A Factor Model for Cryptocurrency Returns*

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Abstract

We investigate the dynamics of daily realised returns and risk premiums for a large cross-section of cryptocurrency pairs through the lens of an Instrumented Principal Component Analysis (IPCA) (see Kelly et al., 2019). We show that a model with three latent factors and time-varying factor loadings significantly outperforms a benchmark model with observable risk factors: the total (predictive) R^2 from the IPCA is 17.2% (2.9%) for individual returns, against a benchmark 9.6% (-0.02%) obtained from a model with six observable risk factors explored in previous literature. By looking at the characteristics that significantly matter for the dynamics of risk premiums, we provide robust evidence that liquidity, size, reversal, and both market and downside risks represent the main driving factors behind expected returns. These results hold for both individual assets and characteristic-based portfolios, pre and post the Covid-19 outbreak, and for weekly individual and portfolio returns.

Keywords: Cryptocurrency markets, Instrumented PCA, asset pricing, factor models, risk premiums

JEL codes: G11, G12, G17, C23

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1 Introduction

A fundamental tenet of asset pricing is that investors should be compensated for their exposure to sources of systematic risk. This should hold for any risky investment, and cryptocurrencies, of which Bitcoin (BTC) is the most prominent example, should be no different.[1] At the time of this writing, total market capitalization of the cryptocurrency market stands at around $2 trillion, which is roughly the size of some of the largest European economies, such as those of Italy and Spain. Therefore, the need to understand the trade-off between risks and rewards within the context of such growing and still largely unknown market is pressing. This is the goal of this paper.

The most common empirical approach to evaluating the trade-offs and the dynamics of risks and returns is based on the assumption that the information content in the cross-section of individual asset or portfolio returns can be reduced to a small set of factors $f_{t+1} \in \mathbb{R}^K$ with $K < N$ where N is the number of test assets. This approach is particularly flexible in the sense that it does not depend on the asset class under investigation but is grounded on fundamental asset pricing theory: assuming no-arbitrage conditions hold, a stochastic discount factor m_{t+1} exists and, for any asset return $r_{i,t+1}$. the Euler equation $E_t\left[m_{t+1} r_{i,t+1}\right] = 0$ is satisfied

$$E_t\left[r_{i,t+1}\right] = \underbrace{-\frac{Cov_t\left(m_{t+1}, r_{i,t+1}\right)}{Var_t\left(m_{t+1}\right)}}_{\beta_{i,t}} \underbrace{\frac{Var_t\left(m_{t+1}\right)}{E_t\left[m_{t+1}\right]}}_{\lambda_t}, \tag{1}$$

where $\beta_{i,t}$ represents the exposure to a given source of systematic risk for asset i at time t and λ_t is the time-varying price of risk. This equation implies that the expected excess return or "risk premium" is high for those assets that have a negative covariance with the stochastic discount factor (SDF) m_{t+1}. Assuming $\lambda_t = E_t\left[f_{t+1}\right]$, one can map the SDF m_{t+1} into a linear model in which factors represent the "state variables" of the investor's consumption-portfolio decision

$$r_{i,t+1} = \alpha_{i,t} + \beta_{i,t} f_{t+1} + \epsilon_{i,t+1}. \tag{2}$$

The idiosyncratic error term $\epsilon_{i,t+1}$ is zero mean and orthogonal to the risk factors, i.e., $E_t\left[f_{t+1}\epsilon_{i,t+1}\right] = 0$. Under mild equilibrium pricing conditions, an asset pricing model should imply $\alpha_{i,t} = 0$ for all i

[1] In this paper, we use the terms "digital assets", "cryptocurrencies", "digital currencies", and "cryptocurrency markets" interchangeably.

and t, that is, the risk factors f_{t+1} capture all systematic variation in expected returns. The nature of factors f_{t+1} is left unspecified by the asset pricing theory. A common approach is to consider f_{t+1} to be observable and proxied by a zero-cost long-short portfolios built upon some observable stock features or characteristics, such as market capitalization, book-to-market, liquidity, idiosyncratic volatility, etc. This approach is exemplified by Fama and French (2015) and the references therein. A second common approach is to treat f_{t+1} as latent and use common data compression techniques, such as Principal Component Analysis (PCA), to simultaneously estimate the factors and betas from the panel of realised returns. This approach was pioneered by Chamberlain and Rothschild (1983) and Connor and Korajczyk (1986).

The two approaches possess both merits and shortcomings when applied to cryptocurrency markets. Assuming the factors are observable, constructing f_{t+1} as a characteristic-based portfolios is an easy task, but requires a perfect understanding of the driving forces behind cryptocurrency markets. In reality, however, our understanding of cross sectional variation in cryptocurrency returns is limited, at best. This is due to a variety of reasons: first, the high degree of market concentration around a handful of assets makes construction of observable risk factors rather problematic. Figure 1 illustrates this case in point. The top-left panel shows the relative market capitalization of the top 50 assets sorted by size relative to the total market.[2] The top 50 assets alone account for roughly 90% of total market capitalization and more than 95% of market activity. Such concentration makes implementing typical long-short portfolios using any meaningful cross-section particularly problematic. For instance, using more than the top 100 assets by market cap, essentially boils down to including penny stocks, which have all sorts of issues in terms of trading costs and liquidity.

Second, the assumption that we can approximate f_{t+1} using only a few observable factors somewhat ignores the decentralised structure of cryptocurrency markets. The top-right panel of Figure 1 shows a case in point. The figure shows the supply of the two main digital assets in circulation at the time of this writing, namely BTC and Ethereum (ETH), held on regular exchanges. By the end of the sample, only around 15% of the supply is actually tradable on common, relatively liquid exchanges such as Binance, Bitfinex, Coinbase, and Poloniex. This implies that the vast majority of assets are either kept in so-called cold storage or are exchanged on decentralised platforms such as UniSwap (UNI). In turn, this makes common long-short strategies difficult to implement in practice.

[2]Since September 21, 2011, there have been more than 11,000 digital assets and currencies actually available on both centralized and decentralised exchanges. Source: CoinMarketCap.

Similarly, using a standard PCA framework to estimate latent factors has both strengths and weaknesses in the context of cryptocurrency markets. Arguably, the main benefit is simplicity. Based on pure statistical criterion, PCA implementation does not require prior knowledge of the market structure. Nevertheless, applying the PCA modeling approach has several drawbacks: first, it implies constant factor loadings, whereas the exposure of assets to sources of systematic risk is often not constant. The bottom-right panel of Figure 1 illustrates this point. It reports the 5th, 50th, and 95th percentiles of the loadings for each asset on the first principal component based on a rolling window PCA estimate using 360 daily observations. The cross-section of cryptocurrencies is the same as the one used in the main empirical analysis, explained in Section 2.1. The loadings are not constant over time and exhibit low-frequency fluctuations that seem to be somewhat pervasive. Constant factor loadings are also against the theoretical implications of Eq. (1).

Second, the structure of cryptocurrency returns is not very dense in itself. The bottom-left panel of Figure 1 shows the explained variance from the first 50 principal components for the same cross-section of returns used in the main empirical analysis. The first 10 score vectors explain at most 30% of the variation in the data. This suggests that there is not much information content in returns to capture sources of co-movements, meaning systematic risk in cryptocurrency markets. The fact that standard PCA methods do not allow a researcher to incorporate data beyond returns could amplify the limitations of the relatively low-density structure in cryptocurrency markets.

To mitigate these issues, we build upon the framework used by Büchner and Kelly (2019) and Kelly et al. (2020) and treat the set of systematic risk factors as latent, but allow for time variation in the factor loadings based on a set of individual assets characteristics. We use the instrumented principal components analysis (IPCA) methodology introduced by Kelly et al. (2019) to understand the dynamics and driving forces of risk premiums in cryptocurrency markets by modelling the factor loadings as a function of observable characteristics of digital assets $z_{i,t}$, i.e., $\beta_{i,t} = f\left(z_{i,t}\right)$. We follow Kelly et al. (2019) and compare the ability of latent and observable risk factor models to capture the dynamics of risk premiums based on three defined metrics: first, we measure the accuracy with which they explain the common variation in realised returns using the total R^2. The total R^2 summarises the amount of explained variation in the returns $r_{i,t+1}$ due to contemporaneous factor realisations – which can be latent or observable – and factor loadings – which can be static or dynamic. Second, we measure how accurately the dispersion on the risk-return profile of individual assets is captured.

We assess this by using a predictive R^2 which is calculated as the explained variation of the returns due to the model-based conditional expected return on a given asset $\widehat{\beta}_{i,t}\widehat{\lambda}$, where $\widehat{\lambda} = E\left[f_{t+1}\right]$ is the vector of estimated factor risk prices. Both R^2_{total} and R^2_{pred} are computed in- and out-of-sample and for both individual assets and characteristic-based portfolios.

Third, we inspect the ability of latent or observable risk factors to "price" anomaly portfolios unconditionally. Specifically, we compare the extent to which alphas on characteristic-based portfolios can be explained by IPCA factors vis-á-vis standard observable risk factor models with either static or dynamic loadings.

1.1 Findings

Empirically, we focus our analysis on daily observations of both market and blockchain data for a cross-section of 809 digital assets over the period from December 2nd 2016 to July 9th 2021. We also consider the same time span with the data aggregated on a weekly basis, following Liu et al. (2019) and Liu and Tsyvinski (2020). We exclude stablecoins, which are directly pegged to fiat currencies, tokens with a market capitalization below hundred million USD, and those assets for which more than 25% of observations are missing over the sample period. A more detailed description of the data is provided in Section 2.1.

The main results are three-fold: first, we show that a restricted model with a zero intercept and three IPCA factors produces a R^2_{total} for individual cryptocurrency returns of 17.2% at the daily frequency. For comparison, a benchmark model with six observable factors: market, size, momentum, volatility, liquidity and reversal, produces a total R^2 of 9.6% for daily returns. Perhaps more importantly, our baseline IPCA specification provides a more accurate description of the daily risk premium dynamics, with a positive R^2_{pred} equal to 2.9% against -0.02% obtained from the benchmark observable risk factor model. Imposing dynamic betas to observable factors only marginally improves the R^2_{pred} to 0.2%, which is still an order of magnitude lower than the IPCA factors. These results hold both in-sample and out-of-sample, when the latter is based on recursive estimates of the IPCA factors.

Second, the baseline three-factor IPCA specification proves to be more mean-variance efficient in an *unconditional* sense with respect to observable risk factors. This is judged by estimating unconditional alphas in a full-sample time series regression of characteristic-based portfolio returns onto each set of factors. The IPCA model delivers substantially lower alphas than the benchmark model with observable risk factors providing a better pricing performance. Still on unconditional mean-variance efficiency, the factors extracted from the IPCA model generate much higher out-of-sample Sharpe ratios from tangency portfolios relative to the benchmark model with observable risk factors. The asset pricing implication of this set of results is that the IPCA factors are more coherent with a mean-variance efficient portfolio allocation with respect to the observable risk factors considered.

Third, we build upon Kelly et al. (2019) and test which characteristics significantly drive the dynamics of factor loadings. The main testing results show that the factor loadings, and in turn risk premiums, are primarily driven by a handful of individual asset characteristics such as liquidity (proxied by volume and synthetic bid-ask spread), market beta, reversal, size and downside risk. Interestingly, reversal seems to be the most prominent driving factor for expected returns. This is consistent with some of the existing evidence on cryptocurrency markets (see, e.g., Dobrynskaya, 2021). The fact that only a small set of individual asset characteristics is significant for the dynamics of factor loadings, coupled with the zero-alpha restriction in the baseline IPCA, suggests that these characteristics truly explain the assets' exposure to sources of systematic risk and not simply represent spurious compensation in absence of risks.

1.2 Related literature

This paper connects to a growing literature that aims at understanding the trade-off between risks and rewards within the context of cryptocurrency markets. The conventional wisdom posits that the pricing kernel of cryptocurrencies is segmented away from traditional asset classes, that is, digital assets are not exposed to the same sources of risks as in other traditional asset classes (see, e.g., Yermack, 2015, Liu and Tsyvinski, 2020, Bianchi, 2020). Based on these evidence, some of the existing research seeks to understand the pricing performance of specific observable risk factors and portfolios by sorting digital assets into portfolios based on a small set of characteristics such as size, momentum, liquidity and reversal. Examples can be found in Bianchi and Dickerson (2019), Liu et al. (2019) and Dobrynskaya (2021) among others. Our paper expands this literature by providing empirical evidence that the IPCA of Kelly et al. (2019) provides a more accurate measurement of the dynamics of risks and returns and mean-variance efficiency in the context of digital assets, with respect to observable risk factor models. This proves to be particularly relevant for cryptocurrency markets as estimates of the latent factors are not based on any ex ante knowledge of the cross-section of returns and, therefore, eliminate the need for the researcher to take a prior stance on the composition of the risk factors. The latter is an aspect that is particularly cumbersome for digital assets given their extremely heterogeneous nature and arguably the lack of clear fundamentals such as earnings and dividends.

More generally, this paper adds to recent literature that aims to understand the pricing dynamics and investment properties of digital assets (Weber, 2016; Biais et al., 2020; Chiu and Koeppl, 2017; Cong and He, 2019; Cong et al., 2021a,b; Sockin and Xiong, 2020; Schilling and Uhlig, 2019; Abadi and Brunnermeier, 2018; Routledge and Zetlin-Jones, 2021). We contribute to this literature by showing that indeed only a handful of characteristics including liquidity, size, downside risk, and reversal, play a decisive, even dominant, role in explaining the variation in both realised and expected returns in cryptocurrency markets.

Due to the inherent differences in cryptocurrencies with respect to traditional asset classes, and their novel and emergent status as a form of investment, we believe that the results of this paper could be relevant to a broad audience; from market participants seeking different sources of returns and diversification, to regulators wishing to understand the risks embedded in cryptocurrency markets, and to academics searching for new insights into the market structure of digital assets.

2 Research design

2.1 Data

We collect prices, trading volume, and a variety of on-chain activity measures on a daily basis for a cross-section of 809 digital assets spanning the period from December 2nd 2016 to July 9th 2021. The data were obtained from CryptoCompare.com and IntoTheBlock.com, website-based data providers that collect data from multiple exchanges. These sources integrate market data transactions and blockchain metrics for more than 350 exchanges and have been used in both existing research (see, e.g., Alexander and Dakos, 2019, Schwenkler and Zheng, 2020, Borri and Shakhnov, 2020 and Bianchi and Babiak, 2021, among others) and leading industry applications.[3]

For each individual asset, the data are aggregated across exchanges based on a volume-weighting

[3]For instance, CryptoCompare provides Refinitiv, one of the world's largest providers of financial market data and infrastructure, with order book and trade data that are integrated into the Refinitiv financial desktop platform Eikon. Recent work by Alexander and Dakos (2019) suggests that CryptoCompare data is among the most reliable for use in both academic and practical settings.

scheme. The aggregation gives relatively more liquid market prices more importance, and market activity on relatively less liquid exchanges, which are more sensitive to exogenous shocks, is negligible. A cryptocurrency needs to meet a list of criteria criteria be listed, such as being traded on a public exchange with an API that reports the last traded price and the last 24-hour trading volume, and having a non-zero trading volume on at least one supported exchange so that a price can be determined. A variety of filters to mitigate the impact of erratic and fraudulent trading activity are also implemented. Outlying trading activity is discarded: for a trade to be considered an outlier, it must deviate significantly either from the median of exchanges, or from the previous aggregate price.[4] Also, the exchanges which the aggregation is based upon are reviewed on a regular basis for each given cryptocurrency pair. Constituent exchanges are excluded if (1) the posted prices are too volatile compared to the market average, (2) trading has been suspended by the exchange on a given day, (3) there are reports of false data being provided, or (4) the public API of a given exchange malfunctions. In order to ensure that exchanges that are excluded in a given month have an expiring price impact, the aggregate market price takes the last trade time into account, so that the aggregation moves with the market without being significantly affected by changes in the exchange composition. These steps should mitigate the effects of suspicious and/or fraudulent market activity and substantially reduce the exposure of the empirical analysis to misreporting trading activity for some exchanges.

From the dataset outlined above, we construct a number of individual characteristics for each day. Characteristics include both blockchain- and market-based variables. On-chain activity measures consist of the sum of new blockchain addresses created for a given asset (`new add`), the sum of addresses that executed at least one transaction during the day (`active add`), the number of valid transactions for a given day, after filtering out failed transactions (`transaction count`), and the average transaction value denominated in native units of the digital asset for a given day (`avg trans value`). These measures have been shown to capture key pricing features such as network growth and development (see, e.g., Pagnotta and Buraschi, 2018). Market variables include daily trading volume, expressed in millions of USD (`trading volume`), a price impact measure calculated as the absolute value of the daily return-to-volume ratio as originally proposed by Amihud (2002) (`illiq`), the daily average between two different synthetic bid-ask spread measures as proposed by Corwin and Schultz (2012) and Abdi and Ranaldo (2017) (`bid-ask`), a de-trended measure of trading volume based on

[4]Such deviations can occur for a number of reasons, such as extremely low liquidity on a particular pair, erroneous data from an exchange, and incorrect mapping of a pair in the API.

two different trending periods (15 and 30 days) as proposed by Llorente et al. (2002) (`vol shock`), total market capitalization (`size`), 30-day rolling-window estimates of the CAPM alpha and beta (`capm` α and `capm` β), in which excess return on the market portfolio is constructed as the difference between the cryptocurrency market index return and the risk-free rate measured as the one-month Treasury bill rate. The cryptocurrency market index return is defined as the value-weighted return of all available underlying coins after filtering (see description below). We then consider also the volatility of the same CAPM residuals (`idio vol`), the daily realised volatility estimate as in Yang and Zhang (2000) (`rvol`), the 5% historical value-at-risk and corresponding expected shortfall based on 90 days of realised returns (`VaR(5%)` and `ES(5%)`), short-term reversal `rev` (see, e.g., Nagel, 2012), and four different time-series momentum factors based on 7, 14, 21 and 30 day look-back periods (`mom`) (see, e.g., Moskowitz et al., 2012). In total, we construct 21 different characteristics and market variables for each individual asset.

2.1.1 Observable risk factors. From the cross-section of 809 digital assets, we exclude stablecoins, which are directly pegged to fiat currencies, and tokens with market capitalization below hundred million USD. This leaves an unbalanced panel of market and blockchain data for 382 digital assets. Despite the shrinkage in size, Figure 2 shows that our cross-section of assets cover the overwhelming majority of total market capitalization. The sum of the market cap of the selected digital assets (red line) includes more than 95% of the total market value (blue line) for almost all of the sample period, with a slight increasing discrepancy over the bull market cycle between the end of 2020 and the beginning of 2021. The median number of daily observations for a given asset is 1200 trading days, while the median size of the cross-section is 250 assets for a given trading day; that is, for at least 50% of the sample observations we have at least 250 assets in the data. Assets included should not necessarily be tradable by the end of the sample to avoid survivorship bias.

In addition to the excess returns on the market portfolio, we analyze the performance of a comprehensive list of zero-investment long-short strategies based on size, momentum, volatility, liquidity, and reversal. We consider these observable factors because they have been shown to capture a significant amount of the variation in realised and expected returns on cryptocurrencies (see e.g., Liu et al., 2019, Brauneis et al., 2021, Leirvik, 2021). We describe each factor and its unconditional historical performance in turn.

We construct the size factor by sorting digital assets based on their market capitalization. The latter is calculated as the circulating supply of tokens/coins times their current market price expressed in USD (see, e.g., Liu et al., 2019). For each trading day, we sort individual cryptocurrencies into quintile portfolios based on the value of their market capitalization. We then construct a value-weighted portfolio for each quintile and track the return on each portfolio in the day that follows. The size factor is constructed as a long-short portfolio which goes long (short) on small (large) assets. We assume that shorting occurs on the margin at a 1x leverage ratio. As a result, each time the portfolio is rebalanced, one can invest only a fraction of wealth in new short positions[5].

Daily rebalancing of the strategy implies that transaction costs should be considered, as they may absorb a substantial fraction of the realised performance. We consider an average bid-ask spread of 100 basis points, which is a rather conservative estimate and roughly corresponds to the cross-sectional average between the Corwin and Schultz (2012) and Abdi and Ranaldo (2017) estimate over the sample. We also assume that opening a short position costs an additional 50 bp, which is again a rather conservative estimate given the fee structures of major cryptocurrency exchanges (see, e.g., Schwenkler and Zheng, 2020 and Bianchi and Dickerson, 2019). Note that this same fee structure is assumed across all factor risk portfolios.

For liquidity risk factors, we consider two alternative portfolio construction procedures. First, for each trading day, we sort individual cryptocurrencies into quintile portfolios based on the value of their Amihud (2002) ratio. This is calculated as the ratio between the absolute daily return and the average daily trading volume expressed in $mln. We then construct a value-weighted portfolio for each quintile and track the return on each portfolio in the day that follows. The `illiquidity` risk factor is constructed as the long-short portfolio which goes long (short) on less liquid (more liquid) assets. An alternative liquidity factor is constructed by replacing the Amihud (2002) ratio with the average between the Corwin and Schultz (2012) and Abdi and Ranaldo (2017) synthetic bid-ask spread measures, to sort assets into quintile value-weighted portfolios. Brauneis et al. (2021) has recently shown that both the Corwin and Schultz (2012) and Abdi and Ranaldo (2017) provide a fairly accurate proxy for liquidity within the context of cryptocurrency markets.

[5]Although short-sales in cryptocurrency markets were rather difficult to implement, especially in the early part of the sample, they were not impossible to execute. The equivalent of a short sale can be implemented via margin trading on major exchanges including Binance, Poloniex, and Bitfinex. In practice, these exchanges offer the possibility to borrow a given crypto at the current market price and to sell it, and then to buy it back later to cover your position. Another interpretation one could give to our long-short portfolio is a weighting scheme with respect to a benchmark; that is, a value-weighted market portfolio. In this respect, a long (short) position could be interpreted in relative terms as overweighting (underweighting) some cryptocurrency pair with respect to its market weight. To summarise, although complex to execute, a long-short strategy can indeed be implemented (see, e.g., Liu et al., 2019).

Next, we consider a variety of alternative specifications for cross-sectional momentum as introduced by Jegadeesh and Titman (2001). We consider four different "look-back" periods of 7, 14, 21, and 30 trading days. Each pair i is allocated to a given quintile at time t based on its cumulative log return over the previous l-days. Portfolios are value-weighted. The `momentum` strategy is constructed as the long-short portfolio which goes long (short) on past winner (loser) assets. The skipping period for returns calculation is one day after the portfolio is constructed to avoid short-term reversal.

The last two observable long-short strategies are based on returns volatility and short-term reversal. For volatility, at each time t, a rolling volatility estimate is computed using the volatility estimator of Yang and Zhang (2000) (with rolling period of 30-days). The volatility estimates are then lagged and the cross-section is sorted into quintiles from low to high volatility. The out-of-sample return is computed by taking the value-weighted mean of each quintile. A short position is initiated in the sub-portfolio with the pairs which have the lowest volatility, whereas a long position is taken in the sub-portfolio with the pairs which have the highest volatility. A similar logic applies to the construction of the short-term reversal, in which assets are clustered into quintiles based on previous-day returns. Each sub-portfolio is value weighted. A zero-cost portfolio is then constructed by going long on the high-volatility sub-portfolio and short on the low-volatility sub-portfolio.

Table 1 reports some of the descriptive statistics of each observable risk factor in turn. Two facts emerge. First, once reasonable transaction costs are accounted for, only few observable factors generate statistically significant risk premiums, including the market portfolio, the liquidity, and the short-term reversal strategies. Second, reversal generates an astonishing Sharpe ratio of 4.58 on an annual basis. As short-term reversal is inherently linked to liquidity (see, e.g., Nagel, 2012), we can assume that the risk of "evaporating liquidity" in the short term may indeed represent a significant source of risk for which investors in cryptocurrency markets may require significant compensation (see, e.g., Bianchi and Dickerson, 2019).

Note that a variety of alternative risk factors could have been constructed based on observable characteristics. For instance, different definitions of volatility could have been implemented to construct a corresponding long-short portfolio. However, Liu et al. (2019) showed that three factors, namely market, size and momentum, can accurately span a much larger set of factor-based portfolios, volatility and liquidity included. For this reason, we limit our analysis to the observable risk factors outlined above and reported in Table 1.

2.2 Econometric framework

Methodologically, we apply the instrumented principal components analysis developed by Kelly et al. (2019) and recently used by Büchner and Kelly (2019) and Kelly et al. (2020). The general IPCA model for the excess return on a given test asset $r_{i,t+1}$ is defined as

$$r_{i,t+1} = \alpha_{i,t} + \beta_{i,t} f_{t+1} + \epsilon_{i,t+1} \tag{3}$$

$$\alpha_{i,t} = z_{i,t}^{'} \Gamma_\alpha + \nu_{\alpha,i,t}, \quad \beta_{i,t} = z_{i,t}^{'} \Gamma_\beta + \nu_{\beta,i,t}$$

with the $K \times 1$ vector of latent factors f_{t+1} extracted from the cross-section of test assets. The intercepts $\alpha_{i,t}$ and factor loadings $\beta_{i,t}$ are allowed to be time-varying and depend on the $L \times 1$ vector of observable cryptocurrency characteristics, $\boldsymbol{z}_{i,t}$. The mapping between observable characteristics and dynamic factor loadings is assumed to be linear and is determined by the matrix Γ_β. The estimation of the IPCA model defined by Eq. (3) is performed using the cross-section of N cryptocurrencies over T periods via an alternating least squares approach, which iterates the first order conditions of $\Gamma = [\Gamma_\alpha, \Gamma_\beta]$ and f_{t+1} (see Kelly et al. (2019) for more details). As outlined in Section 2.1, the panel of the assets data can be unbalanced.

The application of IPCA in the context of digital assets can be motivated in several ways. First, our understanding of the cross sectional variation of the returns on digital assets is limited, at best. For instance, high market concentration around a handful of digital assets makes long-short strategies based on observable characteristics potentially highly dependent on the trading costs and frictions that characterise any asset beyond the top 100 by market capitalization (see Figure 1). Second, risk factor loadings are arguably not constant over time in a highly volatile environment such as cryptocurrency markets. Third, cross-sectional correlation of the returns, especially at the daily level, is rather weak. Thus, by simply using realised returns to build common components to explain the interplay between risks and rewards may not necessarily be very informative a priori. Instead, the IPCA allows a researcher to expand the conditioning information set and to incorporate other data beyond returns, which could mitigate the limitations of the relatively low-density structure in cryptocurrency markets. Fourth, the IPCA framework makes asset pricing tests relatively intuitive and straightforward to implement, even when the factor structure of the returns is latent and dynamic. Specifically, a restricted model with $\Gamma_\alpha = 0$ corresponds to the null hypothesis that systematic factors are the sole determinants of returns. Meanwhile, an unrestricted $\Gamma_\alpha \neq 0$ model represents the alternative hypothesis that conditional expected returns have intercepts that depend on stock characteristics, indicating that compensation for holding cryptocurrencies does not align with their systematic risk exposure.

To assess the performance of the IPCA vis-á-vis observable risk factors, Kelly et al. (2019) propose two alternative metrics. The total R^2 is defined as

$$R^2_{total} = 1 - \frac{\sum_{i,t}\left(r_{i,t+1} - z_{i,t}'\left(\hat{\Gamma}_\alpha + \hat{\Gamma}_\beta \hat{f}_{t+1}\right)\right)}{\sum_{i,t} r^2_{i,t+1}}, \tag{4}$$

which measures the fraction of the total variance of realized returns captured by factor realizations and conditional loadings. The predictive R^2 is defined as

$$R^2_{pred} = 1 - \frac{\sum_{i,t}\left(r_{i,t+1} - z_{i,t}'\left(\hat{\Gamma}_\alpha + \hat{\Gamma}_\beta \hat{\lambda}\right)\right)}{\sum_{i,t} r^2_{i,t+1}}, \tag{5}$$

in which $\hat{\lambda}$ is the unconditional time-series average of factor returns. The predictive R^2 is a "conditional measure", in the sense that it measures how well conditional expected returns implied by the model capture realized return variation.

Both the total and the predictive R^2 outlined above pertain to the variation in the realised and expected returns of individual assets. Furthermore, the asset pricing literature commonly examines the performance of factor models in terms of their ability to explain the behaviour of portfolios in addition to individual assets. For example, when looking at equity markets, researchers tend to use double-sorted portfolios formed on different characteristics, such as size and book-to-market ratios (see, e.g., Fama and French, 2015). Nevertheless, the choice of most appropriate portfolios has been a source of debate (Lewellen et al., 2010; Daniel et al., 2012). Kelly et al. (2019) demonstrate that the IPCA methodology provides a convenient resolution to this problem, since all asset pricing tests can be implemented in a similar way both for individual assets and characteristic-managed portfolios. For instance, consider the $N \times L$ matrix of characteristics at time t, Z_t, and define the $L \times 1$ vector of managed portfolios as

$$x_{t+1} = \frac{Z_t' r_{t+1}}{N_{t+1}}, \tag{6}$$

in which N_{t+1} denotes the number of non-missing cryptocurrency observations. The l-th element of the vector of managed portfolios, x_{t+1}, is a weighted average of cryptocurrency returns, r_{t+1}, where the weights are defined by characteristics, Z_t. Similarly to the performance measures defined for the individual assets, we can determine the total and predictive R^2 for each $l = 1, ..., L$ of characteristic-managed portfolios as

$$R^2_{total,x} = 1 - \frac{\sum_{l,t}\left(x_{l,t+1} - z^{'}_{l,t} z_{l,t}\left(\hat{\Gamma}_\alpha + \hat{\Gamma}_\beta \hat{f}_{t+1}\right)\right)}{\sum_{l,t} x^2_{l,t+1}}, \tag{7}$$

$$R^2_{pred,x} = 1 - \frac{\sum_{l,t}\left(x_{l,t+1} - z^{'}_{l,t} z_{l,t}\left(\hat{\Gamma}_\alpha + \hat{\Gamma}_\beta \hat{\lambda}\right)\right)}{\sum_{l,t} x^2_{l,t+1}}. \tag{8}$$

Although the main focus of our empirical analysis is on individual assets, we also report the whole battery of tests, both in-sample and out-of-sample for characteristic-managed portfolios. This allows for a more direct comparison between the performance of the IPCA and the results obtained in some of the existing research (see, e.g., Liu et al., 2019).

3 Empirical Results

3.1 Asset pricing performance

We begin our empirical investigation by estimating the restricted ($\Gamma_\alpha = 0$) and unrestricted ($\Gamma_\alpha \neq 0$) IPCA models for $K = 1, ..., 6$ factors. We compute R^2_{total} and R^2_{pred} for both individual assets and characteristic-based portfolios. Table 2 summarizes the results. Panel A shows the results for the cross-section of individual assets. Two facts emerge: first, the total R^2 account for 13.00% and 15.89% of the observed variation in returns for a one-factor model with a restricted and unrestricted intercept, respectively. That is, the additional variation explained by the intercept is small compared to the first latent principal component. The spread in the performance of the single-factor specification increases for the R^2_{pred} metric. Second, increasing the number of latent factors leads to gradual improvement in model performance, both related to realised returns and conditional expected returns. In fact, the six-factor IPCA model explaining 18.68% and 18.69% for $\Gamma_\alpha = 0$ and $\Gamma_\alpha \neq 0$. More importantly, when allowing for a non-zero intercept in the model structure, R^2_{pred} increases to a remarkable 2.9% with virtually no differences between the restricted and unrestricted specifications. This suggests that when considering more than two latent factors there is virtually no variation in realised and expected returns that is explained by the model intercept.

It is common practice in the empirical asset pricing literature to examine the explanatory power of asset pricing models using portfolios such as the size and value sorted portfolios as test assets (see, e.g., Liu et al., 2019 and Kelly et al., 2019). The IPCA framework can be approximately stated in terms of managed portfolios $x_t = Z_t' r_{t+1}/N_{t+1}$ (see Section 2 for details), where N_t is the number of assets in the cross-section at time t. This construction yields an $L \times 1$ vector x_t, where L corresponds to the number of characteristics. We then compute the performance measures for the managed portfolios as test assets. Panel B in Table 2 shows the results. The explanatory power of the IPCA is markedly stronger for portfolio returns than for returns on individual assets. For instance, both restricted and unrestricted models with only a single factor generate a total R^2 of above 93%. The predictive R statistics exhibit a similar pattern when we increase the number of IPCA factors; however, their magnitude is slightly smaller: the IPCA generates a predictive R^2 of 1.74% for $\Gamma_\alpha = 0$ and $\Gamma_\alpha \neq 0$ with $K = 6$ factors. The fact that these numbers are smaller than those for individual cryptocurrencies is an interesting result on its own. This finding also stands in stark contrast to prior results for equity, corporate bond, and option returns, where IPCA performance in terms of predictive R^2 statistics tends to be stronger for characteristic-managed portfolios (Kelly et al., 2019, 2020; Büchner and Kelly, 2019), indicating a possible segmentation between risks in cryptocurrencies and traditional asset classes. In fact, as highlighted by Liu and Tsyvinski (2020), typical risk factors that have been used in the equity literature do not seem to enter the pricing kernel for cryptocurrency markets, which inherently implies pricing segmentation.

Panel C in Table 2 reports the bootstrap p-values for the hypothesis test of $H_0 : \Gamma_\alpha = 0$ for IPCA with a number of latent factors ranging from $K = 1$ to $K = 6$. The null hypothesis implies that characteristics help to explain risk through systematic factors, but not on their own.[6] In the $K = 1$ and $K = 2$ specifications of the IPCA model, we reject the null hypothesis that expected returns are driven solely by their compensation to common risk factors. On the other hand, a model with more than two latent factors show that mispricing vanishes to zero in statistical terms. As a result, we choose the three-factor IPCA model as our main *baseline* specification, as it is the smallest model that fails to reject the null at a 5% conventional significance level (p-value = 96.1%).

[6] We follow Kelly et al. (2019) and for each model specification, we construct the test statistic based on the identical implementation of a "wild residual" bootstrap approach. Specifically, we initially draw 10000 pseudo-samples under the null hypothesis $H_0 : \Gamma_\alpha = 0$. For each sample, we construct a Wald-type statistic measuring the distance between the restricted and unrestricted models. We then calculate the fraction of simulated statistics exceeding the corresponding value from the data to obtain the p-value for the IPCA model considered.

3.2 Comparison with observable factors

Liu et al. (2019) shows that three observable risk factors, the excess returns on the market, size, and momentum, can span the cross-sectional variation of a larger set of characteristic-based portfolios. Although factors are latent and dynamic, we find evidence in a similar spirit: as we increase the number of factors above two, the discrepancy in terms of total R^2 between the unrestricted model with $\Gamma_\alpha \neq 0$ and the restricted model with $\Gamma_\alpha = 0$ vanishes. We compare the performance of our IPCA specification against a number of observable risk factors adapted from the existing empirical asset pricing literature. We consider six risk factors: market, size, momentum, liquidity, reversal, and volatility. We describe these factors in Section 2.1 and report some of their descriptive statistics in Table 1.

We begin our analysis with a cryptocurrency counterpart of the capital asset pricing model (CAPM), that is, a single factor specification with a market return (FF1). We then study an augmented two-factor model by adding size (FF2). Motivated by the results of Liu et al. (2019), we consider a three-factor model (FF3) combining the market, size and momentum factors, where the latter corresponds to the $r21\_1$ specification in Table 1. The four- and five-factor models (FF4 and FF5) add liquidity and volatility as additional risk factors. Notice that, between the two different liquidity factor specifications, we consider a long-short portfolio based on the synthetic bid-ask spread, as it appears to generate positive and significant returns.[7] Finally, the reversal strategy appears to be strongly profitable in cryptocurrency markets. For this reason, we include the reversal factor alongside the FF5 factors to obtain the FF6 model (see also Dobrynskaya, 2021).

Table 3 recaps the performance of the restricted IPCA model, i.e., $\Gamma_\alpha = 0$ (Panel A), and provides the results for two alternative specifications of the observable risk factor models. The first specification (Panel B) puts the observable risk factors into a setting similar to the IPCA, that is, factor loadings are instrumented with the same characteristics used for the baseline IPCA model, i.e., dynamic loadings. This specification can be estimated by pre-specifying factors and evaluating only the matrix of loadings Γ_β from the associated first-order condition. The second alternative specification (Panel C) follows a standard factor pricing model with static loadings, with the betas estimated from a panel regression of cryptocurrency returns on observable risk factors (see, e.g., Liu and Tsyvinski, 2020; Liu

[7] In a set of unreported results, we also consider a combination of the market, size, reversal, and volatility plus different momentum specifications and the Amihud (2002) sorted portfolios. All alternative specifications produce lower R^2_{total} and R^2_{pred}, so we choose the best possible specification for the observable factors model. Results for each alternative factor specification are available upon request.

et al., 2019). Loadings are static, as they do not depend on cryptocurrency characteristics, unlike the IPCA specification. We impose a zero intercept constraint for both alternative approaches to align with the baseline IPCA specification and isolate the explanatory power of sources of systematic risk.

The results show three interesting aspects. First, the explanatory power of the IPCA factors outperforms observable risk factors by a significant margin. For instance, our baseline three-factor IPCA model generates a 17.2% R^2_{total}, whereas a six factor model with static loadings delivers a 9.6% R^2_{total}. This is a remarkable result for daily returns in a highly volatile market. Turning to the expected returns, R^2_{pred} from the IPCA is again much larger than the one obtained from the benchmark observable risk factor models. For instance, while the three-factor IPCA specification generates a 2.9% predictive R^2, the best performing six-factor model produces 0.67%. Second, the predictive performance of a dynamic factor model is substantially higher than that of a factor model with static loadings. For instance, the six-factor model with instrumented loadings delivers R^2_{pred} 0.67% compared to -0.02% obtained from the same model with static loadings. This result suggests that significant information is brought by individual asset characteristics to explain the cross sectional variation of returns. Third, the incremental contribution of factors beyond the excess returns on the market is mixed. For instance, the total variation of a model with only market excess returns as a unique risk factor (FF1) is comparable to a more extensive six-factor model with additional proxies of systematic risk (FF6). On the other hand, in terms of R^2_{pred}, the explained variation substantially increases when the reversal factor is included. This suggests that, while exposure to market risk may explain a great deal of the variation in realised returns, short-term reversal might play a key role in the dynamics of risk premiums (see, e.g., Nagel, 2012).

The outperformance of the IPCA framework for individual assets is confirmed for characteristic-based portfolios. For instance, while the baseline three-factor IPCA model explains almost 97% of the variation in realised returns, the best performing models with observable risk factors with either static or dynamic loadings produce a much lower 64%. This value is in line with some of the existing results in the literature (see, e.g., Liu et al., 2019). Panels B and C confirm that both total and predictive R^2's for individual cryptocurrencies and managed portfolios are somewhat comparable. In terms of predictive performance, the empirical results slightly favor time-varying betas. Specifically, the predictive statistics from static observable factor models never rise above -0.02% and 0.22% for individual assets and portfolios. To summarise, the results in Table 3 show that the IPCA factors produce a much more accurate measurement of the dynamics of risk and rewards for individual assets and characteristic-based portfolios.

Table 4 formally tests whether coupling latent and observable risk factors improves the explanatory power of the IPCA model significantly. We test whether the observable risk proxies provide information about and beyond IPCA factors explaining the variation in realised and expected returns. The test is based on an extended IPCA model

$$r_{i,t+1} = \beta_{i,t} f_{t+1} + \delta_{i,t} g_{t+1} + \epsilon_{i,t+1}. \tag{9}$$

The term $\beta_{i,t} f_{t+1}$ is the same as in the main IPCA specification in Eq. (3). The new term is the portion of the returns variation described by the $M \times 1$ vector of observable factors g_{t+1}. For consistency, the loadings on both observable and latent risk factors are instrumented using the same set of individual asset characteristics, i.e., $\delta_{i,t} = z'_{i,t}\Gamma_\delta + \nu_{\delta,i,t}$. A detailed description of the estimation procedure appears in Kelly et al. (2019). To test the incremental explanatory power of observable risk factors, we test the null hypothesis

$$H_0: \; \Gamma_\delta = \mathbf{0}_{L\times M} \quad \text{vs} \quad H_1: \Gamma_\delta \neq \mathbf{0}_{L\times M}. \tag{10}$$

A Wald-type test statistic is constructed as $W_\delta = \text{vec}\left(\widehat{\Gamma}_\delta\right)' \text{vec}\left(\widehat{\Gamma}_\delta\right)$, with $\widehat{\Gamma}_\delta$ denoting the estimated parameters for the loadings on g_{t+1}. W_δ represents the distance between the model with and without additional observable risk factors. The p-values are obtained using the same residual wild bootstrap concept.

Panel A and B in Table 4 report the total and predictive R^2 for the augmented IPCA. For ease of exposition, we repeat the performance statistics obtained from the original IPCA implementation (the first row of both panels). In general, the results show that adding observable factors only marginally improves the performance of the IPCA model, almost regardless of the number of latent factors K. For instance, our baseline model with $K = 3$ produces R^2_{total} of 17.7%. By adding all observable risk factors, the total R^2 increases by a tiny margin to 17.8%. Turning to the bootstrap results, Panel C in Table 4 shows that the market factor is statistically significant up to the baseline IPCA with three latent factors. As we add more IPCA factors, all of the observable factors start to become redundant, that is, for $K \geq 3$ none of the six long-short portfolios are statistically significant at the

1% level after controlling for IPCA factors. In sum, none of the observable risk factors seems to offer an alternative, or incremental, economic explanation of the IPCA factors for the variation in both realised and expected returns.

3.3 Unconditional asset pricing

The results thus far have shown that the IPCA model achieves a more accurate in-sample description of individual assets and managed portfolios in comparison to the model comprising a variety of observable risk factors. This does not necessarily imply that the IPCA factors are unconditionally mean-variance efficient, i.e., whether they can price assets unconditionally. In order to test mean-variance efficiency of the IPCA factors vs observable risk factors, we carry out two asset pricing tests.

We first test the ability of IPCA to price the cross-section of characteristic-managed portfolios (see, e.g., Büchner and Kelly, 2019; Kelly et al., 2020). As a benchmark, we choose the six factor model used in the main empirical analysis so far: a model that includes the market factor in addition to size, momentum, liquidity, reversal, and volatility factors. We study the cross-section of managed portfolios, as these represent test portfolios that are weighted by asset characteristics.

We focus on the IPCA specification with the $K = 3$ factors. Our choice of the three-factor model is motivated by the results of the significance test of Γ_α. We compare the alphas obtained from the IPCA factors with those estimated via a set of time-series regressions of the same managed portfolio returns on the observable risk factors. For the sake of completeness, we consider both conditional and unconditional alphas by instrumenting IPCA and observable factors with individual characteristics. Specifically, the portfolio alphas are computed as the time-series averages of period-by-period portfolio residuals in both the static and dynamic versions of the latent or observable factor models. Figure 4 plots unconditional and conditional versions of portfolio alphas against their raw average excess returns. For convenience, we highlight significant and insignificant alphas with filled and unfilled markers. The plots also report the average absolute alpha for each specification, to quantify the average size of mispricing across factor models.

The main results show that allowing for time-varying factor loadings in the FF6 specification reduces the average absolute alpha from 10.79% to 8.54% on an annual basis, while the number of portfolios with significant alphas remains large. We also find that the estimated alphas from both implementations of observable factors are clustered around the 45-degree line. This indicates that observable factors may have difficulties explaining the cross-section of managed portfolio returns. In contrast, when using the baseline IPCA factors, the average absolute alpha is substantially reduced to 4.28% with static loadings and to 0.61% with instrumented coefficients. Further, all portfolio alphas from the static and dynamic IPCA specifications become insignificant and their magnitudes are economically small.

To gain a better understanding of how portfolio alphas change with the number of factors, we re-run the previous analysis with IPCA factors from the $K = 1$ through $K = 6$ specifications and with observable factors from FF1 through FF6. Table 5 reports the average absolute alphas in the unconditional and conditional implementations. The average pricing error decreases as we increase the number of IPCA factors, while mispricing remains significant regardless of the number of observable risk factors. A single factor from the $K = 1$ IPCA model outperforms observable factors in terms of both unconditional and conditional alphas. Increasing the number of IPCA factors to $K = 6$ reduces mispricing from 9.14% to 3.87% and from 8.63% to 0.58% for specifications with static and instrumented loadings.

3.4 Out-of-sample performance

Thus far, we have shown that the IPCA model achieves a superior description of the in-sample variation of the trade-off between risks and rewards. The total and predictive R^2 reported previously are essentially in-sample statistics, that is, both fits and predictions are generated using the whole history of observations. However, the in-sample outperformance does not necessarily translate into out-of-sample performance. Hence, we now analyze out-of-sample predictions.

Recursive forecasts are carried out by expanding the window of observations starting from September 2019. The first half of the observations available is used as an in-sample period. The computation of the out-of-sample realised factor returns $\widehat{f}_{t+1}$ is implemented as in Kelly et al. (2019). We evaluate the out-of-sample performance of the models with IPCA or observable factors using the total and predictive R^2 computed for individual assets and characteristic-managed portfolios. Table 6 summarises the results. Except for a few nuances, we find that the superior in-sample fit of IPCA translates into strong out-of-sample performance. For instance, R^2_{total} for the baseline three-factor IPCA model declines from 17.15% to 16.16%. Meanwhile, R^2_{pred} remains essentially unchanged, i.e., 2.93% in-sample vs 2.95% out-of-sample. The IPCA performance is also somewhat persistent for characteristic-managed portfolios. For instance, the total (predictive) R^2 slightly decreases from 96.49% (1.75%) in-sample to 95.77% (1.29%) out-of-sample for the IPCA specification with $K = 3$ factors.

Despite this small deterioration in the performance, the IPCA model still significantly outperforms the benchmark model with observable risk factors. For instance, when it comes to individual assets, the out-of-sample R^2_{total} obtained from the FF6 is 7.38% (6.87%) for instrumented (static) loadings. This is quite a sizable deterioration in comparison to the in-sample performance, which was 9.27% and 9.62% for the dynamic and static loadings, respectively. A similar pattern holds for managed portfolios. The in-sample R^2_{total} for the dynamic (static) model with observable risk factors is 64.10% (64.05%), while the out-of-sample value decreases to 53.70% (53.31%). The figure for R^2_{pred} is mixed, with values that remain largely unchanged between in-sample and out-of-sample fits.

Table 7 provides insight into the ability of IPCA to carry over the in-sample mean-variance efficiency to the out-of-sample setting. The out-of-sample mean-variance efficiency for both IPCA and observable risk factors is assessed by computing the Sharpe ratios of individual factors and tangency portfolios formed from the set of factors. Panel A of Table 7 reports the results for the IPCA model. Each column reports the univariate Sharpe ratio of the respective factor as well as the Sharpe ratio of the tangency portfolio combining factors from $K = 1$ to $K = 6$. The IPCA model with $K = 2, 3$ latent factors yields an annualised Sharpe ratio above 13, which is tenfold higher than the best tangency portfolio based on the six observable risk factors. Interestingly, adding more than three IPCA factors is detrimental from a mean-variance efficiency perspective. However, despite the decline in the Sharpe ratios after three factors, they still exceed those from the observable factor models, such as the FF6 model that generates a Sharpe ratio of 1.79 vs 7.82 for the IPCA with $K = 6$ factors. This evidence is consistent with the main empirical evidence that three latent IPCA factors are sufficient to price the cross-section of cryptocurrency returns.

3.5 Factors and characteristics

We now delve further into the drivers of the IPCA model's performance, and examine the marginal contribution of each asset characteristic. This helps to provide an economic interpretation of the latent IPCA factors. We evaluate the marginal relevance of each characteristics for the IPCA model using the procedure outlined in Kelly et al. (2019): an exact bootstrap approach that tests a joint significance of the K loadings for each individual characteristic. Let the l^{th} row in the parameter matrix $\Gamma_\beta = [\gamma_{\beta,1}, \ldots, \gamma_{\beta,L}]'$ correspond to the loadings on the K factors of the l^{th} characteristic. The joint significance test boils down to testing the null hypothesis that the entire l^{th} row must be zero. To test this hypothesis, we begin by estimating an unrestricted IPCA model, in which coefficients of Γ_β are not set to zeros, and save the estimated model parameters $\{\hat{\gamma}_{\beta,l}\}_{l=1}^{L}$, latent factors $\{\hat{f}_t\}_{t=1}^{T}$, and managed portfolio residuals $\{\hat{d}_t\}_{t=1}^{T}$. For each characteristic l, we then compute the Wald-type statistic of the form $\hat{W}_{\beta,l} = \hat{\gamma}_{\beta,l}'\hat{\gamma}_{\beta,l}$. Next, we use the residuals to resample characteristic-managed portfolio returns under the restriction $\gamma_{\beta,l} = 0_{K\times 1}$.[8] Similarly, we re-estimate the IPCA model using these pseudo-portfolio returns and compute the bootstrap test statistic $\hat{W}_{\beta,l}^{b}$ for the b^{th} bootstrap draw. For the l^{th} characteristic, the p-value of the null hypothesis test equals the fraction of bootstrapped $\hat{W}_{\beta,l}^{b}$ statistics exceeding the empirical value $\hat{W}_{\beta,l}$.

The first three columns of Table 8 show the results for the baseline IPCA model with $K = 3$ factors and two "neighbourhood" alternative specifications with $K = 2$ and $K = 4$ factors, which are reported for the sake of comparison. We find that out of the 21 characteristics considered, six (`trading volume`, `bid-ask`, `size`, `capm` β, `ES (5%)` and `rev`) significantly contribute to explain the variation in cryptocurrency returns as indicated by close-to-zero p-values. The `capm` β characteristic is not significant for the IPCA specification with $K = 4$ factors, whereas `active add`, `VaR(5%)` and `mom` 7_1 have a bootstrapped p-value smaller than 5% only for the two-factor IPCA model. The results of the baseline and alternative IPCA specifications for the full sample suggest that the dynamics of factor loadings and therefore of cryptocurrency risk premiums is mostly due to characteristics linked to liquidity, market capitalization, and both market and downside risk.

We now interpret the factors in turn. Because the factors in the IPCA framework are not ordered and are only identifiable up to a rotation, a detailed interpretation of the individual factors is problematic, perhaps even inappropriate. Moreover, we caution that any labeling of the factors is imperfect, because each factor is influenced to some degree by all of the characteristics, and the orthogonality condition implies that none of the latent factors will match an exact characteristic. Nonetheless, we

[8] Starting from the restricted matrix

$$\hat{\Gamma}_\beta^{l} = [\hat{\gamma}_{\beta,1}, \ldots, \hat{\gamma}_{\beta,l-1}, 0_{K\times 1}, \hat{\gamma}_{\beta,l+1}, \hat{\gamma}_{\beta,L}]',$$

bootstrap portfolio returns are defined as $\hat{x}_t^b = Z_t \hat{\Gamma}_\beta^l \hat{f}_t + \hat{d}_t^b$, in which $\{\hat{d}_t^b\}_{t=1}^{T}$ are the residuals for the b^{th} bootstrap draw.

adapt the idea of Ludvigson and Ng (2009) and provide an interpretation of the latent factors based on the marginal R^2 of a univariate regression of each of the 21 different characteristic-based portfolios onto each estimated IPCA factor, one at a time, using the full sample of observations.

Figure 5 summarizes the results for the baseline IPCA model with $K = 3$ factors. The first latent factor strongly relates to short-term reversal (`rev`) as suggested by the marginal R^2 of 85% for the reversal portfolio, and has a negligible association with other characteristics, as indicated by the marginal R^2 of less than 5%. Short-term reversal is typically associated with investor overreaction to past information and correction of that reaction after a short time horizon. Specifically, Nagel (2012) suggests that returns to short-term reversal strategies can be interpreted as a proxy for the returns from liquidity provision. Thus, the reversal anomaly can be associated with liquidity risk.

Factor 2 is primarily driven by the Amihud (2002) price impact measure `illiq` and the total daily volume (`trading volume`). Both characteristics are inherently linked to the intensity of market activity and the dynamics of liquidity. The market beta also has a marginal R^2 of 40%, which is slightly lower than the above 45% marginal R^2's for price impact and trading. At a much smaller magnitude, Factor 2 also appears to be "contaminated" by fundamental blockchain activity and market capitalization. Specifically, the marginal R^2 statistics corresponding to these characteristics are less than 20%, indicating a relatively weaker relationship.

Factor 3 appears to capture the information content of several quantities related to volatility, liquidity, and downside risks, making its interpretation challenging. It exhibits the strongest association with downside risk and idiosyncratic volatility measures, as illustrated by the above 40% marginal R^2 for `VaR(5%)`, `ES(5%)` and `idio vol`. Factor 3 can also be explained in part by liquidity, as proxied by the synthetic bid-ask spread (see Section 2 for an explanation). For instance, the marginal R^2 statistics for `bid-ask` is above 30%. The managed portfolios constructed for liquidity, volatility, and downside risk characteristics tend to be strongly correlated in our sample. Factor 3 recovers these factors due to their common exposure to cryptocurrency tail risk and, hence, it can be labelled downside risk.

In sum, Table 8 and Figure 5 suggest that a few characteristics are primarily responsible for the dynamics of risk premiums in cryptocurrency markets. These are mainly related to liquidity, size, market beta, reversal and possibly to downside risk. These findings expand upon those of Liu and Tsyvinski (2020), Liu et al. (2019), Bianchi and Dickerson (2019) and Dobrynskaya (2021).

3.6 Sub-sample analysis

From the onset of the Covid-19 pandemic, cryptocurrency markets have experienced a significant run-up in value, reminiscent of the ICO-bubble that occured between the end of 2017 and the beginning of 2018. To investigate the performance of the IPCA framework pre- and post-pandemic outbreak, we now split the sample into two non-overlapping periods, from December 2nd 2016 to January 1st 2020 and from January 2nd 2020 to July 9th 2021.

We replicate the main empirical analysis performed for the full sample and then discuss differences and similarities across sub-samples. This should provide additional insights into the robustness of the asset pricing results across different market conditions and cycles. Panels A and B in Table 9 report performance statistics for the restricted and unrestricted IPCA models with $K = 1, \ldots, 6$ factors estimated from the corresponding sub-samples. Two facts emerge: first, the number of factors that set the aggregate intercept to zero is larger in the post-pandemic period. For the pre-pandemic sample, the IPCA model with $K = 3$ factors rejects the null hypothesis at all conventional confidence levels and corresponds to a large jump in both total and predictive R^2 of 18.07% and 2.91% for individual cryptocurrencies. For the post-pandemic sample, the smallest model that fails to reject the null hypothesis at the 1% level includes the $K = 6$ factors. This observation corresponds well to a gradual improvement in the predictive R^2 statistics from 0.04% to 3.41% when we increase the number of IPCA factors from $K = 1$ to $K = 6$. The discrepancy in the number of factors in the pre- and post-pandemic periods does not call into question the ability of the IPCA framework to explain the variation of realised and expected returns in cryptocurrencies. Instead, it suggests that, for the second sub-sample individual asset characteristics are not themselves enough to explain the dynamics of risk premiums, unless we increase the number of latent factors to $K = 6$.

Second, the performance of IPCA is rather stable across sub-samples, although it slightly deteriorates in the post-pandemic period. For instance, the average R^2_{total} for the pre- and post-pandemic periods is around 18% and 16% for individual assets. At the managed portfolios level, the difference in total R^2 between the single factor models estimated from different splits is around 1.1%, and diminishes to a mere 0.3% as we increase the number of factors to $K = 6$. This leads to the conclusion that the explanatory power of IPCA factors is stable. The finding is remarkable given the nature and the rapid development of cryptocurrency markets. In fact, the number of assets in the panel is steadily increasing in the first sub-sample, while it remains relatively stable in the second sub-sample.

Consequently, this is reflected in the number of factors needed to reject the null hypothesis that the intercepts are zero. Regardless of the number of factors required to eliminate the mispricing, the IPCA factors maintain a fine statistical performance throughout. Comparing these results to those reported in Table 2, the key conclusion is that the IPCA fit for the whole sample remains very similar in the two sub-samples.

3.6.1 Comparison with observable factors. The previous results show that the IPCA performance remains relatively stable over different sample periods. In contrast, we find that observable risk factors tend to perform rather differently pre- and post-pandemic outbreak. Table 10 shows this. Indeed, the observable risk factor models with dynamic loadings tend to perform much better over the first sample than over the post-pandemic period. The average R^2_{total} for individual assets (characteristic-managed portfolios) is around 11% (75.5%) for the first sub-sample, and substantially decreases to 7.5% (54.5%) for the second sub-sample. There are two possible reasons for this: the cross-section of cryptocurrencies is smaller in the first sample period and the price run up in the second part of the sample is characterised by considerably higher volatility and possibly greater downside risks (see Fig. 2). This suggests that the performance of models employing observable risk factors could be sensitive to both the size of the cross-section and the aggregate market conditions.

Although the performance of observable risk factors is improved in the first part of the sample, IPCA still explains a significantly larger fraction of the variation in realised and expected returns. For the sake of comparison, consider the IPCA models with $K = 3$ and $K = 6$ factors for the first and second sub-samples, respectively. The chosen benchmarks produce a total R^2 of 18.07% and 18.15% for individual cryptocurrencies. In contrast, the total R^2 reaches the maximum of 12.57% and 8.80% for the pre- and post-pandemic periods in the model with six observable factors and static loadings. Turning to the predictive R^2 at the individual asset level, the baseline IPCA specifications under consideration produce remarkable 2.91% and 3.41% for the respective sub-samples. The performance of observable risk factors is stronger in the models with dynamic loadings, but it never rises above an upper bound of 0.81%. The gap between IPCA and the models' observable risk factors is even larger when it comes to characteristic-based portfolios.

Figure 6 suggests that the superior statistical performance of IPCA across sub-samples translates into unconditional mean-variance efficiency. The top panels compare the factor pricing model comprising six observable factors and static loadings with the IPCA specification with $K = 3$ factors estimated on the pre-pandemic outbreak sample. The spread in the performance is clear. The average absolute pricing error implied by observable risk factors is 10.25% on an annual basis, which is an order of magnitude smaller than 0.86% from the baseline IPCA framework. For the post-pandemic outbreak sample, the model with six observable factors produces an average absolute pricing error of 11.25% in annualised terms, while the IPCA specification with $K = 6$ factors produces a mere 0.53%. Furthermore, we find in the observable factor model that the vast majority of characteristic-managed portfolios have significant alphas, whereas none of the IPCA-implied portfolio alphas is significant at conventional thresholds.

3.6.2 Factors and characteristics. We further investigate the stability of the model by looking at which characteristics matter for the dynamics of risk premiums across sub-samples. The empirical tests are the same as described in Section 3.5. The fourth and fifth columns of Table 8 report the results for the two IPCA specifications with $K = 3$ and $K = 6$ factors estimated on the corresponding sub-samples. Two facts emerge: first, there is relative consistency in the composition of the matrix Γ_β across sub-samples, that is, the set of significant characteristics is somewhat overlapping across different periods. Second, those variables that primarily relate to market activity and liquidity (such as bid-ask spread and short-term reversal) are highly statistically significant. Notice that market capitalization and the Amihud (2002) price impact measure are also borderline significant, although at the 10% threshold.

We now provide an economic interpretation of the IPCA factors. Following the procedure outlined in Section 3.5, we regress each of 21 characteristic-based portfolios onto the IPCA factors, one at a time, for both sub-periods. Figure 7 shows the estimates for the pre-pandemic period. Similar to the full sample results (see Figure 5), Factor 1 clearly correlates with the short-term reversal strategy (`rev`). The corresponding marginal R^2 is an unambiguous 85%. Factor 2 has the largest marginal R^2 for `trading volume`, `illiq` and `capm` β. This evidence is consistent with the full sample findings, even though the magnitudes of the marginal R^2 statistics are smaller for the sub-sample. Interpretation of Factor 3 is not straightforward, however, it is largely in line with the core results based on the full sample. For instance, Factor 3 also exhibits the strongest relationship with volatility and downside risk measures as indicated by marginal R^2 statistics as high as 65%. Compared to the main findings based on a longer period, liquidity measures including `trading volume`, `illiq` and `bid-ask` exhibit higher correlations with Factor 3. This is possibly due to the fact that the correlation between downside risk and liquidity characteristics is quite sizable across assets.

Figure 8 summarises the marginal R^2 of the same auxiliary regressions for the six-factor IPCA model estimated on the second sub-period. Similarly, Factor 1 seems to be unequivocally highly correlated with short-term reversal. Factor 2 and Factor 3 are more correlated with fundamental blockchain activity measures and momentum, respectively. Factor 4 highly correlates with `capm` β, with a marginal R^2 equal to 52%. It is more difficult to interpret Factor 5 and Factor 6 as they seem to combine many different characteristics, though the marginal R^2 statistics of Factor 6 are dominated by volatility and downside risk measures.

3.7 Weekly returns

The main empirical results so far provide evidence that IPCA offers an accurate description of realised returns and risk premiums at the daily frequency across different sub-samples. In this section, we extend this evidence by examining cryptocurrency returns at the weekly frequency. To a large extent, we replicate the core empirical analysis and discuss differences and similarities between the results based on daily and weekly returns. This gives some additional insight into the robustness of our findings to an alternative frequency of observations, which has also been done in some of the existing literature on observable risk factor models (see e.g., Liu and Tsyvinski, 2020; Liu et al., 2019).

3.7.1 Asset pricing performance. Table 11 reports the in-sample fit of different IPCA specifications for individual assets and characteristic-managed portfolios. Comparing the results from daily returns reported in Table 2, several observations are noteworthy. First, the performance of the IPCA factors for individual assets significantly improves at the weekly frequency. For instance, the total R^2 is well above 25% regardless of the number of factors. This compares favourably against the IPCA performance for daily returns, which is, on average, around 17% across the models considered. Second, despite the increase in the total R^2, the predictive R^2 declines for weekly returns. In particular, the predictive R^2 lies consistently around 0.94% for individual cryptocurrencies at the weekly frequency, which is significantly smaller than the average 2.7% obtained from daily returns. We find that similar results hold for characteristic-managed portfolios. For instance, the average $R^2_{pred,x}$ across IPCA specifications decreases from 1.7% for daily returns to 0.83% for weekly data. Third, the null hypothesis of $\Gamma_\alpha = 0$ cannot be rejected at the 10% only for $K = 6$ latent factors. However, the specification with $K = 4$ factors is the smallest for which the null hypothesis is also rejected at a 5% significance level.

For this reason, we pick $K = 4$ as our baseline IPCA specification for weekly returns, as it represents the most parsimonious model that does not strongly reject the null hypothesis of no mispricing.

Table 12 compares IPCA with models comprising different groups of observable risk factors sampled at the weekly frequency. Similarly to the IPCA factors, the performance of the observable risk factor models improves across the board. For instance, compared to the daily frequency, the total (predictive) R^2 from the six-factor model with static loadings increases from 9.62% to 23.41% (from 0.22% to 0.29%). The same holds for the total and predictive R^2 constructed for characteristic-managed portfolios. For the benchmark six-factor model with static loadings, the total R^2 for managed portfolios increases from 64% to 74.7%. As a whole, the reported performance of observable risk factor models for both individual assets and managed portfolios confirms some of the existing results in the literature (see, e.g., Liu et al., 2019; Dobrynskaya, 2021).

Nevertheless, the IPCA factors explain a significantly higher fraction of the variation in realised returns and premiums. The baseline four-factor IPCA model generates almost 25% higher R^2_{total} and three times higher R^2_{pred} with respect to the best performing model with observable factors, either with static or dynamic loadings. For managed portfolios, the gap increases further. For instance, the four-factor IPCA explains up to 98% (0.8%) of the variation in the realised returns (risk premiums), against the total and predictive R^2 of 74.6% and 0.29% for the best performing observable risk factor model.

Table 13 confirms that the performance of the IPCA factors for observations at the weekly frequency holds out-of-sample. Although the total R^2 tends to decrease across specifications, the four-factor IPCA model explains 21.8% of the variation in weekly returns – higher than 16% implied by the IPCA benchmark at the daily frequency. In addition, when it comes to R^2_{pred}, the performance gap increases, with the IPCA factors that explain 0.82% of the variation in risk premiums as opposed to 0.42% from the observable risk factor model with dynamic loadings and six factors. As a whole, comparing Table 13 with Table 6, the results suggest that, although the performance of risk factor models improve almost homogeneously across specifications by using weekly returns, the IPCA factors still explain a substantially higher variation in the dynamics of risks and rewards compared to benchmark models with observable risk factors.

Figure 9 shows that such higher statistical performance seems to translate into greater unconditionally mean-variance efficiency. As a baseline IPCA specification, we use $K = 4$ latent factors.

Recall that our choice of the four-factor model is motivated by our results on the significance of Γ_α. Similarly to the daily frequency case, we compare the alphas obtained from the IPCA factors with alphas obtained by a set of time-series regressions of the same managed portfolio returns on the observable risk factors. The top (bottom) panels of Figure 9 report the plots of the unconditional (conditional) versions of portfolio alphas against their raw average excess returns. The plots also report the average absolute alpha for each specification, to quantify the average size of mispricing across factor models.

Our main results show that allowing for instruments in the FF6 specification reduces the average absolute alpha from 7.63% to 3.62%, however, the number of portfolios with significant alphas remains large. Furthermore, we confirm the result for the daily frequency returns, that is, the estimated alphas from both implementations of observable factors are clustered around the 45-degree line. This indicates that, despite the smaller average absolute pricing error, observable factors still do not satisfactory explain the average returns of managed portfolios at the weekly frequency. On the other hand, using our baseline IPCA specification reduces the average absolute alpha to 2.77% with static loadings and to 0.70% with instrumented coefficients. With the exception of two portfolios, all alphas from the dynamic IPCA specification become insignificant and their magnitudes are economically small.

3.7.2 Factors and characteristics. For the sake of completeness, we now investigate the significance of each characteristic for the dynamics of the loadings at the weekly frequency, and provide a heuristic interpretation of the four factors in the baseline IPCA specification as originally proposed by Ludvigson and Ng (2009).

The last column of Table 8 summarises the results. With only the exception of `ES (5%)`, which is not significant at the 5% confidence level, all of the main results for the daily frequency returns are confirmed. That is, variables that relate to liquidity, including `trading volume`, `bid-ask` and `rev` are all highly significant, as is `size`. In addition to the daily frequency case, both `mom 14_1` and `mom 21_1` prove to be significant when using weekly returns. This confirms the results in Liu et al. (2019), which shows that a relatively short-term momentum factor helps to explain the risk premium variation in cryptocurrency markets. To a large extent, though, the daily results are confirmed at the weekly frequency, as suggested by the large overlaps in the significance of characteristics for the loadings dynamics and therefore for risk premiums variation.

Figure 10 reports the marginal R^2 of the auxiliary regressions of each of the 21 characteristic-based portfolios on each of the latent risk factors for the $K = 4$ specification. The first factor seems to be primarily linked to trading activity, i.e., `trading volume`, liquidity, i.e., `illiq` and exposure to market risk, i.e., `capm` β. Some residual correlation is also related to blockchain activity measures such as new and active addresses, as well as average transaction value. In addition to the Amihud (2002) illiquidy measure and trading volume, the second factor is quite significantly correlated with short-term reversal. `capm` β features a relatively high marginal R^2 also in the third factor, together with time-series momentum at different lags. Finally, the fourth factor seems to be mostly correlated with volatility and downside risk indicators in addition to the bid-ask spread, all sharing a marginal R^2 as high as 45%.

4 Conclusion

This paper employs the dynamic latent factor approach originally proposed by Kelly et al. (2019) to describe the empirically observed trade-off between risks and rewards within the context of cryptocurrency markets. Our findings are threefold. First, we find that a low-dimensional latent factor model successfully captures the variation in cryptocurrency returns. Our results confirm previous evidence from traditional asset classes that the IPCA framework outperforms observable risk factor models in its ability to explain the variation in realised returns and premiums of risky assets (see, e.g., Büchner and Kelly, 2019; Kelly et al., 2020). Importantly, we show that a handful of characteristics can explain the dynamics of risk premiums, and there are no significant intercepts associated with managed portfolios. These findings are confirmed both in-sample and out-of-sample estimation procedures.

Second, the IPCA factors are related to conventional sources of risks, which fit the nature of cryptocurrency markets, including liquidity, size, and the exposure to aggregate market and downside risks. Short-term reversal in particular plays a critical role in the dynamics of risk premiums (see, e.g., Nagel, 2012).

Third, we show that the performance of the IPCA factors remains consistent across sub-samples (the full sample and the periods before/after the outbreak of the Covid-19 pandemic), as well as when using returns and characteristics sampled at the weekly frequency. This suggests that the IPCA factors capture some fundamental structure in the interplay between risks and returns in cryptocurrency markets.

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Table 1: Summary statistics of observable risk factors

This table reports summary statistics of observable risk factors: a value-weighted market portfolio, size, volatility, illiquidity, bid-ask spread, reversal strategies and four momentum portfolios formed on past returns over 7, 14, 21, and 30 trading days. A complete description of the observable risk factors is in Section 2. Mean and standard deviation (both in percent), skewness and kurtosis are reported on the daily basis. Sharpe ratio statistics are annualized. The sample of observations is from December 2nd 2016 to July 9th 2021.

				Liquidity			Momentum			
	VW Market	Size	Volatility	Amihud	bid-ask	Reversal	r7_1	r14_1	r21_1	r30_1
Mean	0.22**	0.06	0.38	-0.12	0.66**	1.55***	-0.06	0.03	0.04	0.07
t(mean)	(2.14)	(1.76)	(1.16)	(-0.79)	(2.18)	(9.34)	(-0.29)	(0.18)	(0.21)	(0.89)
SR (annualised)	0.99	0.12	0.50	-0.22	0.93	4.58	-0.12	0.07	0.08	0.11
Skewness	-1.01	0.64	-0.23	0.14	-0.08	0.47	-0.51	-0.89	-0.33	-0.29

Table 2: In-sample asset pricing performance

This table reports in-sample total R^2_{total} and predictive R^2_{pred} for the restricted ($\Gamma_\alpha = 0$) and unrestricted ($\Gamma_\alpha \neq 0$) IPCA models with $K = 1, \ldots, 6$ factors. Performance statistics are computed for individual assets (Panel A) and characteristic-managed portfolios (Panel B). Panel C reports the p-values for the test of $\Gamma_\alpha = 0$ based on a bootstrap with 10000 draws. All numbers are expressed in percent. The sample of observations is from December 2nd 2016 to July 9th 2021.

		K					
		1	2	3	4	5	6
Panel A: Individual assets							
R^2_{total}	$\Gamma_\alpha = 0$	13.00	16.52	17.15	17.71	18.22	18.68
	$\Gamma_\alpha \neq 0$	15.89	16.56	17.16	17.72	18.23	18.69
R^2_{pred}	$\Gamma_\alpha = 0$	0.01	2.91	2.93	2.95	2.94	2.91
	$\Gamma_\alpha \neq 0$	2.51	2.62	2.91	2.93	2.92	2.95
Panel B: Characteristic-based portfolios							
$R^2_{total,x}$	$\Gamma_\alpha = 0$	93.12	95.16	96.49	97.64	97.79	98.06
	$\Gamma_\alpha \neq 0$	94.70	95.65	96.49	97.64	97.78	98.06
$R^2_{pred,x}$	$\Gamma_\alpha = 0$	0.11	1.73	1.75	1.74	1.72	1.71
	$\Gamma_\alpha \neq 0$	1.25	1.52	1.75	1.74	1.73	1.74
Panel C: Bootstrap Test ($H_0 : \Gamma_\alpha = 0$)							
W_α p-value		0.0	0.0	96.1	73.5	70.9	77.5

Table 3: Latent vs observable factors

This table reports in-sample total R^2_{total} and predictive R^2_{pred} for the restricted ($\Gamma_\alpha = 0$) IPCA models with $K = 1, \ldots, 6$ factors (Panel A) and a set of observable risk factor models with dynamic (Panel B) and static (Panel C) loadings. Observable factor models begin with a cryptocurrency analogue of CAPM (FF1) with a market factor, and then add size, momentum, liquidity, volatility, and reversal factors to obtain FF2, FF3, FF4, FF5 and FF6. Performance statistics are computed for individual cryptocurrencies r_t and characteristic-managed portfolios x_t. All numbers are expressed in percent. The sample of observations is from December 2nd 2016 to July 9th 2021.

Test assets	Statistics	K					
		1	2	3	4	5	6
Panel A: IPCA							
r_t	R^2_{total}	13.00	16.52	17.15	17.71	18.22	18.68
	R^2_{pred}	0.01	2.91	2.93	2.95	2.94	2.91
x_t	$R^2_{total,x}$	93.12	95.16	96.49	97.64	97.79	98.06
	$R^2_{pred,x}$	0.11	1.75	1.75	1.74	1.74	1.74
Panel B: Observable risk factors (dynamic loadings)							
r_t	R^2_{total}	8.84	8.86	8.87	8.89	8.90	9.27
	R^2_{pred}	-0.01	0.00	0.01	0.02	0.03	0.67
x_t	$R^2_{total,x}$	63.81	63.83	63.87	63.90	63.93	64.10
	$R^2_{pred,x}$	-0.17	-0.16	-0.15	-0.14	-0.13	0.26
Panel C: Observable risk factors (static loadings)							
r_t	R^2_{total}	9.18	9.27	9.36	9.43	9.54	9.62
	R^2_{pred}	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02
x_t	$R^2_{total,x}$	63.75	63.76	63.80	63.82	63.85	64.05
	$R^2_{pred,x}$	-0.17	-0.17	-0.16	-0.14	-0.13	0.22

Table 4: IPCA including observable factors

This table reports R^2_{total} (Panel A) and R^2_{pred} (Panel B) R^2 from IPCA specifications with various numbers of latent factors K (corresponding to columns) while also controlling for observable factors. Rows labeled 0, 1, 4, and 6 correspond to no observable factors or the CAPM, FFC4, or FFC6 factors, respectively. The table also reports tests of the incremental explanatory power of each observable factor model with respect to the IPCA model (Panel C). In all specifications, both latent and observable factor loadings are instrumented with observable cryptocurrency characteristics. R^2's and p-values are in percent. The sample of observations is from December 2nd 2016 to July 9th 2021.

Obs. Factors	K					
	1	2	3	4	5	6
Panel A: R^2_{total}						
0	13.00	16.52	17.15	17.71	18.22	18.68
1	13.19	16.61	17.24	17.78	18.29	18.75
2	13.21	16.62	17.25	17.79	18.30	18.76
6	13.57	16.63	17.26	17.80	18.31	18.77
Panel B: R^2_{pred}						
0	0.01	2.91	2.93	2.95	2.94	2.91
1	0.40	2.89	2.91	2.92	2.90	2.93
4	0.40	2.88	2.91	2.90	2.91	2.92
6	0.88	2.87	2.91	2.90	2.92	2.90
Panel C: Individual significance (p-value)						
MKT	0.02	0.01	0.07	0.11	0.13	0.14
SIZE	0.12	0.26	0.12	0.17	0.16	0.12
MOM	0.13	0.11	0.15	0.10	0.32	0.16
LIQ	0.79	0.78	0.89	0.73	0.65	0.45
VOL	0.31	0.97	0.97	0.92	0.97	0.93
REV	0.00	0.51	0.46	0.43	0.28	0.29

Table 5: IPCA portfolio alphas

This table reports unconditional and conditional portfolio alphas when controlling for the factors from the restricted ($\Gamma_\alpha = 0$) IPCA models with $K = 1, \ldots, 6$ factors (Panel A) and the observable factor models FF1 through FF6 (Panel B). The test assets are characteristic-managed portfolios. Unconditional alphas are the intercepts of time-series regressions of portfolio returns on the corresponding factors. Conditional alphas are the time-series average of portfolio residuals from the IPCA or instrumented observable factor models. The reported values are the average absolute alphas across all managed portfolios. All numbers are expressed in percent. The sample of observations is from December 2nd 2016 to July 9th 2021.

Panel A: IPCA factors						
	No. Factors					
	1	2	3	4	5	6
Unconditional	9.14	5.48	4.28	4.16	4.14	3.87
Conditional	8.63	0.84	0.61	0.60	0.59	0.58
Panel B: Observable factors						
	FF1	FF2	FF3	FF4	FF5	FF6
Unconditional	10.15	10.22	10.24	10.19	10.21	10.79
Conditional	9.22	9.24	9.21	9.23	9.25	8.54

Table 6: Out-of-sample asset pricing performance

This table reports in-sample total R^2_{total} and predictive R^2_{pred} for the restricted ($\Gamma_\alpha = 0$) IPCA models with $K = 1, \ldots, 6$ factors (Panel A) and a variety of observable factor models with dynamic (Panel B) and static (Panel C) loadings. Observable factor models begin with a cryptocurrency analogue of CAPM (FF1) including a market factor, and then add size, momentum, liquidity, volatility, and reversal factors to obtain FF2, FF3, FF4, FF5 and FF6. The out-of-sample analysis follows a recursive estimation scheme outlined in the main text starting from the second half of the available data, i.e., the first prediction is made in September 2019. Performance statistics are computed for individual cryptocurrencies r_t and characteristic-managed portfolios x_t. All numbers are expressed in percent. The sample of observations is from December 2nd 2016 to July 9th 2021.

Test assets	Statistics	K					
		1	2	3	4	5	6
Panel A: IPCA							
r_t	R^2_{total}	11.90	15.56	16.16	16.68	17.18	17.61
	R^2_{pred}	-0.07	2.95	2.95	2.95	2.95	2.96
x_t	$R^2_{total,x}$	92.08	94.45	95.77	96.66	97.40	97.62
	$R^2_{pred,x}$	-0.63	1.29	1.29	1.29	1.30	1.30
Panel B: Observable risk factors (dynamic loadings)							
r_t	R^2_{total}	7.05	7.03	7.02	7.02	7.02	7.38
	R^2_{pred}	0.01	0.02	0.02	0.03	0.03	0.67
x_t	$R^2_{total,x}$	53.70	53.65	53.57	53.59	53.59	53.70
	$R^2_{pred,x}$	0.05	0.05	0.05	0.06	0.06	0.46
Panel C: Observable risk factors (static loadings)							
r_t	R^2_{total}	6.90	6.89	6.88	6.88	6.88	6.87
	R^2_{pred}	0.01	0.01	0.00	0.00	0.01	0.00
x_t	$R^2_{total,x}$	53.50	53.46	53.38	53.40	53.40	53.31
	$R^2_{pred,x}$	0.05	0.04	0.04	0.04	0.04	-0.01

Table 7: Out-of-sample mean-variance efficiency

This table reports out-of-sample annualized Sharpe ratios of individual factors ("Univariate") and mean-variance optimal portfolios ("Tangency") combining IPCA (Panel A) or observable (Panel B) factors. Observable factor models begin with a cryptocurrency analogue of CAPM (FF1) with a market factor, and then add size, momentum, liquidity, volatility, and reversal factors to obtain FF2, FF3, FF4, FF5 and FF6 specifications with two through six factors. The out-of-sample analysis follows a recursive estimation scheme outlined in the main text starting from the second half of the available data, i.e., the first portfolio weights are constructed in September 2019.

	K					
	1	2	3	4	5	6
Panel A: IPCA						
Univariate	-0.30	-1.19	1.65	1.75	-0.16	-0.16
Tangency	-0.30	13.72	13.34	10.81	7.82	7.82
Panel B: Observable risk factors						
Univariate	0.73	-0.81	0.59	-0.89	-0.86	6.58
Tangency	0.73	0.54	0.69	0.51	0.46	1.79

Table 8: Significance of the characteristics

This table reports the significance of characteristics to overall fit in the restricted ($\Gamma_\alpha = 0$) IPCA models estimated based on the daily data from the whole sample (the "Full sample" columns) as well as the sub-samples (the "Sub-samples" columns) or based on the weekly data from the whole sample (the "Weekly" column). For the full sample period from December 2016 to July 2021, we report the significance results for the IPCA models with $K = 2, ..., 4$ factors. For the two sub-sample periods from December 2016 to January 2020 and from January 2020 to July 2021, we report the results corresponding to IPCA models with $K = 3$ and $K = 6$ factors, respectively. For the weekly data, we present the results of the $K = 4$ IPCA model estimated from the whole sample of weekly returns. A variable significance is measured jointly for all factors based on the bootstrap test. The significance of the l^{th} characteristic for all factors boils down to testing that the whole l^{th} row in $\Gamma_\beta = [\gamma_{\beta,1}, \ldots, \gamma_{\beta,L}]'$ is equal to zero, that is, the null hypothesis is

$$H_0 : \gamma_{\beta,l} = 0_{K\times 1}.$$

The numbers in the table are the p-values from the significance test. The sample of observations is from December 2nd 2016 to July 9th 2021.

	Full sample			Sub-samples		Weekly
Name	K=2	K=3	K=4	12:16-01:20 (K=3)	01:20-07:21 (K=6)	K=4
new add	0.240	0.390	0.310	0.860	0.227	0.495
active add	0.010	0.320	0.120	0.320	0.816	0.988
transaction count	0.120	0.160	0.190	0.350	0.302	0.698
avg trans value	0.110	0.130	0.080	0.080	0.126	0.911
trading volume	0.000	0.020	0.030	0.030	0.000	0.042
illiq	0.051	0.270	0.210	0.260	0.081	0.112
bid-ask	0.000	0.040	0.030	0.020	0.041	0.021
vol shock 15	0.210	0.210	0.330	0.650	0.486	0.748
vol shock 30	0.230	0.340	0.440	0.350	0.732	0.345
size	0.000	0.031	0.020	0.170	0.063	0.041
capm α	0.270	0.890	0.950	0.620	0.744	0.214
capm β	0.000	0.040	0.730	0.240	0.004	0.707
idio vol	0.120	0.060	0.060	0.240	0.102	0.254
rvol	0.070	0.080	0.250	0.160	0.542	0.251
VaR(5%)	0.000	0.140	0.090	0.260	0.512	0.345
ES (5%)	0.000	0.040	0.040	0.040	0.208	0.174
rev	0.000	0.000	0.000	0.000	0.000	0.000
mom 7_1	0.030	0.240	0.170	0.250	0.066	0.105
mom 14_1	0.070	0.480	0.680	0.680	0.665	0.047
mom 21_1	0.520	0.580	0.310	0.850	0.131	0.044
mom 30_1	0.210	0.670	0.940	0.170	0.340	0.671

Table 9: Asset pricing performance across sub-samples

This table reports in-sample total R^2_{total} and predictive R^2_{pred} for the restricted ($\Gamma_\alpha = 0$) and unrestricted ($\Gamma_\alpha \neq 0$) IPCA models with $K = 1, \ldots, 6$ factors estimated based on the two sub-samples from December 2016 to January 2020 (Panel A) and from January 2020 to July 2021 (Panel B). Performance statistics are computed for individual assets and characteristic-managed portfolios. The bottom row reports the p-values for the test of $\Gamma_\alpha = 0$ based on a bootstrap with 10000 draws. All numbers are expressed in percent.

		Panel A: Sample from 12:2016 to 01:2020						**Panel B:** Sample from 01:2020 to 07:2021					
		K						K					
		1	2	3	4	5	6	1	2	3	4	5	6
Individual assets													
R^2_{total}	$\Gamma_\alpha = 0$	14.04	17.44	18.07	18.66	19.19	19.63	12.34	15.92	16.59	17.16	17.68	18.15
	$\Gamma_\alpha \neq 0$	16.79	17.46	18.10	18.69	19.22	19.66	15.39	16.08	16.67	17.21	17.71	18.18
R^2_{pred}	$\Gamma_\alpha = 0$	0.18	2.10	2.91	2.92	2.89	2.88	0.04	2.00	3.02	3.21	3.32	3.41
	$\Gamma_\alpha \neq 0$	2.00	2.21	2.91	2.93	2.91	2.92	2.12	2.22	3.12	3.12	3.11	3.11
Characteristic-based portfolios													
$R^2_{total,x}$	$\Gamma_\alpha = 0$	93.89	95.76	97.15	97.53	98.20	98.32	92.42	94.68	95.73	97.14	97.65	98.07
	$\Gamma_\alpha \neq 0$	95.33	95.77	97.14	97.52	98.20	98.31	94.22	95.28	96.74	97.36	97.69	98.01
$R^2_{pred,x}$	$\Gamma_\alpha = 0$	0.96	2.09	2.39	2.40	2.41	2.42	0.05	1.95	1.95	1.95	1.93	1.92
	$\Gamma_\alpha \neq 0$	1.91	2.12	2.91	2.90	2.90	2.89	1.96	1.96	1.95	1.95	1.94	1.92
Bootstrap Test ($H_0 : \Gamma_\alpha = 0$)													
W_α p-value		0.00	0.07	61.3	44.5	29.2	28.3	0.00	0.00	0.00	0.00	0.00	33.2

Table 10: Latent vs observable factors: Sub-sample analysis

This table reports in-sample total R^2_{total} and predictive R^2_{pred} for the restricted ($\Gamma_\alpha = 0$) IPCA models with $K = 1, \ldots, 6$ factors and a variety of observable factor models with dynamic and static loadings. Observable factor models begin with a cryptocurrency analogue of CAPM (FF1) with a market factor, and then add size, momentum, liquidity, volatility, and reversal factors to obtain FF2, FF3, FF4, FF5 and FF6. The table presents the results for the models estimated based on the two sub-samples from December 2016 to January 2020 (Panel A) and from January 2020 to July 2021 (Panel B). Performance statistics are computed for individual cryptocurrencies r_t and characteristic-managed portfolios x_t. All numbers are expressed in percent.

		Panel A: Sample from 12:2016 to 01:2020						**Panel B:** Sample from 01:2020 to 07:2021					
		K						K					
		1	2	3	4	5	6	1	2	3	4	5	6
IPCA													
r_t	R^2_{total}	14.04	17.44	18.07	18.66	19.19	19.63	12.34	15.92	16.59	17.16	17.68	18.15
	R^2_{pred}	0.18	2.10	2.91	2.92	2.89	2.88	0.04	2.00	3.02	3.21	3.32	3.41
x_t	$R^2_{total,x}$	93.89	95.76	97.15	97.53	98.20	98.32	92.42	94.68	95.73	97.14	97.65	98.07
	$R^2_{pred,x}$	0.96	2.09	2.39	2.40	2.41	2.42	0.05	1.95	1.95	1.95	1.93	1.92
Observable risk factors (dynamic loadings)													
r_t	R^2_{total}	11.16	11.18	11.22	11.23	11.25	11.64	7.40	7.42	7.46	7.53	7.57	7.95
	R^2_{pred}	0.03	0.05	0.05	0.05	0.06	0.71	0.05	0.06	0.09	0.17	0.19	0.81
x_t	$R^2_{total,x}$	75.66	75.68	75.82	75.83	75.84	76.08	54.67	54.70	54.76	54.94	55.05	55.37
	$R^2_{pred,x}$	0.24	0.25	0.25	0.25	0.25	0.75	0.08	0.09	0.11	0.18	0.19	0.57
Observable risk factors (static loadings)													
r_t	R^2_{total}	11.64	11.80	11.98	12.16	12.42	12.57	7.84	8.03	8.21	8.39	8.61	8.80
	R^2_{pred}	0.03	0.04	0.03	0.03	0.04	0.06	0.01	0.01	0.01	0.01	0.02	0.00
x_t	$R^2_{total,x}$	75.65	75.66	75.78	75.79	75.81	76.06	54.60	54.62	54.68	54.83	54.95	55.31
	$R^2_{pred,x}$	0.25	0.26	0.26	0.26	0.26	0.71	0.09	0.10	0.12	0.18	0.19	0.53

Table 11: Asset pricing performance on weekly returns

This table reports in-sample total and predictive R^2 for the restricted ($\Gamma_\alpha = 0$) and unrestricted ($\Gamma_\alpha \neq 0$) IPCA models with $K = 1, \ldots, 6$ factors estimated based on the weekly data. Performance statistics are computed for individual assets (Panel A) and characteristic-managed portfolios (Panel B). Panel C reports the p-values for the test of $\Gamma_\alpha = 0$ based on a bootstrap with 10000 draws. All numbers are expressed in percent. The sample of observations is from December 2nd 2016 to July 9th 2021.

		K					
		1	2	3	4	5	6
Panel A: Individual assets							
R^2_{total}	$\Gamma_\alpha = 0$	25.53	26.84	27.49	28.04	28.55	29.01
	$\Gamma_\alpha \neq 0$	26.38	27.05	27.64	28.18	28.67	29.12
R^2_{pred}	$\Gamma_\alpha = 0$	0.15	0.93	0.93	0.93	0.91	0.91
	$\Gamma_\alpha \neq 0$	0.96	0.95	0.95	0.95	0.94	0.94
Panel B: Characteristic-based portfolios							
$R^2_{total,x}$	$\Gamma_\alpha = 0$	97.05	97.57	98.16	98.73	99.02	99.17
	$\Gamma_\alpha \neq 0$	97.34	97.95	98.32	98.80	99.08	99.18
$R^2_{pred,x}$	$\Gamma_\alpha = 0$	0.61	0.83	0.83	0.82	0.80	0.80
	$\Gamma_\alpha \neq 0$	0.86	0.85	0.85	0.84	0.83	0.82
Panel C: Bootstrap Test ($H_0 : \Gamma_\alpha = 0$)							
W_α p-value		4.41	4.65	3.32	7.72	4.86	23.3

Table 12: Latent vs observable factors: Weekly data

This table reports total and in-sample predictive R^2 for the restricted ($\Gamma_\alpha = 0$) IPCA models with $K = 1, \ldots, 6$ factors (Panel A) and a variety of observable factor models with dynamic (Panel B) and static (Panel C) loadings estimated based on the weekly data. Observable factor models begin with a cryptocurrency analogue of CAPM (FF1) with a market factor, and then add size, momentum, liquidity, volatility, and reversal factors to obtain FF2, FF3, FF4, FF5 and FF6. Performance statistics are computed for individual cryptocurrencies r_t and characteristic-managed portfolios x_t. All numbers are expressed in percent. The sample of observations is from December 2nd 2016 to July 9th 2021.

Test assets	Statistics	K					
		1	2	3	4	5	6
Panel A: IPCA							
r_t	R^2_{total}	25.53	26.84	27.49	28.04	28.55	29.01
	R^2_{pred}	0.15	0.93	0.93	0.93	0.91	0.91
x_t	$R^2_{total,x}$	97.05	97.57	98.16	98.73	99.02	99.17
	$R^2_{pred,x}$	0.61	0.83	0.83	0.82	0.80	0.80
Panel B: Observable risk factors (dynamic loadings)							
r_t	R^2_{total}	18.71	19.88	19.95	20.05	20.14	20.66
	R^2_{pred}	-0.12	0.04	0.04	0.08	0.15	0.53
x_t	$R^2_{total,x}$	70.35	73.84	73.97	74.04	74.23	74.76
	$R^2_{pred,x}$	-0.54	0.01	0.05	0.03	0.15	1.04
Panel C: Observable risk factors (static loadings)							
r_t	R^2_{total}	19.69	21.32	21.81	22.35	22.96	23.41
	R^2_{pred}	-0.23	-0.06	-0.05	-0.04	0.00	0.29
x_t	$R^2_{total,x}$	70.37	73.85	73.95	74.02	74.18	74.74
	$R^2_{pred,x}$	-0.57	-0.03	-0.01	-0.02	0.15	0.29

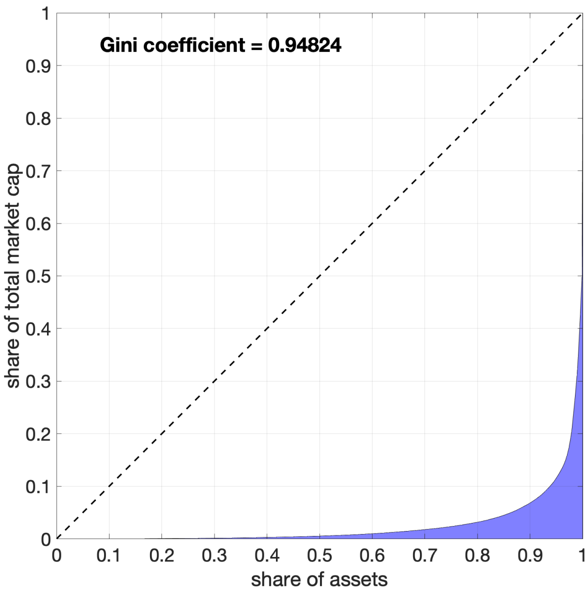
Table 13: Out-of-sample asset pricing performance on weekly returns

This table reports out-of-sample total and predictive R^2 for the restricted ($\Gamma_\alpha = 0$) IPCA models with $K = 1, \ldots, 6$ factors (Panel A) and a variety of observable factor models with dynamic (Panel B) and static (Panel C) loadings estimated based on the weekly data. Observable factor models begin with a cryptocurrency analogue of CAPM (FF1) including a market factor, and then add size, momentum, liquidity, volatility, and reversal factors to obtain FF2, FF3, FF4, FF5 and FF6. The out-of-sample analysis follows a recursive estimation scheme outlined in the main text starting from the second half of the available data, i.e. the first prediction is made in September 2019. Performance statistics are computed for individual cryptocurrencies r_t and characteristic-managed portfolios x_t. All numbers are expressed in percent.

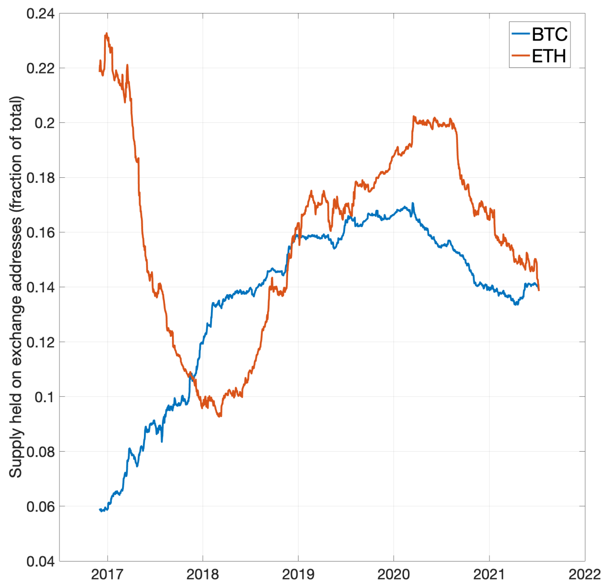
Test assets	Statistics	K					
		1	2	3	4	5	6
Panel A: IPCA							
r_t	R^2_{total}	19.63	21.03	21.49	21.86	22.19	22.57
	R^2_{pred}	1.65	0.82	0.82	0.82	0.81	0.83
x_t	$R^2_{total,x}$	95.29	96.00	96.59	97.01	97.34	97.61
	$R^2_{pred,x}$	8.21	7.51	7.52	7.53	7.53	7.56
Panel B: Observable risk factors (dynamic loadings)							
r_t	R^2_{total}	14.91	15.75	15.73	15.75	15.67	15.97
	R^2_{pred}	0.07	0.00	0.00	0.01	0.03	0.42
x_t	$R^2_{total,x}$	61.28	64.51	64.51	64.46	64.17	64.02
	$R^2_{pred,x}$	0.28	-0.14	-0.15	-0.14	-0.15	-0.63
Panel C: Observable risk factors (static loadings)							
r_t	R^2_{total}	14.60	15.33	15.32	15.29	15.23	15.17
	R^2_{pred}	0.07	-0.04	-0.04	-0.04	-0.04	-0.21
x_t	$R^2_{total,x}$	60.97	64.10	64.07	63.93	63.67	63.39
	$R^2_{pred,x}$	0.29	-0.14	-0.16	-0.15	-0.18	-0.86

Figure 1: **A first look at the data**

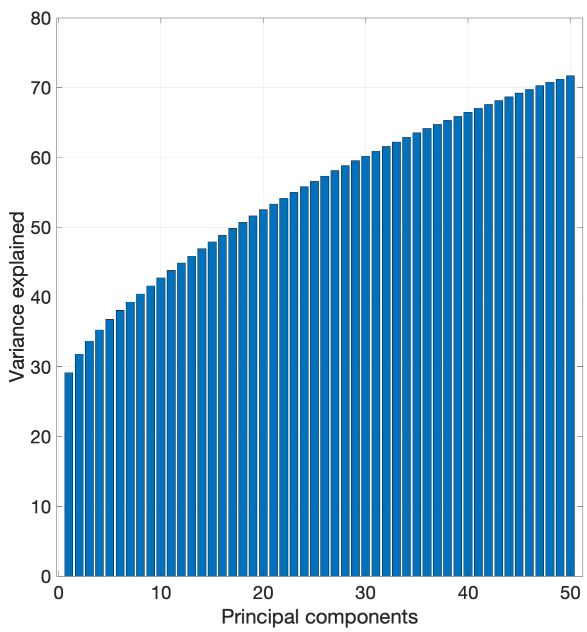
This figure shows the cumulative sum of the market capitalization of the top 50 cryptocurrencies relative to the aggregate market and our sample (the top-left panel). The top-right panel reports the percent supply held on exchange addresses for two largest digital assets, Bitcoin (BTC) and Ethereum (ETH). The bottom-left panel demonstrates the explained variance from the first 50 principal components for the same cross-section of returns used in the main empirical analysis. The bottom-right panel illustrates the median, 5th and 95th percentiles of the estimated loadings for each asset on the first principal component estimated based on a rolling window PCA estimate using 360 daily observations.



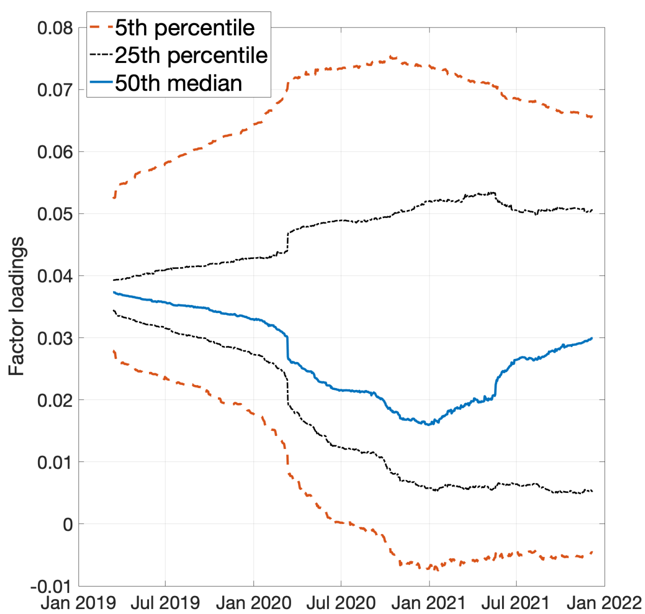
(a) Market cap concentration



(b) The percent supply of BTC and ETH



(c) Cumulative variance explained by PCA (%)



(d) The rolling window factor loadings

Figure 2: **Sample coverage**

This figure shows the market capitalization of the aggregate market and our sample. The sample period is from December 2, 2016 to July 9, 2021.

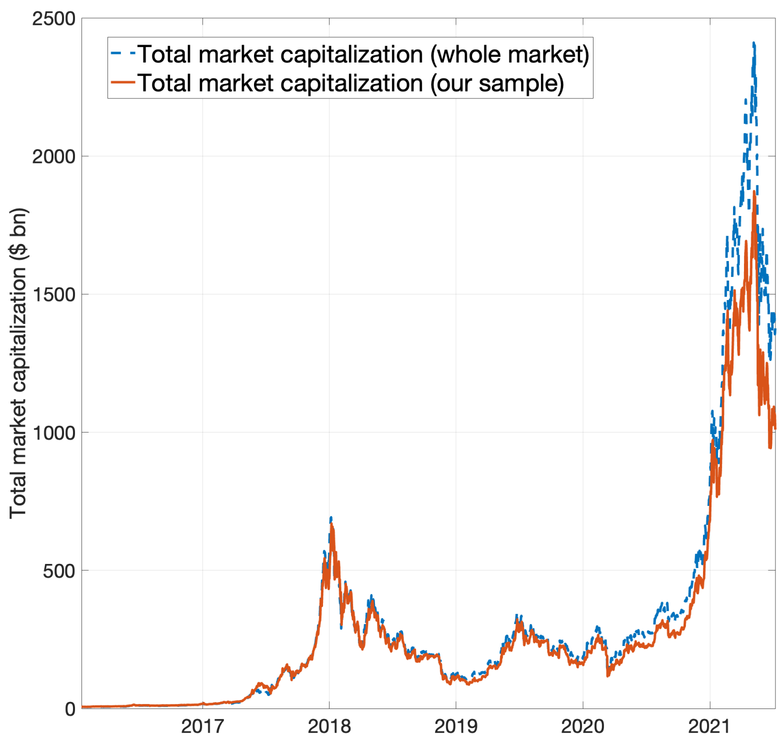
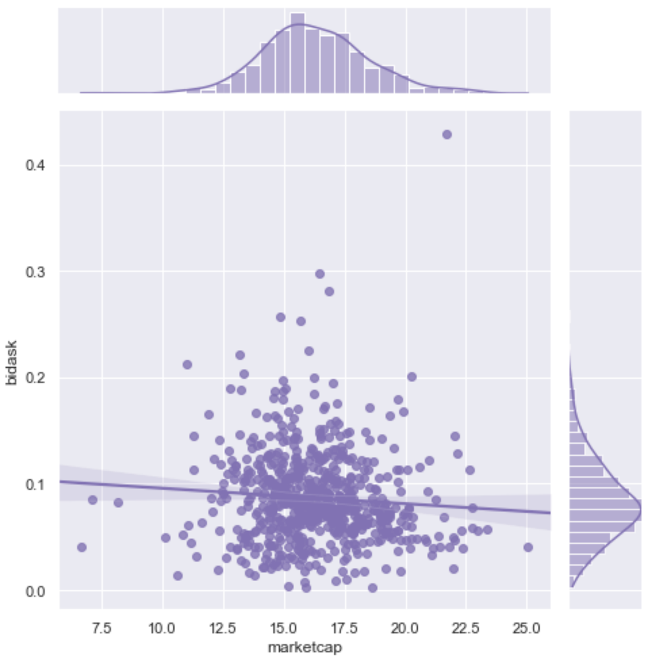
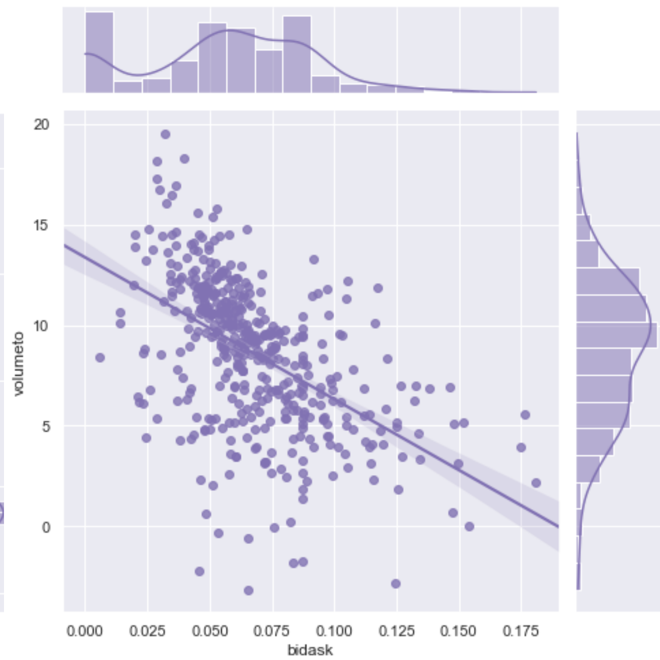


Figure 3: **Individual characteristics**

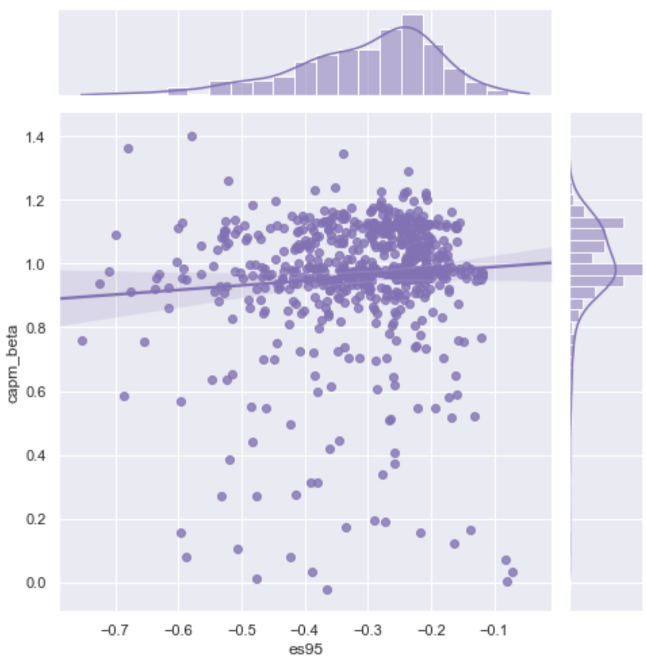
This figure reports the scatter plots of average value in individual characteristics across digital assets. We report the correlation between `size`, `bid-ask`, `es (5%)`, and `capm` β. The sample period is from (put the sample period here).



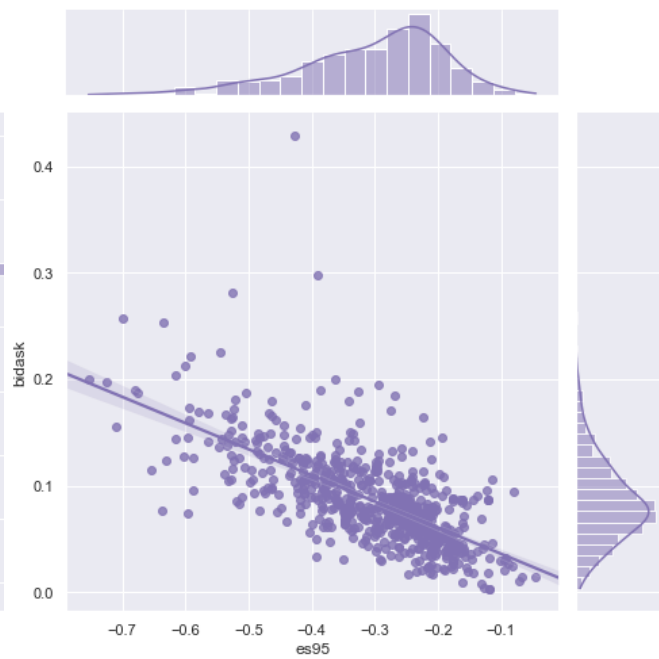
(a) `size` vs `bid-ask`



(b) `volume` vs `bid-ask`



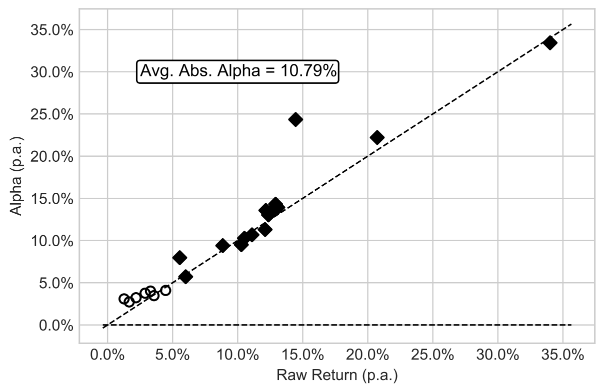
(c) `es (5%)` vs `capm` β



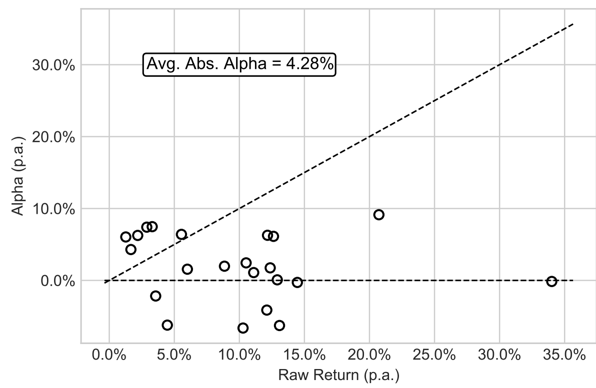
(d) `es (5%)` vs `bid-ask`

Figure 4: **Alphas of characteristic-managed portfolios**

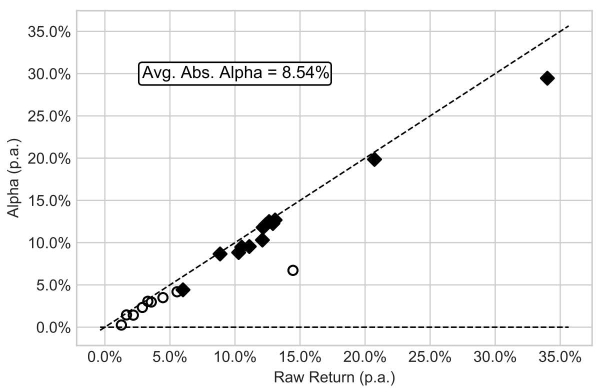
This figure shows unconditional alphas estimated from a time-series regression of portfolio returns on observable factors from the FF6 model (Panel (a)) or IPCA factors from the $K = 3$ specification (Panel (b)). The alphas are computed for characteristic-managed portfolios and are plotted against portfolios' raw average excess returns. Significant alphas with absolute values of t-statistics greater than 2.0 are depicted with filled diamonds, while insignificant alphas are denoted with unfilled circles. The figure also reports conditional alphas from instrumented observable FF6 or three-factor IPCA models (Panels (c) and (d)), which are computed as the time-series averages of period-by-period portfolio residuals. Each panel further shows the average absolute alphas for each specification. All reported values are expressed in percentage per annum.



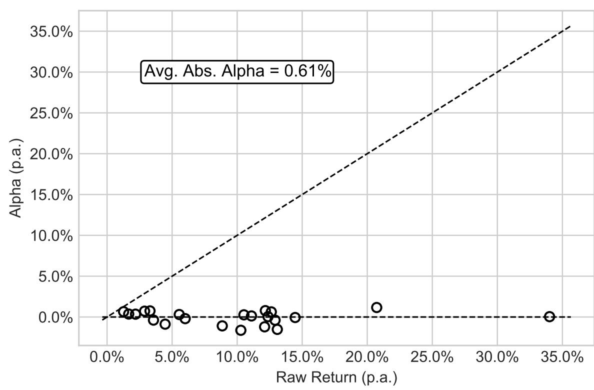
(a) FF6 (Uncond.)



(b) IPCA3 (Uncond.)



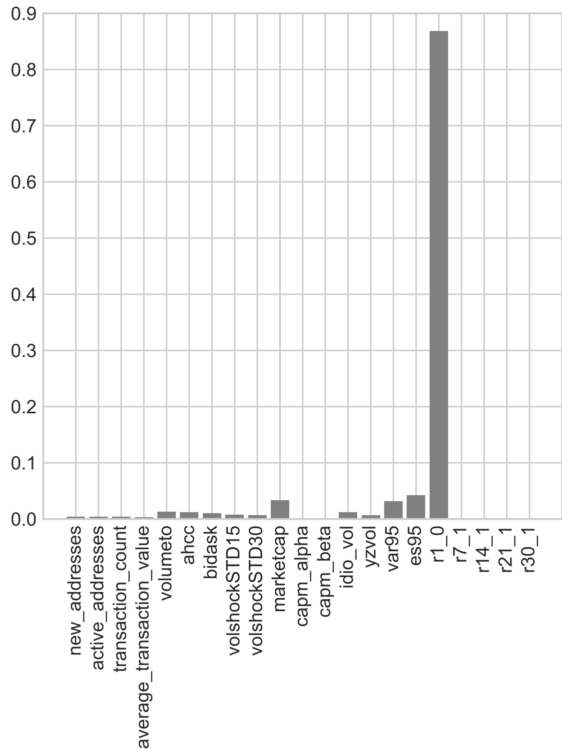
(c) FF6 (Cond.)



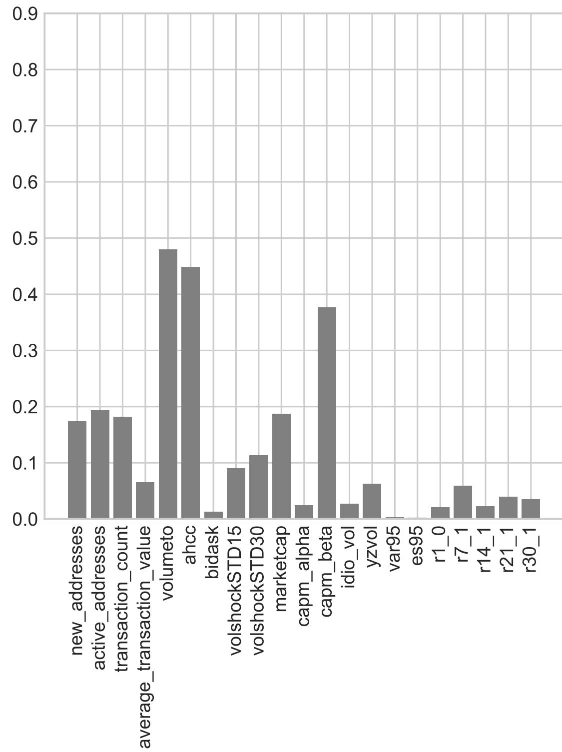
(d) IPCA3 (Cond.)

Figure 5: **Marginal R^2 for IPCA factors**

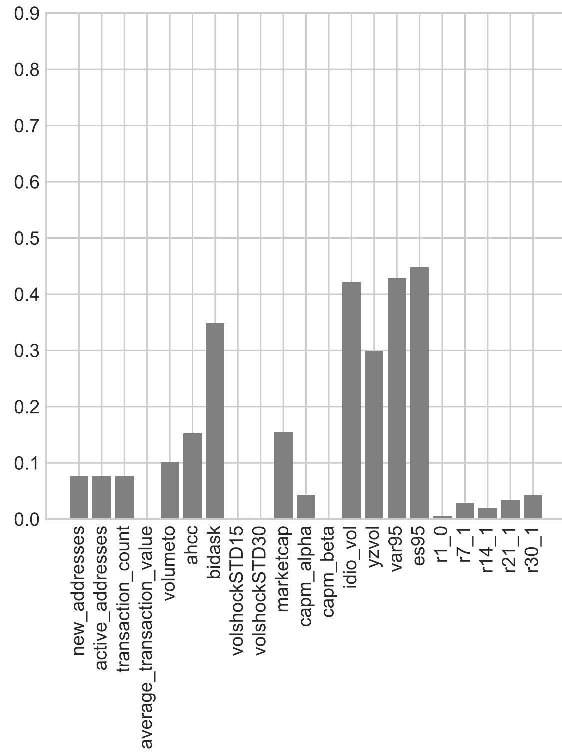
This figure shows the marginal R^2 for the IPCA factors from the restricted ($\Gamma_\alpha = 0$) $K = 3$ specification. The marginal R^2 is the R^2 statistic from regressions of each of characteristic-managed portfolios onto each IPCA factor, one at a time.



(a) Factor 1



(b) Factor 2

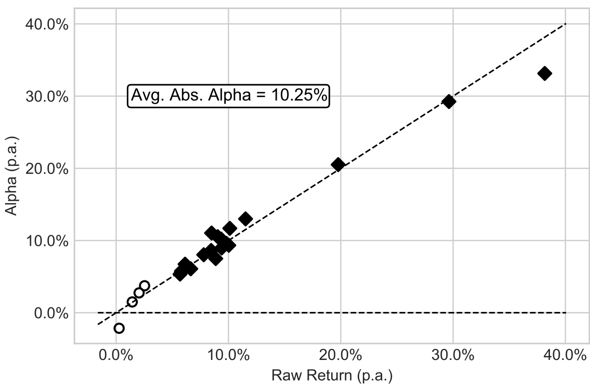


(c) Factor 3

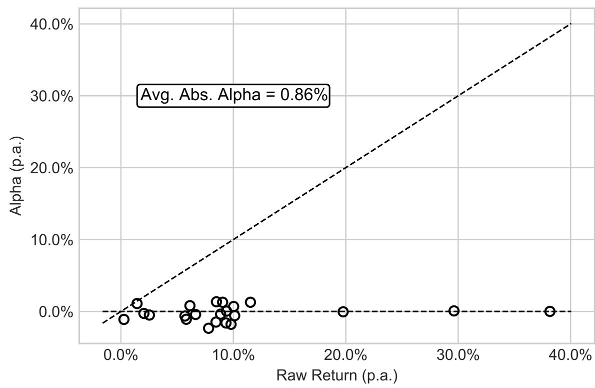
Figure 6: **Alphas of characteristic-managed portfolios: Sub-samples**

This figure shows unconditional alphas estimated from a time-series regression of portfolio returns on observable factors from the FF6 model estimated based on the two sub-samples from December 2016 to January 2020 (Panel (a)) and from January 2020 to July 2021 (Panel (b)). The alphas are computed for characteristic-managed portfolios and are plotted against portfolios' raw average excess returns. Significant alphas with absolute values of t-statistics greater than 2.0 are depicted with filled diamonds, while insignificant alphas are denoted with unfilled circles. The figure also reports conditional alphas from the $K = 3$ (Panel (b)) and $K = 6$ (Panel (d)) IPCA models estimated based on the two sub-samples from December 2016 to January 2020 and from January 2020 to July 2021, respectively. The conditional alphas are computed as the time-series averages of period-by-period portfolio residuals. Each panel further shows the average absolute alphas for each specification. All reported values are expressed in percentage per annum.

Panel A: Sample from 12:2016 to 01:2020

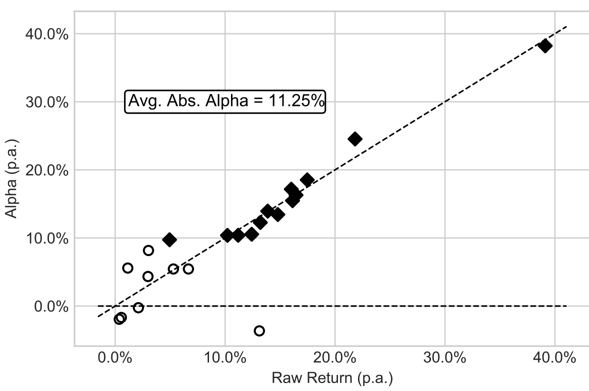


(a) FF6 (Uncond.)

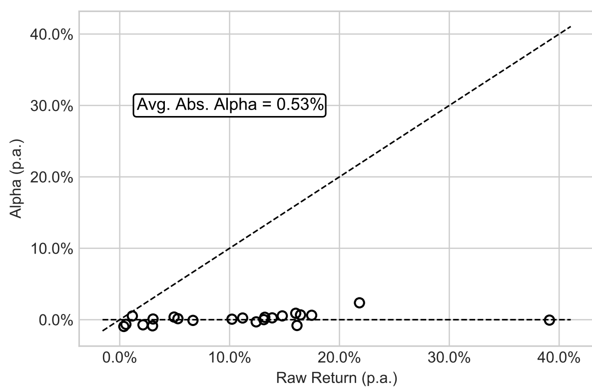


(b) IPCA3 (Cond.)

Panel B: Sample from 01:2020 to 07:2021



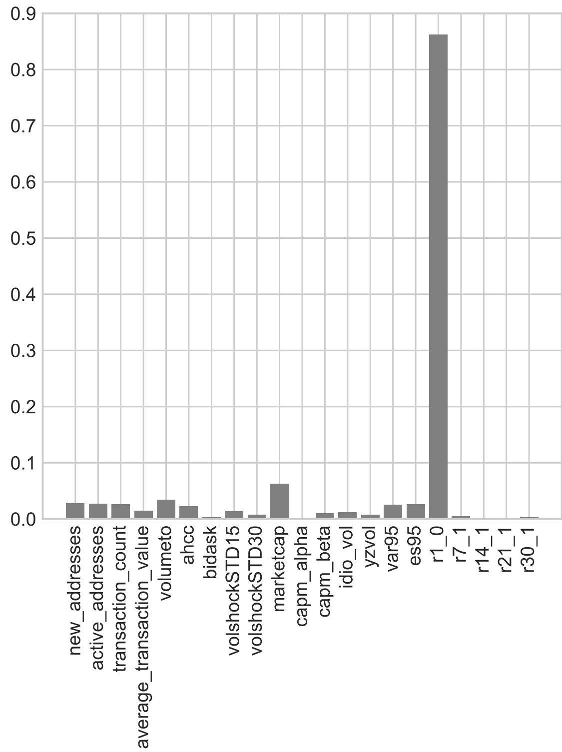
(c) FF6 (Uncond.)



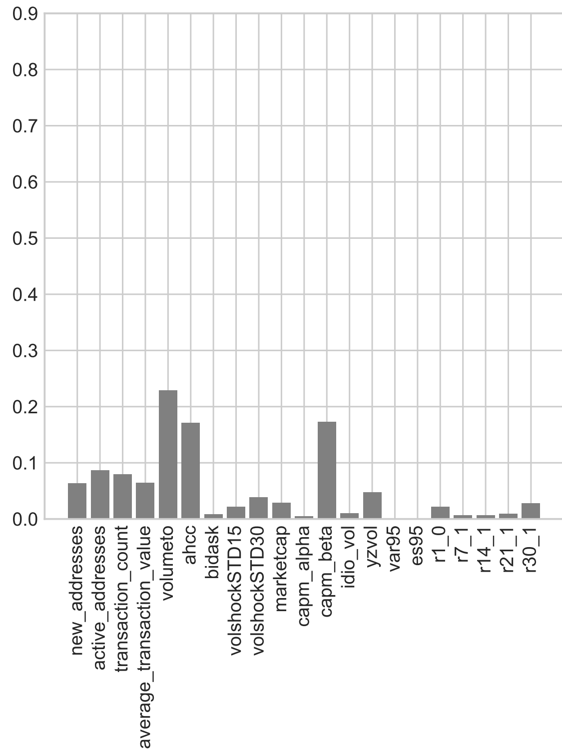
(d) IPCA6 (Cond.)

Figure 7: **Marginal R^2 for IPCA factors: Sub-sample from 12:2016 to 01:2020**

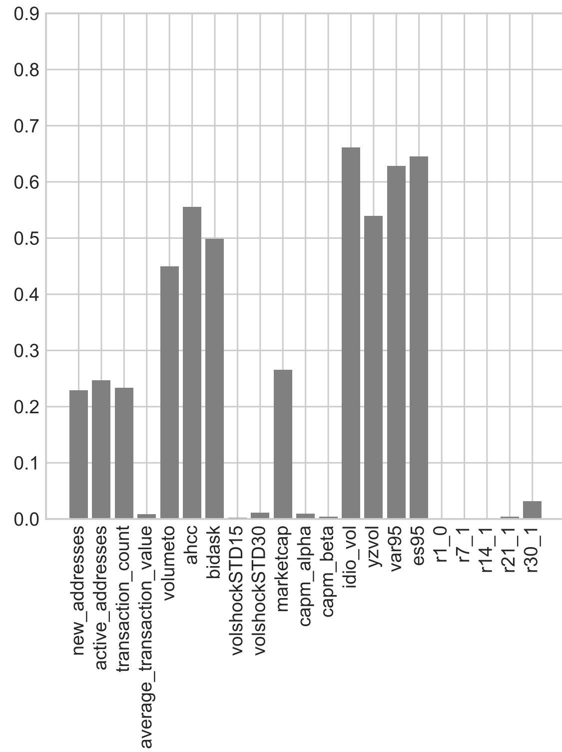
This figure shows the marginal R^2 for the IPCA factors from the restricted ($\Gamma_\alpha = 0$) $K = 3$ specification estimated based on the sub-sample from December 2016 to January 2020. The marginal R^2 is the R^2 statistic from regressions of each of characteristic-managed portfolios onto each IPCA factor, one at a time.



(a) Factor 1



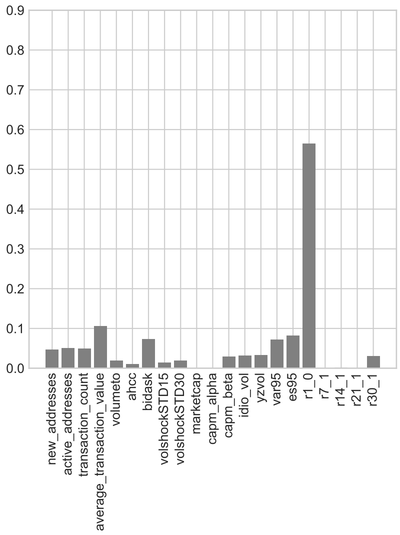
(b) Factor 2



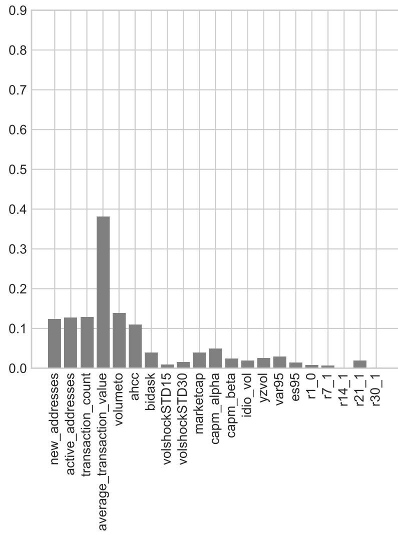
(c) Factor 3

Figure 8: **Marginal R^2 for IPCA factors: Sub-sample from 01:2020 to 07:2021**

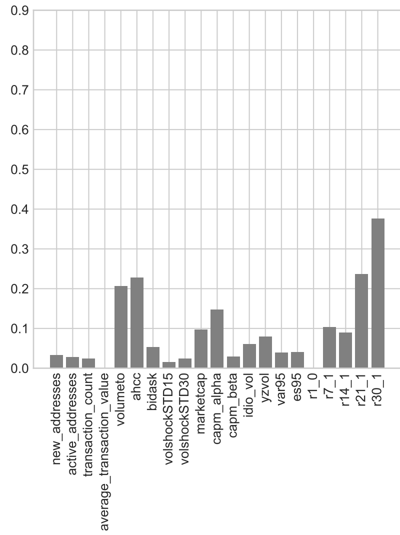
This figure shows the marginal R^2 for the IPCA factors from the restricted ($\Gamma_\alpha = 0$) $K = 6$ specification estimated based on the sub-sample from January 2020 to July 2021. The marginal R^2 is the R^2 statistic from regressions of each of characteristic-managed portfolios onto each IPCA factor, one at a time.



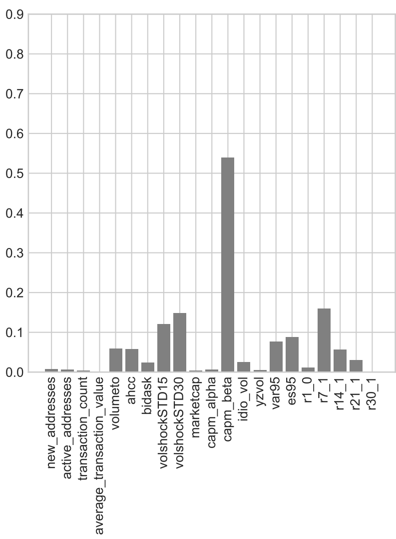
(a) Factor 1



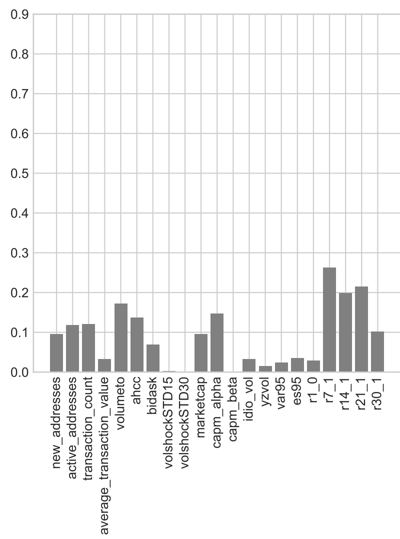
(b) Factor 2



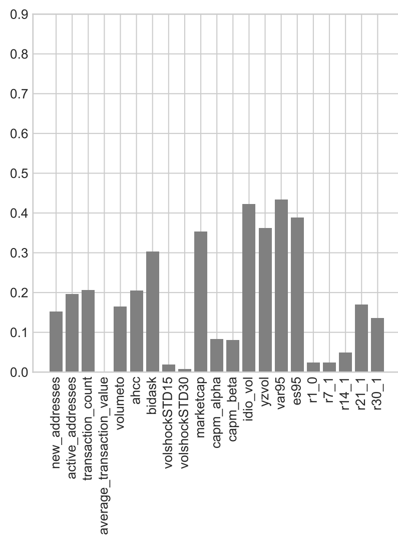
(c) Factor 3



(d) Factor 4



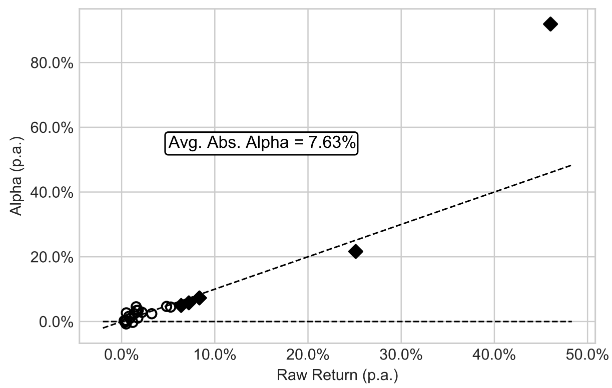
(e) Factor 5



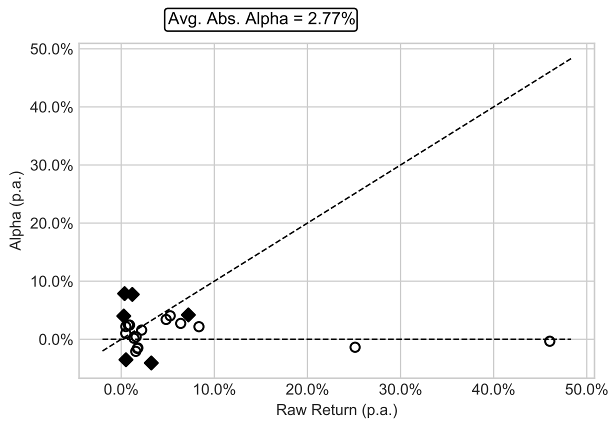
(f) Factor 6

Figure 9: **Alphas of characteristic-managed portfolios: Weekly data**

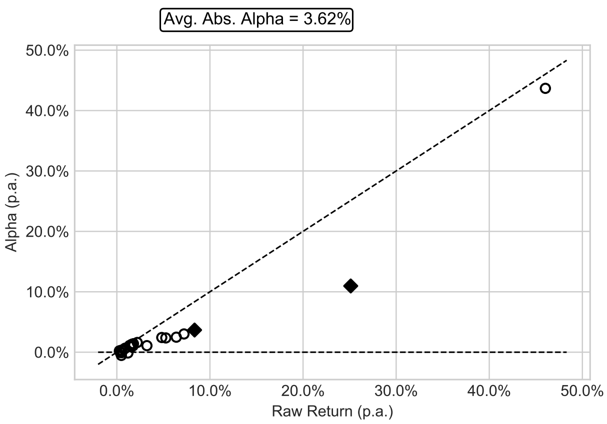
This figure shows unconditional alphas estimated from a time-series regression of portfolio returns on observable factors from the FF6 model (Panel (a)) or IPCA factors from the $K = 4$ specification (Panel (b)). The alphas are computed for characteristic-managed portfolios and are plotted against portfolios' raw average excess returns. Significant alphas with absolute values of t-statistics greater than 2.0 are depicted with filled diamonds, while insignificant alphas are denoted with unfilled circles. The figure also reports conditional alphas from instrumented observable FF6 or four-factor IPCA models (Panels (c) and (d)), which are computed as the time-series averages of period-by-period portfolio residuals. Each panel further shows the average absolute alphas for each specification. All reported values are expressed in percentage per annum. The results are reported for the models estimated based on the weekly data.



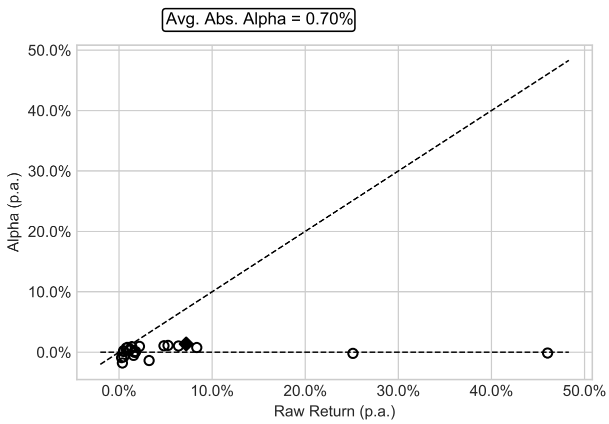
(a) FF6 (Uncond.)



(b) IPCA4 (Uncond.)



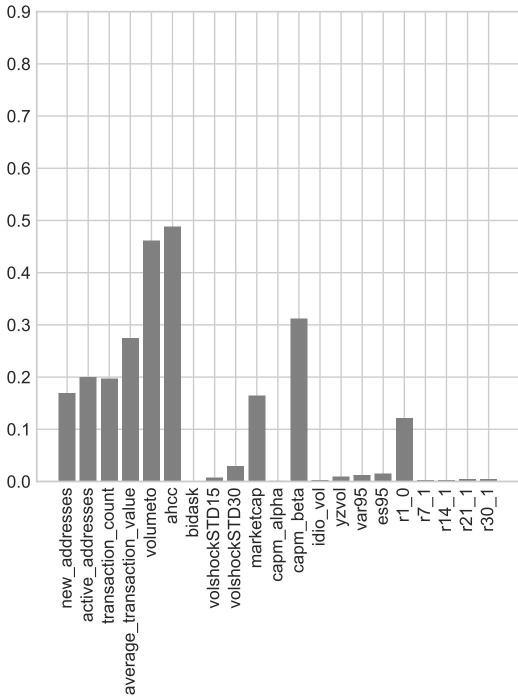
(c) FF6 (Cond.)



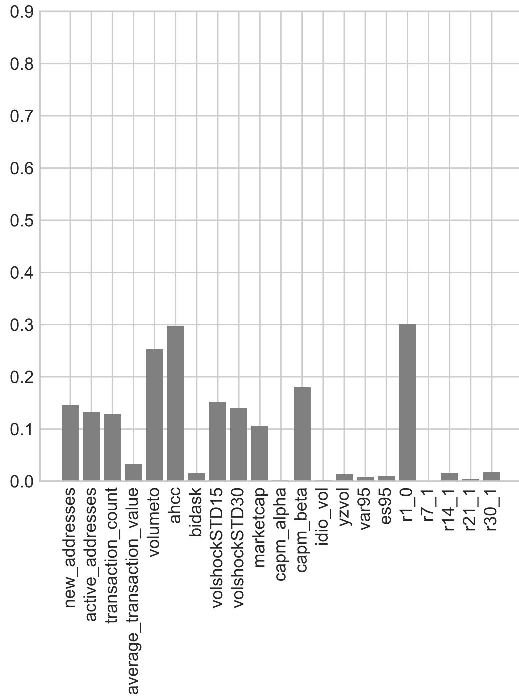
(d) IPCA4 (Cond.)

Figure 10: **Marginal R^2 for IPCA factors: Weekly returns**

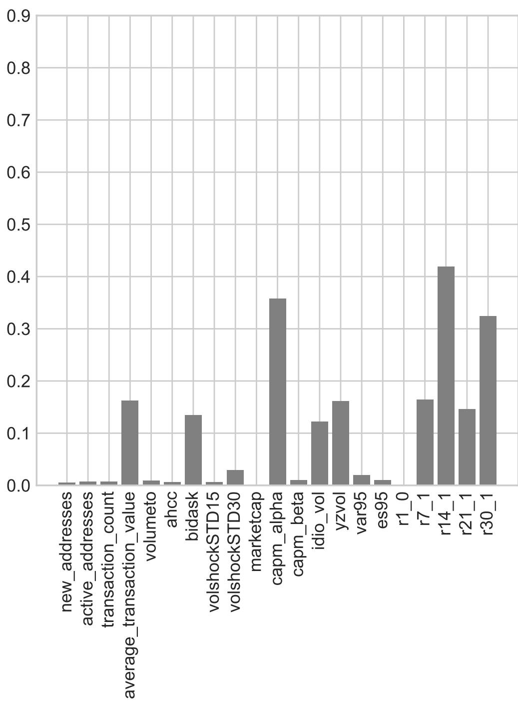
This figure shows the marginal R^2 for the IPCA factors from the restricted ($\Gamma_\alpha = 0$) $K = 4$ specification estimated based on the weekly data. The marginal R^2 is the R^2 statistic from regressions of each of characteristic-managed portfolios onto each IPCA factor, one at a time.



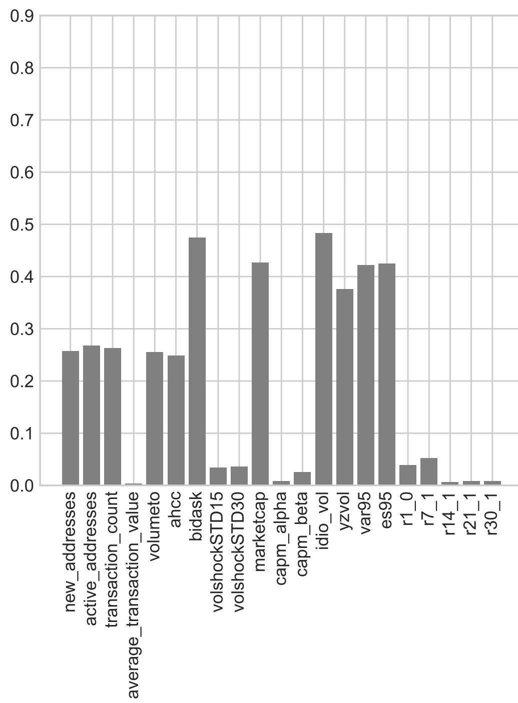
(a) Factor 1



(b) Factor 2



(c) Factor 3



(d) Factor 4