Cryptocurrency Return Predictors - A Replicative Reassessment

Rising Stablecoin Growth - Cryptocurrency Return Predictors in New Market Conditions

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Abstract:
We successfully construct nine significant cryptocurrency return predictor strategies based on market capitalization, momentum and volatility characteristics. We replicate the methods used in the article “Common Risk Factors In Cryptocurrency” using a larger and more recent dataset encompassing changed cryptocurrency market conditions and asset composition (Liu, Tsyvinski, Wu, 2022). Following increasing stablecoin market shares we show unexplained volatility effects in the presented three-factor model, add a volatility factor and create a four-factor model that better prices volatility. Furthermore, we investigate the continued viability of the return predictors facing changed market conditions, and compare them to equity market characteristics.

Keywords: Cryptocurrency, Factors Model, Zero-Investment Long-Short Strategies, Quintiles, Size, Momentum, Volatility Stablecoins, Stable Coins, Stale Coins

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1. Introduction

A. Background and Relevance

An increased growth of the cryptocurrency market has meant rapid addition of coins in various classes. Among these are stablecoins that have significantly increased their market dominance over the past few years and hold ~16% of total cryptocurrency market share as of December 2022 (CoinGecko, 2022). Stablecoins is a coin-class that aims to keep price stable through a currency peg or algorithmically controlling supply (Sveriges Riksbank, 2022). Given their naturally low volatility, remarkably high volume and close to zero returns, their effects on cryptocurrency return predictor models should be substantial going forward. The large growth of the still relatively immature cryptocurrency market should gradually reduce investor uncertainty and thus change the viability of current return predictors (Liu, Tsyvinski, Wu, 2022). Hence, we investigate and reassess common cryptocurrency return predictors with recent data to accommodate these changes.

The changed conditions in the cryptocurrency market could pose issues for the continued viability of the cryptocurrency three-factor model and long-short strategy return predictors as defined in. This is especially presuming one intends to capture coin returns based on common risk factors dependent on an adequate level of price volatility, which would possibly not be the case for stablecoins. We find that a zero-investment long-short quintile volatility strategy conducted after 2017 generates significant 1.7% average weekly excess returns in contrast while remaining insignificant prior to that. This could indicate that the effect of stable coins is present as the period after 2017 has a significantly larger share of stable coins. We attain the same effect when evaluating a long-short decile strategy over the entire period and generate a 2,78% weekly excess returns when longing coins in the highest volatility decile and shorting coins in the lowest decile. The groups with the lowest volatility in both tests successfully manage to obtain the largest stable coins measured in market capitalization, which amplifies this connection and emphasizes the importance of investigating this more closely.

The first goal of this paper is to examine and reassess the viability of a number of common return predictors, given the changed cryptocurrency market conditions.

The second goal of this paper is to, more specifically, examine if the introduction of a new volatility strategy and volatility factor could help explain the possible effects caused by the increasing market share and amount of stablecoins. This new factor model is compared to the cryptocurrency version of the Fama French three factor model, containing cryptocurrency market-, size-. and momentum factors. The generally high volatility of cryptocurrencies, and the increased market share of stale coins and stablecoins, creates reason for accounting for volatility effects in the factor model. We observe certain characteristics in our data attributable to stablecoins, such as low volatility and a large stablecoin trading volume overrepresentation.

To capture the effects of this rapidly growing cryptocurrency class, we will identify stablecoins as *stale coins*, and according to the following definition: stale coins are the coins in the decile of lowest volatility each week. The group is referred to as stale coins, since some non-stablecoins are also included. As illustrated by Figure 2, this group is measured to have the vast majority of coins around 2% weekly volatility and successfully captures most stablecoins, including top stablecoins by market capitalization[1].

B. Contribution

We partially replicate and use the methodology of the article “Common Risk Factors in Cryptocurrency” when constructing strategies and factor models according to the relevant methods carried out by the authors (Liu, Tsyvinski, Wu, 2022). We use the data aggregator CoinGecko to collect cryptocurrency data from January 2014 to May 2022, while the replicated article uses CoinMarketCap to retrieve market data from January 2014 to July 2020. In total, this paper cover a dataset of 3742 coins compared to 1827 coins in the replicated article, and features a time period of ~620% in total market market capitalization growth since July 2020, despite sharp recent market downturns (CoinGecko, 2022)[2]. Given that the total market capitalization share for stale coins in our data have risen from ~5% up to ~12%, compared to the end date of the replicated article, it will also contrast the effects of changing market composition (Appendix 1).

Liu, Tsyvinski, and Wu (2022) show significance for ten out of 24 cryptocurrency return predictor strategies: market capitalization, price, maximum price, past one-, two-, three-, four-, and one-to-four-week return, price volume, and standard deviation of price volume. Furthermore, they found that the cryptocurrency three-factor model consisting of a cryptocurrency market-, size- and momentum-factor, accounts for all of the 10 significant strategy returns.
The methods used when constructing the factor models are originally retrieved from traditional asset pricing methodology and later applied to cryptocurrencies by Liu, Tsyvinski, and Wu (2022). The Fama and French (1993) three-factor model originally contained a value factor. However, since cryptocurrencies do not obtain book-values in the traditional sense, the value factor is not applicable to this type of asset. Instead, a momentum factor is used (Carhart. M, 1997). We use the methods related to sorting composed by Fama French to construct a volatility factor controlling for both size and momentum effects. Hence, this article also evaluates the applicability of Fama-French methodologies on cryptocurrencies.

The strategies are constructed in line with the methods used in the replicated article, which are originally based on traditional asset pricing strategies (Liu, Tsyvinski and Wu, 2022). We sort coins each week based on the value of the strategy characteristics, and divide coins into quintiles, where the 5th quintile represents the coins with highest value by a characteristic.

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[1] Largest Stable Coins (included in our dataset) according to Coingecko: Tether, USD Coin, Binance USD, Dai, Frax, True-USD, USDD, Gemini Dollar, Tether Gold,, Euro Tether, Liquity USD, Alchemix USD, Stasis EUR, Neutrino USD, Magic Internet Money, XSGD, Fei USD, Flex USD and MAI.
[2] (Total Market Capitalization 2022-05-05)/(Total Market Capitalization 2020-07-01) -1
(1.886915e+12)/(261634147225) -1 = 6.212

For the quintile groups, we track the weekly excess returns (based on last-day weekly prices) over the risk free rate for the week that follows the portfolio formation week, and value weigh the returns with the last-day market cap of the portfolio formation week. The value weights and quintile sorting are rebalanced weekly. Zero-investment long-short portfolios are then created by going long on the coins in the 5th portfolio and shorting coins in the 1st portfolio.

We also try to investigate possible differences and similarities between investment strategies in the stock market and the cryptocurrency market. The methodology for investigating the size effect is based on Banz (1981), Miller and Scholes (1982) and George and Hwang (2004) who find that small, low-price, and low-maximum-price stocks generate higher mean returns than bigger stocks. To estimate the momentum effect, the work of Jegadeesh and Titman (1993) is used as reference. They discuss the profitable effects of betting on coins with high past week momentum and that an overreaction of the market can make this trade less beneficial due to a reversal effect, both in the short and long term. We will nuance the discussion by including the conclusions made by Tzouvanas, Kizys and Tsend-Ayush (2020), that support our findings that the cryptocurrency market seems to have an inverse relationship to the stock market in regards to long- and short-term market efficiency. As shown with our significant long-short past 100-week return strategy with a negative coefficient, we also discuss De Bondt and Thaler's (1985) conclusions that the stock market seems to have an inverse effect for winners and losers in the long term. This means that the cryptocurrency market and the stock market both seem to be experiencing the same effects, although the effect past the 100-week period (25 months) is not investigated in this article.

Moreover, related to volume we find that when adjusting for stale coins (including stablecoins), that absorb a large share of total volume and naturally have close to zero returns, we see consistencies with the stock market where high-volume coin portfolios outperform low-volume ones (Wang, 2021). Prior to the adjustment, we found that there were no significant long-short mean returns. This is reasonably due to the high volume portfolio containing stale coins with low returns distorting the results. Hence, like the replicated article, we find no support in the cryptocurrency market that coins with low volume have higher returns as suggested by Chordia, Subrahmanyam, and Anshuman (2001).

Regarding volatility (percent of price standard deviation), we see significant outperformance of coin portfolios with abnormally large volatility versus those with abnormally low volatility. This is consistent with results on the stock market, although those relationships are weak (Baillie and Ramon, 2022). We find that this could be attributed to the increased market dominance of stable coins as the effect could be found sorting for weeks after 2017 and in a long-short decile strategy for the entire period.

C. Disposition

The analysis is divided into three sections. Starting by analyzing the long-short cryptocurrency strategies for the given period of the replicated article (January 2014 - July 2020), we obtain significant results for the market capitalization, price, maximum price, and past one-, two-, three-, four-, and 100-week return strategies. Also, the volume long-short strategy measured a p-value of 10,4% indicating its slightly above indicating it is slightly above the 10% significance level. Thus, we do not achieve the same significance levels as measured by Liu, Tsyvinski, and Wu (2022) for the past one-to-four-week return, price volume and standard deviation of price volume, but support for the newfound significant long-short strategy past 100-week return. Reasons for these discrepancies can mainly be attributed to differences in data aggregation sources and the fact that cryptocurrency price, volume and market cap data naturally differ in cryptocurrency exchanges. This problem arises from the decentralization of the digital asset exchanges that are inefficient and price arbitrage opportunities can be exploited due to different fees, or shifting levels of volume and liquidity (Gemini, 2022). A clear example of this difference can be seen in Figure 1 for Ethereum compared to the corresponding value-weighted market portfolio graph plotted by Liu, Tsyvinski and Wu (2022). The higher value of investment could be explained by the difference in starting price where CoinGecko reports a value of USD 1.33, compared to USD 2.79 in CoinMarketCap the same date whilst growing to more similar figures later in the period. Hence, it is evident that the differences could have an impact on for instance returns. We also discovered that there were anomalies in the initial CoinGecko data obtained from the API which we need to filter out by removing certain coins. Liu, Tsyvinski and Wu (2022) also pointed out an analysis about the risk of fabricated and boosted trading volumes due to inter alia a high ratio of unreliable and deceptive Chinese trading exchanges in CoinmarketCap (Ribes, 2018). This could explain the differences in results for volume-related strategies.

Thereafter, we test the significance of the cryptocurrency investment strategies on our extended time period (January 2014 - May 2022), and conclude that the cryptocurrency strategies market capitalization, price, maximum price, and the past one-, two-, three-, 100-week momentum strategies remained significant. We also obtain a reduced significance level for the volume strategy (p-value=0.113) which could be explained by an increased share of stable coins that represent a large part of the total volume although they have very low returns and volatility. If we then carry out an isolated effect for coins with 90% highest volatility (and therefore sort out stale coins according to our definition), we obtain a significant long-short volume strategy. To evaluate the effect of the increased stable coin market dominance, we construct a volatility zero-investment quintile long-short strategy (defined as percentage of price standard deviation) on our time period. The volatility weekly zero-investment quintile long-short strategy, longing the fifth quintile (highest volatility) and shorting the first quintile, showed insignificant excess returns (p-value: 0.147). The corresponding 10-1 *decile* strategy however, showed weekly significant mean excess returns of 2,78% (p-value: 0.070), which is an unexplained effect that needs to be accounted for in the factor models. Given the significant excess return of the decile volatility strategy (and significant long-short quintile strategy for the period after 2017), we create a volatility factor (CVOLAT) to evaluate if we could account for this return.

Next, we analyze the cryptocurrency factor models by comparing the one-, three-, and four-factor model constructed by a cryptocurrency market factor (CMKT), a cryptocurrency small minus big factor (CSMB), cryptocurrency momentum factor (CMOM), and a cryptocurrency volatility factor (CVOLAT). We confirm that the one-factor model using only the cryptocurrency market factor accounts for the past four-week return strategy, while having significant alphas for the rest of the significant strategies. The three-factor model, consisting of a cryptocurrency size and momentum factor, could account for four of the non-momentum strategies past two-, three-, four-, and 100-week returns, and the market capitalization strategy. Finally, by adding the volatility factor we find that the four-factor model performs better in pricing the volatility strategy than the three-factor model. Overall, it performs somewhat better, but notably, still fails in accounting fully for the size strategies, since it gets significant alphas.

2. Data

The historical data series have been attained from the independent cryptocurrency data aggregator CoinGecko. This database tracks 13,000+ different crypto assets tracked across more than 500+ exchanges worldwide and are frequently cited by different publications (CoinGecko, 2022). This means that there will be separation between the data used in "Common Risk Factors In Cryptocurrency", which uses aggregated data from ~400 exchanges taken from CoinMarketCap.

We set our time horizon from January 2014 until May 2022. Applicable coins were required to meet the following delineations; the currency must be traded on a public exchange, have coin-specific information on price, volume, and market capitalization, and exceed market capitalization of USD 1m. From the historical coin data series, we obtained daily market capitalization, price, and volume measured in dollars. An overview of the data is observed from the summary statistics presented in Table 1, Panel A. As illustrated, the sample of coins starts at 56 in 2014 and grows to 2788 in 2022, and including all coins, the total amounts to 3742. For market capitalization, the daily mean and median amount to USD ~828m and USD ~9.92m. This corresponds to a daily volume mean and median of USD ~118m and USD ~0.32m. Moreover, moving into detail we also found that stale coins (10% lowest by weekly volatility) had an average mean weekly volume of ~8x higher than the other coins (90% highest coins measured in weekly volatility).

In Panel B, summary statistics for the coin market index and major coins are presented. During the period 2014 - 2022, the mean coin market index return is 1.35% per week, which is lower than the weekly mean returns for the major coins. Ethereum measured a weekly return of 3.79%, Bitcoin 1.39% (per week), and Ripple 2.56% (per week). The new entry, Binance Coin delivered a significantly higher weekly mean return of 16.23% during the same period. The weekly standard deviation of the coin market index was measured at 0.102, which is in line with the Bitcoin standard deviation of 0.103 per week. Ethereum and Ripple were found to have higher standard deviations which were measured to be 0.18 and 0.22 respectively. However, the spread on the data was significantly smaller than the standard deviation of Binance Coin of 1.96[3]. The great similarity between the market and Bitcoin is due to the undisputed Bitcoin market dominance.

Table 1: **Summary Statistics**

Panel A. Characteristics by Year					
		Market Cap (mil)		Volume (thous)	
Year	Number	Mean	Median	Mean	Median
2014	56	360.83	6.27	2743.53	56.74
2015	38	233.43	6.08	14802.15	20.97
2016	82	251.23	4.58	48262.93	31.22
2017	374	825.22	16.34	26026.48	233.32
2018	935	556.93	13.29	23523.25	221.08
2019	924	374.14	6.20	123053.17	284.99
2020	1230	509.40	6.59	175643.11	464.15
2021	2921	1192.28	12.73	163159.95	439.74
2022	2788	919.70	10.13	67675.31	220.12
Full	3742	828.33	9.92	118471.13	319.49
Panel B. Return Characteristics					
	Mean	Median	SD	Skewness	Kurtosis
Coin Market Return	0.0135	0.0071	0.1015	0.3081	4.2468
Bitcoin Return	0.0138	0.0040	0.1029	0.6026	5.1238
Ripple Return	0.0255	-0.0083	0.2193	3.5396	24.2569
Ethereum Return	0.0378	0.0123	0.1806	1.9527	11.6902
Binance Coin Return	0.1623	0.0044	1.9685	15.1519	233.2892

To calculate excess return we replicate the daily risk-free rate with the 1-Month United States Bond Yield (“USA 1-månads Obligationsränta”), which we attained from Investing.com.[4]

A. *Data processing and filtering*

We organized and cleaned the daily data, making it feasible to convert into weeks. The original data contains daily historical data series, which was matched with a weekly number based on seven day intervals. However, since the number of days in a year is not a multiple of seven, the last week of the year consists of 8 days - in accordance with the replicated paper.

[3] Bitcoin, Ethereum, Binance Coin and Ripple are four of the largest cryptocurrencies by market capitalization on the 2022-05-05 (dataset end date). Measured from the end date used in “Common Risk Factors In Cryptocurrency” (2020-07-01), Ripple held the position as the third largest Cryptocurrency, a position that Binance Coin has taken at the end of our period

[4] This is a global financial markets platform with 46 million monthly users, and is one of the top three international financial websites according to both SimilarWeb and Alexa (Investing, N.A).

Hence, there is a total of 52 weeks per year and the 31st of December each year was allocated to week one the following year and the 29th of December is allocated to week 52. Considering the additional day during leap years, the 29th of December was excluded for 2016 and 2020, to make it comparable with the residual years.

During the processing, various incorrect data points were also detected. This conclusion was established considering the abnormal cumulative market return, extreme daily value increases, and constant market capitalization for a longer period despite changes in price and trading volume. Three filters were applied, one for price, market capitalization, and volume respectively. These involved excluding coins with constant market capitalization and volume over ten days as well as price changes of a hundred times daily increase. It was often the same coins that had errors. By completely removing coins with incorrect data points, we avoid gaps in the data. A total of 188 coins were removed. Filtering the data, reduced the risk of distorted value weights in portfolios or market performance.
Moreover, data gaps for the risk-free rate during weekend days (Saturday and/or Sundays) were adjusted for copying the last observation.

3. Cross-Sectional Return Predictors

The first step in the cross-sectional return analysis of the investment characteristics involves constructing the 23 strategies using the price, volume and market capitalization data (strategy definitions are presented in Appendix 2). These data characteristics are advantageous due to the consistent availability and applicability which can contribute to a more reliable result. Each week, the coins are divided into quintiles based on the value of the strategy characteristic, which is related to size, momentum, volatility or volume. All quintile strategies are constructed with the same methodology. For the quintile groups, we track the weekly excess returns (based on last-day weekly prices) over the risk free rate for the week that follows the portfolio formation week, and value weigh the returns with the last-day market cap of the portfolio formation week. The value weights and quintile sorting are rebalanced weekly. We then create the zero-investment value-weighted quintile portfolio excess returns by subtracting the value-weighted quintile returns in the fifth quintile by the value-weighted quintile returns in the first quintile. Moreover, we also construct a coin market return index consisting of all coins in the dataset. Each week we value-weighted the one-week returns with last-day market capitalisation.

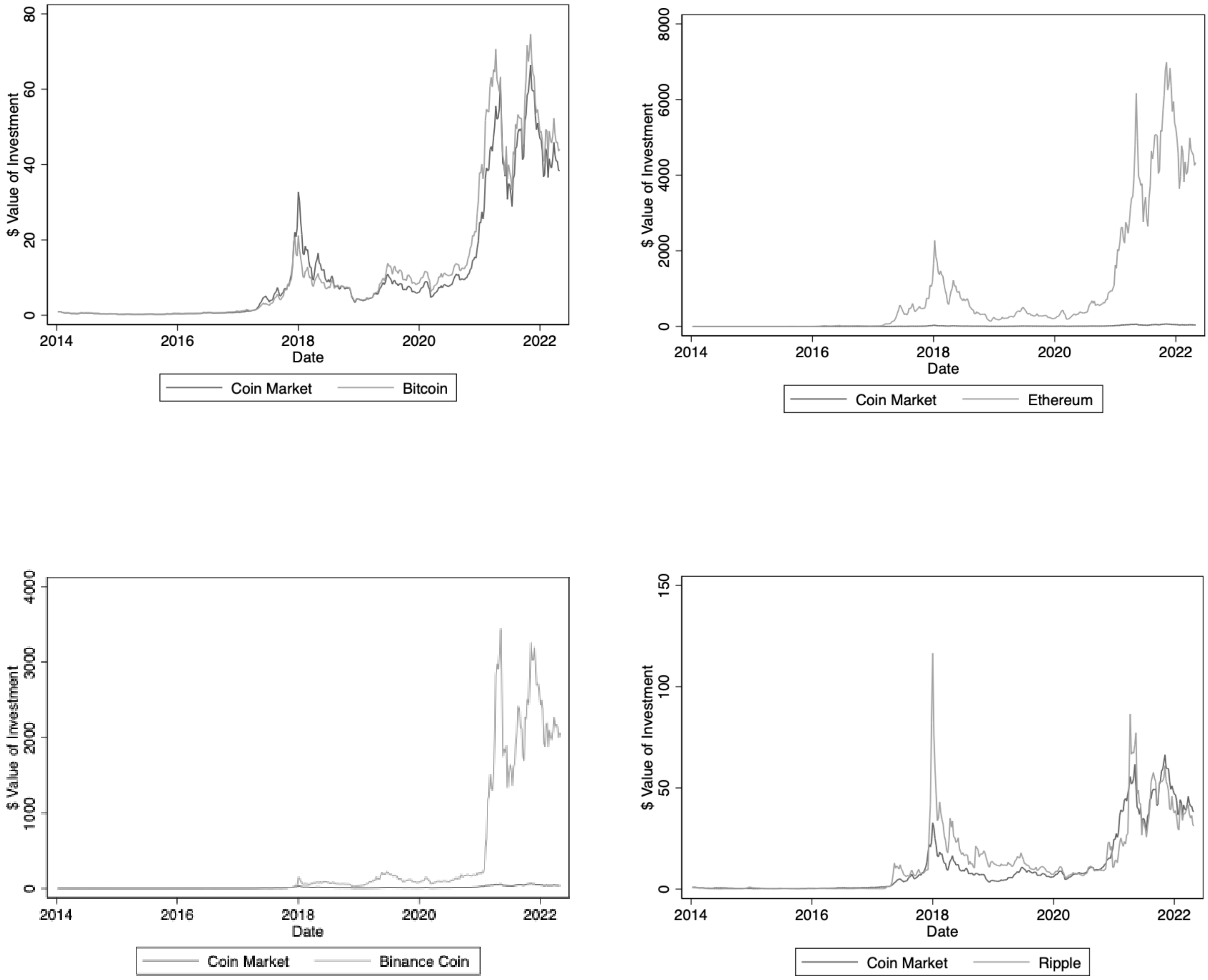

Figure 1. This figure plots the aggregate cryptocurrency market[5] (3742 coins value-weighted) against Bitcoin, Ethereum, Ripple, and Binance Coin.

[5]Value of investment is the value of investing one dollar from the first day.

A. Size characteristics

The methodology for creating the weekly zero-investment quintile long-short strategies is described in the beginning of this section. For the size group we analyzed the performance of the zero-investment long-short strategies based on the size-related characteristics of market capitalization, price and maximum day price. Table 3 illustrates the results of the three significant strategies in the size group. The mean excess return for the fifth over the first quintile amounts to -9.0% (MCAP), -2.6% (PRC), and -2.7% (MAXDPRC). Intuitively, a zero-investment strategy that longs the coins in the first quintile and shorts the coins in the fifth quintile provides a 9.0% weekly excess return for the market capitalization strategy. Like the replicated article, we confirm a size effect for the cryptocurrency size long-short strategies, where smaller coins outperform larger ones.

Table 2: **Size Strategy Returns**

Quintiles						
	1	2	3	4	5	5-1
MCAP	**Low**				**High**	
Mean	.103***	.026***	.015**	.024**	.013***	-.090***
t(mean)	(8.87)	(3.00)	(2.25)	(2.54)	(2.69)	(-8.26)
PRC	**Low**				**High**	
Mean	.040***	.0356***	.010	.019*	.014***	-.026***
t(mean)	(3.49)	(3.34)	(1.31)	(1.66)	(2.77)	(-2.64)
MAXDPRC	**Low**				**High**	
Mean	.041***	.033***	.011	.017	.014***	-.027***
t(mean)	(3.55)	(3.04)	(1.47)	(1.52)	(2.77)	(-2.72)

This table reports the mean quintile portfolio returns based on the market capitalization, last-day price, and maximum day price measures. The mean returns are the time-series averages of weekly value-weighted portfolio excess returns. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

B. Momentum Characteristics

The methodology for creating the weekly zero-investment quintile long-short strategies is described in the beginning of this section. Corresponding to the momentum group, we analyze the performance of the zero-investment long-short strategies based on past one-, two-, three-, four-, one-to-four-, eight-, 16-, 50-, and 100-week returns. Analysis of the nine momentum strategies concluded that only the past one-, two-, three-, four-, and 100-week return strategies provided significant results. The mean weekly excess return for the fifth over the first quintile ranges from -2.4% to 4.4%. All strategies except the past 100-week momentum yield a positive mean return. A long-short strategy that longs the coins in the highest quintile for past one, two, three and four-week returns and shorts the coins in the lowest quintile in the same categories, provides a mean weekly return of 3%. For the momentum strategies, we observe reversed momentum effects for the 16-, 50- and 100-week momentum, where the lowest momentum quintile outperforms the highest one, although the 16- and 50-week momentum strategies were not statistically significant. This means that if an investor shorts the coins in the upper quintile of past 100-week momentum and longs the coins in the smaller quintile, the portfolio generates a weekly return of 2.4%.

Table 3: **Momentum Strategy Returns**

Quintiles						
	1	2	3	4	5	5-1
r 1.0	**Low**				**High**	
Mean	.011	.004	.007	0.025***	.030***	.019**
t(mean)	(1.39)	(0.60)	(1.14)	(3.31)	(3.34)	(1.99)
r 2.0	**Low**				**High**	
Mean	-.001	.004	.010	.020***	.043***	.044***
t(mean)	(-0.13)	(0.58)	(1.59)	(2.95)	(4.14)	(4.2)
r 3.0	**Low**				**High**	
Mean	.001	.010	.008	.017***	.039***	.038***
t(mean)	(0.15)	(1.45)	(1.25)	(2.61)	(3.59)	(3.54)
r 4.0	**Low**				**High**	
Mean	.009	.004	.005	.021***	.028***	.019**
t(mean)	(1.16)	(0.64)	(0.88)	(3.06)	(3.42)	(2.39)
r 100.0	**Low**				**High**	
Mean	.043***	.033***	.020***	.022**	.019**	-.024**
t(mean)	(4.36)	(3.42)	(2.85)	(2.57)	(2.71)	(-2.41)

This table reports the mean quintile portfolio returns based on the two-week return measure. The mean returns are the time-series averages of weekly value-weighted portfolio excess returns. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

C. Volatility Characteristics

In addition to the strategies examined in "Common Risk Factors in Cryptocurrency", we test an additional volatility decile long-short strategy, defined as the percent of closing price standard deviation each week. It is constructed by calculating the return of the value-weighted returns of the tenth minus first deciles by volatility each week. The decile volatility strategy was significant, with significant weekly excess returns for the highest minus lowest decile portfolio, meaning one would, on average, earn weekly returns of 2.78% by longing the top volatility decile and shorting the lowest one. The lower decile successfully captures the largest stablecoins and stale coins by market capitalization and stale coins. The quintile volatility is not significant during the full time period (p-value of 0.147), but turns significant at the 10% level on a segmented period Jan. 2017 - May. 2022, which is further discussed in section IV *Additional Return Predictor Findings*.

Table 4: **Volatility Strategy Returns**

Quintiles						
	1	2	3	4	5	5-1
Quintile Volatility	**Low**				**High**	
Mean	011**	.0138**	.023**	.017*	.024**	.019**
t(mean)	(2.15)	(1.96)	(2.31)	(1.89)	(2.40)	(1.45)
						10-1
Decile volatility						..0128*
t(mean)						(1,82)

This table reports the mean quintile portfolio returns based on the volatility measure. It also reports the long-short decile portfolio. The mean returns are the time-series averages of weekly value-weighted portfolio excess returns. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

D. Significant strategies

In this section we discuss the significant return predictors in relation to literature, theory and driving mechanisms. The 23 strategies in the different groups are based on previous research in the stock market, and we also discuss how the results for cryptocurrencies compare.

Significant size return predictors

Banz (1981), Miller and Scholes (1982), and George and Hwang (2004) demonstrated three breakthrough discoveries relating to size. They find that small, low-priced and low-maximum priced stocks attain higher returns than stocks with the opposite characteristics relating to size. We demonstrated that the long-short strategies MCAP, PRC and MAXDPRC measured greater returns in the lowest quintile compared to the top one, meaning the findings for coins within cryptocurrencies are analogous to equity markets. Also, the results are in line with the findings made by Liu, Tsyvinski, and Wu (2022) on cryptocurrencies using the same strategies - thus indicating consistency in both theory and methodology.

Significant momentum return predictors

As mentioned, the momentum strategies are based on the work of Jegadeesh and Titman (1993), who conclude that a long-short strategy on stocks longing those with high past three- to twelve-month returns and shorting those with low past three- to twelve-month returns yield statistically significant positive returns. Jegadeesh and Titman (1993) also found that the long-short strategy had a reversal effect for the past one-month momentum. Our results indicate that the momentum effects hold for a one to four week horizon and that one attains statistically significant mean returns from longing coins with high past one-, two-, three, and four-week momentum and shorting coins with low corresponding momentum.

These findings are in line with the results of Liu, Tsyvinski, and Wu (2022), indicating that there in fact could be a positive momentum effect within a four week horizon. However, the results obtained from the cryptocurrency long-short momentum strategies stand in contrast to the equity market. Moreover, the research made by Tzouvanas, Kizys and Tsend-Ayush (2020) on the cryptocurrency market is in line with our findings that profitable momentum-based investing can be performed in the short run. This gives indications on the short-term inefficiency of the cryptocurrency market, which transitions to improved efficiency after just over a month - hence reverse results compared to the stock market.

Further, we obtained significant results from the past 100-week long-short strategy. However, the past 100-week long-short strategy excess return yielded negative 2,4%, implying the 100-week momentum strategy of going long on low momentum and shorting high momentum would yield a positive return. The results for the 50-, 16- and 100-week momentum strategies indicate the momentum reversal effect comes into effect sometime after the past 16- or 50-week returns, although these strategies are insignificant. Support for these findings can be found in De Bondt and Thaler (1985) that suggest former “losers" outperform previous “winners” after longer periods. As the past 100-week return held significant negative mean return in the long-short strategy it would suggest a possible overreaction by investors exists after 100 weeks after the portfolio formation week (or possibly earlier but not statistically significant). We can also argue that this element suggests that the cryptocurrency market does not either follow Bayes' efficient market.

Significant volatility return predictor

The lower decile captures stale coins with price standard deviation within weeks of mainly between 0%-4% (Figure 2), and also successfully includes the largest stablecoins. The few instances of higher-volatility coins are mainly attributable to the beginning of the dataset, such as in 2014, where the number of coins each week are fewer. We observe statistically significant positive weekly excess returns of 2,78% for coins with top 10% volatility over those with lower 10% volatility. This is consistent with results on the stock market, although the relationships are weak (Baillie and Ramon, 2022).

The period after 2017 contains substantially larger market shares of stablecoins (Appendix 1). Given that the excess returns and significance of high-volatility coins increases when we sort for weeks after 2017 as opposed to before 2017, a plausible reason for the statistically significant returns for the volatility strategy post-2017, could be the increased market dominance of stablecoins. This lines up with theory, since the number of non-volatile coins with low returns should increase, and thus create more significant returns for the long-short strategy. However, as concluded by Liu, Tsyvinski, and Wu (2022), most strategies increased in significance during this period, possibly due to less investor uncertainty - further discussed in section IV.

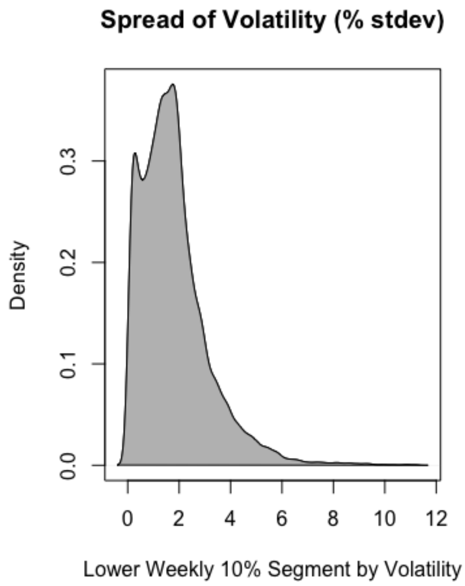

Figure 2. High density centered around 2% weekly volatility

E. Insignificant strategies

Insignificant Strategy Returns
Our results indicate that 14 out of our 23 long-short strategies did not generate significant results. These strategies are: past one-to-four-, eight-, 16-, and 50-week returns, price volume, standard deviation of price volume, volume, scaled volume, beta, beta squared, the standard deviation of returns, maximum day return, delay, and the Amihud illiquidity measure. Reasons for the insignificance and differences to the replicated paper regarding volume strategies are discussed more in depth in section IV A. Volume data sourcing issues, discussed by Liu, TSYVINSKI and WU (2022), are also of special interest in explaining error sources and insignificance for the volume strategies. They present evidence of manipulated volume data on certain cryptocurrency exchanges (Ribes, 2018).

4. Further Return Predictor Findings

In this section, we present additional findings related to our contribution of assessing the robustness of the return predictors on more recent data encompassing a different market climate and new asset classes.

A. The Stablecoin Volume Characteristics Affecting Return Predictors

In the context of this paper, an interesting finding is related to the volume strategies. As previously discussed, we found that the coins placed in the lower 10% by volatility (representing the major stablecoins by market capitalization) had ~8x higher mean weekly trading volume than the upper 90% by volatility. Our long-short volume strategy was insignificant (p-value of 11.3%), but when testing on the upper 90% weekly volatility segment data, we found that the volume strategy delivered significant results at the 5% level (p-value of 2,5%) and 2,0% average weekly returns. Tests on this data segment attempting to control for the volume distortion caused mainly by stablecoins, shows high-volume coins outperform lower-volume ones, which is in contrast to effects observed in the stock market, where (Chordia, Subrahmanyam and Anshuman, 2001). It makes sense that increasing amounts of stablecoins, that generally have high volume and low returns, would affect the significance of the long-short volatility strategy since they end up in the top quintile together with other high-volume coins that do not have an inherent mechanism to limit returns. However, one may also note possible bias from excluding coins with low volatility in this segment. The volume strategy was almost significant (p-value of 0.104) for our replication on time period of "Common Risk Factors In Cryptocurrency" with excess return of 1,82%.

B. Evaluation on different time periods

Further, we present results on segmented data in two time periods to evaluate the viability of the return predictors in an early-market condition and a period of less market immaturity and investor uncertainty. In the first period, Jan. 2014 - Jan. 2017, all zero-investment quintile long-short strategies turned insignificant except the 2-week-momentum and market capitalization strategies. The period from Jan. 2017 - May. 2022, featured all previously significant strategies. Additionally, the long-short quintile volatility strategy turned significant, which was previously only the case for the decile volatility strategy. Liu, Tsyvinski and Wu (2022) confirm there is major cryptocurrency market uncertainty in this first subperiod. By segmenting the period and proving increased strategy significance for the second subperiod and in more current market conditions, we ensure our results should not be short lived.

5. Fama-MacBeth Cross-Sectional Regression

In this section, the significant strategies will be evaluated using Fama-Macbeth Cross-Sectional Regression (1973). We use the portfolio rank number of each return predictor characteristic as the explanatory variable, following the methodology used by Liu, Tsyvinski and Wu (2022). Table 6 reports the results from the Fama-MacBeth regression. Panel A shows that all size strategies are significant at the 1% level both individually and jointly.

Panel B reports the quintile volatility return predictor, which is *significant* at the 1% level. This differs from the findings in the previous section, where only the decile volatility strategy was significant for the entire period.
Panel C reports the momentum strategies, which are all individually significant, but only 100-week momentum is jointly significant. This is interesting, given that Liu, Tsyvinski and Wu (2022) found none of the momentum strategies significant in their shorter time period using Fama-MacBeth. Only when they sorted for market capitalization above 10 MUSD all momentum strategies turned individually significant but, consistent with our results, none was jointly significant. This indicates that momentum return predictors work better in pricing all coins in the time period Jan. 2014 - May. 2022 than Jan. 2014 - July. 2020.

Table 5
Fama-MacBeth Cross-Sectional Return Predictor Regression

This table reports results from the Fama-MacBeth regression results with the return predictor quintile portfolios as explanatory variables, according to the methodology by Liu, Tsyvinski and Wu (2022). t-statistics for each coefficient is reported within parenthesis and *,**,*** denote the 10%, 5% and 1% significance levels.

			Panel A. Size			
MCAP	-0.022***			-0.018***		
	(-8.439)			(-7.731)		
PRC		-0.018***		-0.047***		
		(-6.555)		(-4.190)		
MAXDPRC			-0.017***	0.037***		
			(-6.277)	(3.300)		
			Panel B. Volatility			
VOLATILITY	0.007***					
	(3.721)					
			Panel C. Momentum			
r 1.0	-0.007***					-0.003
	(-3.101)					(-0.651)
r 2.0		-0.005**				-0.008
		(-2.144)				(-1.114)
r 3.0			-0.007***			0.015
			(-3.566)			(1.338)
r 4.0				-0.010***		-0.004
				(-5.107)		(-1.004)
r 100.0					-0.010**	-0.013**
					(-2.493)	(-2.048)

6. Cryptocurrency Factors

As ascertained in the previous section, nine cross-sectional cryptocurrency return predictors (strategies) were proven to have significant returns. In this section we will build on these discoveries and test whether four factors can span all significant strategies. We first evaluate a

one-factor model, or the cryptocurrency CAPM, using the cryptocurrency market factor (CMKT). Then, we create a two-factor model for cryptocurrency market factor and cryptocurrency size factor (CSMB). Using the same methodology, we create two more two-factor models where we combine the cryptocurrency market factor with either the cryptocurrency momentum factor (CMOM) or our new cryptocurrency volatility factor (CVOLAT). Thereafter, we combine the mentioned factors to construct and test a three-factor model that includes the cryptocurrency market factor, cryptocurrency size factor and the cryptocurrency momentum factor, following the methodology in "Common Risk Factors in Cryptocurrency". Next, we create a four-factor model, adding a volatility factor to the three-factor model.
Considering that stale coins have ~8x higher weekly trading volume than the upper 90% measured by volatility, and holding only 12% of total market capitalization (Appendix 1) in May 2022, and given that they naturally have low volatility and low returns, makes long-short strategies not very applicable to coins of this nature. The share of stablecoins has risen substantially since the end of 2020, which poses issues for testing the continued viability of the cryptocurrency three-factor model, presuming it intends to mainly capture "normal coins" (not stablecoins and stale coins). In previous sections, we have shown that the excess returns for high-volatility coins increases in more recent time periods. We attempt to control for this effect by creating a four factor model including a volatility factor. Our results show that this model performs mostly the same as the three-factor model, but better accounts for the high-volatility premium, and reduces alpha for the volatility strategy tenfold from 3,3% to 0,33%. Given a continued trend in the rise of stablecoin market share, our factor model results are of importance for the evaluation of cryptocurrency factor models going forward.

The cryptocurrency excess market return (CMKT) is constructed summarizing the weighted one-week returns for all coins each week, which adds up to value-weighted weekly market portfolio returns, representing returns in the week following the portfolio formation week. Both returns and market weekly returns are then subtracted by the corresponding weekly risk-free rate, calculated from the one-month US Treasury bill rate. The CMKT one-factor model (cryptocurrency CAPM) has significant exposure to all significant long-short strategies except four-week return, volatility and volume, but, like its stock-market counterpart, performs poorly in predicting returns and does not account fully for any of the strategies.

$$CMKT = \sum_{i=1}^{n} Mkt - rf$$

We are creating the cryptocurrency size and momentum factors close to the method by Fama and French (1993), and in accordance with "Common Risk Factors in Cryptocurrency". The size factor (CSMB) is constructed by dividing the coins' weekly market capitalization into relative size groups: Bottom 30% (Small), middle 40% (Middle), and top 30% (Big). We then form value-weighted portfolios for each of the three groups and measure the differences between the portfolios of the small and the big-size portfolios, representing the returns in the week following the portfolio formation week.

$$CSMB = \sum_{i=1}^{n} (Small - Big)$$

As for the momentum factor (CMOM), each week we divide all coins into two 50/50 equal size groups (Big and Small) based on weekly market capitalization (represented by the last-day market capitalization in the portfolio formation week) to control for size bias. Within each size bucket we create three groups based on the three-week momentum constructed using the last-day closing price in the portfolio formation week; bottom 30% (Low), middle 40%, and top 30% (High). We then organize value-weighted portfolios with the returns in the week following the portfolio formation week, representing the bottom and top groups in regards to three-week returns. Lastly, CMOM is attained by the difference between the two equally weighted size groups, representing returns for the week following the portfolio formation week.

$$CMOM = \sum_{i=1}^{n} \frac{1}{2} * (SmallHigh + BigHigh) - \frac{1}{2} * (SmallLow + BigLow)$$

We extend on the replicated paper by adding a volatility factor (CVOLAT) to account for the observed significant return differences between volatile coins and stale coins in the long-short decile volatility strategy (described in section III. B). We control for both size and momentum effects, and construct the CVOLAT factor by dividing the coins into two size groups each week; Small (bottom 50%) and Big (top 50%), whereby the two size groups are then segmented into two buckets each based on the three week momentum, top 50% (High) and bottom 50% (Low), creating four momentum groups in total. Within each momentum group we track the one-week returns of the week following the portfolio formation week, and calculate the differences between two value weighted groups sorted by volatility; top volatility (top 10%, V) minus non-volatile/*stale* coins (bottom 10%, S). The four groups are then summed up with equal weights.

$$CVOLAT = \sum_{i=1}^{n} 1/4 * (BigHighV + BigLowV + SmallHighV + SmallLowV) -$$
$$1/4 * (BigHighS + BigLowS + SmallHighS + SmallLowS)$$

Because of the lower amount of coins in the initial 2 years (Table 1), the weekly factor portfolios are affected. Especially for the volatility factor, when applying both the size and momentum sorts, it is not feasible to create the factor on the earlier part of the data set because of missing entries. Moreover, given the smaller coin market in earlier periods (2014-2016), including them would risk the upper and lower volatility deciles to not accurately represent stale and volatile coins, and thus not allow the volatility factor to work as intended. Hence, we will evaluate the factor models starting from 2016. Thereby, we get a fair comparison with equal periods between especially the three-and four-factor models. As previously presented, no strategies are significant between Jan. 2014 - Jan. 2017 except 2-week-momentum and market capitalization. After this period, also the quintile volatility strategy turns significant. Liu, Tsyvinski and Wu (2022) show major uncertainty for the cryptocurrency market in this first subperiod and also, by testing the model on the later period, we ensure our results should not be short lived.

A. Cryptocurrency One-Factor Model

The results from the Cryptocurrency One-Factor model (CAPM) are presented in Table 6. The results indicate that from the significant strategies, the past one-, two-, three- and 100-week returns as well as last day price, maximum price of the portfolio formation week and market capitalization and volatility have significant exposures to the coin market excess return. This means that the remaining zero-investment long-short strategies are not significantly exposed to the coin market return. The long-short strategy R^2 ranges from 0.1% to 6.9% which means the one-factor model explains a small portion of the excess returns for all strategies, but reasonably better for last day price and the maximum price of the portfolio formation week zero-investment long-short strategies. Moreover, the long-short alphas for all strategies, except the past four-week return are significant, meaning it does not account for their excess returns.

Table 6: **Cryptocurrency One-Factor Model**

Market factor model					
	α	t(α)	β_{CMKT}	t(β_{CMKT})	R^2
MCAP	-0.094***	-9.536	-0.053	-0.567	0.001
PRC	-0.029**	-2.320	-0.566***	-4.842	0.069
MAXDPRC	-0.030**	-2.396	-0.565***	-4.780	0.068
r 1,0	0.019**	2.210	0.139*	1.720	0.009
r 2,0	0.037***	3.415	0.135	1.329	0.006
r 3,0	0.021**	2.518	0.106	1.347	0.006
r 4,0	0.010	1.182	0.061	0.782	0.002
r 100,0	-0.029***	-2.748	0.243**	2.476	0.019

This table shows the alph, alpha t-statistic, cryptocurrency CAPM market beta, its corresponding t-statistic R-squared for the cryptocurrency one-factor model. *,**,*** denote significance at the 1%,5% and 10% levels.

Table 7

Cryptocurrency Two-Factor Models

This table reports results on the three different cryptocurrency two-factor model regressions on the 9 successful long-short quintile strategies, where the significant decile volatility strategy is also represented as a quintile strategy. Each two-factor model consists of the the cryptocurrency excess market return factor (*CMKT)*, and (1) is with the cryptocurrency size factor (*CSMB)*, (2) is with the cryptocurrency momentum factor (CMOM), and (3) is with the cryptocurrency volatility factor (CSTALE). We report *t*-Statistics in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels. m.a.e is the mean absolute pricing error of the quintile portfolios, and $\bar{R}^2$ is the average R^2 of the five portfolios.

		Cons	t	CMKT	t	CSMB	t	CMOM	t	CVOLAT	t	m.a.e	$\bar{R}^2$
MCAP	(1)	-0.122***	(-13.192)	-0.207**	(-2.469)	-0.837***	(-9.399)					0.221	0.639
	(2)	-0.025	(-1.527)	0.128	(1.333)			-0.113***	(-5.210)			0.081	0.587
	(3)	-0.090***	(-8.538)	0.013	(0.121)					-0.036	(-1.347)	0.007	0.607
PRC	(1)	-0.057***	(-4.737)	-0.726***	(-6.607)	-0.871***	(-7.462)					0.210	0.546
	(2)	0.091***	(4.622)	-0.253**	(-2.192)			-0.196***	(-7.476)			0.210	0.550
	(3)	-0.023*	(-1.726)	-0.482***	(-3.662)					-0.046	(-1.373)	0.075	0.575
MAXDPRC	(1)	-0.062***	(-5.189)	-0.746***	(-6.850)	-9.80***	(-8.480)					0.242	0.546
	(2)	0.091***	(4.558)	-0.250**	(-2.135)			-0.198***	(-7.454)			0.208	0.550
	(3)	-0.024*	(-1.808)	-0.482***	(-3.621)					-0.046	(-1.339)	0.073	0.578
r 1,0	(1)	0.026***	(2.853)	0.176**	(2.159)	0.204**	(2.352)					0.027	0.618
	(2)	-0.038***	(-2.632)	-0.008	(-0.099)			0.092***	(4.868)			0.079	0.617
	(3)	0.024**	(2.585)	0.201**	(2.214)					-0.035	(-1.484)	0.016	0.609
r 2,0	(1)	0.043***	(3.821)	0.172*	(1.661)	0.198*	(1.804)					0.016	0.562
	(2)	-0.017	(-0.940)	-0.006	(-0.053)			0.088***	(3.641)			0.046	0.559
	(3)	0.016	(1.417)	-0.160	(1.466)					0.163***	(5.837)	0.103	0.572
r 3,0	(1)	0.024***	(2.728)	0.123	(1.531)	0.091	(1.071)					0.009	0.616
	(2)	-0.026*	(-1.835)	-0.016	(-0.194)			0.077***	(4.098)			0.056	0.616
	(3)	0.024***	(2.686)	0.145	(1.627)					-0.021	(-0.935)	0.009	0.613
r 4,0	(1)	0.009	(1.057)	0.058	(0.727)	-0.017	(-0.200)					0.002	0.604
	(2)	-0.021	(-1.477)	-0.019	(-0.227)			0.050***	(2.667)			0.024	0.605
	(3)	0.014	(1.614)	0.121	(1.381)					-0.033	(-1.482)	0.009	0.605
r 100,0	(1)	-0.037***	(-3.381)	0.197**	(1.978)	-0.252**	(-2.391)					0.037	0.470
	(2)	0.001	(0.049)	0.320***	(3.055)			-0.048**	(-2.033)			0.032	0.490
	(3)	-0.022*	(-1.959)	0.340***	(3.084)					-0.054*	(-1.902)	0.03	0.459
Volatility	(1)	0.014	(1.479)	0.436***	(5.241)	0.269***	(3.037)					0.092	0.557
	(2)	-0.048***	(-3.256)	0.250***	(2.896)			0.086***	(4.400)			0.12	0.552
	(3)	-0.008	(-0.930)	0.205**	(2.256)					0.101***	(4.326)	0.118	0.580

B. Cryptocurrency Two-Factor Model

Size

As presented in Table 8, Model (1) constructing a two factor combining the cryptocurrency size factor to the cryptocurrency CAPM model, we can observe that all the size-based strategies MCAP, PRC and MAXDPRC have significant exposure to the size factor at the 1%

level. In addition, it also has significant betas for the one-, two-,100-week momentum and volatility strategies. This two-factor model has insignificant alfa's and accounts for four-week momentum and volatility. This means, in contrast to the findings in *Risk Factors in Cryptocurrency*, the size factor alone no longer succeeds to account for all the size-related strategies in our longer time period. This suggests other mechanisms, perhaps effects from price volatility or changing market conditions may be in effect.

However, we obtain considerably larger R-squared values for the zero-investment long-short size strategies, ranging between 21%-24.2%. The residual strategies indicate no significant changes compared to the one-factor model except for significant exposure to the cryptocurrency size factor for the past one-, two-, and 100-week momentum strategies. This indicates that the two-factor market and size model explains the excess returns for the past four-week investment strategy. However, it is not significantly exposed to the market- or size factors. Also, the volatility strategy has significant exposure to both the market and size factor, whilst the alpha is insignificant, meaning this two-factor model accounts for the volatility strategy.

Momentum

As presented in Table 7, model (2), the two factor model containing a cryptocurrency momentum factor and a cryptocurrency market factor increase the explanatory value (R^2) for all the long-short momentum strategies. This could be explained by strategies increased exposure to the cryptocurrency momentum factor. In this model, the long-short momentum strategies have R^2 ranging from 2.4% based on past four-week return to 7.9% based on past-one week return. This indicates significant improvements to the CAPM model R^2 for the momentum strategies that ranged between 0.2% to 1.9%. As discussed, all non-momentum long-short strategies have significant exposures to the momentum factor, but overall the explanatory value of the return fluctuations decreased when replacing the size factor with the momentum factor. Also, the long-short alphas for the PRC and MAXDPRC factor remain significant whilst MCAP is estimated to have insignificant results. This would suggest that the momentum factor, which controls for size in its creation, captures the mean return difference between the small and big coins better than the size factor, which has significant alpha for all size strategies. Moreover, using the momentum factor could not account for the volatility strategy as it holds a significant alpha. However, the strategy has significant exposure to both the market- and momentum factors.

Volatility

Next, we adjust the nine significant zero-investment long-short strategies to an alternative two-factor model consisting of the market factor (CMKT) and the volatility factor (CVOLAT) to the nine significant strategies. The results of this model are reported in Table 8, model (4). The volatility factor has significant exposure to two- and 100-week momentum and volatility strategies, with factor loadings of 16,3%, -10,54%, 10,1% at the one-, ten- and one-percent levels, respectively. R-squared for the zero-investment quintile long-short strategy ranges from 11,8% on the volatility strategy, between 0,2% and 3% on the momentum strategy and between 7% and 7,5% on the size strategies. The model performs poorly in explaining the variance in the size strategies, but has at least equal performance compared to the other two two-factor models in regards to both explaining the variance for the momentum long-short strategies and their corresponding quintile portfolios. The model has insignificant alfas for and accounts for the following quintile long-short strategies: volatility and two-and four-week-momentum. two-week-momentum is of interest since the strategy has twice the volume and variance explained by the volatility factor compared to momentum, although they both account for the strategy. This also suggests the high volatility corresponds to high two-week momentum vice-versa, and that these factors could be related.

C. Cryptocurrency Three-Factor Model

We thereafter evaluate a three-factor model consisting of CMKT, CSMB and CMOM. As seen in Table 8, model (4), the model has adjusted R-squared values for the zero-investment quintile long-short size strategies ranging between 25,0% and 32,3%, whereas for the corresponding quintile portfolios the R-squared averages are between 57,3% and 65,1%. For the momentum long-short strategies the adjusted R-squared values are between 1,7% and 7,7%, and for the quintile portfolios the R-squared averages are between 49,9% and 62,6%. The model explains 12,5% of the variance in the volatility long-short strategy, and 56,4% for the quintile portfolio. The model still holds significant long-short alphas for the past one-week momentum, the size strategies and volatility, meaning there are still returns the model does not explain.

$$r - rf = \alpha + \beta_{i,1} CMKT_t + \beta_{i,2} CSMB_t + \beta_{i,3} CMOM_t + \varepsilon_t$$

Table 8
Cryptocurrency Three- and Four-Factor Model

This table reports results on the cryptocurrency three-factor (4) and four factor (5) model regressions on the 9 successful long-short quintile strategies, where the significant decile volatility strategy is also represented as a quintile strategy. *CMKT* is the coefficient of the cryptocurrency excess market return, *CSMB* is the cryptocurrency size factor, and *CMOM* is the cryptocurrency momentum factor. We report *t*-Statistics in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels. R^2 and adjusted R^2 relates to the long-short quintile portfolios, and $\bar{R}^2$ is the average R^2 of the five quintile portfolios.

		Cons	t	CMKT	t	CSMB	t	CMOM	t	CVOLAT	t	R^2	Adj. R^2	$\bar{R}^2$
MCAP	(4)	-0.072***	-4.560	-0.070	(-0.781)	-0.765***	-(8.608)	-0.078***	(-3.901)			0,257	0.250	0,651
	(5)	-0.071***	(-4.523)	-0.079	(-0.830)	-0.765***	(-8.590)	-0.080***	(-3.771)	0.007	(0,283)	0.257	0.248	0,695
PRC	(4)	0.047**	2.390	-0.440***	(-3.907)	-0.723***	-6.443	-0.163***	(-6.457)			0,303	0.297	0,573
	(5)	0.049**	(2.457)	-0.484***	(-4.029)	-0.721***	(-6.429)	-0.172***	(-6.444)	0.033	(1.052)	0.306	0.297	0,6356
MAXDPRC	(4)	0.040**	2.053	-0.465***	(-4.166)	-0.835	(-7.505)	-0.160***	(-6.378)			0,329	0.323	0,573
	(5)	0.042**	(2.124)	-0.511***	(-4.288)	-0.833***	(-7.492)	-0.169***	(-6.384)	0.034	(1.096)	0.332	0.323	0,6378
r 1.0	(4)	-0.030**	-1.974	0.024	(0.278)	0.125	(1.454)	0.087***	(4.476)			0,085	0.077	0,626
	(5)	-0.033**	(-2.234)	0.131	(1.449)	0.121	(1.432)	0.109***	(5.416)	-0.080***	(-3.395)	0.118	0.107	0,6302
r 2.0	(4)	-0.010	-0.500	0.026	(0.234)	0.122	(1.111)	0.083***	(3.338)			0,05	0.041	0,570
	(5)	-0.003	(-0.181)	-0.169	(-1.484)	0.130	(1.218)	0.042	(1.646)	0.145***	(4.903)	0.118	0.107	0,5876
r 3,0	(4)	-0.025	-1.629	-0.010	(-0.119)	0.022	(0.264)	0.076***	(3.951)			0,057	0.048	0,622
	(5)	-0.027*	(-1.809)	0.068	(0.754)	0.020	(0.232)	0.092***	(4.580)	-0.058**	(-2.483)	0.075	0.063	0,627
r 4,0	(4)	-0.025	-1.649	-0.036	(-0.416)	0.065	(-0.764)	0.053***	(-2.765)			0,026	0.017	0,608
	(5)	-0.028*	(-1.835)	0.045	(0.501)	-0.068	(-0.806)	0.070***	(3.479)	-0.060**	(-2.562)	0.046	0.034	0,6148
r 100.0	(4)	-0.012	-0.651	0.264**	(2.447)	-0.217**	(-2.021)	-0.038	(-1.585)			0,044	0.035	0,499
	(5)	-0.014	(-0.741)	0.318***	(2.762)	-0.219**	(-2.042)	-0.027	(-1.058)	-0.040	(-1.335)	0.050	0.038	0,5006
Volatility	(4)	-.033**	(-2.114)	0.199**	(2.133)	0.202**	(2.319)	0.056***	(2.676)			0,134	0.125	0,564
	(5)	-0.033**	(-2.114)	0.199**	(2.133)	0.202**	(2.319)	0.056***	(2.676)	0.076***	(3.129)	0.160	0.1492	0,5998

D. Cryptocurrency Four-Factor Model

Next, we test a four-factor model consisting of CMKT, CSMB, CMOM and CVOLAT (the volatility factor) following the methodology above. The results are presented in Table 8, model (5). Given that the two-factor model consisting of the market and volatility factor could account for the volatility long-short strategy, but not the three-factor model with the market, size and momentum factors, we now test whether the four-factor model adding the volatility factor could improve the three-factor model. The model explains 14,92% of the variance (adjusted R-squared) in the volatility long-short strategy (compared to 12,5% in the three-factor model), and 60,0% for the corresponding quintile portfolios (unadjusted). The model still fails to account fully for the volatility zero-investment long-short strategy, but the significant alfa decreases tenfold down to 0,33% from 3,3% in the three-factor model. The

factor loadings on the other factors remain the same, and the exposure to the volatility factor amounts to 7,6%.
The four-factor model has adjusted R-squared values for the zero-investment quintile long-short size strategies ranging between 24,8% and 32,3%, whereas for the corresponding quintile portfolios the averages are between 63,6% and 69,5%. For the momentum long-short strategies adjusted R-squared is between 3,4% and 10,1%, and for the quintile portfolios between 50,1% and 63,0%. The model still holds significant long-short alphas for the size strategies and there is no notable change in alpha values. The model fails to account for the one-,three- and four-week-momentum strategies which now have statistically significant alpha, but once again, there are no large alfa increases compared to the three-factor model (0,1 percentage point). In essence, the four-factor model performs mainly the same as the three-factor model for the size strategies, but accounts for about twice the variance for the momentum strategies, when comparing adjusted R-squares. Although it does not fully account for the cross-sectional volatility return predictor, the alpha for the volatility long-short strategy alpha decreases substantially.

$$r - rf = \alpha + \beta_{i,1} CMKT_t + \beta_{i,2} CSMB_t + \beta_{i,3} CMOM_t + \beta_{i,4} CVOLAT + \varepsilon_t$$

7. Conclusion

This paper concludes that a number of standard cryptocurrency return predictors representing size, momentum, volatility and volume characteristics can be successfully constructed, which is consistent with Fama-Macbeth regressions. We also show that the significance of many return predictors used in the replicated article increase in the later time periods.
This could mainly be attributed to decreased investor uncertainty, and indicates continued viability for the significant return predictors going forward. We also show that the three-factor model proposed by (Liu, Tsyvinski, and Wu (2022) no longer accounts for the size strategies. Further, we document many results consistent with observations on the equity markets; such as size premium, momentum effects, long-term momentum reversal effects and positive excess returns for volume and volatility 5-1 long-short quintile strategies. We investigate the trend and effects of increasing market shares of stablecoins and stale coins, and indicate that they negatively affect the significance and usefulness of some return predictors, and especially those relating to volume. We find indications that they magnify the excess returns of high-volatility coins over low-volatility ones. We therefore create a four-factor model encompassing a volatility factor, that overall performs better than the three-factor model, and especially in pricing the cross-section of the volatility strategy excess returns. Given the rising share of stablecoins, these results are of importance for the evaluation of cryptocurrency asset pricing models going forward.

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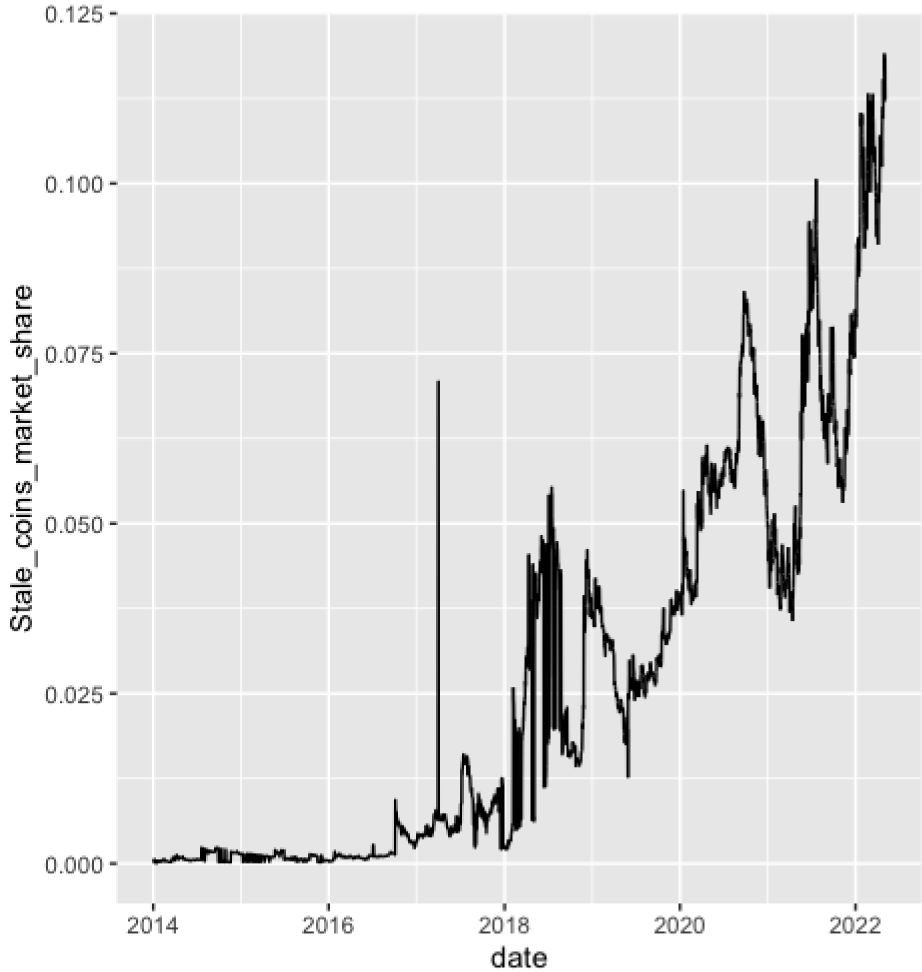
Appendix

Appendix 1



Appendix 2 - Attained from “Common Risk Factors in Cryptocurrency” (Liu, Tsyvinski, and Wu, 2022)

Return Predictor Definitions

Category	Predictor	Reference	Definition
Size	MCAP	Banz (1981)	Log last-day market capitalization in the portfolio formation week.
Size	PRC	Miller and Scholes (1982)	Log last-day price in the portfolio formation week.
Size	MAXDPRC	George and Hwang (2004)	Maximum price of the portfolio formation week.
Mom	r 1,0	Jegadeesh and Titman (1993)	Past one-week return.
Mom	r 2,0	Jegadeesh and Titman (1993)	Past two-week return.
Mom	r 3,0	Jegadeesh and Titman (1993)	Past three-week return.
Mom	r 4,0	Jegadeesh and Titman (1993)	Past four-week return.
Mom	r 4,1	Jegadeesh and Titman (1993)	Past one-to-four-week return.
Mom	r 8,0	Jegadeesh and Titman (1993)	Past eight-week return.
Mom	r 16,0	Jegadeesh and Titman (1993)	Past 16-week return.
Mom	r 50,0	De Bondt and Thaler (1985)	Past 50-week return.
Mom	r 100,0	De Bondt and Thaler (1985)	Past 100-week return.
Volume	VOL	Chordia, Subrahmanyam, and Anshuman (2001)	Log average daily volume in the portfolio formation week.
Volume	PRCVOL	Chordia, Subrahmanyam, and Anshuman (2001)	Log average daily volume times price in the portfolio formation week.
Volume	VOLSCALED	Chordia, Subrahmanyam, and Anshuman (2001)	Log average daily volume times price scaled by market capitalization in the portfolio formation week.
Vol	BETA	Fama and MacBeth (1973)	The regression coefficient β^i_{CMKT} in $R_i - R_f = \alpha^i + \beta^i_{CMKT} CMKT + \epsilon_i$. The model is estimated using daily returns of the previous 365 days before the formation week.
Vol	BETA2	Fama and MacBeth (1973)	Beta squared.

Category	Predictor	Reference	Definition
Vol	RETVOL	Ang et al. (2006)	Standard deviation of daily returns in the portfolio formation week.
Vol	MAXRET	Bali, Cakici, and Whitelaw (2011)	Maximum daily return of the portfolio formation week.
Vol	DELAY	Hou and Moskowitz (2005)	The improvement of R^2 in $R_i - R_f = \alpha^i + \beta^i_{CMKT} CMKT + \beta^i_{CMKT_{-1}} CMKT_{-1} + \beta^i_{CMKT_{-2}} CMKT_{-2} + \epsilon_i$, where $CMKT_{-1}$ and $CMKT_{-2}$ are the lagged one- and two-day coin market index excess returns, compared to using only current coin market excess returns. The model is estimated using daily returns of the previous 365 days before the formation week.
Vol	STDPRCVOL	Chordia, Subrahmanyam, and Anshuman (2001)	Log standard deviation of price volume in the portfolio formation week.
Vol	DAMIHUD	Amihud (2002)	Average absolute daily return divided by price volume in the portfolio formation week.