

Master Thesis

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To all my family, who always support me no matter the time and distance, and to Pedro Torres, my great-grand father, who sadly passed away during the course of my studies (...-2024). Gracias por el amor y los momentos que compartimos. Tu recuerdo estará siempre en mi corazón. Que Dios ilumine tu alma y la llene de paz. Q.E.P.D.

Special thanks to my supervisor, Prof. David Preinerstorfer, for all his guidance during the writing of this thesis, and to all my friends, who made my life in Vienna easier and more enjoyable.

Abstract

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1. Introduction

The first cryptocurrency, Bitcoin, was created in 2009 by Satoshi Nakamoto, who presented it as a peer-to-peer electronic coin with secured and verified transactions through an encrypted proof-of-work mechanism (Nakamoto, 2008). As originally proposed, Bitcoin was designed as an alternative, decentralized cash system offering low-cost and near-real-time transactions, while avoiding currency controls imposed by national governments or financial institutions¹ (Dwyer, 2015). These features quickly attracted widespread public attention. However, due to its high volatility, researchers have questioned its role as a purely digital currency and instead classified it as an investment or speculative asset (Baur et al., 2018; Baur & Dimpfl, 2021; Glaser et al., 2014).

Since then, the cryptocurrency market has expanded rapidly, giving rise to thousands of new coins. In the second quarter of 2025, the total cryptocurrency market capitalization amounted to nearly 3.5 trillion USD, according to data from CoinGecko (n.d.). Despite this rapid growth, perceptions of cryptocurrencies remain divided. Some view them as investments tied to the underlying technologies, such as blockchain and smart contracts, or simply as a form of speculation (Baek & Elbeck, 2015; Vasudeva, 2023). Others, however, see them as bubbles, fraud schemes, or scams, often driven by internet and social media marketing—for example, rug pulls involving so-called “memecoins,” or, more recently, the LIBRA cryptocurrency scandal in February 2025, when the coin was promoted by Argentinian president Javier Milei, soared in value, and collapsed only a few hours later (Kalacheva et al., 2025; Nicas et al., 2025; Yaffe-Bellany, 2024).

As mentioned earlier, a key characteristic of cryptocurrencies is their high volatility, which greatly exceeds that of other traditional assets such as equity indices, gold, silver, foreign exchange currencies, and commodities (Conlon et al., 2020; Klein et al., 2018). According to the standard asset pricing theory, investors should be compensated for bearing such risks. The principle that higher risk should be associated with higher expected returns is central in finance, beginning with the capital asset pricing model

¹Contrary to the common belief, Bitcoin is not anonymous. All Bitcoin transactions are publicly visible in the network and only the identity of the user behind a Bitcoin address is unknown, until their identity is revealed through a purchase or another action. See Meiklejohn et al. (2013) and <https://bitcoin.org/en/you-need-to-know>.

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(CAPM) of Sharpe (1964) and Lintner (1965), and later extended by Merton (1973), who introduced state variables to capture changes in investment and consumption decisions through the intertemporal CAPM, and by Ross (1976), who formalized multi-factor risk pricing through the arbitrage pricing theory (APT). In particular, the APT shows that, in the absence of arbitrage opportunities, asset returns can be represented by a linear factor model, where returns are explained by their exposures to systematic risk factors. In empirical applications, this relation is often estimated through time-series regressions (Cochrane, 2005). Let $r_{i,t+1} \in \mathbb{R}$ denote the excess return on asset i from period t to $t + 1$, and let $f_{t+1} \in \mathbb{R}^n$ be a vector of risk factors. The model can then be written as

$$r_{i,t+1} = \alpha_{i,t} + \beta'_{i,t} f_{t+1} + \epsilon_{i,t+1},$$

where $\beta_{i,t} \in \mathbb{R}^n$ measures the exposure of asset i to the risk factors, $\alpha_{i,t}$ represents a pricing error (equal to zero under correct specification), and $\epsilon_{i,t+1}$ is the idiosyncratic component of returns.

A major challenge of the framework described above is identifying the set of factors that best capture asset returns, as these factors are not directly observable. This raises the question of whether they truly explain the cross-section of excess returns or whether such returns should instead be attributed to asset mispricing. This motivates the main questions addressed in this thesis:

- Which factors account for the variation in cryptocurrency returns?
- To what extent can the return cross-section be explained by systematic risk factors?
- Does allowing for dynamic factor loadings improve the prediction of cross-sectional excess returns?

The main goal of this thesis is to apply established factor models from the financial literature to a large panel of cryptocurrency data and to compare their predictive performance under static and dynamic loadings. In particular, I replicate the approaches of Kelly et al. (2019) and Bianchi & Babiak (2021b) for the cryptocurrency market. The analysis relies on a model that allows factor loadings to vary over time through observable characteristics, using the Instrumented Principal Component Analysis (IPCA) methodology.

1.1. Literature review

Linear factor pricing models play a fundamental role in the field of finance. Building on the theoretical foundations of APT, a large body of academic research have worked to identify the sources of economic risks and the factors that explain the cross-section of asset returns. Broadly speaking, two main strands have emerged in the empirical literature (Kelly et al., 2019).

One strand of the literature pre-specifies the factors f_{t+1} and represents them with long-short portfolios, often referred to as factor-mimicking portfolios or sorted portfolios. These long-short portfolios are based on well-established knowledge of the empirical behavior of asset returns and are therefore treated as fully observable (Kelly et al., 2019). The main drawback of this approach is that it presumes a prior understanding of the cross-sectional dynamics of asset returns, even though such knowledge is incomplete or imperfect.

Although the construction of each factor varies across studies, the process typically involves sorting assets into quintiles (or deciles) based on a given characteristic and forming the factor return as the difference between the top and bottom groups. Fama & French (1993) were the first to formalize this approach in the context of linear factor models, introducing a three-factor model (FF3) that included the market, size, and value factors to explain stocks and bond returns. Carhart (1997) expanded the FF3 by adding a momentum factor, which captures the one-year asset momentum, forming in this way a 4-factor model. Later, Fama & French (2015) extended the FF3 by incorporating profitability and investment factors, creating a 5-factor model to capture additional stock return variation beyond size and value.

The number of risk factors proposed in the literature is vast, with hundreds of them reported across different studies (Cochrane, 2011; Harvey & Liu, 2021). Feng et al. (2020) developed a model selection framework to evaluate the contribution of newly proposed factors, finding that most are redundant relative to existing ones. Hou et al. (2020) and A. Y. Chen & Zimmermann (2021) replicated 452 and 319 long-short strategies from the literature, respectively. Hou et al. failed to reproduce the results of more than half of predictors in their set, finding most of them statistically insignificant and concluding that many published return predictors are not reliable. By contrast, Chen and Zimmerman showed that nearly all of the literature results can be successfully replicated.

A second strand of research views the factors as latent and applies data-compression techniques, such as Principal Component Analysis (PCA), to simultaneously extract

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common factors and estimate their betas directly from the panel of realized returns (Bianchi & Babiak, 2021b). This method derives factors purely from a statistical criteria and therefore requires no prior knowledge of the cross-sectional behavior of returns. Its main limitation, however, is that PCA can only estimate static loadings, implying that asset exposures to systematic risk are assumed constant over time. Moreover, PCA cannot incorporate additional information beyond returns, which restricts its ability to identify more appropriate asset pricing models (Kelly et al., 2019).

The pioneers in this approach are Chamberlain & Rothschild (1983) and Connor & Korajczyk (1986). Chamberlain & Rothschild (1983) defined the concept of approximate factor structure and showed that asset returns on large markets can be represented by a small number of common factors that can be extracted with PCA, as long as the covariance matrix of asset returns has K unbounded eigenvalues. Building on this, Connor & Korajczyk (1986) developed an econometric method using asymptotic principal components that estimates latent factors and their loadings from large panels of returns, providing consistent APT-based performance measures and an application to portfolio evaluation.

More recently, Kelly et al. (2019) introduced the Instrumented PCA (IPCA). Unlike PCA, which assumes static factor loadings, IPCA allows loadings to vary with observable asset characteristics such as size, volatility, or momentum. These characteristics serve as instruments for conditional loadings, enabling the method to incorporate more information than returns alone and to handle unbalanced panels of data. Bali et al. (2023) extended the IPCA approach to a joint factor model that explains the risk-return trade-off across different asset classes –bonds, stocks, and options–. In a related work, Z. Chen et al. (2024) proposed the Regressed PCA (RPCA), which extracts common latent factors across stocks, bonds, and options by combining cross-sectional Fama–MacBeth regressions (Fama & MacBeth, 1973) on asset characteristics with standard PCA.

While most of the literature has focused on understanding stock market returns, a growing body of research has examined the dynamics of cryptocurrency returns. Inspired by the FF3 model in equities, Y. Liu et al. (2022) and W. Liu et al. (2020) construct a similar three-factor model for cryptocurrency returns using market, size, and momentum factors. Using weekly data, they show that this model captures a large share of cryptocurrency returns and, in particular, reveals strong anomaly effects in the momentum and size factors. However, Jung & Park (2024) show that the three-factor model of Y. Liu et al. (2022) explains only about one-third of cryptocurrency return variation. They attribute the remaining variation to a common component out-

side the three-factor model, closely linked to the value of fiat money, highlighting the role of global macroeconomic variables in cryptocurrency pricing. Further work by Y. Liu & Tsyvinski (2021) shows that cryptocurrency returns are also linked to network factors, which capture user adoption. They also find strong momentum effects and show that investor attention can predict future returns. Building on these findings, Cong et al. (2022) show that value and network adoption provide strong risk premia across more than 4,000 cryptocurrencies. They propose a five-factor “C-5” model – market, size, momentum, value, and network – that performs better than earlier models in- and out-of-sample, and also report market segmentation across different categories of cryptocurrencies.

Studies adopting a latent-factor structure include Bouri et al. (2022) and Bianchi & Babiak (2021b). Bouri et al. (2022) apply a regime-switching factor model, where the comovement of cryptocurrency returns depends on market states. They show that accounting for these state-dependent comovements improves the forecasting performance of major cryptocurrencies compared to standard PCA and a random-walk model. In contrast, Bianchi & Babiak (2021b) apply the IPCA model to the cryptocurrency market, constructing 32 characteristics to instrument the dynamic factor loadings. They show that this time-varying latent-factor framework measures the variation in realized returns more accurately than conventional observable-factor models or standard PCA, both at the daily and weekly frequency. They also find that characteristics related to speculative demand and liquidity are the most significant in capturing the systematic mispricing of returns.

1.2. Data concerns

One of the main challenges in this thesis was obtaining a large panel of cryptocurrency data. I extracted market data from the free [CoinCodex](#) API, which provides access to the full historical data of the cryptocurrencies listed on its platform. In contrast, most crypto market data providers –also called coin-ranking sites, such as CoinMarketCap, CoinGecko, CryptoCompare (CoinDesk)– offer limited access to historical data (usually one year) or none at all without a paid subscription. Some exchange platforms, such as Bybit, Binance, Coinbase, and Cex, allow users to extract market data for free through their public APIs. However, the number of cryptocurrencies (and thus, the cross-section) available from these sources was relatively small compared with CoinCoindex, and the time span was shorter ².

²For example, Bitcoin data started from late 2013 in CoinCodex, compared to November, 2022 in Bybit, January, 2019, in Binance, and June, 2021, in Coinbase. The available cryptocurrencies

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The choice of which data source is appropriate for scientific research is subject to debate. For example, Alexander & Dakos (2020) examine different cryptocurrency data providers and find inconsistencies in regression estimates, suggesting that the source of cryptocurrency data can influence empirical results. Moreover, they document distorted coin prices on coin-ranking sites, caused by inflated or artificial trading volumes³, emphasizing the importance of using traded data from crypto exchanges. By contrast, Vidal-Tomás (2022) argue that coin-ranking sites use the same underlying process as crypto exchanges and other platforms to compute a cryptocurrency price, and they report no significant differences in empirical results when using alternative data sources. To address these concerns, I apply a series of pre-processing filters, described in Section 3, to mitigate the impact of potential inaccuracies in my dataset.

The remainder of the thesis is structured as follows. Section 2 summarizes the IPCA model, the estimation strategy and the performance measures applied in the analysis. Section 3 describes the data extraction and the sample construction process. Section 4 presents the empirical findings, and Section 5 concludes.

paired with Tether USD (USD) were 763 in Bybit, 623 in Binance, and 116 (USD) in Coinbase.

³Coin-ranking sites rank coins and exchanges by trading volume and market capitalization. As highlighted by Alexander & Dakos (2020), the prices quoted on some of these sites are calculated by aggregating the prices from hundreds of exchanges using a volume-weighted average. Because many exchanges artificially inflate their volume to boost their position in the rankings, the resulting aggregated prices are influenced by fake volumes and therefore inconsistent with traded prices.

2. Methodology

The Instrumented Principal Component Analysis (IPCA) model was introduced in the seminal work of Kelly et al. (2019, 2020). The main model used in this thesis is the IPCA with different K number of factors

Explicar la metodologia de IPCA. Si hay tiempo, entonces explicar tambien como funciona el RPCA de Chen and Roussanov. Explicar las R^2 (en lugar de R^2 , entonces poner Total score y predictive score), mencionar como pie de pagina que son las medidas definidas por Kelly et al. (2019).

Explicar los bootstrap para medir la significancia cada caracteristica, y quiza mencionar tambi'en brevemente los characteristic managed portfolios, en que consisten y como se emplean (quiza tomar inspiracion de Kelly, Bianchi, o creo que puede ser mejor en Liu et al.)

2.1. Instrumented Principal Component Analysis

3. Data

In this section, I introduce the cryptocurrency data used in this thesis, and describe the series of filters applied to clean and prepare the dataset, and the summary statistics of the cryptocurrency excess returns. In addition, I present the set of asset-specific characteristics constructed from the cryptocurrency market data, which are used as instruments for latent factor exposures in the IPCA model. Finally, I construct a set of observable risk factors, or factor-mimicking portfolios, which are used as pre-specified factors in the analysis. Appendix A.2 and A.3 provides a detailed description of the set of characteristics and factors, respectively.

The data extraction and pre-processing are primarily conducted in R 4.5.1 (R Core Team, 2025), using, among other packages¹, the `tidyverse` (v. 2.0.0; Wickham et al., 2019). Additional cleaning steps and visualizations are performed in Python 3.13.5 (Python Software Foundation, 2025). The full reproducible code is available in Appendix A.1.

3.1. Data extraction and sample construction

I collect daily cryptocurrency data on open, high, close, and low (OHCL) prices, 24-hour volume, and market capitalization (calculated as the cryptocurrency’s USD price multiplied by its circulating supply) from [CoinCodex](#), a website-data provider that gathers and aggregates data from more than 400 exchanges. I extract the data, all expressed in US dollars, using the CoinCodex API as follows:

1. I retrieve the list of all available cryptocurrencies and extract each cryptocurrency shortname, also referred to as the “slug”. At the time of writing, there are 14,907 unique cryptocurrency shortnames listed in the API.
2. Using the slug, I construct an URL for each cryptocurrency to obtain the meta-data from the API. I parse the JSON API response into a dataframe and extract

¹See Appendix A.4 for the full list of software used in the empirical study.

3.1. Data extraction and sample construction

the OHCL prices, volume, and market capitalization daily data. I exclude those observations with non-zero or missing values in any of these fields.

Out of the 14,907 cryptocurrencies listed, only 7,272 entries contained available data. Next, following the methodology of Bianchi & Babiak (2021b) and Mercik et al. (2025), I apply a series of cleaning and filtering steps in order to remove possible inaccuracies in the dataset:

1. Non-positive and missing values. As mentioned earlier, I remove observations where prices, volume, or market capitalization were non-positive or missing.
2. Small cryptocurrencies. Similar to Y. Liu et al. (2022), I screen out small cryptocurrencies and consider only those with a market capitalization greater than one million USD. Therefore, I exclude observations for coins whose market capitalization falls below this minimum threshold, which allows for the possibility that a coin may become “small” after a certain period or event.
3. Cryptocurrency type. Based on the cryptocurrency classification from [CoinMarketCap](#) and [CoinCodex](#), I exclude:
 - stablecoins. I include (i) centralized stablecoins, which are backed and pegged to fiat currency or physical assets by a third party, such as Tether (USDT), USD Coin (USDC), and Euro Coin (EURC), and (ii) algorithmically stabilized stablecoins, which use algorithms to adjust the circulating supply in response to changes in demand to maintain a stable value with the underlying asset, such as DAI and AMPL (FSB, 2020).
 - wrapped cryptocurrency tokens, which mirror the value of another cryptocurrency from a different blockchain, e.g., Wrapped Bitcoin (wBTC) or Wrapped Ethereum (wETH) ([Coinbase](#), n.d.).
 - cryptocurrencies backed by or pegged to gold or precious metals, including Pax Gold (PAXG) or XAGx Silver Token (XAGX).
4. Erroneous trading volume. To filter out cryptocurrencies with “fake” or “erroneous” trading volume, I calculate the daily volume-to-market-capitalization ratio for each token and exclude observations where the ratio exceeds 1.
5. Extreme returns. To minimize the influence of extreme values in my results, I winsorize daily cryptocurrency returns to lie within the range of -90% to 500%.
6. Time period. Even though cryptocurrency data are available since 2014, I use data from June 1, 2018 for the empirical analysis due to the low amount of coins

3. Data

available before this date (see Figure 3.1).

7. Minimum observations. In order to maintain practical relevance, I keep cryptocurrencies that have at least 365 consecutive daily observations and those with at least 730 observations in the complete panel of coin characteristics (see Section 3.3), which is equivalent to 2 years of historical data. Therefore, I exclude very short-lived coins, but retain failed coins with this relatively large number of observations, which help to lessen the so called “survivorship bias”.

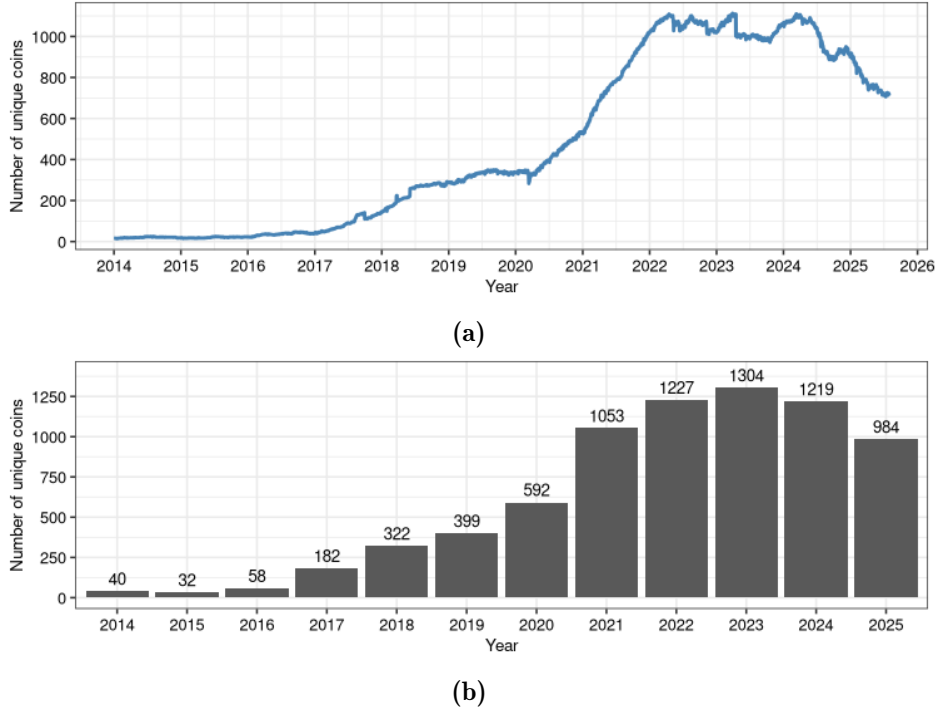


Figure 3.1.: Number of cryptocurrencies over time. Panel A shows the daily time series of the number of unique cryptocurrencies. Panel B displays the number of unique cryptocurrencies recorded each year. Both panels correspond to the dataset after applying the filtering steps (1) to (5), covering the period from January 1, 2014, to July 31, 2025, and including 1,416 unique cryptocurrencies. Note that coins may enter or exit the market over time.

3.2. Sample overview

After applying all the filters, the resulting sample consists of 973 unique cryptocurrencies and 1,478,936 observations from June 1, 2018, to July 31, 2025, where a day starts at 00:00:00 UTC. It is important to mention that the number of cryptocurrencies fluctuates over the entire period, which results in an unbalanced panel of data. Table 3.1 provides a description of the yearly cross-sectional statistics: the sample starts with 254 different cryptocurrencies in 2018 and peaks in 2023 with 939 unique cryptocurrencies, before decreasing to 780 in 2025. The minimum daily cross-section is 121 in 2018,

Table 3.1.: Cross-section size of the sample. The table reports the number of unique coins per year, as well as the minimum daily cross-section size in the filtered sample.

| Year | 2018 | 2019 | 2020 | 2021 | 2022 | 2023 | 2024 | 2025 |
|--------------------------|------|------|------|------|------|------|------|------|
| Unique coins | 254 | 337 | 420 | 714 | 938 | 939 | 906 | 780 |
| Min. daily cross-section | 121 | 239 | 207 | 381 | 699 | 793 | 710 | 578 |

and then increases drastically up to 793 in 2023. For context, at the time of writing, CoinMarketCap tracks around 19 million cryptocurrencies, and CoinGecko around 19 thousands. When compared to these numbers, the size of the sample may seem small; however, it actually covers most of the whole cryptocurrency market capitalization (see Figure 3.2). The sample period includes important events in the market, such as

Table 3.2 summarizes the descriptive statistics for the cryptocurrency daily returns across different subsamples and Bitcoin, Ethereum, and Ripple, which are the three largest cryptocurrencies in the sample. Interestingly, the larger samples exhibit a larger volatility and more pronounced extreme returns, both positive and negative. Bitcoin shows the lowest mean return during the sample period (0.16% per day), though this value very close to that of Ethereum (0.17%) and Ripple (0.20%), and only slightly below other cryptocurrency subsamples.

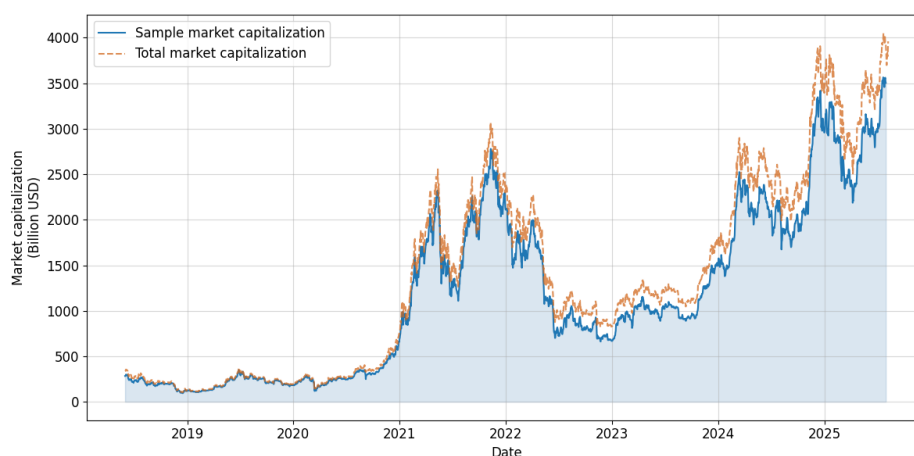


Figure 3.2.: Cryptocurrency market capitalization. The figure compares the cryptocurrency market capitalization in the filtered sample (blue line) with the total market capitalization (yellow line) from June 1, 2018 to July 31, 2025. Source: total market capitalization from [CoinGecko](#).

The sample period spans several major market, economic, and political events, these include: the start of the COVID-19 pandemic and the subsequent crypto bubble in 2020-2021, El Salvador adoption of Bitcoin as legal tender in September 2021, and China’s ban on cryptocurrency exchanges and mining in October 2021. The period also experienced multiple cryptocurrency exchange hacks², and geopolitical shocks such as

²For example, Binance, largest crypto exchange in the world, was hacked in 2019, and KuCoin and

3. Data

Table 3.2.: Summary statistics of daily returns. The table reports summary statistics of daily returns for the filtered sample, the top 100 and top 10 cryptocurrencies ranked by market capitalization, and for Bitcoin, Ethereum, and Ripple individually. Reported statistics include the number of daily observations, the number of unique coins over the sample period, the mean and standard deviation of returns, and the 10th percentile, lower quartile, median, upper quartile, and 90th percentile of the distribution of the returns. The sample period is from June 1, 2018, to July 31, 2025.

| | No. Obs | Unique coins | Mean | Std | P10 | P25 | P50 | P75 | P90 |
|----------|-----------|--------------|-------|--------|--------|--------|--------|-------|-------|
| Sample | 1,478,936 | 973 | 0.36% | 12.25% | -6.83% | -3.00% | -0.16% | 2.57% | 6.85% |
| Top 100 | 176,400 | 100 | 0.21% | 6.93% | -5.64% | -2.52% | -0.03% | 2.44% | 5.86% |
| Top 10 | 24,747 | 10 | 0.25% | 5.74% | -4.71% | -2.00% | 0.07% | 2.14% | 5.07% |
| Bitcoin | 2,618 | 1 | 0.16% | 3.33% | -3.24% | -1.27% | 0.09% | 1.52% | 3.67% |
| Ethereum | 2,611 | 1 | 0.17% | 4.35% | -4.33% | -1.77% | 0.10% | 2.14% | 4.88% |
| Ripple | 2,540 | 1 | 0.20% | 5.31% | -4.48% | -1.87% | 0.08% | 1.89% | 4.70% |

¹ As of July 31, 2025, the top 10 cryptocurrencies are Bitcoin, Ethereum, Ripple, Binance Coin, Solana, Dogecoin, Tron, Cardano, Stellar, and Chainlink.

the Russia-Ukraine war in February 2022, and the Palestine-Israel war in October 2023. More recently, in 2024, the U.S. Securities and Exchange Commission (SEC) approved the listing and trading of several crypto spot ETFs in January, and Donald Trump’s election as U.S. president, with Elon Musk playing an important role in his campaign (Bianchi & Babiak, 2021b; C. Chen & Liu, 2022; S. Liu & Yang, 2024; Mercik et al., 2025; Zhou, 2025).

3.3. Characteristic construction and description

For the analysis, I construct 41 asset-specific characteristics from the cross-section of 973 cryptocurrencies using data on prices, volume, and market capitalization. Specifically, I follow the methodology of Bianchi & Babiak (2021b), Y. Liu et al. (2022), and Mercik et al. (2025) to construct the set of characteristics widely used in the cryptocurrency and financial literature, which serve as return predictors in the empirical analysis. These characteristics are grouped into six categories: market and size, volatility and risk, trading activity, liquidity, past returns, and distribution. Table 3.3 summarizes the set of characteristics, while Appendix A.2 provides detailed definitions and construction procedures.

3.4. Observable risk factors

In addition to the set of characteristics described above, I construct a set of observable risk factors. In the asset pricing literature, the convention is to analyze the risk

Crypto.com were hacked in 2020 and 2022, respectively. (Zhou, 2025)

Table 3.3.: Cryptocurrency characteristics. The table presents the 41 cryptocurrency characteristics used as return predictors in the empirical analysis. The characteristics are grouped in six categories: price and size, volatility and risk, trading activity, liquidity, past returns, and distribution.

| No. | Characteristic | Symbol | Definition |
|---------------------------------------|-----------------------------------|-----------|--|
| Panel A: Price & size | | | |
| (1) | Market capitalization | mcap | Last day's market capitalization. |
| (2) | Price | prc | Last day's logged closing price. |
| (3) | Closeness to the 90-day high | dh90 | Last day's price over the maximum price in the previous 90 days. |
| Panel B: Volatility & risk | | | |
| (4) | Market beta | beta | CAPM market beta, estimated from 30 days of daily returns. |
| (5) | Idiosyncratic volatility | ivol | Volatility of CAPM residuals over 30 days of daily returns. |
| (6-7) | Realized volatility | rvol_*d | Realized volatility, calculated from 7 and 30 days of OHCL prices. |
| (8) | Return volatility | retvol | Standard deviation of daily returns over 7 days. |
| (9) | Value-at-Risk | var | The historical Value-at-Risk at 5% level over 90 days. |
| (10) | Expected Shortfall | es_5 | The expected shortfall at the 5% level over 90 days. |
| (11) | Price delay | delay | Improvement in R^2 after adding lagged one-and two-day market excess return to the CAPM. |
| Panel C: Trading activity | | | |
| (12) | Trading volume | volume | Last day's daily trading volume in US dollars. |
| (13) | Average volume | volume_*d | Mean volume over the past 7 and 30 days. |
| (15) | Turnover | turn | The last day's trading volume over current market capitalization. |
| (16) | Average 7-day turnover | turn_7d | Mean turnover over the past 7 days. |
| (17) | Turnover volatility | std_turn | Turnover volatility over the past 30 days. |
| (18) | Trading volume volatility | std_vol | Volume's logged volatility over the past 30 days. |
| (19) | Volume's coefficient of variation | cv_vol | Volume's volatility over its mean in the previous 30 days. |
| Panel D: Liquidity | | | |
| (20) | Bid-ask spread | bidask | Mean estimated bid-ask spread calculated over the past 30 days. |
| (21) | Illiquidity | illiq | Mean absolute daily return over trading volume over the past 30 days. |
| (22) | Standardized abnormal turnover | sat | Last day's turnover minus its 30-day average, divided its volatility over 30 days. |
| (23) | De-trended turnover | dto | De-trended turnover minus the value-weighted daily market turnover. |
| (24) | Volume Shock 15-day | volsh_15d | Log deviation of trading volume from its rolling 15-day average. |
| (25) | Volume Shock 30-day | volsh_30d | Log deviation of trading volume from its rolling 30-day average. |
| Panel E: Past returns | | | |
| (26) | Daily reversal | r2_1 | Return on the previous trading day. |
| (27-30) | Momentum | r*_1 | 7, 14, 21, and 30-day cumulative return ending 1 day before the prediction date. |
| (31) | Intermediate momentum | r30_14 | Cumulative return from 30 to 14 days before the prediction date. |
| (32) | Long-term reversal | r180_60 | Cumulative return from 180 to 60 days before the prediction date. |
| (33) | CAPM alpha | alpha | CAPM intercept, estimated from 30 days of daily returns. |
| Panel F: Distribution | | | |
| (34-35) | Skewness | skew_*d | Skewness of the daily return distribution over a 7-and 30-day period. |
| (36-37) | Kurtosis | kurt_*d | Kurtosis of the daily return distribution over a 7-and 30-day period. |
| (38-39) | Maximum daily return | maxret_*d | The maximum daily return in the past 7-and 30 days. |
| (40-41) | Minimum daily return | minret_*d | The minimum daily return in the past 7-and 30 days. |

3. Data

compensation of asset returns using factor-mimicking portfolio (e.g. [Carhart, 1997](#); [Fama & French, 1993, 2015](#)). This typically involves sorting assets cross-sectionally into quintiles based on a specific characteristic and forming a factor return, calculated as the difference in returns between the top and the bottom quintiles. This approach replicates a strategy that buys the portfolio of assets with high values of a particular characteristic (long), and sells the portfolio with the lowest values (short).

Building on this methodology, I construct a series of observable risk factors that prior literature have shown to explain the cross-section of cryptocurrency returns. Specifically, I include the market, size, momentum, liquidity, and volatility factors, following Y. Liu et al. ([2022](#)), Bianchi & Babiak ([2021a](#)), and Lan & Frömmel ([2025](#)). Details on their construction are provided in Appendix [A.3](#). As described in Section [2](#), the IPCA allows for the inclusion of pre-specified factors within the more general model specification. I make use of this feature and pre-specify the observable factors in the IPCA model, with and without using asset-characteristics to instrument for dynamic loadings.

4. Results

Write this in the following section of “Empirical application” or This is for the model:
7. (Still undecisive) Minimum cross-section. Following the criterion by Kelly, I Convert variables in the -0.5 - 0.5 range

The sample period ranges from January 1st, 2014, to May 31st, 2025.

Implemented in python, based on the IPCA python code of Seth Pruitt ¹ and the `ipca` python package of Buechner & Bybee (2019) ².

Following Kelly et al. (2019), I cross-sectionally transform the instrument variables period-by-period in the following manner: first,

Important: mention the shift of characteristics: the conditional APT of Kelly, Pruitt, Su (JFE 2019) says that the characteristics known at $\text{Date}=\text{d}-1$ determine the exposures associated with the returns realized at $\text{Date}=\text{d}$; hence, here we should have shifted the characteristics in Z relative to the returns in R

This is a template of the table of the results of the IPCA model. I need to add a caption to the table. Here I reference Table 4.1.

Some test for quarto and latex

Quarto: 1. Sees the caption line after the table. 2. Wraps the `tabular` inside a LaTeX `table` environment. 3. Adds `\caption{Some letters with LaTeX}` and `\label{tbl-letters}` automatically. 4. Gives it a table number and puts it in the List of Tables.

Inline LaTeX way inside Quarto

Here we see the summary statistics in Table 4.2.

¹See <https://sethpruitt.net/research/>.

²See <https://bkelly-lab.github.io/ipca/>.

4. Results

Table 4.1.: Results of IPCA regression. Model Performance. Panel A and B report total and predictive R^2 in percent for the restricted ($\Gamma_\alpha = 0$) and unrestricted ($\Gamma_\alpha \neq 0$) IPCA model for K number of factors on daily and weekly data, respectively. Panel C reports the corresponding total and predictive R^2 for a simple PCA model on weekly data.

| | | K | | |
|------------------------------|------------------------|---------|---------|---------|
| | | $K = 3$ | $K = 5$ | $K = 8$ |
| Panel C: PCA on weekly data | | | | |
| R^2_{Total} | | 0.0000 | 0.0000 | 0.0000 |
| $R^2_{\text{Predictive}}$ | | 0.0000 | 0.0000 | 0.0000 |
| Panel B: IPCA on weekly data | | | | |
| R^2_{Total} | $\Gamma_\alpha = 0$ | 0.2625 | 0.2817 | 0.2934 |
| | $\Gamma_\alpha \neq 0$ | 0.2661 | 0.2826 | 0.2937 |
| $R^2_{\text{Predictive}}$ | $\Gamma_\alpha = 0$ | 0.1725 | 0.1551 | 0.1511 |
| | $\Gamma_\alpha \neq 0$ | 0.1719 | 0.1584 | 0.1554 |
| Panel A: IPCA on daily data | | | | |
| R^2_{Total} | $\Gamma_\alpha = 0$ | 0.2301 | 0.2509 | 0.2681 |
| | $\Gamma_\alpha \neq 0$ | 0.2322 | 0.2524 | 0.2690 |
| $R^2_{\text{Predictive}}$ | $\Gamma_\alpha = 0$ | -0.3904 | -0.4082 | -0.4169 |
| | $\Gamma_\alpha \neq 0$ | -0.3857 | -0.4055 | -0.4156 |

Table 4.2.: Some letters with LaTeX

A B C
D E F

5. Conclusion

References

- Alexander, C., & Dakos, M. (2020). A critical investigation of cryptocurrency data and analysis. *Quantitative Finance*, 20(2), 173–188. <https://doi.org/10.1080/14697688.2019.1641347>
- Allaire, J. J., Teague, C., Scheidegger, C., Xie, Y., Dervieux, C., & Woodhull, G. (2025). *Quarto* (Version 1.7) [Computer software]. <https://doi.org/10.5281/zenodo.5960048>
- Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets*, 5(1), 31–56. [https://doi.org/10.1016/S1386-4181\(01\)00024-6](https://doi.org/10.1016/S1386-4181(01)00024-6)
- Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2006). The Cross-Section of Volatility and Expected Returns. *The Journal of Finance*, 61(1), 259–299. <https://doi.org/10.1111/j.1540-6261.2006.00836.x>
- Ardia, D., Guidotti, E., & Kroencke, T. A. (2024). Efficient estimation of bid–ask spreads from open, high, low, and close prices. *Journal of Financial Economics*, 161, 103916. <https://doi.org/10.1016/j.jfineco.2024.103916>
- Babiak, M., & Erdis, M. B. (2022). *Variations in Trading Activity, Costly Arbitrage, and Cryptocurrency Returns* (SSRN Scholarly Paper 4291073). Social Science Research Network. <https://doi.org/10.2139/ssrn.4291073>
- Baek, C., & Elbeck, M. (2015). Bitcoins as an investment or speculative vehicle? A first look. *Applied Economics Letters*, 22(1), 30–34. <https://doi.org/10.1080/13504851.2014.916379>
- Bali, T. G., Beckmeyer, H., & Goyal, A. (2023). *A Joint Factor Model for Bonds, Stocks, and Options* (SSRN Scholarly Paper 4589282). Social Science Research Network. <https://doi.org/10.2139/ssrn.4589282>
- Baur, D. G., & Dimpfl, T. (2021). The volatility of Bitcoin and its role as a medium of exchange and a store of value. *Empirical Economics*, 61(5), 2663–2683. <https://doi.org/10.1007/s00181-020-01990-5>
- Baur, D. G., Hong, K., & Lee, A. D. (2018). Bitcoin: Medium of exchange or speculative assets? *Journal of International Financial Markets, Institutions and Money*, 54, 177–189. <https://doi.org/10.1016/j.intfin.2017.12.004>

- Bianchi, D., & Babiak, M. (2021a). A factor model for cryptocurrency returns. *CERGE-EI Working Paper Series*, 710.
- Bianchi, D., & Babiak, M. (2021b). *Mispricing and Risk Compensation in Cryptocurrency Returns* (SSRN Scholarly Paper 3935934). Social Science Research Network. <https://doi.org/10.2139/ssrn.3935934>
- Bouri, E., Christou, C., & Gupta, R. (2022). Forecasting returns of major cryptocurrencies: Evidence from regime-switching factor models. *Finance Research Letters*, 49, 103193. <https://doi.org/10.1016/j.frl.2022.103193>
- Buechner, M., & Bybee, L. (2019). *ipca: Instrumented principal components analysis* [Computer software]. <https://github.com/bkelly-lab/ipca>
- Carhart, M. M. (1997). On Persistence in Mutual Fund Performance. *The Journal of Finance*, 52(1), 57–82. <https://doi.org/10.1111/j.1540-6261.1997.tb03808.x>
- Chamberlain, G., & Rothschild, M. (1983). Arbitrage, Factor Structure, and Mean-Variance Analysis on Large Asset Markets. *Econometrica*, 51(5), 1281–1304. <https://doi.org/10.2307/1912275>
- Chen, A. Y., & Zimmermann, T. (2021). *Open Source Cross-Sectional Asset Pricing* (SSRN Scholarly Paper 3604626). Social Science Research Network. <https://doi.org/10.2139/ssrn.3604626>
- Chen, C., & Liu, L. (2022). How effective is China’s cryptocurrency trading ban? *Finance Research Letters*, 46, 102429. <https://doi.org/10.1016/j.frl.2021.102429>
- Chen, Z., Roussanov, N. L., Wang, X., & Zou, D. (2024). *Common Risk Factors in the Returns on Stocks, Bonds (and Options), Redux* (SSRN Scholarly Paper 4703281). Social Science Research Network. <https://doi.org/10.2139/ssrn.4703281>
- Cochrane, J. H. (2005). *Asset pricing: Revised edition*. Princeton University Press.
- Cochrane, J. H. (2011). Presidential Address: Discount Rates. *The Journal of Finance*, 66(4), 1047–1108. <https://doi.org/10.1111/j.1540-6261.2011.01671.x>
- Coinbase. (n.d.). *What is wrapped crypto?* Retrieved August 6, 2025, from <https://www.coinbase.com/learn/your-crypto/what-is-wrapped-crypto>
- CoinGecko. (n.d.). *2025 Q2 Crypto Industry Report*. CoinGecko Cryptocurrency Reports. Retrieved July 25, 2025, from <https://www.coingecko.com/en/publications/reports>
- Cong, L. W., Karolyi, G. A., Tang, K., & Zhao, W. (2022). *Value Premium, Network Adoption, and Factor Pricing of Crypto Assets* (SSRN Scholarly Paper 3985631). Social Science Research Network. <https://doi.org/10.2139/ssrn.3985631>
- Conlon, T., Corbet, S., & McGee, R. J. (2020). Are cryptocurrencies a safe haven for equity markets? An international perspective from the COVID-19 pandemic. *Research in International Business and Finance*, 54, 101248. <https://doi.org/10.1016/j.ribuf.2020.101248>

References

- [1016/j.ribaf.2020.101248](https://doi.org/10.1016/j.ribaf.2020.101248)
- Connor, G., & Korajczyk, R. A. (1986). Performance measurement with the arbitrage pricing theory: A new framework for analysis. *Journal of Financial Economics*, 15(3), 373–394. [https://doi.org/10.1016/0304-405X\(86\)90027-9](https://doi.org/10.1016/0304-405X(86)90027-9)
- Datar, V. T., Y. Naik, N., & Radcliffe, R. (1998). Liquidity and stock returns: An alternative test. *Journal of Financial Markets*, 1(2), 203–219. [https://doi.org/10.1016/S1386-4181\(97\)00004-9](https://doi.org/10.1016/S1386-4181(97)00004-9)
- Dwyer, G. P. (2015). The economics of Bitcoin and similar private digital currencies. *Journal of Financial Stability*, 17, 81–91. <https://doi.org/10.1016/j.jfs.2014.11.006>
- Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1), 3–56. [https://doi.org/10.1016/0304-405X\(93\)90023-5](https://doi.org/10.1016/0304-405X(93)90023-5)
- Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1), 1–22. <https://doi.org/10.1016/j.jfineco.2014.10.010>
- Fama, E. F., & MacBeth, J. D. (1973). Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy*, 81(3), 607–636. <https://www.jstor.org/stable/1831028>
- Feng, G., Giglio, S., & Xiu, D. (2020). Taming the Factor Zoo: A Test of New Factors. *The Journal of Finance*, 75(3), 1327–1370. <https://doi.org/10.1111/jofi.12883>
- Financial Stability Board. (2020). *Addressing the regulatory, supervisory and oversight challenges raised by “global stablecoin” arrangements: Consultative document*. <https://www.fsb.org/2020/04/addressing-the-regulatory-supervisory-and-oversight-challenges-raised-by-global-stablecoin-arrangements-consultative-document/>
- Garfinkel, J. A. (2009). Measuring Investors’ Opinion Divergence. *Journal of Accounting Research*, 47(5), 1317–1348. <https://doi.org/10.1111/j.1475-679X.2009.00344.x>
- Garfinkel, J. A., Hsiao, L., & Hu, D. (n.d.). Disagreement and returns: The case of cryptocurrencies. *Financial Management*, n/a(n/a). <https://doi.org/10.1111/fima.12491>
- George, T. J., & Hwang, C.-Y. (2004). The 52-Week High and Momentum Investing. *The Journal of Finance*, 59(5), 2145–2176. <https://doi.org/10.1111/j.1540-6261.2004.00695.x>
- Glaser, F., Zimmermann, K., Haferkorn, M., Weber, M. C., & Siering, M. (2014). *Bitcoin - Asset or Currency? Revealing Users’ Hidden Intentions* (SSRN Scholarly Paper 2425247). Social Science Research Network. <https://papers.ssrn.com/abstract=2425247>
- Harris, C. R., Millman, K. J., Walt, S. J. van der, Gommers, R., Virtanen, P., Courn-

- peau, D., Wieser, E., Taylor, J., Berg, S., Smith, N. J., Kern, R., Picus, M., Hoyer, S., Kerkwijk, M. H. van, Brett, M., Haldane, A., Río, J. F. del, Wiebe, M., Peterson, P., ... Oliphant, T. E. (2020). Array programming with NumPy. *Nature*, 585(7825), 357–362. <https://doi.org/10.1038/s41586-020-2649-2>
- Harvey, C. R., & Liu, Y. (2021). Lucky factors. *Journal of Financial Economics*, 141(2), 413–435. <https://doi.org/10.1016/j.jfineco.2021.04.014>
- Hou, K., & Moskowitz, T. J. (2005). Market Frictions, Price Delay, and the Cross-Section of Expected Returns. *The Review of Financial Studies*, 18(3), 981–1020. <https://doi.org/10.1093/rfs/hhi023>
- Hou, K., Xue, C., & Zhang, L. (2020). Replicating Anomalies. *The Review of Financial Studies*, 33(5), 2019–2133. <https://doi.org/10.1093/rfs/hhy131>
- Hunter, J. D. (2007). Matplotlib: A 2D graphics environment. *Computing in Science & Engineering*, 9(3), 90–95. <https://doi.org/10.1109/MCSE.2007.55>
- Jung, W., & Park, H. (2024). Common factors in the returns on cryptocurrencies. *Finance Research Letters*, 65, 105485. <https://doi.org/10.1016/j.frl.2024.105485>
- Kalacheva, A., Kuznetsov, P., Vodolazov, I., & Yanovich, Y. (2025). Detecting Rug Pulls in Decentralized Exchanges: The Rise of Meme Coins. *Blockchain: Research and Applications*, 100336. <https://doi.org/10.1016/j.bcra.2025.100336>
- Kelly, B. T., Pruitt, S., & Su, Y. (2019). Characteristics are covariances: A unified model of risk and return. *Journal of Financial Economics*, 134(3), 501–524. <https://doi.org/10.1016/j.jfineco.2019.05.001>
- Kelly, B. T., Pruitt, S., & Su, Y. (2020). *Instrumented Principal Component Analysis* (SSRN Scholarly Paper 2983919). Social Science Research Network. <https://doi.org/10.2139/ssrn.2983919>
- Klein, T., Pham Thu, H., & Walther, T. (2018). Bitcoin is not the New Gold – A comparison of volatility, correlation, and portfolio performance. *International Review of Financial Analysis*, 59, 105–116. <https://doi.org/10.1016/j.irfa.2018.07.010>
- Komsta, L., & Novomestky, F. (2022). *moments: Moments, cumulants, skewness, kurtosis and related tests*. <https://doi.org/10.32614/CRAN.package.moments>
- Lan, T., & Frömmel, M. (2025). Risk factors in cryptocurrency pricing. *International Review of Financial Analysis*, 105, 104389. <https://doi.org/10.1016/j.irfa.2025.104389>
- Lewellen, J., & Nagel, S. (2006). The conditional CAPM does not explain asset-pricing anomalies. *Journal of Financial Economics*, 82(2), 289–314. <https://doi.org/10.1016/j.jfineco.2005.05.012>
- Lintner, J. (1965). The Valuation of Risk Assets and the Selection of Risky Investments

References

- in Stock Portfolios and Capital Budgets. *The Review of Economics and Statistics*, 47(1), 13–37. <https://doi.org/10.2307/1924119>
- Liu, S., & Yang, C. (2024). Spot cryptocurrency ETFs: Crypto investment products or stepping stones toward tokenization. *Finance Research Letters*, 69, 106150. <https://doi.org/10.1016/j.frl.2024.106150>
- Liu, W., Liang, X., & Cui, G. (2020). Common risk factors in the returns on cryptocurrencies. *Economic Modelling*, 86, 299–305. <https://doi.org/10.1016/j.econmod.2019.09.035>
- Liu, Y., & Tsyvinski, A. (2021). Risks and Returns of Cryptocurrency. *The Review of Financial Studies*, 34(6), 2689–2727. <https://doi.org/10.1093/rfs/hhaa113>
- Liu, Y., Tsyvinski, A., & Wu, X. (2022). Common Risk Factors in Cryptocurrency. *The Journal of Finance*, 77(2), 1133–1177. <https://doi.org/10.1111/jofi.13119>
- Llorente, G., Michaely, R., Saar, G., & Wang, J. (2002). Dynamic Volume-Return Relation of Individual Stocks. *The Review of Financial Studies*, 15(4), 1005–1047. <https://doi.org/10.1093/rfs/15.4.1005>
- Meiklejohn, S., Pomarole, M., Jordan, G., Levchenko, K., McCoy, D., Voelker, G. M., & Savage, S. (2013). A fistful of bitcoins: characterizing payments among men with no names. *Proceedings of the 2013 Conference on Internet Measurement Conference*, 127–140. <https://doi.org/10.1145/2504730.2504747>
- Mercik, A., Bdowska-Sójka, B., Karim, S., & Zaremba, A. (2025). Cross-sectional interactions in cryptocurrency returns. *International Review of Financial Analysis*, 97, 103809. <https://doi.org/10.1016/j.irfa.2024.103809>
- Merton, R. C. (1973). An Intertemporal Capital Asset Pricing Model. *Econometrica*, 41(5), 867–887. <https://doi.org/10.2307/1913811>
- Nakamoto, S. (2008). *Bitcoin: A peer-to-peer electronic cash system*.
- Nicas, J., Nicas, D. Y.-B. J., Argentina, who covers, Yaffe-Bellany, reported from R. de J. D., Industry, W. C. the C., & Francisco, reported from S. (2025, February 28). Milei, \$Melania and Memecoins: Unraveling Argentina’s Crypto Fiasco. *The New York Times*. <https://www.nytimes.com/2025/02/28/world/americas/argentina-crypto-scandal-president.html>
- Peterson, B. G., & Carl, P. (2024). *PerformanceAnalytics: Econometric tools for performance and risk analysis*. <https://doi.org/10.32614/CRAN.package.PerformanceAnalytics>
- Posit team. (2025). *RStudio: Integrated development environment for r*. Posit Software, PBC. <http://www.posit.co/>
- Python Software Foundation. (2025). *Python programming language* (Version 3.13.5) [Computer software]. <https://www.python.org/>

- R Core Team. (2025). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. <https://www.R-project.org/>
- Ross, S. A. (1976). The arbitrage theory of capital asset pricing. *Journal of Economic Theory*, 13(3), 341–360. [https://doi.org/10.1016/0022-0531\(76\)90046-6](https://doi.org/10.1016/0022-0531(76)90046-6)
- Ryan, J. A., & Ulrich, J. M. (2025). *quantmod: Quantitative financial modelling framework*. <https://doi.org/10.32614/CRAN.package.quantmod>
- Sharpe, W. F. (1964). Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. *The Journal of Finance*, 19(3), 425–442. <https://doi.org/10.2307/2977928>
- Stacklies, W., Redestig, H., Scholz, M., Walther, D., & Selbig, J. (2007). pcaMethods – a bioconductor package providing PCA methods for incomplete data. *Bioinformatics*, 23, 1164–1167.
- The pandas development team. (2020). *Pandas-dev/pandas: pandas* [Computer software]. Zenodo. <https://doi.org/10.5281/zenodo.3509134>
- Vasudeva, S. (2023). Cryptocurrency as an investment or speculation: a bibliometric review study. *Business Analyst Journal*, 44(1), 34–50. <https://doi.org/10.1108/BAJ-07-2022-0008>
- Vaughan, D. (2024). *slider: Sliding window functions*. <https://doi.org/10.32614/CRAN.package.slider>
- Vidal-Tomás, D. (2022). Which cryptocurrency data sources should scholars use? *International Review of Financial Analysis*, 81, 102061. <https://doi.org/10.1016/j.irfa.2022.102061>
- Virtanen, P., Gommers, R., Oliphant, T. E., Haberland, M., Reddy, T., Cournapeau, D., Burovski, E., Peterson, P., Weckesser, W., Bright, J., van der Walt, S. J., Brett, M., Wilson, J., Millman, K. J., Mayorov, N., Nelson, A. R. J., Jones, E., Kern, R., Larson, E., ... SciPy 1.0 Contributors. (2020). SciPy 1.0: Fundamental Algorithms for Scientific Computing in Python. *Nature Methods*, 17, 261–272. <https://doi.org/10.1038/s41592-019-0686-2>
- Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L. D., François, R., Grolemund, G., Hayes, A., Henry, L., Hester, J., Kuhn, M., Pedersen, T. L., Miller, E., Bache, S. M., Müller, K., Ooms, J., Robinson, D., Seidel, D. P., Spinu, V., ... Yutani, H. (2019). Welcome to the tidyverse. *Journal of Open Source Software*, 4(43), 1686. <https://doi.org/10.21105/joss.01686>
- Yaffe-Bellany, D. (2024, July 27). A Digital Coin Based on Baby Trump? Yup. *The New York Times*. <https://www.nytimes.com/2024/07/27/technology/memecoins-crypto-surge.html>
- Zeileis, A., & Grothendieck, G. (2005). zoo: S3 infrastructure for regular and irregular

References

- time series. *Journal of Statistical Software*, 14(6), 1–27. <https://doi.org/10.18637/jss.v014.i06>
- Zhou, F. (2025). Application of Event Study Methodology in the Analysis of Cryptocurrency Returns. *Emerging Markets Finance and Trade*, 61(4), 989–1009. <https://doi.org/10.1080/1540496X.2024.2404173>

A. Appendix

A.1. Supplementary Material

A.2. Cryptocurrency Characteristics

Following Bianchi & Babiak (2021b), Y. Liu et al. (2022), and Mercik et al. (2025), I construct 41 asset-specific characteristics from OHCL prices, volume, and market capitalization of each cryptocurrency and group them into six categories: prize and size, volatility and risk, trading activity, liquidity, past returns, and distribution. The following list provides the definition of each characteristic and a description of their construction.

Price and size

mcap. Last day's market capitalization. The market capitalization is the current cryptocurrency circulating supply multiplied by its current price in USD.

prc. Last day's logged closing price.

dh90. The closeness to the 90-day high is defined as the ratio of the last day's price to the maximum price observed over the past 90 days (e.g., George & Hwang, 2004).

Volatility and risk

beta. The market beta is calculated as the slope coefficient from a 30-day rolling regression of cryptocurrency's excess returns on the market portfolio excess returns (e.g., Lewellen & Nagel, 2006). The coin market portfolio is constructed daily as the value-weighted average of cryptocurrency returns in the sample.

ivol. Idiosyncratic volatility is computed as the standard deviation of the residuals from the 30-day rolling CAPM regression, following the same approach as for **beta**.

A. Appendix

rvol_*d. Realized volatility, computed using the estimator of Yang and Zhang (2000) based on OHCL prices. I compute the daily realized volatility over rolling 7-and 30-day windows, denoted **rvol_7d** and **rvol_30d**, respectively. For $n > 1$ number of periods, the volatility estimate at time t is:

$$\sigma_t = \sqrt{\sigma_O^2 + k\sigma_C^2 + (1 - k)\sigma_{RS}^2}$$

where σ_{RS}^2 is the variance estimator of Rogers et al. (1994), and σ_O^2 , σ_C^2 , k are given by

$$\sigma_O^2 = \frac{1}{n-1} \sum_{i=1}^n (o_i - \bar{o})^2,$$

$$\sigma_C^2 = \frac{1}{n-1} \sum_{i=1}^n (c_i - \bar{c})^2,$$

$$k = \frac{\alpha - 1}{\alpha + \frac{n+1}{n-1}}$$

with $o = \ln O_t - \ln C_{t-1}$, and $c = \ln C_t - \ln O_t$. Here, C_{t-1} denotes the previous day's closing price and O_t the current day's opening price. I set the constant $\alpha = 1.34$, following Yang and Zhang (2000), who recommend this as the best value in practice.

retvol. Standard deviation of daily returns over the past 7 days (e.g., [Ang et al., 2006](#)).

var. The historical Value-at-Risk at the 5% level, based on daily returns over the past 90 days.

es_5. The expected shortfall at the 5% level, based on daily returns over the past 90 days.

delay. From the regression

$$R_i - R_f = \alpha^i + \beta_{CMKT}^i CMKT + \beta_{CMKT_{-1}}^i CMKT_{-1} + \beta_{CMKT_{-2}}^i CMKT_{-2} + \epsilon_i,$$

where R_i is the return on asset i , R_f is the risk-free rate, and $CMKT$, $CMKT_{-1}$, and $CMKT_{-2}$ are the current, lagged one-and two-day coin market portfolio excess returns, **delay** is the improvement in R^2 relative to the standard CAPM regression using only the current market portfolio excess returns (e.g., [Hou & Moskowitz, 2005](#)). The coin market portfolio is constructed as in **beta**.

Trading activity

volume. Last day's daily trading volume expressed in US dollars. The trading volume is the total amount of a cryptocurrency exchanged in a given day, measured in USD.

volume_*d. The average trading volume over the past 7 and 30 days, denoted **volume_7d** and **volume_30d**, respectively.

turn. Turnover, computed as the last day's trading volume over the current market capitalization (e.g., [Datar et al., 1998](#)).

turn_7d. Average turnover over the past 7 days.

std_turn. The standard deviation of the turnover over the past 30 days.

std_vol. The log standard deviation of trading volume over the past 30 days.

cv_vol. The coefficient of variation is the standard deviation of the daily trading volume divided by its mean, over the past 30 days (e.g., [Babiak & Erdis, 2022](#)).

Liquidity

bidask. The cryptocurrency bid-ask spread, computed from OHCL prices using the approximation of Ardia et al. ([2024](#)).

illiq. The Amihud ([2002](#)) price impact (illiquidity) measure, computed as the 90-day average of the ratio of the absolute daily return to daily trading volume.

sat. The standardized abnormal turnover, following Garfinkel et al. ([n.d.](#)). The measure is calculated as the last day's turnover minus its average over the past 30 days, divided by the turnover's standard deviation over the same 30-day period.

dto. De-trended turnover (e.g., [Garfinkel, 2009](#)). It is computed as turnover minus the value-weighted average daily market turnover, de-trended by its 180-day median.

volsh_*d. Volume shock, defined as the log-deviation of daily trading volume from its k -day rolling average (e.g., [Llorente et al., 2002](#)). For **volsh_15d** and **volsh_30d**, $k = 15$ and $k = 30$, respectively. For cryptocurrency i at time t :

$$v_{i,t} = \log(\text{Volume}_{i,t}) - \log\left(\frac{1}{k} \sum_{s=1}^k \text{Volume}_{i,t-s}\right)$$

A. Appendix

Past returns

r2_1. Daily reversal, defined as the previous day’s cryptocurrency return.

r*_1. The 7, 14, 21, and 30-day momentum, denoted **r7_1**, **r14_1**, **r21_1**, and **r30_1**, respectively. Momentum is defined as the cumulative return from the previous $k \in \{7, 14, 21, 30\}$ days up to one day before the return prediction.

r30_14. Cumulative return from the previous 30 days up to 14 days before the return prediction.

r180_60. Cumulative return from the previous 180 days up to 60 days before the return prediction.

alpha. The CAPM alpha, defined as the intercept from a 30-day rolling regression of cryptocurrency’s excess returns on the market portfolio excess returns. The market portfolio is constructed as in **beta**.

Distribution

skew_*d. Skewness of daily returns over the previous 7 and 30 days, denoted **skew_7d** and **skew_30d**, respectively.

kurt_*d. Kurtosis of daily returns over the previous 7 and 30 days, denoted **kurt_7d** and **kurt_30d**, respectively.

maxret_*d. The maximum daily return over the past 7 and 30 days, denoted **maxret_7d** and **maxret_30d**, respectively.

minret_*d. The minimum daily return over the past 7 and 30 days, denoted **minret_7d** and **minret_30d**, respectively.

A.3. Observable risk factors

Following Y. Liu et al. (2022), I construct a daily cryptocurrency market return as the value-weighted average return of all the cryptocurrencies in the sample. For cryptocurrencies $i = 1, \dots, N$, the daily market return at time t is computed as:

$$r_t^M = \frac{\sum_{i=1}^N r_{it} \cdot \text{marketcap}_{it}}{\sum_{i=1}^N \text{marketcap}_{it}}$$

The cryptocurrency market excess return is constructed as the difference between the cryptocurrency market return and the risk-free rate. To proxy the risk-free rate, I used the (daily) 1-month Treasury bill rate from the FRED.

A.4. Software

This thesis was fully written using [Quarto](#) ([Allaire et al., 2025](#)), running in RStudio (v. 2025.5.1.513; [Posit team, 2025](#)) on Fedora Linux 42 (Workstation Edition).

I used R 4.5.1 ([R Core Team, 2025](#)) and the following R packages: `bidask` v. 2.1.4 ([Ardia et al., 2024](#)), `moments` v. 0.14.1 ([Komsta & Novomestky, 2022](#)), `pcaMethods` v. 2.0.0 ([Stacklies et al., 2007](#)), `PerformanceAnalytics` v. 2.0.8 ([Peterson & Carl, 2024](#)), `quantmod` v. 0.4.28 ([Ryan & Ulrich, 2025](#)), `slider` v. 0.3.2 ([Vaughan, 2024](#)), `tidyverse` v. 2.0.0 ([Wickham et al., 2019](#)), and `zoo` v. 1.8.14 ([Zeileis & Grothendieck, 2005](#)).

Additionally, I used Python 3.15.3 ([Python Software Foundation, 2025](#)) and the following packages: `numpy` ([Harris et al., 2020](#)), `pandas` ([The pandas development team, 2020](#)), `matplotlib` ([Hunter, 2007](#)), and `scipy` ([Virtanen et al., 2020](#)).