Cross-Sectional Return Predictors of Utility Tokens

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Abstract

This paper takes into account the differences between crypto-coins and crypto-tokens, and investigate the performances of cross-sectional return predictors based on a large sample solely consisting of utility tokens (over 1,000 ERC-20 tokens). Besides the most famous and long-standing predictors such as size and momentum, we thoroughly examine the fundamental-related predictors formed by using on-chain variables including dollar-value of transactions, transfer counts and unique active addresses, which reflect real economic activity on the blockchain and proxy intrinsic values of the tokens. We further construct a pricing-factor model including a quasi value factor, which is a counterpart of the value factor HML in equity market. By following Fama and French (1996), we found that the pricing model could to some extent explain the excess returns of 25 double-soring portfolios.

Key Words: Crypto-coins vs. Crypto-tokens, Utility Tokens (ERC-20), On-Chain Variables, Fundamental-related Predictors, Quasi Value Factor

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1. Introduction

With the invention of blockchain technology in the early 2000's, the world has been standing by excited to see what becomes of it. In recent years, the rise of cryptocurrencies has demonstrated the value of this technology. A blockchain is a decentralized/distributed and immutable ledger that records all transactions and tracks assets through a peer-to-peer network. In traditional monetary system, operations often waste effort on duplicate record keeping and the third-party validations. This centralized record-keeping system can be vulnerable to fraud and cyberattack. Its limited transparency can also slow the transaction verification. The blockchain technology coupled with smart contracts stored on the chain can provide and maintain a decentralized consensus without a third-part authority. This decentralized consensus on data is required from all network members. All validated transactions are immutable since they are recorded permanently and even a system administrator cannot alter a consensus transaction. This distributed ledger speed transactions by eliminating record reconciliations.

To support this decentralized consensus, there are two major consensus mechanisms have applied to verify new transactions and to guarantee no double-spending issue without a central authority. The original blockchain consensus mechanism is Proof of Work (PoW), which requires record keepers to contribute a large amount of processing power (e.g., computation power and electric) to solve complicated cryptographical puzzles for verifying transactions and adding new blocks. The one who firstly solve the puzzle and create a new block will be rewarded by a predetermined amount of crypto. Thus, the process of PoW is also called mining. The other consensus mechanism is Proof of Stake (PoS), which selects the validator of the latest block depending on his or her staked crypto funds in the network.

The cryptos mentioned above usually have their own blockchains. These cryptos are generated through confirming new transactions and used as a unit of account to store value to fuel their underlying blockchains (Bariviera et al., 2017). We specifically name this kind of cryptos as "Coin". Meanwhile, empowered by blockchain technology, it is possible to decentralize not only money but also other scarce assets such as currencies, securities, properties, loyalty points and gift certificates (Tapscott, 2016; Buterin, 2014). These assets can be tokenized by issuing the other type of crypto coin through initial coin offering (ICO), similar to the initial public offering (IPO) for stocks, on top of existing blockchains. We define this type of crypto coin as "Token", which usually has some utility related to the product or service offered by the company or represents a stake in a company's project.

Since the emergency of the cryptocurrency, a number of researches have focused on developing theoretical models of cryptocurrencies. Weber (2016) imagines a monetary system depending on Bitcoin standards and investigate the similarities and differences between the new standards and the gold standard. Even though the Bitcoin standard would dominate the fiat standards, the author still believe that the cryptocurrency standard will not come into existence. Huberman et al. (2017) establish a model of the decentralized payment system of Bitcoin, and find that this system can avoid monopoly pricing. They also use computational power as an exogenous variable in the model to build the equilibrium. Chiu and Koeppl (2017) consider bitcoin as a mean of payment and formalize the system from the feasibility and security for example double-spending.

The fundamental problem in digital record keeping is to establish consensus on an update to a ledger (Abadi and Brunnermeier, 2018). Due to the advantages of decentralized consensus over centralized authority in efficiency and security, researchers are interested in whether the decentralized consensus can improve social welfare and consumer surplus. Cong and He (2018) exploit the blockchains mechanisms for generating the decentralized consensus and the potential economic outcomes by reaching market equilibria. They further discuss the effectiveness of the blockchain technology on realistic implications such as industrial organization and competition. Schilling and Uhlig (2019) provide a model of an endowment economy with two competing, but intrinsically worthless currencies (Dollar, Bitcoin) serving as medium of exchange. BIAIS et al. (2023) model the proof-of-work blockchain protocol as a stochastic mining game and discuss multiple equilibria. Pagnotta and Buraschi (2018) consider bitcoin as a decentralized network asset, and conclude that the equilibrium price is related to the fundamental properties of demand and supply. Pagnotta (2018) exploit the evolution of bitcoin prices by capturing the effect of its decentralized network and establish the relation between network security and the coin price.

There are other researches in cryptocurrencies from the perspective of empirical asset pricing. Liu and Tsyvinski (2018) pioneeringly conduct a comprehensive analysis of to examine cryptocurrencies' returns. They investigate how do major cryptocurrencies comove with traditional assets, macroeconomic factors, and the cryptocurrency market specific factors and conclude that the variations of crypto returns can only be explained by the crypto specific factors such as momentum and investor attention.

Our research is in the line of exploiting empirical patterns in cryptocurrencies returns. The previous empirical analyses in the pricing drivers of cryptocurrency either have small samples (Liu and Tsyvinski, 2018; Bhambhwani et al., 2019) or big samples without distinguishing between coins and tokens (Liu, Tsyvinski and Wu, 2021). Coins are usually used as a store of value, while tokens are used to power decentralized applications. Thus, the price of a coin should be driven by demand for storing value, while the price of a token is often determined by demand for utility. Since coins and tokens may share different fundamentals, we intend to apply empirical pricing research solely on crypto tokens.

The characteristics of equity market returns are the most studied in traditional asset pricing literature, which has established a certain number of factors for explaining the cross-sectional variations of stock returns. Among the potential predictors that have been widely tested in the equity market, we select those that can be constructed based only on market information including price, market capitalization, and trading volume and form their cryptocurrency counterparts.

The reason for choosing ERC-20 tokens is first of all, the ERC20 standard has been a dominant pathway for the creation of new tokens in the cryptocurrency space for some time. It has been particularly popular with ICOs and crowdfunding companies. There have now been tens of thousands of distinct tokens that have been issued and are operating according to the ERC20 standard. This will provide us with a large sample base. Meanwhile, ERC-20 tokens are solely issued on Ethereum blockchain, which is one of the most successful blockchain. These ERC20 tokens have well-established properties and the contract code is straightforward to read, which may reassure investors (Howell, Niessner, and Yermack, 2018).

With the support of Ethereum block scanners (i.e., Ethereum.io), we can access to the on-chain information of each ERC-20 tokens such as the dollar value of transactions, the counts of transactions and the daily active unique addresses, which may reflect the true economic activity happened on the blockchain. Thus, besides the traditional return predictors, we can construct crypto-specific predictors by using those on-chain characteristics and test the cross-sectional relationship between them and token returns. More importantly, the on-chain characteristics can be used as proxies of the intrinsic value of tokens, with which we can construct the counterpart of the value factor (BE/ME) in the equity market.

In the following sections, we first construct the ERC-20 tokens' characteristics and investigate their performance in explaining cross-sectional returns of the sample tokens. We analyze totally 15 characteristics including & market-related predictors, 3 on-chain predictors and 2 quasi-value predictors. For each of them, we also apply the zero-investment strategy by using the long-short operation based on the difference between the first quintile and the fifth quintile.

For the market-related predictors, we exploit size (market capitalization), trading volume, liquidity and momentum. On every Sunday, all ERC-20 tokens are re-allocated to quintile portfolios based on value of a given predictor. Each quintile is held for one week. After that, we calculate the weekly value-weighted and equal-weighted time-series average excess return over the risk-free rate for each quintile. By long the fifth quintile and short the first quintile, we further calculate the risk premium of zero-investment strategy for every cross-sectional return predictor. The results indicate the statistically significant size, volume and liquidity related long-short strategies. However, for the 8 momentum predictors, we observe only 4 significant long-short strategies related to the past one-week (r_{-1}), two-week (r_{-2}), three-week (r_{-3}) and four-week (r_{-4}) return.

The two quasi value predictors are the counterparts of the BE/ME ratio applied in the equity market. By considering the on-chain transaction as the proxy of the true economic activity happened on the blockchain (Hubrich, 2017), we use the dollar-value of the on-chain transaction to replace the BE and construct the ratio of the on-chain dollar-value transaction over the market capitalization (VTM). On the other hand, ERC-20 tokens are used to power the corresponding peer-to-peer network; the user base of the network is positively related to token price (Cong, Li and Wang, 2018). Therefore, we consider the number of active unique addresses (N) as an estimate of the "fair value" of the network, and use the ratio of the number (N) to the market capitalization (M) (NTM) as the other "value" predictor.

Different from coins, crypto tokens can be considered as venture capitalization for projects; thus, we treat them as assets and follow the asset pricing rules. Thus, in the next part, we intend to test whether a small number of characteristics can span other cross-sectional token return predictors. By following the beta-pricing model, which is a case of APT, we further build 4 pricing factors, including the crypto market factor, size factor, "value" factor, and the momentum factor. We use the S&P broad index as the proxy of the entire cryptocurrency market and calculate the excess return of the index as the crypto-market factor ($R_{CM} - R_f$). The size factor is based on the market capitalization. More importantly, by using the network as the fair value, we construct the "value" factor (TNTM). Finally, the momentum factor (TMOM) is based on the past two-week return (r_{-2}) simply due to its highest return of zero-investment strategy. The performances of these crypto-specific factors are tested by using the cross-sectional zero-investment premiums and the double-sorting 25 Size – NTM ratio portfolios.

2. Data

Our sample is consisting of all active ERC-20 tokens listed on Coingecko.com with over one million dollars of market capitalization from 2016 to the beginning of 2022. We collected all of ERC-20 tokens available through the API provided by Coingecko.com. By excluding the tokens due to missing values and too short data period, we have 1,031 remained.

With the complete name list of these 1,031 tokens, we further collect the values of on-chain characteristics including the dollar-value of transactions, the counts of transactions, the number of unique receivers, the number of unique senders and the number of total unique address from the Ethereum blockchain scanner – etherscan.io. The summary statistics of all variables presented in Table 1 indicate a high level of skewness; thus, we winsorized the dataset at 1% to limit extreme values and reduce the effect of possibly spurious outliers.

3. The Cross-Sectional Structure of Token Returns

The relationship between firm characteristics and stock returns has been widely exploited in stock market. There is considerable evidence that the cross-sectional pattern of stock returns can be explained by firm characteristics such as size, book-to-market ratio, and past returns (momentum). Fama and French (1993) suggest that the co-movement between these firm characteristics and their stock returns arises because size and book-to-market ratios are proxies for non-diversifiable factor risk. Based on the same method, we can exploit the cross-sectional relationship between token characteristics and weekly excess returns.

The breakpoints are calculated using all the tokens in the sample for the given period. To guarantee sufficient amount tokens in each portfolio, we split the sample into five portfolios by using the 20^{th}, 40^{th}, 60^{th}, and 80^{th} percentiles as the portfolio breakpoints. At the end of each week t, all tokens in the sample with values of the sort variable will be assigned to one of the five portfolios by comparing the values with the breakpoint's percentiles. The variable sorted portfolios are formed or rebalanced on each Sunday and then held without further trading for the following week t+1. The one-week-ahead excess portfolio returns (r_{t+1}) will be calculated as the outcome variable.

Size Quintiles Portfolios

Size effect has long been considered as one of the important anomalies to the classic Capital Asset Pricing Model (CAPM). This effect was first documented by Banz (1981) and Reinganum (1981). Although many recent empirical findings indicate that the firm size may not be a stable source of risk premium, it still be naturally considered as a proxy of the risks from low productivity and high financial leverage (Chan and Chen, 1991). In the crypto markets, the size effect has also been observed by Liu, Tsyvinski and Wu (2021) based on the sample of over 1,000 coins and tokens. In our research, we are interested in the performance of the size effect within the sample solely consisting of Ethereum-based tokens (ERC-20).

– Table 2 about here –

The table presents the results of weekly excess returns for the size quintiles. Both value-weighted and equal-weighted weekly average returns present monotonically decreasing trend from the small size group to the big size group. The differences in the average returns of the smallest and biggest quintiles are 6.1% and 5.0% respectively, which are statistically significant at the 1% level. Consistent with the evidence of Chan and Chen (1988) that size produces a wide spread of average returns, the returns of tokens also present significant spread corresponding to their size values.

Volume Quintile Portfolios

Another sort variable we intend to investigate is the daily trading volume, which measures the daily trading amount in USD. Chordia, Subrahmanyam, and Anshuman (2000) treated the trading volume as a proxy of liquidity. This variable has been further tested in cryptocurrency market by for instance Liu, Tsyvinski, and Wu (2021). The volume variable could relate to the liquidity of tokens. The higher trading volume means the higher level of liquidity and less exposure to the liquidity-related risk.

We form the quintile portfolios sorted on volume variable and report the time-series weekly excess returns in Table 3. The results of value-weighted returns monotonically increase from the 1st quintile, the low-volume portfolio, to the 5th quintile, the high-volume portfolio. The average excess returns of the difference portfolios indicate that the low-volume portfolio has higher future returns than the high-volume portfolio.

– Table 3 about here –

The results reported in the Table 3 indicate that the both value-weighted and equal-weighted weekly average excess-returns decrease from the portfolio of the lowest volume quintile to the portfolio of the highest quintile. The differences in the average returns between the lowest and highest quintiles are 1.8% and 3.8% respectively, which are significant at 1% level. Thus, the long-short strategy for ERC-20 tokens can generate over 2% weekly excess-returns on average.

Momentum Quintiles Portfolios

Since Jegadeesh and Titman (1993) who first observe the tendency of stocks that performed well in the last months to keep performing well in the following months, the momentum effect has become a widely-documented phenomenon in financial market. Exploiting whether the same effect exist in the crypto market is also another important goal of this research.

The results reported in the Table 4 indicate that the past one-week, two-week, three-week and four-week momentum quintile portfolios have the average excess returns almost monotonic with the quintiles. All of these 4 momentum predictors have significant positive returns for zero-investment strategies by long the winner quintiles and short the loser quintiles.

– Table 4 about here –

Liquidity Quintile Portfolios

As one of the key assumptions of CAPM, all securities are perfectly liquid. However, Amihud and Mendelson (1989), by using the bid-ask spread as the measure of liquidity, find that the level of liquidity has a positive cross-sectional relation with future stock returns after controlling for other related variables. In our research, we apply the measurement developed by Amihud (2002). The key advantage of this measure is that it requires only return and trading volume data to calculate.

This measure is actually a measure of illiquidity; therefore, the higher value means the lower liquid the security is. The idea of the measure is to estimate the magnitude of the return driven by the trading volume. If a security generates a certain absolute return from a large trading volume, this security is relatively liquid; in opposite, if this security realizes a large absolute return on a small trading volume, it is quite illiquid, since a small amount of trading volume can largely affect the price of the security.

$$Illiquidity_t = \frac{1}{D}\sum_{d=1}^{D}\frac{|R_{i,d}|}{Volume_{i,d}}$$

In the formula of illiquidity, $R_{i,d}$ is the daily return of security i; the denominator $Volume_{i,d}$ is the USD volume of the security i traded on day d; and D is the number of days used as estimation period. Here, we use $D = 7$ days to calculate the illiquidity. This means the current illiquidity equals to the average illiquidity of the previous 7 days.

The time-series average excess returns are presented in Table 5. Both value-weighted and equal-weighted excess returns of the low-liquid quintile portfolio (I5) are higher than the excess returns of the high-liquid quintile portfolio (I1).

– Table 5 about here –

On-Chain Quintile Portfolios

Besides the market-related predictors, we have also collected the information of 3 on-chain characteristics including the dollar value of on-chain transactions ($ of Trans), the counts of transactions (C of Trans) and the number of active unique addresses (Uni_address) from the Ethereum blockchain scanner, and then use the log values of these characteristics to construct the quintile portfolios.

The results reported in Table 6 to Table 8 present that the patterns are almost universally monotonic and the average weekly excess returns decrease from the low quintile portfolios to the high quintile portfolios. This means that the tokens with lower log value of on-chain characteristics tend to have higher exposure to the underlying risk factors and receive higher expected excess returns. However, only the dollar-value transactions quintile portfolios have significant value-weighted return of 1.2% for zero-investment strategy.

– Table 6, 7 and 8 about here –

Quasi Value Quintile Portfolios

In traditional asset pricing factor models, the value factor (BE/ME) plays a very important role in fundamental valuation. The purpose of the value factor is to determine whether the market value of a certain asset is over- or underestimated by the market. For traditional assets, we obtain a fair value through discounting their future cash flows by an appropriate discount rate. For instance, we apply dividend-discount models to estimate the fair value of a stock and discount coupons generated by a bond for calculating a bond's fair value. However, cryptocurrencies do not generate usual cash flow as the traditional assets do.

To deal with this issue, Hubrich (2017) creates a quasi-value factor, which is the ratio of on-chain dollar amount of transactions (V) to the current market capitalization (M). The dollar value of on-chain transactions might be a potential proxy for the actual economic activity served by the blockchain. Hubrich believes that the "fair" value could be reflected by the value of daily on-chain transactions. More important, the time-series VTMs of sample cryptocurrencies indicate strong and frequent meaning-reverting, which suggest that the market sufficiently under- or overestimates their "fair values".

In our research, we replicate this cross-sectional excess predictor by using the on-chain transaction volume collected from etherscan.io. The tokens with high VTM ratios are considered to be undervalued and have higher expected returns than the tokens with low VTM ratios. We set the breakpoints by using the z-score of VTM to construct the quintile portfolios. The results in Table 9 are not in line with the expectations and even the return differences between the high quintiles and the low quintiles are insignificant.

– Table 9 about here –

Network economics has been crucial for understanding the adoption of the internet and social media. Sarnoff's law states that the value of a broadcast network is directly proportional to the number of viewers. Metcalfe's law indicates that as more people join a network, they add to the value of the network nonlinearly. Reed (2001) believes that due to the number of possible sub-groups on network participants, the utility of networks grows much more rapidly than either the number of users (N), or the number of possible pair connections (N^2).

The blockchain technology provides a peer-to-peer network, a decentralized communication model between two peers (also known as nodes) who can communicate with each other without the need for a central server. ERC-20 tokens are the cryptocurrencies that apply the "ERC20" scripting standard and exclusively. Cong, Li and Wang (2018) developed a dynamic model of cryptocurrencies and conclude a positive relation between user base and token price. The reason behind it is that the more users there are, the easier for each user to meet a transaction counterparty, which will generate a higher utility for being a user of this platform and raise the token price.

Based on the network effect theorem, we use the number active addresses as the proxy of "fair value" and build the value factor by using the ratio of the number of active addresses (N) to the market capitalization (M). Tokens that the platform judges to have good prospects, reflected by high market value of each active address and low ratios of the number of active addresses to the market capitalization (NTM), have lower expected returns than tokens with high NTM ratio and poor prospects.

The results presented in Table 10 follow the expectation. For both value- and equal-weighted, the low NTM ratio quintiles have much less expected excess returns than the high ratio quintiles. The zero-investment strategy also gain significant positive returns. The double-sorting portfolios results reported in Table 11 further confirm the expectation. The consistent patterns for each NTM quintiles and Size quintiles indicate that the size and NTM ratio may be relatively independent and be good proxies for the underlying state variables of the crypto market.

– Table 10 and 11 about here –

4. Factors and Empirical Results

One of the purposes of this research is to test the performance of cryptocurrency specific factors, which are also the counterparts of the most studied pricing factors in equity market such as size, value, and momentum factors. According Fama and French (2015), we construct factors from independent 2×3 sorts by interacting size with volume, liquidity and momentum respectively. On every Sunday of week t, all tokens are split into two groups, small (S) and big (B), and independently into three groups, low (L), median (M) and high (H) volume. Taking intersections yields six Size – NTM portfolios; weekly value-weighted portfolio returns are calculated for the following week t+1, and the portfolios are rebalanced on the Sunday of week t+1. After that, the Network/ME factor ($TNTM$) return is the average of the returns of two high NTM ratio portfolios (SH, BH) minus the average of the returns two low NTM ratio portfolio (SL, BL):

$$TNTM = (SH + BH)/2 - (SL + BL)/2$$

Following the same method, we can build six size – momentum portfolios by splitting the tokens into two separately two size groups and three momentum groups, loser (L), median (M), and winner (W). The momentum factor (TMOM) is the average returns of the two winner portfolios (*SW, BW*) minus the average return of the two loser portfolios (*SW, BW*):

$$TMOM = (SW + BW)/2 - (SL + BL)/2$$

Finally, the size factor (TSMB) is the average return of six small portfolios minus the average return of the six big portfolios.

$$TSMB = \frac{(SL + SM + SH + SL + SM + SW)}{6} - \frac{(BL + BM + BH + BL + BM + BW)}{6}$$

– Table 12 about here –

5. Tests on the Premiums of Long-Short Strategies

In this part, we test the performance of the four crypto-specific factors in pricing the seven cross-sectional zero-investment strategies. Adjusted for the four-factor model, the alpha of the volume and liquidity strategies become statistically insignificant, the highly significant coefficients of the factors TSMB, TNTM and TMOM show the strong pricing power of these factors, which effectively reduce the pricing error and turn the alphas into insignificant. All coefficients of the crypto-market factor $R_{CM} - R_f$ are insignificant or slightly significant, since the zero-investment strategy eliminates the common component that is related to the entire market through long the fifth quintile portfolio and short the first quintile portfolio. The positive significant coefficients of size factor (TSMB) and "value" factor (TNTM) indicate that the tokens with low trading volume and the tokens with liquidity issue tend to be the tokens with small size and the tokens in distress that is estimated by the NTM ratio.

However, the four-factor model cannot fully explain the return premiums of the other five strategies. For the size strategy, the momentum factor (TMOM) presents no pricing power. Even though it has highly significant coefficients in the regressions of all momentum strategies, it still cannot eliminate the pricing error and turn the alphas into insignificant. The significant alphas of size and momentum strategies may be caused by some extreme values, since in the early sample period, there are limited number of tokens in each quintile portfolio, which make the portfolios less-diversified.

– Table 13 about here –

6. Tests on the 25 Size-NTM Portfolios

The results of double-sorting portfolios of Size and NTM factors indicate the excess return spreads in the rows and columns. In this part, we intend to investigate whether the 3 factors formed in the last part can properly price all of the excess returns of the 25 Size-NTM portfolios. Following Fama and French (1996), we regress the time-series portfolios' excess returns on the returns of factor mimicking portfolios. If the three factors can describe portfolios' expected returns, the time-series regression intercepts should be close to 0.

In the regression analysis, we intend to investigate whether the risk factors formed in the last part capture the cross-section variation of the ERC-20 tokens' average excess returns. In Table 14, we report the results of the set of regressions for the 25 Size – NTM portfolios on the broad cryptocurrency market excess return. The highly significant coefficient values of b indicate a strong explanation power of the cryptocurrency market factor on the LHS portfolios; however, the market factor still left certain variation of portfolio excess returns unexplained due to the significant values of most intercepts, for instance, the portfolio with the smallest size and highest NTM ratio has the highest significant intercept 10.7% with t-statistics 7.55.

– Table 14 about here –

By including size factor (TSMB), “value” factor (TNTM), and momentum factor (TMOM), we apply the four-factor regression model for all 25 portfolios and report the result in the Table 15. Almost every portfolio has significant size factor coefficient, s, and “value” factor coefficient, n. The portfolios in the smaller size groups (S_1, S_2 and S_3), as we expected tend to have higher and positive size coefficients than the portfolios in the bigger size groups (S_4 and S_5) due to the higher exposure of the smaller size portfolios to the size factor. Similarly, because high NTM ratio portfolios have higher exposure to the “value” factor than low NTM ratio portfolios, we can observe a growth pattern of “value” factor coefficients from the low NTM quintile to the high quintile.

Comparing with the intercepts in Table 14, the majority of the intercepts in Table 15 are insignificant; also, with the higher average R^2 and lower Root MSEs, the four-factor model has better pricing power on the 25 Size-NTM portfolios than the one-factor model. However, some portfolios in small size and high NTM ratio groups still have significant intercepts;

– Table 15 about here –

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Table1: Summary Statistics for Ethereum-based tokens (ERC-20)

This table presents summary statistics for sample of 1031 ERC-20 tokens. The sample covers the years t from 2016 to 2022, inclusive, and includes the ERC-20 tokens with over 1 million market value. The mean (Mean), standard deviation (SD), skewness (Skew), excess kurtosis (Kurt), minimum (Min), 5th percentile (5%), 25th percentile (25%), median (Median), 75th percentile (75%), 95th percentile (95%), and maximum (Max) values are presented for the following variables: MktCap (market value in $millions), Volume (daily trading volume on exchanges in $millions), Transfer_$ (on chain daily transfer dollar amount in $millions), Transfers Count (on-chain daily number of transactions), Unique Receivers (on-chain daily active addresses of receivers), Unique Senders (on-chain daily active addresses of senders), Total Uniques (on-chain daily total active addresses).

	Mean	SD	Skew	Kurt	Min	Q5	Q25	Median	Q75	Q95	Max	N_Tokens
MktCap	140.86	857.25	20.20	509.42	0.06	1.46	6.43	18.86	62.98	429.94	23106.71	1031
Volume	14.27	61.00	9.36	108.23	0.00	0.03	0.29	1.19	5.84	48.43	921.75	1031
Transfer_$	10.32	108.28	26.84	785.82	0.00	0.04	0.27	0.83	2.91	25.95	3250.30	1031
Transfers Count	317	2186	28	830	2	8	35	85	216	908	66738	1031
Unique Receivers	134	1079	29	908	2	5	17	39	92	356	33648	1031
Unique Senders	78	203	10	136	1	4	13	29	71	256	3781	1031
Total Uniques	166	1112	28	833	3	7	24	52	124	452	33967	1031

Table 2: Size Portfolios

This table reports the time-series averages of weekly value-weighted and equal-weighted excess returns for all the size (Market Capitalization) quintile portfolios over the entire sample period from 2016 to 2022 and the return differences by long small size portfolio and short big size portfolio. On every Sunday, Tokens are re-allocated to five Size groups (Small to Big). Each group is held for one week. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

		Small	2	3	4	Large	Small - Large
Size Portfolios							
Value Weighted	**Mean**	0.063***	0.017**	0.017**	0.012	0.002	0.061***
	t-stat	(6.20)	(2.10)	(2.00)	(1.41)	(0.20)	(7.97)
Equally Weighted	**Mean**	0.059***	0.011	0.015*	0.013*	0.008	0.050***
	t-stat	(6.51)	(1.52)	(1.86)	(1.72)	(1.06)	(6.72)

Table 3: Volume Quintile Portfolios

This table reports the univariate portfolio analysis results based on trading volume. The results show the time-series averages of weekly value-weighted and equal-weighted returns and the return difference by long low volume portfolio and short large volume portfolio. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

		Low	2	3	4	High	Low - High
Volume Portfolios							
Value Weighted	**Mean**	0.016	0.018	0.012	0.006	-0.002	0.018***
	t-stat	(2.01)	(2.17)	(1.47)	(0.74)	(-0.30)	(2.93)
Equally Weighted	**Mean**	0.043	0.024	0.015	0.012	0.005	0.038***
	t-stat	(5.19)	(3.11)	(2.00)	(1.56)	(0.58)	(5.37)

Table 4: Momentum Quantiles

This table reports the univariate portfolio analysis results based on multiple momentum strategies including past one-week r_{-1}, two-week r_{-2}, three-week r_{-3}, four-week r_{-4}, eight-week r_{-8}, half-year (26 weeks r_{-26}), one-year (52 weeks r_{-52}) and two-year (104 weeks r_{-104}) returns. The time-series of weekly value-weighted and equal weighted returns are presented from Panel A to Panel H, respectively. The return differences by long winner portfolio and short loser portfolio are reported in the last column. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Momentum Portfolios		Loser	2	3	4	Winner	Winner - Loser
Panel A: One Week							
Value-Weighted	Mean	-0.006	-0.003	0.005	0.006	0.008	0.013*
	t-value	(-0.72)	(-0.34)	(0.55)	(0.65)	(0.88)	(1.72)
Panel B: Two Weeks							
Value Weighted	Mean	-0.003	0.000	0.002	0.003	0.016	0.019**
	t-value	(-0.37)	(0.04)	(0.25)	(0.34)	(1.75*)	(2.35)
Panel C: Three Weeks							
Value Weighted	Mean	-0.003	-0.002	0.005	0.000	0.014	0.016**
	t-value	(-0.34)	(-0.18)	(0.67)	(0.05)	(1.52)	(2.17)
Panel D: One Month							
Value Weighted	Mean	-0.002	-0.005	0.003	0.001	0.015	0.017**
	t-value	(-0.26)	(-0.71)	(0.35)	(0.09)	(1.61)	(2.16)
Panel E: Two Months							
Value Weighted	Mean	0.005	0.000	0.010	-0.001	0.003	-0.001
	t-value	(0.57)	(0.03)	(1.16)	(-0.09)	(0.37)	(-0.16)
Panel F: half-year							
Value Weighted	Mean	0.000	0.001	-0.011	-0.002	0.001	0.001
	t-value	(-0.01)	(0.13)	(-1.39)	(-0.18)	(0.16)	(0.21)
Panel G: One year							
Value Weighted	Mean	-0.003	-0.006	-0.006	0.003	-0.007	-0.003
	t-value	(-0.43)	(-0.72)	(-0.56)	(0.26)	(-0.74)	(-0.41)
Panel H: Two year							
Value Weighted	Mean	-0.010	-0.002	-0.006	-0.016	-0.010	0.000
	t-value	(-1.27)	(-0.2)	(-0.68)	(-2.02)	(-1.22)	(0.00)

Table 5: Illiquidity Quintiles

This table reports the mean of time-series weekly returns of illiquidity quintiles. The value of illiquidity equals to the results of the equation: $Illiquidity_t = \frac{1}{D}\sum_{d=1}^{D}\frac{|R_{i,d}|}{Volume_{i,d}}$. The results include the time-series averages of weekly value-weighted and equal-weighted excess returns for all illiquidity quintile portfolios over the entire sample period from 2016 to 2022 and the return differences by long low illiquidity portfolio (I5) and short high illiquidity (or liquidity) portfolio (I1). On every Sunday, all ERC-20 tokens are re-allocated to five illiquidity groups (Low to High). Each group is held for one week. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

		Liquidity(I1)	I2	I3	I4	Illiquidity(I5)	I5 – I1
Illiquidity Portfolios							
Value Weighted	**Mean**	0.004	0.002	0.010	0.011	0.024***	0.020***
	t-stat	(0.48)	(0.29)	(1.26)	(1.34)	(2.66)	(3.13)
Equally Weighted	**Mean**	0.012	0.009	0.012	0.016	0.051***	0.038***
	t-stat	(1.62)	(1.16)	(1.63)	(2.21)	(5.36)	(5.21)

Table 6: Dollar Value Transactions ($ of Trans)

This table reports the univariate portfolio analysis results of log value of on-chain dollar-value transactions ($ of Trans). The results show the time-series averages of weekly value-weighted and equal-weighted returns and the return difference by long the low transaction quintile portfolio (the 1st quintile) and short the high transaction quintile portfolio (the 5th quintile). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

		Low	2	3	4	High	Low - High
$ of Trans							
Value Weighted	**Mean**	0.01	0.008	0.006	0.005	-0.003	0.012**
	t-value	(1.17)	(0.78)	(0.71)	(0.56)	(-0.32)	(2.01)
Equally Weighted	**Mean**	0.038***	0.029***	0.013	0.012	0.004	0.034***
	t-value	(4.65)	(2.98)	(1.61)	(1.46)	(0.52)	(5.83)

Table 7: Counts of Transactions (C of Trans)

This table reports the univariate portfolio analysis results based on log value of the counts of on-chain transactions (C of Trans). The results show the time-series averages of weekly value-weighted and equal-weighted returns and the return difference by long the low transaction quintile portfolio (the 1st quintile) and short the high transaction quintile portfolio (the 5th quintile). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

		Low	2	3	4	High	Low - High
C of Trans							
Value Weighted	**Mean**	0.005	0.002	0.003	-0.003	-0.001	0.006
	t-value	(0.58)	(0.23)	(0.38)	(-0.41)	(-0.13)	(0.95)
Equally Weighted	**Mean**	0.035***	0.020***	0.017**	0.009	0.009	0.025***
	t-value	(4.18)	(2.51)	(2.10)	(1.20)	(1.14)	(4.10)

Table 8: Number of Unique Active Address (Uni_address)

This table reports the univariate portfolio analysis results based on log value of the number of unique active address (Uni_address). The results show the time-series averages of weekly value-weighted and equal-weighted returns and the return difference by long the low transaction quintile portfolio (the 1st quintile) and short the high transaction quintile portfolio (the 5th quintile). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

		Low	2	3	4	High	Low - High
Uni_address							
Value Weighted	**Mean**	0.007	0.003	0.001	-0.001	-0.001	0.007
	t-value	(0.77)	(0.30)	(0.07)	(-0.17)	(-0.08)	(1.18)
Equally Weighted	**Mean**	0.036***	0.018**	0.014*	0.015*	0.009	0.027***
	t-value	(4.34)	(2.31)	(1.79)	(1.81)	(1.13)	(4.32)

Table 9: VTM Quintile Portfolios

This table reports the univariate portfolio analysis results of VTM variable, which is defined as the z-score of the ratio of the trailing 7-day average of dollar-valued on-chain transactions current market capitalization. The results include the time-series averages of weekly value-weighted and equal-weighted excess returns for all the VTM quintile portfolios over the entire sample period from 2016 to 2022 and the return differences by long low VTM portfolio and short high VTM portfolio. On every Sunday, all ERC-20 tokens are re-allocated to five VTM groups (Low to High). Each group is held for one week. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

		Low	2	3	4	High	High - Low
VTM Portfolios							
Value Weighted (VW)	**Mean**	0.002	0.001	-0.002	0.003	-0.005	-0.007
	t-stat	(0.19)	(0.09)	(-0.30)	(0.41)	(-0.64)	(-1.23)
Equally Weighted (EW)	**Mean**	-0.007	-0.004	-0.001	-0.003	-0.010	-0.003
	t-stat	(-0.91)	(-0.46)	(-0.10)	(-0.32)	(-1.23)	(-0.77)

Table 10: NTM Quintile Portfolios

This table reports the univariate portfolio analysis results of the z-score of NTM variable (Network to Market Cap). The network equals to the previous 7-days average number of unique active addresses. The results include the time-series averages of weekly value-weighted and equal-weighted excess returns for all the NTM quintile portfolios over the entire sample period from 2016 to 2022 and the return differences by long low NTM portfolio and short high NTM portfolio. On every Sunday, all ERC-20 tokens are re-allocated to five NTM groups (Low to High). Each group is held for one week. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

		Low	2	3	4	High	Low - High
NTM Quintiles							
Value Weighted	**Mean**	-0.003	-0.006	-0.003	0.014	0.031***	0.030***
	t-stat	(-0.36)	(-0.80)	(-0.38)	(1.39)	(2.73)	(3.73)
Equally Weighted	**Mean**	0.010	0.006	0.012	0.022***	0.051***	0.043***
	t-stat	(1.49)	(0.83)	(1.49)	(2.66)	(4.91)	(5.89)

Table 11

Average Weekly Returns for Portfolios Formed on Size and NTM: ERC-20 Tokens Sorted on Market Capitalization (Vertical) then NTM (Horizontal): 2016 to 2022

Portfolios are formed weekly. The breakpoints for the size (the value of market capitalization) quintiles are determined on Sunday of week *t* by using all available ERC-20 tokens on Ethereum blockchain. And then, the breakpoints for the z-score of NTM (the ratio of the amount of active unique addresses to market capitalization) quintiles are further determined for the same token sample on the same Sunday. After that, the 5 by 5 value-weighted two-dimensional portfolios at the intersections of the rankings can be constructed. The value-weighted returns on the resulting 25 Size-NTM portfolios are then calculated for week *t+1*. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Size quintile	NTM Quintiles					
	Low	2	3	4	High	High - Low
Small	-0.006	0.024*	0.042***	0.059***	0.096***	0.107***
	(-0.55)	(1.94)	(3.43)	(4.88)	(6.12)	(6.59)
2	-0.010	0.000	0.009	0.020*	0.039***	0.053***
	(-1.17)	(0.05)	(0.95)	(1.75)	(3.12)	(4.87)
3	-0.004	0.000	0.006	0.019*	0.027**	0.036***
	(-0.43)	(0.03)	(0.56)	(1.92)	(2.23)	(4.15)
4	-0.009	0.002	-0.008	0.009	0.026**	0.033***
	(-1.02)	(0.20)	(-0.92)	(0.91)	(2.20)	(3.75)
Big	-0.014	−0.015*	-0.008	0.000	-0.007	0.009
	(-1.59)	(-1.86)	(-0.91)	(-0.02)	(-0.76)	(1.26)
Small - Big	0.012	0.038***	0.048***	0.056***	0.109***	
	(1.19)	(3.93)	(5.19)	(4.86)	(8.02)	

Table 12: Summary statistics for time-series factor returns

	R_{CM} - R_f	TSMB	TNTM	TMOM
Mean	-0.010	0.021***	0.024***	0.011**
Std. dev.	0.113	0.056	0.094	0.085
t(Mean)	(-1.48)	(6.22)	(4.31)	(2.22)

Table 13
Cryptocurrency Specific Factor Regressions for Simple Weekly Excess Returns on 7 Long-Short Strategies

This table reports the regressions of long-short strategy return premiums on the four crypto-specific factors, including the crypto-market factor $R_{CM} - R_f$, crypto-size factor $TSMB$, crypto- "value" factor $TNTM$, and crypto-momentum factor $TMOM$. The alpha is the intercept of the regression and represent the pricing error. The LHS of each regression is the time-series weekly return premium of each zero-investment (long-short) strategy including Size, Volume (trading volume), Illiquidity, Past One-week (r_{-1}), Two-week (r_{-2}), Three-week (r_{-3}) and Four-week (r_{-4}) returns. The RHS are the time-series mimicking portfolios returns based on each crypto-specific factor. The values of alpha, coefficients, R-squares and the root of mean squared error (Root MSE) are reported for each strategy, and the t-statistics for coefficients and F-value for R-squares are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Long-Short Strategies	alpha	$R_{CM} - R_f$	TSMB	TNTM	TMOM	R2	Root MSE
Size Premium	0.038***	0.093**	0.865***	0.381***		0.376	0.083
	(6.90)	(2.03)	(9.74)	(7.06)		(55.97)	
	0.048***	0.162***	0.859***		0.015	0.264	0.090
	(8.17)	(3.36)	(8.86)		(0.20)	(33.40)	
	0.039***	0.093**	0.871***	0.385***	-0.044	0.377	0.083
	(6.91)	(2.04)	(9.74)	(7.08)	(-0.64)	(41.99)	
Volume Premium	0.002	-0.061	0.614***	0.09526**		0.207	0.069
	(0.40)	(-1.61)	(8.28)	(2.12)		(24.28)	
	0.007	-0.039	0.632***		−0.146**	0.213	0.069
	(1.46)	(-1.05)	(8.52)		(-2.59)	(25.20)	
	0.004	-0.059	0.636***	0.111**	−0.163***	0.230	0.068
	(0.84)	(-1.57)	(8.64)	(2.48)	(-2.90)	(20.79)	
Illiquidity Premium	0.003	−0.078*	0.534***	0.195***		0.157	0.081
	(0.58)	(-1.77)	(6.19)	(3.72)		(17.31)	
	0.010*	-0.038	0.549***		−0.126*	0.126	0.082
	(1.91)	(-0.86)	(6.22)		(-1.89)	(13.45)	
	0.005	−0.076*	0.555***	0.210***	−0.158**	0.174	0.080
	(0.94)	(-1.72)	(6.46)	(4.01)	(-2.41)	(14.66)	
r_{-1} Premium	0.028***	0.049	−0.189*	0.080		0.018	0.106
	(3.89)	(0.85)	(-1.66)	(1.16)		(1.66)	
	0.018***	0.037	−0.298***		0.796***	0.311	0.089
	(3.05)	(0.79)	(-3.11)		(10.98)	(41.89)	
	0.018***	0.037	−0.297***	0.003	0.795***	0.311	0.089
	(2.94)	(0.75)	(-3.10)	(0.06)	(10.87)	(31.31)	
r_{-2} Premium	0.023***	-0.049	−0.293**	0.206***		0.051	0.110
	(3.16)	(-0.81)	(-2.49)	(2.89)		(4.97)	
	0.013**	-0.046	−0.437***		1.047***	0.488	0.081
	(2.45)	(-1.06)	(-5.03)		(15.93)	(88.64)	
	0.010*	-0.065	−0.434***	0.107**	1.031***	0.496	0.080

	(1.90)	(-1.48)	(-5.02)	(2.03)	(15.66)	(68.26)	
	0.025^{***}	-0.042	-0.320^{***}	0.122^{*}		0.040	0.107
	(3.47)	(-0.72)	(-2.80)	(1.75)		(3.83)	
r_{-3} Premium	0.015^{***}	-0.049	-0.438^{***}		0.862^{***}	0.367	0.087
	(2.65)	(-1.04)	(-4.70)		(12.20)	(53.84)	
	0.014^{**}	-0.056	-0.437^{***}	0.039	0.856^{***}	0.368	0.087
	(2.41)	(-1.17)	(-4.68)	(0.69)	(12.01)	(40.42)	
	0.024^{***}	0.019	-0.153	-0.049		0.008	0.110
	(3.26)	(0.32)	(-1.30)	(-0.69)		(0.72)	
r_{-4} Premium	0.011^{*}	-0.015	-0.255^{**}		0.757^{***}	0.260	0.095
	(1.81)	(-0.30)	(-2.50)		(9.78)	(32.62)	
	0.014^{**}	0.007	-0.259^{**}	-0.124^{**}	0.776^{***}	0.270	0.094
	(2.24)	(0.13)	(-2.55)	(-2.01)	(10,00)	(25.74)	

Table 14

This table presents the results of 25 regressions. The LHS variables in each set of the 25 regressions are the weekly excess returns on the 25 Size-NTM portfolios. The RHS variable is the cryptocurrency market factor defined as the excess market return, $R_{CM} - R_f$. The results include intercepts, slopes for the market factor, R-squares and the root of mean squared error (Root MSE). All the t-statistics for these coefficients are also reported. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

$$\boldsymbol{R(t) - R_f(t) = a + b\left[R_M(t) - R_f(t)\right] + e(t)}$$

	NTM quintiles									
Size quintile	**Low**	**2**	**3**	**4**	**High**	**Low**	**2**	**3**	**4**	**High**
			a					t-value		
Small	0.010	0.037***	0.058***	0.075***	0.107***	1.04	3.55	5.71	7.15	7.55
2	-0.001	0.011	0.024***	0.039***	0.052***	-0.17	1.45	3.14	4.57	4.67
3	0.004	0.015*	0.020**	0.031***	0.040***	0.59	1.82	2.30	3.80	3.98
4	0.002	0.015**	0.004	0.020**	0.041***	0.31	2.13	0.57	2.50	4.03
Big	-0.004	-0.001	0.004	0.008	0.006	-0.51	-0.15	0.61	1.08	0.79
			b					t-value		
Small	0.912***	1.033***	1.046***	1.027***	1.001***	10.38	11.12	11.73	10.97	8.01
2	0.664***	0.909***	0.901***	1.130***	0.913***	10.14	13.91	13.13	14.83	9.26
3	0.896***	0.842***	0.930***	0.874***	0.982***	13.62	11.42	12.37	12.24	11.03
4	0.882***	0.956***	0.910***	0.876***	0.956***	13.63	15.17	14.89	12.23	10.44
Big	0.766***	0.833***	0.847***	0.665***	0.802***	11.69	16.52	14.53	10.22	11.71
			R2					Root MSE		
Small	0.282	0.310	0.326	0.303	0.184	0.161	0.171	0.171	0.174	0.240
2	0.264	0.406	0.392	0.447	0.235	0.126	0.123	0.126	0.139	0.184
3	0.398	0.320	0.354	0.353	0.304	0.125	0.135	0.142	0.134	0.167
4	0.395	0.454	0.440	0.347	0.290	0.122	0.119	0.115	0.133	0.166
Big	0.329	0.502	0.434	0.272	0.344	0.123	0.092	0.109	0.124	0.122

Table 15

Summary Statistics and Four-Factor Regressions for Simple Weekly Excess Returns on 25 Portfolios Formed on Size (ME) and Network/ME (NTM)

This table presents the results of 25 regressions. The LHS variables in each set of the 25 regressions are the weekly excess returns on the 25 Size-NTM portfolios. The RHS variables are the cryptocurrency market factor defined as the market excess return, $R_{CM} - R_f$, size factor $TSMB$, "value" factor $TNTM$, and momentum factor $TMOM$. The results include intercepts, slopes for the market factor, size factor, NTM factor and momentum factor coupled with R-squares and root of mean squared error (Root MSE). All the t-statistics for these coefficients are also reported. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

$$R(t) - R_f(t) = a + b\left[R_M(t) - R_f(t)\right] + sTSMB(t) + nTNTM(t) + mTMOM(t) + e(t)$$

	NTM quintiles									
Size quintile	**Low**	**2**	**3**	**4**	**High**	**Low**	**2**	**3**	**4**	**High**
			a					t-value		
Small	-0.002	0.021*	0.032**	0.051***	0.067***	-0.17	1.80	2.96	4.47	4.61
2	−0.014*	-0.009	0.009	0.013	0.005	-1.73	-1.09	1.09	1.46	0.45
3	-0.008	-0.008	0.006	0.009	0.028***	-1.05	-0.95	0.69	1.08	2.92
4	-0.005	0.008	-0.007	0.006	0.029***	-0.64	1.05	-0.89	0.74	2.67
Big	0.000	0.005	0.009	0.015*	-0.008	-0.05	0.86	1.28	1.78	-1.10
			b					t-value		
Small	0.878	0.993	0.884	0.930	0.801	9.61	10.36	10.09	9.86	6.75
2	0.624	0.822	0.815	1.022	0.702	9.35	12.71	11.92	14.35	8.24
3	0.820	0.746	0.831	0.774	0.868	13.06	10.27	11.22	11.08	10.84
4	0.803	0.864	0.848	0.785	0.845	12.49	14.01	13.96	11.45	9.57
Big	0.770	0.836	0.835	0.665	0.686	11.48	16.49	14.16	9.99	10.75
			s					t-value		
Small	0.428	0.350	0.159	0.599	0.817	2.35	1.86	0.93	3.15	3.45
2	0.264	0.366	0.313	0.592	1.037	2.03	2.87	2.22	4.03	6.14
3	0.211	0.530	0.251	0.244	-0.430	1.70	3.66	1.68	1.74	-2.70
4	-0.272	-0.060	0.060	-0.172	-0.315	-2.15	-0.48	0.50	-1.26	-1.69
Big	-0.371	-0.380	-0.440	-0.486	-0.259	-2.76	-3.79	-3.73	-3.66	-2.06
			n					t-value		
Small	0.138	0.165	0.456	0.448	1.064	1.26	1.41	4.36	3.85	7.39
2	0.326	0.379	0.414	0.526	0.927	4.12	4.95	4.83	5.91	8.81
3	0.266	0.442	0.493	0.403	0.902	3.47	4.86	5.45	4.81	9.42
4	0.386	0.268	0.357	0.524	0.691	5.01	3.59	4.98	6.21	6.20
Big	0.113	0.121	0.213	0.146	0.620	1.38	1.96	2.95	1.82	7.97
			m					t-value		
Small	-0.106	0.251	0.319	0.014	0.027	-0.78	1.78	2.42	0.10	0.15
2	-0.089	0.123	-0.017	-0.144	0.159	-0.90	1.27	-0.15	-1.29	1.22
3	0.053	0.077	-0.296	0.302	-0.058	0.56	0.68	-2.60	2.84	-0.48

4	0.133	-0.126	0.028	0.144	0.053	1.39	-1.30	0.31	1.38	0.39
Big	0.175	-0.053	-0.023	0.024	-0.006	1.67	-0.70	-0.26	0.23	-0.07
			R2					Root MSE		
Small	0.314	0.342	0.375	0.371	0.355	0.159	0.168	0.160	0.166	0.216
2	0.334	0.483	0.452	0.548	0.471	0.121	0.116	0.120	0.126	0.154
3	0.455	0.418	0.434	0.436	0.490	0.114	0.126	0.131	0.126	0.144
4	0.455	0.473	0.496	0.442	0.395	0.115	0.111	0.110	0.123	0.155
Big	0.356	0.534	0.482	0.309	0.493	0.121	0.090	0.105	0.121	0.108