WEB3 USAGE AND ITS VALUE FOR CRYPTO

A NOVEL APPROACH TO CRYPTOCURRENCY ASSET PRICING

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Abstract:

Cryptocurrencies have grown significantly in recent years, and their role in society remains a highly debated subject. In "Common Risk Factors in Cryptocurrency," Liu, Tsyvinski, and Wu explore whether models from traditional finance can be applied to the cryptocurrency market to create successful trading strategies. This thesis replicates their work and extends it by exploring whether web3 usage can help explain market behavior. The experiment includes all cryptocurrencies with a market capitalization of over $1 million between January 1, 2014, and May 5, 2022, and 24 characteristics of the cryptocurrencies are considered. The results show that what strategies deliver significant excess returns have changed for the extended time frame. Furthermore, the web3 usage factor is shown to improve the three-factor model created in Liu et al (2022).

Keywords:

Cryptocurrency, Web3, Factor model, Decentralized finance, Asset pricing

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CRYPTOCURRENCIES AND THE IMPORTANCE OF their role in society is regularly a highly debated subject. Another highly debated subject is what that role actually is. In such a novel market, it is impossible to say what specific purpose cryptocurrencies will have in the future. The cryptocurrency debate is a polarized one, with popular opinions ranging from the entire concept being a bubble and a scam to it being the solution to all problems related to our financial and economic systems. Only time will tell what the future holds with regard to cryptocurrencies, but one thing is for sure: There is money to be made trading them.

The first half of the 2010s saw the emergence of the cryptocurrency market, which at the time consisted of only a few well-known coins such as Bitcoin, Litecoin, Ripple, and Ethereum. During most of that period, Bitcoin dominated the market, accounting for an overwhelming majority of the total cryptocurrency market capitalization. Today, however, the market has grown significantly and now consists of tens of thousands of different cryptocurrencies, though most of them are relatively insignificant in terms of market capitalization. While Bitcoin's share of the total cryptocurrency market capitalization has dropped below 40%, the top one percent of cryptocurrencies by market capitalization represent over 90% of the total market. This growth in the market has also led to increased volatility and risk, requiring frequent testing of risk factors and trading strategies to stay ahead. In order to stay competitive, investors and traders must constantly monitor and adapt to the changing market conditions.

Liu, Tsyvinski, and Wu wrote Common Risk Factors in Cryptocurrency, published in 2022, exploring if models from the traditional finance world, with some tweaking, could be applied to the cryptocurrency market to act as the base for significant strategies delivering meaningful excess returns. Under the assumption that cryptocurrency will play some sort of important role in the future of technology, it is engrossing to explore what similarities cryptocurrencies might share with publicly traded securities and if models that are significant to these securities can help us explain and understand more of cryptocurrency markets' behaviors. Seeing as a replication of the Liu et al (2022) models today would extend the timeframe by about two years, equating to an extension of over 25%, the replication itself would provide information on potential changes in the behavior of the cryptocurrency market. However, since the publication of the paper, the fundamentals of the cryptocurrency market have changed, with some blockchains and protocols facilitating accounting metrics such as revenue. Therefore, an extension of the strategies, exploring whether or not web3 usage can help explain market behavior, should be added.

Included in this thesis experiment are all cryptocurrencies with a market capitalization of over $1 million between January 1st 2014, and May 5th 2022. Seeing as the factors used in this thesis are built upon factors including price, volume, and market capitalization, we have also chosen to exclude stablecoins. Stablecoins are intended to remain stable in price, as the name suggests, and are commonly used as substitutes for the U.S. Dollar, the Euro, or other currencies (Hampl, Gyönyörová 2021). They rarely display any meaningful fluctuation in price, though their market capitalizations and volumes do as a result of issuance, trading of other cryptocurrencies, or the moving of funds. In addition to this, stablecoins have also grown significantly, both in terms of the number of them and in terms of their total market capitalization. The number of cryptocurrencies within our limitations was 23 at the beginning of 2014, peaked at 2,291 in April 2022, and subsequently dropped to 2,207 at the end of our examined period on the 5th of May 2022. Replicating Liu, Tsyvinsky, and Wu's paper, we consider 24 characteristics of cryptocurrencies. Eight of these characteristics are shown to create long-short trading strategies that successfully deliver significant excess returns. Two factors stick out, capturing most of the returns: Size and Momentum. The total of 3,742 cryptocurrencies considered is also used to create a market return index.

The 22 characteristics are analyzed by creating quintile portfolios that are constructed and evaluated weekly. Each week, the cryptocurrencies are sorted after their values for each characteristic. The quintile portfolios consist of the lowest-performing fifth and the highest-performing fifth, for each characteristic. The returns of the quintile portfolios are the sum of the market capitalization-weighted returns of the cryptocurrencies that the quintile portfolios consist of, minus the risk-free rate. The quintile portfolio excess returns are then used to create a long-short zero-investment strategy: long the fifth quintile, and short the first quintile. The strategies are evaluated on their excess return for the week following the portfolio construction. This means the excess return of the fifth quintile minus the excess return of the first quintile equals the strategy's return for the given week. The analysis of the 22 strategies, one for each of the characteristics, shows that eight of them produce statistically significant returns. Following are the details of the significant strategies and their returns.

The significant strategies within the momentum group generate excess weekly returns spread between -2.4% and 19.5%. Three of the strategies generate excess weekly returns of around 3.5%. A zero-investment long-short strategy that longs the best-performing coins and shorts the worst-performing coins, in terms of returns, generates around 5% excess weekly returns.[1] The individual strategies' excess returns are shown in Table I.

Table I
Momentum Strategies' Returns
The excess weekly returns of the individual significant strategies belonging to the Momentum group.

Momentum Strategy	Excess Weekly Return
wret	1.9%
cumret2	4.4%
cumret3	3.8%
cumret4	19.5%
cumret100	-2.4%

The significant strategies within the size group generate excess weekly returns of between -2.6% and -9%. A zero-investment long-short strategy that longs the smallest coins and shorts the largest coins, therefore, generates between 2.6% and 9% in excess weekly returns. The individual strategies' returns are shown in Table II.

[1] Note outlier cumret4. Excluding outlier, strategy returns around 2% excess weekly returns.

Table II

Size Strategies' Returns

The excess weekly returns of the individual significant strategies belonging to the Size group.

Size Strategy	Excess Weekly Return
logmcap	9%
logprc	2.6%
logmax_dprc	2.8%

Our next step is analyzing which, if any, factors can represent these statistically significant characteristics. To do this, we begin by creating a one-factor model consisting of the coin market factor, a cryptocurrency adaptation of the Capital Asset Pricing Model. The model is not a good fit, and cannot explain the returns of the cryptocurrency assets in the model. Next, we create a three-factor model consisting of a cryptocurrency market factor CMKT, a cryptocurrency size factor CSIZE, and a cryptocurrency momentum factor CMOM. It captures the returns of five significant strategies' excess returns, leaving those the strategies' alphas non-significant when the three-factor model is accounted for. The alphas that are no longer significant correspond to the past one-, two-, three-, four-, and 100-week return strategies.

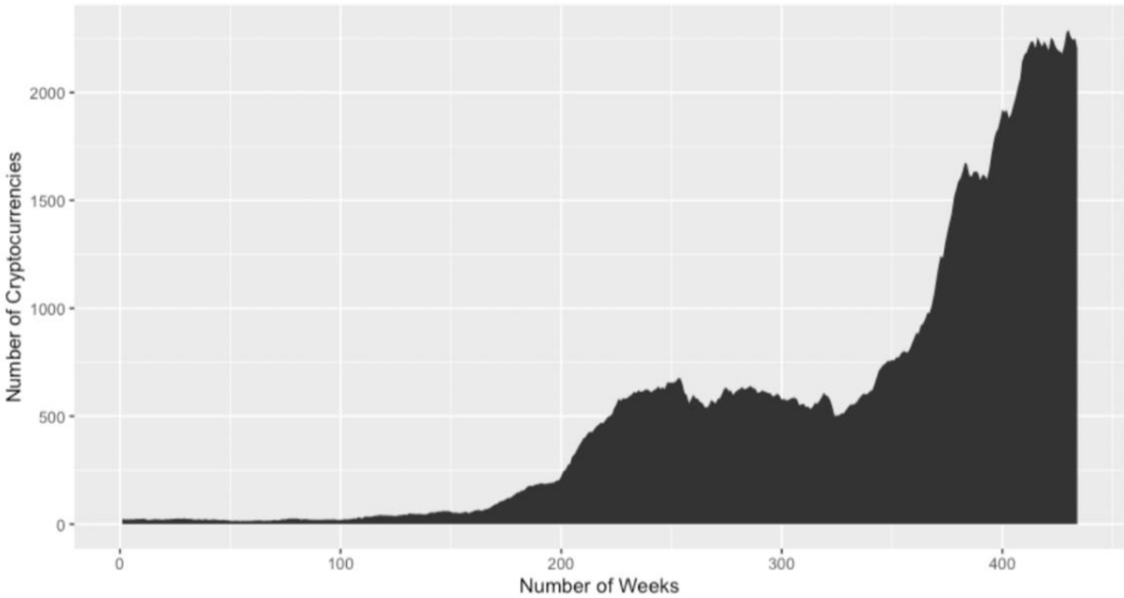
After this, we add a web3 usage factor DFUSG. It is a market capitalization weighted index of revenue through leading decentralized finance protocols. These decentralized finance protocols' revenues are similar to the revenue of equities, and thus quantify the actual customer usage of decentralized products such as decentralized exchanges, decentralized liquidity protocols, and other decentralized applications. These protocols' revenues are public by nature since they are technically fees paid to use the service, and these fees are included in each transaction hash that corresponds to a use of the protocol. For some decentralized finance protocols, fees are shared with protocol token holders (Gogel 2021).

I. Data

We collected cryptocurrency market data from all cryptocurrencies available on CoinGecko.com. CoinGecko collects cryptocurrency data from 600 cryptocurrency exchanges worldwide, and tracks over 13,000 cryptocurrencies. On their website, CoinGecko provides daily data on cryptocurrencies' closing price, market capitalization, and volume. In our data collected from CoinGecko, the price is the volume-weighted average price across all exchanges. The market capitalization is calculated by multiplying price by the circulating supply. Volume is the total trading volume of all trading pairs with the cryptocurrency. There are certain criteria a cryptocurrency must fulfill to be listed on CoinGecko, such as a project team owned and functional website with sufficient information on the listed cryptocurrency which has to be listed on an active exchange that CoinGecko is integrated with. In turn, for an exchange to be integrated it must fulfill CoinGecko's Crypto Exchange API Standards and have a working website with trading data that matches the information in the API.

Our sample consists of all cryptocurrencies, existing and defunct, with a market capitalization of over $1 million between January 2nd 2014, and May 5th 2022. By including observations with over $1 million in market capitalization in our sample data, rather than including cryptocurrencies that have over $1 million in market capitalization today, we minimize the risk of eventual sampling errors, such as survivorship bias. The number of cryptocurrencies has varied between the low of 15 in late 2014, peaked at 2,291 in early 2022, and has since then dropped to 2,207 at the end of our examined period in May 2022. In Figure I we present a more detailed description of how the number of cryptocurrencies with a market capitalization of over $1 million has fluctuated in our examined period.

Figure I
Number of Cryptocurrencies in dataset
Total number of cryptocurrencies with a market capitalization above $1 million for each week between week 1 (2014-01-02) and week 433 (2022-05-05).



To construct our weighted market portfolio, we first analyzed the entire dataset of cryptocurrency assets, calculating the weights based on each asset's market capitalization. This allowed us to construct a representative market portfolio that accurately reflects the overall market. We then periodically rebalanced this portfolio to maintain the desired weights of the assets, ensuring that it remained a true representation of the market.

Using this weighted market portfolio, we were able to compare the returns of various strategies, allowing us to evaluate their performance relative to the market. To create our weekly data, we used the closing price of each asset on the last day of each week. To calculate the cryptocurrency market excess return (CMKT), a cryptocurrency market version of the CAPM, we subtracted the risk-free rate, measured as the yield of the one-month U.S. treasury bill, from the value-weighted aggregate cryptocurrency market return.

Table III
Momentum Characteristics Definitions and Sources
The names, definitions and sources of all characteristics belonging to the Momentum group.

Momentum Characteristics	Definition	Source
wret	Past one-week return	Jegadeesh and Titman (1993)
cumret2	Past two-week return	Jegadeesh and Titman (1993)
cumret3	Past three-week return	Jegadeesh and Titman (1993)
cumret4	Past four-week return	Jegadeesh and Titman (1993)
cumret8	Past eight-week return	Jegadeesh and Titman (1993)
cumret16	Past 16-week return	Jegadeesh and Titman (1993)
cumret50	Past 50-week return	De Bondt and Thaler (1985)
cumret100	Past 100-week return	De Bondt and Thaler (1985)

Table IV
Size Characteristics Definitions and Sources
The names, definitions and sources of all characteristics belonging to the Size group.

Size Characteristics	Definition	Source
MCAP	The tenth logarithm of the market capitalization at the weekly close of the portfolio formation week.	Banz (1981)
PRC	The tenth logarithm of the price at the weekly close of the portfolio formation week.	Miller and Scholes (1982)
MAXDPRC	The highest recorded price traded in the portfolio formation week.	George and Hwang (2004)

Table V
Volume Characteristics Definitions and Sources
The names, definitions and sources of all characteristics belonging to the Volume group.

Volume Characteristics	Definition	Source
VOL	The tenth logarithm of the average daily volume in the portfolio formation week	Chordia et al (2001)
PRCVOL	The tenth logarithm of the average daily volume times price in the portfolio formation week	Chordia et al (2001)
VOLSCALED	The tenth logarithm of the average daily volume times price, scaled by market capitalization, in the portfolio formation week	Chordia et al (2001)

Table VI
The names, definitions and sources of all characteristics belonging to the Volatility group.

Volatility Characteristics	Definition	Source
BETA	The beta coefficient of the one-factor model formula $R_i - R_f = \alpha^i + \beta^i_{CMKT} CMKT + \epsilon_i$	Fama and MacBeth (1973)
BETA2	Beta squared	Fama and MacBeth (1973)
RETVOL	The standard deviation of the daily returns in the portfolio formation week	Ang et al (2006)
MAXRET	The highest daily return in the portfolio formation week	Bali et al (2011)
DELAY	The increase of R^2 in the three-factor model formula $R_i - R_f = \alpha^i + \beta^i_{CMKT} CMKT + \beta^i_{CMKT-1} + \beta^i_{CMKT-2} CMKT_{-2} + \epsilon_i$ where the two CMKT factors represent the one- and two day lagged market portfolio excess returns.	Hou and Moskowitz (2005)
STDPRCVOL	The tenth logarithm of the standard deviation of price volume in the portfolio formation week	Chordia et al (2011)
DAMIHUD	The average of daily returns divided by price volume in the portfolio formation week	Amihud (2002)

Table VII
Factors Definitions and Sources
The names, definitions and sources of all factors belonging to the three-factor model.

Factor	Definition	Source
Leadmkt	Market portfolio with one week lead	
Leadcsize	Small-Minus-Big factor for the cryptocurrency market	Liu et al (2022)
Leadcmom	High-Minus-Low factor for the cryptocurrency market	Liu et al (2022)
Leadmktrf	The excess return of the market	Liu et al (2022)
Leadrf	The risk-free return with one week lead	
Mkt	Market portfolio	
Constant	Alpha	

A. Web3 Usage Data

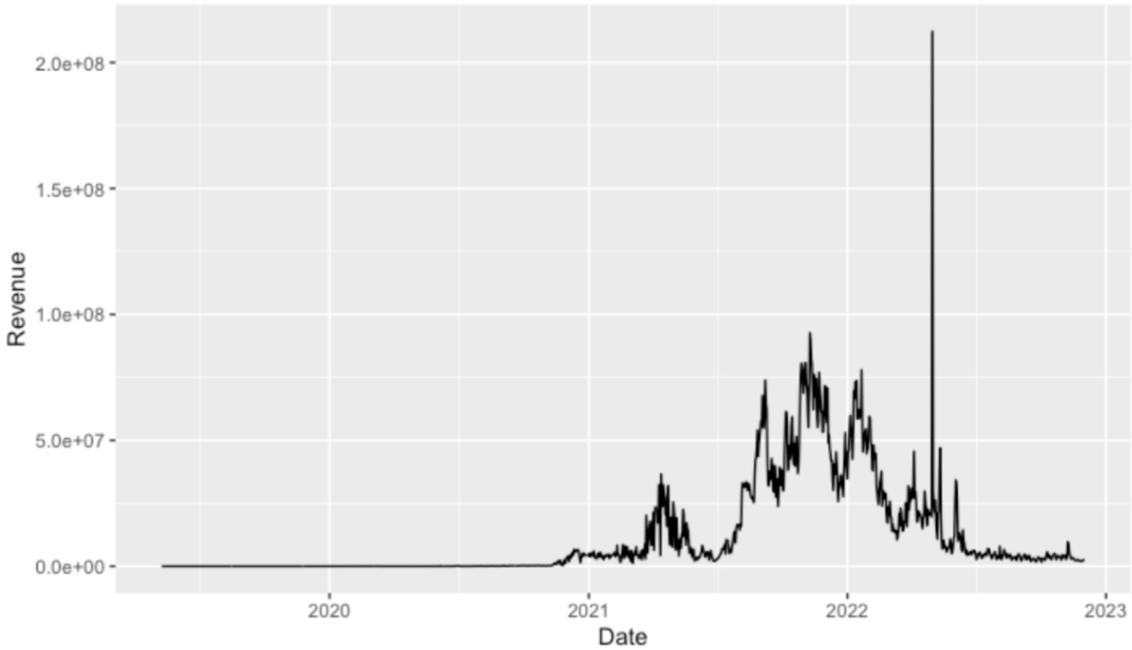
The web3 usage factor DFUSG data was gathered from Token Terminal. Token Terminal is a platform that aggregates over 100 000 daily transactions from more than ten blockchains. On their website, Token Terminal provides financial data from blockchains and decentralized applications, including revenues, earnings, fees, P/F ratios, P/S ratios, treasuries, and total value locked from the listed projects. For projects to be listed on Token Terminal, they need to fulfill a list of requirements. There must be an actual usage of the project and an active team or community with a long-term mindset. The project must have a secure development process in place, a sensible token model with sufficient documentation, and provide a reliable end-point for extracting data.

We construct the DFUSG factor by collecting daily data on revenue and market capitalization from 27 different DeFi protocols between 2021-09-13 and 2022-09-13. Since the time frame of the replication data ends 2022-05-05, the time frame analyzed in our four-factor model is between 2021-09-13 and 2022-05-05. This gives us data covering 33 weeks.[2] The revenue data refers to the cryptocurrency denominated monetary value that fees have generated for the token holders.

The DFUSG factor is constructed by weighting the weekly change in revenue for decentralized finance protocols by market capitalization. The top 30% of the protocols in terms of revenue growth each week, as well as the bottom 30% of the protocols in terms of revenue growth each week, are subsetted. The sum of the weighted revenue growth of the bottom subset is subtracted from the sum of the weighted revenue growth of the top subset.

[2] Non-applicable data for two observations.

Figure II
Protocol Revenues
The daily total revenue of the top 20 decentralized finance protocols since the end of the period in Liu et al (2022)



II. Literature Review

Asset pricing has been a crucial area of research in finance since the emergence of the capital asset pricing model (CAPM) in the 1960s by William Sharpe (1964), Jack Treynor (1962), John Litner (1965), and Jan Mossin (1966) (Perold, 2004). Since then, various researchers have published work dedicated to different aspects of asset pricing theory and expanded on the CAPM. For example, Eugene Fama has published a series of articles and research with valuable findings that we will make use of in our theoretical framework. In particular, we will incorporate the size and value premium factors from the three-factor model (Fama and French, 1993) and the CAPM anomalies analysis (Fama and French, 1996) into our analysis.

With the advent of cryptocurrencies, researchers have started to apply the traditional methods of pricing financial assets to this new asset class. Among them are Liu, Tsyvinski, and Wu (2022), who discuss the implications, results, and significance of adopting the methods used by Fama and French (1993) in a cryptocurrency market setting compared to the traditional stock market. In accordance with Liu et al. (2022), we will in this study analyze the significance of established market-based cross-sectional stock return predictors reported by Chen and Zimmermann (2020) in a cryptocurrency market setting. The list of established market-based cross-sectional stock return predictors includes the last-day market capitalization predictor defined by Banz (1981), the last-day price predictor as in Miller and Scholes (1982), and the maximum predictor (George and Hwang, 2004). The past one-, two-, three-, four-, one-to-four-, eight-, and 16-week returns are constructed following Jegadeesh and Titman (1993), and the past 50-

and 100-week returns as in De Bondt and Thaler (1985). The average daily volume, average daily volume times price, and average daily volume times price scaled by market capitalization predictors are all from the findings of Chordia, Subrahmanyam, and Anshuman (2001). The beta and beta squared return predictors as defined in Fama and MacBeth (1973), the standard deviation of daily returns discussed in Ang, Hodrick, Xing, and Zhang (2006), maximum daily return from Bali, Cakici, and Whitelaw (2011), delay as in Hou and Moskowitz (2005), the standard deviation of price volume from Chordia et al. (2011), and average absolute daily return divided by price volume, Amihud (2002), will also be included in our analysis.

Asset pricing research and models analyzing the cryptocurrency market are constantly in need of re-fitting due to the immaturity and ever-changing nature of the market. Liu et al. (2022) focus solely on market-based data for the cross-section of cryptocurrencies because financial and accounting data were not readily available or not applicable at the time. Only 24 strictly market-based significant strategies out of the total 158 significant financial, accounting, and market-based strategies with t-stats above 1.96 from Chen and Zimmermann (2020) were analyzed. However, with the changes in the cryptocurrency market over the past years and the emergence of decentralized finance (DeFi) protocols and data source aggregators of financial data, we aim to fill the research gaps and contribute to the existing literature by creating a web3 usage factor built on financial data that would add a dimension to the cryptocurrency factor model in Liu et al. (2022). Similar to how Fama and French (2015) expanded upon the three-factor model by introducing the additional profitability and investment factors, thus creating the five-factor model, we aim to expand upon the three-factor cryptocurrency model discussed in Liu et al. (2022) and analyze whether a four-factor model including the DFUSG factor could further improve the model's precision of predicting movements in the cryptocurrency market. By incorporating this new factor, we hope to provide a more comprehensive and accurate representation of the cryptocurrency market and improve the ability of our model to predict future movements and trends.

Furthermore, we plan to conduct a robustness analysis to test the stability and reliability of our model. We will compare the performance of our four-factor model with the three-factor model discussed in Liu et al (2022).

Overall, our goal is to contribute to the existing literature on asset pricing and expand upon the existing models for predicting movements in the cryptocurrency market. By incorporating the DFUSG factor into our analysis, we aim to provide a more comprehensive and accurate representation of the market and improve the ability of our model to predict future movements and trends.

III. Methodology

Apart from the web3 usage factor and the four-factor cryptocurrency model, we try to follow the methodology from Liu et al (2022) as closely as possible without reassessing its validity. We have focused our study on replicating their cryptocurrency factor model. The analysis consists of six steps where traditional asset pricing models are applied to our cryptocurrency dataset.

Table VIII

Method Steps

The steps taken from the original market data, through quintile portfolio strategies and different factor models. Additionally, the creation of the fourth factor for the four-factor model.

Steps	Explanation
Plotting dollar value of investment in individual cryptocurrencies	We plot the dollar value of investment in Bitcoin, Ethereum and BNB respectively. The values are plotted against the dollar value of investment in the market capitalization weighted market return index.
Generating quintile portfolios for size and momentum characteristics	The wret, cumret2, cumret3, cumret4, cumret8, cumret16, cumret50, cumret100, logvol, logprcvol, logvolscaled, logmcap, logprc, logstdprcvol, idovol, avg_damihud, std_dret, max_dprc, max_dret, lag24, and age characteristics are analyzed. The coins are divided into quintiles based on the value for each characteristic, and a portfolio is constructed for each by subtracting the weighted excess return of the first quintile from the weighted excess return of the fifth quintile.
Generating quintile portfolio for volatility factors	The beta and beta squared factors, belonging to the volatility factor group, are analyzed. Again, quintile portfolios are used to make a long-short strategy, by subtracting the weighted excess return of the first quintile from the weighted excess return of the fifth quintile.
Generating quintile portfolio for delay factor	Lagged market returns are analyzed and the results create long-short strategies from quintile portfolios. The strategy returns are calculated as the weighted excess return of the fifth quintile minus the weighted excess return of the first quintile.
Applying pricing models to the strategies showcasing significant excess returns	A one-factor pricing model is used to analyze whether it, a cryptocurrency-compatible version of the Capital Asset Pricing Model, can capture the returns of the significant characteristics. A three-factor model is used to analyze whether it can capture the significant characteristics' strategies' returns.

Generating web3 usage factor	Decentralized finance protocols' historical revenues and market capitalizations are used to create a market capitalization weighted revenue growth factor. It is added to the previous model to create a four-factor model.

IV. Results

In the following section, we present the results of the analysis outlined in Table VIII of our study. We have performed a series of steps to evaluate the performance of the different models, and we now present the results of these steps. We also provide a comparison of the results between some of the different models. These results provide valuable insights into the effectiveness of different financial models in predicting cryptocurrency market movements, and they will be discussed in further detail throughout the remainder of this section as well as throughout the thesis.

A. Plotting Dollar Values

We start by plotting the aggregate cryptocurrency market against the three biggest cryptocurrencies in terms of market capitalization: Bitcoin, Ethereum, and Binance Coin.

Figure III
Bitcoin vs. Market
The dollar value of investment in Bitcoin and the market portfolio, respectively, plotted over time.

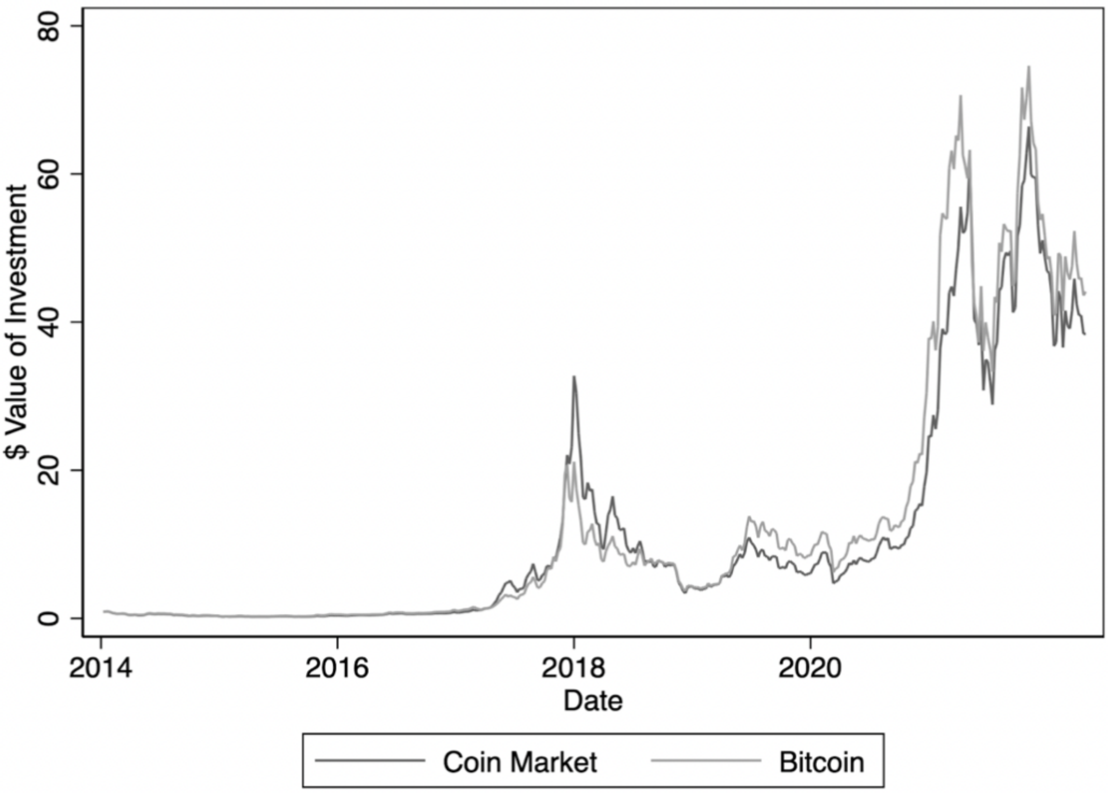


Figure IV

Ethereum vs. Market

The dollar value of investment in Ethereum and the market portfolio, respectively, plotted over time.

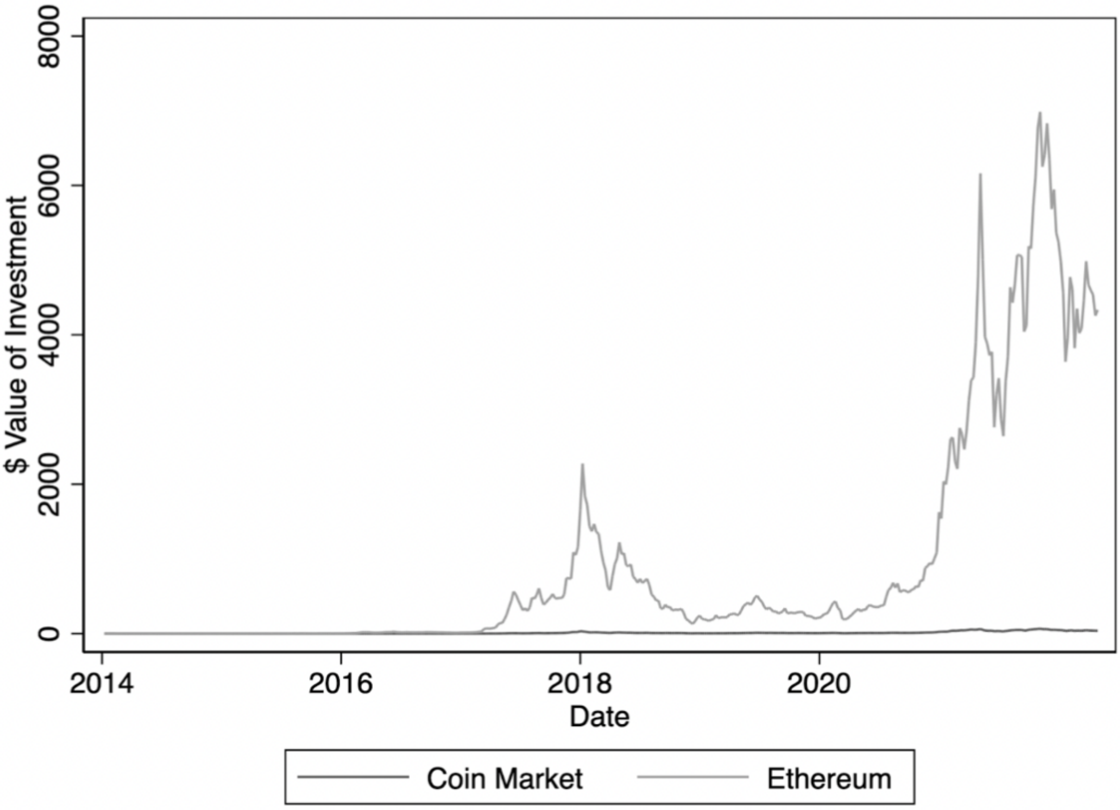
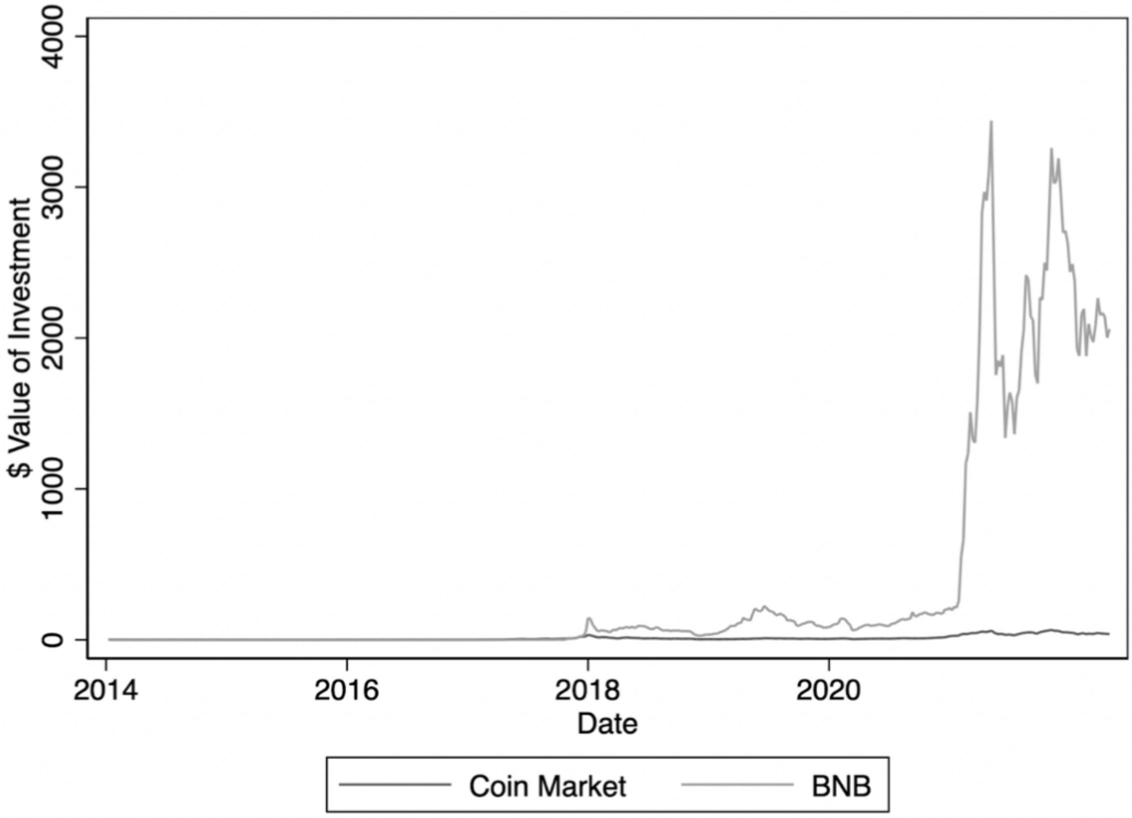


Figure V

BNB vs. Market

The dollar value of investment in BNB and the market portfolio, respectively, plotted over time.



B. Generating Quintile Portfolios

As we want to replicate the conditions, factors, and portfolios used in Liu et al (2022), we use the same list of established return predictors for the cross-section of stock returns from Chen and Zimmermann (2020) that can be directly constructed from price, volume and market capitalization. Except for idovol and age.[3] Each return predictor is then given a group based on its characteristics. The groups in which the strategies are allocated are Size, Momentum, Volume, and Volatility. See the full list of all strategies and their respective groups in (hänvisa till table). The returns of the strategies are thereafter divided into quintile portfolios, and a long-short strategy portfolio is constructed for each strategy. The long-short strategy portfolio consists of the excess return of having a long position in the fifth quintile portfolio and a short position in the first quintile. For each statistically significant long-short strategy we apply a pricing quintile model and showcase them in Table IX and Table X. The results of the statistically insignificant strategies are shown in Table XVII.

C. Portfolios

Size

Out of the three return predictors in the Size group, last day market capitalization in the portfolio formation week, last daily price in the portfolio formation week, and maximum daily price in the portfolio formation week, we found all three long-short strategy returns to be statistically significant at a less than 5% level. The mean excess return from the highest to lowest quintile for market capitalization is -8.99%, the mean excess return for the last daily price in the portfolio formation week is -2.64% and the mean excess return for the maximum daily price in the portfolio formation week is -2.75%. That is, a strategy that longs the smallest and shorts the largest cryptocurrencies generates a weekly return of at least 2.64%. Excluding the costs that are removed as we assume an efficient market, such as transaction costs, and feasibility of short selling.[4]

Table IX

Size Strategies Results

The mean quintile portfolio returns based on the Size group characteristics.

Size	1	2	3	4	5	5-1
logmcap	0.103***	0.026***	0.015**	0.024**	0.013***	-0.090***
t (mean)	(8.87)	(3.00)	(2.25)	(2.54)	(2.69)	(-8.26)
logprc	0.040***	0.036***	0.010	0.019*	0.014***	-0.026***
t (mean)	(3.49)	(3.34)	(1.31)	(1.66)	(2.77)	(-2.64)
logmax_dprc	0.041***	0.335***	0.011	0.017	0.014***	-0.028***
t (mean)	(3.55)	(3.04)	(1.47)	(1.52)	(2.77)	(-2.72)

t-statistics in parentheses

*** p<0.01. ** p<0.05. * p<0.1

[3] The idiosyncratic volatility and age factor were deemed unnecessary in our analysis and were therefore removed from the code.

[4] We assume access to liquidity for short-selling as well as no interest or other added costs associated with short selling.

Momentum

Among the nine different return predictors within the momentum group, the past one-, two-, three-, four-, one-to-four-, eight-, 16-, 50- and 100-week returns, we found the past one-, two-, three-, four-, and 100-week long-short strategy returns to be statistically significant at a 5% level. The difference in average weekly returns between the highest and lowest quintiles for the past one-, two-, three-, four-, and 100-week long-short strategy returns are 1.88%, 4.35%, 3.75%, 19.45%, and -2.39% respectively. In other words, a strategy that longs the cryptocurrencies with large returns and shorts cryptocurrencies with small returns over the past one-, two-, three-, and four-week generates a weekly return of at least 1.88%. And a strategy that longs the cryptocurrencies with small increases and shorts the cryptocurrencies with large increases over the past 100-week returns generates a weekly return of 2.39%.

Table X

Momentum Strategies Results

The mean quintile portfolio returns based on the Momentum group characteristics.

Momentum	1	2	3	4	5	5-1
wret	0.011	0.004	0.007	0.025***	0.030***	0.019**
t (mean)	(1.39)	(0.6)	(1.14)	(3.31)	(3.34)	(1.99)
cumret2	-0.001	0.004	0.010	0.020***	0.043***	0.044***
t (mean)	(-0.13)	(0.58)	(1.59)	(2.95)	(4.14)	(4.20)
cumret3	0.001	0.010	0.008	0.017***	0.039***	0.038***
t (mean)	(0.15)	(1.45)	(1.25)	(2.61)	(3.59)	(3.54)
cumret4	0.009	0.004	0.005	0.021***	0.028***	0.195**
t (mean)	(1.16)	(0.64)	(0.88)	(3.06)	(3.42)	(2.39)
cumret100	0.043***	0.033***	0.020***	0.022**	0.019***	-0.024**
t (mean)	(4.36)	(3.42)	(2.85)	(2.57)	(2.71)	(-2.41)

t-statistics in parentheses

*** p<0.01. ** p<0.05. * p<0.1

Volume

Out of the three volume-related long-short strategy returns, we found all strategies to be statistically insignificant. See results for all statistically insignificant quintiles and long-short strategies in Table XVII.

Volatility

Analyzing the performance of the long-short portfolio strategy returns within the volatility group, we found that out of the seven long-short strategies, none were statistically significant. Table XVII.

D. Cryptocurrency Factors

Market Excess Return

The CMKT factor consists of two components. A value-weighted weekly aggregate cryptocurrency market return, and the risk-free rate, measured as the weekly yield of the one-month U.S Treasury Bill.

The market portfolio is constructed by taking the weekly returns of each of the cryptocurrencies within our dataset. The weekly return is calculated using the closing prices of each of the cryptocurrencies. The return for each week and cryptocurrency is then multiplied by the cryptocurrency's share of the total market capitalization at the start of the portfolio formation week. The market portfolio is rebalanced weekly.

Size Effect

We start by constructing a size factor by dividing the cryptocurrency dataset into three groups based on market capitalization, in accordance with Liu et al (2022). One group containing the bottom 30% (Small), a second group containing the middle 40% (Medium), and a third group containing the top 30% (Big) currencies. Value-weighted portfolios are then created for each of the size groups S, M, and B. The size factor is calculated as the return difference between the small and big size portfolios.

Momentum Effect

The momentum factor is constructed based on the intersection of 2 x 3 portfolios. The first two portfolios are based on market capitalization size, where each portfolio consists of the bottom and top 50% respectively. Three portfolios are then formed within each of the two size-related portfolios. One portfolio containing the bottom 30%, a second portfolio containing the middle 40%, and a third portfolio containing the top 30% in terms of past three-week returns.

CMOM = ½(Small High + Big High) – ½(Small Low + Big Low)

Web3 Usage Effect

The DFUSG factor is constructed by weighting the weekly change in revenue for decentralized finance protocols by market capitalization. The weighted revenue growths are summed. The top 30% of the protocols in terms of revenue growth each week, as well as the bottom 30% of the protocols in terms of revenue growth each week, are subsetted. The sum of the weighted revenue growth of the bottom subset is subtracted from the sum of the weighted revenue growth of the top subset. The choice to subset and subtract growth values was made in order for the factor to focus on the relative performance rather than the macro perspective of the cryptocurrency market.

E. Factor Models

One-Factor Model

We start by applying a one-factor model to the eight successful Size, Momentum, Volume, and Volatility strategies. The one-factor model consists of an alpha, the CMKT, and an error term. See the full list of all error terms in Table IXX.

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

Table XI

One-Factor Model Results

The results of the eight significant long-short strategies, adjusted for the one-factor model.

VARIABLES	logmcap	logprc	max_dprc	wret	cumret2	cumret3	cumret4	cumret100
leadmktrf	0.141	-0.341***	-0.343***	0.135	0.091	0.080	0.088	0.234**
	(1.315)	(-3.500)	(-3.486)	(1.453)	(0.890)	(0.765)	(1.093)	(2.450)
Constant	-0.092***	-0.022**	-0.023**	0.017*	0.043***	0.037***	0.018**	-0.028***
	(-8.362)	(-2.252)	(-2.332)	(1.810)	(4.064)	(3.424)	(2.242)	(-2.795)
Observations	433	433	433	432	431	430	429	333
R-squared	0.004	0.028	0.027	0.005	0.002	0.001	0.003	0.018
Mean quintile R-squared	0.474	0.444	0.445	0.486	0.471	0.469	0.511	0.444

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The results show that the one-factor model does not capture the returns of the significant strategies. Three of the strategies can be significantly predicted by the one-factor model at a significance level equal to or less than 5%, but for each of those strategies, the alphas are significant, meaning that the one-factor model does not fully explain the returns of the strategies. The mean quintile R-squared, or the average coefficient of determination for all five quintiles in each of the eight long-short strategies, ranges between 0.444 and 0.511. For the long-short strategies, the R-squared ranges between 0.001 and 0.028.

Two-Factor Model

Next, we add the size factor to the one-factor model to construct the two-factor model.

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

Table XII

Two-Factor Model Results: Size

The results of the eight significant long-short strategies, adjusted for the two-factor model with the market and size factors.

VARIABLES	logmcap	logprc	max_dprc	wret	cumret2	cumret3	cumret4	cumret100
leadmktrf	-0.044	-0.523***	-0.543***	0.167*	0.122	0.113	0.085	0.185*
	(-0.423)	(-5.604)	(-5.857)	(1.742)	(1.159)	(1.048)	(1.024)	(1.914)
leadcsize	-0.801***	-0.784***	-0.865***	0.135	0.132	0.140	-0.013	-0.242**
	(-7.548)	(-8.252)	(-9.149)	(1.382)	(1.233)	(1.279)	(-0.154)	(-2.406)
Constant	-0.119***	-0.049***	-0.053***	0.022**	0.047***	0.041***	0.018**	-0.036***
	(-10.879)	(-5.004)	(-5.418)	(2.164)	(4.246)	(3.656)	(2.067)	(-3.433)
Observations	433	433	433	432	431	430	429	333
R-squared	0,121	0,161	0,186	0.009	0.005	0.005	0.003	0.035
Mean quintile R-squared	0.541	0.480	0.483	0.502	0.488	0.483	0.520	0.462

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The results show that the excess cryptocurrency market return is significant at a less than 1% level for the last daily price in the portfolio formation week and the maximum daily price in the portfolio formation week. The significance and the negative coefficients implies that the logprc and the max_dprc long-short strategies have a negative exposure to the cryptocurrency market. All long-short strategies in the Size group in addition to the past 100-week return have a significant and negative exposure to the size factor. All the alphas remain statistically significant, to an even higher degree than in the one-factor model. This suggests that the two-factor model including the size factor fails to explain the returns of all eight long-short strategies, to an even lower degree than the one-factor model. The mean quintile R-squared and the R-squared for each of the eight long-short strategies except the past-100 week return increased with the addition of the size factor. The mean quintile R-squared ranges from 0.462 to 0.541, and the long-short strategy R-squared now ranges from 0.003 to 0.186.

Since the two-factor model containing the cryptocurrency market excess return and the size factor does not address the long-short strategies' exposure to the momentum factor, we also consider an alternative two-factor model consisting of the cryptocurrency market excess return and the momentum factor.

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

Table XIII

Two-Factor Model Results: Momentum

The results of the eight significant long-short strategies, adjusted for the two-factor model with the market and momentum factors.

VARIABLES	logmcap	logprc	max_dprc	wret	cumret2	cumret3	cumret4	cumret100
leadmktrf	0.337***	-0.055	-0.055	0.032	-0.067	-0.015	0.027	0.308***
	(3.052)	(-0.586)	(-0.578)	(0.328)	(-0.632)	(-0.137)	(0.315)	(3.041)
leadcmom	-0.138***	-0.201***	-0.202***	0.073***	0.112***	0.067***	0.043**	-0.048**
	(-5.347)	(-9.102)	(-9.078)	(3.220)	(4.514)	(2.607)	(2.192)	(-2.112)
Constant	-0.014	0.092***	0.092***	-0.025	-0.021	-0.002	-0.007	0.002
	(-0.748)	(5.917)	(5.847)	(-1.531)	(-1.224)	(-0.100)	(-0.465)	(0.101)
Observations	433	433	433	432	431	430	429	333
R-squared	0.066	0.185	0.184	0.028	0.047	0.017	0.014	0.031
Mean quintile R-squared	0.501	0.480	0.479	0.497	0.486	0.477	0.520	0.482

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

In this model, the last daily market capitalization in the portfolio formation week and the past 100-week return have a positive and significant exposure to the cryptocurrency market excess return, at a significance level of less than 1%. All long-short strategies have a significant exposure to the momentum factor, logmcap, logprc, and max_dprc have a negative exposure and all the past week returns have a positive exposure to the cryptocurrency market excess return. The alphas are notably less significant compared to the two-factor size model. Only the alphas for the logprc and max_dprc long-short strategies remain statistically significant. This suggests that the two-factor momentum model performs better at capturing the returns of the long-short strategies compared to the two-factor size model. There have only been incremental changes to the R-squared values compared to the two-factor size model. The mean R-squared for the quintile portfolios ranges from 0.477 to 0.520 and the R-squared for the long-short strategies ranges from 0.014 to 0.185. The most significant change is an increase in the coefficient of determination for the long-short strategies that have significant exposure to the momentum factor.

Three-Factor Model

We construct a three-factor model including the CMKT or cryptocurrency CAPM, as well as the size factor and the momentum factor.

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

The three-factor model combines the alternative two-factor models. In the longer time period, it captures the return variation and exposure to the size and momentum factor of four of the successful long-short portfolio strategies. In the shorter time period, used to compare the three-factor model to the four-factor model, it captures the returns of all eight successful strategies.

Table XIV

Three-Factor Model Results: Time Frame 1

The results of the eight significant long-short strategies, adjusted for the three-factor model with the market, momentum and size factors over 316 weeks.

VARIABLES	logmcap	logprc	max_dprc	wret	cumret2	cumret3	cumret4	cumret100
leadmktrf	0.125	-0.246***	-0.271***	0.055	-0.055	0.011	0.012	0.251**
	(1.138)	(-2.630)	(-2.902)	(0.540)	(-0.492)	(0.099)	(0.130)	(2.405)
leadcsize	-0.713***	-0.641***	-0.724***	0.077	0.042	0.088	-0.051	-0.207**
	(-6.719)	(-7.088)	(-8.034)	(0.783)	(0.391)	(0.797)	(-0.594)	(-2.012)
leadcmom	-0.105***	-0.171***	-0.169***	0.070***	0.110***	0.063**	0.046**	-0.038*
	(-4.184)	(-8.028)	(-7.956)	(3.004)	(4.348)	(2.402)	(2.264)	(-1.652)
Constant	-0.057***	0.053***	0.048***	-0.020	-0.019	0.003	-0.010	-0.011
	(-3.076)	(3.388)	(3.074)	(-1.165)	(-1.014)	(0.179)	(-0.641)	(-0.608)
Observations	433	433	433	432	431	430	429	333
R-squared	0.155	0.270	0.291	0.030	0.048	0.018	0.015	0.043
Mean quintile R-squared	0.555	0.504	0.506	0.510	0.499	0.488	0.527	0.491

t-statistics in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

In the longer time period three-factor model, three long-short strategies have significant exposure to the cryptocurrency market excess return. The last daily price in the portfolio formation week, the maximum price in the portfolio formation week, and the past 100-week return. Four long-short strategies have significant and negative exposure to the size factor, while the other strategies remain statistically insignificant. All long-short strategies apart from the past 100-week return have exposure to the momentum factor at a significance level of less than 5%. The strategies within the Size group have a negative exposure and all the significant strategies of the momentum group have a positive exposure to the momentum factor, apart from the past 100-week return which has a negative exposure. All the long-short strategies in the Size group have significant alphas. Hence, the factors in the three-factor model can only fully explain the returns of the past one-, two-, three-, four-, and 100-week long-short strategy returns. The R-squared has increased for both the quintile portfolios and the long-short strategies compared to the one-, and two-factor models. The lowest to highest mean quintile R-squared ranges from 0.488 to 0.555, and the R-squared for the long-short strategies ranges between 0.015 and 0.291.

Table XV

Three-Factor Model Results: Time Frame 2

The results of the eight significant long-short strategies, adjusted for the three-factor model with the market, momentum and size factors over 33 weeks.

VARIABLES	logmcap	logprc	max_dprc	wret	cumret2	cumret3	cumret4	cumret100
leadmktrf	0.062	-0.825**	-0.815**	-0.103	-0.380*	-0.326	-0.483**	0.063
	(0.544)	(-2.593)	(-2.611)	(-0.565)	(-1.707)	(-1.511)	(-2.292)	(0.482)
leadcsize	-0.607**	-1.372*	-1.351*	0.034	0.167	-0.045	-0.307	-0.504*
	(-2.425)	(-1.960)	(-1.966)	(0.085)	(0.341)	(-0.096)	(-0.663)	(-1.759)
leadcmom	-0.042	-0.001	-0.005	-0.042	0.086	0.046	0.075	-0.040
	(-1.078)	(-0.014)	(-0.051)	(-0.671)	(1.124)	(0.630)	(1.047)	(-0.905)
Constant	-0.043	-0.093	-0.089	0.036	-0.027	-0.015	-0.040	-0.008
	(-1.681)	(-1.303)	(-1.271)	(0.880)	(-0.551)	(-0.316)	(-0.851)	(-0.275)
Observations	33	33	33	33	33	33	33	33
R-squared	0.316	0.197	0.200	0.040	0.187	0.108	0.185	0.208
Mean quintile R-squared	0.880	0.843	0.844	0.844	0.826	0.829	0.858	0.865

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

For the shorter time period, none of the long-short strategies have significant exposure to any of the three factors at a significance level equal to or less than 1%. However, the last daily price in the portfolio formation week, the maximum daily price in the portfolio formation week and the past four-week return long-short strategies have significant and negative exposure to the cryptocurrency market excess return at a 5% significance level. The last daily market capitalization is the only long-short strategy with exposure at a significance level of 5% or less. The last daily price in the portfolio week, the maximum daily price in the portfolio formation week, and the past-100 week returns are also statistically significant but only at a 10% level. The smaller data sample for the shorter time period produces a three-factor model in which no alpha is statistically significant. Indicating that the three factors significantly explain the long-short strategy returns. The shorter time frame three-factor model produces high R-squared for both quintile portfolios and long-short strategies. The mean quintile R-squared from 0.826 to 0.880, and the long-short strategy R-squared from 0.040 to 0.316.

Four-Factor Model

We construct a four-factor model including the market factor, size factor, and momentum factor from the three-factor model, as well as the web3 usage factor. The four-factor model is an extension of the three-factor model created by Liu et al (2022), adding a factor of real-world cryptocurrency utility usage. The four-factor model captures the returns of all eight successful long-short strategies and does so with similar coefficients of determination, and with alpha values closer to zero.

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

Table XVI
Four-Factor Model Results
The results of the eight significant long-short strategies, adjusted for the three-factor model with the market, momentum and size factors over a 33 week period.[9]

VARIABLES	logmcap	logprc	max_dprc	wret	cumret2	cumret3	cumret4	cumret100
leadmktrf	0.043	-0.856**	-0.844**	-0.177	-0.449*	-0.377*	-0.592***	0.031
	(0.354)	(-2.479)	(-2.489)	(-0.943)	(-1.908)	(-1.712)	(-2.793)	(0.220)
leadcsize	-0.640**	-1.289*	-1.270*	-0.051	0.148	-0.017	-0.406	-0.468
	(-2.441)	(-1.724)	(-1.729)	(-0.125)	(0.289)	(-0.037)	(-0.884)	(-1.560)
leadcmom	-0.032	-0.005	-0.009	-0.026	0.097	0.062	0.095	-0.040
	(-0.798)	(-0.041)	(-0.076)	(-0.405)	(1.226)	(0.836)	(1.327)	(-0.869)
DFUSG	-0.064	0.088	0.087	-0.169	-0.080	-0.018	-0.209	0.026
	(-0.783)	(0.375)	(0.379)	(-1.328)	(-0.500)	(-0.119)	(-1.459)	(0.274)
Constant	-0.030	-0.112	-0.108	0.077	-0.008	-0.016	0.012	-0.012
	(-0.926)	(-1.201)	(-1.179)	(1.506)	(-0.128)	(-0.275)	(0.209)	(-0.332)
Observations	31	31	31	31	31	31	31	31
R-squared	0.310	0.210	0.212	0.118	0.233	0.154	0.298	0.174
Mean quintile R-squared	0.880	0.836	0.836	0.837	0.810	0.853	0.853	0.868

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The four-factor model shows somewhat similar results to the three-factor model for the same time period with regards to the coefficient of determination as well as the alphas, but there are differences. The coefficients of determination are higher in the four-factor model than in the three-factor model for six out of the eight significant strategies. The coefficient of determination is higher in the four-factor model for logprc, max_dprc, wret, cumret2, cumret3, and cumret4. This means that the four-factor model explains more of the variation than the three-factor model for these six strategies. The average coefficient of determination for the four-factor model over the eight strategies is 0.214, while the average for the three-factor model over the eight strategies is 0.180.

As for the alphas, they are closer to zero in the four-factor model compared to the three-factor model for six of the eight strategies. The strategies for which the alphas are closer to zero in the four-factor model than in the three-factor model are logmcap, logprc, max_dprc, cumret2, cumret3, and cumret 4. This means that the four-factor model captures more of these six strategies' returns than the three-factor model does. The average alpha for the four-factor model is 0.720 away from 0. The average alpha for the three-factor model is 0.891 away from 0.

V. Empirical Analysis

A. Different Time Frames

The time frame used in the replicated article by Liu et al (2022) spans from the beginning of 2014 to July 2020, or around 339 weeks. Replicating the article resulted in an extension in the time period of 96 weeks or about 28%. The models showcase different results in the two time periods, both with regard to which strategies are significant and with regard to what strategies' returns are captured by the three-factor model.

In order to compare the three-factor model to our four-factor model, we shortened the time frame to 33 weeks. The reason for this is that decentralized finance protocols have not been around for long and that the data on their revenue does not stretch far back. In order to be able to include multiple decentralized finance protocols that have revenue, the time frame's start was set to September 2021. Accordingly, the time frame for the cryptocurrency data was set to start at the same time.

The time frame used for the four-factor model, and thus for the comparison with the three-factor model, tests the models on the same eight significant strategies that were significant in the longer time frame. When the individual zero-investment long-short strategies are tested on the shorter time frame, the output is different. Only the logvol, logvolscaled, and logmcap strategies are significant. This is not relevant for the comparison between the three- and four-factor strategy comparison, though. It is shown that the eight originally significant strategies are significant in a longer time frame, and therefore, it is those strategies that are interesting to look at with regard to the factor models, even though they might not be significant in the shorter time frame. According to the three-factor model, those eight strategies are the significant ones, and we can only assume that this result is more reliable than the one for the shorter time frame. This logic also implies that the comparison between the three- and four-factor models in the short time frame is not reliable, which is true. Had a longer time frame for decentralized finance protocols been available, that data would have provided more reliable results. The short time frame is all that is available at the moment, even though the eight strategies are not individually significant in the shorter time frame, the four-factor model does capture more of their returns than the three-factor model does. There is nothing explicitly indicating that the four-factor model would not capture more of the eight originally significant strategies' returns in a longer time frame, but as time goes on, the comparisons will have to be updated in order to explore whether the four-factor model can remain dominant over time.

B. Availability of Cryptocurrency Data

An important fact when analyzing historical cryptocurrency data is that the data has not always been available to the extent it is today, and that it has not always been as unambiguous as today, even though it is still not perfect. Although cryptocurrency had its birth in 2009 with the launch of Bitcoin, there was not a sufficient amount of data on cryptocurrencies to analyze until later in the 2010s. Large reliable data sources regarding cryptocurrencies (coinmarketcap and coingecko) launched at the end of 2013 and the beginning of 2014 respectively. Thus our timeframe starts at the beginning of 2014. Our use of another data source for our project than Liu et al (2022) used, means that the data for any given cryptocurrency at any given date, will not necessarily be equal.

C. Cryptocurrency Data Sources

Liu et al (2022) collected their data from APIs listed on coinmarketcap.com. In our study, we collected data from CoinGecko. The reason for this is that

Coinmarketcap is an expensive tool for gathering historical data on cryptocurrencies while CoinGecko provides all historical data for free. The difference in data sources has made it harder to cross-check our variables and compare our results with the replicated article.

D. Removal of Faulty Data

The dataset used initially contained around 150 million data points. Removing duplicates resulted in almost 90% of the data points being removed. In this dataset, some smaller coins displayed behaviors such as sustaining the same market capitalization for the entire period, or price dropping to zero, just for it to increase by over an undecillion percent[5]. These observations were either replaced with correct data or, in the cases this was not feasible, removed. While the observations removed did not account for a large share of the total market capitalization, and thus not a large share of the portfolios they would have been included in, the fact that the data had to be cleaned of faulty data could have changed the outcome.

E. Size Effect

For the one-, two- and three-factor models, the significant strategies belonging to the Size group are all exposed to the size factor at a significance level of less than 1%. The three long-short strategies belong to the Size group and are specifically designed to take advantage of the size factor, and thus their exposure to the size factor is not peculiar in itself. However, the results are ambiguous. Highly significant exposure to both the cryptocurrency market excess return and the size factor implies that the model to a certain degree of certainty can be said to successfully explain the returns of the long-short strategies. Yet, the alphas remain statistically significant, implying that the cryptocurrency market excess return and the size factor do not successfully capture the returns of the long-short strategies.

We have analyzed the reason why this is the case and found the possible explanation that it is correlated to how the market capitalization data is filtered in our variable construction process. In one of these filters, we remove all cryptocurrencies that have had the same market capitalization for ten consecutive days, which resulted in 140 cryptocurrencies being removed from our data sample. By experimenting with, and changing the limit from ten consecutive days we found that the alphas change significance level depending on the number of consecutive days we allow the cryptocurrencies in our data sample to have the same market capitalization. However, the lower the filter limit, the more cryptocurrencies we remove from our data sample. By reducing the filter limit to two consecutive days we effectively remove over 1000 cryptocurrencies from the data sample. To motivate such a large decrease in sample size, we would have to embark on the tedious process of manually ensuring that all of these cryptocurrencies indeed should be excluded from our data sample. Additionally, hardening the limit for the consecutive day filter had a negative impact on the momentum factor's performance of capturing the return of the long-short strategies in the Momentum group. Therefore, we have in this study decided to have the limit set to four

[5] Over 1,000,000,000,000,000,000,000,000,000,000,000,000,000%

consecutive days as it provides a more reliable data composition from on which to apply strategies and factors.

F. Cryptocurrency Data Filtering

We decided to only include observations where the coin or token has a market capitalization of at least $1 million. Since cryptocurrencies can be created and listed on an exchange in just a few minutes, a market capitalization restriction helps filter out coins that are created as a joke or that never gained any traction or recognition. A cryptocurrency with a market capitalization of at least $1 million implies, to some extent, that some actor has invested in it with the hopes of making a return on the investment. Additionally, cryptocurrencies with a market capitalization below $1 million, regardless of return, would have such a minimal weight representation in our market return index, as well as any portfolios they would be included in, that they would not contribute with a significant impact on the results.

During the past few years, and after the end of the data timeframe used by Liu et al (2022), the cryptocurrency market has changed. From just consisting of a few cryptocurrencies in 2014, the market now also consists of decentralized finance protocol tokens, "meme coins", data storage tokens, non-fungible token project tokens, stablecoins, and more. Most of these different kinds of tokens and coins are built in a unique way, and all of them cannot reasonably be included in asset pricing experiments. For example, stablecoins are programmed to have a set value denominated in another currency, without much fluctuation (Hampl, Gyönyörová 2021). The biggest one is USDT or Tether. Tether is a stablecoin backed by securities and other currencies made to stay valued at $1. It has done its job so far, and in doing so, its price has remained at about $1. Meanwhile, its market capitalization has grown from $304,000 in February 2015, peaking at around $83 billion in April 2022, and dropping to $66 billion in November 2022. These fluctuations in market capitalization, paired with a non-fluctuating price, stablecoins impact asset pricing models differently than traditional cryptocurrencies and other tokens. This is because the 22 market-based characteristics take into account, among other things, changes in market capitalization, price, and the relationship between the two. Thus, an asset with a stagnant price and a large market capitalization will take up a big weight, in the market return index and any portfolios it is part of, with its zero percent returns.

G. Insignificant Strategies

The list of established return predictors from Chen and Zimmermann (2020) predicts cross-sectional stock returns, not cross-sectional cryptocurrency returns. Although all 22 strategies used in this study are statistically significant return predictors in the original papers, only eight strategies remain statistically significant when applied to our cryptocurrency data. And none of the statistically significant strategies belong to the Volume or Volatility group. An explanation for this could be that the cryptocurrency market is relatively younger and less mature than the stock market. It does not have the same level of liquidity, depth, and efficiency as the stock market, which could affect the results of volume and volatility-related strategies (Hamed Al-yahyaee, Mensi, Ko, Yoon, and Hoon Kang 2020). Furthermore, another possible explanation could be that the cryptocurrency market is more volatile than the stock market which could make it harder to predict movements and returns in the cryptocurrency market using volume and volatility-related strategies (Corbet, Lucey, Urquhart, and Yarovaya 2019). See results for insignificant strategies in Table XVIII.

H. Possible Theoretical Explanations

Theoretical explanations explored by Liu et al (2022) are applied to our results in order to provide possible explanations for the factors and their relationship with returns. The paper suggests two mechanisms that could explain the size premium: the liquidity effect and the capital gains versus convenience yield trade-off. The convenience yield is higher for larger cryptocurrencies in equilibrium and with regard to market capitalization. This means their capital gains should be lower (Sockin and Xiong 2018), (Prat, Danos, and Marcassa 2019), (Cong, Li, and Wang 2021). The paper also suggests that the investor overreaction model could explain the momentum premium (Daniel, Hirshleifer, and Subrahmanyam 1998), (Sockin and Xiong 2018). The big moves in the cryptocurrency markets, time after time displaying powerful, often parabolic, returns, before reversing and retracing quickly to previous price levels, reinforces the argument that the investor overreaction model could explain the momentum premium. The fact that most cryptocurrencies, as opposed to equities, for example, do not have cash flows or a business model to rely on, could explain why investors rely more on what other investors do - what the market does - leading to a display of investor overreaction.

I. Comparing Results

The three-factor model in this thesis and the one in Liu et al (2022) are identical, but the replication examines a longer time period and one where a lot happened in the cryptocurrency market, at that. The model captured fewer strategies' returns over a longer time period. One of the possible reasons for this is increased competition and saturation in the cryptocurrency market. As evident in our data, the number of cryptocurrency projects has increased since the creation of the replicated article, and growing competition could reduce the potential returns for investors. This, paired with the unregulated nature of the cryptocurrency market possibly leading to information asymmetry, could skew the potential returns to some actors' advantage. Funds, firms, and persons being able to utilize spoofing, or simply having more insight into projects and the market as a whole, could reduce the share of returns captured by a model such as the three-factor model. Macroeconomic factors could also contribute to the lower prediction power of the three-factor model. The implications of the COVID-19 pandemic, as well as trade tensions and other macroeconomic factors, have affected markets globally, and the cryptocurrency market is no exception.

The time period covered by the DFUSG factor is shorter than the period covered by the three-factor model. Thus, the three-factor model was applied to the shorter time period, before adding the DFUSG factor for comparison. In the shorter time period, the three-factor model did capture all significant strategies’ returns, displaying non-significant alphas for every strategy. The three-factor model also displays higher coefficient of determination values in the short time period than in the long time period. The addition of the DFUSG factor does not affect the coefficient of determination values much, but it does display strategy alphas closer to zero for six of the eight strategies, compared to the three-factor model in the same time period. One possible reason for the lower alphas in the four-factor model is the fact that new decentralized finance protocols show accounting metrics such as revenue publicly per the design of their technology. Such information, commonly used in the valuation of equities, was not available to the same extent as today when Liu et al (2022) was created. The accounting metrics give insight into the actual performance of the cryptocurrency assets, which could help predict price moves in the assets themselves, but also give an indication of the performance of the cryptocurrency market as a whole.

VI. Conclusion

We show that traditional asset pricing models can be used to analyze the cross-section of the cryptocurrency market and that the addition of a web3 usage factor increases the power of the model. First, zero-investment long-short strategies based on 24 characteristics - in turn, based on cryptocurrency price, market capitalization, and volume - are analyzed, and eight of the strategies are shown to deliver statistically significant excess returns.

Second, a one-factor model, similar to the Capital Asset Pricing Model and consisting of the leadmkt factor, is shown not to capture the returns of the cryptocurrency market. The leadcmom and leadcsize factors are added, creating a three-factor model that captures the returns of five out of the eight significant strategies. In the time period of the paper that the model is replicated from, the three-factor model captures more strategies' returns.

We add a new factor to the model, making it a four-factor model. The new factor, DFUSG, represents web3 usage. It is applied to a smaller time period, where the three-factor model captures the returns of all eight significant strategies. The four-factor model, however, displays similar coefficient of determination values, and strategy alpha values closer to zero.

Liu, Tsyvinsky, and Wu bring up the possibility that the dynamics of the cryptocurrency markets change after the publication of their paper. The fundamentals and the conversation on cryptocurrencies have changed, and our results replicating their paper show that the market has changed as well. Our extension of their model is an addition that showed to improve the traditional asset pricing models. As the cryptocurrency market progresses, retracts, fluctuates, and eventually (possibly) finds some stability in price, purpose, and role, these models will most likely have to be modified again.

In conclusion, our research has shown that traditional asset pricing models can be applied to the cryptocurrency market and that the addition of a web3 usage factor can increase the power of the model. We found that zero-investment long-short strategies based on cryptocurrency characteristics can deliver statistically significant excess returns and that a one-factor model is not sufficient to capture the returns of the cryptocurrency market. By adding two additional factors, we were able to create a three-factor model that captures the returns of several

strategies. Furthermore, we showed that the addition of a web3 usage factor to the model improved its ability to capture the returns of the significant strategies.

Overall, our findings suggest that asset pricing models can be useful for analyzing the cryptocurrency market, but that they may need to be modified as the market evolves. As the fundamentals and conversation around cryptocurrencies continue to change, it will be important for researchers to update and refine these models in order to better understand and predict the behavior of the market.

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Appendix

Table XVII

Protocol Definitions and Links

The decentralized finance protocols whose revenue data make up the base of the web3 usage factor DFUSG.

Protocol	Description	Link
Aave	Open Source Protocol to create Non-custodial Liquidity Markets	https://aave.com/
Bancor	DeFi trading and staking protocol with Single-Sided Liquidity	https://home.bancor.network/
BENQI	Liquid Staking and Algorithmic Liquidity Market Protocol	https://benqi.fi/
Cap	Decentralized Perpetual Exchange	https://www.cap.finance/
Compound	Algorithmic and Autonomous Interest Rate Protocol	https://compound.finance/
Curve	Decentralized Exchange Liquidity Pool	https://curve.fi/#/ethereum/swap
dYdX	Decentralized Exchange	https://dydx.exchange/
Euler	Non-Custodial DeFi Protocol	https://www.euler.finance/
GMX	Decentralized Perpetual Exchange	https://gmx.io/#/
Goldfinch	Decentralized Credit Protocol	https://goldfinch.finance/
Homora	Multi-Chain lending and leveraged yield Farming Protocol	https://homora.alphaventuredao.io/
Kyber	Decentralized Liquidity Protocol	https://kyber.network/

Liquity	Decentralized Borrowing Protocol	https://www.liquity.org/
Loopring	Open-Source, non-Custodial Exchange and Payment Protocol	https://loopring.org/#/
MakerDAO	Open-Source, Decentralized Autonomous Currency creator	https://makerdao.com/en/
Maple Finance	Institutional Crypto-Capital Network	https://www.maple.finance/
MCDEX	Decentralized Perpetual Exchange	https://mcdex.io/homepage/
Notional Finance	Decentralized Lending and Borrowing Protocol	https://www.notional.finance/
Pangolin	Multichain Decentralized Digital Assets Exchange	https://www.pangolin.exchange/
Perpetual Protocol	Decentralized Perpetual Contract Protocol	https://perp.com/
Reflexer	Decentralized Borrowing Protocol	https://reflexer.finance/
Rook	MEV Marketplace	https://www.rook.fi/
Spooky Swap	Decentralized Exchange	https://spooky.fi/#/
Sushi Swap	Decentralized Exchange	https://www.sushi.com/
Synthetix	Decentralized Perpetual Exchange	https://synthetix.io/

Trader Joe	Decentralized Exchange	https://traderjoexyz.com/home#/
1inch	Decentralized Liquidity and Aggregation Protocol	https://1inch.io/

Table XVIII
Insignificant Strategies Results
The mean quintile portfolio returns for all statistically insignificant long-short strategies.

Insignificant	1	2	3	4	5	5-1
lag 24	0.008	0.012	0.007	0.020***	0.019***	0.011
t (mean)	(0.95)	(1.58)	(1.18)	(2.94)	(2.58)	(1.30)
cumret8	0.020***	0.016	0.012**	0.013**	0.029***	0.006
t (mean)	(2.59)	(1.56)	(2.02)	(2.15)	(3.17)	(0.68)
cumret16	0.022***	0.0185***	0.014**	0.020***	0.020***	-0.002
t (mean)	(2.79)	(2.64)	(2.18)	(2.99)	(2.89)	(-0.20)
cumret50	0.028***	0.020***	0.014**	0.021***	0.018**	-0.01
t (mean)	(3.56)	(2.71)	(2.13)	(3.05)	(2.52)	(-1.27)
logvol	0.007	0.019***	0.015**	0.015**	0.021**	0.014
t (mean)	(0.90)	(2.60)	(1.99)	(2.009	(2.31)	(1.59)
logprcvol	0.016**	0.029**	0.016**	0.013**	0.01	-0.005
t (mean)	(2.06)	(1.96)	(2.52)	(2.03)	(1.54)	(-0.74)
logvolscaled	0.015**	0.022*	0.014**	0.009	0.016**	0.001
t (mean)	(1.99)	(1.82)	(1.99)	(1.51)	(2.42)	(0.19)
logstdprcvol	0.018***	0.017**	0.016**	0.009	0.016*	-0.002
t (mean)	(2.58)	(2.32)	(2.57)	(1.20)	(1.81)	(-0.19)
avg_damihud	0.008	0.013*	0.018**	0.022***	0.016**	0.008
t (mean)	(1.14)	(1.92)	(2.46)	(2.84)	(1.98)	(1.05)
std_dret	0.021***	0.017**	0.01	0.008	0.018**	-0.003
t (mean)	(2.77)	(2.45)	(1.49)	(1.19)	(2.14)	(-0.34)
max_dret	0.016**	0.024**	0.014**	0.016**	0.016*	-0.001
t (mean)	(2.14)	(2.28)	(2.20)	(2.16)	(1.86)	(-0.08)
beta	-0.001	0.007	-0.005	0.002	0.004	0.006
t (mean)	(.0.16)	(0.85)	(-0.50)	(0.23)	(0.41)	(0.71)
beta squared	-0.001	0.007	-0.005	0.002	0.004	0.006
t (mean)	(-0.16)	(0.85)	(-0.50)	(0.23)	(0.41)	(0.71)
delay	0.003	0.001	-0.01	-0.002	-0.002	-0.005
	(0.53)	(0.15)	(-1.24)	(-0.20)	(-0.37)	(-0.74)

Table XVIII
Error Terms
The root-mean-squared errors (RMSEs) for each of the significant
long-short strategies in the different factor models

One-Factor Model	Root-MSE
logmcap	0.22709
logprc	0.20570
max_dprc	0.20782
wret	0.19626
cumret2	0.21566
cumret3	0.22029
cumret4	0.16891
cumret100	0.18001

Two-Factor Model Size	Root-MSE
logmcap	0.21364
logprc	0.19135
max_dprc	0.19036
wret	0.19605
cumret2	0.21553
cumret3	0.22013
cumret4	0.16910
cumret100	0.17872

Two-Factor Model Momentum	Root-MSE
logmcap	0.22016
logprc	0.18857
max_dprc	0.19060
wret	0.19416
cumret2	0.21095
cumret3	0.21882
cumret4	0.16816
cumret100	0.17908

Three-Factor Model	Root-MSE
logmcap	0.20966
logprc	0.17862
max_dprc	0.17791
wret	0.19424
cumret2	0.21116
cumret3	0.21891
cumret4	0.16829
cumret100	0.17826

Four-Factor Model Short	Root-MSE
logmcap	0.04688
logprc	0.13385
max_dprc	0.13142
wret	0.07293
cumret2	0.09123
cumret3	0.08537
cumret4	0.08216
cumret100	0.05364

Three-Factor Model Short	Root-MSE
logmcap	0.04585
logprc	0.12819
max_dprc	0.12580
wret	0.07342
cumret2	0.08960
cumret3	0.08691
cumret4	0.08486
cumret100	0.05240