A Factor Model for Digital Assets

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Contents

1 Introduction

Cryptocurrencies, such as Bitcoin and Ethereum, have rapidly transformed the financial landscape, captivating investors worldwide. These digital assets, decentralised and immune to traditional banking systems, offer unprecedented opportunities and challenges. In this context, our research aims to explore the intersection of mathematics, finance, and technology, specifically focusing on quantitative approaches for cryptocurrency investment.

The rise of cryptocurrencies has been meteoric. Bitcoin, the pioneer, emerged in 2009, followed by a proliferation of altcoins. Their appeal lies in their potential for high returns, diversification, and hedging against traditional market volatility. However, this nascent market lacks the well-established frameworks that govern traditional investments. As a result, investors face uncertainty, regulatory ambiguity, and a dearth of proven investment strategies and risk management frameworks.

Our study will encompass developing mathematical frameworks for risk factor assessment in cryptocurrencies, and applying these models to historical data, evaluating their efficacy. We start by defining a set of distinct style factors for digital assets, and leverage this to construct the first institutional grade factor model for digital assets. In summary, our research is designed to revolutionise how modern investors perceive and engage with cryptocurrencies. By combining mathematical rigour, technological insights, and financial acumen, we aim to pave the way for a more informed, secure, and inclusive digital asset investment landscape.

This investigation holds substantial value for several reasons. While stocks and bonds benefit from decades of research and empirical evidence, cryptocurrencies remain relatively uncharted territory. By bridging this gap, our work can empower investors with reliable tools to navigate digital asset markets. Furthermore, cryptocurrencies exhibit extreme volatility, making risk management crucial. Quantitative models can help identify risk factors, optimise portfolios, and enhance decision-making. Our research contributes directly to optimising portfolios and managing investment risks specific to digital assets.

2 Literature Review

2.1 Traditional assets

The rigorous systematic quantitative investment approach in traditional assets like equities can be traced back to the 1950s. The initial breakthrough came through Markowitz's seminal work on Portfolio Selection in [12], This pioneering study introduced the concept of portfolio theory and modern investment analysis. Building upon the groundwork laid by Markowitz, Sharpe, 1964 [14] introduced the Capital Asset Pricing Model (CAPM). This groundbreaking model laid the foundation for understanding the risk-return trade-off in the financial market. Since then, there has been a wealth of progression in the field of financial economics, exploring the underpinnings of CAPM. A notable follow-up was the introduction of the Arbitrage Pricing Theory (APT) by Ross [13]. The APT extended CAPM by acknowledging multiple sources of market risk and eliminating the assumption of normally distributed returns. It suggested that the return of a financial asset could be modelled as a linear function of various macroeconomic factors.

Expanding beyond CAPM, Banz (1981) [1] investigated the relationship between return and market value of common stocks, bringing forth the idea that smaller companies tend to have higher risk premiums. His work further opened the discussion on risk factors, adding another layer to the dimensions of equity risk models. From the 1990s, two important studies by Fama and French [7], and Jegadeesh and Titman [9] extended the scope of understanding about equity markets. Fama and French [7] proposed their revolutionary Three-Factor Model, a statistical model that uses Market Risk, Size and Value factors to predict stock returns. Fama and French further extended their three-factor model by adding two more factors - profitability and investment - to predict the cost of equity (Fama and French, 2015) [6] while Jegadeesh and Titman (1993) [9] introduced a strategy based on short-term momentum in stock returns, implicating that the stock market was not as efficient as previously thought. These models have since been refined and adapted to meet investors' changing needs and market fluctuations, but continue to serve the same basic purpose: to give investors the tools needed to make informed decisions based on factor approaches.

2.2 Cryptocurrency assets

The cryptocurrency market has been analysed through multiple studies, each dissecting various elements to tap into understanding which factors significantly contribute to formulating a cryptocurrency's value and returns. Liu, Tsyvinski and Wu (2021, 2022) [10] [11] extensively studied the role of information disclosure and common risk factors in the cryptocurrency market. Their research underscores the relevance of blockchain information disclosure for market values with new address information explaining a material amount of the variation in cryptocurrency returns. Nevertheless, there is an absence of drift around this disclosure, a finding that highlights the unique information environment within this market (Liu et al., 2021) [10]. In another work, they identify three dominant factors, namely, cryptocurrency market, size, and momentum, which encapsulate cross-sectional expected cryptocurrency returns. Further delving into the risk factors, downside risk, a critical component in traditional multi-factor asset-pricing models, has also been examined by Dobrynskaya [5]. His results reveal a significant heterogeneity in the exposure of approximately 2000 cryptocurrencies to downside market risk, linking a higher exposure to higher average returns. There has also been research aimed at understanding the implications of blockchain characteristics on cryptocurrency returns. Bhambhwani et al [2] deftly demonstrate that market dynamics such as network size and computing power significantly influence cryptocurrency prices and returns. Drawing parallels with theoretical models, they show that cryptocurrency prices, in fact, comove with these blockchain features. In addition to these, Bianchi and Babiak [3] reaffirm that liquidity, size, reversal, and market and downside risks remain key drivers of expected returns. However, their IPCA model shows that these factors play more significant roles than once believed. Cong et al's (2022) interesting study [4] puts forward novel factors derived from the observed cryptocurrency return anomalies. They add value premium and network adoption to the traditional factors of market, size, and momentum, hence proposing a new model (C-5) that demonstrates significant efficiency over existing models in pricing the cross-section. Moreover, they emphasise the value of considering token categories for investment strategies and regulatory policymaking. This assortment of literature accentuates the multifaceted elements that determine the pricing and the returns of cryptocurrencies. It becomes evident that while the market, size and momentum factors remain significant to cryptocurrency pricing, the inclusion of variables such as blockchain characteristics, downside risk and value premium further enhances the predictive power of the models used in digital asset pricing. It also brings to light the significance of network adoption, network size, and disclosure of new address information in shaping the market authenticity associated with cryptocurrencies.

We note from the above review that the use of fundamental on-chain data, like total fees, isn't firmly grounded in solid research yet. In our paper, we will discuss this area in detail to fill up the gaps in understanding and help make future models more explainable.

3 Data

In our thesis, we leverage a broad scope of CF Benchmarks sourced data and resources to ensure a comprehensive examination of data quality. Primarily, we utilize exchange public Application Programming Interfaces (APIs), which offer order book and transactional data of different cryptocurrencies. Furthermore, open-source smart contract parsers and blockchain nodes also serve as a crucial data source to extract and analyse on-chain data such as protocol fees, TVL (total value locked), active users, code commits, active developers and token supply data, giving us a deeper understanding of blockchain transactions and fee metrics. We leverage Token Terminal [15] to validate our own on-chain sourced data. The data spans the period from January 1, 2015, to November 10, 2024, based on the best available information and is downloaded on daily frequency at 00:00:00 hours. Collectively, these diverse data sources have supported us in building a robust base for our study.

3.1 Universe Estimation

Our analysis centres on a curated selection of cryptocurrencies, primarily focusing on larger, more established ones such as Bitcoin and Ethereum. This focus is justified by the fact that the top 50 cryptocurrencies, ranked by market capitalization, account for nearly 99% of the total market capitalization. Smaller cryptocurrencies, characterized by lower market cap and liquidity, often experience price volatility and market manipulation. Additionally, the fundamentals of these smaller assets can be unstable and change rapidly, potentially compromising any models based on their data. To ensure the reliability and practicality of our study, we opt to exclude these less liquid digital assets. This will ensure that the factor risk premia resulting from our investigation are replicable by market participants.

We determine our estimation universe at the start of each quarter, specifically on the first business day, which we refer to as the 'universe snapping date'. At each of these dates, we identify 'liquidity snapping dates', comprising the 30 days following the previous universe snapping date, to ensure that all assets considered have at least one month of trading history. We then select assets with a median daily trading volume of no less than 0.05% the median trading volume of the largest cryptocurrency during the same period to ensure sufficient liquidity.

Subsequently, we rank the remaining assets by circulating market cap, excluding tokens that are not yet minted or released. From this ranking, we select the top 50 assets, excluding a list of exceptions whose price movement information is either not relevant to the cryptocurrency context in our research or highly correlated with existing assets in the universe. These categories include:

- Fiat-pegged: Examples include stablecoins such as USDT.
- Crypto-pegged: Examples include derivatives such as wrapped Bitcoin.
- Crypto-derived: Examples include assets like staked Ethereum.
- Commodity-pegged: Examples include tokens like Tether Gold.

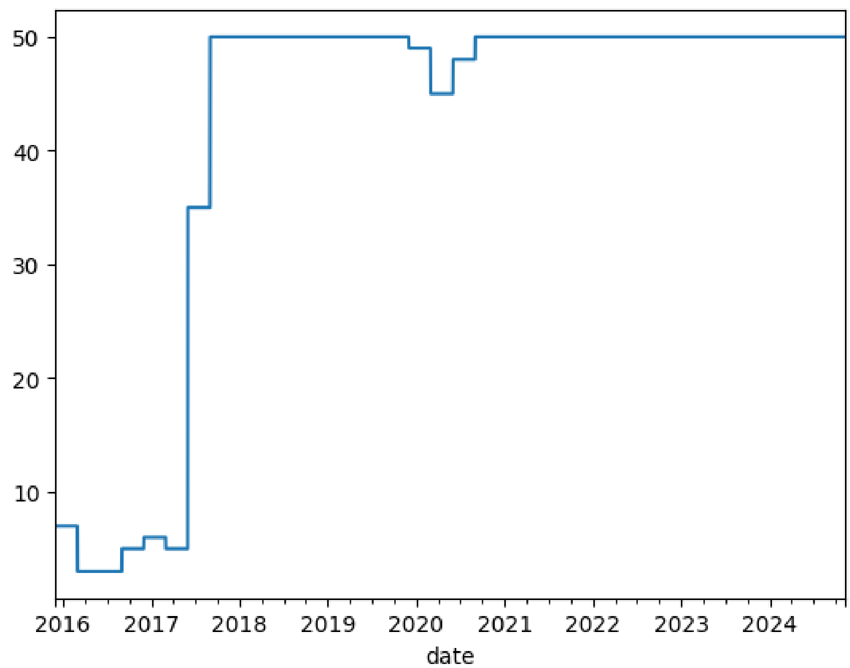

Figure 1: Top 50 Universe

Figure 1 shows the number of assets that satisfy our estimation universe selection criteria on each universe snapping date. In the early years, such as 2016 and 2017, we could not find enough assets with sufficient liquidity. However, as digital assets have evolved over time, liquidity has become less of an issue, allowing us to find all 50 assets satisfying our criteria in recent years.

4 Methodology

In this section, we outline the approach to deriving a robust set of factors and a factor model capable of explaining a significant portion of digital asset return variation. First we evaluate factor descriptors via long-short portfolio analysis to isolate the existence of robust risk premia, and then combine relevant descriptors into style factors to construct return factor portfolios and assess the associated historical performance. Finally, we construct factor models through time-series and cross-sectional regressions, leveraging the isolated set of factors to assess model significance.

4.1 Descriptors

First, we examine the nature and distribution of our descriptors to ensure robustness and accuracy; however, for the sake of conciseness, these results are not shown here. We then leverage this raw descriptor data such as market cap based observations and on-chain metrics to compute cross-sectional pairwise Pearson correlations. Our goal is to identify meaningful relationships among metrics such as low or highly correlated ones which will be relevant during the factor building exercise, and thereby help us isolate unique potential return drivers for digital assets. Analyzing the pairwise correlations output in Figure 7 in Appendix A, we observe a clearly steep correlation between market cap metrics and token trading volume. This is also the case for the pairwise correlation of Fees and TVL, which is only natural given the dynamics and value generation mechanism of cryptocurrency protocols. On the other hand we observe significant de-correlation between token turnover metrics and the remaining variables.

As a next step, we leverage the above correlation analysis to calculate historical long-short portfolio returns, commonly referred to as factor portfolio returns in the Fama-French [7] model context. Long-short portfolios are constructed by establishing a long exposure in the top 50% of assets with higher descriptor rankings (e.g. higher price returns, higher daily active users growth etc), and at the same time implementing a short position in the bottom 50% of assets exhibiting lower descriptor rankings. Each portfolio distributes weights equally among its constituents. For each relevant descriptor, we compute long only, short only and an equally weighted long-short portfolio performance across different rebalancing periods, investible universes (such as top 30 in addition to the top 50) and different manipulations of underlying descriptors to ensure robustness in our results. We calculate return metrics both in-sample and out-of-sample, with the in-sample period ending on November 30th, 2023. The objective of this analysis is to isolate descriptors showcasing consistent performance over time with acceptable volatility and statistically well-behaved time series. As we can see in Figure Figure 3, in the case of 7 day protocol fee growth descriptor, the weekly rebalanced long-short portfolio based on the Top 50 universe, exhibits a desired performance profile, making it eligible for further analysis during the factor construction process and a strong candidate for contributing to a growth-like factor.

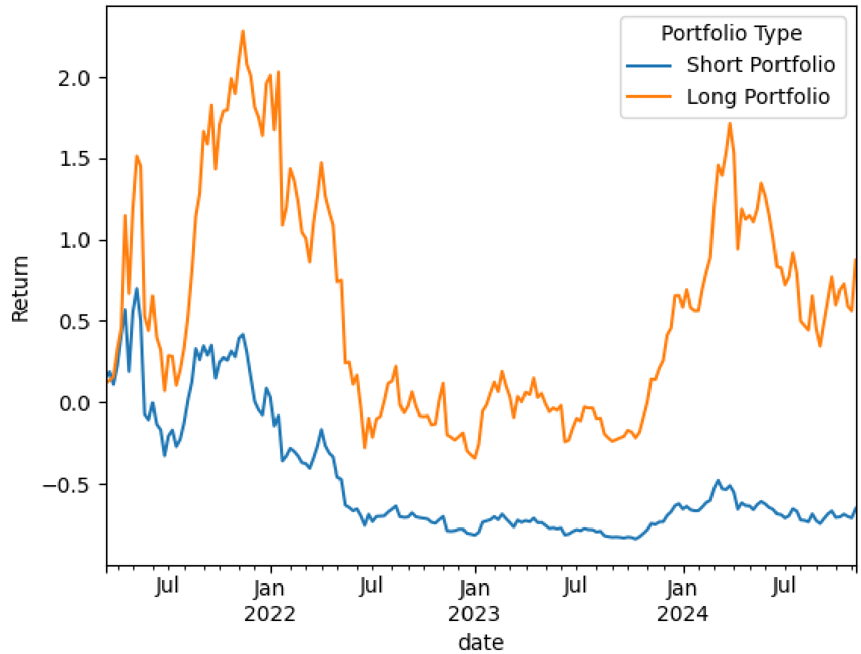

Figure 2: 7-day Fee Growth, Long vs. Short Portfolio Returns (Weekly Rebalance)

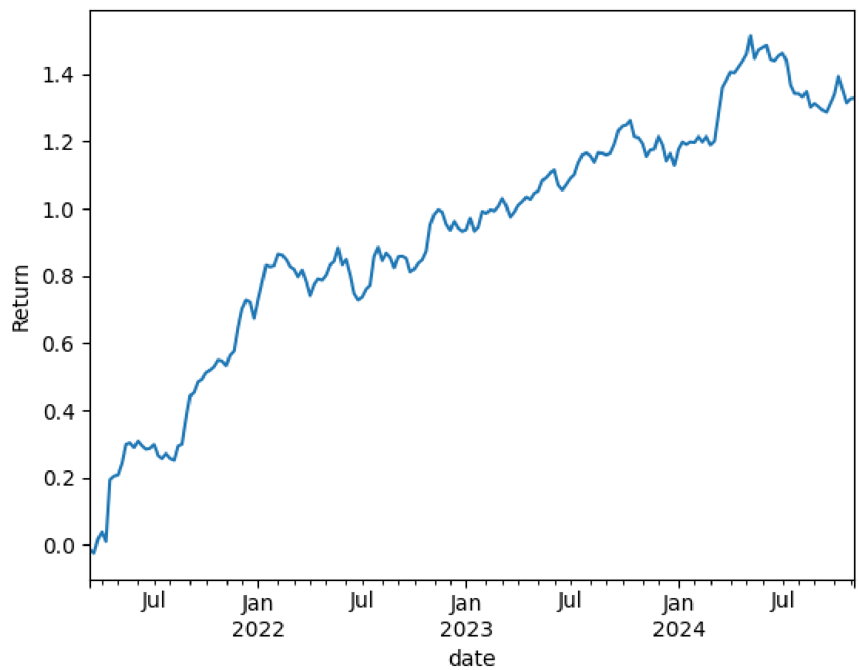

Figure 3: 7-day Fee Growth, Long-Short Portfolio Returns (Weekly Rebalance)

Having analysed factor portfolio returns across all descriptors, associated performance metrics such as sharpe ratios, portfolio turnover and time-series normality tests are aggregated and analysed for clusters of robustness and consistency across different variants, such as differing investible universes, rebalancing periods and experimenting with descriptor variations, including different look-back windows, incorporating risk adjustments in momentum calculations among other. We furthermore test the time-consistency and stability of eligible descriptors across different historical regimes as shown in Figure 4. To ensure clarity and conciseness, we focus on presenting key results for the Top 50 universe and weekly rebalanced factor portfolios (i.e weekly returns) to facilitate replicability, and highlight only the descriptors that were ultimately selected to construct the risk factors.

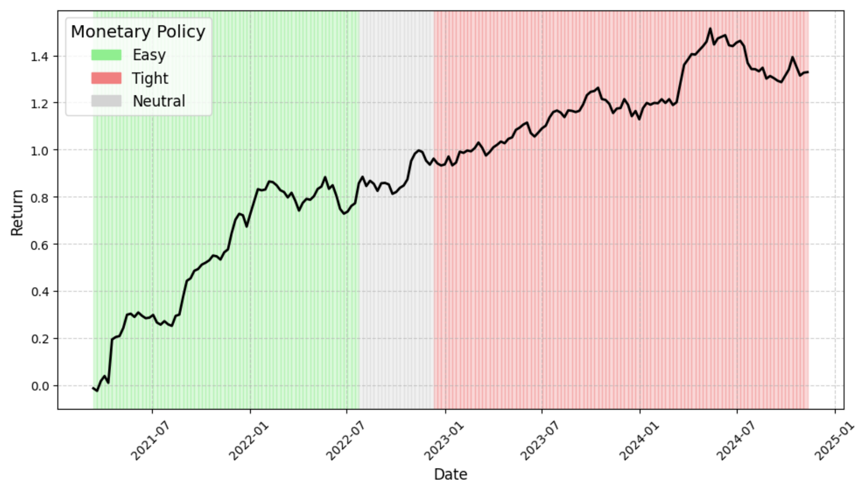

Figure 4: 7 Days Fee Growth Descriptor Analysis Across Macroeconomic Cycles

Figure 4 shows the long-short portfolio performance (weekly rebalanced) relevant for the 7 days fee growth descriptor, mapped against historical monetary policy regimes, where Easy Policy is defined as EFFR (Effective Federal Funds Rate) $\leq 2\%$, Tight as EFFR $\geq 4\%$ and Neutral elsewhere. We note in this example that the 7 days fee growth performance does not appear to exhibit significant adverse dependency on the monetary policy cycle, especially during tightening periods.

4.2 Factors

Based on fundamental analysis of the raw descriptor data, the factor portfolio returns and the perceived associated narratives for digital asset markets corresponding to traditional factor models, the isolated factors deemed to be exhibiting significant risk premia are Market, Size, Value, Momentum, Growth, Downside Beta and Liquidity.

4.2.1 Market

The market factor is an essential component of a digital asset factor model as it captures the broad, systematic risk that affects all assets in the cryptocurrency market. Given the high correlation among cryptocurrencies, especially during significant market-wide events, the market factor provides a foundation for understanding risk premiums and distinguishing systemic from asset-specific effects. It accounts for the extreme volatility inherent in digital asset markets and reflects overarching dynamics like macroeconomic trends, investor sentiment, and speculative behavior. To that end we construct the market factor as a market cap weighted portfolio of (BTC) and Ethereum (ETH) and that is rebalanced on a monthly basis. We present this in figure 8, Appendix A, which yields an annualized return of 80.99% and a Sharpe ratio of 1.15, highlighting its significance and relevance within the cryptocurrency asset class.

4.2.2 Size

In the context of equities, the size factor is vital in a factor model due to its link with risk and return. Small-cap companies often offer higher returns to compensate for increased operational and financial risks, while reacting differently to economic changes compared to large-cap firms. Including the size factor diversifies portfolio risk and exploits market inefficiencies - for example small companies are often undervalued due to limited analyst coverage. Similarly, in the digital asset space, the size factor exhibits comparable patterns, and therefore has the potential to enhance the explanatory power of our model, leading to more accurate return estimates. With this in mind, our size factor is determined by the inverse of the fully diluted market cap of each asset in our universe, with the hypothesis that small-cap assets outperform larger-cap ones. Figure 9 in Appendix A, displays the time-series performance for this factor. We find a significant risk premium in the form of 9.56% annualized return and Sharpe ratio of 0.5. Circulating market cap was also investigated as a potential descriptor for this factor, however no significant risk premium was identified, hence for this reason we define the size factor as the fully diluted market cap on a stand alone basis. This factor portfolio, like all the subsequent factors, is constructed by allocating 50% of the capital to an equally weighted long position in assets with the top 50% highest size score (in this case the smallest assets) and the remaining 50% to an equally weighted short position in assets with the bottom 50% lowest scores (largest assets), as detailed in the methodology section.

4.2.3 Value

Transaction fees are a crucial metric for digital assets, as they provide insight into the economic utility and demand for blockchain protocols. In the case of Bitcoin, fees reward miners for securing the network and are influenced by transaction volume and network congestion, reflecting the intensity of network usage. Ethereum's gas fees support activities like DeFi, NFTs, and token swaps, with a portion burned to reduce supply and the rest compensating validators, showcasing Ethereum's utility as a programmable asset. Lastly, protocols such as Uniswap and Aave link fees directly to demand for services like swaps and lending, offering a clear gauge of user valuation. It is for these reasons that transaction fees are key as a metric to quantify intrinsic value and therefore vital in factor model analysis.

Similarily, daily active users (DAUs) serve as a fundamental metric for assessing blockchain network adoption and user engagement. This measure reflects the number of unique participants interacting with the network within a given day, offering insights into the level of activity and interest in the platform. Higher DAUs generally indicate greater utility, user reliance, and network vibrancy, serving as a proxy for the platform's overall health and value proposition. In the context of our research, DAUs are a critical variable for quantifying user-driven demand and correlating network activity with the intrinsic value of digital assets.

Total Value Locked in the context of DeFi and decentralized protocols represents the total amount of assets locked in a protocol, indicating its scale and trustworthiness. A higher TVL often signifies robust economic activity - for example, in the case of decentralized exchanges it highlights liquidity and the ability to facilitate large trades with minimal slippage. Substantial TVL not only underscores a protocol's efficiency but also attracts developers and fosters innovation, enhancing the overall value of its ecosystem. Notably, we exclude staking from TVL calculations to provide a sharper focus on metrics that reflect economic utility, liquidity, and adoption. This approach ensures a clearer and more accurate depiction of a digital asset's role in the ecosystem, emphasizing productive capital rather than collateralized security.

With this in mind, we define the value factor as the z-score average of Fees/TVL and DAU/MCap.[1] This combined metric aims to capture protocol efficiency and user engagement, largely aligning with the principles of traditional financial productivity metrics. By incorporating both Fees/TVL and DAU/MCap, it evaluates how effectively a protocol generates economic value relative to its capital while also reflecting user-driven activity. A higher combined score indicates not only efficient resource utilization but also strong user engagement, providing a comprehensive indicator of a protocol's operational and economic performance. In Figure 10, Appendix A, we display the performance of this factor. It showcases a significant risk premium that sits at a comfortable 13.21% annualized return and Sharpe ratio of 0.84, therefore endorsing its potential as a relevant factor for our purposes. While, Fees/TVL exhibits slightly better annualized performance on a standalone basis, the combination of the two descriptors increases factor robustness and yields a better Sharpe ratio.

4.2.4 Momentum

The literature review has highlighted the importance of momentum in financial analysis, and our descriptor analysis confirms this is the case for digital assets. In our study, we define momentum based on historical returns to predict future market trends. This approach, validated by numerous

[1] For the purposes of this paper, the value score for non-programmable assets, such as BTC or LTC, is computed solely using the DAU/MCap metric. Similarly, for any asset where only one of the two ratios is available, the value score is determined based exclusively on the available ratio.

academic studies, enables us to produce a comprehensive and precise analysis of the cryptocurrency market. In our context, we define momentum as the average of the 2 weeks cumulative performance z-score and the risk-adjusted 2 weeks cumulative performance z-score, as depicted in Figure 11, Appendix A. We observe a positive and significant risk premium of 13.41% annualized return and a Sharpe Ratio of 0.78. The reason for choosing a short lookback window is that digital assets exhibit high volatility, which directly translate to rapidly shifting price regimes. As noted above, analysis for different lookback windows was conducted; however, only the most relevant results are presented here for brevity.

4.2.5 Growth

The growth factor, central to traditional asset pricing models, is equally relevant in cryptocurrency markets, offering insights into high-growth assets. In equities, it reflects companies with strong revenue or earnings growth, while for cryptocurrencies, it captures metrics like network effects, adoption rates, and platform activity. These metrics, such as user engagement, fees or transaction volume highlight the value derived from a digital asset's ecosystem. Including the growth factor in cryptocurrency risk models helps identify assets with robust adoption trends or innovative use cases, signaling potential for long-term success. Following this we define it as the average of the 30 days fee growth z-score and the 30 days daily active users growth z-score, as depicted in Figure 12, Appendix A. Once again we can see a positive and significant risk premium as showcased by the 25.5% annualized return and the 1.48 Sharpe Ratio. While the stand alone 30 days fee growth descriptor yields slightly better results than the actual factor, we opted for the latter as it proved more robust across different investible universes and rebalancing periods.

4.2.6 Downside Beta

Downside beta captures an asset's sensitivity to market downturns, offering insights into performance during periods of stress — a critical aspect for cryptocurrency markets known for volatility and sharp drawdowns. Moreover, it is essential for understanding an asset's performance asymmetry, as investors are generally more concerned with losses than gains. Unlike traditional beta, which measures overall market correlation, downside beta focuses on negative market movements, aiding in tailored risk assessment. This metric helps identify assets less reactive to adverse conditions, making it invaluable for building resilient portfolios in a market often driven by sentiment shifts, regulatory changes, and macroeconomic pressures. Consequently we estimate downside beta by regressing 4 weeks worth of returns of the underlying asset against the market index returns when these are negative. The factor portfolio is estimated in the same way as all the above factors, with the exception that we invert its score sign as the working hypothesis is that assets with lower exposure to downside events fare better in the longer term than their counterparts. Figure 13, Appendix A, shows that while this factor experiences a heavy crash in late 2017, it exhibits a consistent and robust upward trend ever since. During the entire span of our data, it outputs a negative annualized trend of -5.01% as a result of the initial crash, however, in removing this outlying event, we can see that it exhibits a relatively healthy annualized risk premium of 4.78% and Sharpe ratio of 0.36. For this reason we retain this factor as it suggest potential in explaining cryptocurrency returns.

4.2.7 Liquidity

The liquidity factor is particularly relevant in cryptocurrency markets due to their dynamic and fragmented trading environments. It measures how easily an asset can be traded without major price impact, using metrics such token turnover or trading volume. Highly liquid assets are less volatile and more attractive to investors, while illiquid ones may offer higher return premiums but at the cost of greater price volatility and trading friction. Including the liquidity factor in our model enables the capture of risk premiums tied to liquidity constraints, and therefore has the potential to enhance its ability to explain variations in asset returns. Taking this into consideration we estimate this factor by means of the token's turnover as a % of its circulating supply. We once again invert the score's sign so as to gain long exposure to illiquid assets and short exposure to their counterparts. Figure 14, Appendinx A, displays an annualized risk premium of 3.26% and Sharpe ratio of 0.18. Note that while the risk premium is comparatively lower, the factor can still hold explanatory power in our context.

Having calculated the above risk factors, we also present in Figure 15, Appendix A, factor performance across the different monetary policies as described in section 4.1. While the performance of cryptocurrency risk factors aligns with monetary policy regimes in some cases, in others, it deviates from expectations, highlighting unique dynamics. During easy monetary policy periods (green), factors like Growth, Momentum, and Size show strong upward trends, consistent with favorable liquidity conditions. However, Downside Beta remains negative throughout the 2018 easing period, indicating persistent sensitivity to downside beta's risk even in a supportive macro environment. During the tight monetary policy periods (red), some factors, decline or remain subdued due to reduced liquidity (Liquidity and Size or Momentum and Downside Beta). However, the likes of Market, Value and Growth continue to rise sharply, reflecting resilience in broader cryptocurrency adoption or speculative behavior independent of macro pressures. In the neutral regime (gray), factors like Size and Value display contrasting behaviors, with Value strengthening while Size delivers negative performance. These deviations emphasize the complexity of digital asset markets, where risk factors are influenced not only by monetary regimes but also by intrinsic market characteristics, investor behavior and possibly other macroeconomic regimes.

Last but not least, we again leverage correlation heatmap analysis to determine the level of historical interdependence between factors. Figure 5 shows that factors have exhibited low correlations during the observed time period, suggesting they are suitable for inclusion in a factor model. Notably, the value and growth factors show a near-zero correlation. While growth assets were initially viewed as the short portfolio of the value factor and not a factor per se - resulting therefore into a strong negative correlation with value - it quickly evolved into a factor of its own and with a definition that is clearly distinct from that of value, as we showed in section 4.2.5. It is for this reason why we do not expect nor do observe a meaningful correlation between the two.

Lastly, some factors exhibit slightly higher correlations, namely Liquidity and Downside Beta (0.42). This relationship may stem from the behavior of high-liquidity and high-downside-beta assets, which often attract short-term traders and speculators during periods of heightened volatility. As such, these assets tend to underperform concurrently during market downturns, reinforcing the observed correlation. However, a correlation of 0.42 is generally regarded as weak to moderate and unlikely to pose any issues for our purposes i.e. in the context of regressions for example. Specifically, it falls well below the commonly accepted threshold of 0.6 for regression multicollinearity concerns.

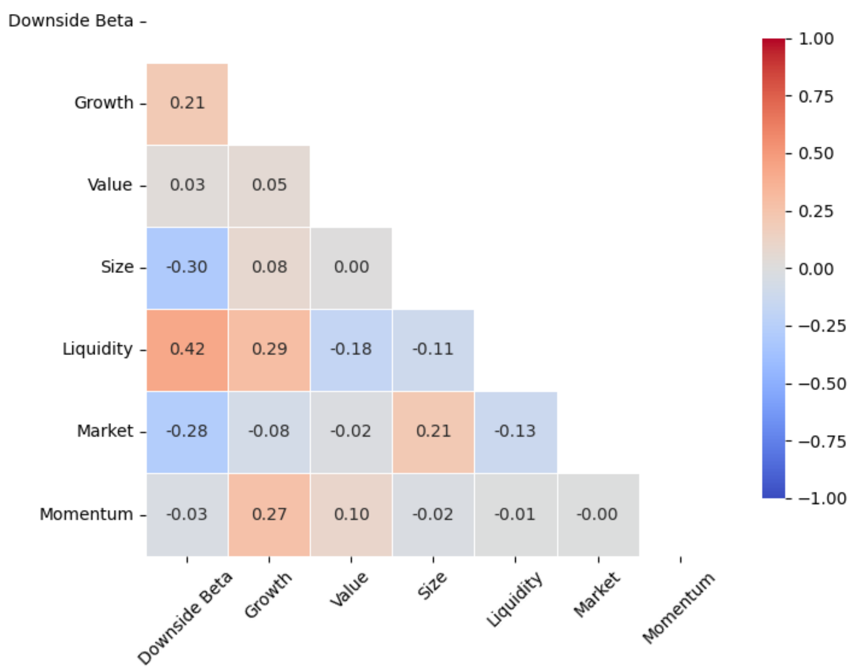

Figure 5: Factor Correlation Heatmap

4.3 Factor Model

In this section, we construct a factor model using the aforementioned factors and evaluate its significance and effectiveness in explaining return variations in digital assets. There are two primary approaches to building factor models, each with its own advantages and limitations: the Fama-French approach [7] and the Fama-MacBeth approach [8]. We will begin with the Fama-French time-series approach.

4.3.1 Time-Series Regression Model

The Fama and French approach provides a framework for understanding how different factors contribute to the variation in returns of a given asset or portfolio. Their general methodology is the following.

1. Identify factors: The first step in constructing a factor model involves identifying and quantifying different factors that could relate to the variability of a portfolio's return. Some generic examples in equities could include company size, market risk, book-to-market ratio, momentum, etc. In general, the goal is to capture as many dimensions of risk as possible.
2. Create factor portfolios: To capture these identified factors, we construct portfolios that represent each one. For example, to capture the size factor, we can create two portfolios: one consisting of small-cap stocks, and the other of large-cap stocks. The return on the small-cap portfolio minus the return on large-cap portfolio becomes the size or SMB (Small Minus Big) factor.
3. Calculate factor returns: For each period in our sample, calculate the return for each of the factor portfolios. These calculations yield time series returns for each factor.
4. Run Regression Analysis: The final step involves running a time-series regression analysis. Here, the returns of a particular asset or portfolio are regressed on the returns of the factor portfolios.

The factor model regression for a given asset or portfolio i is given by:

$$R_{i,t} = \alpha_i + \beta_{i,1} F_{1,t} + \beta_{i,2} F_{2,t} + \cdots + \beta_{i,k} F_{k,t} + \varepsilon_{i,t} \tag{1}$$

where:

- $R_{i,t}$ represents the returns of the asset or portfolio i at time t
- α_i is the intercept for asset or portfolio i.
- $\beta_{i,k}$ are the factor loadings (coefficients) of asset or portfolio i for factor k.
- $F_{k,t}$ is the factor portfolio k at time t.
- $\varepsilon_{i,t}$ represents an error term for asset or portfolio i at time t.

On this basis we perform liner regressions with respect to the asset returns. Table 4, Appendix B, provides a comprehensive distribution summary of the absolute T-Statistic values, R-squared and F-Statistics. The last column highlights how frequently each factor produces statistically significant T-Statistics (greater than 1.96 or less than -1.96) across 126 regressions. The risk factor model reveals that the Market factor is the most significant driver of returns, with 97.62% of regressions showing statistically significant T-Statistics, highlighting its dominant role in explaining asset performance. Downside Beta (38.10%) and Growth (37.30%) emerge as critical contributors, with Downside Beta capturing performance during market downturns and Growth emphasizing the influence of network expansion and adoption. Size (28.57%) and Liquidity (23.02%) also demonstrate significance, underscoring their relevance in explaining return variations linked to asset market capitalization scale and trading activity. Similarly, Value (19.05%) and Momentum (15.08%) provide meaningful contributions, reflecting valuation dynamics and price trends, respectively. Finally, the constant term shows low significance frequency (5.56%), reinforcing the model's ability to capture key risk factors over baseline returns. The overall strong R-squared values (median: 0.45) in the context of a factor model, validate the model's explanatory power across most regressions, while the significant F-Statistics (median p-value: 0.00) further confirm the robustness of the included factors in explaining asset performance.

To ensure robustness in our results, we investigate the variation in the Median Absolute Constant Term (MAC) across various factor models applied to all 126 regressions, as shown in Table 5, Appendix B. A lower MAC indicates that the included factors more effectively capture the systematic drivers of asset returns, leaving less unexplained variation in the constant term. The analysis reveals that virtually all models with multiple factors exhibit lower MAC values compared to single-factor models, demonstrating improved explanatory power. For instance, the Market model has an MAC of 0.0070, while the multi-factor model combining Market, Downside Beta, Value, and Size achieves one of the lowest MAC of 0.0051 with a minimal set of independent variables, indicating that this combination captures systematic drivers of returns very effectively. This finding is consistent with the results in Table 4, Appendix B, where these factors exhibit relatively high T-Statistic significance frequencies (e.g., Downside Beta: 38.10%, Size: 28.57%, and Value: 19.05%).

As for the addition of the remaining factors, this provides diminishing returns in reducing MAC. The addition of Momentum appears to only marginally improve the aforementioned model, while the inclusion of Liquidity does not provide any further enhancement. Conversely, the addition of Growth appears to slightly worsen the model, resulting in slightly higher MAC values. For example, the fully extended model with all factors, including Momentum, Growth, and Liquidity, results in a MAC of 0.0064 compared to 0.0051 for the more streamlined model. While these factors may appear less impactful in reducing the MAC, they are likely to still contribute valuable depth and nuances to the model, enhancing its robustness and balance, as indicated in the T-Statistic analysis (Momentum: 15.08%, Liquidity: 23.02%, Growth: 37.30%).

We also show in Table 1 the variation in R-squared across the different models and draw largely the same conclusions as above. Namely the Market, Downside Beta, Value, Size & Momentum model improves R-squared from 38.11% to 42.76%, emphasizing their relevance. Extending the model with the Growth and Liquidity factors further improves the R-squared to 45.25%, reinforcing the importance of incorporating additional factors to capture the complexities of asset returns.

Next and for illustration purposes, we present the regression summary for the top 50 assets ranked by market cap in our universe as of November 2024, shown in Table 2. The coefficients represent the sensitivities of asset returns to each risk factor, quantifying how changes in these factors influence performance. Significance levels are indicated by stars: one star ($*$) denotes significance at the 10% level, two stars ($**$) at the 5% level, and three stars ($***$) at the 1% level.

- The constant term (intercept) generally represents the baseline return of an asset that cannot be explained by the included factors. Significant constants (denoted by the number of ***) are observed for a few assets, such as DOGE and KAS, suggesting the model has not fully explained the average return of these assets. This could point to omitted variables not included in the model or unique features of such assets driving consistent returns. For most assets, however, the constant is not significant, implying that the factors included explain a good part of the return variation.
- Market Factor: highly significant across all assets, with positive coefficients ranging from

Model	Median R-squared
Market	0.3811
Market, Size	0.3883
Market, Value	0.3850
Market, Downside Beta	0.3975
Market, Momentum	0.3867
Market, Liquidity	0.3892
Market, Growth	0.3919
Market, Size, Value	0.3929
Market, Downside Beta, Value	0.4036
Market, Downside Beta, Size	0.4099
Market, Downside Beta, Value, Size	0.4137
Market, Downside Beta, Value, Momentum	0.4131
Market, Downside Beta, Value, Size, Momentum	0.4276
Market, Downside Beta, Value, Size, Growth	0.4405
Market, Downside Beta, Value, Size, Liquidity	0.4207
Market, Downside Beta, Value, Size, Liquidity, Growth	0.4473
Market, Downside Beta, Value, Size, Liquidity, Momentum	0.4361
Market, Downside Beta, Value, Size, Momentum, Growth	0.4459
Market, Downside Beta, Value, Size, Momentum, Growth, Liquidity	0.4525

Table 1: Median R-squared Across Different Factor Models

moderate (ADA: *0.83****) to high (LDO: *1.76****, FLOKI: *1.93****). These coefficients represent the sensitivity of asset returns to overall market movements, indicating that market-wide trends are the dominant driver of returns. This aligns with the notion that systematic market risk plays a central role in asset pricing.

- Downside Beta exhibits significant negative coefficients for several assets, such as DOGE (*-4.90****) and FLOKI (*-4.82****), emphasizing their susceptibility to adverse market movements. However, some assets like LDO (*1.81**, significant) show negligible or insignificant downside risk exposure, reflecting their relative stability compared to smaller or more speculative assets.

- The significance and magnitude of the Value factor vary across assets, reflecting differing sensitivities to this factor. Assets such as BNB (*0.92****), TRX (*0.97****), and OP (*1.91****) show positive exposure, indicating higher valuation metrics and potential to capture risk premium associated with the Value factor, albeit with greater exposure to its inherent risks. In contrast, assets like AR (*-1.41****) and FET (*-1.72****) exhibit significant negative exposure, suggesting they may be perceived as overvalued or tied to lower valuation metrics. These sensitivities can guide investment strategies: positively exposed assets might perform well in stable or growth-oriented markets, while negatively exposed assets could offer opportunities for contrarian strategies or in specific market regimes.

- The Momentum factor exhibits varied significance across assets. For example, BCH (-*1.16***) displays significant negative exposure, indicating that this asset fails to gather any momentum risk premium and in fact tends to perform poorly when the momentum factor performs well and viceversa. This also suggests that assets like BCH exhibit low momentum, characterized by weak or negative past performance. In contrast, JASMY (*1.55*) displays positive but insignificant momentum, hinting at weak trend-following behavior, where past positive performance might lead to continued gains.
- Size factor exposure shows notable variation. For instance, FET (*2.33****) demonstrates significant positive exposure, likely linked to its speculative nature and smaller capitalization while DOGE (*-5.25****) highlights negative exposure.
- Growth: generally significant, with assets like NEAR (*2.54****) and FET (*1.27***) showing strong positive returns tied to growth metrics. This indicates that such growth-oriented assets will naturally tend to perform nicely when growth premium is substantial, albeit in exchange for taking on the inherent risks associated with the growth factor
- Liquidity sensitivity is mixed. AR (*1.25***) demonstrates positive exposure, likely due to its low liquidity nature, while the likes of BCH (*-0.90***) exhibit negative exposure, indicating characteristics more aligned with liquid assets.

Overall, all factors demonstrate significant and relevant influence across assets, highlighting their importance in capturing the diverse risk-return characteristics within the digital assets market.

The model also demonstrates strong R-squared values for most assets, validating its ability to explain return variability effectively. However, for a few assets like TON (*R-squared: 0.09*), the model performs poorly, indicating potential influences from unaccounted factors. F-statistics are significant for the majority of assets (*p-value: 0.00****), further supporting the validity of the included factors.

Asset	Constant	Market	Downside Beta	Value	Momentum	Size	Growth	Liquidity	R-squared	Adjusted R-squared	F-statistic
ADA	-0.01	0.83***	-1.06***	-0.44	-0.48	-0.46	0.90***	-0.07	0.45	0.43	0.00***
APT	-0.01	1.11***	-1.37	-0.86	-0.80	0.28	3.58***	-1.75*	0.56	0.53	0.00***
AR	0.01	1.18***	-2.74***	-1.41***	0.49	0.31	2.01***	1.25**	0.41	0.39	0.00***
ATOM	-0.01	0.92***	-1.20***	-0.41	-0.25	-0.24	1.37***	-0.59	0.49	0.47	0.00***
AVAX	-0.00	1.27***	-1.79***	-1.63***	0.53	-0.73	2.80***	0.60	0.50	0.48	0.00***
BCH	0.00	1.11***	-0.62	-0.24	-1.16**	-1.40***	-0.27	-0.90**	0.51	0.50	0.00***
BNB	0.00	0.86***	-0.43	0.92***	0.54*	0.16	0.05	0.47*	0.57	0.56	0.00***
BTC	0.00	0.95***	-0.08	0.00	0.07	0.06	-0.04	0.08	0.96	0.96	0.00***
DOGE	0.03**	0.98***	-4.90***	0.87	-0.57	-5.25***	-4.25***	-1.52*	0.54	0.53	0.00***
DOT	-0.01**	1.05***	-1.08***	-0.34	0.23	-0.00	0.62**	0.36	0.65	0.64	0.00***
ETC	0.01	1.31***	0.59	1.29**	-0.62	-1.06	-0.02	-2.14***	0.40	0.38	0.00***
ETH	0.00	1.14***	0.26	0.04	-0.18	-0.17	0.11	-0.32*	0.82	0.81	0.00***
FET	0.02*	1.32***	-1.90***	-1.72***	-0.32	2.33***	1.27**	-0.98*	0.55	0.53	0.00***
FIL	-0.01	1.07***	-0.82	-0.13	0.00	0.47	0.79*	-0.82*	0.45	0.43	0.00***
FLOKI	0.03	1.93***	-4.82***	3.15**	-5.55***	-3.93***	-2.88*	-1.27	0.50	0.47	0.00***
FTM	0.01	1.47***	-2.05**	-1.90***	0.10	0.95	2.65***	-1.68**	0.47	0.45	0.00***
GRT	-0.01	1.13***	-1.06**	-0.88***	0.17	1.27***	0.65*	-0.73**	0.62	0.60	0.00***
HBAR	-0.00	0.82***	-0.69	-0.53	0.27	1.29***	0.51	-0.60	0.44	0.42	0.00***
ICP	-0.01	1.04***	-0.60	-0.14	-1.34**	2.13***	0.89*	-0.16	0.41	0.38	0.00***
IMX	-0.00	1.24***	-0.11	-0.53	-0.15	1.80***	2.10***	-1.24*	0.50	0.47	0.00***
INJ	0.01	1.23***	-0.87	-0.67	-0.20	0.78	0.86*	-0.14	0.42	0.39	0.00***
JASMY	0.01	1.25***	-0.98	-0.86	1.55	2.49**	-0.17	1.47	0.21	0.17	0.00***
KAS	0.05*	0.60	1.63	-0.47	-1.47	-0.63	4.32**	-0.59	0.08	0.02	0.22
LDO	0.01	1.76***	1.81*	-0.15	-0.99	0.63	2.37***	-1.77**	0.34	0.32	0.00***
LINK	-0.00	1.00***	-0.19	-0.32	-0.67*	-0.25	0.06	-1.10***	0.58	0.56	0.00***
LTC	-0.01	0.92***	-0.58*	0.14	-0.84***	-0.50*	0.24	-0.65**	0.62	0.60	0.00***
MATIC	0.01	1.09***	-1.59**	-0.15	-1.33**	1.23*	0.82	-0.14	0.38	0.35	0.00***
MKR	0.00	0.69***	-0.58	-0.08	-0.31	0.27	-0.51	-0.14	0.30	0.28	0.00***
NEAR	0.00	1.29***	-2.38***	-0.62	0.21	1.31**	2.54***	0.16	0.53	0.51	0.00***
OP	-0.00	1.49***	-1.13	1.91*	-0.36	0.82	1.16	-0.70	0.48	0.45	0.00***
RENDER	0.03	1.04***	-1.78	-1.40	0.49	1.31	3.48***	-1.64	0.21	0.18	0.00***
SHIB	0.03**	1.02***	-6.82***	0.30	1.37	0.36	-3.69***	1.88**	0.41	0.39	0.00***
SOL	0.01	1.22***	-1.19**	-0.95**	0.23	-1.15**	2.76***	0.06	0.47	0.45	0.00***
STX	0.01	1.12***	-0.29	-0.09	0.71	1.85***	-0.43	-0.36	0.39	0.37	0.00***
THETA	-0.00	1.13***	-1.37***	-0.01	-0.18	0.30	0.29	-0.54	0.54	0.53	0.00***
TON	0.01	0.27	-0.27	0.49	-0.61	-0.78	1.37*	-0.06	0.09	0.02	0.23
TRX	0.01	0.63***	0.34	0.97***	0.16	0.03	-0.29	-0.51*	0.39	0.37	0.00***
UNI	-0.00	1.08***	-1.06**	0.38	-0.16	0.09	-0.20	-0.09	0.54	0.52	0.00***
VET	0.00	1.07***	-0.98**	0.41	0.54	0.32	-0.89**	-0.39	0.55	0.53	0.00***
XLM	-0.01	0.74***	-0.34	0.05	-0.08	0.03	0.11	-0.33	0.47	0.44	0.00***
XMR	-0.00	0.74***	-0.22	0.87***	-0.34	-0.33	-0.11	0.14	0.49	0.47	0.00***
XRP	0.00	0.81***	-0.02	0.36	0.77	0.20	-0.11	-0.84	0.26	0.23	0.00***

Table 2: Regression Output for Top 50 Assets (by MCap) as of Nov 10th, 2024

Overall, applying the Fama-French approach to analyze cryptocurrency returns yields robust results. All factors demonstrate significance, capturing the diverse nuances of cryptocurrency behavior, with each asset exhibiting varying levels of exposure across factors—highlighting distinct return drivers for different assets. The model achieves good R-squared values, indicating a reasonable ability to explain return variability across assets. While the insights provided by the model are valuable, the inherent volatility of cryptocurrencies underscores the need for caution and due diligence in investment decisions. Conclusively, the Fama-French approach proves instrumental in cryptocurrency asset pricing and risk management strategies.

4.3.2 Cross-Sectional Regression Model

Unlike the Fama-French Time-Series approach, the Fama-MacBeth procedure is a two-stage process that uses cross-sectional regressions and involves no factor time-series at the estimation stage. The first step estimates asset betas using individual asset time-series regressions, while the second step runs a cross-sectional regression each period to estimate the factor risk premiums. This is designed to estimate whether risk factors are capable of explaining asset returns in the cross-section and in understanding whether the estimated risk premiums are significant and if so, how they evolve over time

Below we provide the methodology we follow to implement the Fama-MacBeth two-stage procedure:

First Stage: Run time-series regressions for each asset i $(i = 1, \ldots, N)$ to estimate the factor loadings (betas):

$$R_{i,t} = \alpha_i + \beta_{i,F_1} F_{1,t} + \beta_{i,F_2} F_{2,t} + \cdots + \beta_{i,F_m} F_{m,t} + \epsilon_{i,t} \tag{2}$$

where R_{it} represents the return for asset or portfolio i at time t, F_{jt} denotes the factor j at time t, and β_{i,F_m} the factor exposures of the asset or portfolio returns.

Second Stage: For each period t $(t = 1, \ldots, T)$, run cross-sectional regressions to estimate risk premia λ:

$$R_{it} = \gamma_t + \beta_i \lambda_t + u_{it} \tag{3}$$

In this equation, R_{it} represents the cross-section of assets, namely asset's i return at time t, β_i is the vector of factor loadings estimated from the first stage, and λ_t reflects the risk premium for each factor. The time average of the λ_t estimates provides the Fama-MacBeth estimate of the risk premium associated with each factor.

To conduct our analysis using the Fama-MacBeth approach, we employ the same set of factors as in the Fama-French model: market, size, value, momentum, growth, downside beta and liquidity. The time-series regression is performed on a rolling basis with a 30-week lookback window. In the second step, the estimated factor loadings from the rolling regressions are used to perform cross-sectional regressions for each week in the sample, yielding weekly estimated risk premiums for each factor.

First, we present the Fama-MacBeth regression output for the week ending on November 10th, 2024, in Table 3. This table reflects the risk premiums generated by each factor during this period. The Market factor (0.1843^{***}) provided a substantial premium for systematic risk exposure, while Value (-0.0232^{**}) and Downside Beta (-0.0302^{***}) showed negative premiums, penalizing undervalued assets and those with lower downside risk. Growth (0.0175^{**}) delivered a modest positive premium, rewarding assets linked with high network or fee expansion, whereas Liquidity (-0.0328^{***}) indicated a penalty for assets with low token turnover. Size (0.0099) and Momentum (0.0047) were insignificant, suggesting that neither the scale of an asset nor its prior price trends were significant drivers of returns in this specific period. These results underscore the diverse economic and risk drivers influencing cryptocurrency returns for the given week. The model demonstrates solid explanatory power, comparable to what is typically observed in traditional financial markets. With an R-squared of 0.4413, the included factors collectively explain approximately 44% of the return variability. Moreover, the F-statistic ($p - value = 0.0000$) confirms the model's overall significance, underscoring the relevance of the selected factors in capturing the key drivers of cryptocurrency returns.

Variable	Market	Value	Downside Beta	Growth	Size	Liquidity	Momentum	Const
Coefficient	0.1843***	-0.0232**	-0.0302***	0.0175**	0.0099	-0.0328***	0.0047	-0.0306
T-Statistic	(7.96)	(-3.29)	(-5.60)	(2.80)	(1.48)	(-5.45)	(0.52)	(-1.27)
R-squared	Adjusted R-squared	F-statistic P-Value						
0.4413	0.4103	0.0000						

Table 3: Regression Results as of November 10th, 2024

Table 6, Appendix B, highlights the significance of the included factors in explaining cryptocurrency returns, with absolute T-Statistic values greater than 1.96 indicating strong statistical relevance. The Market factor stands out with a mean T-Statistic of 3.22, confirming its dominant role across regressions. Downside Beta (2.88), Growth (2.33), and Liquidity (2.63) demonstrate substantial significance, capturing critical dimensions such as downside risk exposure, network expansion, and trading activity. Similarly, Size (2.77), Momentum (2.57), and Value (2.07) also exhibit strong contributions, reflecting their relevance in explaining asset scale, price trends, and valuation dynamics, respectively.

In contrast, the constant term, with a mean T-Statistic of 1.60, consistently falls short of significance, reinforcing the robustness of the model in capturing systematic drivers of return variability. The model's overall performance is further validated by a mean R-squared of 0.32, indicating the factors collectively explain a meaningful portion of return variability, and consistently low F-statistic p-values (0.04), once again confirming the statistical significance of the model.

We next present in Figure 6 the Fama-MacBeth weekly R-squared values, alongside its 8-week moving average to better visualize the underlying trend. As shown, the model demonstrates strong reliability during this period, capturing between 20% and 70% of the variation in cross-sectional cryptocurrency returns. Peaks in R-squared, such as those observed in mid-2022 and early 2024, highlight periods where the factors collectively provided substantial explanatory power, while troughs, such as those in early 2023, reflect times of reduced explanatory power, potentially due to heightened idiosyncratic risk or unaccounted factors. The smoothed trend further emphasizes the model's consistent ability to capture key drivers of cryptocurrency returns over time.

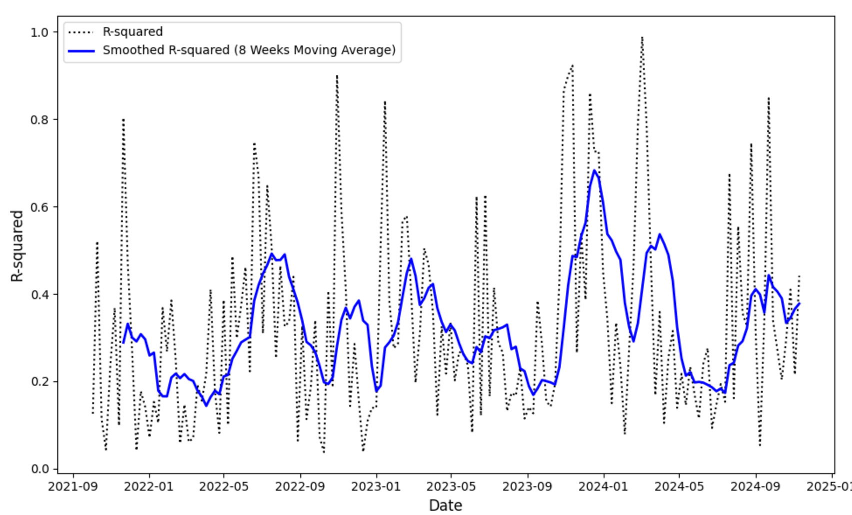

Figure 6: R-squared Time-series

Figure 16 displays the 12 weeks smoothed risk premiums. Notably, the weekly market risk premium, while fluctuating around zero, exhibits a consistent trend above the 0% mark, albeit a time varying one which also turns negative at times (representing a bearish market). This further underscores the significance of the market's risk premium in the digital asset context, as it displays substantial variance and power in explaining cryptocurrency returns. The constant term portrays a similar picture as the market factor, except that it is consistently below 0%, suggesting that although our model does a good job at capturing cryptocurrency return variation, there are still components not explained by the included factors. Moving on, we can observe that the Downside Beta and Liquidity factors generally exhibit more negative risk premiums over the analyzed period, penalizing assets with low downside risk and low liquidity. However, they also display intermittent positive trends, suggesting that their effects can vary depending on specific market conditions. Value and Growth follow a similar pattern but rather on the upside, with prolonged periods of positive returns followed by occasional downturns, and hence rewarding undervalued and high growth assets during our timeframe. As is common across asset classes, Momentum exhibits extremely high returns during positive phases, but also pronounced downturns during negative ones (often referred to as a momentum crash) and hence highlighting the risk premium that can be gathered based on past price trends. Last but not least, the size risk premium also displays clustered and time-varying returns similar to the other factors, with smaller assets outperforming larger ones in selected periods, and therefore highlighting their potential for higher returns in specific market conditions and increased sensitivity to risk. These observations underline the inherent complexities within the digital assets market and the differential impact of various factors on different cryptocurrencies. Consequently, understanding such dynamics can empower us to make more informed investment decisions in this continually evolving digital currency landscape.

5 Conclusion

Cryptocurrencies have become a focal point in the financial world due to their rapid growth and increasing prominence. This study seeks to better understand the factors that influence their value and returns. To achieve this, we employ two well-established financial models: the Fama-French and the Fama-MacBeth model. Our analysis investigates seven distinct risk factors: market, size, value, momentum, growth, downside beta, and liquidity.

The Fama-French model provides valuable insights into how these factors influence cryptocurrency asset or portfolio returns. However, the effects of these factors are not always the same as they vary across time, reflecting the complexity and dynamism of the cryptocurrency market. This variability is part of what makes the digital assets market so intriguing and challenging to analyze.The Fama-MacBeth model, on the other hand, offers a dynamic perspective by capturing how cryptocurrency cross-section risk premiums evolve over time, mirroring the market's unpredictable and ever-changing nature.

Our analysis reveals that the seven factors exhibit significant risk premiums and explanatory power for digital asset returns, albeit to differing degrees. Specifically, we find that value, momentum, and growth factors display the highest risk premiums in the Fama-French framework (aside from the market factor), while the remaining factors—size, liquidity, and downside beta—demonstrate positive but comparatively smaller returns. Consistent with findings in traditional finance, the market factor accounts for the largest share of the explanatory power in the Fama-French model. However, we also establish that the value, growth, downside beta, and size factors contribute significantly to capturing additional variance in asset returns not explained by the market. The remaining factors (momentum and liquidity) contribute to a lesser extent, yet still offer complementary insights by capturing unique nuances of the digital assets ecosystem. From the Fama-MacBeth perspective, our findings are consistent with the above observations. All seven risk premiums exhibit strong statistical significance, underscoring their relevance in explaining cross-sectional asset returns. Additionally, we observe notable time variability in these premiums, reflecting the dynamic nature of risk pricing over the observed period. This reinforces the importance of incorporating time-varying factors into asset pricing models for a more nuanced understanding of return drivers.

While these seven factors demonstrate significant capability in capturing risk premiums and explaining digital asset returns, our research also highlights a substantial portion of variance in returns that remains unexplained. This underscores the need for further exploration of additional factors that could better capture this unexplained variance. The unique transparency of blockchain technology, with its real-time recording and streaming of financial and activity-related data, offers an unparalleled opportunity to explore new descriptors. Future research could investigate factors such as supply inflation, staking activity, on-chain sentiment, and other crypto-native metrics to expand our understanding.

Moreover, while we present a (monetary) regime analysis framework in this study, it merely scratches the surface. A more comprehensive approach incorporating advanced traditional financial regime classifications, alongside crypto-specific regimes, is likely to yield deeper insights into the behavior of these factors under different macroeconomic and crypto-specific conditions.

In conclusion, this research lays the groundwork for further studies into cryptocurrency risk factors, highlighting the importance of both traditional finance principles and crypto-specific innovations. The dynamic and evolving nature of the cryptocurrency market presents an exciting journey to fully understand the digital assets world and its place in modern finance.

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Appendix A

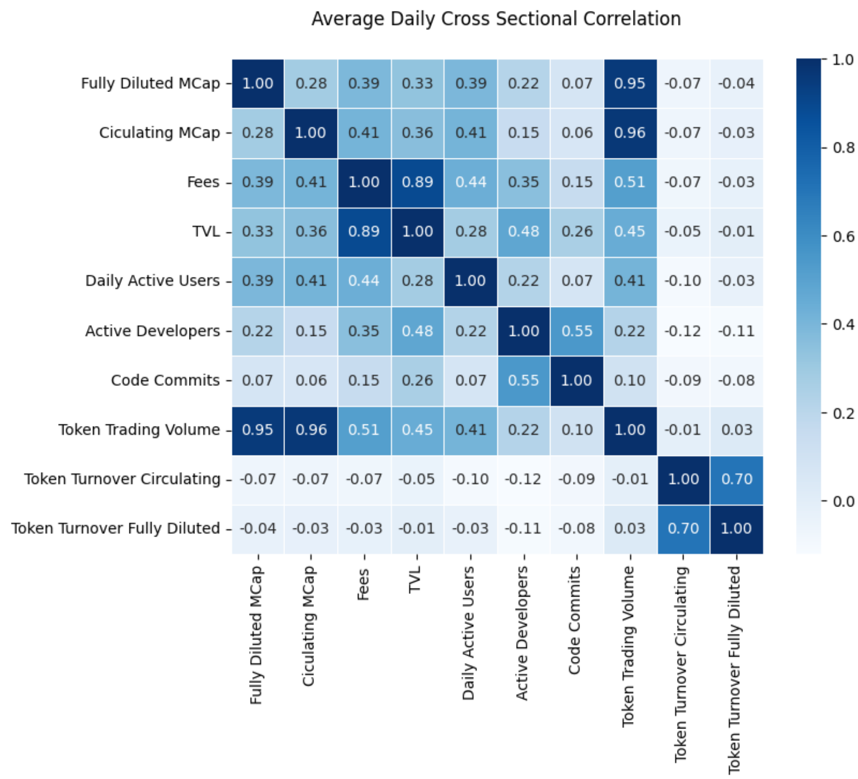

Figure 7: Descriptor Correlation Heatmap

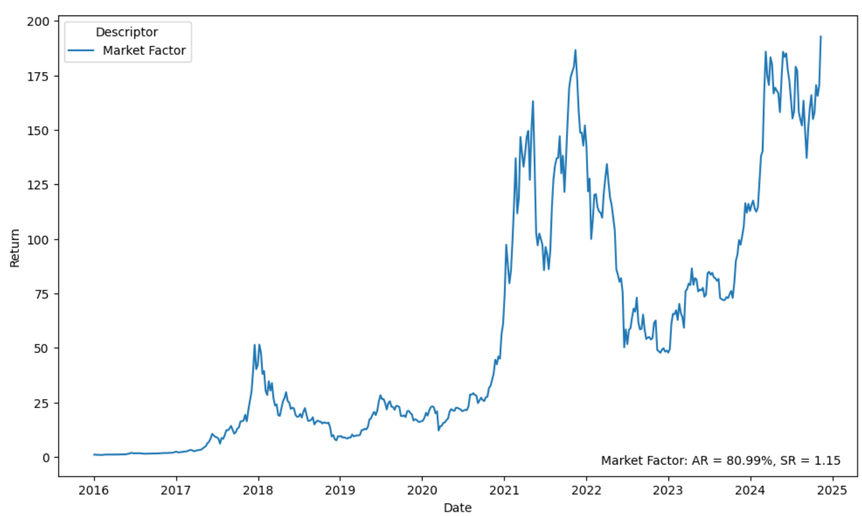

Figure 8: Market Factor

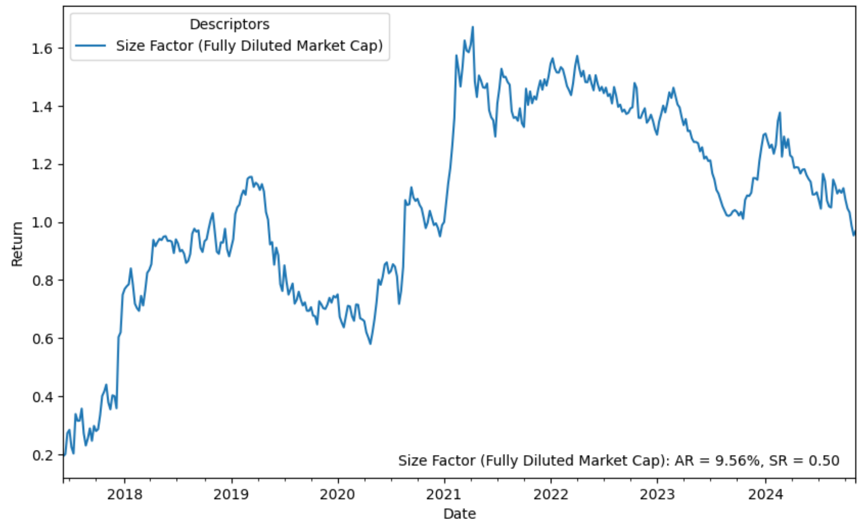

Figure 9: Size Factor

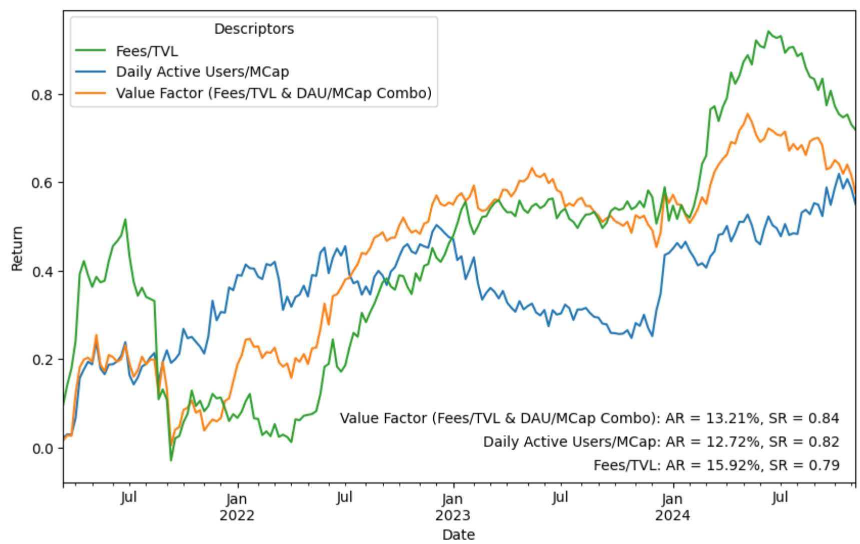

Figure 10: Value Factor

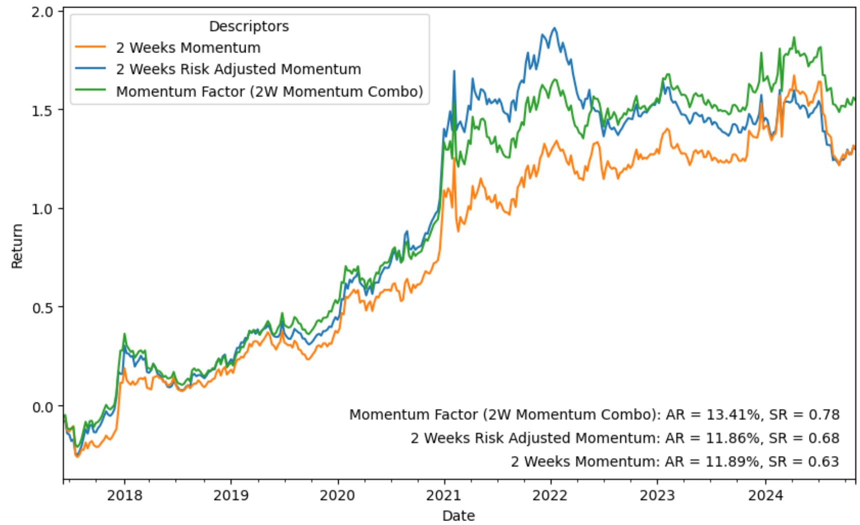

Figure 11: Momentum Factor

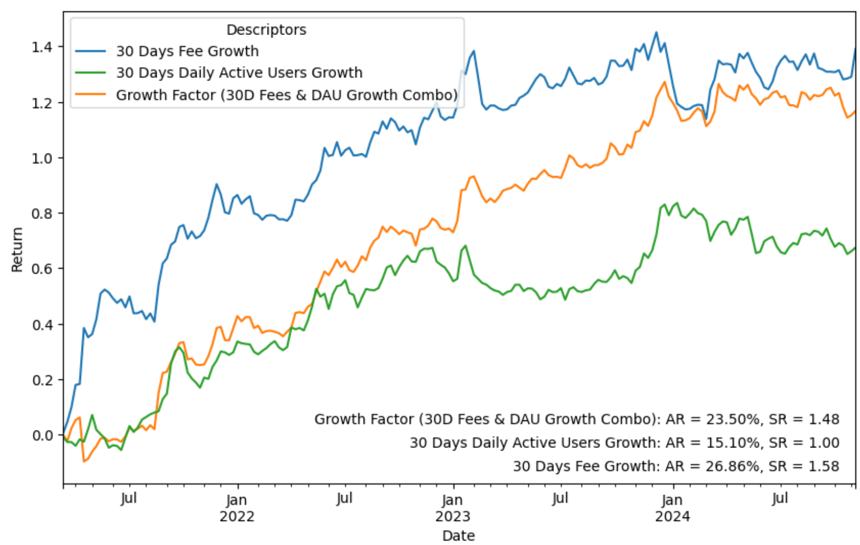

Figure 12: Growth Factor

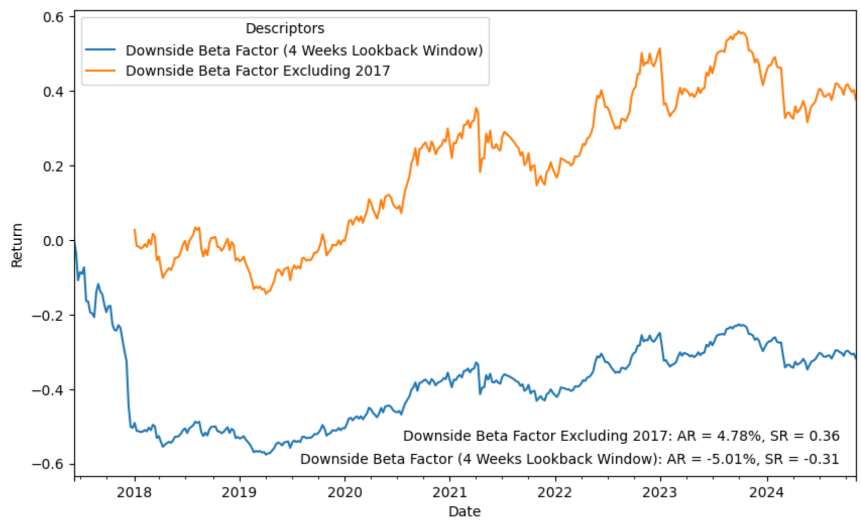

Figure 13: Downside Beta Factor

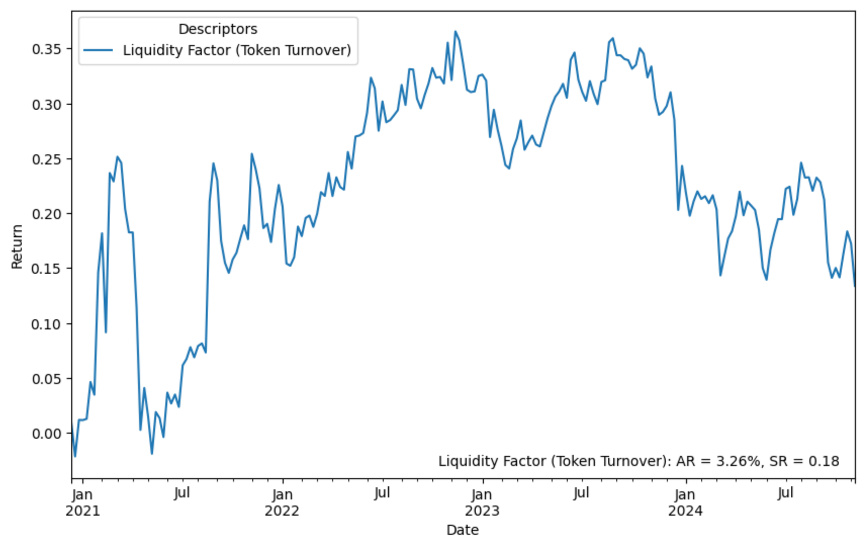

Figure 14: Liquidity Factor

Figure 15: Factor Analysis Across Macroeconomic Cycles

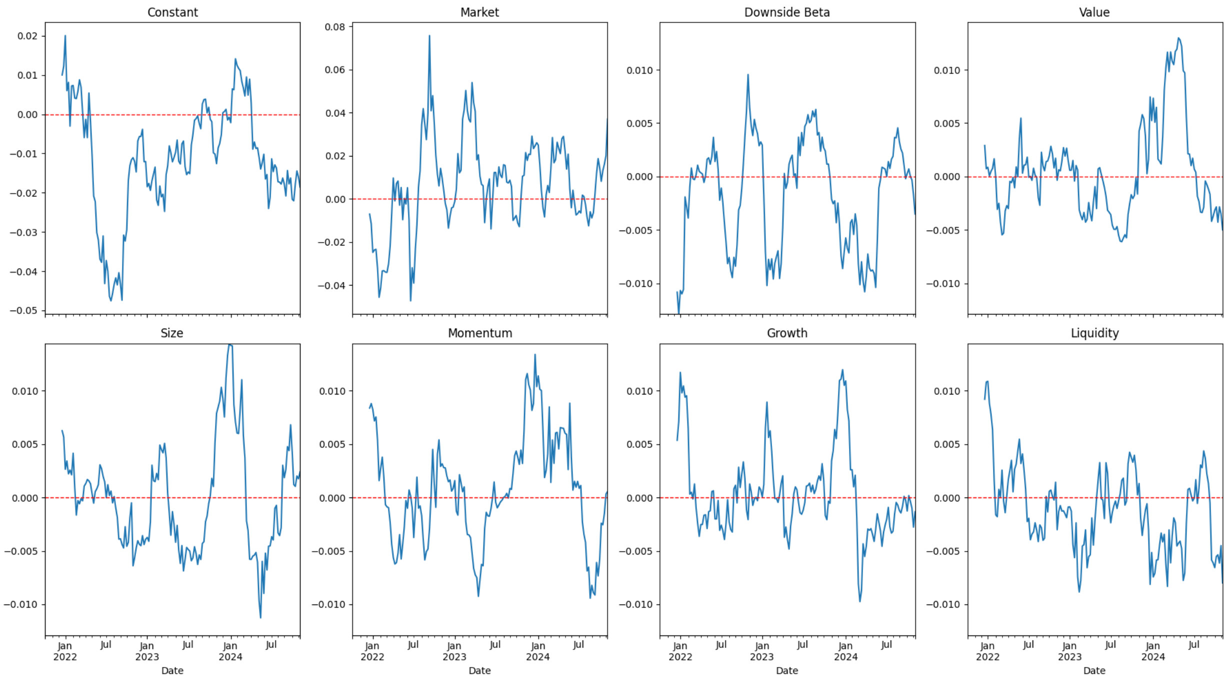

Figure 16: Fama-MacBeth Daily Risk Premiums

Appendix B

Variable	Count	Mean	Std	Min	25%	50%	75%	Max	% of Significant T-Stats
Constant	126	0.78	0.58	0.01	0.32	0.71	1.04	2.31	5.56
Momentum	126	1.13	0.81	0.00	0.53	1.00	1.51	4.29	15.08
Value	126	1.17	1.06	0.00	0.36	0.87	1.51	4.79	19.05
Liquidity	126	1.26	0.93	0.01	0.48	1.09	1.86	4.17	23.02
Size	126	1.44	1.05	0.01	0.63	1.24	2.06	6.06	28.57
Growth	126	1.70	1.22	0.03	0.77	1.45	2.37	5.79	37.30
Downside Beta	126	1.75	1.20	0.04	0.86	1.50	2.44	6.54	38.10
Market	126	9.62	6.00	1.12	7.08	8.93	11.35	63.96	97.62
R-squared	126	0.43	0.14	0.05	0.35	0.45	0.54	0.96	–
F-Statistic P-Value	126	0.01	0.04	0.00	0.00	0.00	0.00	0.26	–

Table 4: Summary for Absolute T-Statistic Values, Regression Metrics, and Frequency of Significant T-Statistics across 126 Fama-French Regressions

Model	Median Absolute Constant Term
Market	0.0070
Market, Size	0.0068
Market, Value	0.0066
Market, Downside Beta	0.0061
Market, Momentum	0.0066
Market, Liquidity	0.0069
Market, Growth	0.0073
Market, Size, Value	0.0057
Market, Downside Beta, Value	0.0060
Market, Downside Beta, Size	0.0061
Market, Downside Beta, Value, Size	0.0051
Market, Downside Beta, Value, Momentum	0.0057
Market, Downside Beta, Value, Size, Momentum	0.0051
Market, Downside Beta, Value, Size, Growth	0.0059
Market, Downside Beta, Value, Size, Liquidity	0.0051
Market, Downside Beta, Value, Size, Liquidity, Growth	0.0062
Market, Downside Beta, Value, Size, Liquidity, Momentum	0.0051
Market, Downside Beta, Value, Size, Momentum, Growth	0.0060
Market, Downside Beta, Value, Size, Momentum, Growth, Liquidity	0.0064

Table 5: Summary of Median Absolute Constant Term Across Different Fama-French Factor Models

Variable	Count	Mean	Std	Min	25%	50%	75%	Max
Downside Beta	163	2.88	4.10	0.001	0.73	1.78	3.74	43.28
Growth	163	2.33	2.50	0.042	0.90	1.64	3.06	16.96
Liquidity	163	2.63	2.62	0.005	0.95	1.92	3.58	19.34
Market	163	3.22	3.60	0.013	1.00	2.67	3.94	31.26
Momentum	163	2.57	3.71	0.035	0.76	1.50	2.71	29.64
Size	163	2.77	3.45	0.005	0.79	1.84	3.72	30.36
Value	163	2.07	2.59	0.012	0.61	1.22	2.66	18.34
Constant	163	1.60	1.45	0.008	0.59	1.27	2.02	8.29
R-squared	163	0.32	0.22	0.04	0.15	0.27	0.41	0.99
F-statistic p-Value	163	0.04	0.14	0.00	0.00	0.00	0.01	0.73

Table 6: Summary Fama-MacBeth Absolute T-Statistics Values and Regression Metrics

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