 2021/01/04.

| | Core Sample | | | | | |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 5-1 |
| **BAgrowth** | **Low** | | | | **High** | |
| Mean | 0.008 | 0.013 | 0.015 | 0.018 | 0.048 | 0.040 |
| t(Mean) | 0.847 | 1.444 | 1.528 | 2.003 | 2.929 | 2.846 |
| **TAgrowth** | **Low** | | | | **High** | |
| Mean | 0.014 | 0.013 | 0.021 | 0.006 | 0.043 | 0.028 |
| t(Mean) | 1.529 | 1.249 | 1.864 | 0.929 | 2.544 | 2.030 |

**Table 6. Summary Statistics of Factor Returns (2014/01/22-2021/01/04, 363 weeks)**

This table presents the summary statistics of six factors, **MKT**, **SMB**, **MOM, REV, VAL**, and **NET**, and correlations among them. **MKT**, **SMB, MOM, REV,** and **VAL** factors are constructed by the Full sample, and the **NET** factor is constructed by the Core Sample. The **SMB** and **VAL** factor are constructed as follows: each week, cryptocurrencies are independently sorted into 3 value portfolios and 2 size portfolios. The three value portfolios are low (bottom 30% value), neutral (middle 40% value), and high (top 30% value) cryptocurrencies, and the two size portfolios are small (bottom 50%) and big (top 50%) cryptocurrencies. The independent 2×3 sorts on size and value produce six value-weighted portfolios. **SMB** is the equal-weight average of the returns on the three small cryptocurrency portfolios minus the average of the returns on the three big cryptocurrency portfolios. **VAL** is the equal-weight average of the return difference of the high and low portfolios within small and big groups of cryptocurrencies. The **MOM** and **REV** factors are constructed as follows: each week, all cryptocurrencies in the Full Sample are independently split into two [80% smallest, 20% largest] size portfolios of the ranked market capitalization, and three [30% lowest, 40% middle, 30% highest] momentum portfolios by the past 2-week returns. **MOM** is the return difference between the highest and the lowest past 2-week return portfolios in the largest size group, and **REV** is the return difference in the smallest group. Due to the limitation of the sample size, each week we split the cryptocurrencies into three network groups: bottom 30%, middle 40%, and top 30%. Then, we form value-weighted portfolios for each of the three network groups. The network factor (**NET**) is the return difference between the top and the bottom network portfolios. **MKT** is the return of the market index minus the one-month Treasury bill rate. Panel A reports the summary statistics of four factors' weekly returns during the sample period. Panel B reports the correlations among the four factors' weekly returns during the sample period. To meet the period of the Core Sample, the sample period is from 2014/01/22 to 2021/01/04.

| Panel A: Summary statistics of factors | | | | | | |
|---|---|---|---|---|---|---|
| | MKT | SMB | MOM | REV | VAL | NET |
| Mean | 0.02 | 0.05 | 0.03 | -0.06 | 0.04 | 0.04 |
| Std | 0.01 | 0.01 | 0.01 | 0.02 | 0.01 | 0.01 |
| t-statistics | 2.39 | 4.57 | 3.29 | -2.73 | 5.63 | 2.82 |
| Panel B: Factor Correlation | | | | | | |
| | MKT | SMB | MOM | REV | VAL | NET |
| MKT | 1.00 | 0.03 | 0.06 | 0.04 | -0.04 | 0.06 |
| SMB | 0.03 | 1.00 | -0.03 | 0.15 | 0.07 | 0.04 |
| MOM | 0.06 | -0.03 | 1.00 | 0.08 | -0.08 | 0.06 |
| REV | 0.04 | 0.15 | 0.08 | 1.00 | -0.11 | 0.02 |
| VAL | -0.04 | 0.07 | -0.08 | -0.11 | 1.00 | 0.03 |
| NET | 0.06 | 0.04 | 0.06 | 0.02 | 0.03 | 1.00 |

**Table 7. Summary Asset Pricing tests for Single sorted and Double sorted Portfolios (2014/01/22-2021/01/04, 363 weeks)**

The table shows summary tests of different asset pricing models for In-Sample and Out-of-Sample test asset portfolios. Panel A reports the GRS statistic, which tests whether the expected values of all intercept estimates in the regressions are zero. Also shown are: Panel B, $A|a|$, the average absolute value of the intercepts; Panel C, $AR^2$, the average of the regression $R^2$, adjusted for degrees of freedom; Panel D, $R_C^2$, which denotes the constrained $R^2$ in which the risk price estimates are constrained to be equal to the factor sample means in two-pass regressions. To meet the period of the Core Sample, the sample period is from 2014/01/22 to 2021/01/04.

| | In-Sample | | | | | | Out-of-Sample | | | | | | All |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Market Cap | ret-2week | NPast52 | BAgrowth | Size-Mom | Size-Value | PRC | MAXPRC | VaR | IVOL | ILLIQ | CoreSet | |
| Panel A: GRS | | | | | | | | | | | | | |
| MKT | 18.337 | 2.592 | 2.646 | 1.399 | 14.239 | 5.563 | 1.157 | 1.004 | 1.531 | 0.734 | 1.295 | 1.476 | 3.765 |
| MKT_LTW, SMB_LTW, MOM_LTW | 18.163 | 2.361 | 2.500 | 1.367 | 13.979 | 5.628 | 1.051 | 0.881 | 1.356 | 0.768 | 1.262 | 1.213 | 3.700 |
| MKT, SMB, MOM | 14.358 | 1.222 | 2.758 | 1.250 | 11.618 | 4.091 | 0.905 | 0.629 | 1.200 | 1.886 | 1.077 | 0.880 | 3.228 |
| MKT, SMB, REV | 17.594 | 2.208 | 2.066 | 1.473 | 11.414 | 4.218 | 2.027 | 0.609 | 3.958 | 1.328 | 0.892 | 1.430 | 3.244 |
| MKT, SMB, VAL | 13.088 | 2.197 | 1.008 | 1.596 | 11.271 | 3.038 | 1.327 | 0.794 | 2.285 | 1.964 | 1.024 | 1.151 | 3.102 |
| MKT, SMB, NET | 14.341 | 1.863 | 2.553 | 0.190 | 11.986 | 4.145 | 0.904 | 0.633 | 1.165 | 1.702 | 1.121 | 0.888 | 3.315 |
| MKT, SMB, VAL, MOM | 12.375 | 1.018 | 1.030 | 1.510 | 10.496 | 2.812 | 1.146 | 0.645 | 1.848 | 1.994 | 1.046 | 0.840 | 2.922 |
| MKT, SMB, VAL, REV | 16.054 | 2.224 | 0.935 | 1.795 | 10.726 | 3.181 | 2.852 | 1.221 | 4.582 | 1.483 | 0.921 | 1.392 | 3.005 |
| MKT, SMB, VAL, NET | 12.619 | 1.921 | 1.033 | 0.669 | 11.028 | 2.995 | 1.500 | 0.999 | 2.002 | 1.894 | 1.207 | 0.892 | 3.045 |
| MKT, SMB, VAL, MOM, NET | 12.009 | 0.902 | 1.084 | 0.620 | 10.330 | 2.782 | 1.313 | 0.819 | 1.624 | 1.941 | 1.226 | 0.622 | 2.880 |
| MKT, SMB, VAL, MOM, REV | 15.194 | 0.934 | 0.946 | 1.796 | 9.893 | 2.960 | 2.178 | 0.844 | 4.262 | 1.522 | 0.906 | 1.052 | 2.817 |
| MKT, SMB, VAL, REV, NET | 15.701 | 1.951 | 0.946 | 0.882 | 10.483 | 3.137 | 3.183 | 1.513 | 4.428 | 1.435 | 1.047 | 1.097 | 2.957 |
| MKT, SMB, VAL, MOM, REV, NET | 14.945 | 0.830 | 0.988 | 0.913 | 9.728 | 2.926 | 2.508 | 1.105 | 4.158 | 1.492 | 1.031 | 0.804 | 2.784 |

**Table 7. Summary Asset Pricing tests for Single sorted and Double sorted Portfolios (2014/01/22-2021/01/04, 363 weeks)** (continued)

| | In-Sample | | | | | | Out-of-Sample | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Market Cap | ret-2week | NPast52 | BAgrowth | Size-Mom | Size-Value | PRC | MAXPRC | VaR | IVOL | ILLIQ | CoreSet | All |
| Panel B: $A|\alpha|$ | | | | | | | | | | | | | |
| MKT | 0.111 | 0.010 | 0.016 | 0.007 | 0.067 | 0.048 | 0.024 | 0.020 | 0.030 | 0.013 | 0.015 | 0.010 | 0.036 |
| MKT_LTW, SMB_LTW, MOM_LTW | 0.108 | 0.007 | 0.015 | 0.006 | 0.066 | 0.045 | 0.020 | 0.016 | 0.029 | 0.013 | 0.013 | 0.008 | 0.034 |
| MKT, SMB, MOM | 0.092 | 0.006 | 0.015 | 0.008 | 0.067 | 0.040 | 0.018 | 0.012 | 0.025 | 0.015 | 0.011 | 0.008 | 0.032 |
| MKT, SMB, REV | 0.110 | 0.011 | 0.013 | 0.008 | 0.067 | 0.039 | 0.017 | 0.010 | 0.035 | 0.009 | 0.010 | 0.007 | 0.033 |
| MKT, SMB, VAL | 0.061 | 0.012 | 0.007 | 0.008 | 0.050 | 0.028 | 0.014 | 0.008 | 0.023 | 0.023 | 0.011 | 0.006 | 0.025 |
| MKT, SMB, NET | 0.087 | 0.009 | 0.014 | 0.002 | 0.062 | 0.038 | 0.015 | 0.010 | 0.022 | 0.017 | 0.011 | 0.005 | 0.030 |
| MKT, SMB, VAL, MOM | 0.062 | 0.007 | 0.007 | 0.008 | 0.052 | 0.029 | 0.015 | 0.006 | 0.022 | 0.019 | 0.011 | 0.005 | 0.024 |
| MKT, SMB, VAL, REV | 0.096 | 0.012 | 0.007 | 0.008 | 0.066 | 0.028 | 0.021 | 0.010 | 0.041 | 0.015 | 0.011 | 0.006 | 0.031 |
| MKT, SMB, VAL, NET | 0.059 | 0.011 | 0.007 | 0.005 | 0.048 | 0.028 | 0.014 | 0.008 | 0.020 | 0.023 | 0.011 | 0.006 | 0.024 |
| MKT, SMB, VAL, MOM, NET | 0.061 | 0.008 | 0.007 | 0.005 | 0.050 | 0.029 | 0.014 | 0.006 | 0.020 | 0.019 | 0.012 | 0.004 | 0.023 |
| MKT, SMB, VAL, MOM, REV | 0.094 | 0.007 | 0.007 | 0.008 | 0.066 | 0.029 | 0.018 | 0.008 | 0.039 | 0.011 | 0.011 | 0.005 | 0.030 |
| MKT, SMB, VAL, REV, NET | 0.097 | 0.012 | 0.007 | 0.005 | 0.067 | 0.028 | 0.021 | 0.011 | 0.041 | 0.014 | 0.012 | 0.006 | 0.031 |
| MKT, SMB, VAL, MOM, REV, NET | 0.095 | 0.007 | 0.007 | 0.005 | 0.067 | 0.029 | 0.019 | 0.008 | 0.039 | 0.013 | 0.012 | 0.004 | 0.030 |

**Table 7. Summary Asset Pricing tests for Single sorted and Double sorted Portfolios (2014/01/22-2021/01/04, 363 weeks)** (continued)

| | In-Sample | | | | | | Out-of-Sample | | | | | | All |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Market Cap | ret-2week | NPast52 | BAgrowth | Size-Mom | Size-Value | PRC | MAXPRC | VaR | IVOL | ILLIQ | CoreSet | |
| Panel C: $AR^2$ | | | | | | | | | | | | | |
| MKT | 0.105 | 0.147 | 0.150 | 0.253 | 0.096 | 0.095 | 0.084 | 0.086 | 0.030 | 0.123 | 0.130 | 0.232 | 0.127 |
| MKT_LTW, SMB_LTW, MOM_LTW | 0.155 | 0.203 | 0.161 | 0.269 | 0.147 | 0.128 | 0.109 | 0.111 | 0.029 | 0.157 | 0.162 | 0.257 | 0.161 |
| MKT, SMB, MOM | 0.149 | 0.194 | 0.166 | 0.253 | 0.170 | 0.161 | 0.095 | 0.099 | 0.025 | 0.154 | 0.142 | 0.250 | 0.165 |
| MKT, SMB, REV | 0.231 | 0.153 | 0.162 | 0.256 | 0.192 | 0.158 | 0.150 | 0.114 | 0.035 | 0.158 | 0.166 | 0.238 | 0.181 |
| MKT, SMB, VAL | 0.174 | 0.169 | 0.193 | 0.262 | 0.170 | 0.196 | 0.115 | 0.116 | 0.023 | 0.163 | 0.153 | 0.246 | 0.177 |
| MKT, SMB, NET | 0.146 | 0.155 | 0.160 | 0.342 | 0.156 | 0.158 | 0.097 | 0.103 | 0.022 | 0.154 | 0.142 | 0.269 | 0.164 |
| MKT, SMB, VAL, MOM | 0.174 | 0.209 | 0.198 | 0.262 | 0.185 | 0.198 | 0.115 | 0.116 | 0.022 | 0.164 | 0.154 | 0.257 | 0.184 |
| MKT, SMB, VAL, REV | 0.256 | 0.170 | 0.193 | 0.264 | 0.207 | 0.197 | 0.169 | 0.130 | 0.041 | 0.170 | 0.178 | 0.247 | 0.201 |
| MKT, SMB, VAL, NET | 0.172 | 0.172 | 0.193 | 0.350 | 0.171 | 0.196 | 0.118 | 0.120 | 0.020 | 0.165 | 0.154 | 0.277 | 0.184 |
| MKT, SMB, VAL, MOM, NET | 0.173 | 0.212 | 0.198 | 0.352 | 0.187 | 0.198 | 0.119 | 0.121 | 0.020 | 0.166 | 0.155 | 0.289 | 0.192 |
| MKT, SMB, VAL, MOM, REV | 0.256 | 0.210 | 0.198 | 0.264 | 0.221 | 0.198 | 0.169 | 0.130 | 0.039 | 0.173 | 0.178 | 0.258 | 0.208 |
| MKT, SMB, VAL, REV, NET | 0.255 | 0.173 | 0.193 | 0.353 | 0.208 | 0.196 | 0.173 | 0.135 | 0.041 | 0.172 | 0.179 | 0.278 | 0.208 |
| MKT, SMB, VAL, MOM, REV, NET | 0.255 | 0.212 | 0.198 | 0.355 | 0.223 | 0.198 | 0.172 | 0.135 | 0.039 | 0.174 | 0.179 | 0.290 | 0.216 |

**Table 7. Summary Asset Pricing tests for Single sorted and Double sorted Portfolios (2014/01/22-2021/01/04, 363 weeks)** (continued)

| | In-Sample | | | | | | Out-of-Sample | | | | | | All |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Market Cap | ret-2week | NPast52 | BAgrowth | Size-Mom | Size-Value | PRC | MAXPRC | VaR | IVOL | ILLIQ | CoreSet | |
| Panel D: $R_C^2$ | | | | | | | | | | | | | |
| MKT | 0.832 | 0.610 | 0.143 | -0.129 | -0.047 | 0.060 | 0.217 | 0.189 | 0.038 | 0.419 | 0.339 | 0.022 | -0.029 |
| MKT_LTW, SMB_LTW, MOM_LTW | 0.601 | 0.000 | 0.223 | -0.144 | -0.228 | 0.144 | 0.331 | 0.440 | -0.075 | 0.528 | 0.364 | 0.267 | -0.075 |
| MKT, SMB, MOM | 0.130 | 0.000 | 0.177 | -0.271 | -0.742 | -0.876 | 0.302 | 0.533 | 0.091 | 0.475 | 0.557 | 0.336 | -0.214 |
| MKT, SMB, REV | 0.992 | 0.646 | 0.240 | -0.345 | -1.158 | -0.716 | 0.263 | 0.740 | -0.919 | 0.849 | 0.347 | 0.157 | -0.556 |
| MKT, SMB, VAL | 0.016 | 0.270 | 0.660 | -0.296 | 0.361 | -0.369 | 0.511 | 0.722 | 0.662 | -0.323 | 0.236 | 0.256 | 0.412 |
| MKT, SMB, NET | 0.125 | 0.015 | 0.060 | 0.944 | -0.320 | -0.750 | 0.613 | 0.807 | 0.409 | 0.255 | 0.480 | 0.800 | -0.018 |
| MKT, SMB, VAL, MOM | 0.014 | 0.000 | 0.741 | -0.444 | 0.222 | -0.413 | 0.558 | 0.825 | 0.612 | 0.219 | 0.398 | 0.298 | 0.382 |
| MKT, SMB, VAL, REV | 0.906 | 0.561 | 0.681 | -0.478 | -1.360 | -0.316 | -0.349 | 0.200 | -1.181 | 0.684 | 0.117 | 0.112 | -0.486 |
| MKT, SMB, VAL, NET | 0.020 | 0.041 | 0.649 | 0.840 | 0.416 | -0.314 | 0.553 | 0.655 | 0.736 | -0.119 | 0.241 | 0.706 | 0.452 |
| MKT, SMB, VAL, MOM, NET | 0.013 | 0.000 | 0.727 | 0.757 | 0.291 | -0.356 | 0.616 | 0.793 | 0.684 | 0.335 | 0.378 | 0.724 | 0.425 |
| MKT, SMB, VAL, MOM, REV | 0.825 | 0.000 | 0.759 | -0.680 | -1.447 | -0.355 | -0.034 | 0.524 | -1.262 | 0.843 | 0.325 | 0.406 | -0.537 |
| MKT, SMB, VAL, REV, NET | 0.910 | 0.147 | 0.673 | 0.715 | -1.558 | -0.263 | -0.496 | -0.010 | -1.313 | 0.767 | 0.154 | 0.541 | -0.574 |
| MKT, SMB, VAL, MOM, REV, NET | 0.838 | 0.000 | 0.747 | 0.589 | -1.631 | -0.299 | -0.170 | 0.347 | -1.395 | 0.843 | 0.334 | 0.691 | -0.622 |

**Table 8. Factor Span (2014/01/22-2021/01/04, 363 weeks)**

This table presents the regressions of one factor on the other four factors. **MKT** is the return of the cryptocurrency market index minus the one-month Treasury bill rate. The **SMB** and **VAL** factors are constructed as follows: each week, cryptocurrencies are independently sorted into 3 value portfolios and 2 size portfolios. The three value portfolios are growth (bottom 30% value), neutral (middle 40% value), and value (top 30% value) cryptocurrencies, and the two size portfolios are small (bottom 50%) and big (top 50%) cryptocurrencies. The independent 2×3 sorts on Size and Value produce six value-weighted portfolios. **SMB** is the equal-weight average of the returns on the three small cryptocurrency portfolios minus the average of the returns on the three big cryptocurrency portfolios. **VAL** is the equal-weight average of the return difference of the value and growth portfolios within small and big groups of cryptocurrencies. The **MOM** factor is constructed as follows: each week, all cryptocurrencies in the Full Sample are independently split into two [80% smallest, 20% largest] size portfolios of the ranked market capitalization, and three [30% lowest, 40% middle, 30% highest] momentum portfolios by the past 2-week returns. **MOM** is the return difference between the highest and the lowest past 2-week return portfolios in the largest size group. The **NET** factor is constructed as follows: each week, the cryptocurrencies of the Core Sample are split into three network groups according to the growth rate in total addresses with balance: bottom 30%, middle 40%, and top 30%. Then, we form value-weighted portfolios for each of the three network groups. The **NET** factor is the return difference between the top and the bottom network portfolios. The t-statistics (in parentheses) are adjusted for heteroskedasticity and autocorrelations. To match the sample period of the Core Sample, the sample period is from 2014/01/22 to 2021/01/04.

| | MKT | SMB | MOM | VAL | NET |
|---|---|---|---|---|---|
| Intercept | 0.014 | 0.051 | 0.038 | 0.036 | 0.030 |
| | (2.039)** | (4.284)*** | (3.380)*** | (5.502)*** | (1.820)* |
| MKT | | 0.037 | 0.081 | -0.035 | 0.112 |
| | | (0.470) | (0.620) | (-0.409) | (1.011) |
| SMB | 0.015 | | -0.043 | 0.064 | 0.044 |
| | (0.509) | | (-1.019) | (1.109) | (0.716) |
| MOM | 0.031 | -0.040 | | -0.047 | 0.066 |
| | (0.625) | (-1.163) | | (-1.238) | (0.807) |
| VAL | -0.027 | 0.122 | -0.098 | | 0.054 |
| | (-0.395) | (1.214) | (-1.420) | | (0.443) |
| NET | 0.033 | 0.031 | 0.051 | 0.020 | |
| | (0.998) | (0.695) | (0.783) | (0.424) | |
| Adjusted R square | -0.004 | 0.021 | 0.005 | 0.013 | -0.004 |

**Table 9. Maximum Squared Sharpe Ratios and Factor Marginal Contributions (2014/01/22-2021/01/04, 363 weeks)**

This table shows the max squared Sharpe ratios and factor marginal contributions to them for 12 models: five 3-factor models, the 3-factor model proposed by LTW, and four alternative 3-factor models that combine the three factors, **SMB**, **MOM, REV, VAL** and **NET**; three 4-factor models and three 5-factor models, adding one or two of the MOM, REV, and NET factors to the three factor model of MKT+SMB+VAL; one 6-factor model. **MKT** is the return of the market index minus the one-month Treasury bill rate; **SMB** is the size factor; **MOM** is the momentum factor; **VAL** is the value factor; **NET** is the network factor. **MKT**, **SMB, MOM, REV**, and **VAL** factors are constructed by the Full sample, the **NET** factor is constructed by the Core Sample. We also use the LargeCap sample to construct the **MKT_LTW**, **SMB_LTW** and **MOM_LTW** following LTW. The first three columns show actual $Sh^2(f)$ and means and medians of $Sh^2(f)$ from 10,000 bootstrap simulation runs. And left columns of the table show the marginal contributions of **MKT, SMB, MOM, REV, VAL** and **NET** to actual $Sh^2(f)$. The marginal contribution of a factor to the max squared Sharpe ratio is the square of the ratio of the intercept in the spanning regression of the factor on the model's other factors to the standard error of the regression residuals. The sample period is from 2014/01/22 to 2021/01/04.

| | | Bootstrap Simulation | | Marginal Contributions to $Sh^2(f)$ | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $Sh^2(f)$ | Mean | Median | MKT | SMB | MOM | REV | VAL | NET |
| MKT_LTW, SMB_LTW, MOM_LTW | 0.0327 | 0.0399 | 0.0376 | 1.46% | 0.05% | 1.32% | | | |
| MKT, SMB, MOM | 0.1295 | 0.1522 | 0.1458 | 1.34% | 8.25% | 3.23% | | | |
| MKT, SMB, REV | 0.1355 | 0.1968 | 0.1792 | 1.81% | 9.46% | | 3.83% | | |
| MKT, SMB, VAL | 0.1807 | 0.2001 | 0.1973 | 1.89% | 6.69% | | | 8.35% | |
| MKT, SMB, NET | 0.1217 | 0.1399 | 0.1349 | 1.36% | 7.55% | | | | 2.45% |
| MKT, SMB, VAL, MOM | 0.2215 | 0.2467 | 0.2442 | 1.58% | 6.99% | 4.08% | | 9.20% | |
| MKT, SMB, VAL, REV | 0.2071 | 0.2781 | 0.2525 | 2.05% | 7.91% | | 2.64% | 7.16% | |
| MKT, SMB, VAL, NET | 0.2028 | 0.2250 | 0.2223 | 1.62% | 6.40% | | | 8.11% | 2.21% |
| MKT, SMB, VAL, MOM, NET | 0.2402 | 0.2689 | 0.2656 | 1.37% | 6.69% | 3.74% | | 8.93% | 1.87% |
| MKT, SMB, VAL, MOM, REV | 0.2530 | 0.3326 | 0.3113 | 1.73% | 8.38% | 4.59% | 3.15% | 7.91% | |
| MKT, SMB, VAL, REV, NET | 0.2300 | 0.3078 | 0.2817 | 1.77% | 7.61% | | 2.72% | 6.92% | 2.28% |
| MKT, SMB, VAL, MOM, REV, NET | 0.2723 | 0.3601 | 0.3369 | 1.51% | 8.08% | 4.23% | 3.21% | 7.65% | 1.93% |

**Table 10. Summary Statistics of Five Classifications**

This table reports the number of cryptocurrencies, the start state, and the time series averages of cross-sectional averages of various coin characteristics for cryptocurrencies in each classification. **Mean**, **Skewness** and **Kurtosis** are the mean, skewness and kurtosis of daily market capitalization in the portfolio formation week, respectively. **Volume** is the trading volume at the end of each week. **Volatility** is the standard deviation of daily returns in the portfolio formation week. **Total addresses, Total addresses with balances** and **Active addresses** are the average of the number of total addresses, the number of addresses with balance and the number of active addresses in the portfolio formation week. **Active addresses** measures the number of addresses that made one or more on-chain transaction(s) on a given day. The sample period ends of all classifications at 2021/01/04.

| | Number | Start date | Mean | Skewness | Kurtosis | Volume | Volatility | Total addresses | Total addresses with balances | Active addresses |
|---|---|---|---|---|---|---|---|---|---|---|
| General | 28 | 2014/1/1 | 5,362,838,000 | 2.590 | 9.632 | 499,788,000 | 0.033 | 33,538,650 | 2,004,398 | 78,094 |
| Platform | 483 | 2016/5/11 | 138,725,100 | 3.616 | 15.438 | 31,412,470 | 0.060 | 1,183,589 | 105,168 | 11,407 |
| Product | 72 | 2017/6/7 | 40,319,800 | 3.052 | 12.981 | 4,537,450 | 0.078 | 33,055 | 19,392 | 138 |
| Security | 26 | 2016/12/28 | 33,073,930 | 1.634 | 4.602 | 2,825,987 | 0.096 | 24,514 | 16,113 | 101 |
| Total | 605 | | | | | | | | | |

**Table 11. Excess Returns for Different Four Categories**

For each category, we split cryptocurrencies into quintiles according to different characteristics, including MarketCap, NPast52, ret-2 week and BAgrowth. Quintile 1 (5) includes the 20% cryptocurrencies with the lowest(highest) related characteristic. A long-short portfolio High-Low that buys cryptocurrencies in quintile 5 and shorts cryptocurrencies in quintile 1 is also constructed at the same time. Each portfolio is then held for 1 week and all the portfolio returns are value-weighted. Panel A shows the excess returns of quintile portfolios split according to market capitalization. Panel B shows the excess returns of quintile portfolios split according to the negative of the past 12-month (52-week) performance. Panel C shows the excess returns of quintile portfolios split according to the 2-week momentum. Panel D shows the excess returns of quintile portfolios split according to the growth rate in total addresses with balance. Mean is the average weekly value-weighted returns of each portfolio, and *t*-statistic (Mean) is the ratio of Mean to its standard error, which is adjusted for heteroskedasticity and autocorrelations.

| | Panel A: MarketCap | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Low** | 2 | 3 | 4 | **High** | H-L | **Low** | 2 | 3 | 4 | **High** | H-L |
| | Mean | | | | | | *t*-statistic (Mean) | | | | | |
| General | 0.098 | 0.022 | 0.015 | 0.019 | 0.015 | -0.083 | 2.101 | 1.340 | 1.373 | 1.921 | 2.500 | -1.748 |
| Platform | 0.064 | 0.039 | 0.027 | 0.026 | 0.030 | -0.034 | 3.157 | 2.131 | 1.917 | 1.705 | 2.295 | -2.221 |
| Product | 0.102 | 0.039 | 0.034 | 0.017 | 0.008 | -0.094 | 2.799 | 1.445 | 1.276 | 1.135 | 0.664 | -2.549 |
| Security | 0.084 | 0.046 | 0.026 | 0.019 | 0.033 | -0.051 | 2.560 | 2.160 | 1.194 | 1.195 | 1.238 | -1.508 |
| | Panel B: NPast52 | | | | | | | | | | | |
| | **Low** | 2 | 3 | 4 | **High** | H-L | **Low** | 2 | 3 | 4 | **High** | H-L |
| | Mean | | | | | | *t*-statistic (Mean) | | | | | |
| General | 0.014 | 0.030 | 0.014 | 0.023 | 0.029 | 0.015 | 1.555 | 1.944 | 1.204 | 1.719 | 2.016 | 1.026 |
| Platform | 0.015 | 0.026 | 0.015 | 0.017 | 0.032 | 0.017 | 1.053 | 1.643 | 1.100 | 1.256 | 1.880 | 1.676 |
| Product | 0.000 | -0.009 | 0.001 | 0.011 | 0.039 | 0.039 | 0.039 | -0.897 | 0.101 | 0.680 | 2.005 | 2.050 |
| Security | -0.010 | 0.005 | 0.008 | -0.003 | 0.009 | 0.018 | -0.778 | 0.354 | 0.529 | -0.219 | 0.603 | 1.244 |
| | Panel C: ret-2 week | | | | | | | | | | | |
| | **Low** | 2 | 3 | 4 | **High** | H-L | **Low** | 2 | 3 | 4 | **High** | H-L |
| | Mean | | | | | | *t*-statistic (Mean) | | | | | |
| General | 0.090 | 0.007 | 0.009 | 0.019 | 0.033 | -0.057 | 2.138 | 0.867 | 1.012 | 2.363 | 2.039 | -1.253 |
| Platform | 0.024 | 0.031 | 0.031 | 0.020 | 0.023 | -0.002 | 1.842 | 1.686 | 1.812 | 1.786 | 1.660 | -0.142 |
| Product | 0.037 | 0.012 | 0.028 | 0.026 | 0.034 | -0.003 | 1.527 | 0.954 | 1.668 | 1.434 | 1.083 | -0.092 |
| Security | 0.056 | 0.035 | 0.014 | 0.021 | 0.038 | -0.018 | 2.433 | 1.903 | 0.843 | 1.129 | 1.370 | -0.628 |
| | Panel D: BAgrowth | | | | | | | | | | | |
| | **Low** | 2 | 3 | 4 | **High** | H-L | **Low** | 2 | 3 | 4 | **High** | H-L |
| | Mean | | | | | | *t*-statistic (Mean) | | | | | |
| General | 0.016 | 0.015 | 0.045 | 0.009 | 0.036 | 0.020 | 1.269 | 1.464 | 2.320 | 1.294 | 2.014 | 1.124 |
| Platform | 0.017 | 0.017 | 0.023 | 0.029 | 0.036 | 0.019 | 1.181 | 1.318 | 1.730 | 2.004 | 2.210 | 1.964 |
| Product | 0.034 | -0.001 | 0.030 | 0.023 | 0.012 | -0.022 | 1.140 | -0.075 | 1.578 | 1.586 | 0.864 | -0.848 |
| Security | 0.055 | 0.005 | 0.063 | 0.019 | 0.029 | -0.026 | 2.370 | 0.227 | 2.246 | 1.327 | 1.173 | -0.990 |

**Table 12. Tests of Global, Local, and International Versions of the C-5 Model**

This table reports the summary tests of global, local and "international" versions of the C-5 model. We use General Payment, Platform Token, Product Token and Security Token decile portfolios formed on size, value, momentum and network as test assets. The GRS statistic and its p-value, p(GRS), test whether the expected values of all 10 intercept estimates in the regressions are zero. Also shown are (1) $A|a|$, the average absolute value of the intercepts; (2) $AR^2$, the average of the regression $R^2$, adjusted for degrees of freedom. (3) $R_C^2$ denotes the constrained $R^2$ in which the risk price estimates are constrained to be equal to the factor sample means in two-pass regressions, and $p\left(R_C^2\right)$ is its p-value. Total for p(GRS) indicates how many tests fail; Total for GRS F-statistics, average absolute alpha ($A|a|$), average adjusted R square ($AR^2$), and constrained R square ($R_C^2$) denote the average value; Total for $p\left(R_C^2\right)$ indicates how many tests have positive constrained R square with p-value <=0.05, i.e., p value is positive at the 5% level.

| Panel C: C-5 Model | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Global factor model | | | | | | Local factor model | | | | | | International factor model | | | | | |
| | GRS | p(GRS) | $A\|a\|$ | $AR^2$ | $R_C^2$ | $p(R_C)$ | GRS | p(GRS) | $A\|a\|$ | $AR^2$ | $R_C^2$ | $p(R_C)$ | GRS | p(GRS) | $A\|a\|$ | $AR^2$ | $R_C^2$ | $p(R_C)$ |
| **General Payment** | | | | | | | | | | | | | | | | | | |
| Size | 0.828 | 0.602 | 0.022 | 0.260 | 0.915 | 0.000 | 0.871 | 0.562 | 0.012 | 0.382 | 0.940 | 0.000 | 0.488 | 0.896 | 0.011 | 0.447 | 0.955 | 0.000 |
| Value | 0.879 | 0.554 | 0.016 | 0.169 | 0.198 | 0.000 | 1.046 | 0.407 | 0.011 | 0.294 | 0.692 | 0.000 | 0.902 | 0.532 | 0.011 | 0.338 | 0.698 | 0.000 |
| Network | 1.634 | 0.100 | 0.018 | 0.216 | 0.165 | 0.001 | 1.511 | 0.139 | 0.014 | 0.290 | 0.527 | 0.000 | 2.274 | 0.016 | 0.015 | 0.354 | 0.494 | 0.000 |
| Momentum | 2.203 | 0.020 | 0.031 | 0.218 | 0.889 | 0.000 | 2.058 | 0.030 | 0.018 | 0.407 | 0.943 | 0.000 | 2.336 | 0.013 | 0.018 | 0.472 | 0.930 | 0.000 |
| **Platform Token** | | | | | | | | | | | | | | | | | | |
| Size | 1.760 | 0.071 | 0.014 | 0.538 | 0.806 | 0.000 | 2.157 | 0.022 | 0.013 | 0.721 | 0.607 | 0.000 | 2.375 | 0.012 | 0.013 | 0.734 | 0.617 | 0.000 |
| Value | 1.531 | 0.132 | 0.005 | 0.317 | 0.436 | 0.000 | 1.636 | 0.100 | 0.006 | 0.680 | 0.411 | 0.000 | 1.687 | 0.087 | 0.006 | 0.689 | 0.328 | 0.000 |
| Network | 0.772 | 0.656 | 0.013 | 0.372 | 0.419 | 0.013 | 1.106 | 0.360 | 0.010 | 0.574 | 0.186 | 0.086 | 1.545 | 0.127 | 0.012 | 0.590 | -0.259 | 0.740 |
| Momentum | 2.215 | 0.019 | 0.015 | 0.396 | -0.718 | 0.136 | 1.300 | 0.234 | 0.012 | 0.581 | 0.177 | 0.012 | 1.544 | 0.128 | 0.012 | 0.606 | 0.140 | 0.021 |
| **Product Token** | | | | | | | | | | | | | | | | | | |
| Size | 1.696 | 0.089 | 0.027 | 0.246 | -0.209 | 0.713 | 0.542 | 0.858 | 0.010 | 0.189 | 0.844 | 0.000 | 0.810 | 0.620 | 0.014 | 0.344 | 0.644 | 0.008 |
| Value | 2.039 | 0.035 | 0.024 | 0.210 | 0.254 | 0.000 | 1.126 | 0.348 | 0.018 | 0.115 | 0.422 | 0.000 | 1.327 | 0.224 | 0.018 | 0.268 | 0.353 | 0.000 |
| Network | 0.568 | 0.838 | 0.010 | 0.236 | -0.419 | 0.780 | 0.600 | 0.811 | 0.008 | 0.141 | -0.096 | 0.506 | 0.820 | 0.610 | 0.011 | 0.288 | -0.296 | 0.502 |
| Momentum | 0.954 | 0.487 | 0.017 | 0.279 | 0.081 | 0.322 | 0.364 | 0.960 | 0.009 | 0.111 | 0.728 | 0.003 | 0.780 | 0.648 | 0.013 | 0.314 | 0.549 | 0.055 |
| **Security Token** | | | | | | | | | | | | | | | | | | |
| Size | 3.808 | 0.000 | 0.085 | 0.203 | -2.957 | 0.000 | 1.149 | 0.330 | 0.059 | 0.199 | 0.838 | 0.000 | 2.059 | 0.032 | 0.078 | 0.350 | 0.996 | 0.000 |
| Value | 0.717 | 0.707 | 0.020 | 0.198 | -0.157 | 0.000 | 0.215 | 0.995 | 0.009 | 0.145 | -0.033 | 0.000 | 1.106 | 0.362 | 0.023 | 0.308 | -0.181 | 0.000 |
| Network | 1.701 | 0.086 | 0.058 | 0.169 | -5.644 | 0.000 | 2.737 | 0.004 | 0.055 | 0.194 | 0.735 | 0.000 | 2.781 | 0.004 | 0.065 | 0.331 | 0.985 | 0.000 |
| Momentum | 3.138 | 0.001 | 0.030 | 0.241 | -1.640 | 0.000 | 0.539 | 0.860 | 0.009 | 0.197 | 0.850 | 0.000 | 1.949 | 0.043 | 0.023 | 0.367 | 0.527 | 0.000 |
| **Total** | 1.614 | 5 | 0.025 | 0.256 | -0.487 | 8 | 1.185 | 3 | 0.017 | 0.326 | 0.548 | 13 | 1.549 | 6 | 0.021 | 0.425 | 0.468 | 12 |

## Appendix

### Part A. Test asset portfolios construction

In Section 4.2.1, we use six In-Sample and six Out-of-Sample sets of test asset portfolios to compare the explanatory power of different factor models in the LHS method.

*In Sample*

**MarketCap**. As shown in Table A1, MarketCap is the last day market capitalization in the portfolio formation week. We split cryptocurrencies of the Full Sample into 10-decile portfolios according to the MarketCap characteristic, just as Section 3.1.

**ret-2 week**. As shown in Table A1, ret-2 week is the past 2-week cumulative return. We split cryptocurrencies of the LargeCap Sample into 10-decile portfolios according to the ret-2 week characteristic, just as Section 3.2.

**NPast52.** As shown in Table A1, NPast52 is the negative of past 52-week return. We split cryptocurrencies of the Full Sample into 10-decile portfolios according to the NPast characteristic, just as Section 3.3.

**BAgrowth**. As shown in Table A1, BAgrowth is the first difference of log values of total addresses with balance. We split cryptocurrencies of the Core Sample into 5-quintile portfolios according to the BAgrowth characteristic, just as Section 3.4.

**Size-Mom**. Just as Section 3.2, we construct the independently 5×5 double sorted portfolios on size (MarketCap) and momentum (ret-2 week).

**Size-Value**. Just as Section 3.3, we construct the independently 5×5 double sorted portfolios on size (MarketCap) and value (NPast52).

*Out-of-Sample*

**PRC**. PRC is the last day price in the portfolio formation week. We split cryptocurrencies of the Full Sample into 10-decile portfolios according to PRC.

**MAXPRC**. MAXPRC is the maximum price in the portfolio formation week. We split cryptocurrencies of the Full Sample into 10-decile portfolios according to MAXPRC.

**VaR**. Following Zhang, W., Li, Y., Xiong, X. and Wang (2021), we use value-at-risk to measure the downside risk in the cryptocurrency market. We calculate 5$^{th}$ percentile of past 90 days daily return as the proxy of value-at-risk and label it VaR, and then split cryptocurrencies of the Full Sample into 10-decile portfolios according to VaR.

**IVOL**. We measure the idiosyncratic volatility (IVOL) as the standard deviation of the residuals of the Crypto-CAPM model, $r_{it} - r_{ft} = \alpha_i + \beta_i MKT_t + \epsilon_i$. We use daily returns of the past 30 days as of the last day in the portfolio formation week to estimate the Crypto-CAPM model, and IVOL = $\sqrt{var(\epsilon_i)}$.

**ILLIQ**. Due to the wash trading problem, we use the covariance of the change in price rather than trading volume to measure the liquidity in cryptocurrency market. Following Roll (1984) and Goyenko, Holden, and Trzcinka (2009), we use the serial covariance of the change in price as the proxy of liquidity,

$$Roll = \begin{cases} \sqrt{-Cov(\Delta P_t, \Delta P_{t-1})}, & Cov(\Delta P_t, \Delta P_{t-1}) < 0 \\ x, & Cov(\Delta P_t, \Delta P_{t-1}) \geq 0 \end{cases}$$

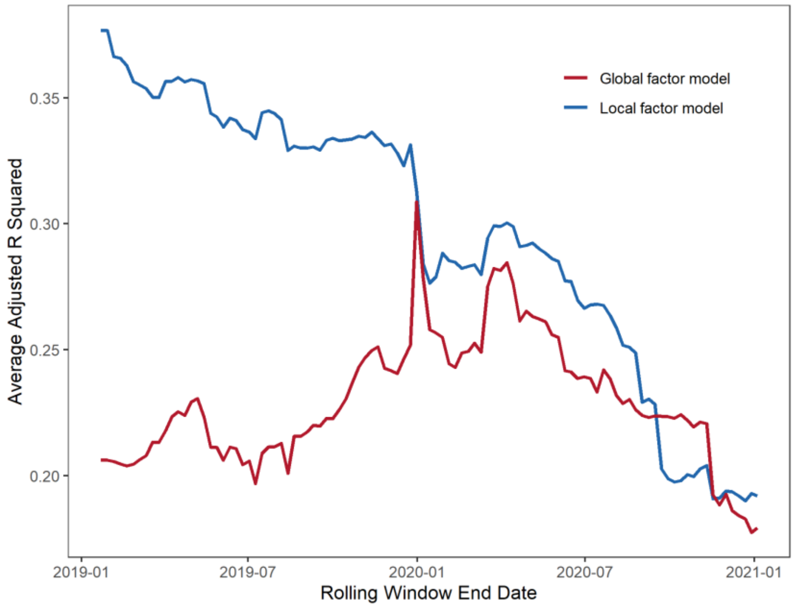
**CoreSet**. This set contains three 5-quntile portfolios constructed from Core sample according to MarketCap, ret-2 week, and NPast52.

## Part B. Figures and Tables

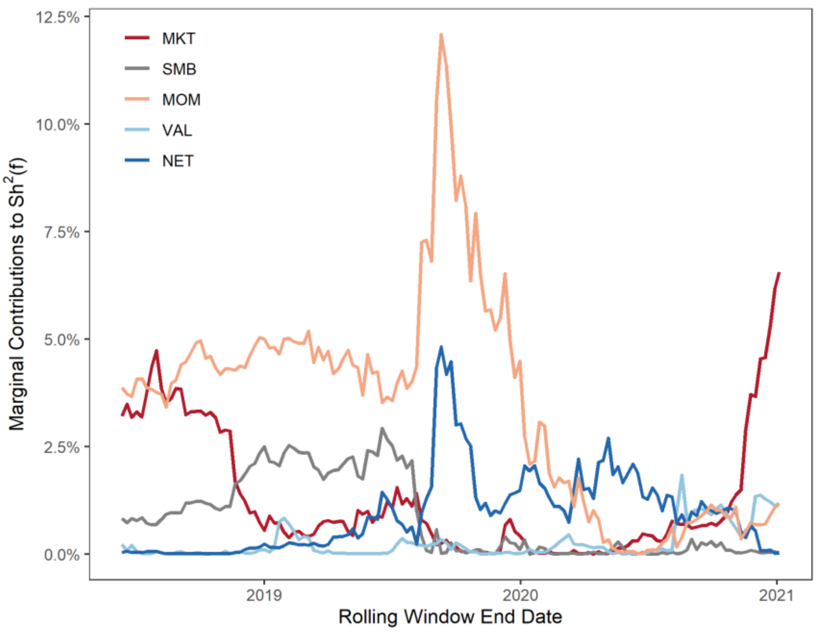
**Figure A1. Dynamics of Market Segmentation Using Bootstrap Sample of Platform Token**

We conduct a random subsampling of 50 tokens from the Platform Token category as the new sample of Platform Token, and combine them with the other three categories to form a global sample containing all cryptocurrencies in the four categories. Repeating the above process 100 times, this figure reports the average of the results generated by the 100 random subsamplings. Panel A plots the average adjusted R squared for the 160 rolling regressions on global and local C-5 factor models. Panel B and C plot factor marginal contributions to maximum squared sharpe ratios of the global C-5 model and the local C-5 model for each category, respectively.

A. Time Series of Average Adjusted R Squared for Global and Local C-5 Factor Models




B. Time Series of the Global C-5 Model's Factor Marginal Contributions



C. Time Series of the Local C-5 Model's Factor Marginal Contributions

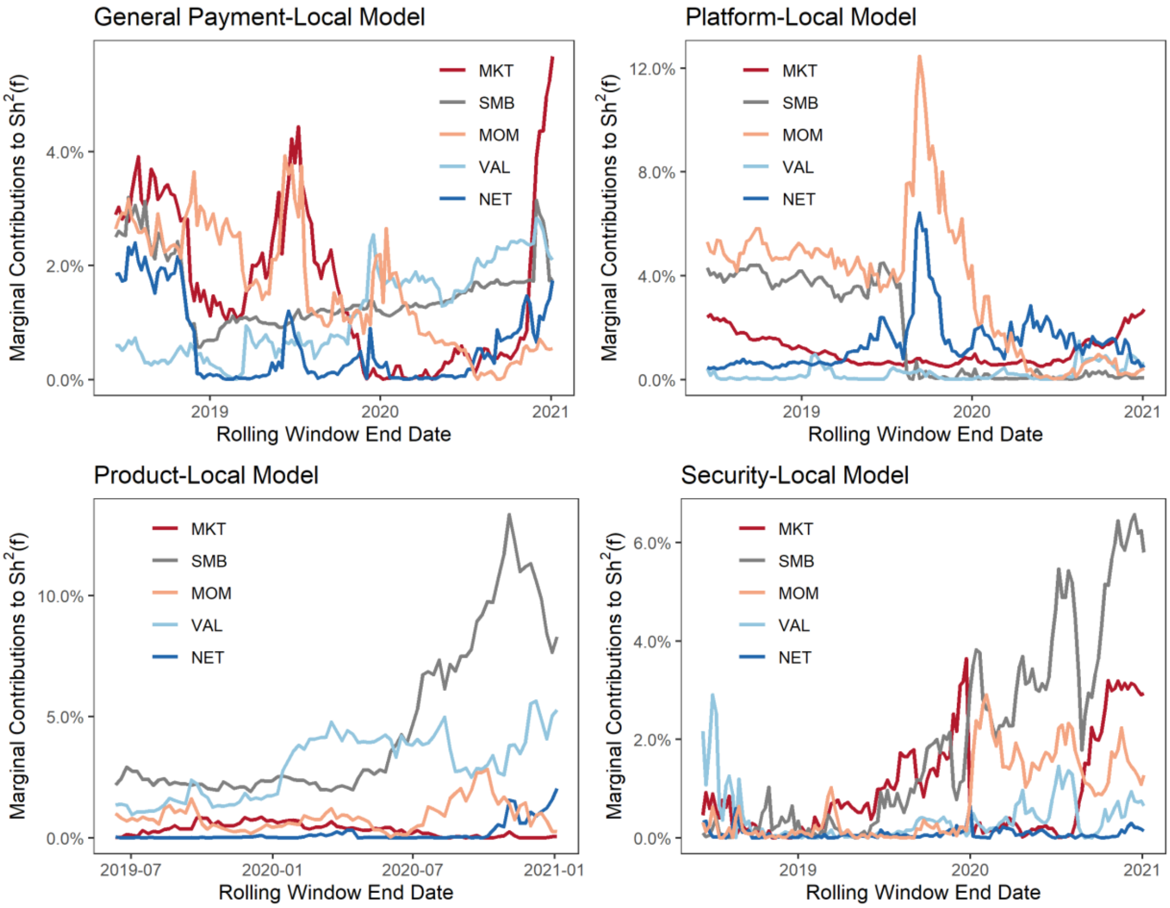


**Table A1. Definition of Crypto Characteristics**

| Category | Characteristic | Definition |
|---|---|---|
| Size | MarketCap | Last day market capitalization in the portfolio formation week |
| Momentum | ret-1 week | One-week momentum |
| Momentum | ret-2 week | Two-week momentum |
| Momentum | ret-3 week | Three-week momentum |
| Momentum | ret-4 week | Four-week momentum |
| Value | NPast52 | The negative of past 52-week return. |
| Value | T/M ratio | Transaction-to-market ratio, where the transaction is the aggregate volume of transactions recorded on-chain. |
| Value | A/M ratio | Address-to-market ratio, where the address is the total addresses ever created one point have held a particular cryptocurrency, including those that still do. |
| Value | U/M ratio | User-to-market ratio, where user is approximated by the total addresses with balance. |
| Network | BAgrowth | The first difference of log values of total addresses with balance |
| Network | TAgrowth | The first difference of log values of total addresses |
| Network | Volgrowth | The first difference of log values of total transaction volume on chain |
| Network | VolUSDgrowth | The first difference of log values of total transaction volume on chain in USD |

**Table A2. Cross-section Returns of Alternative Momentum Characteristics (2014/01/01-2021/01/04, 366 weeks)**

This table presents the cross-section returns of alternative three momentum-related characteristics. They are ret-1 week, ret-3 week, and ret-4 week, which are defined in Table A1. Panel A reports mean excess returns and their t-statistics for single sorted portfolios constructed by both Full Sample and the Large Cap Sample. Panel B shows the independently double-sort results of the intersection between market capitalization and the momentum-related characteristics. And Panel C shows the dependently double sort results. Each portfolio is then held for 1 week and all the portfolio returns are value-weighted. Mean is the average weekly value-weighted returns of each portfolio, and t(Mean) is the ratio of Mean to its standard error, which is adjusted for heteroskedasticity and autocorrelations. The sample period is from 2014/01/01 to 2021/01/04.

| Panel A: Single sort | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 10-1 |
| **ret-1 week** | **Low** | | | | | | | | | **High** | |
| | | | | | (1) Full Sample | | | | | | |
| Mean | 0.062 | 0.008 | 0.013 | 0.010 | 0.008 | 0.002 | 0.020 | 0.028 | 0.022 | 0.021 | -0.041 |
| t(Mean) | 3.511 | 0.788 | 1.324 | 0.889 | 0.767 | 0.285 | 2.193 | 2.110 | 2.089 | 0.984 | -1.664 |
| | | | | | (2) Large Cap Sample | | | | | | |
| Mean | 0.004 | -0.001 | 0.003 | 0.008 | 0.011 | 0.009 | 0.022 | 0.024 | 0.022 | 0.018 | 0.014 |
| t(Mean) | 0.336 | -0.137 | 0.342 | 0.641 | 1.198 | 1.070 | 2.278 | 1.860 | 1.848 | 0.962 | 0.752 |
| **ret-3 week** | **Low** | | | | | | | | | **High** | |
| | | | | | (1) Full Sample | | | | | | |
| Mean | 0.044 | 0.032 | 0.015 | 0.007 | 0.002 | 0.012 | 0.023 | 0.020 | 0.027 | 0.019 | -0.025 |
| t(Mean) | 3.397 | 1.858 | 1.231 | 0.658 | 0.288 | 1.311 | 1.764 | 2.144 | 2.545 | 1.405 | -1.706 |
| | | | | | (2) Large Cap Sample | | | | | | |
| Mean | 0.009 | 0.017 | 0.002 | 0.006 | 0.007 | 0.015 | 0.015 | 0.012 | 0.031 | 0.027 | 0.018 |
| t(Mean) | 0.615 | 1.215 | 0.217 | 0.644 | 0.638 | 1.252 | 1.643 | 1.209 | 2.688 | 1.993 | 1.023 |
| **ret-4 week** | **Low** | | | | | | | | | **High** | |
| | | | | | (1) Full Sample | | | | | | |
| Mean | 0.034 | 0.012 | 0.018 | -0.003 | 0.011 | 0.017 | 0.014 | 0.028 | 0.029 | 0.022 | -0.012 |
| t(Mean) | 2.898 | 1.131 | 1.765 | -0.286 | 0.903 | 1.766 | 1.578 | 2.513 | 2.517 | 1.519 | -0.826 |
| | | | | | (2) Large Cap Sample | | | | | | |
| Mean | -0.013 | 0.007 | 0.002 | 0.003 | 0.012 | 0.022 | 0.018 | 0.023 | 0.031 | 0.010 | 0.022 |
| t(Mean) | -1.357 | 0.743 | 0.242 | 0.334 | 1.181 | 1.694 | 1.755 | 2.395 | 2.552 | 0.734 | 1.936 |

**Table A2. Cross-section Returns of Alternative Momentum Characteristics (2014/01/01-2021/01/04, 366 weeks)** (continued)

| Panel B: Independent Double sort | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | | | | | | t-statistic | | | | | |
| | **Low** | 2 | 3 | 4 | **High** | H-L | **Low** | 2 | 3 | 4 | **High** | H-L |
| **ret-1 week** | | | | | | | | | | | | |
| Small | 0.284 | 0.133 | 0.082 | 0.079 | 0.079 | -0.205 | 8.843 | 6.351 | 5.123 | 5.179 | 2.741 | -5.609 |
| 2 | 0.151 | 0.060 | 0.168 | 0.064 | 0.033 | -0.118 | 7.675 | 4.589 | 1.663 | 3.452 | 1.801 | -4.865 |
| 3 | 0.098 | 0.060 | 0.048 | 0.032 | 0.005 | -0.093 | 6.855 | 3.231 | 2.449 | 2.408 | 0.335 | -5.668 |
| 4 | 0.083 | 0.023 | 0.020 | 0.012 | -0.006 | -0.089 | 5.825 | 2.196 | 1.631 | 1.101 | -0.460 | -6.722 |
| Big | -0.001 | 0.006 | 0.006 | 0.026 | 0.017 | 0.018 | -0.121 | 0.666 | 0.803 | 2.312 | 1.317 | 1.416 |
| **ret-3 week** | | | | | | | | | | | | |
| Small | 0.267 | 0.208 | 0.086 | 0.109 | 0.034 | -0.233 | 10.820 | 3.160 | 5.203 | 2.489 | 1.775 | -8.882 |
| 2 | 0.552 | 0.069 | 0.070 | 0.048 | 0.109 | -0.443 | 1.442 | 5.164 | 4.366 | 3.119 | 1.277 | -1.123 |
| 3 | 0.092 | 0.057 | 0.036 | 0.037 | 0.009 | -0.083 | 6.184 | 3.687 | 2.898 | 2.216 | 0.540 | -5.460 |
| 4 | 0.092 | 0.022 | 0.021 | 0.010 | 0.018 | -0.074 | 4.216 | 1.706 | 1.811 | 0.800 | 1.333 | -3.196 |
| Big | 0.000 | 0.007 | 0.004 | 0.023 | 0.029 | 0.029 | -0.043 | 0.661 | 0.539 | 2.310 | 2.495 | 2.521 |
| **ret-4 week** | | | | | | | | | | | | |
| Small | 0.250 | 0.129 | 0.074 | 0.082 | 0.040 | -0.211 | 9.547 | 6.736 | 4.129 | 3.361 | 1.229 | -6.529 |
| 2 | 0.200 | 0.083 | 0.062 | 0.038 | 0.545 | 0.345 | 5.771 | 4.465 | 3.365 | 2.894 | 1.323 | 0.832 |
| 3 | 0.109 | 0.045 | 0.040 | 0.031 | 0.002 | -0.107 | 6.567 | 3.227 | 2.713 | 2.355 | 0.110 | -6.621 |
| 4 | 0.055 | 0.024 | 0.030 | 0.019 | 0.016 | -0.039 | 4.674 | 2.165 | 1.954 | 1.522 | 1.208 | -3.257 |
| Big | -0.010 | 0.007 | 0.013 | 0.025 | 0.024 | 0.034 | -1.055 | 0.706 | 1.366 | 2.634 | 2.099 | 2.879 |

**Table A2. Cross-section Returns of Alternative Momentum Characteristics (2014/01/01-2021/01/04, 366 weeks)** (continued)

Panel C: Sequential Double sort

| | Mean | | | | | | t-statistic | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Low** | 2 | 3 | 4 | **High** | H-L | **Low** | 2 | 3 | 4 | **High** | H-L |
| **ret-1 week** | | | | | | | | | | | | |
| Small | 0.354 | 0.159 | 0.087 | 0.084 | 0.079 | -0.276 | 8.485 | 7.940 | 5.510 | 5.571 | 2.615 | -6.018 |
| 2 | 0.152 | 0.090 | 0.147 | 0.060 | 0.022 | -0.130 | 9.111 | 4.357 | 1.656 | 3.836 | 1.246 | -6.162 |
| 3 | 0.100 | 0.065 | 0.029 | 0.050 | 0.001 | -0.099 | 6.971 | 3.249 | 2.492 | 2.648 | 0.063 | -6.181 |
| 4 | 0.069 | 0.020 | 0.016 | 0.015 | -0.001 | -0.070 | 5.627 | 1.775 | 1.348 | 1.325 | -0.086 | -6.422 |
| Big | -0.004 | 0.006 | 0.017 | 0.022 | 0.026 | 0.030 | -0.405 | 0.564 | 1.984 | 1.862 | 1.995 | 2.465 |
| **ret-3 week** | | | | | | | | | | | | |
| Small | 0.345 | 0.234 | 0.088 | 0.076 | 0.035 | -0.310 | 10.271 | 4.293 | 6.186 | 4.405 | 1.924 | -8.830 |
| 2 | 0.156 | 0.714 | 0.084 | 0.046 | 0.111 | -0.045 | 9.477 | 1.170 | 2.833 | 2.706 | 1.245 | -0.495 |
| 3 | 0.094 | 0.053 | 0.041 | 0.033 | 0.012 | -0.081 | 6.600 | 3.759 | 3.306 | 2.009 | 0.698 | -5.014 |
| 4 | 0.070 | 0.020 | 0.019 | 0.009 | 0.020 | -0.050 | 3.836 | 1.619 | 1.654 | 0.725 | 1.464 | -2.804 |
| Big | -0.003 | 0.005 | 0.019 | 0.013 | 0.032 | 0.035 | -0.372 | 0.539 | 1.644 | 1.561 | 2.690 | 3.773 |
| **ret-4 week** | | | | | | | | | | | | |
| Small | 0.304 | 0.162 | 0.115 | 0.086 | 0.033 | -0.271 | 9.513 | 6.991 | 6.152 | 3.765 | 1.356 | -9.098 |
| 2 | 0.188 | 0.076 | 0.072 | 0.045 | 0.597 | 0.409 | 8.825 | 4.899 | 3.925 | 2.462 | 1.245 | 0.851 |
| 3 | 0.117 | 0.047 | 0.037 | 0.040 | -0.007 | -0.124 | 6.137 | 3.362 | 2.423 | 2.429 | -0.628 | -7.446 |
| 4 | 0.045 | 0.018 | 0.024 | 0.021 | 0.018 | -0.028 | 4.275 | 1.509 | 1.613 | 1.575 | 1.364 | -2.896 |
| Big | 0.001 | 0.003 | 0.011 | 0.022 | 0.032 | 0.031 | 0.115 | 0.347 | 1.133 | 2.306 | 2.517 | 3.039 |

**Table A3. Excess Returns for the Second Type Value Proxies (2014/01/22-2021/01/04, 363 weeks)**

We use two types of proxies to measure the value of cryptocurrencies. The second type aims to measure the cryptocurrency fundamental-to-market value: the user-to-market ratio (U/M ratio), the address-to-market ratio (A/M ratio), and the volume-to-market ratio (T/M ratio). This table reports mean excess return and their t-statistics for single sorted portfolios based on these second type characteristics. Due to the limitation of sample size, we construct a single sort portfolio only and the cryptocurrencies are split into 5 quintiles. Mean is the average weekly value-weighted returns of each portfolio, and t(Mean) is the ratio of Mean to its standard error, which is adjusted for heteroskedasticity and autocorrelations. The sample period is from 2014/01/22 to 2021/01/04.

| | Core Sample | | | | | |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 5-1 |
| **T/M ratio** | **Low** | | | | **High** | |
| Mean | 0.011 | 0.028 | 0.014 | 0.017 | 0.026 | 0.014 |
| t(Mean) | 1.862 | 2.228 | 1.633 | 1.510 | 1.562 | 1.009 |
| **U/M ratio** | **Low** | | | | **High** | |
| Mean | 0.023 | 0.016 | 0.029 | 0.016 | 0.018 | -0.005 |
| t(Mean) | 2.147 | 1.536 | 2.247 | 1.611 | 1.659 | -0.510 |
| **A/M ratio** | **Low** | | | | **High** | |
| Mean | 0.021 | 0.017 | 0.026 | 0.018 | 0.014 | -0.008 |
| t(Mean) | 1.810 | 1.509 | 2.113 | 1.832 | 1.444 | -0.775 |

**Table A4. Excess Returns for the Network-related Characteristics: based on the Transaction Volume on Chain (2014/01/22-2021/01/04, 363 weeks)**

Each week, we construct 5 network single sorted portfolios based on the Core Sample containing 616 cryptocurrencies. Due to the limitation of sample size, we split cryptocurrencies into quintiles according to the weekly growth rate of total transaction volume on chain, Volgrowth, and of total transaction volume on chain in USD, VolUSDgrowth. Quintile 1 (5) includes the 20% cryptocurrencies with the lowest(highest) Volgrowth or VolUSDgrowth. And a long-short portfolio network 5-1 that buys cryptocurrencies in network quintile 5 and shorts cryptocurrencies in network quintile 1 is also constructed at the same time. Each portfolio is then held for 1 week and all the portfolio returns are value-weighted. Mean is the average weekly value-weighted returns of each portfolio, and t(Mean) is the ratio of Mean to its standard error, which is adjusted for heteroskedasticity and autocorrelations. The sample period is from 2014/01/22 to 2021/01/04.

| | Core Sample | | | | | |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 5-1 |
| **Volgrowth** | **Low** | | | | **High** | |
| Mean | 0.021 | 0.025 | 0.030 | 0.016 | 0.010 | -0.012 |
| t(Mean) | 1.596 | 2.658 | 3.246 | 1.825 | 0.741 | -0.871 |
| **VolUSDgrowth** | **Low** | | | | **High** | |
| Mean | 0.023 | 0.021 | 0.023 | 0.021 | 0.006 | -0.017 |
| t(Mean) | 1.606 | 2.255 | 2.789 | 2.124 | 0.540 | -1.301 |

**Table A5. Cross-section Returns of Core Sample (2014/01/22-2021/01/04, 363 weeks)**

This table reports the mean weekly excess returns of the five quintile and the long-short portfolios constructed by the Core Sample based on ten size-, momentum- and value-related characteristics that have been tested in the Full Sample. Due to the limitation of the size of Core Sample, we split cryptocurrencies into quintiles according to the corresponding characteristics each week. The time period is from 2014/01/22 to 2021/01/04.

| | Quintiles | | | | | |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 5-1 |
| **MarketCap** | **Low** | | | | **High** | |
| Mean | 0.058 | 0.015 | 0.025 | 0.021 | 0.015 | -0.044 |
| t(Mean) | 3.548 | 1.443 | 2.151 | 1.961 | 2.302 | -2.960 |
| **ret-2 week** | **Low** | | | | **High** | |
| Mean | 0.007 | 0.011 | 0.015 | 0.017 | 0.036 | 0.029 |
| t(Mean) | 0.846 | 1.260 | 1.451 | 1.962 | 2.701 | 2.267 |
| **NPast52** | **Low** | | | | **High** | |
| Mean | 0.017 | 0.018 | 0.018 | 0.019 | 0.028 | 0.011 |
| t(Mean) | 2.027 | 1.976 | 2.132 | 1.859 | 2.718 | 1.124 |

**Table A6. Summary Statistics of LTW Factor Returns (2014/01/22-2021/01/04, 363 weeks)**

This table presents the summary statistics of three factors proposed by LTW, **MKT_LTW**, **SMB_LTW**, **and MOM_LTW**, and correlations among them. All three factors are constructed by the Large Cap Sample. The **SMB_LTW** factor is constructed as follows: each week we split the cryptocurrencies into three size groups according to MarketCap: bottom 30%, middle 40%, and top 30%. Then, we form value-weighted portfolios for each of the three size groups. The size factor is the return difference between the top and the bottom network portfolios. The **MOM_LTW** factor is constructed in the same way as SMB_LTW with MarketCap replaced by ret-2 week. We construct a Large Cap market index using the value-weighted price of all available cryptocurrencies in the Large Cap Sample. **MKT_LTW** is the return of the Large Cap market index minus the one-month Treasury bill rate. Panel A reports the summary statistics of three factors' weekly returns during the sample period. Panel B reports the correlations among the three factors' weekly returns during the sample period. To meet the period of the Core Sample and to be comparable with Table 6, the sample period is from 2014/01/22 to 2021/01/04.

| Panel A: Summary statistics of factors | | | |
|---|---|---|---|
| | MKT_LTW | SMB_LTW | MOM_LTW |
| Mean | 0.02 | 0.01 | 0.03 |
| Std | 0.01 | 0.01 | 0.01 |
| t-statistics | 2.37 | 0.77 | 4.07 |
| **Panel B: Factor Correlation** | | | |
| | MKT_LTW | SMB_LTW | MOM_LTW |
| MKT_LTW | 1.00 | 0.03 | 0.07 |
| SMB_LTW | 0.03 | 1.00 | -0.05 |
| MOM_LTW | 0.07 | -0.05 | 1.00 |

**Table A7. Summary Asset Pricing tests for Single sorted and Double sorted Portfolios (2014/01/22-2021/01/04, 363 weeks)** (continued)

The table shows additional several summary statitics of different asset pricing models for In-Sample and Out-of-Sample test asset portfolios. Panel A reports the p-value of GRS, $p$(GRS), test whether the expected values of all intercept estimates in the regressions are zero. Panel B reports the p-value of $R_C^2$, $p(R_C^2)$. Panel C reports Cross Section $R^2$, which evaluates the performance of different factor models in the cross-sectional dimension. To meet the period of the Core Sample, the sample period is from 2014/01/22 to 2021/01/04.

| | In-Sample | | | | | | Out-of-Sample | | | | | | All |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Market Cap | ret-2week | NPast52 | BAgrowth | Size-Mom | Size-Value | PRC | MAXPRC | VaR | IVOL | ILLIQ | CoreSet | |
| Panel A: $p$(GRS) | | | | | | | | | | | | | |
| MKT | 0.000 | 0.005 | 0.004 | 0.224 | 0.000 | 0.000 | 0.319 | 0.440 | 0.126 | 0.693 | 0.231 | 0.111 | 0.000 |
| MKT_LTW, SMB_LTW, MOM_LTW | 0.000 | 0.010 | 0.007 | 0.236 | 0.000 | 0.000 | 0.400 | 0.551 | 0.200 | 0.660 | 0.250 | 0.259 | 0.000 |
| MKT, SMB, MOM | 0.000 | 0.275 | 0.003 | 0.285 | 0.000 | 0.000 | 0.528 | 0.789 | 0.290 | 0.046 | 0.379 | 0.587 | 0.000 |
| MKT, SMB, REV | 0.000 | 0.017 | 0.027 | 0.198 | 0.000 | 0.000 | 0.030 | 0.806 | 0.000 | 0.214 | 0.540 | 0.131 | 0.000 |
| MKT, SMB, VAL | 0.000 | 0.018 | 0.436 | 0.160 | 0.000 | 0.000 | 0.214 | 0.635 | 0.013 | 0.036 | 0.423 | 0.309 | 0.000 |
| MKT, SMB, NET | 0.000 | 0.049 | 0.005 | 0.966 | 0.000 | 0.000 | 0.529 | 0.786 | 0.313 | 0.079 | 0.345 | 0.578 | 0.000 |
| MKT, SMB, VAL, MOM | 0.000 | 0.428 | 0.418 | 0.186 | 0.000 | 0.000 | 0.327 | 0.775 | 0.051 | 0.033 | 0.404 | 0.633 | 0.000 |
| MKT, SMB, VAL, REV | 0.000 | 0.016 | 0.501 | 0.113 | 0.000 | 0.000 | 0.002 | 0.276 | 0.000 | 0.144 | 0.514 | 0.148 | 0.000 |
| MKT, SMB, VAL, NET | 0.000 | 0.041 | 0.415 | 0.647 | 0.000 | 0.000 | 0.137 | 0.444 | 0.032 | 0.045 | 0.285 | 0.573 | 0.000 |
| MKT, SMB, VAL, MOM, NET | 0.000 | 0.532 | 0.374 | 0.684 | 0.000 | 0.000 | 0.221 | 0.611 | 0.098 | 0.039 | 0.273 | 0.857 | 0.000 |
| MKT, SMB, VAL, MOM, REV | 0.000 | 0.502 | 0.491 | 0.113 | 0.000 | 0.000 | 0.019 | 0.587 | 0.000 | 0.130 | 0.528 | 0.401 | 0.000 |
| MKT, SMB, VAL, REV, NET | 0.000 | 0.038 | 0.491 | 0.493 | 0.000 | 0.000 | 0.001 | 0.133 | 0.000 | 0.163 | 0.403 | 0.357 | 0.000 |
| MKT, SMB, VAL, MOM, REV, NET | 0.000 | 0.600 | 0.454 | 0.473 | 0.000 | 0.000 | 0.006 | 0.358 | 0.000 | 0.140 | 0.416 | 0.673 | 0.000 |

**Table A7. Summary Asset Pricing tests for Single sorted and Double sorted Portfolios (2014/01/22-2021/01/04, 363 weeks)** (continued)

| | In-Sample | | | | | | Out-of-Sample | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Market Cap | ret-2week | NPast52 | BAgrowth | Size-Mom | Size-Value | PRC | MAXPRC | VaR | IVOL | ILLIQ | CoreSet | All |
| Panel B*:* $p(R_C^2)$ | | | | | | | | | | | | | |
| MKT | 0.009 | 0.352 | 0.028 | 0.880 | 0.750 | 0.124 | 0.032 | 0.025 | 0.000 | 0.007 | 0.006 | 0.343 | 0.000 |
| MKT_LTW, SMB_LTW, MOM_LTW | 0.053 | 0.722 | 0.016 | 0.818 | 0.933 | 0.048 | 0.020 | 0.003 | 0.000 | 0.006 | 0.011 | 0.012 | 0.000 |
| MKT, SMB, MOM | 0.270 | 0.838 | 0.109 | 0.791 | 0.982 | 0.999 | 0.084 | 0.009 | 0.000 | 0.026 | 0.011 | 0.048 | 0.000 |
| MKT, SMB, REV | -0.059 | 0.327 | 0.078 | 0.801 | 0.992 | 0.995 | 0.115 | 0.002 | 0.000 | 0.004 | 0.066 | 0.195 | 0.000 |
| MKT, SMB, VAL | 0.637 | 0.282 | 0.002 | 0.759 | 0.069 | 0.965 | 0.031 | 0.002 | 0.000 | 0.247 | 0.117 | 0.107 | 0.000 |
| MKT, SMB, NET | 0.293 | 0.566 | 0.264 | 0.000 | 0.907 | 0.999 | 0.009 | 0.001 | 0.000 | 0.061 | 0.020 | 0.000 | 0.000 |
| MKT, SMB, VAL, MOM | 0.672 | 0.755 | 0.001 | 0.830 | 0.137 | 0.957 | 0.029 | 0.000 | 0.000 | 0.087 | 0.058 | 0.096 | 0.000 |
| MKT, SMB, VAL, REV | 0.185 | 0.212 | 0.002 | 0.832 | 0.995 | 0.909 | 0.774 | 0.157 | 0.000 | 0.016 | 0.240 | 0.283 | 0.000 |
| MKT, SMB, VAL, NET | 0.650 | 0.358 | 0.004 | 0.001 | 0.064 | 0.935 | 0.027 | 0.005 | 0.000 | 0.187 | 0.123 | 0.002 | 0.000 |
| MKT, SMB, VAL, MOM, NET | 0.683 | 0.734 | 0.001 | 0.008 | 0.125 | 0.929 | 0.024 | 0.001 | 0.000 | 0.063 | 0.067 | 0.003 | 0.000 |
| MKT, SMB, VAL, MOM, REV | 0.166 | 0.308 | 0.001 | 0.882 | 0.990 | 0.906 | 0.414 | 0.024 | 0.000 | 0.009 | 0.106 | 0.019 | 0.000 |
| MKT, SMB, VAL, REV, NET | 0.229 | 0.769 | 0.003 | 0.013 | 0.996 | 0.860 | 0.854 | 0.370 | 0.000 | 0.013 | 0.207 | 0.003 | 0.000 |
| MKT, SMB, VAL, MOM, REV, NET | 0.208 | 0.760 | 0.001 | 0.039 | 0.992 | 0.861 | 0.543 | 0.083 | 0.000 | 0.007 | 0.103 | 0.000 | 0.000 |

**Table A7. Summary Asset Pricing tests for Single sorted and Double sorted Portfolios (2014/01/22-2021/01/04, 363 weeks)** (continued)

| | In-Sample | | | | | | Out-of-Sample | | | | | | All |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Market Cap | ret-2 week | NPast52 | BAgrowth | Size-Mom | Size-Value | PRC | MAXPRC | VaR | IVOL | ILLIQ | CoreSet | |
| Panel C: $Cross\ Section\ R^2$ | | | | | | | | | | | | | |
| MKT | 0.009 | 0.352 | 0.470 | 0.635 | 0.053 | 0.200 | 0.422 | 0.480 | 0.212 | 0.527 | 0.554 | 0.596 | 0.098 |
| MKT_LTW, SMB_LTW, MOM_LTW | 0.053 | 0.722 | 0.561 | 0.699 | -0.043 | 0.295 | 0.563 | 0.673 | 0.153 | 0.643 | 0.659 | 0.745 | 0.098 |
| MKT, SMB, MOM | 0.270 | 0.838 | 0.577 | 0.626 | -0.246 | 0.161 | 0.603 | 0.778 | 0.324 | 0.631 | 0.788 | 0.769 | 0.081 |
| MKT, SMB, REV | -0.059 | 0.327 | 0.656 | 0.642 | -0.358 | 0.233 | 0.716 | 0.893 | -0.338 | 0.886 | 0.743 | 0.752 | -0.084 |
| MKT, SMB, VAL | 0.637 | 0.282 | 0.888 | 0.721 | 0.552 | 0.425 | 0.816 | 0.935 | 0.784 | 0.072 | 0.719 | 0.833 | 0.578 |
| MKT, SMB, NET | 0.293 | 0.566 | 0.590 | 0.986 | 0.055 | 0.221 | 0.766 | 0.886 | 0.574 | 0.477 | 0.775 | 0.914 | 0.239 |
| MKT, SMB, VAL, MOM | 0.672 | 0.755 | 0.903 | 0.683 | 0.449 | 0.405 | 0.828 | 0.956 | 0.744 | 0.446 | 0.779 | 0.867 | 0.554 |
| MKT, SMB, VAL, REV | 0.185 | 0.212 | 0.898 | 0.680 | -0.491 | 0.445 | 0.497 | 0.819 | -0.556 | 0.755 | 0.678 | 0.818 | -0.030 |
| MKT, SMB, VAL, NET | 0.650 | 0.358 | 0.889 | 0.898 | 0.592 | 0.448 | 0.834 | 0.922 | 0.834 | 0.209 | 0.723 | 0.910 | 0.610 |
| MKT, SMB, VAL, MOM, NET | 0.683 | 0.734 | 0.904 | 0.913 | 0.499 | 0.429 | 0.854 | 0.952 | 0.796 | 0.516 | 0.773 | 0.950 | 0.588 |
| MKT, SMB, VAL, MOM, REV | 0.166 | 0.308 | 0.900 | 0.878 | -0.619 | 0.467 | 0.436 | 0.769 | -0.676 | 0.790 | 0.752 | 0.903 | -0.066 |
| MKT, SMB, VAL, REV, NET | 0.229 | 0.769 | 0.914 | 0.628 | -0.545 | 0.427 | 0.615 | 0.892 | -0.619 | 0.836 | 0.688 | 0.845 | -0.092 |
| MKT, SMB, VAL, MOM, REV, NET | 0.208 | 0.760 | 0.915 | 0.883 | -0.663 | 0.449 | 0.560 | 0.851 | -0.736 | 0.807 | 0.750 | 0.936 | -0.126 |

**Table A8. The Relative Alpha of Out-of-Sample Characteristics to Different Factor Models (2014/01/22-2021/01/04, 363 weeks)**

This table reports the mean excess returns, the relative alpha to the Crypto-CAPM, the LTW-3, and our C-5 model of the Out-of-Sample characteristics, and their t-statistics, which are adjusted for heteroskedasticity and autocorrelations. The time period is from 2014/01/22 to 2021/01/04.

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 10-1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **PRC** | **Low** | | | | | | | | | **High** | |
| Mean | 0.098 | 0.044 | 0.072 | 0.034 | 0.022 | 0.034 | 0.020 | 0.020 | 0.006 | 0.010 | -0.089 |
| t-statistics | 2.468 | 1.526 | 1.482 | 1.690 | 1.443 | 2.158 | 1.597 | 1.698 | 0.549 | 1.048 | -2.386 |
| CAPM | 0.083 | 0.027 | 0.044 | 0.023 | 0.007 | 0.028 | 0.013 | 0.013 | -0.001 | 0.001 | -0.081 |
| t-statistics | 2.039 | 1.208 | 1.419 | 1.259 | 0.498 | 1.698 | 1.063 | 1.058 | -0.112 | 0.155 | -2.160 |
| LTW-3 | 0.073 | 0.016 | 0.041 | 0.015 | 0.005 | 0.026 | 0.012 | 0.009 | -0.002 | -0.001 | -0.075 |
| t-statistics | 1.691 | 1.009 | 1.185 | 1.031 | 0.337 | 1.583 | 1.024 | 0.822 | -0.246 | -0.195 | -1.788 |
| C-5 | 0.016 | -0.022 | 0.035 | 0.003 | -0.011 | 0.021 | 0.008 | 0.001 | -0.008 | -0.011 | -0.026 |
| t-statistics | 0.522 | -1.279 | 0.831 | 0.183 | -0.928 | 1.209 | 0.545 | 0.100 | -0.898 | -1.310 | -0.972 |
| **MAXPRC** | **Low** | | | | | | | | | **High** | |
| Mean | 0.073 | 0.038 | 0.042 | 0.033 | 0.028 | 0.033 | 0.023 | 0.021 | 0.008 | 0.011 | -0.062 |
| t-statistics | 2.651 | 1.806 | 1.400 | 1.787 | 1.777 | 2.096 | 1.914 | 1.748 | 0.820 | 1.103 | -2.742 |
| CAPM | 0.056 | 0.026 | 0.020 | 0.024 | 0.014 | 0.024 | 0.017 | 0.014 | 0.001 | 0.002 | -0.054 |
| t-statistics | 2.120 | 1.357 | 1.010 | 1.377 | 0.950 | 1.511 | 1.429 | 1.116 | 0.108 | 0.236 | -2.509 |
| LTW-3 | 0.043 | 0.022 | 0.012 | 0.019 | 0.011 | 0.021 | 0.016 | 0.010 | -0.001 | -0.001 | -0.045 |
| t-statistics | 1.841 | 1.160 | 0.627 | 1.322 | 0.782 | 1.314 | 1.368 | 0.889 | -0.081 | -0.129 | -2.146 |
| C-5 | -0.004 | -0.004 | 0.001 | 0.008 | -0.001 | 0.015 | 0.010 | 0.002 | -0.004 | -0.011 | -0.007 |
| t-statistics | -0.163 | -0.207 | 0.040 | 0.442 | -0.105 | 0.880 | 0.641 | 0.157 | -0.415 | -1.354 | -0.298 |
| **VaR** | **Low** | | | | | | | | | **High** | |
| Mean | 0.188 | 0.030 | 0.087 | 0.025 | -0.005 | 0.008 | 0.012 | 0.025 | 0.012 | 0.017 | -0.172 |
| t-statistics | 1.638 | 1.770 | 1.150 | 1.666 | -0.370 | 0.624 | 1.186 | 1.862 | 1.117 | 2.513 | -1.484 |
| CAPM | 0.182 | 0.018 | 0.040 | 0.016 | -0.013 | -0.001 | 0.003 | 0.022 | 0.001 | 0.004 | -0.178 |
| t-statistics | 1.509 | 1.143 | 1.030 | 0.993 | -1.065 | -0.104 | 0.277 | 1.396 | 0.128 | 0.936 | -1.476 |
| LTW-3 | 0.191 | 0.012 | 0.038 | 0.011 | -0.015 | -0.003 | 0.001 | 0.016 | -0.002 | 0.003 | -0.188 |
| t-statistics | 1.376 | 0.853 | 0.862 | 0.766 | -1.233 | -0.213 | 0.129 | 1.130 | -0.229 | 0.819 | -1.352 |
| C-5 | 0.059 | -0.016 | 0.051 | -0.011 | -0.030 | -0.020 | -0.009 | 0.003 | -0.010 | 0.002 | -0.058 |
| t-statistics | 0.977 | -0.998 | 0.715 | -0.801 | -2.562 | -1.340 | -0.803 | 0.160 | -1.009 | 0.394 | -0.958 |

**Table A8. The Relative Alpha of Out-of-Sample Characteristics to Different Factor Models (2014/01/22-2021/01/04, 363 weeks)** (Continued)

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 10-1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **ILLIQ** | **Low** | | | | | | | | | **High** | |
| Mean | 0.007 | 0.021 | 0.018 | 0.020 | 0.018 | 0.014 | 0.034 | 0.063 | 0.029 | 0.032 | 0.025 |
| t-statistics | 0.863 | 1.892 | 1.909 | 1.734 | 1.549 | 1.049 | 2.236 | 1.371 | 1.891 | 1.881 | 1.715 |
| CAPM | -0.004 | 0.011 | 0.006 | 0.004 | 0.008 | 0.002 | 0.025 | 0.034 | 0.020 | 0.021 | 0.025 |
| t-statistics | -0.532 | 1.179 | 0.721 | 0.432 | 0.846 | 0.180 | 1.595 | 1.242 | 1.185 | 1.313 | 1.811 |
| LTW-3 | -0.004 | 0.010 | 0.003 | 0.001 | 0.006 | -0.001 | 0.026 | 0.030 | 0.018 | 0.017 | 0.021 |
| t-statistics | -0.650 | 1.155 | 0.384 | 0.133 | 0.635 | -0.085 | 1.450 | 1.020 | 1.057 | 1.166 | 1.747 |
| C-5 | -0.009 | -0.008 | -0.005 | -0.009 | -0.002 | -0.005 | 0.003 | -0.011 | 0.051 | -0.007 | 0.002 |
| t-statistics | -1.183 | -0.919 | -0.639 | -1.057 | -0.251 | -0.309 | 0.229 | -1.049 | 1.165 | -0.394 | 0.109 |
| **IVOL** | **Low** | | | | | | | | | **High** | |
| Mean | 0.012 | 0.024 | 0.011 | 0.005 | 0.011 | 0.005 | 0.022 | -0.004 | 0.011 | 0.117 | 0.106 |
| t-statistics | 1.649 | 1.942 | 1.053 | 0.518 | 0.955 | 0.401 | 1.451 | -0.247 | 0.684 | 1.325 | 1.201 |
| CAPM | 0.001 | 0.016 | 0.003 | -0.003 | 0.001 | -0.003 | 0.013 | -0.009 | 0.000 | 0.082 | 0.081 |
| t-statistics | 0.172 | 1.307 | 0.283 | -0.310 | 0.107 | -0.291 | 0.939 | -0.575 | -0.012 | 1.266 | 1.249 |
| LTW-3 | 0.000 | 0.014 | 0.003 | -0.004 | -0.002 | -0.010 | 0.006 | -0.007 | -0.009 | 0.070 | 0.070 |
| t-statistics | -0.007 | 1.253 | 0.319 | -0.442 | -0.170 | -1.010 | 0.515 | -0.410 | -0.628 | 1.182 | 1.181 |
| C-5 | -0.005 | 0.006 | 0.001 | -0.010 | -0.008 | -0.024 | -0.013 | -0.011 | -0.050 | 0.062 | 0.067 |
| t-statistics | -1.005 | 0.467 | 0.042 | -1.034 | -0.702 | -2.251 | -1.042 | -0.612 | -3.529 | 0.847 | 0.920 |

**Table A9. Factor Regressions for Individual Cryptocurrencies (2014/01/22-2021/01/04, 363 weeks)**

This table reports the regressions of the weekly return of five individual cryptocurrencies, Bitcoin, Ethereum, Litecoin, Xrp, and Polkadot, on different factor models. The t-statistics (in parentheses) are adjusted for heteroskedasticity and autocorrelations. The time period is from 2014/01/22 to 2021/01/04.

| | Bitcoin | Ethereum | Litecoin | Xrp | Polkadot |
|---|---|---|---|---|---|
| | Panel A. Crypto-CAPM model | | | | |
| Intercept | 0.002 | 0.028 | 0.004 | 0.025 | -0.021 |
| | (0.928) | (2.047)** | (0.463) | (1.406) | (-0.739) |
| MKT | 0.864 | 0.505 | 0.986 | 0.264 | 0.926 |
| | (33.977)*** | (5.032)*** | (5.862)*** | (2.168)** | (3.756)*** |
| Adjusted R square | 0.904 | 0.101 | 0.338 | 0.010 | 0.259 |
| | Panel B. LTW-3 model | | | | |
| Intercept | 0.002 | 0.023 | 0.004 | 0.024 | -0.031 |
| | (0.849) | (2.127)** | (0.451) | (1.425) | (-1.666) |
| MKT_LTW | 0.862 | 0.482 | 0.986 | 0.262 | 0.868 |
| | (34.188)*** | (5.539)*** | (5.738)*** | (2.087)** | (1.965)* |
| SMB_LTW | -0.009 | 0.097 | -0.015 | -0.084 | 0.044 |
| | (-0.677) | (1.327) | (-0.322) | (-1.205) | (0.949) |
| MOM_LTW | 0.025 | 0.245 | 0.014 | 0.041 | 0.251 |
| | (1.325) | (3.161)*** | (0.217) | (0.290) | (0.392) |
| Adjusted R square | 0.904 | 0.138 | 0.334 | 0.007 | 0.259 |
| | Panel C. C-5 model | | | | |
| Intercept | 0.001 | 0.013 | 0.006 | 0.033 | -0.023 |
| | (0.424) | (1.144) | (0.635) | (1.640) | (-1.320) |
| MKT | 0.863 | 0.432 | 0.993 | 0.266 | 0.770 |
| | (34.954)*** | (5.022)*** | (5.920)*** | (2.225)** | (1.537) |
| SMB | 0.010 | 0.001 | 0.054 | 0.070 | -0.429 |
| | (1.078) | (0.024) | (0.805) | (0.550) | (-0.992) |
| MOM | -0.008 | -0.053 | -0.033 | -0.002 | 0.138 |
| | (-0.795) | (-0.757) | (-0.552) | (-0.021) | (0.490) |
| VAL | 0.005 | 0.134 | -0.039 | -0.207 | 0.381 |
| | (0.291) | (1.826)* | (-0.331) | (-0.937) | (1.271) |
| NET | 0.015 | 0.536 | -0.069 | -0.111 | -0.303 |
| | (1.354) | (4.1365)*** | (-1.771)* | (-1.685) | (-0.443) |
| Adjusted R square | 0.905 | 0.378 | 0.340 | 0.019 | 0.312 |

**Table A10. Tests of Global, Local, and International Versions of the Crypto-CAPM and LTW-3**

This table reports the summary tests of global, local and "international" versions of the Crypto-CAPM and LTW-3 models. We use General Payment, Platform Token, Product Token and Security Token decile portfolios formed on size, value, momentum and network as test assets. Panel A shows the performance of Crypto-CAPM model; Panel B shows that of the LTW-3 model. The GRS statistic and its p-value, p(GRS), test whether the expected values of all 10 intercept estimates in the regressions are zero. Also shown are (1) $A|a|$, the average absolute value of the intercepts; (2) $AR^2$, the average of the regression $R^2$, adjusted for degrees of freedom. (3) $R_C^2$ denotes the constrained $R^2$ in which the risk price estimates are constrained to be equal to the factor sample means in two-pass regressions, and $p(R_C^2)$ is its p-value. Total for p(GRS) indicates how many tests fail; Total for GRS F-statistics, average absolute alpha ($A|a|$), average adjusted R square ($AR^2$), and constrained R square ($R_C^2$) denote the average value; Total for $p(R_C^2)$ indicates how many tests have positive constrained R square with p-value <=0.05, i.e., p value is positive at the 5% level.

Panel A: Crypto-CAPM Model

| | Global factor model | | | | | | Local factor model | | | | | | International factor model | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | GRS | p(GRS) | $A\|a\|$ | $AR^2$ | $R_C^2$ | $p(R_C^2)$ | GRS | p(GRS) | $A\|a\|$ | $AR^2$ | $R_C^2$ | $p(R_C^2)$ | GRS | p(GRS) | $A\|a\|$ | $AR^2$ | $R_C^2$ | $p(R_C^2)$ |
| **General Payment** | | | | | | | | | | | | | | | | | | |
| Size | 0.837 | 0.593 | 0.037 | 0.194 | 0.061 | 0.004 | 0.760 | 0.667 | 0.034 | 0.226 | 0.086 | 0.004 | 0.707 | 0.717 | 0.033 | 0.259 | 0.096 | 0.005 |
| Value | 1.267 | 0.252 | 0.020 | 0.145 | 0.241 | 0.000 | 1.246 | 0.264 | 0.018 | 0.182 | 0.228 | 0.000 | 1.241 | 0.268 | 0.018 | 0.222 | 0.218 | 0.000 |
| Network | 1.366 | 0.199 | 0.019 | 0.174 | 0.089 | 0.001 | 1.486 | 0.148 | 0.018 | 0.220 | 0.112 | 0.001 | 1.780 | 0.067 | 0.018 | 0.269 | 0.111 | 0.001 |
| Momentum | 1.823 | 0.059 | 0.041 | 0.146 | 0.043 | 0.000 | 1.995 | 0.036 | 0.040 | 0.196 | 0.052 | 0.000 | 2.167 | 0.022 | 0.040 | 0.262 | 0.040 | 0.000 |
| **Platform Token** | | | | | | | | | | | | | | | | | | |
| Size | 2.027 | 0.033 | 0.021 | 0.166 | 0.106 | 0.036 | 2.337 | 0.013 | 0.019 | 0.378 | 0.085 | 0.029 | 2.251 | 0.017 | 0.017 | 0.403 | 0.122 | 0.029 |
| Value | 1.886 | 0.050 | 0.008 | 0.203 | -0.061 | 0.001 | 2.032 | 0.032 | 0.007 | 0.601 | -0.041 | 0.000 | 2.200 | 0.020 | 0.008 | 0.610 | -0.051 | 0.000 |
| Network | 0.568 | 0.839 | 0.006 | 0.178 | -0.036 | 0.558 | 0.429 | 0.931 | 0.005 | 0.343 | 0.372 | 0.003 | 0.578 | 0.830 | 0.007 | 0.377 | 0.224 | 0.035 |
| Momentum | 0.802 | 0.627 | 0.007 | 0.182 | 0.141 | 0.011 | 0.455 | 0.916 | 0.005 | 0.349 | 0.472 | 0.000 | 0.743 | 0.683 | 0.007 | 0.390 | 0.392 | 0.001 |
| **Product Token** | | | | | | | | | | | | | | | | | | |
| Size | 1.392 | 0.191 | 0.024 | 0.160 | 0.114 | 0.106 | 1.451 | 0.166 | 0.026 | 0.086 | -0.026 | 0.750 | 1.399 | 0.188 | 0.024 | 0.199 | 0.101 | 0.144 |
| Value | 1.909 | 0.050 | 0.023 | 0.132 | 0.226 | 0.000 | 1.812 | 0.065 | 0.025 | 0.053 | 0.046 | 0.000 | 1.904 | 0.051 | 0.023 | 0.149 | 0.231 | 0.000 |
| Network | 0.697 | 0.726 | 0.011 | 0.158 | -0.106 | 0.782 | 0.440 | 0.924 | 0.007 | 0.091 | -0.092 | 0.904 | 0.799 | 0.630 | 0.011 | 0.196 | -0.137 | 0.805 |
| Momentum | 0.708 | 0.716 | 0.017 | 0.179 | 0.203 | 0.052 | 0.757 | 0.670 | 0.015 | 0.059 | 0.001 | 0.432 | 0.740 | 0.685 | 0.017 | 0.197 | 0.196 | 0.065 |
| **Security Token** | | | | | | | | | | | | | | | | | | |
| Size | 1.535 | 0.132 | 0.137 | 0.039 | 0.095 | 0.000 | 1.275 | 0.279 | 0.025 | 0.104 | 0.010 | 0.330 | 1.567 | 0.174 | 0.029 | 0.265 | 0.153 | 0.115 |
| Value | 0.502 | 0.887 | 0.016 | 0.067 | -0.051 | 0.000 | 1.505 | 0.192 | 0.012 | 0.104 | 0.048 | 0.161 | 2.017 | 0.080 | 0.014 | 0.222 | 0.088 | 0.201 |
| Network | 2.798 | 0.003 | 0.091 | 0.028 | 0.098 | 0.000 | 0.635 | 0.674 | 0.009 | 0.109 | -0.142 | 0.919 | 0.768 | 0.574 | 0.010 | 0.251 | -0.172 | 0.783 |
| Momentum | 0.797 | 0.631 | 0.016 | 0.043 | 0.028 | 0.000 | 0.180 | 0.970 | 0.003 | 0.103 | -0.281 | 0.958 | 0.516 | 0.763 | 0.009 | 0.279 | 0.243 | 0.092 |
| **Total** | 1.307 | 4 | 0.031 | 0.128 | 0.063 | 10 | 1.175 | 3 | 0.013 | 0.198 | 0.038 | 8 | 1.336 | 3 | 0.015 | 0.295 | 0.116 | 8 |

**Table A10. Tests of Global, Local, and International Versions of the Crypto-CAPM, LTW-3 and C-5 Model** (continued)

Panel B: LTW-3 Model

| | Global factor model | | | | | | Local factor model | | | | | | International factor model | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | GRS | p(GRS) | $A\|a\|$ | $AR^2$ | $R_C^2$ | $p(R_C^2)$ | GRS | p(GRS) | $A\|a\|$ | $AR^2$ | $R_C^2$ | $p(R_C^2)$ | GRS | p(GRS) | $A\|a\|$ | $AR^2$ | $R_C^2$ | $p(R_C^2)$ |
| **General Payment** | | | | | | | | | | | | | | | | | | |
| Size | 0.769 | 0.659 | 0.021 | 0.254 | 0.911 | 0.000 | 0.999 | 0.446 | 0.012 | 0.345 | 0.933 | 0.000 | 0.474 | 0.905 | 0.010 | 0.401 | 0.944 | 0.000 |
| Value | 0.858 | 0.574 | 0.018 | 0.162 | 0.198 | 0.000 | 1.309 | 0.229 | 0.018 | 0.192 | 0.061 | 0.000 | 1.044 | 0.409 | 0.017 | 0.230 | 0.057 | 0.000 |
| Network | 1.478 | 0.151 | 0.018 | 0.195 | 0.235 | 0.001 | 1.625 | 0.103 | 0.018 | 0.234 | 0.213 | 0.000 | 2.077 | 0.029 | 0.018 | 0.281 | 0.236 | 0.001 |
| Momentum | 2.164 | 0.022 | 0.031 | 0.197 | 0.884 | 0.000 | 2.156 | 0.023 | 0.020 | 0.350 | 0.924 | 0.000 | 2.380 | 0.011 | 0.021 | 0.408 | 0.906 | 0.000 |
| **Platform Token** | | | | | | | | | | | | | | | | | | |
| Size | 1.326 | 0.219 | 0.014 | 0.518 | 0.800 | 0.000 | 2.009 | 0.035 | 0.014 | 0.671 | 0.608 | 0.000 | 2.040 | 0.032 | 0.015 | 0.681 | 0.590 | 0.000 |
| Value | 1.522 | 0.135 | 0.006 | 0.253 | 0.333 | 0.000 | 1.780 | 0.067 | 0.006 | 0.606 | 0.219 | 0.000 | 1.880 | 0.051 | 0.007 | 0.618 | 0.161 | 0.000 |
| Network | 0.773 | 0.655 | 0.013 | 0.357 | 0.402 | 0.014 | 0.806 | 0.623 | 0.012 | 0.466 | 0.129 | 0.118 | 1.087 | 0.374 | 0.013 | 0.483 | -0.116 | 0.579 |
| Momentum | 2.044 | 0.031 | 0.015 | 0.383 | -0.524 | 0.134 | 1.203 | 0.292 | 0.013 | 0.527 | 0.317 | 0.002 | 1.499 | 0.143 | 0.014 | 0.552 | 0.341 | 0.003 |
| **Product Token** | | | | | | | | | | | | | | | | | | |
| Size | 1.644 | 0.102 | 0.027 | 0.209 | -0.144 | 0.707 | 0.717 | 0.707 | 0.014 | 0.176 | 0.711 | 0.000 | 1.038 | 0.416 | 0.018 | 0.315 | 0.528 | 0.015 |
| Value | 2.229 | 0.020 | 0.027 | 0.183 | 0.070 | 0.000 | 1.715 | 0.084 | 0.025 | 0.058 | 0.147 | 0.000 | 2.128 | 0.027 | 0.028 | 0.182 | -0.265 | 0.001 |
| Network | 0.787 | 0.641 | 0.012 | 0.218 | -0.226 | 0.694 | 0.528 | 0.868 | 0.008 | 0.098 | -0.169 | 0.732 | 1.168 | 0.319 | 0.012 | 0.239 | -0.450 | 0.782 |
| Momentum | 0.992 | 0.454 | 0.019 | 0.231 | -0.014 | 0.444 | 0.402 | 0.943 | 0.009 | 0.109 | 0.756 | 0.002 | 0.702 | 0.721 | 0.013 | 0.275 | 0.693 | 0.010 |
| **Security Token** | | | | | | | | | | | | | | | | | | |
| Size | 3.516 | 0.000 | 0.079 | 0.199 | -2.918 | 0.000 | 1.090 | 0.374 | 0.046 | 0.191 | 0.937 | 0.000 | 1.515 | 0.140 | 0.049 | 0.328 | 0.993 | 0.000 |
| Value | 0.647 | 0.771 | 0.020 | 0.188 | -0.038 | 0.000 | 0.198 | 0.996 | 0.009 | 0.071 | -0.004 | 0.000 | 0.501 | 0.887 | 0.018 | 0.233 | 0.042 | 0.000 |
| Network | 1.627 | 0.104 | 0.048 | 0.166 | -6.085 | 0.000 | 2.804 | 0.003 | 0.041 | 0.135 | 0.928 | 0.000 | 2.797 | 0.003 | 0.028 | 0.265 | 0.772 | 0.000 |
| Momentum | 2.880 | 0.003 | 0.028 | 0.235 | -1.858 | 0.000 | 0.564 | 0.841 | 0.009 | 0.188 | 0.847 | 0.000 | 1.817 | 0.062 | 0.020 | 0.360 | 0.415 | 0.000 |
| **Total** | 1.579 | 5 | 0.025 | 0.247 | -0.499 | 8 | 1.244 | 3 | 0.017 | 0.276 | 0.472 | 13 | 1.509 | 5 | 0.019 | 0.366 | 0.365 | 13 |