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Mispricing and Risk Compensation in Cryptocurrency Returns

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Abstract

We examine the role of systematic mispricing and risk compensation in explaining cryptocurrency returns using instrumented principal component analysis. We demonstrate that both elements make meaningful contributions to the variation in returns through distinct economic mechanisms. Mispricing primarily operates through behavioral channels, capturing speculative demand and liquidity frictions. A pure-alpha strategy delivers large and significant Sharpe ratios, confirming the economic importance of mispricing. Risk compensation is driven by fundamental factors, including past performance and exposures to both cryptocurrency and equity market risk. Consistent with this equity exposure, we document increasing correlation between cryptocurrency and equity returns over time.

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I. Introduction

A central question in empirical asset pricing is to what extent the variation in asset returns is driven by exposure to common risk factors and to what extent by a mispricing component. This distinction is not merely statistical; it reflects the fundamental economic forces at work. Traditional asset pricing theory posits that mispricing is idiosyncratic and transient, quickly eliminated by arbitrageurs, leaving risk compensation as the sole determinant of return variation. However, when arbitrage is costly or limited, predictable return variation that is unrelated to common factors can emerge (Stambaugh and Yuan, 2017).

Cryptocurrency markets present a particularly compelling setting for this analysis. On the one hand, Makarov and Schoar (2020) show how trading fragmentation and frictions, limited arbitrage capital, and heterogeneous investor bases—ranging from sophisticated institutions to retail speculators—generate persistent mispricing that arbitrageurs cannot efficiently eliminate. On the other hand, cryptocurrencies exhibit systematic return patterns related to common factors, such as size and momentum (Liu, Tsyvinski, and Wu, 2022), suggesting that risk-based explanations of return predictability retain relevance.

We investigate this tension by leveraging the flexibility of instrumented principal component analysis (IPCA) – a conditional latent factor model where alphas and betas are explicitly linked to asset characteristics (Kelly, Pruitt, and Su, 2019). IPCA is particularly suited for our analysis because it allows us to directly assess the extent to which systematic mispricing can explain the variation in expected returns conditional on common factor components.[1] We refer to Giglio, Kelly, and Xiu (2022) for a complete review of factor models in asset pricing.

Crucially, within the IPCA framework, asset characteristics can be associated with systematic mispricing, risk compensation, or both. If a characteristic significantly affects

[1]Conventional static factor models are often not designed to accommodate systematic mispricing, as their primary focus is on modeling comovements (Chen, Roussanov, and Wang, 2023).

conditional alphas, it indicates predictable mispricing related to fundamental asset properties. Conversely, if a characteristic affects conditional betas, it signals a role in determining time-varying exposures to common risk factors. This distinction is key to our contribution, as it allows us to empirically quantify which characteristics primarily drive mispricing and which drive risk compensation.

Using an unbalanced panel of over 600 cryptocurrencies from September 2017 to May 2023, we document three main findings that directly address the relative importance of systematic mispricing versus risk compensation in cryptocurrency returns. First, we establish that systematic mispricing and time-varying risk compensation play distinct but complementary roles in cryptocurrency markets. Systematic mispricing represents a substantial source of predictable return variation that operates independently of factor structure. Alphas conditioning on speculative demand, liquidity, and reversal remain strongly significant even after including up to eight latent factors. Furthermore, allowing for systematic mispricing substantially improves the model's predictive R^2 compared to specifications that restrict mispricing to zero. This improvement holds across latent IPCA factors, observable factors, and characteristic-managed portfolios. Pure-alpha portfolios generate economically and statistically significant returns that systematic factors cannot explain, demonstrating that mispricing represents genuine economic value rather than a statistical artifact.

Second, we quantify the relative contributions of different characteristics to mispricing and risk compensation. Recursive bootstrap tests reveal that speculative demand represents the most significant contributor to pricing inefficiencies throughout the sample, with this contribution intensifying during market run-ups. This suggests investors associate cryptocurrencies with lottery-like assets. Liquidity and volatility-related variables provide additional explanatory power for mispricing, while reversal characteristics become the primary drivers of weekly alphas. In contrast, core attributes—market exposure, size, and past performance—represent the most robust determinants of conditional betas for both daily and weekly returns. This quantitative

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decomposition demonstrates that both systematic mispricing and risk compensation play economically meaningful but distinct roles.

Third, we demonstrate that the risk compensation component is increasingly reflecting exposure to broader equity market factors rather than cryptocurrency-specific risks. Characteristics capturing individual cryptocurrency exposure to equity market returns significantly drive conditional betas, challenging conventional views on market segmentation (Liu and Tsyvinski, 2021). A simple spanning regression analysis supports this integration by showing that IPCA latent factors exhibit significant correlations with equity market factors, with these correlations increasing over time. This pattern is consistent with Pástor and Veronesi (2009): as investors and institutions gain more exposure to innovative sectors, information asymmetry and cross-market barriers diminish, leading to increased risk spillovers.

Our work is related to a growing body of literature that aims to understand the determinants of cryptocurrency returns. Following the blueprint proposed by Fama and French (1993) for equities, Liu et al. (2022) and Cong, Karolyi, Tang, and Zhao (2021) suggest a series of long-short portfolios based on cryptocurrency characteristics such as market capitalization, network growth, or past returns, to elucidate beta pricing relationships. In contrast, Borri, Massacci, Rubin, and Ruzzi (2022) assume that risk factors are latent. However, these approaches share a common limitation: they assume that mispricing is either absent or akin to an idiosyncratic error term, rather than recognizing it as an economically significant and systematic determinant of expected returns. This assumption may be particularly problematic for cryptocurrency markets where systematic mispricing may be endemic rather than transitory (Makarov and Schoar, 2020).

Existing studies have not examined the economic importance of mispricing versus risk compensation, nor quantified their respective contributions to cryptocurrency return variation. Our contribution fills this gap by explicitly modeling and quantifying both mispricing and risk compensation within the IPCA framework. Our results suggest that focusing solely on return comovement, whether captured by observable or latent factors, is suboptimal in the presence of structural fragmentation and market frictions.

In this respect, our work aligns with recent advances in equity markets (Kelly et al., 2019; Windmüller, 2022; Langlois, 2023), options markets (Büchner and Kelly, 2022; Goyal and Saretto, 2022), and corporate bonds (Kelly, Palhares, and Pruitt, 2022), which underscore the importance of distinguishing between systematic mispricing and risk compensation. Our findings suggest this distinction may be even more crucial for cryptocurrency markets given their unique structural features and the persistence of pricing inefficiencies.

II. Data and Empirical Design

We collect daily data on open, high, low, and close (OHLC) prices and 24-hour trading volume from CryptoCompare.com and the data on on-chain activity from IntoTheBlock.com. We screen out the so-called "wrapped" coins (e.g., WBTC), as they are copies of existing tokens, all stablecoins, and all synthetic derivatives (e.g., stETH, stSOL).

The main sample is from September 1st, 2017, to May 1st, 2023, where a day is defined with a start time of 00:00:00 UTC.[2] The price and volume data are aggregated across over 80 centralized exchanges based on the exchange-specific trading volume.[3] This implies that more prominent exchanges have relatively more weight in the aggregation than more peripheral ones.

[2]The sample period covers key events: the ICO mania of late 2017, the so-called "crypto-winter" of 2018-2019, the COVID-19 crash in March 2020, and the boom-bust cycle from 2021 to early 2022. It also covers significant institutional changes: the introduction of Bitcoin and Ether futures and Ethereum's transition from a proof-of-work to a proof-of-stake protocol.

[3]The exchanges that we include in the aggregation are the ones ranked from AA to B by CryptoCompare.com and thus deemed to provide a sufficiently reliable trading platform. The precise ranking of all exchanges appears on the company website at https://www.cryptocompare.com/exchanges/#/overview.

In addition to volume-weighted aggregated data, we consider OHLC prices and volume from four major centralized exchanges: Binance, Bitfinex, Kraken, and Poloniex. We take the perspective of a US investor, meaning that cryptocurrencies are traded against the USD or stablecoins, such as Tether USD (USDT), USD Coin (USDC), and Binance USD (BUSD).

To ensure sample quality, we implement several data filters. First, to address survivorship bias, we include failed coins that have had at least six months of transactions. Second, we remove observations with data quality issues, such as those with a closing price of zero or negative values, as well as those with missing returns, market capitalization, or trading volume. Third, we exclude returns below -100% or above $+150\%$ on a given day to mitigate the impact of extreme outliers, which eliminates less than 0.5% of erroneous or extreme observations. Appendix I provides more details.

The final sample comprises 630 cryptocurrencies. The cross-section contains just over 70 assets in September 2017, which restricts the beginning of our sample analysis to this date due to a too small cross-section in earlier periods. We note that the size of the cross-section is primarily determined by the availability of on-chain and social media activity data, and in this respect, is comparable to existing studies, such as Cong et al. (2021). Although the cross-section is smaller than the number of existing cryptocurrencies, the market value coverage is significant, ranging from 85% at the start of the sample to 70% towards the end. Appendix I provides more details, including summary statistics for daily returns of individual cryptocurrencies in our sample.

[Insert Table I here]

For our empirical analysis, we construct 35 asset characteristics, following existing practice in the cryptocurrency literature (Liu et al., 2022) and adapting several measures from the mainstream asset pricing literature (Kelly et al., 2019; Freyberger, Neuhierl, and Weber, 2020). We group them into nine categories: core characteristics (market, size, and momentum); reversal; on-chain activity; trading activity; liquidity; speculative demand; volatility and downside risk;

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social media activity; and equity market exposure measures such as the equity capm beta, the equity co-skewness (Harvey and Siddique, 2000), and the equity downside beta (Ang, Chen, and Xing, 2006). Table I defines characteristics briefly, while Appendix II provides more details.

A. A Brief Review of Instrumented PCA

Instrumented principal component analysis (IPCA) is particularly well-suited for examining the relative importance of systematic mispricing and risk compensation, as it allows both alphas and betas to vary over time as functions of observable asset characteristics. IPCA is defined as a conditional latent factor model for returns of a cryptocurrency i at time $t+1$:[4]

$$r_{i,t+1} = \alpha_{i,t} + \beta_{i,t} f_{t+1} + \epsilon_{i,t+1}, \tag{1}$$

where $\mathbb{E}_t\left[\epsilon_{i,t+1}\right] = 0,\ \mathbb{E}_t\left[f_{t+1}\epsilon_{i,t+1}\right] = 0$ and f_{t+1} is the vector of K latent factors extracted from cryptocurrency returns. Unlike standard factor models in which mispricing and factor loadings are static parameters, IPCA assumes these evolve based on asset characteristics:

$$\alpha_{i,t} = \boldsymbol{z}_{i,t}^{'}\Gamma_\alpha + \nu_{i,t}^{\alpha}, \qquad \beta_{i,t} = \boldsymbol{z}_{i,t}^{'}\Gamma_\beta + \nu_{i,t}^{\beta}, \tag{2}$$

[4]We use raw returns rather than excess returns for two reasons. First, cryptocurrency markets operate continuously 24/7, whereas risk-free rate data (e.g., short-term Treasury bills) are only available during business days. This creates a fundamental data mismatch. Second, and more importantly, the risk-free rate during our sample period was economically negligible (averaged 0.01%–0.02% daily at the beginning and end of the sample, and zero during 2020–2022). This compares to average cryptocurrency returns spanning from -7% to $+12\%$ daily (see Table A2). In a set of unreported results, we document that the IPCA asset pricing performance and the factor loadings are virtually identical when using raw returns or excess returns. The results are available from the authors upon request.

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where $\Gamma = [\Gamma_\alpha, \Gamma_\beta]$ are the loadings on the $L \times 1$ vector of asset characteristics $\boldsymbol{z}_{i,t}$. The scalar $\nu_{i,t}^{\alpha}$ and the $K \times 1$ vector $\nu_{i,t}^{\beta}$ are orthogonal to $\boldsymbol{z}_{i,t}$, allowing for the possibility that conditional alphas and betas may not be perfectly recoverable from observable characteristics.[5] Critically for our analysis, this framework allows us to assess whether a given characteristic contributes to systematic mispricing (if it significantly affects Γ_α) or risk compensation (if it significantly affects Γ_β). By comparing model specifications with ($\Gamma_\alpha \neq 0$) and without ($\Gamma_\alpha = 0$) the mispricing component, we can quantify the relative importance of these two explanations for cryptocurrency returns.

The model is estimated via an alternating least squares approach, which iterates the first order conditions of f_{t+1} and $\Gamma = [\Gamma_\alpha, \Gamma_\beta]$:

$$f_{t+1} = \left(\Gamma_\beta' Z_t' Z_t \Gamma_\beta\right)^{-1} \Gamma_\beta' Z_t' \left(r_{t+1} - Z_t \Gamma_\alpha\right) \qquad \forall t, \tag{3}$$

$$\operatorname{vec}(\Gamma) = \left(\sum_{t=1}^{T-1} Z_t' Z_t \otimes \widetilde{f}_{t+1} \widetilde{f}_{t+1}'\right)^{-1} \left(\sum_{t=1}^{T-1} \left[Z_t \otimes \widetilde{f}_{t+1}'\right]' r_{t+1}\right), \tag{4}$$

where $\widetilde{f}_{t+1} = \left[1, f_{t+1}'\right]'$, and $Z_t,\ r_{t+1}$ denote the stacked arrays of instruments and returns, respectively. To address the skewed cross-sectional distribution of some characteristics (such as market capitalisation), we cross-sectionally rank, demean, and scale $\boldsymbol{z}_{i,t}$ to be in the $[-0.5,\ 0.5]$ interval.[6]

Kelly et al. (2019) show that latent factors in IPCA can be replaced with observable

[5]This specification enables returns to update quickly based on timely information contained in characteristics rather than relying on stale parameter estimates from rolling window regressions.

[6]We follow the scaling rule of Kelly et al. (2019). For robustness, we replicate the empirical analysis by rescaling $\boldsymbol{z}_{i,t}$ to a wider $[-1,\ 1]$ interval. The results are virtually the same and are available upon request. We thank the anonymous referee for suggesting this check.

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portfolios while maintaining the characteristic-based conditioning:

$$r_{t+1} = \boldsymbol{z}_{i,t}'\Gamma\widetilde{g}_{t+1} + \eta_{t+1} = \mathrm{vec}\,(\Gamma)'\left(\boldsymbol{z}_{i,t} \otimes \widetilde{g}_{t+1}\right) + \eta_{i,t+1}, \tag{5}$$

where $\widetilde{g}_{t+1} = [1,\ g_{t+1}']'$ and g_{t+1} denotes the set of observable risk factors. We refer to this specification as an instrumented observable factor model and use it to verify that the importance of mispricing is robust to the choice of common factors.

III. Main Empirical Results

In this section, we address our central research question regarding the importance of systematic mispricing and risk compensation in explaining cryptocurrency returns. First, we compare different IPCA specifications that allow for time-varying alphas ($\Gamma_\alpha \neq 0$) against restricted versions that force systematic mispricing to zero ($\Gamma_\alpha = 0$). Second, we investigate the economic value of systematic mispricing by computing the out-of-sample performance of portfolios formed using predicted alphas. Third, we examine the distinct sources of mispricing and risk compensation via a series of bootstrap tests.

A. Asset Pricing Performance

Following Kelly et al. (2019), we compute total and predictive R^2 as:

$$R^2_{tot} = 1 - \frac{\sum_{i,t}\left(r_{i,t+1} - \widehat{\alpha}_{i,t} - \widehat{\beta}_{i,t}'\widehat{f}_{t+1}\right)^2}{\sum_{i,t} r_{i,t+1}^2}, \qquad R^2_{pred} = 1 - \frac{\sum_{i,t}\left(r_{i,t+1} - \widehat{\alpha}_{i,t} - \widehat{\beta}_{i,t}'\widehat{\lambda}\right)^2}{\sum_{i,t} r_{i,t+1}^2}, \tag{6}$$

where $\widehat{\alpha}_{i,t} = \boldsymbol{z}_{i,t}'\widehat{\Gamma}_\alpha$, $\widehat{\beta}_{i,t} = \boldsymbol{z}_{i,t}'\widehat{\Gamma}_\beta$, and $\widehat{\lambda}$ is the vector of the unconditional time-series mean of the latent factors computed as $\widehat{\lambda}_k = \frac{1}{T}\sum_{t=1}^{T} f_{t,k}$. The R^2_{tot} indicates the ability of a model to describe the comovements of returns and R^2_{pred} the proportion of predictable variation captured by the model.

We first implement an IPCA with eight latent factors and all characteristics in Table I as instruments. Next, we consider an instrumented observable factor model where alphas and betas are conditioned on the same characteristics, but latent factors are replaced with observable portfolios. We employ an eleven-factor model that combines the market, size, momentum, and value factors from Liu et al. (2022), Cong et al. (2021), and Liebi (2022) with seven additional characteristic-managed portfolios, selected based on their incremental explanatory power.[7] Appendix II provides descriptive statistics for the daily returns of all observable risk factors. Finally, we implement a static PCA to assess the contribution of time-varying parameters.

The comparison is based on the full sample (in-sample) and recursive (out-of-sample) estimates. The out-of-sample performance is based on an expanding window estimation starting from March 1st, 2020. In each period t, we re-estimate the corresponding parameter $\widehat{\Gamma}_t = \left[\widehat{\Gamma}_{\alpha,t}, \widehat{\Gamma}_{\beta,t}\right]$ using all the data through t, i.e., expanding window, and compute the realised factor return at $t+1$ as $\widehat{f}_{t+1} = \left(\widehat{\Gamma}'_{\beta,t} Z'_t Z_t \widehat{\Gamma}_{\beta,t}\right)^{-1} \widehat{\Gamma}'_{\beta,t} Z'_t \left(r_{t+1} - Z_t \widehat{\Gamma}_{\alpha,t}\right)$. Thus, the realised IPCA factors at $t+1$ require no information beyond time t. To test statistically the difference in asset pricing performance between models, we test the null hypothesis $\mathcal{H}_0 : E\left[\overline{\Delta} L_j\right] = 0$ where $\overline{\Delta} L_j \equiv \frac{1}{nT}\sum_{t=1}^{T}\sum_{i=1}^{n} \Delta L_{j,i,t}$ and $\Delta L_{j,i,t} = \widehat{e}^2_{j,i,t} - \widehat{e}^2_{bench,i,t}$ is the squared error loss differential between the model j and a benchmark unrestricted IPCA. Appendix III details this procedure.

Table II presents our findings for both daily and weekly returns.[8] The results show how

[7] The seven additional long-short portfolios are formed on characteristics that provide the highest increase in R^2_{tot} within a given group: price to 90-day high price (reversal), trading volume (trading activity), maximum returns (speculative demand), Value-at-Risk (volatility and downside risk), bid-ask spread (liquidity), Facebook likes (social media activity), and equity beta (equity market exposure).

[8] For weekly aggregation, we follow the procedure of Liu et al. (2022). Specifically, we divide each year into 52

systematic mispricing and time-varying risk compensation differentially affect the model's ability to capture return comovements (R^2_{tot}) versus predictable return variation (R^2_{pred}).

[Insert Table II here]

Allowing for systematic mispricing ($\Gamma_\alpha \neq 0$) primarily enhances return predictability without affecting comovement patterns. Restricting mispricing to zero ($\Gamma_\alpha = 0$) leaves the total R^2 virtually unchanged (-0.43% for IPCA) but dramatically reduces predictive R^2 by 18.11% in-sample and 15.06% out-of-sample for daily returns. This pattern indicates that systematic mispricing represents a substantial source of predictable return variation that operates independently of the underlying factor structure. The importance of systematic mispricing extends beyond latent factors. For instrumented observable factors, eliminating mispricing reduces predictive R^2 by 68.99% (0.26% versus 0.08%) and 58.52% (1.62% versus 0.67%) for daily and weekly returns.

Time-varying risk compensation involves a fundamental trade-off between capturing comovements and generating predictable returns. The comparison between IPCA and static PCA reveals this tension clearly. Static PCA achieves a higher total R^2 (an increase of 11.03% for daily returns), indicating a superior ability to capture pure return comovements. However, PCA dramatically underperforms in terms of the predictive R^2 as we observe a reduction of 62.20% (0.26% versus 0.10%) in predictive metrics. Furthermore, static PCA generates negative out-of-sample R^2 statistics.

The complementary nature of these components explains IPCA's superior performance. Using latent factors enhances the model's ability to capture return comovements compared to pre-specified portfolios, i.e., higher total R^2. Simultaneously, instrumenting alphas on

weeks, where the first week of the year comprises the first seven days. We take the last daily observation of each characteristic in the week.

characteristics substantially improves the model's ability to generate predictable return variation, i.e., higher predictive R^2.

B. Economic Evaluation of Mispricing

We now investigate whether investors can profit from detecting systematic mispricing, as captured by the IPCA. To this end, we form a "pure-alpha" portfolio based on IPCA's estimate of $\widehat{\Gamma}_{\alpha}$. At the end of the day (week) $t-1$, we estimate the model using the historical data and obtain parameter estimates $\widehat{\Gamma}_{\alpha,t-1}$. We construct the portfolio with weights $w_{t-1} = \boldsymbol{z}_{t-1}\left(\boldsymbol{z}'_{t-1}\boldsymbol{z}_{t-1}\right)^{-1}\widehat{\Gamma}_{t-1}$, which combines the individial assets in proportion to their expected returns beyond the exposure to the latent factors. The portfolio construction starts in March 2020, which corresponds to the beginning of the out-of-sample period.

Table III reports the daily and weekly results. The pure-alpha portfolios generate highly significant risk-adjusted returns, with t-statistics consistently exceeding 7 (10) for daily (weekly) estimation across specifications. The Sharpe ratios exceed 0.7 per week in most cases. Most interestingly, the performance of the portfolios remains stable as we increase the number of latent factors to eight, which is consistent with significant systematic mispricing irrespective of return commonality. The robustness of these results across different risk adjustment models—from simple CAPM to the extended eleven-factor specification—demonstrates that additional risk factors cannot explain away the economic value of systematic mispricing. This further supports the assumption that systematic mispricing represents a persistent and economically relevant feature in cryptocurrency markets rather than a statistical artifact.

[Insert Table III here]

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C. Which Characteristics Matter for Alphas and Betas?

We now investigate which groups of characteristics drive systematic mispricing and risk compensation. In our analysis, we identify the distinct sources of two components of cryptocurrency returns and quantify their significance over time. We implement bootstrap simulations to test the significance of groups of characteristics for conditional alphas ($\alpha_{i,t}$) and betas ($\beta_{i,t}$). For systematic mispricing, we test $\mathcal{H}_0 : \Gamma_\alpha^g = 0$, where Γ_α^g is the subvector corresponding to a particular characteristic group. We compute a Wald-type test statistic $W_\alpha^g = \widehat{\Gamma}_\alpha^{g\prime}\widehat{\Gamma}_\alpha^g$ and obtain p-values using wild bootstrap simulations following Kelly et al. (2019).[9] For risk compensation, we implement analogous tests for factor loadings ($\Gamma_\beta^g = 0$).

Systematic mispricing drivers. Table IV reveals distinct patterns for daily (Panel A) and weekly (Panel B) returns. For daily returns, two groups of characteristics are important for systematic mispricing: speculative demand maintains strong significance across models (p-values below 0.05), and liquidity shows robust significance throughout. All other characteristic groups lose significance as more factors are included. For weekly returns, reversal characteristics become highly significant across all specifications, although speculative demand and liquidity remain important. This suggests that mispricing operates through behavioral channels (speculative demand) and microstructure frictions (liquidity and reversal).

[Insert Table IV here]

To examine the time-varying nature of systematic mispricing, we estimate the eight-factor IPCA using a two-year rolling window and implement bootstrap tests for each period. Figure 1 shows test statistics along with bootstrap percentiles for daily returns. Mispricing is a persistent phenomenon throughout our sample. Speculative demand exhibits the strongest and most

[9] The null hypothesis $\mathcal{H}_0 : \Gamma_\alpha^g = 0$ does not rule out temporary mispricing, as long as mispricing is truly idiosyncratic and unassociated with asset characteristics.

consistent significance, intensifying during the 2021 cryptocurrency boom and remaining elevated through 2022. Liquidity effects are pronounced during the early period and the COVID-19 pandemic, when trading frictions were most severe.

[Insert Figure 1 here]

Weekly results (Figure 2) show the persistent statistical significance of conditional alphas over time. Consistent with unconditional bootstrap tests, reversal characteristics drive systematic mispricing throughout the whole sample, whereas volatility characteristics gain prominence during the 2021-2022 market cycle. Appendix IV reports the significance of other groups for daily (Figure A1) and weekly (Figure A2) returns. These results show that other characteristics do not influence mispricing over time.

[Insert Figure 2 here]

We note that the evidence of significant mispricing in cryptocurrency returns, reflecting behavioral biases (speculative demand) and microstructural frictions (liquidity risk), presents an interesting comparison with findings from equity markets, which show that demand for lottery-like assets leads to overpricing of illiquid assets (Kumar, 2009; Bali, Cakici, and Whitelaw, 2011).

Risk compensation drivers. Table V shows that the determinants of conditional betas differ substantially from those of alphas. Core characteristics (market, size, and momentum) are consistently significant across factor specifications. For daily returns, equity market exposure becomes strongly significant in larger factor models (p-value = 0.00 with $K = 7, 8$), while speculative demand and volatility characteristics also gain significance. For weekly returns, core characteristics maintain strong significance, alongside reversal and trading activity.

[Insert Table V here]

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Figure 3 shows how different characteristics affect factor loadings over time. Core characteristics and equity market exposure consistently demonstrate importance, particularly after 2020, suggesting a growing integration between cryptocurrency and equity markets. Volatility and downside risk also represent a key feature for risk compensation, whereas speculative demand shows relevance at the beginning and towards the end of the sample.

[Insert Figure 3 here]

Figure 4 reports the bootstrap statistics for weekly betas over time. The main insights align with the daily results. Core characteristics have a significant influence on risk compensation, with exposure to the equity market also representing a considerable feature that drives conditional betas. Unlike daily results, volatility and downside risks are less relevant, whereas reversal and trading activity gain significant prominence in the dynamics of factor loadings.[10]

[Insert Figure 4 here]

The results overall suggest that while mispricing persists through behavioral and structural channels that resist arbitrage, risk compensation increasingly follows established asset pricing mechanisms. Furthermore, exposure to equity markets suggests that cryptocurrency systematic risk reflects broader market factors rather than solely crypto-specific risks.

We complement our analysis by performing two additional exercises. First, we further test the relevance of individual characteristics instead of groups for betas. This provides a more granular picture of which characteristics are most important within groups. We show that a few characteristics drive the significance of the most important groups. Regarding the strong role of equity characteristics in driving factor loadings, exposure to equity market returns (including their downside movements) matters for the risk compensation of cryptocurrencies.

[10]As detailed in the appendix, the significance for other characteristic groups confirms the patterns observed in the unconditional tests - most groups do not systematically drive risk compensation over time.

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Second, we augment the bootstrap significance tests by measuring the relative contribution of different groups of characteristics to the sum of squared alpha and beta parameters. We delegate the details of this exercise to the appendix and discuss the main results here. Focusing on contributions to daily alphas, speculative demand tends to account for the large share throughout the sample, with its impact increasing from mid-2020 to the end of 2022, consistent with the strong statistical significance reported in Figure 1. Similarly, the economic impact of liquidity characteristics is more substantial during the early sample period, consistent with their statistical importance. We observe a similar degree of association between the statistical and economic relevance of variables for weekly alphas. Turning to betas, we find that the relative contributions of various groups exhibit similar patterns for daily and weekly factor loadings. Furthermore, the economic impact of groups of characteristics on daily and weekly betas is also associated with their statistical significance.

D. Asset Quality and Model Performance

To gain additional insight into the impact of modelling mispricing and risk compensation on asset pricing performance, we compute the R^2 statistics for coins grouped by different characteristics. Each day, we sort the cryptocurrencies into quartiles based on various variables, one at a time. For each quartile, we compute the total and predictive R^2 for the eight-factor IPCA, eight-factor PCA, and a dynamic observable eleven-factor model instrumented by all characteristics. We compare these different approaches to better understand where various modelling mechanisms (time-varying coefficients and latent factors) are most relevant. Following Kelly et al. (2019), we do not re-estimate models for different subsamples, as this would mechanically improve fit. Instead, we keep factors and parameters fixed at their full-sample estimates and recalculate R^2 statistics within each subsample.

Table VI shows daily results for quartiles with the lowest and highest values of a given characteristic. Focusing on the total R^2, IPCA maintains substantial advantages over instrumented observable factors for volatile and illiquid assets, with IPCA outperforming by 62-63% for high volatility cryptocurrencies. For larger, more liquid assets, instrumented observable factors often align with IPCA performance. Static PCA shows mixed performance relative to IPCA. For lower-quality assets, it typically underperforms IPCA in R^2_{pred} by 75-90%, but often outperforms in R^2_{tot} by 10-20%. This suggests that while static PCA can capture realized return variation, it struggles with prediction for assets where mispricing effects are most pronounced.

[Insert Table VI here]

Turning to the predictive R^2, IPCA demonstrates its strongest relative performance among lower-quality assets. For instance, IPCA achieves an R^2_{pred} of 0.42% among cryptocurrencies with the highest idiosyncratic volatility compared to 0.10% for observable factors, representing a 76% underperformance by the conditional observable factor model that ignores mispricing. Similar patterns emerge for illiquid assets with the highest bid-ask spreads, where IPCA generates 0.58% R^2_{pred} versus 0.12% for observable factors (a 79% underperformance). The pattern extends to speculative demand (`max`), where observable factors achieve only 0.09% compared to IPCA's 0.40%. In contrast, IPCA's R^2_{pred} is negative or near-zero for large, more liquid, less volatile assets with more social media and on-chain activity.

These results suggest that the impact of mispricing on the R^2_{pred} is not straightforward. The time-varying alphas make a positive contribution to the predictive performance for smaller and illiquid cryptocurrencies. This likely happens because the mispricing of these cryptocurrencies is more significant and time-varying. However, frequent changes in alphas are detrimental to the return prediction of larger and liquid cryptocurrencies, as their mispricing is likely less significant. Since the cross-section tends to be skewed towards smaller and illiquid cryptocurrencies, the IPCA produces, on average, the higher R^2_{pred} statistics when allowing for systematic mispricing.

Overall, Table VI provides strong empirical validation that the advantages from

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time-varying alphas are systematically concentrated where economic theory predicts mispricing should be most prevalent—among assets with high arbitrage costs and limited liquidity. The weekly frequency—as shown in Table A5 in in the appendix—amplifies the distinction between asset quality segments, suggesting that the benefits of modeling systematic mispricing and time-varying exposures are particularly pronounced over coarser frequencies, especially for assets where arbitrage constraints are most binding.

E. Additional Checks

Volatility-scaled returns. We examine the impact of extreme volatility on the role of time-varying mispricing and risk compensation on cryptocurrency returns. To this end, we scale individual returns by their previous month's realised volatility. This transformation reduces cross-sectional heteroskedasticity. While keeping the characteristics unchanged, we re-estimate IPCA, PCA, and observable factors using scaled returns. We delegate the details of this exercise to the appendix and discuss the main results here.

Regarding the total R^2, volatility scaling diminishes the gap between observable and latent factor models, although it remains statistically significant. More importantly, Table A6 in the appendix confirms that the role of mispricing remains crucial irrespective of return scaling. For IPCA, restricting alphas to zero ($\Gamma_\alpha = 0$) significantly reduces predictive R^2 by 5.44% for daily returns. Similarly, for instrumented observable factors, constraining alphas reduces predictive metrics by 67.24%, and for PCA by 67.34%. The results for weekly returns show similar patterns. This provides evidence that the role of systematic mispricing in explaining cryptocurrency returns is not merely an artifact of extreme differences in volatility.

Data sampled from individual exchanges. The main empirical results are based on a volume-weighted aggregation of prices and volume across different exchanges. To mitigate concerns that the aggregation might critically affect the IPCA performance, we now replicate the

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main analysis for daily returns of cryptocurrencies from major exchanges: Kraken, Coinbase, Binance, and Bitfinex. These rank among the largest exchanges in terms of trading volume.

The results, reported in the appendix, show that IPCA's outperformance becomes even more pronounced, with performance gaps of 30–59$\%$ relative to observable factors compared to smaller gaps in aggregated data. The results also reveal substantial heterogeneity across exchanges, with some venues exhibiting much stronger evidence of systematic mispricing. Comparing the unrestricted IPCA with the constrained version ($\Gamma_\alpha = 0$) reveals that modeling systematic mispricing is particularly critical on certain exchanges. For instance, Bitfinex shows a 63$\%$ decline in predictive R^2 when alphas are constrained to zero, while Kraken shows a 7$\%$ decline. This suggests that volume-weighted aggregation may actually understate the extent of mispricing. In this respect, our main results likely represent a lower bound for the importance of mispricing to explain the predictable variation in cryptocurrency returns.

It is important to note that, since we focus on data from individual exchanges, the cross-sectional and time-series dimensions differ for each separate estimation compared to the aggregate sample. As a result, the heterogeneity in the results might be due to sample differences. Yet, the results provide widespread evidence in favour of allowing for systematic mispricing in the IPCA specification, especially for predictive R^2.

Replacing observable factors with managed portfolios. Guided by the previous insights, we investigate the asset pricing performance of IPCA when observable risk factors are replaced by characteristic-managed portfolios. The latter are constructed based on the 35 asset characteristics described in Table I as $x_{t+1} = \frac{Z_t' r_{t+1}}{N_{t+1}}$, where N_{t+1} is the number of non-missing observations at time $t+1$, r_{t+1} is the $N_{t+1} \times 1$ vector of individual asset returns, and Z_t is the $N_{t+1} \times L$ matrix that stacks individual characteristics.[11]

[11]In this respect, each element of x_{t+1} represents a weighted average of cryptocurrency returns with weights determined by the value of characteristics at a given time.

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We select a parsimonious set of managed portfolios that jointly approximate latent factors by regressing each IPCA factor on the value-weighted cryptocurrency market and all managed portfolios. Given the large number of characteristics, we perform regularisation via elastic-net (Zou and Hastie, 2005) and allow at most two non-zero coefficients in each regression. This selection procedure identifies eleven characteristic-managed portfolios formed on capm β, r21_1, bm, to, bidask, max 30, rvol, down β, equity capm β, equity down β, and the value-weighted cryptocurrency market. These eleven portfolios jointly explain from 60% to 80% of the variation in IPCA factors.

Table A4 in the appendix shows that IPCA retains the highest explanatory power, followed by the instrumented managed portfolios, with instrumented observable factors performing worse. Managed portfolios achieve an R^2_{tot} of 13.99%, compared to 10.56% for observable factors — a statistically significant 32% performance gap.

More importantly, the role of mispricing is retained when observable risk factors are replaced with characteristic-managed portfolios. When mispricing is unrestricted ($\Gamma_\alpha \neq 0$), the out-of-sample predictive R^2 from instrumented managed portfolios increases from 0.05% to 0.25%, almost a fivefold increase. These results demonstrate that allowing for unconstrained mispricing increases predictive ability regardless of whether factors are latent or approximated using characteristics.

IV. Interpreting the IPCA Factors

The factors extracted from IPCA are ordered by their variance and are only identifiable up to a rotation. By construction, each factor may be influenced by all characteristics. Since characteristics are likely correlated, the orthogonality condition on latent factors implies that none of them will exactly match a single characteristic. Thus, any labelling is imperfect. Nevertheless,

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we attempt to provide an economic interpretation of latent cryptocurrency factors in the eight-factor IPCA estimated on the full sample of daily returns.

A. Latent Factors and Characteristic-Managed Portfolios

Following Ludvigson and Ng (2009), we first examine the correlation between latent factors and managed portfolios. The left panel in Figure 5 shows the marginal R^2, which is the R^2 statistic from univariate regressions of each characteristic-managed portfolio on each latent factor.[12] The first latent factor (F1) is primarily associated with volatility measures, showing the highest correlations with `rvol`, `rskew`, and `std_vol`. The second factor (F2) captures the exposure to the equity market and liquidity risk, with the strongest correlations observed for `equity capm` β, `to` (turnover), and `illiq`.

[Insert Figure 5 here]

The third factor (F3) correlates most strongly with `down` β and `capm` β. This echoes the sixth factor, which shows the highest correlations with `down` β, `capm` β, in addition to `std_vol`. The fourth factor (F4) emerges as the primary momentum factor, showing strong explanatory power for `r30_1`, `r21_1`, and `r7_1`. The fifth factor (F5) exhibits a distinctive pattern, correlating most strongly with equity downside risk (`equity down` β). The seventh factor (F7) can be unambiguously identified as the value-weighted cryptocurrency market factor, accounting for 77.3% of the variation in the `vw_mkt` portfolio. Finally, the eighth factor (F8) is associated with trading frictions, exhibiting strong correlations with `bidask`, `rvol`, and speculative demand measures such as `max 30`.

The right panel of Figure 5 shows the results of a complementary regression analysis. We implement a multivariate regression in which all standardized latent factors are projected onto each standardized managed portfolio. Since the regression does not include an intercept, each

[12] Notice the individual R^2 for each factor can be cumulated as they are orthogonal to each other.

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coefficient can be interpreted as a partial correlation coefficient. The darker the colour in the heatmap, the larger the partial correlation.

The results largely confirm the evidence from the left panel in Figure 5. Factor 1 (F1) exhibits strong positive correlations with volatility measures, and Factor 2 (F2) shows strong correlations with trading activity, in addition to a strong correlation with the equity market `equity capm` β. Factor 3 (F3) displays a strong positive correlation with `down` β but a negative correlation with `capm` β. Factor 4 (F4) confirms its role as the momentum factor, whereas Factor 5 (F5) shows an interesting dual pattern, with a strong negative correlation with `equity down` β but positive correlations with momentum measures. Factors 6 (F6) and 7 (F7) exhibit strong correlations with broad market risk measures. In particular, the return on F7 is highly related to the return on the market portfolio `vw_mkt`. Finally, Factor 8 (F8) demonstrates strong positive correlations with liquidity frictions and extreme returns.

B. Correlation With Equity Risk Factors

In this section, we address a fundamental question that has been central to the debate among market participants and researchers: do cryptocurrencies and traditional asset classes share common risk factors? The factor structure we have identified via IPCA suggests potential linkages with equity markets that warrant investigation. Notably, the fifth IPCA factor (F5) shows a distinctive pattern with equity-related characteristics, exhibiting the strongest correlation with `equity down` β in the marginal R^2 analysis and a strong negative partial correlation in the multivariate regression analysis. Similarly, the second factor (F2) demonstrates significant correlations with `equity capm` β, suggesting potential cross-market risk transmission.

IPCA bootstrap tests To investigate these linkages more formally, we start by leveraging the flexibility of IPCA and consider an extended model that includes both latent cryptocurrency

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factors and observable equity factors:

$$r_{i,t+1} = \alpha'_{i,t} + \beta'_{i,t} f_{t+1} + \delta'_{i,t} g_{t+1} + \epsilon_{i,t+1}, \tag{7}$$

in which $\alpha'_{i,t}$, $\beta'_{i,t}$, and $\delta'_{i,t}$ are time-varying coefficients instrumented with all characteristics. Here, f_{t+1} and g_{t+1} represent the latent cryptocurrency factors and the observable equity factors, respectively. The incremental explanatory power of equity factors can be tested using a Wald-like statistic for the null hypothesis $\mathcal{H}_0 : \Gamma_\delta = \mathbf{0}_{L\times M}$ (see Appendix IV for details).[13]. We consider the five equity factors of Fama and French (2015) – the market (MKT), size (SMB), value (HML), profitability (RMW), and investment (CMA) – and momentum (MOM) of Jegadeesh and Titman (1993).[14]

Table VII reports the p-values on testing the significance of $\delta'_{i,t}$. The results on individual tests, which examine the individual significance of each equity factor separately, provide mixed evidence. The p-values for HML decline systematically from 0.60 in the single-factor model to 0.02 in the eight-factor specification. This finding aligns with recent evidence that value-like characteristics matter for cryptocurrency pricing (Cong et al., 2021; Liebi, 2022). The market factor (MKT) shows moderate evidence of correlation, with p-values improving from 0.79 to 0.50 as the number of latent factors increases, though this falls short of conventional significance levels. The momentum factor (MOM) displays marginal significance in higher-factor specifications, particularly in IPCA6 (p-value = 0.11) and IPCA7 (p-value = 0.07). In contrast, the

[13]The incremental explanatory power of equity factors can be tested using a Wald-like statistic $W_\delta = \text{vec}\left(\widehat{\Gamma}_\delta\right)' \text{vec}\left(\widehat{\Gamma}_\delta\right)$ for the null hypothesis $\mathcal{H}_0 : \Gamma_\delta = \mathbf{0}_{L\times M}$. W_δ measures the distance between the model with and without g_{t+1}. If it is large relative to bootstrap values, g_{t+1} contributes significantly to explaining the cryptocurrency returns.

[14]Notice that, unlike equity markets, cryptocurrency markets operate on a 24/7 basis. Thus, we merge the datasets by retaining only those dates for which we have available observations for both.

size (SMB), profitability (RMW), and investment (CMA) factors show no significance across all specifications.

[Insert Table VII here]

When including all equity factors simultaneously, the results reveal more substantial evidence for certain factors. Most notably, MOM achieves statistical significance in several specifications, with p-values of 0.05 in IPCA5, 0.01 in IPCA7, and 0.06 in IPCA8. The value factor (HML) maintains its significance in joint tests, particularly in IPCA6 and IPCA8, where p-values reach 0.03 and 0.06, respectively.

Factor-spanning regressions In addition to the IPCA-based bootstrap tests, we conduct factor-spanning regressions that directly test whether IPCA factors can be replicated using linear combinations of equity risk factors. Table VIII reports the results where each IPCA latent factor is regressed on the six equity risk factors. Five out of eight IPCA factors exhibit negative adjusted R^2 values, indicating that most equity factors provide no meaningful explanatory power. However, a notable exception is the seventh factor (F7), which exhibits a substantial correlation with equity risk factors, achieving an adjusted R^2 of 9.1%. This finding is consistent with our earlier interpretation of F7 (see Figure 5), which showed the strongest correlation with the value-weighted cryptocurrency market portfolio ($R^2 = 77.3\%$).

[Insert Table VIII here]

The regression intercepts provide additional evidence on the correlation between equity and cryptocurrency market returns. If equity risk factors could fully explain IPCA factors, the intercepts should be statistically indistinguishable from zero. This is indeed the case for the seventh IPCA latent factor (F7). The statistically insignificant intercept suggests that the equity market returns fully capture the presence of systematic components in the seventh IPCA cryptocurrency factor.

To provide additional insight into the temporal evolution of cryptocurrency-equity correlations, Figure 6 presents 2-year rolling-window estimates of the significance of market (MKT) and value (HML) factors for the two IPCA factors that showed the strongest correlations in our spanning regression analysis. The results provide important context for interpreting the static regression results in Table VIII.

[Insert Figure 6 here]

The rolling window analysis reveals a dramatic structural shift around March 2020. Panel A shows that F6 and F7 exhibited virtually no significant correlation with the equity market during 2018 to early 2020, with p-values consistently above 0.6. However, from March 2020 onward, both factors exhibit much stronger and more persistent correlations with equity markets, with p-values frequently dropping below the 5% significance threshold. F7 shows particularly strong significance during 2020-2021, with p-values near zero. Panel B shows intermittent but significant correlations between the value factor and IPCA factors, with distinct periods of high significance during 2019-2020 and 2021-2022.

The sharp increase in correlations after March 2020 aligns with accelerated institutional adoption and the integration of cryptocurrencies into traditional investment portfolios during the pandemic (Didisheim and Somoza, 2022). Increasingly correlated trading could lead to cross-asset class correlations, even if the two markets are not fully integrated (Kyle, 1989). This evolution supports the theoretical framework of Pástor and Veronesi (2009), where increased investor exposure to innovative sectors reduces information asymmetries and strengthens risk spillovers between asset classes.

The convergence of evidence from our empirical approaches reveals a nuanced picture of cryptocurrency-equity factor relationships. While the bootstrap tests show mixed significance patterns, the spanning regressions provide more convincing evidence in favour of strong time-varying correlations between cryptocurrency and equity markets. These seemingly

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contradictory results are reconciled by recognizing that the modest correlations documented in our static tests mask substantial temporal variation in the underlying relationships.

V. Conclusion

Our analysis reveals that cryptocurrency returns reflect both systematic mispricing and risk compensation, each operating through distinct economic mechanisms. The persistence of behavioral-driven mispricing alongside increasingly traditional risk-return relationships suggests that cryptocurrency markets occupy a unique position—more efficient than pure speculation, yet less efficient than mature asset classes.

The growing correlation between cryptocurrency and equity factors indicates market evolution toward greater integration with traditional finance. This has important implications as institutional adoption continues: while systematic risk compensation may converge toward equity market patterns, the structural features that enable persistent mispricing—such as fragmentation, high arbitrage costs, and heterogeneous investor bases—are likely to remain.

An interesting venue for future research could be to examine how regulatory developments and institutional infrastructure affect the balance between mispricing and risk compensation, and whether the patterns we document extend to other emerging asset classes characterized by high speculation and limited arbitrage capital.

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TABLE I

Cryptocurrency Characteristics

This table defines 35 asset characteristics used in the empirical analysis. We group them into nine categories: market, size, and momentum; reversal; on-chain activity; trading activity; liquidity; speculative demand; volatility and downside risk; social media activity; and equity market exposure.

Market, size, and momentum		
(1)	capm β	Crypto CAPM beta based on the previous 60 days of returns.
(2)	size	Current available supply times the current USD price.
(3-5)	r*_1	Return from 14, 21, and 30 to one day before the prediction.
Reversal		
(6)	r2_1	Short-term reversal (it is used only for a daily frequency and is equivalent to r7_1 on a weekly frequency).
(7)	r7_1	Return from 7 to one day before prediction.
(8)	r180_60	Return from 180 to 60 days before prediction.
(9)	rel_to_high	Price to 90-day high price.
On-chain activity		
(10)	new_add	Number of unique addresses that appeared for the first time in a network.
(11)	act_add	Number of unique active addresses.
(12)	bm	Network-to-marke value.
Trading activity		
(13)	$vol	Trading volume in $.
(14)	to	Last day's trading volume in $ over the current market capitalization.
(15)	std_vol	Volatility of log-daily trading volume in the previous 30 days.
(16)	cv_vol	Volatility to mean of daily trading volume in the previous 30 days.
Liquidity		
(17)	bidask	Average of daily bid-ask spreads.
(18)	illiq	The 30-day average of daily ratios between the absolute return and volume.
(19)	vol_shock	Log daily trading volume minus its trend in the previous 30 days.
(20)	dto	De-trended volume minus market turnover.
Speculative demand		
(21)	co-skew	Crypto co-skewness based on the previous 60 days of returns.
(22)	max 30	Maximum daily return in the previous 30 days.
(23)	max 30(4)	Average of the four highest daily returns in the previous 30 days.
(24)	rskew	The realised skewness of daily returns in the previous 30 days.
Volatility and downside risk		
(25)	ivol	Volatility of crypto CAPM residuals based on the previous 60 days of returns.
(26)	rvol	Realised volatility based on RiskMetrics with $\lambda = 0.94$.
(27)	Downside β	Crypto downside beta based on the previous 60 days of returns.
(28)	VaR(5%)	The historical Value-at-Risk at 5% on the previous 90 daily returns.
Social media activity		
(29)	fb_likes	The daily number of cumulative Facebook likes.
(30)	reddit_act	The number of active Reddit subscribers in a day.
(31)	reddit_posts	The daily number of Reddit posts.
(32)	twitter_f	The daily number of Twitter followers.
Equity market exposure		
(33)	Equity capm β	Equity CAPM beta based on the previous 60 days of returns.
(34)	Equity co-skew	Equity co-skewness based on the previous 60 days of returns.
(35)	Equity downside β	Equity downside beta based on the previous 60 days of returns.

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TABLE II

Asset Pricing Performance

This table compares the in-sample and out-of-sample R^2_{tot} and R^2_{pred} reported in percentages for models with IPCA, observable, and PCA factors. The models are estimated on daily or weekly returns. For each model, it also displays the percentage change in R^2_{tot} and R^2_{pred} statistics relative to the unconstrained eight-factor IPCA model, where all characteristics are used as instruments. We highlight with * those performance differentials that are statistically significant at a 1% threshold level.

Panel A: In-sample estimation

		Daily returns				Weekly returns			
Method	K	$R^2_{tot}(\%)$	$\Delta(\%)$	$R^2_{pred}(\%)$	$\Delta(\%)$	$R^2_{tot}(\%)$	$\Delta(\%)$	$R^2_{pred}(\%)$	$\Delta(\%)$
`IPCA8` (all characteristics)	8	15.55		0.26		31.92		1.62	
`IPCA8` (all characteristics) & $\Gamma_\alpha = 0$	8	15.49	-0.43*	0.21	-18.11*	31.84	-0.25	1.61	-0.63
Instrumented observable	11	10.56	-32.10*	0.27	2.59	27.53	-13.76*	1.62	0.17
Instrumented observable & $\Gamma_\alpha = 0$	11	10.36	-33.37*	0.08	-68.99*	26.41	-17.26*	0.67	-58.52*
`PCA8` & $\Gamma_\alpha = 0$	8	17.27	11.03*	0.10	-62.20*	38.45	20.46*	0.67	-58.80*

Panel B: Out-of-sample estimation

		Daily returns				Weekly returns			
Method	K	$R^2_{tot}(\%)$	$\Delta(\%)$	$R^2_{pred}(\%)$	$\Delta(\%)$	$R^2_{tot}(\%)$	$\Delta(\%)$	$R^2_{pred}(\%)$	$\Delta(\%)$
`IPCA8` (all characteristics)	8	16.06		0.23		29.51		1.08	
`IPCA8` (all characteristics) & $\Gamma_\alpha = 0$	8	15.54	-3.22*	0.20	-15.06*	29.06	-1.53*	1.05	-2.21
Instrumented observable	11	9.88	-38.49*	0.24	2.10	23.49	-20.42*	1.12	4.39*
Instrumented observable & $\Gamma_\alpha = 0$	11	8.24	-48.71*	0.05	-78.30*	22.02	-25.40*	0.29	-72.94*
`PCA8` & $\Gamma_\alpha = 0$	8	14.27	-11.11*	-0.01	-	25.04	-15.18*	-0.58	-

TABLE III

Pure-Alpha Portfolios

This table reports the out-of-sample performance of pure-alpha portfolios. Panel A (B) shows summary statistics for daily (weekly) estimation. Alphas are computed relative to the crypto CAPM, four-factor (F4), and eleven-factor (F11) models. The four-factor model employs the market, size, momentum, and value factors, whereas the eleven-factor specification additionally includes seven observable cryptocurrency factors selected in Section III.A.

Panel A: Daily returns

IPCA Factors	Mean (%)	Std (%)	SR	$\alpha_{CAPM}(\%)$	t_{CAPM}	$\alpha_{F4}(\%)$	t_{F4}	$\alpha_{F11}(\%)$	t_{F11}
$K=1$	1.412	1.951	0.724	1.411	7.450	1.282	6.863	1.064	5.811
$K=2$	1.009	1.883	0.536	1.007	4.832	0.929	4.642	0.767	3.986
$K=3$	1.064	1.772	0.601	1.063	5.625	0.983	5.420	0.809	4.679
$K=4$	1.041	1.423	0.732	1.041	7.620	0.969	7.456	0.856	6.807
$K=5$	0.949	1.206	0.787	0.949	8.192	0.889	7.881	0.786	7.086
$K=6$	0.772	1.017	0.759	0.771	7.385	0.733	7.197	0.653	6.526
$K=7$	0.573	0.800	0.717	0.573	7.426	0.541	7.347	0.482	6.496
$K=8$	0.491	0.722	0.680	0.490	7.289	0.469	7.379	0.414	6.460

Panel B: Weekly returns

IPCA Factors	Mean (%)	Std (%)	SR	$\alpha_{CAPM}(\%)$	t_{CAPM}	$\alpha_{F4}(\%)$	t_{F4}	$\alpha_{F11}(\%)$	t_{F11}
$K=1$	1.092	1.485	0.736	1.086	12.791	1.083	12.977	1.072	15.456
$K=2$	1.023	1.332	0.768	1.021	8.918	1.019	8.682	1.046	10.308
$K=3$	1.002	1.343	0.746	1.002	7.603	1.002	7.465	1.026	9.163
$K=4$	1.003	1.318	0.761	1.002	8.987	1.002	8.711	1.027	10.708
$K=5$	0.953	1.229	0.775	0.953	9.098	0.951	8.710	0.973	10.673
$K=6$	0.875	1.085	0.807	0.879	9.371	0.873	9.073	0.883	11.589
$K=7$	0.765	1.043	0.734	0.768	8.074	0.764	7.730	0.771	10.407
$K=8$	0.746	0.977	0.764	0.748	10.363	0.741	9.854	0.755	13.964

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TABLE IV

Characteristics and Systematic Mispricing

This table reports p-values for the $\Gamma_{\alpha}^{g} = 0$ test in models with different numbers of factors, using all characteristics as instruments. The table shows the results for models estimated on daily and weekly returns.

Panel A: Daily returns

Groups	L	Number of factors							
		1	2	3	4	5	6	7	8
All characteristics	35	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.03
Market, size and momentum	5	0.00	0.00	0.01	0.54	0.32	0.43	0.64	0.95
Reversal	9	0.00	0.01	0.06	0.10	0.14	0.15	0.19	0.25
On-chain activity	8	0.04	0.17	0.46	0.48	0.48	0.63	0.73	0.63
Trading activity	9	0.03	0.56	0.68	0.48	0.49	0.95	0.99	0.98
Liquidity	9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Speculative demand	9	0.00	0.00	0.00	0.00	0.00	0.02	0.05	0.04
Volatility and downside risk	9	0.00	0.01	0.00	0.03	0.07	0.19	0.37	0.82
Social media activity	9	0.00	0.00	0.00	0.01	0.04	0.23	0.19	0.10
Equity market exposure	8	0.22	0.40	0.43	0.52	0.52	0.93	0.96	0.89

Panel B: Weekly returns

Groups	L	Number of factors							
		1	2	3	4	5	6	7	8
All characteristics	34	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Market, size and momentum	5	0.00	0.00	0.00	0.00	0.00	0.07	0.32	0.69
Reversal	8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
On-chain activity	8	0.22	0.19	0.21	0.07	0.07	0.16	0.24	0.54
Trading activity	9	0.58	0.70	0.67	0.47	0.49	0.59	0.70	0.82
Liquidity	9	0.03	0.02	0.02	0.01	0.02	0.16	0.10	0.08
Speculative demand	9	0.12	0.04	0.02	0.01	0.10	0.07	0.06	0.02
Volatility and downside risk	9	0.32	0.25	0.31	0.24	0.44	0.37	0.21	0.12
Social media activity	9	0.07	0.08	0.11	0.14	0.10	0.09	0.47	0.39
Equity market exposure	8	0.97	0.80	0.81	0.77	0.85	0.34	0.34	0.25

TABLE V

Characteristics and Risk Compensation

This table reports p-values for the $\Gamma_{\beta}^{g} = 0$ test in the models with different numbers of factors where all characteristics are used as instruments. The table shows the results for the models estimated on daily (Panel A) or weekly (Panel B) returns.

Panel A: Daily returns

Groups	L	Number of factors							
		1	2	3	4	5	6	7	8
Market, size and momentum	5	0.00	0.08	0.05	0.01	0.02	0.04	0.05	0.04
Reversal	9	0.01	0.21	0.62	0.22	0.19	0.38	0.54	0.75
On-chain activity	8	0.06	0.29	0.61	0.80	0.93	0.99	0.96	0.99
Trading activity	9	0.19	0.67	0.47	0.79	0.91	0.63	0.35	0.42
Liquidity	9	0.18	0.05	0.23	0.41	0.61	0.71	0.67	0.51
Speculative demand	9	0.31	0.15	0.03	0.02	0.04	0.05	0.08	0.01
Volatility and downside risk	9	0.00	0.59	0.44	0.21	0.04	0.02	0.01	0.01
Social media activity	9	0.01	0.27	0.68	0.82	0.92	0.94	0.98	1.00
Equity market exposure	8	0.80	0.83	0.88	1.00	0.21	0.04	0.00	0.00

Panel B: Weekly returns

Groups	L	Number of factors							
		1	2	3	4	5	6	7	8
Market, size and momentum	5	0.13	0.02	0.00	0.01	0.03	0.01	0.00	0.00
Reversal	8	0.01	0.07	0.13	0.11	0.09	0.02	0.05	0.00
On-chain activity	8	0.12	0.82	0.68	0.08	0.17	0.24	0.07	0.00
Trading activity	9	0.09	0.28	0.49	0.29	0.00	0.06	0.01	0.02
Liquidity	9	0.25	0.38	0.64	0.68	0.42	0.25	0.49	0.65
Speculative demand	9	0.40	0.76	0.53	0.62	0.40	0.68	0.25	0.26
Volatility and downside risk	9	0.05	0.76	0.76	0.79	0.95	0.90	0.84	0.79
Social media activity	9	0.04	0.46	0.62	0.88	0.85	0.54	0.65	0.49
Equity market exposure	8	0.65	0.65	0.41	0.61	0.62	0.20	0.44	0.44

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TABLE VI

Asset Quality and Asset Pricing Performance

This table reports R^2_{tot} (Panel A) and R^2_{pred} (Panel B) in percentages for models with IPCA, observable, or PCA factors by cryptocurrency groups sorted on selected characteristics. $\Delta L(\%)$ and $\Delta H(\%)$ show the percentage difference in R^2 between each alternative model and IPCA for low and high quartiles, respectively. Negative values indicate IPCA outperforms the alternative model. The models are estimated on daily returns.

Panel A: $R^2_{tot}(\%)$

	IPCA		Instrumented observable factors				Static PCA			
	Low	High	Low	High	ΔL(%)	ΔH(%)	Low	High	ΔL(%)	ΔH(%)
capm β	12.11	16.61	5.46	10.77	-55	-35	14.68	18.58	21	12
size	12.75	25.04	5.64	26.28	-56	5	13.14	27.45	3	10
new_add	13.18	22.30	6.98	20.34	-47	-9	13.27	23.51	1	5
act_add	12.88	22.82	7.13	21.07	-45	-8	14.04	24.36	9	7
bm	18.37	13.72	16.78	6.48	-9	-53	21.78	14.06	19	2
$vol	12.30	26.28	4.86	25.74	-61	-2	13.62	28.37	11	8
bidask	21.95	12.54	18.42	5.24	-16	-58	25.46	13.42	16	7
ivol	36.94	12.02	37.93	4.40	3	-63	41.33	14.17	12	18
illiq	32.25	12.04	33.08	4.54	3	-62	35.86	13.87	11	15
VaR(5%)	11.78	24.39	4.65	23.25	-61	-5	14.20	29.44	21	21
max 30	29.43	11.57	29.30	5.03	0	-57	32.57	13.66	11	18
reddit_act	12.89	27.86	7.82	26.96	-39	-3	13.74	29.19	7	5
reddit_post	12.38	26.89	7.25	26.77	-41	0	11.88	29.23	-4	9
twitter_f	13.66	23.02	7.61	20.71	-44	-10	14.67	24.18	7	5
Equity capm β	12.89	15.23	6.73	8.89	-48	-42	14.90	17.33	16	14

Panel B: $R^2_{pred}(\%)$

	IPCA		Instrumented observable factors				Static PCA			
	Low	High	Low	High	ΔL(%)	ΔH(%)	Low	High	ΔL(%)	ΔH(%)
capm β	0.38	0.31	0.10	0.08	-73	-73	0.16	0.15	-58	-51
size	0.44	-0.14	0.11	0.11	-75	-	0.14	0.05	-68	-
new_add	0.23	0.06	0.05	0.08	-78	37	0.00	0.06	-102	-8
act_add	0.30	0.03	0.08	0.08	-74	151	0.08	0.07	-73	121
bm	0.03	0.48	0.09	0.13	223	-73	0.14	0.14	388	-72
$vol	0.45	-0.11	0.12	0.05	-73	147	0.16	0.03	-65	-
bidask	-0.18	0.58	0.04	0.12	-	-79	0.19	0.09	-	-84
ivol	-0.66	0.42	-0.03	0.10	-	-76	-0.07	0.17	-	-59
illiq	-0.39	0.42	0.04	0.11	-	-75	0.03	0.17	-	-61
VaR(5%)	0.43	-0.24	0.11	0.03	-75	-	0.17	0.14	-60	-
max 30	-0.15	0.40	0.04	0.09	-	-78	-0.01	0.10	-	-75
reddit_act	0.30	-0.02	0.08	0.06	-73	-	0.13	0.01	-57	-
reddit_post	0.37	-0.19	0.09	0.04	-75	-	0.09	0.04	-76	-
twitter_f	0.31	0.09	0.08	0.07	-74	-18	0.09	0.06	-71	-34
Equity capm β	0.32	0.39	0.08	0.11	-77	-72	0.16	0.12	-51	-69

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TABLE VII

IPCA-Based Tests for Equity Factors

The table reports p-values for the test $\Gamma_\delta = 0$ on instrumented loadings of equity factors when those are included with IPCA factors. We employ all characteristics as instruments for latent and observable factor loadings. The left panel reports the p-values of beta loadings when equity factors are included one at a time, whereas the right panel reports the p-values of beta loadings when all equity factors are included jointly in the estimation.

IPCA	Individual Tests						Joint Tests					
	MKT	SMB	HML	RMW	CMA	MOM	MKT	SMB	HML	RMW	CMA	MOM
$K = 1$	0.79	0.98	0.60	0.66	0.97	0.49	0.71	0.60	0.21	0.48	0.44	0.40
$K = 2$	0.71	0.97	0.59	0.43	0.92	0.27	0.68	0.92	0.47	0.34	0.74	0.08
$K = 3$	0.70	0.90	0.42	0.15	0.94	0.15	0.58	0.90	0.34	0.72	0.96	0.08
$K = 4$	0.51	0.94	0.29	0.27	0.91	0.25	0.68	0.98	0.24	0.39	0.71	0.17
$K = 5$	0.65	0.85	0.16	0.26	0.88	0.17	0.54	0.91	0.23	0.35	0.65	0.05
$K = 6$	0.65	0.67	0.03	0.20	0.84	0.11	0.71	0.78	0.03	0.31	0.56	0.09
$K = 7$	0.57	0.57	0.06	0.22	0.73	0.07	0.61	0.80	0.12	0.31	0.69	0.01
$K = 8$	0.50	0.47	0.02	0.33	0.76	0.46	0.70	0.77	0.06	0.34	0.67	0.06

TABLE VIII

Factor-Spanning Regressions

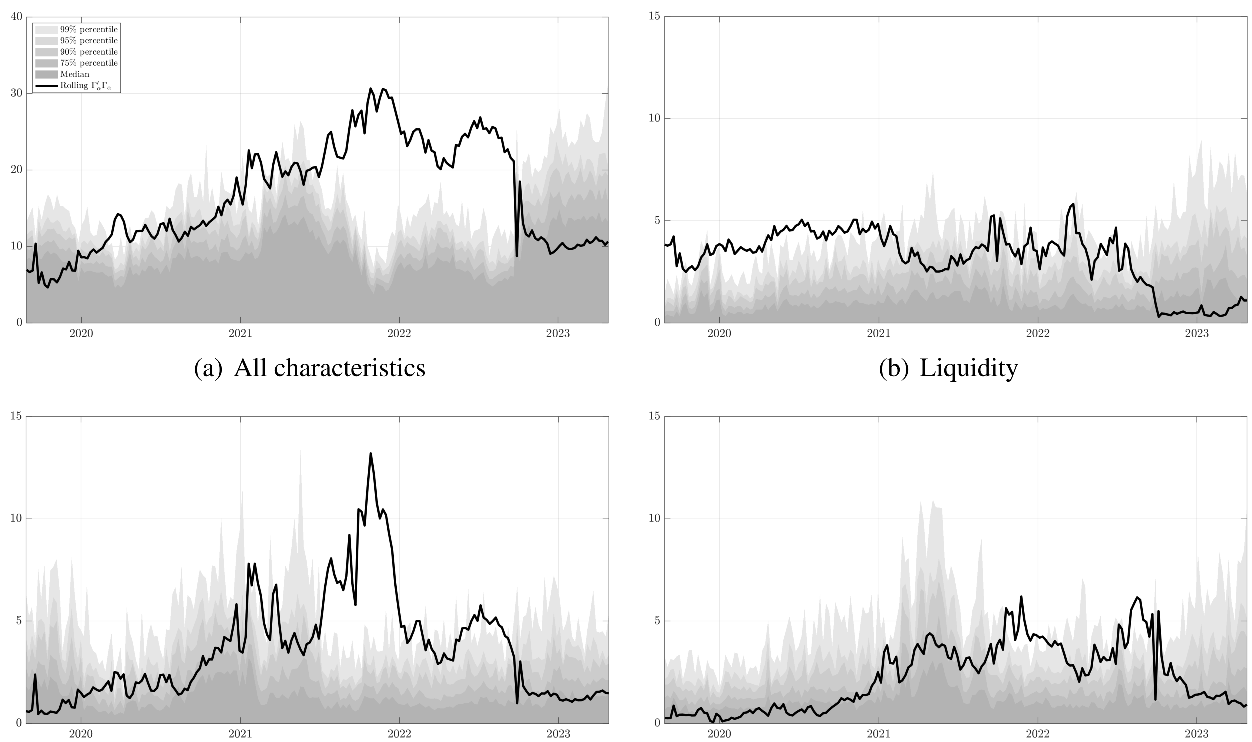
This table reports the results of factor-spanning regressions, in which we regress each latent factor from the eight-factor IPCA model on equity factors. We label with ***,**,* those coefficients significant at the 1%, 5%, 10% confidence levels based on robust standard errors.

IPCA factors		F1	F2		F3		F4		F5	F6		F7		F8	
	$\alpha(\%)$	0.10	1.60	***	0.60	***	2.50	***	0.20	0.70	***	0.20		1.40	***
	MKT	0.30	-0.30		-0.40	*	0.00		0.10	-0.40	***	-1.20	***	0.00	
	SMB	-0.50	-0.50		-0.70	*	0.50		0.00	0.00		-0.20		0.20	
Equity	HML	0.40	0.60		0.70	**	-0.30		0.10	-0.30		0.40	**	0.10	
	RMW	-0.20	-0.90		0.10		-0.10		-0.10	0.20		0.40		0.00	
	CMA	-0.80	-1.20		-0.70		0.30		-0.40	0.40		-0.40		-0.20	
	MOM	-0.20	-0.40		0.10		-0.20		0.00	0.00		0.00		0.00	
Adj. $R^2(\%)$		-0.20	0.00		0.40		-0.10		-0.30	0.70		9.10		-0.20	

FIGURE 1

Bootstrap Statistics for Daily Alphas over Time

This figure illustrates the daily Wald-type test statistics (black line) and different percentiles of bootstrap statistics (grey areas) for the conditional alphas from an eight-factor IPCA model estimated on daily returns in a two-year rolling window.



(a) All characteristics

(b) Liquidity

(c) Speculative demand

(d) Volatility and downside risk

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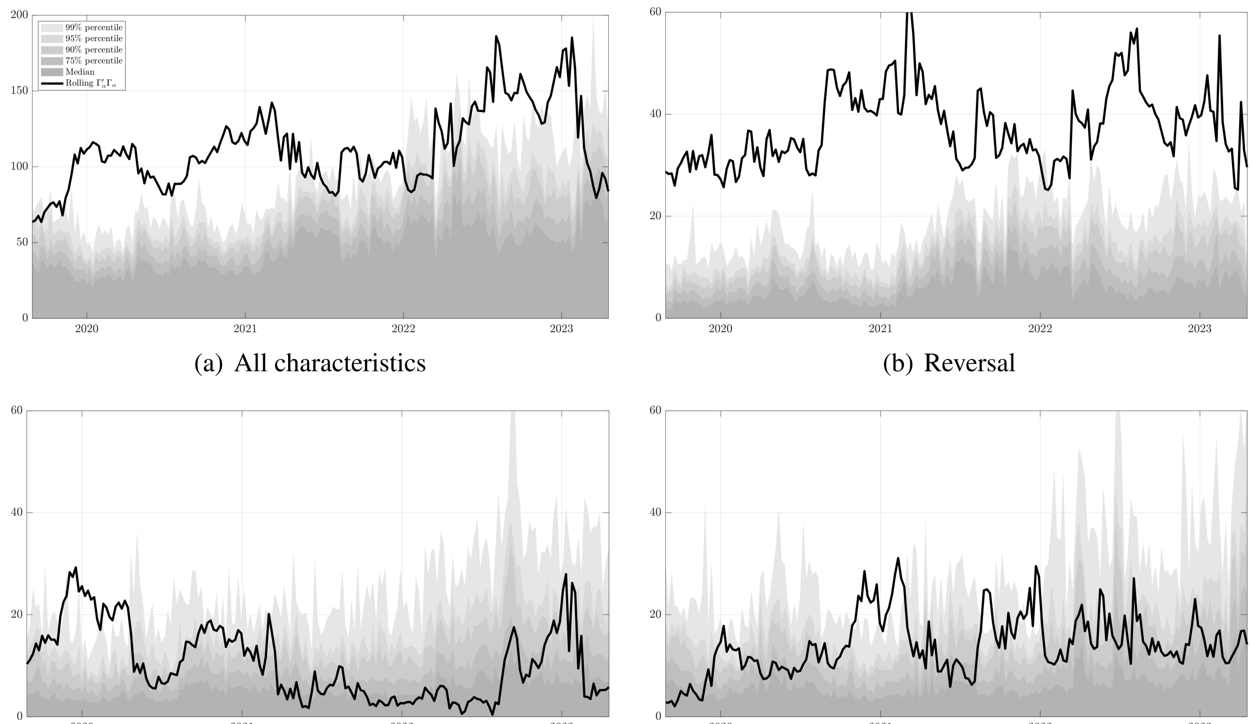
FIGURE 2

Bootstrap Statistics for Weekly Alphas over Time

This figure illustrates the weekly Wald-type test statistics (black line) and different percentiles of bootstrap statistics (grey areas) for the conditional alphas from an eight-factor IPCA model estimated on weekly returns in a two-year rolling window.



(a) All characteristics

(b) Reversal

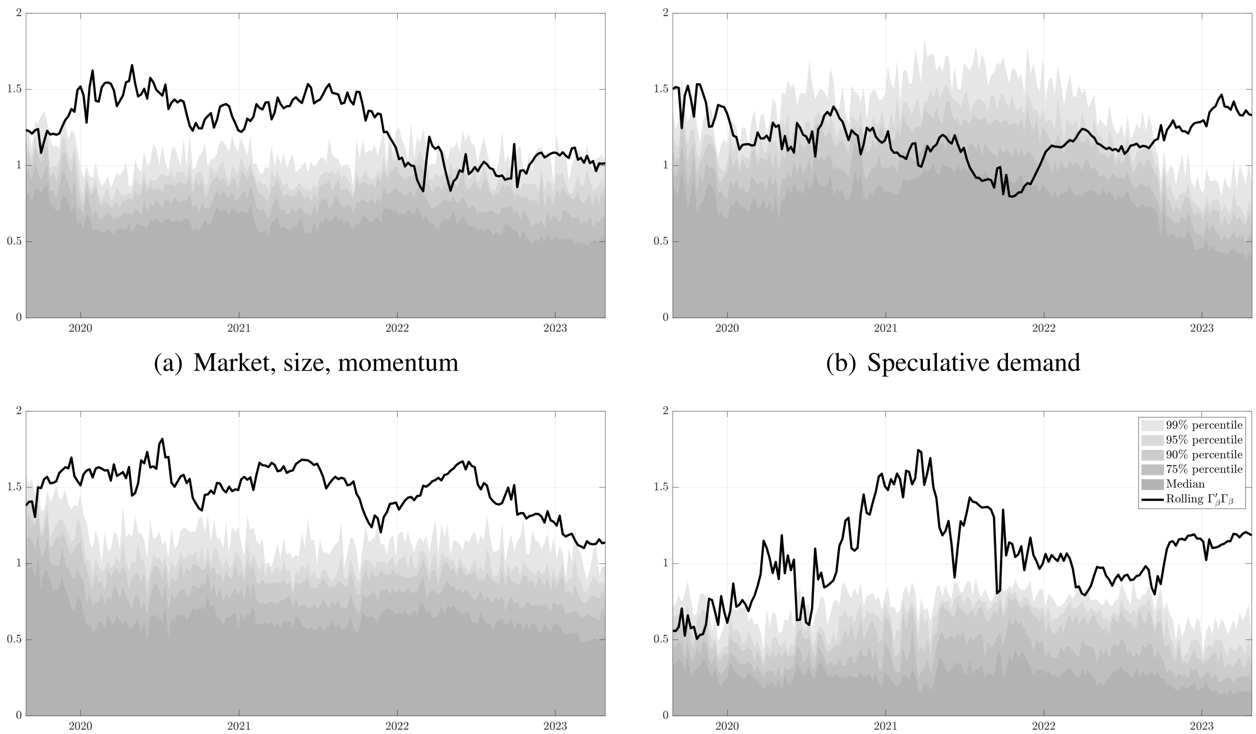
(c) Speculative demand

(d) Volatility and downside risk

FIGURE 3

Bootstrap Statistics for Daily Betas over Time

This figure illustrates the daily Wald-type test statistics (black line) and different percentiles of bootstrap statistics (grey areas) for the conditional betas from an eight-factor IPCA model estimated on daily returns in a two-year rolling window.



(a) Market, size, momentum

(b) Speculative demand

(c) Volatility and downside risk

(d) Equity market exposure

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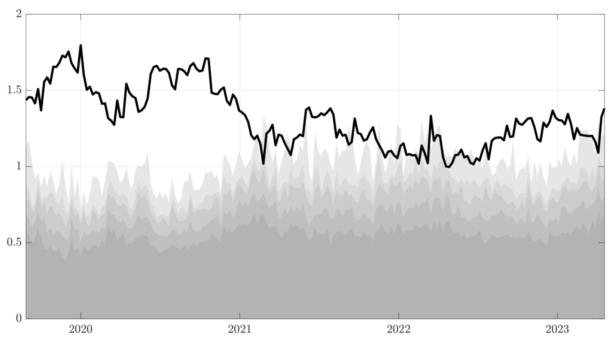
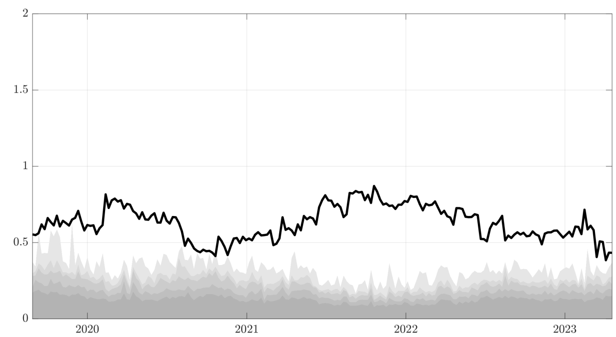
FIGURE 4

Bootstrap Statistics for Weekly Betas over Time

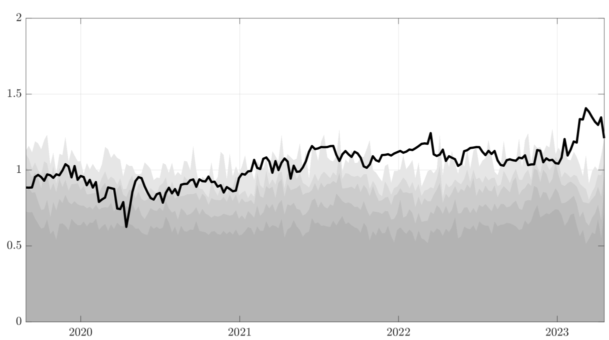
This figure illustrates the weekly Wald-type test statistics (black line) and different percentiles of bootstrap statistics (grey areas) for the conditional betas from an eight-factor IPCA model estimated on weekly returns in a two-year rolling window.



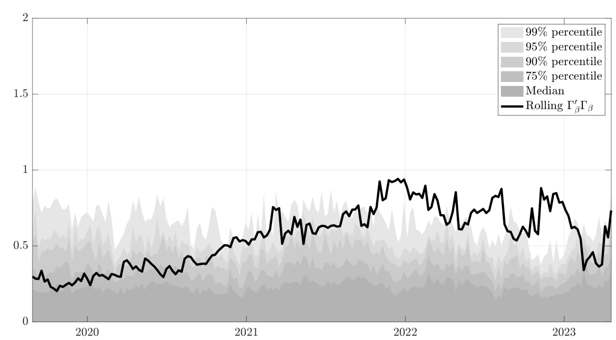
(a) Market, size, momentum



(b) Reversal



(c) Trading activity



(d) Equity market exposure

FIGURE 5

Characteristic-Managed Portfolios and IPCA Latent Factors

Panel A shows the marginal R^2, which are R^2 statistics from univariate regressions of each of the 35 characteristic-managed portfolios on each latent factor. Panel B shows the regression coefficients of a series of multivariate regressions in which all latent factors are projected onto each characteristic-managed portfolio.

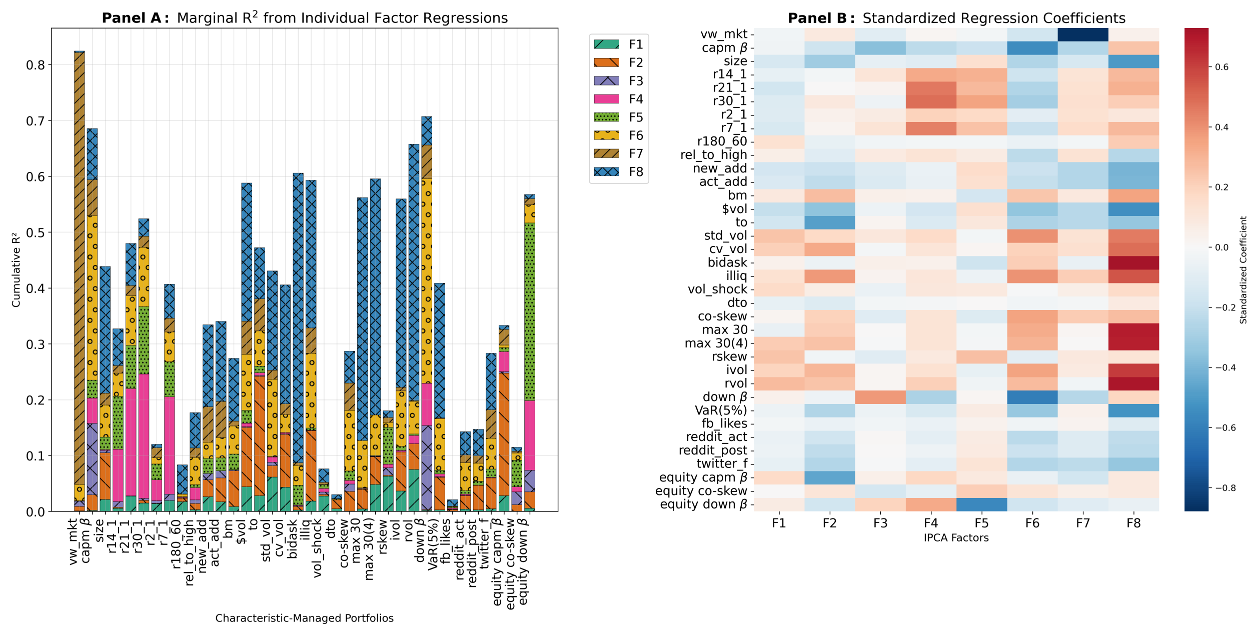


FIGURE 6

Rolling-Window P-Values for Equity Factor Correlations

Panel A shows the p-values from rolling 2-year window regressions of IPCA factors F6 and F7 on the market factor (MKT). Panel B shows the p-values from rolling 2-year window regressions of the same factors on the value factor (HML). The dashed horizontal lines indicate conventional significance thresholds of 5% (red) and 10% (orange).