Financial Data Analysis course assignment: replication and extension of the article “Common Risk Factors in Cryptocurrency” by YUKUN LIU, ALEH TSYVINSKI, and XI WU

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The cryptocurrency market has emerged as a compelling investment possibility, attracting a global audience with the accessibility afforded by the Internet. The ease with which individuals can trade and invest in cryptocurrencies, coupled with generally low transaction fees and straightforward fund deposits and withdrawals facilitated by P2P or alternative methods on cryptocurrency exchanges, has made this market particularly appealing to retail investors. Furthermore, the absence of comprehensive cryptocurrency regulations in many countries contributes to a unique advantage, as earnings from cryptocurrency investments remain largely untaxed—a contrast to investments in traditional stocks or other asset classes.

Nevertheless, the relative novelty of cryptocurrencies poses a challenge for investors, as the intricate dynamics influencing cryptocurrency price movements are still being deciphered. In contrast to more established forms of investment, there is a noticeable dearth of academic research in this domain. Despite the increasing interest from institutional investors, comprehensive insights into the factors steering cryptocurrency prices stay limited. Therefore, it becomes imperative to delve into the potential determinants of cryptocurrency price movements and to formulate effective investment strategies to address this gap in understanding.

To contribute to the ongoing discourse, this study seeks to replicate and extend the article published by Yukun Liu, Aleh Tsyvinski, and Xi Wu, entitled "Common Risk Factors in Cryptocurrency." The method employed adheres closely to the data collection and processing procedures outlined by the authors. Subsequently, we construct a summary statistics table mirroring their approach, thus elucidating potential disparities in data handling that may account for variations between our regression results and the study under consideration.

The replication part also includes Tables III to VI of the study, where the mean weekly excess returns are presented for each of the five quintile portfolios. These portfolios are derived based on the value of ten cryptocurrency characteristics, identified as robust and statistically significant among 24 characteristics selected from the most frequently employed metrics in fundamental research within equity markets. The ten characteristics are market capitalization, price, and maximum price; past one-, two-, three-, four-, and one-to-four-week return; price volume; and standard deviation of price volume. In essence, these factors parallel widely acknowledged metrics in equity market research, reflecting the authors' considered application to cryptocurrency return analysis. Additionally, we reproduce the outcomes of a zero-investment long-short strategy which involves computing the difference in weekly excess returns between the first and the fifth quintile, illustrating the weekly excess returns of a zero-investment approach that short sells the first quintile and simultaneously goes long on the fifth quintile portfolios on a weekly basis. While our findings align with the general trends articulated by the authors, noteworthy distinctions appear as our excess weekly returns are observed to be twice as substantial for characteristics that stand for size, volume, and volatility.

We expand the study to explore the collective predictive capabilities of all ten characteristics through the application of machine learning models, specifically Ridge and XGB. To guide our method, we reference the approach outlined in the paper titled "Forecasting Cryptocurrency Returns with Machine Learning" by Yujun Liu, Zhongfei Li, Ramzi Nekhili, and Jahangir Sultan. Following this framework, we employ the machine learning models to forecast the upcoming week's excess returns, using the characteristics as independent variables within the models. Additionally, we calculate the difference between the first and tenth portfolios, illustrating the weekly excess returns of a zero-investment strategy that shorts the first quintile and longs the tenth quintile portfolios.

Expanding further, we conduct a Monte Carlo simulation to explore the distribution of yearly excess returns resulting from utilizing machine learning models with the ten identified characteristics for predicting weekly excess returns during one year period. The results indicate a mean yearly excess return of 63% for the Ridge algorithm and 50% for the XGB algorithm, representing a substantial annual return compared to conventional investment assets.

Building upon the foundations laid by Yukun Liu, Aleh Tsyvinski, and Xi Wu, and incorporating the machine learning method introduced by Yujun Liu, Zhongfei Li, Ramzi Nekhili, and Jahangir Sultan, this study makes a substantial contribution to existing academic research on cryptocurrency price predictions. Unlike preceding research, which primarily focuses on distinctive features of the cryptocurrency market, such as mining costs, hardware expenses, changes in underlying blockchain mechanisms, or macroeconomic factors, our study serves as a bridge by assimilating fundamental theories traditionally employed in predicting stock returns.

The overarching objective is to deepen our comprehension of the dynamics within the cryptocurrency market, utilizing a perspective that has been less commonly explored by other researchers. The outcomes of our research demonstrate that machine learning models employing factors traditionally associated with explaining the cross-section of stock returns can yield significant returns when applied to predict cryptocurrency returns. These findings suggest practical applications for both manual and automated cryptocurrency trading strategies.

The paper is structured as follows. In Section I, we summarize the results of the paper that we aim to replicate. Section II details the process of replication, presenting a comparison between our findings and those of the original paper. Moving on to Section III, we expand on the original paper and share the outcomes of a Monte Carlo simulation, illustrating the distribution of yearly returns predicted by our model. Lastly, Section IV draws conclusions from our study.

I. Summary of the replication article

The article conducts an in-depth analysis of historical data encompassing all cryptocurrencies with a market capitalization exceeding 1 million USD, spanning from 2014 to July 2020 and sourced from various cryptocurrency exchanges. Employing a stock returns predictors list compiled by Feng, Giglio, and Xiu (2020) and Chen and Zimmermann (2020), the authors select 24 characteristics that can be derived solely from price and market information. These 24 characteristics are categorized into four groups: size, momentum, volume, and volatility.

To identify the most robust factors for predicting future returns, the authors implement a systematic approach. According to the authors, “Each week, we sort individual cryptocurrencies' returns into quintile portfolios based on a specific characteristic, tracking the next week's return for each portfolio. The average excess return over the risk-free rate is then calculated for each portfolio. A long-short strategy is formed based on the difference between the fifth and first quintiles.”

The results show that only 10 out of the 24 characteristics exhibit statistical significance in predicting returns. Notably, long-short strategies based on cryptocurrency size, momentum, volume, or volatility generate approximately 3% excess weekly returns on average (Tables III~VI). Conversely, the excess weekly returns for the remaining characteristics are found to be statistically and numerically insignificant (Table VII).

In an effort akin to Fama and French (1996), the authors explore whether one, two, or three-factor models can adequately explain the returns of strategies based on the 10 successful characteristics. The findings suggest that a one-factor model with the cryptocurrency CAPM, a two-factor model with the cryptocurrency CAPM and size factor, as well as a two-factor model with the cryptocurrency CAPM and a cryptocurrency momentum factor fall short in fully accounting for the returns. However, a cryptocurrency three-factor model, encompassing the market factor, size factor, and momentum factor, successfully explains the excess returns of all 10 strategies.

Further analysis employs principal component analysis, aligning with the earlier findings. The first three principal components, strongly correlated with the cryptocurrency market factor, size factor, and momentum factor, collectively account for the majority (72.9%) of the variation in portfolios' excess returns.

The subsequent sections of the paper present additional results, including checks that corroborate the primary findings, reinforcing the robustness of the study's conclusions.

II. Replication Process Description and Results

1. Data Collection, Handling and Summary Statistics Table Construction

To replicate the summary statistics table from the paper titled "Common Risk Factors in Cryptocurrency," we tried to closely adhere to the methodology outlined by the authors. However, certain aspects of data handling were not explicitly specified, causing us to rely on our intuition. Some of the authors' recommendations were ambiguous, leaving room for interpretation.

Challenges arose early in the data acquisition process. The authors sourced their dataset from Coinmarketcap.com, a reputable platform for cryptocurrency information. However, accessing the full historical data through their API required a prohibitive $500 subscription fee. Alternative methods, such as web scraping, presented legal and implementation difficulties. Consequently, we obtained Coinmarketcap's historical data from Kaggle.com, a data analytics platform (Link: https://www.kaggle.com/datasets/bizzyvinci/coinmarketcap-historical-data?select=historical.csv).

The utilized dataset included daily observations, limited to the period from January 1, 2014, to July 31, 2020. We excluded observations with missing values for market cap, close price, or daily volume and imposed a minimum market cap threshold of one million dollars. Assigning one of 52 weeks for each year per observation, as recommended by the authors, we treated the last week of the year (52) as equal to 8 days, except for 2016, where it consisted of 9 days.

Observations with zero daily trading volume were removed, a sensible action despite not being explicitly stated in the paper. Additionally, observations with a coin status of 'untracked' were excluded.

Upon constructing pane A of the summary statistics table, we identified discrepancies in mean market cap and mean volume compared to the authors' figures. Outliers, particularly in market cap, were addressed by manually removing seven extreme values. For daily volume outliers, no removal was justified due to their prevalence.

Moving to pane B, to derive statistics for Coin Market Return, we computed a value-weighted weekly returns variable. Lacking explicit guidance from the authors, we multiplied market cap by close price to obtain coin market value. We then calculated total market value for each day, establishing weights by dividing each observation's market value by the total market value. Daily weighted returns were derived by multiplying daily returns by weights.

Regarding the returns for Bitcoin, Ethereum, and Ripple, the authors did not explicitly specify whether the summary pertains to weekly returns or value-weighted returns. Consequently, we opted for weekly log returns to align with the structure of the summary statistics table, although we acknowledge uncertainty about the legitimacy of this choice. Unfortunately, we lack precise information on the type of returns the authors intended for Bitcoin, Ethereum, and Ripple in their table.

Comparing our results (Table II) with the authors' summary statistics table (Table I), notable differences appeared. The number of coins, especially in 2020, nearly doubled in our dataset. Significant variations in total mean volume were observed, with our figure at 62,916.57 compared to the authors' 44,991.04. Notable differences also surfaced in skewness and kurtosis for Bitcoin returns, indicating potential disparities in the distribution of returns for Bitcoin and the overall market in our dataset.

Upon comparing our results in Table II with the authors' summary statistics table (Table I), significant discrepancies became apparent. Firstly, the number of coins, particularly in the year 2020, nearly doubled in our dataset compared to the authors' original findings. This noteworthy variance raises questions about potential changes in the cryptocurrency landscape during that period.

Moreover, substantial differences were observed in the total mean volume, with our calculated figure standing at 62,916.57, in stark contrast to the authors' reported value of 44,991.04. This divergence suggests the presence of notable variations in trading activity, potentially stemming from differences in data sources.

Concerning the replication results of pane B, our examination revealed that the mean, median, and standard deviation values for Coin Market Return, as well as Bitcoin, Ripple, and Ethereum returns, closely aligned with the figures reported by the authors. This consistency suggests a degree of robustness in the replication process, reinforcing the reliability of our calculated summary statistics.

However, noteworthy disparities emerge in the skewness and kurtosis values for Coin Market Returns. Our dataset exhibits significantly higher skewness, registering at 1.67, compared to the authors' reported value of 0.234. This discrepancy implies a leftward skewness in our returns distribution, indicating an elevated prevalence of extreme values on the right side compared to the authors' dataset. Similarly, the kurtosis value for our Coin Market Returns is substantially higher, recording 13.906, in contrast to the original paper's figure of 4.658. This suggests that while the original paper's returns approach normal kurtosis, our returns display an exceptionally high kurtosis, signifying an increased likelihood of extreme values.

Conversely, the kurtosis for Bitcoin returns in our dataset is nearly half of that reported in the original paper. While it's acknowledged that asset returns often exhibit high skewness, the considerably elevated skewness and kurtosis values in our overall coin market returns, compared to the article, hint at a potential need for outlier treatment.

Table I. Original Summary Statistics

Panel A. Characteristics by Year					
		Market Cap (mil)		Volume (thous)	
Year	Number	Mean	Median	Mean	Median
2014	109	239.83	3.89	1,146.09	36.24
2015	77	134.53	2.76	1,187.64	11.51
2016	155	160.60	3.41	1,795.03	23.96
2017	795	439.42	9.02	18,661.07	131.36
2018	1,559	363.17	8.85	21,184.20	124.92
2019	1,085	300.52	5.36	59,115.13	139.70
2020	665	440.21	5.38	125,249.20	210.77
Full	1,827	353.26	6.64	44,991.04	121.91

Panel B. Return Characteristics					
	Mean	Median	*SD*	Skewness	Kurtosis
Coin Market Return	0.013	0.005	0.112	0.234	4.658
Bitcoin Return	0.013	0.001	0.111	0.394	4.749
Ripple Return	0.026	−0.003	0.237	3.890	26.296
Ethereum Return	0.036	0.011	0.210	1.971	12.161

Table II. Replication of Summary Statistics

Panel A. Characteristics by Year					
		Market Cap (mil)		**Volume (thous)**	
Year	Number	Mean	Median	Mean	Median
2014	141	238.86	3.81	1143.23	31.04
2015	79	136.55	2.78	1195.38	9.63
2016	167	172.57	3.54	1956.52	20.85
2017	707	490.72	10	21686.09	132.17
2018	1293	433.04	10.66	25309.67	155.85
2019	1202	287.99	5.91	73670.79	175.82
2020	1149	330.88	5.96	139938.75	282.05
Full	1986	357.87	7.19	62816.57	157.27

Panel B. Return Characteristics					
	Mean	Median	SD	Skewness	Kurtosis
Coin Market Return	0.023	0.014	0.126	1.67	13.906
Bitcoin Return	0.014	0.004	0.111	0.385	1.782
Ripple Return	0.026	-0.003	0.236	3.904	24.236
Ethereum Return	0.042	0.013	0.209	2.085	9.199

Despite recognizing the necessity for addressing outliers, attempts to winsorize the values proved challenging. Winsorizing introduced distortions in the mean and median, deviating significantly from the values in the original paper. Consequently, we made the informed decision to refrain from winsorizing our data. It's crucial to note that this decision, while maintaining the integrity of the calculated summary statistics, could impact subsequent analyses, particularly in the context of long-short strategy weekly returns in the subsequent regression tables.

Nevertheless, both the summary statistics table and the regression tables show a consistent and congruent general trend with the original article. This alignment indicates that, although we utilized a different dataset, our replication effectively substantiates the primary findings and key insights presented in the original paper.

2. Replication of Regression Tables III~VI

The following tables replicate the key findings from the analyzed paper titled "Common Risk Factors in Cryptocurrency." There are four tables in total, presenting mean excess weekly returns based on size-related characteristics, momentum-related characteristics, volume, and volatility-related characteristics. Each table details mean excess weekly returns for five portfolios, along with returns for zero-investment long-short strategies (the difference between the first and fifth portfolios).

In line with the original paper, here's a breakdown of the ten independent variables used in the regression analyses:

<u>Size</u>

MCAP - log last-day market capitalization in the portfolio formation week

PRC - log last-day price in the portfolio formation week

MAXDPRC - Maximum price of the portfolio formation week

<u>Momentum</u>

r1,0 - past one-week return

r2,0 - past two-week return

r3,0 - past three-week return

r4,0 - past four-week return

r4,1 - past one-to-four-week return

<u>Volume</u>

PRCVOL - log avg daily volume times price in the portfolio formation week

<u>Volatility</u>

STDPRCVOL - log standard deviation of price volume in the portfolio formation week

These variables are crucial for the regression analyses, providing insights into the relationship between cryptocurrency returns and the specified characteristics. The ensuing tables emphasize the importance of these factors, offering a detailed perspective on their impact in the cryptocurrency market.

The guidelines for constructing factors were generally clear, except for the momentum characteristics, which lacked detailed descriptions. The authors' descriptions for r1,0 to r4,0 did not specify whether they used aggregate or cumulative returns or simply weekly returns for the past one to four weeks. After exploring various calculation methods, we found that the results for aggregate returns resembled those in the paper the most. Therefore, we chose this approach for our calculations. For the past one-to-four-week returns, it was also ambiguous how this variable should be constructed. After experimenting with different calculation methods, we opted for finding the difference between the fourth week returns and the first week returns.

Before delving further, it's prudent to explain the zero-investment long-short strategy. This strategy, widely used in investment-related studies, entails considering the initial investment as zero. The term "long-short" implies that returns arise from shorting one portfolio and simultaneously taking a long position on another. In our case, we assigned each coin to a portfolio based on one of the ten characteristics mentioned earlier at the beginning of each week. We then calculated the sum of returns by portfolio for each week, resulting in weekly returns for each portfolio. To create tables similar to those in the article, we computed the mean of weekly portfolio returns and the difference between the fifth and the first portfolio. It's crucial to note that the authors did not consider transaction fees in their calculations, although transaction fees during the analyzed period were relatively small, averaging around 0.2% across all cryptocurrency exchanges.

Our process for constructing the regression tables can be outlined as follows: We created a separate dataframe with aggregate weekly returns for each coin. Subsequently, we sorted each coin based on the value of one of the ten characteristics and assigned each coin to one of the five portfolios. We then summed up the weekly returns for each portfolio by week, calculated next-week value-weighted returns, and determined the difference between the fifth and the first portfolio. For each week, we subtracted the value of one-month treasuries divided by 4 (to obtain weekly treasuries returns) from each portfolio's returns, resulting in weekly excess returns by portfolio. Following that, we conducted a simple regression on each portfolio to obtain the final mean values, as presented in the tables we are replicating. Having explained our approach to calculations, let's now transition to the results of our replication.

Size strategy returns

The primary distinction between the original table and our replication lies in the size of long-short strategy excess returns presented in column 5-1. Our long-short strategy returns are nearly twice as large for portfolios created based on the MCAP characteristic, with our returns at 9.39% compared to the article's 5.8%. Additionally, for the PRC and MAXDPRC characteristics, our long-short returns are almost three times higher than those reported in the original paper. Specifically, our PRC returns reached 8.73% against the paper's 3.2%, and our MAXDPRC returns were 8.9% compared to the paper's 3.3%.

Despite our long-short strategy excess weekly returns being higher than those reported in the article, we successfully replicated the overall trend, demonstrating that smaller coins, on average, generate higher returns, while larger coins generate lower returns.

Table III. Original Size strategy returns

	Quintiles					
	1	2	3	4	5	5–1
MCAP	**Low**				**High**	
Mean	0.071***	0.018**	0.013	0.012	0.013**	−0.058**
t(Mean)	(2.84)	(2.00)	(1.62)	(1.59)	(2.16)	(−2.45)
PRC	**Low**				**High**	
Mean	0.045***	0.026**	0.004	0.015	0.013**	−0.032**
t(Mean)	(3.02)	(2.45)	(0.50)	(1.45)	(2.13)	(−2.51)
MAXDPRC	**Low**				**High**	
Mean	0.046***	0.023**	0.004	0.016	0.013**	−0.033**
t(Mean)	(3.05)	(2.17)	(0.50)	(1.51)	(2.13)	(−2.55)

Table IV. Replication of Size strategy returns

	Size Strategy Returns					
	Quintiles					
	1	2	3	4	5	5-1
MCAP	**Low**				**High**	
Mean	0.1056	0.0508	0.0318	0.023	0.0118	**-0.0939**
t(Mean)	13.0456	5.382	4.0479	3.0116	2.1154	-12.5217
PRC	**Low**				**High**	
Mean	0.0981	0.0307	0.0263	0.0023	0.0108	**-0.0873**
t(Mean)	3.6475	2.9317	2.3948	0.267	1.9581	-3.2886
MAXDPRC	**Low**				**High**	
Mean	0.0998	0.0344	0.0243	0.0041	0.0108	**-0.089**
t(Mean)	3.2135	3.0902	2.1993	0.4977	1.9588	-2.8832

Momentum strategy returns

Concerning the momentum strategy returns table, our findings for the weekly excess returns of long-short strategies based on past one, two, three, four, and one-to-four week returns closely align with those presented in the article, except for the past two-weeks returns strategy, where our returns turned out to be higher at 4.38% excess weekly returns compared to the authors' 3.1%. However, it's crucial to note that the long-short strategy weekly excess returns for the past one, two, and one-to-four weeks are not statistically significant, with t-values falling below the necessary threshold to reject the null hypothesis.

Additionally, while the first quintile portfolios in the article almost generate no positive returns, our returns for the first quintile portfolios do show above 1% weekly excess returns, even though neither our results nor the authors' results are statistically significant. It's worth noting that weekly excess returns do not exhibit a monotonic increase with the quintile, as observed in the article. However, this observation may be deemed irrelevant since the values in the first, second, and third quintiles are not statistically significant in the original paper, suggesting a high likelihood of not replicating the authors' results precisely.

The implications of the results for momentum strategies in the original article indicated that coins with high short-term past returns exhibit higher future returns than those with small past returns. Although our results did not achieve statistical significance for all momentum characteristics, they are more likely to support the authors' findings than not.

Table V. Original Momentum Strategy returns

	Quintiles					
	1	2	3	4	5	5–1
r 1,0	**Low**				**High**	
Mean	−0.002	0.000	0.010	0.036**	0.023**	0.025**
t(Mean)	(−0.19)	(0.04)	(1.45)	(2.52)	(2.03)	(2.19)
r 2,0	**Low**				**High**	
Mean	0.000	0.005	0.009	0.017**	0.031***	0.031***
t(Mean)	(0.01)	(0.66)	(1.33)	(2.15)	(2.93)	(2.90)
r 3,0	**Low**				**High**	
Mean	0.005	0.002	0.016*	0.017**	0.036***	0.031***
t(Mean)	(0.60)	(0.28)	(1.94)	(2.30)	(3.21)	(2.65)
r 4,0	**Low**				**High**	
Mean	0.002	0.005	0.009	0.020**	0.025**	0.022**
t(Mean)	(0.30)	(0.66)	(1.28)	(2.45)	(2.32)	(2.26)
r 4,1	**Low**				**High**	
Mean	0.003	0.007	0.021**	0.011	0.020**	0.017*
t(Mean)	(0.35)	(0.94)	(2.34)	(1.51)	(2.02)	(1.82)

Table VI. Replication of Momentum Strategy returns

	Momentum Strategy Returns					
	Quintiles					
	1	2	3	4	5	5-1
r 1,0	**Low**				**High**	
Mean	0.034	0.0129	0.0139	0.0146	0.0591	**0.0251**
t(Mean)	1.652	1.6566	1.9597	1.6365	2.9725	0.9019
r 2,0	**Low**				**High**	
Mean	0.0148	0.0115	0.0091	0.0174	0.0586	**0.0438**
t(Mean)	1.6182	1.5362	1.3728	2.1197	3.1782	2.2616
r 3,0	**Low**				**High**	
Mean	0.0129	0.012	0.0082	0.0098	0.0457	**0.0329**
t(Mean)	1.2848	1.7887	1.3338	1.2703	2.8673	1.8921
r 4,0	**Low**				**High**	
Mean	0.019	0.0116	0.0164	0.0118	0.0488	**0.0299**
t(Mean)	1.8352	1.5616	2.5	1.5343	2.4397	1.3978
r 4,1	**Low**				**High**	
Mean	0.043	0.0036	0.0234	0.0093	0.0577	**0.0147**
t(Mean)	1.8996	0.5162	2.0831	1.1792	3.1027	0.5139

Volume strategy returns

The most conspicuous distinction between our replication of Volume Strategy Returns and the original results lies in significantly higher excess weekly returns for the long-short strategy, with our returns standing at 21.54%, in stark contrast to the authors' reported returns of 3.3%. The statistical significance of our results suggests that the notable disparity is likely attributable to differences in raw data. As previously mentioned in our summary statistics table replication, we highlighted that mean and median volume values were considerably higher in our dataset, and we encountered numerous extreme values for daily volume. Given that the PRCVOL variable is essentially the product of price and volume, it is unsurprising that returns based on the volume strategy turned out to be more extreme.

Returns for portfolios 2 to 5 closely align with the results reported by the authors. However, a substantial difference in outcomes is evident in the returns for the first portfolio. This difference may be attributed to the prevalence of outliers for volume in our raw data. While it might have been prudent to winsorize the outliers, it was impractical due to the abundance of such observations in our dataset.

It is crucial to note that despite our returns for the long-short strategy being considerably higher than those in the original paper due to outliers in volume, we successfully replicated the main trend for volume strategies. This implies that low-volume coins generate superior weekly excess returns compared to those with high transaction volumes.

Table VII. Original Volume Strategy Returns

	Quintiles					
	1	2	3	4	5	5–1
PRCVOL	**Low**				**High**	
Mean	0.046***	0.023**	0.015	0.014	0.013**	−0.033**
t(Mean)	(2.97)	(2.28)	(1.59)	(1.49)	(2.15)	(−2.44)

Table VIII. Replication of Volume Strategy Returns

	Volume Strategy Returns					
	Quintiles					
	1	2	3	4	5	5-1
PRCVOL	**Low**				**High**	
Mean	0.226	0.0418	0.016	0.0214	0.0107	**-0.2154**
t(Mean)	3.3527	4.2284	1.9125	2.3459	1.9126	-3.1793

Volatility strategy returns

Our replication of volatility strategy returns encounters similar challenges as observed in the replication of volume returns. The calculation of the STDPRCVOL variable relies on volume data, which, as noted earlier, contains numerous outliers. Consequently, although our returns are statistically significant and comparable for the fifth, fourth, and third portfolios, our long-short strategy weekly excess returns approach 20%, markedly surpassing the authors' reported returns of 3.2%. This discrepancy is primarily driven by the portfolio with the lowest volume generating returns of 21.51%, as opposed to the article's 4.5%, even though the returns for the fifth quintile closely resemble those reported in the original paper.

Despite this, our replicated table captures the general trend of the original paper's findings, showing that lower price volume volatility corresponds to higher weekly excess returns. It's worth noting that while the authors report results of approximately 3% excess weekly returns for the long-short strategies for both volume and volatility, our table reveals that the returns for volume and volatility long-short strategies are similar, approximating 21%. This suggests that the disparities between our replication results and the original paper's results stem from differences in raw data rather than incorrect calculations of characteristics or an erroneous approach to conducting regressions.

Table IX. Original Volatility Strategy Returns

	Quintiles					
	1	2	3	4	5	5–1
STDPRCVOL	**Low**				**High**	
Mean	0.045***	0.027**	0.019*	0.017*	0.013**	−0.032***
t(Mean)	(3.20)	(2.29)	(1.95)	(1.67)	(2.14)	(−2.65)

Table X. Replication of Volatility Strategy Returns

	Volatility Strategy Returns					
	Quintiles					
	1	2	3	4	5	5-1
STDPRCVOL	**Low**				**High**	
Mean	0.2151	0.0407	0.0184	0.0176	0.0109	-0.2042
t(Mean)	3.045	4.7988	1.9349	2.0179	1.9514	-2.8774

III. Paper Extension Process and Results

1. Predicting Weekly Excess Returns with Ridge and XGB Algorithms

In the pursuit of predicting weekly excess returns, we applied Ridge and XGB algorithms, incorporating 10 successful characteristics as pivotal factors. Our approach draws inspiration from a noteworthy reference paper titled "Forecasting Cryptocurrency Returns with Machine Learning," written by Yujun Liu, Zhongfei Li, Ramzi Nekhili, and Jahangir Sultan. This paper serves as the bedrock for extending our analysis, employing established methodologies within the cryptocurrency price prediction research domain.

Before delving further, we shall provide a concise elucidation of the reference paper under consideration. The authors of said paper compile an extensive array of features, classifiable into categories such as indicators of cryptocurrency market conditions, macroeconomic factors, movements within the equity market, and the valuations of major global currencies or commodities, among others. These diverse features serve as input variables for Ordinary Least Squares (OLS) and XGBoost (XGB) machine learning models, employed to forecast the mean daily excess returns across 10 portfolios.

Daily, the authors utilize OLS or XGB models to predict the following day's returns, then categorizing each cryptocurrency into one of the ten portfolios based on the model-derived predictions. Then the authors calculate the realized mean excess returns for each portfolio, including the long-short strategy portfolio, which stands for the variance between the returns of the top and bottom portfolios. Additionally, the authors calculate the average standard deviation and

Sharpe ratio values for each portfolio and the long-short strategy. It is pertinent to highlight that the authors provide results for both equal-weighted returns and marketcap-weighted returns.

Noteworthy is the observation that the mean equal-weighted returns for the long-short strategy significantly surpass market-capital-weighted returns, approximating 6% for both OLS and XGB prediction models, in contrast to market-capital-weighted returns of 1.287% for OLS and 1.982% for XGB prediction models. Table XI reflects the findings of the reference paper about mean daily excess returns based on OLS and XGB prediction models utilizing the complete set of input features.

Table XI. Mean daily excess returns for OLS and XGB models

Table 5
Prediction model portfolio performance.

Panel A: All input features												
	Equal-weighted						Market-capital-weighted					
	OLS			XGB			OLS			XGB		
	Mean	SD	Sharpe	Mean	SD	Sharpe	Mean	SD	Sharpe	Mean	SD	Sharpe
1 (Low)	-0.957	3.889	-0.247	-0.953	4.100	-0.234	-0.032	4.378	-0.009	-0.481	5.235	-0.093
2	-0.069	3.908	-0.019	-0.047	4.255	-0.012	0.076	4.561	0.015	-0.101	5.210	-0.020
3	0.049	4.232	0.010	0.078	4.396	0.017	-0.068	4.673	-0.016	-0.104	4.806	-0.023
4	0.075	4.394	0.016	0.077	4.618	0.015	-0.014	4.862	-0.004	0.031	4.913	0.005
5	0.142	4.464	0.031	0.129	4.638	0.027	-0.118	4.944	-0.025	-0.025	5.199	-0.006
6	0.238	4.519	0.051	0.240	4.718	0.050	-0.102	5.175	-0.021	-0.027	5.342	-0.006
7	0.313	4.562	0.067	0.378	4.817	0.077	-0.163	5.422	-0.031	0.165	5.688	0.028
8	0.603	4.625	0.129	0.499	4.946	0.100	-0.153	5.525	-0.029	0.009	5.782	0.001
9	1.103	4.645	0.236	0.917	4.838	0.188	-0.126	6.175	-0.021	0.032	6.339	0.004
10 (High)	5.274	5.125	1.028	5.734	5.307	1.079	1.255	8.965	0.139	1.501	9.075	0.165
H-L	6.231	3.622	1.719	6.687	3.508	1.905	1.287	8.906	0.144	1.983	8.959	0.221

Differences in our approach

In contrast to mirroring the method employed in the reference paper for predicting coin portfolio returns, our approach diverges to accommodate the unique characteristics of our data and prediction factors. Utilizing the same dataset and 10 input variables employed in replicating the paper titled "Common Risk Factors in Cryptocurrency". Additionally, we use weekly data, as most of our factors, which have demonstrated robustness through simple regression analyses, are computed on a weekly timeframe.

Unlike the reference paper, we opt not to implement the "rolling window" approach. This method involves dividing the entire dataset into subsets and running prediction algorithms on each subset independently. The authors of the reference paper employ an overlapping rolling window mechanism, adept at capturing temporal dependencies and changes in the data, particularly beneficial for time-series analysis. However, due to our use of weekly data, the efficiency of the "rolling window" approach is compromised by a limited number of observations. Consequently, we segment our weekly data into training and testing datasets, allocating 50% for model training and the remaining 50% for model testing.

Furthermore, we construct our set of hyperparameters to align with the nuances of our data. Employing a four-fold cross-validation for Ridge and a two-fold cross-validation for XGBoost (XGB) algorithms, we tune hyperparameters through a training-validation process conducted four or two times, respectively.

The hyperparameter tuning is executed using the GridSearchCV library in Python. Due to computational constraints, we employ distinct sets of hyperparameters for XGB and Ridge models, optimizing tuning efforts based on resource availability. In Table XII below, we present the specific set of hyperparameters utilized for the tuning process. This strategic adaptation ensures a balanced and efficient hyperparameter optimization for both models, given our computational constraints.

Table XII. Hyperparameters

Model	Hyperparameters
XGB	'learning_rate': [0.00001], 'max_depth': [2, 20, 100, 300, 1000], 'n_estimators': [200], 'subsample': [0.5, 1], 'colsample_bytree': [0.5, 1], 'min_child_weight': [50, 10, 300], 'gamma': [0.0005, 0.0000001, 0.2], 'n_rounds': [10], 'eval_metric': ['rmse'], 'early_stopping_rounds': [0]
Ridge	'alphas' : [0.000000001, 0.0001, 1, 10, 100, 1000, 2000, 3000, 10000]

Explanation of Machine Learning Models and Evaluation Metrics

We shall provide a brief description of the operational principles of Ridge and XGBoost (XGB) models, the metrics employed for assessing their performance, and the rationale behind selecting these models.

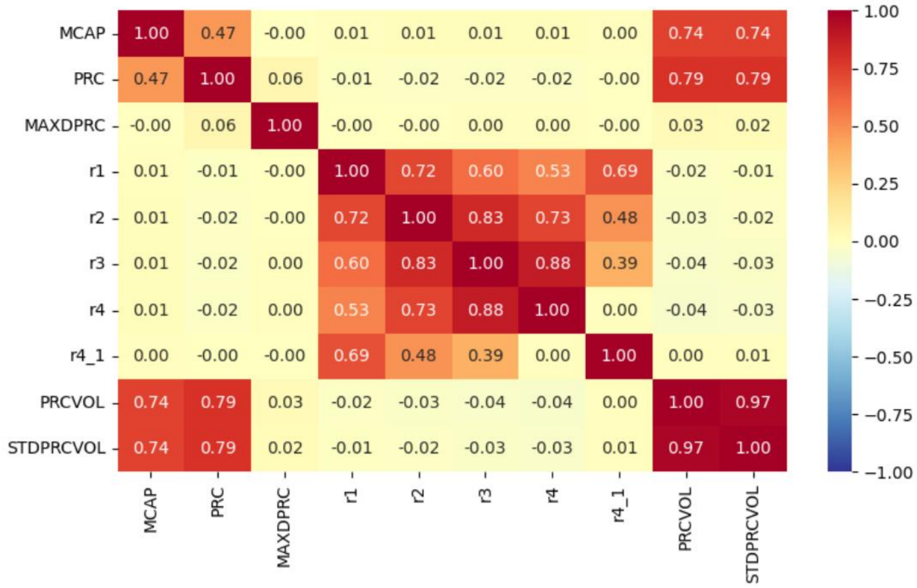
In alignment with the primary methodologies of the reference paper for machine learning return predictions, we opt for a linear regression model (Ridge) and a non-linear decision tree-based model (XGB) to compare the predictive efficacy of both model types.

While the reference paper utilizes Ordinary Least Squares (OLS) and XGB models, citing superior R-squared results after testing various machine learning algorithms, we favor Ridge regression over OLS. This preference stems from the high correlation among our input variables, potentially leading to multicollinearity issues and inaccurate predictions. Correlation coefficients presented in Table XIII indicate significant positive correlations among momentum factors (variables labeled r1~r4,1). Additionally, variables such as MCAP exhibit high correlation with PRCVOL (0.74) and moderate correlation with PRC (0.47), with PRC displaying a high correlation with PRCVOL (0.79). Furthermore, PRCVOL and STDPRC volume demonstrate a substantial correlation of 0.97. Given the interdependence of these variables, we employ Ridge regression as a regularization technique to mitigate multicollinearity issues. Ridge regression shrinks coefficients of highly correlated variables, reducing the impact of individual predictors. The model's alpha hyperparameter is adjusted through cross-validation to optimize its performance.

In contrast, XGB does not assume linear relationships between independent and dependent variables, making it conducive for capturing non-linear patterns in the data. Utilizing decision trees as the base algorithm, XGB sequentially grows trees to rectify errors in previous iterations. As shown in the reference paper, XGB exhibits superior R-squared results among various machine learning models, prompting its inclusion in our analysis.

For evaluating model performance, we employ Mean Standard Error (MSE) and Root Mean Standard Error (RMSE). MSE, calculated by averaging squared differences between predicted and actual values, is complemented by RMSE, providing a more interpretable measure. Percentage MSE and percentage RMSE offer a perspective on prediction errors relative to the target variable's scale. These metrics are crucial for gauging model effectiveness on new data, with smaller MSE or RMSE values for the test dataset considered favorable.

Table XIII. Correlation between 10 factors



	MCAP	PRC	MAXDPRC	r1	r2	r3	r4	r4_1	PRCVOL	STDPRCVOL
MCAP	1.00	0.47	-0.00	0.01	0.01	0.01	0.01	0.00	0.74	0.74
PRC	0.47	1.00	0.06	-0.01	-0.02	-0.02	-0.02	-0.00	0.79	0.79
MAXDPRC	-0.00	0.06	1.00	-0.00	-0.00	0.00	0.00	-0.00	0.03	0.02
r1	0.01	-0.01	-0.00	1.00	0.72	0.60	0.53	0.69	-0.02	-0.01
r2	0.01	-0.02	-0.00	0.72	1.00	0.83	0.73	0.48	-0.03	-0.02
r3	0.01	-0.02	0.00	0.60	0.83	1.00	0.88	0.39	-0.04	-0.03
r4	0.01	-0.02	0.00	0.53	0.73	0.88	1.00	0.00	-0.04	-0.03
r4_1	0.00	-0.00	-0.00	0.69	0.48	0.39	0.00	1.00	0.00	0.01
PRCVOL	0.74	0.79	0.03	-0.02	-0.03	-0.04	-0.04	0.00	1.00	0.97
STDPRCVOL	0.74	0.79	0.02	-0.01	-0.02	-0.03	-0.03	0.01	0.97	1.00

Additionally, we utilize the SHAP (SHapley Additive exPlanations) measure for both Ridge and XGB models to elucidate each variable's contribution to predictive power. Positive SHAP values indicate contributions elevating the model's output, while negative values signify contributions lowering the output.

In tandem with reporting mean weekly excess returns, we incorporate the mean Sharpe ratio for all portfolios to assess the risk-adjusted returns. Calculated by subtracting risk-free returns from portfolio returns and dividing by the portfolio's excess returns, the Sharpe ratio offers valuable insights into portfolio performance in relation to risk.

In tandem with reporting mean weekly excess returns, we incorporate the mean Sharpe ratio for all portfolios to assess the risk-adjusted returns. Calculated by subtracting risk-free returns from portfolio returns and dividing by the portfolio's standard deviation of the returns, the Sharpe ratio offers valuable insights into portfolio performance in relation to risk.

Results

Table XIV presents the outcomes of weekly excess returns prediction utilizing Ridge and XGBoost (XGB) models. The "Mean Returns" column displays the actual mean weekly excess returns by portfolio and for the long-short strategy. Following the reference paper, we provide Standard Deviation and Sharpe ratio, along with Mean Standard Deviation and Root Mean Standard Deviation as well as their representation in percentage.

The actual mean excess returns for the long-short strategy, as derived from the Ridge model, approximate 1.1%. This figure signifies the returns associated with shorting the first portfolio and simultaneously adopting a long position on the tenth portfolio. These portfolio assignments are made on a weekly basis, guided by the Ridge model's weekly return predictions for each cryptocurrency.

Interestingly, the calculated Sharpe ratio is nearly half of the mean returns for the long-short strategy, registering at 0.53%. This ratio serves as a metric for risk-adjusted returns, providing insight into the efficiency of the strategy.

Upon closer examination of the presented table, a discernible pattern appears. Both mean returns and Sharpe ratio show a monotonically increasing trend with the rise in predicted returns by the Ridge model. This trend underscores the model's efficacy in forecasting returns, implying a positive correlation between predicted and realized returns.

Notably, both Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) values are comparatively small, indicative of the model's commendable accuracy in predicting returns. This observation lends support to the notion that our Ridge model demonstrates a low margin of error in its predictions, reinforcing its viability as a robust tool in the realm of cryptocurrency return forecasting.

Table XIV. Portfolio returns using Ridge and XGB models

	Ridge				XGB		
	Mean returns	**STD**	**Sharpe**		**Mean returns**	**STD**	**Sharpe**
P1	0.0003	0.0035	-0.4718	P1	0.0034	0.0134	0.1093
P2	0.0002	0.0033	-0.5435	P2	0.0004	0.0029	-0.5395
P3	0.0004	0.0032	-0.4834	P3	0.0003	0.0027	-0.6166
P4	0.0010	0.0040	-0.2333	P4	0.0007	0.0036	-0.3546
P5	0.0019	0.0064	-0.0127	P5	0.0005	0.0029	-0.5043
P6	0.0012	0.0027	-0.2843	P6	0.0019	0.0067	-0.0042
P7	0.0016	0.0037	-0.0985	P7	0.0010	0.0031	-0.3177
P8	0.0015	0.0028	-0.1458	P8	0.0017	0.0030	-0.0731
P9	0.0036	0.0091	0.1835	P9	0.0025	0.0052	0.1055
P10	0.0116	0.0179	0.5369	P10	0.0110	0.0147	0.6139
P10-1	**0.0113**	**0.0174**	**0.5373**	**P10-1**	**0.0076**	**0.0198**	**0.2836**

MSE	**RMSE**	**Perc_MSE**	**Perc_RMSE**	**MSE**	**RMSE**	**Perc_MSE**	**Perc_RMSE**
0.000002	0.001444	0.002	1.164	0.000002	0.001454	0.002	1.172

In comparison to the Ridge model, the XGBoost (XGB) model exhibits diminished returns for the long-short strategy, recording a figure of 0.76% as opposed to Ridge's 1.1%. Furthermore, the Sharpe ratio for XGB experiences a twofold reduction compared to Ridge's Sharpe ratio. The underlying reason for the lower long-short strategy returns in the XGB model can be attributed to the substantial returns associated with the first portfolio. Interestingly, while mean returns for portfolios 2 to 10 display a monotonic growth with decile, XGB predicts comparatively lower returns for coins in the first portfolio, despite their actual returns being higher.

A closer examination of Table XV unveils SHAP coefficients for the 10 factors in both Ridge and XGB models. Notably, PRCVOL emerges as the feature with the highest predictive power for both models. However, the importance of the remaining features diverges between Ridge and XGB models, indicating distinct factors influencing the predictive capabilities of each model in the cryptocurrency return forecasting landscape.

Table XV. SHAP for Ridge and XGB

Ridge			XGB		
SHAP			SHAP		
Rank	Feature	Coeff	Rank	Feature	Coeff
1	PRCVOL	0.000161970	1	PRCVOL	0.000000314
2	PRC	0.000048887	2	MCAP	0.000000232
3	STDPRCVOL	0.000020068	3	MAXDPRC	0.000000213
4	r1	0.000016986	4	r2	0.000000184
5	r4	0.000011037	5	PRC	0.000000164
6	r2	0.000009259	6	r4_1	0.000000134
7	r3	0.000008667	7	STDPRCVOL	0.000000120
8	MCAP	0.000007952	8	r4	0.000000101
9	r4_1	0.000002347	9	r3	0.000000097
10	MAXDPRC	0.000000003	10	r1	0.000000082

2. Monte Carlo simulation

In the context of presenting weekly mean excess returns for the long-short strategy, comprehending whether these returns are considered high or low can be challenging. To enhance interpretability, we conduct a Monte Carlo simulation, leveraging the predictions from the Ridge and XGB models. This simulation illuminates the yearly returns for a strategy that, over a one-year period, shorts coins in the first portfolio and longs coins in the tenth portfolio on a weekly basis.

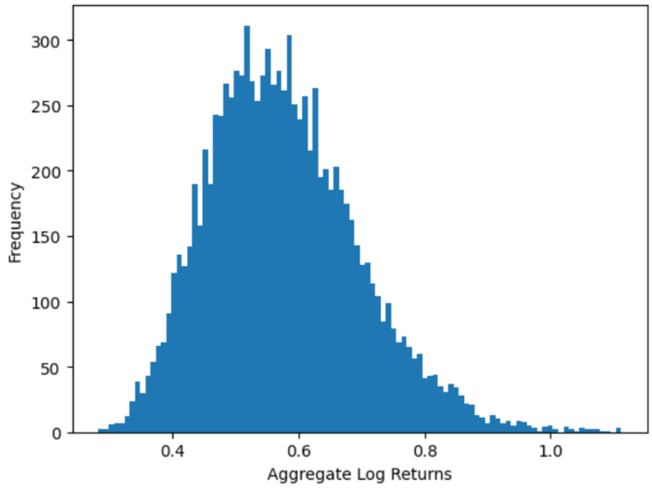
Specifically, we report the distribution of yearly expected returns for strategies grounded in Ridge and XGB predictions. Additionally, we provide insights into the mean expected yearly returns and standard error, facilitating a clearer understanding of the diverse outcomes and their associated probabilities.

Table XVI encapsulates the aggregate log returns after one year of implementing a long-short strategy based on Ridge model predictions. The mean of aggregate returns approximates 58%, representing a high return value that substantiates the merit of our model implementation. Moreover, the distribution analysis reveals a notable absence of negative returns, signifying a minimal likelihood of unfavorable outcomes. This observation underscores the robustness of our model in generating positive returns and hints at the potential for even more favorable results.

Table XVII displays the aggregate log returns following one year of investment based on a long-short strategy driven by XGBoost (XGB) model predictions. In parallel with the weekly returns analysis, the aggregate one-year returns for XGB model predictions are nearly half of those derived from Ridge model predictions, amounting to approximately 38%, with a standard error of 0.0027. Akin to Ridge predictions, there remains a negligible chance of encountering negative returns.

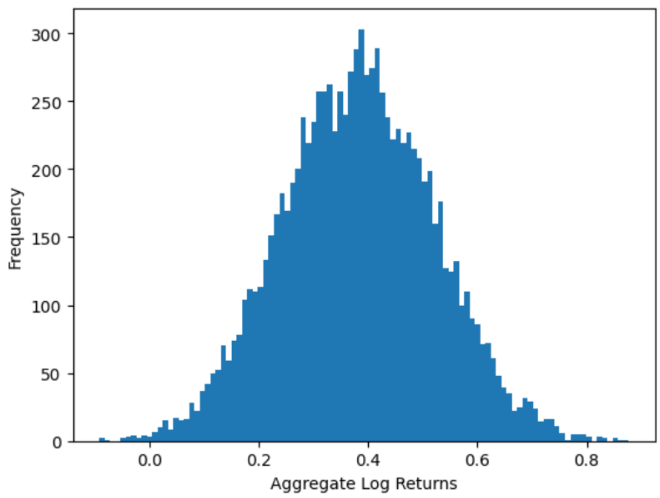
A noteworthy distinction emerges in the distribution patterns. In the case of XGB predictions, the distribution approximates a normal distribution, suggesting a more symmetrical spread of outcomes. Conversely, the yearly returns distribution for Ridge predictions is skewed to the left, indicating a prevalence of outcomes on the lower end of the return spectrum. This variance in distribution patterns provides additional insights into the unique characteristics and potential risks associated with the long-short strategy based on each model's predictions over a one-year horizon.

Table XVI. Distribution of returns after 1 year of Ridge long-short strategy implementation




```
The monte carlo mean estimate is: 0.58
The monte carlo standard error is: 0.0023
```

Table XVII. Distribution of returns after 1 year of XGB long-short strategy implementation




```
The monte carlo mean estimate is: 0.38
The monte carlo standard error is: 0.0027
```

Conclusion.

In conclusion, our replication and extension of the original article, "Common Risk Factors in Cryptocurrency," encompassed a meticulous process of data collection, handling, and analysis. The replication process involved overcoming challenges in data acquisition, addressing discrepancies in summary statistics, and faithfully reproducing regression tables. Despite encountering variations in certain summary statistics, our results consistently mirrored the primary trends and findings of the original article.

The extension phase introduced machine learning models, Ridge and XGBoost, to predict weekly excess returns for a long-short strategy based on the identified risk factors. The Ridge model showed promising results, displaying a positive correlation between predicted and realized returns. The XGBoost model, while still effective, demonstrated lower returns.

The Monte Carlo simulation further enriched our analysis by providing insights into the potential yearly returns of the long-short strategy based on both models. The Ridge model's simulation indicated a higher mean return with a skewed distribution, emphasizing the likelihood of positive outcomes. In contrast, the XGBoost model presented a more symmetric distribution with slightly lower expected returns.

It's imperative to acknowledge the limitations of our study, including data discrepancies, potential outliers, and the inherent uncertainty in cryptocurrency markets. Despite these challenges, our replication and extension contribute to the ongoing discourse on cryptocurrency risk factors and provide a foundation for future research in this dynamic and evolving field.

In the rapidly evolving landscape of cryptocurrencies, continuous scrutiny and exploration of risk factors are essential for informed decision-making and the development of robust investment strategies. Our study contributes to this ongoing effort, emphasizing the significance of rigorous analysis and the integration of machine learning techniques in understanding and predicting cryptocurrency market dynamics.