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## Predictive sorting of cryptocurrencies based on fundamentals and sentiment<sup>☆</sup>

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### ABSTRACT

This paper examines the predictive power of blockchain characteristics and sentiment indicators for cryptocurrency returns. We construct three weekly factor-mimicking portfolios based on network activity (active users), computing intensity (hashrate), and a sentiment measure from Google search trends. Using an out-of-sample forecasting framework, we find that all three predictors show strong performance across 40 cryptocurrencies. The certainty equivalent returns are often well above the risk-free rate, which supports the economic relevance of the blockchain-driven predictors. We also implement a portfolio sorting methodology that ranks cryptocurrencies by earlier, realized factor-based predictability scores and forms long-short portfolios accordingly. The resulting return spreads confirm the value of combining blockchain and sentiment-based signals. Overall, our findings emphasize the joint relevance of both fundamental and behavioral factors in predicting cryptocurrency returns.

### 1. Introduction

The exponential growth and extreme swings in the cryptocurrency markets have made the need to understand the fundamental drivers of cryptocurrency valuations more acute. When compared to traditional asset classes, cryptocurrencies are characterized by fewer identifiable fundamental characteristics; this makes their valuation particularly challenging. While traditional finance has long relied on cash dividends, earnings, free cash flows and other company-specific fundamental notions to price traditional assets (such as stocks and bonds, [Gordon, 1959](#); [Campbell and Shiller, 1988](#)), the valuation of cryptocurrencies has often hinged on blockchain-specific fundamental features such as network activity and security. Additionally, recent insights from behavioral finance have emphasized the importance of sentiment-based variables in explaining asset price deviations from their underlying, rational values ([Shiller, 1981](#); [Baker and Wurgler, 2006](#); [Stambaugh et al., 2012](#)), also with reference to cryptocurrency prices ([Jo et al., 2020](#); [Rognone et al., 2020](#); [Koutmos, 2023](#)). Although a number of theoretical advancements concerning the relationship between

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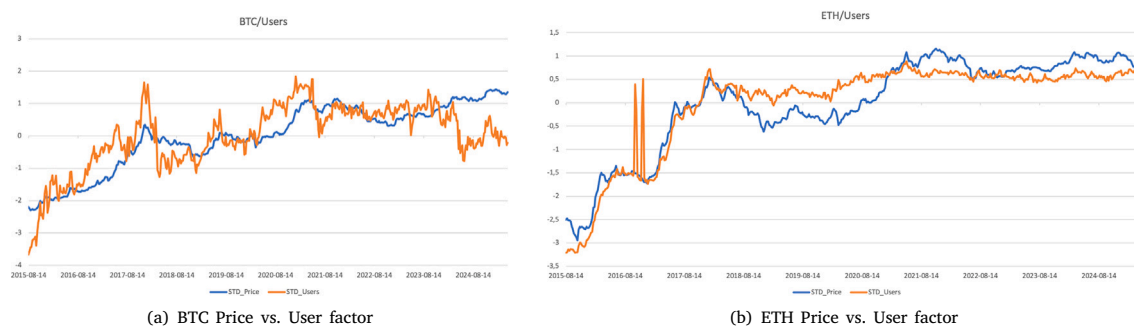
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**Fig. 1.** Cryptocurrency prices vs. the User factor.

The charts show the logarithm of the weekly prices of BTC and ETH and the associated log-User index factor. The two panels report standardized values (the original value minus the mean, everything scaled by standard deviation). The sample covers the period August 21, 2015–September 30, 2022 (372 weekly observations).

blockchain fundamentals and cryptocurrencies have occurred (Pagnotta and Buraschi, 2018; Cong et al., 2021; Biais et al., 2023), the systematic, empirical validation of their importance has remained limited.

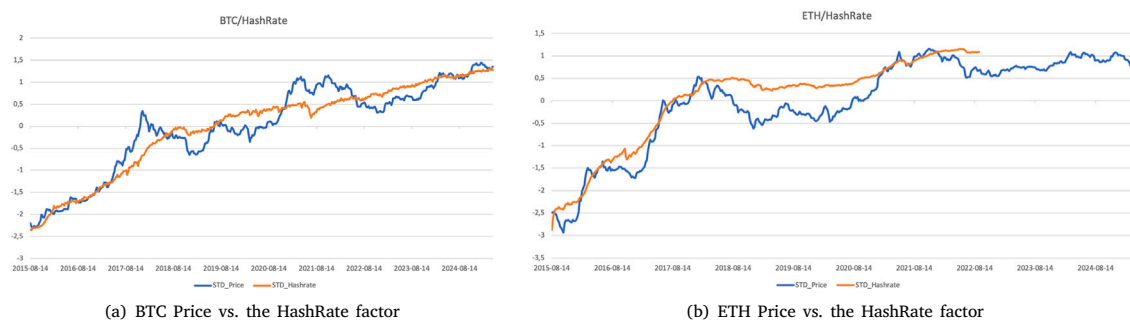
Against this background, our study aims to bridge this gap by offering robust, data-driven evidence to support cryptocurrency pricing models that leverage on the features of the underlying blockchain. We systematically investigate the role played by both fundamental and sentiment-based factors in the modeling and prediction of cryptocurrency monthly returns. Specifically, we consider the blockchain hashrate and the active user count as fundamental characteristics, and we resort to Google Trends data to capture market sentiment. A cryptocurrency's hashrate, expressed in terahashes, serves as a proxy for the resources miners commit to securing the network; the active user count reflects instead the size of the cryptocurrency network. Sentiment, measured through Google Search Trends scores (Liu and Tsyvinski, 2021), is conceptually distinct from blockchain fundamentals but included as a complementary factor: while fundamentals capture the technological and economic underpinnings of blockchain systems, sentiment reflects behavioral forces and investor attention that can drive prices away from these fundamentals. This distinction allows us to jointly account for both fundamental and behavioral determinants of cryptocurrency valuations, controlling for the latter in our analysis of the former drivers.

Our dataset spans an August 2015–April 2025 sample and initially focuses on five major Proof-of-Work (PoW) cryptocurrencies – Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Monero (XMR), and Dash (DASH) – which together accounted for 70% to 90% of total market capitalization during the sample period.<sup>1</sup> These high-cap cryptocurrencies provide long and reliable time series for both prices and blockchain fundamentals. In a second stage, we expand the sample to 40 cryptocurrencies to evaluate the robustness and generalizability of our results. We implement a dynamic out-of-sample (OOS) forecasting framework based on a rolling window procedure, where we construct and update predictor-specific factor-mimicking portfolios (based on blockchain fundamental characteristics and sentiment) and evaluate their predictive power using both statistical accuracy metrics (such as the  $R^2_{\text{OOS}}$ ) and economic performance indicators, including certainty equivalent returns (CER) measures. The analysis also includes a systematic sorting methodology: cryptocurrencies are ranked at each point in time by the past, measured OOS predictive power of each factor and we next build long-short portfolios accordingly, to quantify the investability of the sorting criterion.

Figs. 1–3 display the logarithm of the weekly prices of BTC and ETH, arguably the two oldest and most traded cryptocurrencies worldwide, along with the corresponding User, HashRate, and Google factor indices, respectively, to be constructed later. Visibly, we observe a positive relationship between prices and the three fundamental factors examined in this paper. Interestingly, in the case of Fig. 1, the user factor even appears to move at a higher frequency than the price index does, which is arguably unexpected. Apart from providing a sense of the dynamics of the phenomena under investigation over time, these plots reveal rather stark and precise connections between cryptocurrency prices and blockchain characteristics.

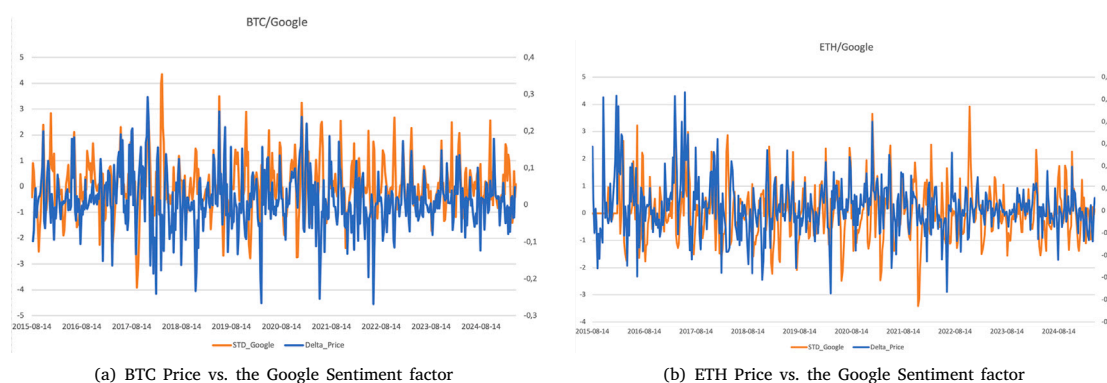
The first part of the analysis employs two- and three-factor linear regressions to evaluate the role of Bitcoin alongside fundamental and momentum factors in explaining cryptocurrency returns. While Bitcoin returns' impact appears less pronounced when additional blockchain-specific variables are included in the three-factor model, it remains consistently significant in the simpler two-factor specification. Adding blockchain characteristics improves the (in-sample) explanatory power, enhancing the models' overall performance. Yet, the main contribution of our paper lies in the second part, in which we systematically assess the predictive capabilities of blockchain factors and sentiment data in a OOS context. Our empirical findings reveal that blockchain-based predictors such as network activity and computing power retain significant OOS forecasting power even for non-mineable cryptocurrencies (NMCs). This result supports the view that these factors proxy for broader structural features of the crypto market – namely, perceived trustworthiness and transactional utility – rather than merely reflecting mining activity in a technical sense.

<sup>1</sup> Although Ethereum adopted a Proof-of-Work consensus mechanism during most of the sample period, it transitioned to Proof-of-Stake in September 2022 with the implementation of so called "The Merge".



**Fig. 2.** Cryptocurrency prices vs. the HashRate factor.

The charts show the logarithm of the weekly prices of BTC and ETH and the associated log-HashRate index factor. The two panels report standardized values (the original value minus the mean, everything scaled by the standard deviation). The sample covers the period August 21, 2015–September 30, 2022 (372 weekly observations).



**Fig. 3.** Cryptocurrency prices vs. the Google Sentiment factor.

The charts plot the log-differences of the weekly prices of BTC and ETH and the associated Google search index. While prices are shown in log-differences, the Google index is reported in standardized form (the original value minus the mean, scaled by the standard deviation). The sample covers the period August 21, 2015–September 30, 2022 (372 weekly observations).

Long-short portfolios constructed on the basis of earlier measures of predictive performance lead to a notable increase in alpha, in particular when the long-short portfolios are built on the basis of predictability assessed through certainty equivalent returns, as opposed to OOS  $R^2$ . The portfolio sorting method consistently achieves positive and large returns, supporting the existence of remarkable economic value in combining blockchain fundamentals with sentiment indicators to understand and forecast cryptocurrency market dynamics.

Although our paper builds on the work by [Bhambhwani et al. \(2019, 2023\)](#), we extend their analysis in several dimensions. First, we adopt a forecasting-oriented framework, focusing on OOS predictive accuracy rather than cross-sectional DOLS or GMM estimation. Although solid estimation of factor models and in-sample inference are key, our OOS approach is more aligned with typical asset management criteria and with recent trends in asset pricing ([Rapach et al., 2010](#)). Equivalently, while we follow [Bhambhwani et al. \(2019\)](#) in the construction of factor-mimicking portfolios based on blockchain fundamentals, our approach diverges in how we test their economic value. Second, we develop a dynamic portfolio sorting strategy based on the predictive performance of each factor. This methodology allows us to directly quantify the economic relevance of the predictors through long-short portfolio return spreads, which consistently yield high Sharpe ratios and statistically significant alphas. These findings emphasize the practical value of our signals for asset allocation. Third, while they focus on blockchain fundamentals (network size and computing power), we introduce a sentiment-based variable derived from Google search volumes and treat it as a distinct predictive factor.<sup>2</sup> Finally, we work with a more recent and extended dataset, covering observations up to April 2025, thus ensuring

<sup>2</sup> Although [Bhambhwani et al. \(2023\)](#) include a sentiment control in some specifications, they do not consider it as a standalone predictor nor assess its role in forecasting. In our framework, sentiment is incorporated as a core predictive signal, and we demonstrate its forecasting relevance both individually and in combination with fundamental factors.

robustness to recent developments in the crypto asset market. As a result, also the cross-sectional composition of our cryptocurrency universe differs from theirs.

Apart from creating a connection between predictability and a viable investment strategy, our paper therefore emphasizes the superior value of risk-adjusted measures in assessing predictive accuracy. Our methodology resorts to typical techniques in the asset pricing literature that naturally connect the size of the risk premia derived from predictability to the variability of the stochastic discount factor (SDF) induced by the predictors and especially the correlation of the SDF with the predictors (see, e.g., Kan and Zhou, 2007). Hence, assuming the absence of segmentation, our empirical findings of substantial predictability from fundamental blockchain variables to asset returns and of the associated cross-sectional risk premia, are consistent with the fact that such technological parameters may have become pervasive enough to affect the vary nature of the fundamental pricing measure characterizing the financial markets (under completeness).

The rest of the paper is organized as follows. Section 2 reviews relevant literature on cryptocurrency valuation and return predictability. Section 3 introduces a theoretical framework that motivates the empirical approach. In this section we also use a streamlined model of crypto asset valuation to derive testable implications for the relevance of the hashrate, of network size, and of sentiment for cryptocurrency valuations. Section 4 details the data and the empirical methodology. Section 5 presents the main predictive results, while Section 6 provides an extensive robustness analysis. Section 7 concludes.

## 2. Literature review

Because the literature on cryptocurrencies is too vast to be summarized here (see, instead, the surveys by Zheng et al., 2018; Härdle et al., 2020; Valdeolmillos et al., 2020, and Allen et al., 2022), we devote this section to a review of the main findings concerning the role played by the fundamental characteristics of blockchain technology in the asset pricing of digital currencies and, more generally, on the positioning cryptocurrencies in relation to traditional asset classes, especially standard currencies, see, e.g., Mohamad and Stavroyiannis (2022) and Xu and Kinkyo (2023).

Yermack (2024) argues that Bitcoin lacks comparability with traditional currencies, given its limited use as a medium of exchange and its high volatility that undermines its reliability as a store of value. However, this view may deserve reconsideration, as a growing number of businesses and financial institutions are adopting cryptocurrency payment systems.<sup>3</sup> Another argument used to distinguish cryptocurrencies from conventional currencies is the lack of a secondary market for the efficient and secure trading of crypto assets. Research has particularly focused on the peculiar features and risks of the exchanges where cryptocurrencies are traded. For example, Makarov and Schoar (2020) analyze the prices of Bitcoin, Ethereum, and Ripple, finding discrepancies across different exchanges for the same cryptocurrencies, leading to potential arbitrage opportunities and pointing to a lack of either liquidity or of adequate technological platforms.<sup>4</sup>

In a different vein, Baur et al. (2018) examine the statistical properties of Bitcoin returns and found that it exhibited no correlation with traditional asset classes, such as stocks, bonds, and commodities. This occurs during both periods of stability and times of financial crises. Their analysis concludes that Bitcoin is still primarily used as a speculative asset rather than an alternative to conventional currencies. Selgin (2015) in fact suggests that Bitcoin shared certain characteristics with commodities, particularly because of its programmed scarcity.<sup>5</sup>

An emerging literature has sought to identify market factors that can explain cryptocurrency returns, once more in comparison with other asset classes. Liu and Tsyvinski (2021) identify two key drivers: a momentum factor based on historical cryptocurrency returns and an investor attention factor that captures popular interest in cryptocurrencies using data from platforms like Google and Twitter. Liu et al. (2022) reach similar conclusions, expanding their research to include a broader range of cryptocurrencies. In related research, Bianchi et al. (2023) investigate the predictability of returns in cryptocurrency markets and the forecasting power of market risk factors, cryptocurrency-specific predictors, and sentiment variables for digital currencies compared to traditional asset classes. Using a dynamic model to account for time-varying coefficients and model selection, they find that unlike traditional assets, cryptocurrencies are not systematically predicted by stock market factors or commodity prices, but exhibit significant exposure to investor attention.<sup>6</sup> Bianchi et al. (2022) focus on trading dynamics and found that price variations and trading volumes offer valuable information to forecast price movements, in a manner that is unique to cryptocurrencies. The pioneering paper by Easley et al. (2019) focus on Bitcoin's blockchain mechanics. Their work explores the interactions between the mining reward algorithm,

<sup>3</sup> In 2021 T announced its willingness to accept Dogecoin as a means of payment of some purchases, see Bloomberg, 2021. Foley et al. (2019) estimate that between 2009 and 2017, approximately 46% of Bitcoin transactions were linked to illicit activities, though this fraction declined significantly after 2013. The historical evolution of Bitcoin suggests that its value and usage have diverged from criminal activities, as its price continued to rise even after the decline in illicit transactions, reinforcing the view that such activities are not a primary value driver for digital currencies.

<sup>4</sup> These price inefficiencies were found to persist for extended periods, sometimes lasting for several weeks. Furthermore, the security of these platforms has historically relied on algorithms created and managed by third parties, without authoritative oversight to ensure safety and compliance, raising concerns over potential frauds. A well-known case is the Canadian exchange QuadrigaCX, which, at its peak, was considered to be the largest cryptocurrency market in Canada but then turned out to be a scam valued at approximately 190 million USD, see Telford (2019) and Yousaf et al. (2023).

<sup>5</sup> Programmed scarcity refers to the design choice made in many blockchain-based systems to limit the total supply of a cryptocurrency or control its issuance rate. Scarcity is typically encoded into the cryptocurrency's protocol and enforced by its decentralized network; it is a feature intended to promote long-term value stability. The controlled issuance rate instead ensures a predictable supply curve. For instance, Bitcoin carries a fixed upper limit on the number of coins (21 million) that can be created.

<sup>6</sup> This lack of predictability compared to traditional assets, combined with the benefits of diversification, results in realized expected utility gains for a power utility investor when cryptocurrencies are used in portfolio diversification.

the transaction fees, and the waiting times associated with recording transactions on the blockchain ledger. They find that as Bitcoin prices rise, transaction fees increase, which in turn limits blockchain capacity and user participation, hindering Bitcoin's development as a transaction medium.

Finally, as already mentioned in the introduction, two studies closely related to ours are [Bhambhwani et al. \(2019, 2023\)](#). The earlier study by [Bhambhwani et al. \(2019\)](#) investigates the relationship between cryptocurrency prices and blockchain fundamentals – specifically, computing power and network size – using data on five major PoW cryptocurrencies over the period 2015–2019. To address the non-stationarity of the price time series, they estimate cointegrating relationships via dynamic OLS regressions. They then construct factor-mimicking portfolios (FMPs) by projecting the growth rates of the fundamental variables onto the space of cryptocurrency returns. These FMPs are subsequently used in asset pricing tests, including pooled OLS on an extended cross-section of 34 cryptocurrencies not used in the factor construction step. The resulting blockchain-based factors are found to be statistically significant, to carry positive risk premia, and to help explain cross-sectional return variation, both in-sample and in their cross-sectional OOS setting.

[Bhambhwani et al. \(2023\)](#) focus on a broader sample of 18 major cryptocurrencies for a 2017–2021 sample, selected on the basis of data availability and market size. At the individual level, they estimate cointegration relationships between prices, network size, and computing power using dynamic OLS, documenting significant long-term positive trends. To analyze returns at the aggregate level, they construct fundamental factors based on the average weekly growth rates in network activity and computing power across the 18 cryptocurrencies. These factors are used in GMM cross-sectional regressions. In a subsequent step, they expand their test assets by including 36 additional cryptocurrencies, and use pooled cross-sectional regressions to assess the explanatory power of the factors. The results confirm that the blockchain-based predictors are significant and economically relevant across a wider set of digital currencies.

Both studies perform OOS tests in a cross-sectional framework, assessing the generalizability of their factors to cryptocurrencies outside the initial factor construction sample. However, these papers stop short from employing time-series, recursive forecasting methods. Our paper builds on these studies but moves beyond a static asset pricing framework by adopting a dynamic, OOS forecasting perspective. Unlike previous work that constructs factors on the full sample and tests them in pooled regressions, we re-estimate predictors recursively and evaluate their performance through forecast accuracy measures and their implied portfolio strategy CER. In addition, to evaluate the performance of these predictors, we implement a characteristic-based portfolio sorting methodology that is robust to non-linearities, functional misspecification, and multicollinearity—all common limitations of traditional regression-based approaches (see [Cattaneo et al., 2020](#); [Kagkadis et al., 2023](#); [Bali et al., 2016](#)). This approach highlights the relevance of blockchain fundamentals and sentiment in real-time cryptocurrency return forecasting.

### 3. Testable hypotheses on the blockchain fundamentals

#### 3.1. Fundamental characteristics of blockchains

Originally conceived for the validation of digital documents, blockchain is a technology that facilitates the creation of decentralized and immutable ledgers. It is a digital record-keeping system that stores transaction data in a secure and transparent way. It consists of a “block” containing data, a unique hash, and the hash of the previous block. These are linked in a chain. While a blockchain by itself is not a cryptocurrency, it serves as the underlying technology for many cryptocurrencies, enabling decentralized transaction validation.

Cryptocurrencies are either mineable, like Bitcoin, and hence rely on miners solving puzzles, or non-mineable tokens, pre-allocated through protocols ([Cong et al., 2021](#)). The key distinction between the two types lies in the consensus mechanism, which governs transaction validation and blockchain operations. The most widely used algorithms are PoW and Proof of Stake (PoS). PoW, the oldest and most recognized, relies on miners' computational work to validate transactions and secure the network. Although slow and energy-intensive, it is considered the most decentralized and secure mechanism ([Chaudhry and Yousaf, 2018](#)). PoS, by contrast, replaces miners with validators who stake their assets to validate transactions, improving speed and energy efficiency while reducing decentralization costs ([Cong et al., 2021](#)).<sup>7</sup>

The computational power, or hashrate, is a crucial metric to size up a blockchain system. It quantifies the effort miners spend to solve cryptographic puzzles, influencing both the security and the distribution of the corresponding rewards. The higher the associated computational power, the more secure the blockchain becomes, as it would require a ill-intentioned hacker significant resources to compromise the system.<sup>8</sup> However, this increase in computational power has made mining more challenging, requiring greater resources for a diminishing reward. The relationship between cryptocurrency valuation and computational power is addressed by [Pagnotta and Buraschi \(2018\)](#), [Chiu and Koepl \(2022\)](#), who present theoretical models linking hashpower to network security, showing how mining effort reduces attack risk and stabilizes prices. In line with this, [Prat and Walter \(2021\)](#) point out that while the hashrate correlates with Bitcoin prices, the implied elasticity is not one as miners' investments create stability. [Pagnotta \(2022\)](#) finds indeed that the prices of Bitcoin, Ethereum, and Litecoin are positively related to their hashrates.

<sup>7</sup> Other algorithms, such as Proof of Authority (PoA), are less common but have potential applications in areas like central banking ([Dziembowski et al., 2015](#)).

<sup>8</sup> Bitcoin's hashrate, for example, is currently around 900 EH/s and this implies a massive computational effort ([Noda et al., 2020](#)). One EH/s equals 1,000,000,000,000,000,000 or one quintillion hashes per second.

The size of a blockchain network is the other key fundamental factor, typically measured by the number of daily active users. Active users are the unique IP addresses that have engaged with the blockchain in the past 24 h, whether through transactions, mining, staking, or other activities. A larger number of active users correlates with higher liquidity and enhanced resilience to attacks or failures due to the decentralized nature of the system. The size of the network also serves as an indicator of the blockchain's overall adoption and health, as a higher number of active users reflects broader engagement, increased trust in the platform, and a stronger ecosystem supporting its functionality.<sup>9</sup>

Investor sentiment, often driven by so-called “noise traders” who are presumed to be more influenced by market trends and recent price changes than by underlying fundamentals, represents another key behavioral component in cryptocurrency markets (see, e.g., Jo et al., 2020; Mokni et al., 2022; Li et al., 2022, and Sakariyahu et al., 2024). One way to gauge investor sentiment is through Google Trends, which tracks search activity and provides insights into public attention towards specific assets. A growing body of research has documented that Google search data can capture collective patterns of behavior and expectations. For instance, Ginsberg et al. (2009) show that search intensity can anticipate real-world outcomes such as influenza epidemics, highlighting the potential of search-based indicators to predict aggregate behavior. In this regard, Da et al. (2011) provide foundational evidence that online search activity, measured through Google's Search Volume Index for stock tickers, serves as a direct and revealed measure of investor attention, particularly among retail traders. They show that spikes in search intensity predict short-term increases in trading volume and prices, followed by reversals, consistent with waves of sentiment-driven trading rather than responses to new fundamental information. Similarly, Guidolin et al. (2018) demonstrate that Google-based variables possess predictive power in financial applications, linking search activity to fluctuations in asset prices. In financial markets, Joseph et al. (2011) construct a “Google ticker index” based on the search intensity of stock ticker symbols and show that this measure captures fluctuations in individual investors' enthusiasm for specific securities. As they note, the intensity of searches for ticker symbols serves as a valid proxy for investor sentiment, which in turn is useful for forecasting stock returns and volumes. Their results suggest that search activity primarily reflects speculative buying pressure and non-fundamental trading motives, linking online attention directly to sentiment-driven behavior. Further evidence strengthens the connection between attention and sentiment in speculative environments. Preis et al. (2013) document that increases in Google search volumes for financially relevant terms (e.g., “debt”, “crisis”) systematically precede market downturns, reflecting heightened investor concern and negative sentiment. In a related context, Liu and Tsyvinski (2021) show that Google search intensity for cryptocurrency-related terms, such as “Bitcoin”, significantly forecasts short-horizon returns – with a one-standard-deviation increase in searches leading to roughly a 3% rise in one-week-ahead returns – and is correlated with contemporaneous and lagged prices, suggesting that attention operates as a sentiment channel in highly speculative markets. Taken together, these studies support the interpretation of Google search data as a high-frequency behavioral proxy that captures both investors' information-seeking activity (*attention*) and their prevailing optimism or pessimism (*sentiment*) towards cryptocurrencies. Consistent with this literature, we treat the Google-based factor as a sentiment measure that complements blockchain fundamentals by accounting for behavioral deviations from intrinsic value.<sup>10</sup>

Despite the theoretical advancements described above, there has been limited empirical validation of these insights, leaving a significant gap in the asset pricing literature. Our work seeks to bridge this gap by offering an empirical counterpart to theoretical models that highlight the critical roles of hashrate, network size, and sentiment in the valuation of digital assets. The next section recalls the testable implications of a simple model that identifies exactly these three fundamental characteristics as the key drivers in our empirical analysis.

### 3.2. Testable hypotheses from a simple theoretical framework

An on-line Appendix presents a theoretical, equilibrium model that borrows a number of elements from the seminal work by Pagnotta and Buraschi (2018) and is built on the view that cryptocurrencies are “blockchain tokens” whose value is determined by demand and supply forces. On the *demand side*, consumers value the ability to engage in trustless exchanges in a decentralized peer-to-peer network (DP2PN). Trustless networks allow for the coordination of resources towards the production of services in a manner that does not require that the parties either know or trust each other. The number of network users plays a crucial role in driving the demand component, reflecting the strength of network externalities. On the *supply side*, the miners provide computing resources (in our paper, measured by the system hashrate) that affect the network's trustworthiness in terms of the absence of frauds and resistance to attacks. A digital payment system must include entities whose role is to confirm transfers. These validators (miners) are motivated by clearly defined rewards: as more computational power is devoted to securing the ledger, it becomes progressively harder for any single actor to either double-spend tokens or block others' transactions, thereby bolstering trust in the network. Based on this property, we model trust in the network as a function of the total, aggregate hashrate ( $H$ ) that verifiers supply. The cryptocurrency token thus *simultaneously* serves two functions, as a medium of trustless exchange and as a payment device to support supply.

To find the value of the token, we solve a fixed-point problem that characterizes the interaction between consumers and miners. Let us consider a DP2PN where only the blockchain-related asset is traded. Verifier  $j$  contributes a hashrate  $h_j$  resources to the

<sup>9</sup> Cong et al. (2021) develop a theoretical model of network externalities, in which a larger user base amplifies transactional benefits and induce equilibrium multiplicity. Sockin and Xiong (2023) provide a theoretical framework for cryptocurrency valuation based on positive network externalities, emphasizing decentralized control through tokenization.

<sup>10</sup> In addition, we have performed our own regression of cryptocurrency returns on lagged, contemporaneous, and future Google search intensity, and the results indicate that search activity is broadly endogenous to cryptocurrency prices (see the Online Appendix, Table A1).

verification task at a cost  $C(p_C, h_j)$ , where  $p_C$  is the price of the cryptocurrency, and receives in exchange revenues  $R(p_C, h_j)$ . The network trust, depends on the total contribution of resources,  $H = \sum_{j=1}^m h_j$ . With homogeneous verifiers, the total amount of resources is then a multiple  $m$  of the resources  $h$  invested by each verifier, i.e.,  $H = hm$ . We consider a trust mapping  $\tau : H \rightarrow \mathbb{R}$  that depends on the specifics of the network consensus protocol, with  $\tau'(H) > 0$ , i.e., in which a higher hashrate increases the users' trust in the DP2PN.

To establish the overall value of a digital financial network we assume all users are equally important and therefore characterize the network effects by a network law function  $\lambda : n \rightarrow \mathbb{R}$ , where  $\lambda'(n) \geq 0$  and  $\lambda''(n) > 0$ .<sup>11</sup> Call  $v(\lambda(n), \tau(H))$  the value of network in units of a consumption good that serves as a numeraire, which depends on the number of users and the strength of the network effects, captured by the network law  $\lambda(n)$ , and on the trust it commands, which is driven by the total hashrate  $H$  supplied by the  $m$  verifiers,  $\tau(H)$ . Crucially, we assume

$$v(\lambda(n), \tau(H)) = \lambda(n)\tau(H) \tag{1}$$

with  $\lambda(1) = 0$  and  $\tau(0) = 0$ . This implies that, independently of its size, the value of the network is zero if the trust attached to it is zero, i.e.,  $v(\lambda(n), 0) = 0$  for  $\forall n$ . Moreover, if an agent were the only participant, the network's value would be zero to him/her, i.e.,  $v(1, \tau(H)) = 0 \forall \tau$ .

There are two periods,  $t$  and  $t + 1$ , and a single asset, whose price  $p_C(t)$  we seek to determine. For simplicity, we fix the total asset supply to a constant  $B$ .<sup>12</sup> Agents have heterogeneous preferences that can be represented by an additively separable utility function of CRRA type:

$$u(bv) = \frac{[b\lambda(n_{t+1})\tau(H_{t+1})]^{1-\gamma}}{1-\gamma}, \quad \gamma \neq 1 \tag{2}$$

At time  $t$  agents can either consume or purchase a number of bitcoins  $b$  which, at time  $t + 1$ , entitles them to the DP2PN services. Their utility is therefore equal to  $e_t + u(b\lambda(n_{t+1})\tau(H_{t+1}))$ , where  $e$  represents an endowment,  $n_{t+1}$  is the future network size, and  $H_{t+1}$  is a short for  $H(p_C(t + 1))$ . At time  $t$ , there are  $n_t$  users who form expectations over future network size  $n_{t+1} \in [0, N)$  according to a cumulative distribution  $F_n$ . An agent then solves:

$$\max_b (e_t - p_C(t)b) + \delta \mathbb{E}_n [e_{t+1} + u(b\lambda(n_{t+1})\tau(H_{t+1})) \mid \mathcal{I}_t] \tag{3}$$

where  $\delta$  is the time discount factor. Expected utility maximization yields:

$$\hat{b}(p_C(t)) = \left( \frac{\delta}{p_C(t)} \right)^{\frac{1}{\gamma}} \left\{ (\tau(H_{t+1}))^{1-\gamma} \mathbb{E}_n \left[ (\lambda(n_{t+1}))^{1-\gamma} \mid \mathcal{I}_t \right] \right\}^{\frac{1}{\gamma}} \tag{4}$$

We can now formally define an equilibrium as a set of holdings decisions by consumers,  $b^*$ , network hashrate provision decisions by miners,  $h^*$ , and a price,  $p_C^*$ , such that: (i) consumers maximize expected utility, (ii) miners maximize profits, and (iii) the asset market clears,  $b^*(p_C^*(t))n_t = B$ . Consider  $m$  identical risk-neutral miners who act as price takers and contribute hashrate  $h$  in a competition to verify blocks of transactions. Let  $C : h \rightarrow \mathbb{R}$  be an increasing, convex, twice-differentiable function that represents the cost of mining. The expected revenue of a miner  $j$  providing  $h_{j,t}$  is  $R(p_C(t), h_{j,t}, h_{-j,t}) = Bp_C(t)\pi_{win}(h_{j,t}, h_{-j,t})$  where  $\pi_{win}(\cdot, \cdot)$  is the probability of winning the PoW race and  $h_{-j,t}$  represents the hashrate provision of the other  $m - 1$  miners. Assume  $\pi_{win}$  to be proportional to each miner  $j$ 's hashrate:  $\pi_{win}(h_{j,t}, h_{-j,t}) = h_{j,t}/H_t$ . Optimization of the miner's profits,

$$\max_{h_{j,t}} R(p_C(t), h_{j,t}, h_{-j,t}) - C(h_{j,t}) = Bp_C(t) \frac{h_{j,t}}{H_t} - C(h_{j,t}) \tag{5}$$

yields that the symmetric, competitive provision of hashrate  $H_t^*$  is given by  $mh_t^*$ , where

$$h_t^* C'(h_t^*) = Bp_C(t) \frac{m-1}{m^2} \tag{6}$$

such that  $\frac{\partial H^*}{\partial p_C} > 0$ ,  $\frac{\partial H^*}{\partial m} > 0$ , and  $\frac{\partial H^*}{\partial C'(h^*)} > 0$ . As already anticipated, the resulting optimal network trust  $\tau(H_t)$  is a function of  $p_C(t)$ : ceteris paribus, a higher cryptocurrency price induces miners to supply more computing resources. Moreover, with homogeneous miners, we find a monotonically increasing relation between the number of miners and the hashrate. Thus, in this environment, the system hashrate is a sufficient statistic for the level of network decentralization.

At this point, if the consumers maximize intertemporal expected utility by selecting at time  $t$  optimal cryptocurrency holdings, the demand function is

$$b(p_C(t)) = \left\{ \frac{\delta}{p_C(t)} \int (\lambda(n_{t+1})\tau(H_{t+1}))^{1-\gamma} dF_n \right\}^{\frac{1}{\gamma}} \tag{7}$$

<sup>11</sup> Because the number of possible connections in digital networks typically increase more than linearly with the number of participants, it is reasonable to assume that the value of the network is convex in  $n$ .

<sup>12</sup> This makes our analysis a short-term one as – either in a deterministic, pre-determined way (like in the case of Bitcoin) or stochastically – the supply of many blockchain tokens does increase over time.

the network hashrate is given by  $mh_t^*(p_c^*(t))$ , and the time  $t$  cryptocurrency price satisfies:

$$p_c^*(t) = \delta \left(\frac{n_t}{B}\right)^\gamma (\tau(mh_t^*(p_c^*(t))))^{1-\gamma} E_n \left[ (\lambda(n_{t+1}))^{1-\gamma} | I_t \right] \quad (8)$$

Because  $p_c^*(t)$  appears on both sides of the equation, the equilibrium implies a fixed point solution. Pagnotta and Buraschi (2018) prove that if  $\gamma < 1$  (so that  $E_n [(\lambda(n_{t+1}))^{1-\gamma} | I_t]$  is always positive),  $\tau(\cdot)$  is a bounded, continuous differentiable function,  $\lambda(N)$  is finite (with  $n \leq N$ ),  $C'(0)$  and  $C''(0)$  are both finite, then not only an equilibrium with  $p_c^* = 0$  exists, but also one (called Satoshi's) with a strictly positive price exists. Indeed, without mining rewards, a zero token price is always a self-fulfilling equilibrium: if the cryptocurrency traded at zero, no miner would expend resources to secure the network, network trust would collapse to zero, and users would gain no benefit—so they would not pay anything for the token. However, if network trust rises sufficiently rapidly as price moves above zero, a positive-price equilibrium emerges provided there is a nontrivial group of agents who value the ledger's exchange functionality. In this equilibrium, demand-side forces drive the token's price up as both current and anticipated future participation grow. Conversely, on the supply side, higher marginal mining costs (for example, from electricity expenses) erode miner profitability, reduce hashrate, and thereby lower network trust, putting downward pressure on price. As a result, total network capacity (hashrate) and token price end up moving together: they are positively correlated.

The expression (8) implies the following expression for the continuously compounded return on a crypto asset:

$$r_c^*(t+1) \equiv p_c^*(t+1) - p_c^*(t) = \gamma \ln \left( \frac{n_{t+1}}{n_t} \right) + (1-\gamma) \ln \left( \frac{\tau(H_{t+1}^*)}{\tau(H_t^*)} \right) + (1-\gamma) \ln \left( \frac{E_n [(\lambda(n_{t+2}))^{1-\gamma} | I_t]}{E_n [(\lambda(n_{t+1}))^{1-\gamma} | I_t]} \right) \quad (9)$$

In fact, the on-line Appendix proposes a simple extension that, by allowing for heterogeneous beliefs, micro-founds the appearance of a sentiment variable in the equation for  $r_c^*(t+1)$ .<sup>13</sup> A fraction of investors forms model-consistent (rational) expectations, while the remaining fraction extrapolates from recent fundamentals:

$$\mathbb{E}_t^{\text{agg}} [(\lambda(n_{t+1}))^{1-\gamma}] = \omega_t \mathbb{E}_t^R [(\lambda(n_{t+1}))^{1-\gamma}] + (1-\omega_t) \mathbb{E}_t^X [(\lambda(n_{t+1}))^{1-\gamma}] \quad (10)$$

Here  $R$  denotes the rational type and  $X$  the extrapolative type. The time-varying weight  $\omega_t \in (0, 1)$  is decreasing in a standardized internet-related (e.g., Google) index  $G_t$ :

$$\omega_t = \frac{1}{1 + \kappa G_t}, \quad \kappa > 0, \quad (11)$$

or, more generally,  $\omega_t = 1 - s(G_t)$  with  $s'(G) > 0$  and  $s(G) \in (0, 1)$ . The assumption that the time-varying weight  $\omega_t$  decreases with the standardized search-based index  $G_t$  reflects the intuition that periods of intense online activity coincide with stronger participation by attention-driven or extrapolative traders, whereas when online attention is low, market expectations are dominated by rational, model-consistent agents (see Barber and Odean, 2008; Da et al., 2011; Liu and Tsyvinski, 2021; Vlastakis and Markellos, 2012). Therefore the aggregate expectation is a convex combination with a weight that depends on a standardized internet search index, which we interpret as a sentiment/attention shifter.

If we define  $A_t \equiv \mathbb{E}_t^R [(\lambda(n_{t+1}))^{1-\gamma}]$  and  $X_t \equiv \mathbb{E}_t^X [(\lambda(n_{t+1}))^{1-\gamma}]$ , we have

$$\mathbb{E}_t^{\text{agg}} [(\lambda(n_{t+1}))^{1-\gamma}] = \omega_t A_t + (1-\omega_t) X_t \quad (12)$$

Assuming once more that the pricing fixed point is proportional to

$$P_t \propto (\lambda(n_t))^{1-\gamma} (\tau(H_t))^{1-\gamma} \mathbb{E}_t^{\text{agg}} [(\lambda(n_{t+1}))^{1-\gamma}], \quad (13)$$

(which nests the original formulation when  $\omega_t \equiv 1$  or  $\omega_t \equiv 0$ ), it follows by taking logs and first differences that

$$r_c(t+1) \equiv \ln P_{t+1} - \ln P_t = (1-\gamma) \Delta \ln \lambda(n_{t+1}) + (1-\gamma) \Delta \ln \tau(H_{t+1}) + \Delta \ln \mathbb{E}_{t+1}^{\text{agg}} [(\lambda(n_{t+2}))^{1-\gamma}]. \quad (14)$$

Using  $\Delta \ln \lambda(n_{t+1}) = \ln \lambda(n_{t+1}) - \ln \lambda(n_t)$  and  $g_{n,t+1} \equiv \ln(n_{t+1}/n_t)$ , a convenient local approximation is  $\Delta \ln \lambda(n_{t+1}) \approx \gamma_\lambda(n_t) g_{n,t+1}$  with  $\gamma_\lambda(n_t) \equiv \partial \ln \lambda(n) / \partial \ln n|_{n=n_t}$ . Substituting these gives the empirical approximation

$$r_c(t+1) \approx \gamma \Delta \ln n_{t+1} + (1-\gamma) \Delta \ln \tau(H_{t+1}) + (1-\gamma) \Delta \ln \mathbb{E}_t^{\text{agg}} [(\lambda(n_{t+2}))^{1-\gamma}], \quad (15)$$

where the third term is the *sentiment channel* operating through  $\omega_t$  and the relative optimism  $(X_t - A_t)$  embedded in  $\mathbb{E}_t^{\text{agg}}[\cdot]$ .

Holding  $n_{t+1}$  and  $H_{t+1}$  fixed with respect to  $G_t$  yields the comparative statics

$$\frac{\partial r_c(t+1)}{\partial G_t} = \frac{\partial}{\partial G_t} \ln \mathbb{E}_t^{\text{agg}} [(\lambda(n_{t+1}))^{1-\gamma}] = \frac{\omega_t'}{\mathbb{E}_t^{\text{agg}} [(\lambda(n_{t+1}))^{1-\gamma}]} (X_t - A_t), \quad (16)$$

<sup>13</sup> We thank an anonymous referee for suggesting this fruitful qualitative extension of the model.

with  $\omega'_t < 0$ , so the sign of (16) is positive whenever  $X_t > A_t$ , i.e., when recent fundamental signals make extrapolation optimistic relative to the model-consistent belief. Because the exact measurement of  $\omega'_t$ ,  $X_t$  and  $A_t$  remains difficult, in our empirics we simply augment our predictive regressions using a Google attention index variable.

Eq. (15) shows that returns are affected by:

- the rate of growth of network size,  $\ln(n_{t+1}/n_t)$ , both directly (through  $\lambda$ ) and indirectly via the growth in the expected future network value;
- the rate of growth of trust/security,  $\ln(\tau(H_{t+1})/\tau(H_t))$ , generated by computational resources  $H_t$ ;
- sentiment/attention, through the time-varying aggregate expectation  $E_t^{\text{agg}} \left[ (\lambda(n_{t+1}))^{1-\gamma} | \mathcal{I}_t \right]$ .

Hence our paper performs a systematic OOS assessment of the predictive power of network size, hashrate, and sentiment for the cross-section of cryptocurrency returns. Our conjecture is that under the class of models introduced above, these characteristics ought to affect cryptocurrency returns in such a structural way to provide direct predictive power even in a linearized (regression) version of Eq. (9) and especially when the OOS predictability scores of the various factors are used to perform portfolio sorting, as typical of the asset pricing literature.

#### 4. Data and methodology

In the first part of the analysis, we focus on the construction of relevant factors and perform an in-sample evaluation of their explanatory power for cryptocurrency returns. Our initial dataset cover the period August 21, 2015–April 25, 2025 and include 505 weekly observations. To construct weekly returns, we average the daily log prices over rolling 7-day periods ending on Fridays, and compute the difference between consecutive weekly averages. We use weekly returns to mitigate any day-of-the-week effects (see, e.g., [Biais et al., 2023](#)) and problems due to the existence of outliers. To build the factors, we select five major cryptocurrencies – BTC, ETH, LTC, XMR, and Dash – which together represent a substantial portion of the overall cryptocurrency market, accounting for approximately between 70% to 90% of the total market capitalization over our sample. These cryptocurrencies were specifically chosen because their blockchain operations rely on miners for transaction validation and network functionality. To compute (log-) returns, similarly to [Bhambhwani et al. \(2023\)](#), we sourced weekly prices from Coin Metrics, which aggregates and weights prices from the most liquid cryptocurrency exchanges worldwide, with data derived from 22 exchanges worldwide. Cryptocurrency prices are reported in U.S. dollars (USD) and are recorded at 00:00 UTC on each day.

As discussed in Section 3, two fundamental blockchain metrics are used to capture the key characteristics of the cryptocurrencies in our study: computational power and active user count. Computational power, measured in terahashes, reflects the processing power used by miners to secure the blockchain, while network size, measured by the number of unique active users (crucially, Coin Metrics does not double count active addresses with multiple transactions on a given day), provides insights into the scale of network participation. However, due to specific technical and structural features of certain blockchains, these metrics are not always observable. In the case of XMR, retrieving user data was not possible due to the privacy-focused design of its blockchain, which obfuscates the users' IP addresses ([Narayanan, 2016](#)). Similarly, for Ethereum ETH, it was not possible to construct the hashrate-based factor due to its transition to a PoS consensus mechanism in September 2022. As for the measurement of sentiment, we resort to Google Trends data, which on a standardized 0-100 scale, reflect the relative search interest for each cryptocurrency. This search data, specifically focused on cryptocurrency names and their tickers applied to the entire world, serves as a proxy for investor sentiment. We construct the weekly sentiment indicator following [Liu and Tsyvinski \(2021\)](#), as the standard deviation of current Google search volume from the average of the previous four weeks.

In the final stage of the analysis, we used benchmark weekly return data from the Coin Metrics Bletchley Index (CMBI) to assess the significance of the average excess abnormal returns (alpha) derived from the managed portfolios that we shall build based on our sorting methodology. The benchmark is the CMBI10 index, which tracks the overall performance of the top ten cryptocurrencies by market capitalization.

In terms of methodology, our analysis is divided into two key stages. The first step involves an in-sample analysis, through which we outline the construction of the factors and validate our hypotheses on the role of fundamentals and sentiment variables. The second step extends to an analysis, where we develop portfolios aimed at exploiting the predictability of cryptocurrency returns. In the OOS analysis, we extend our selection to a total of 40 cryptocurrencies, listed in [Table 1](#), chosen based on data availability in terms of return series coverage and time span. The selected assets, drawn from an initial universe comprising the top 100 cryptocurrencies by trading volume, include both mineable and NMCs, ensuring a broad representation of the cryptocurrency market. Given the many hybrid cases in terms of cryptocurrency design, the classification into NMCs should be viewed as a broad and general one, as the underlying definitions can vary across platforms and consensus models. For this reason, we deliberately avoid using the PoS label and opt instead for the more general NMC category.<sup>14</sup>

<sup>14</sup> We excluded XMR from the OOS analysis because the data required to compute the user factor were completely missing throughout our sample.

**Table 1**  
Cryptocurrencies grouped by consensus mechanism.

Ticker	Name	Mean (%)	Standard deviation
<b>Proof of Work (PoW)</b>			
BTC	Bitcoin	0.48	0.08
BTG	Bitcoin Gold	-1.56	0.15
DASH	Dash	-1.04	0.11
DCR	Decred	-0.51	0.10
DGB	DigiByte	-0.50	0.13
DOGE	Dogecoin	0.78	0.16
ETC	Ethereum Classic	-0.15	0.13
ETH	Ethereum	0.22	0.10
LTC	Litecoin	-0.31	0.10
VTC	Vertcoin	-0.39	0.14
WTC	Waltonchain	-2.32	0.18
XVG	Verge	-0.95	0.15
ZEC	Zcash	-0.73	0.12
<b>Non Mineable Currencies (NMCs)</b>			
ADA	Cardano	0.12	0.13
ANT	Aragon	0.15	0.13
BAT	Basic Attention Token	-0.26	0.12
CVC	Civic	-0.55	0.14
DRGN	Dragonchain	-1.21	0.17
ELF	Aelf	-0.40	0.13
FUN	FunToken	-0.59	0.14
GAS	GAS	-0.55	0.14
GNO	Gnosis	-0.16	0.11
GNT	Golem	-0.27	0.13
KNC	Kyber Network Crystal	-0.49	0.13
LEND	Aave	0.74	0.16
LINK	Chainlink	0.86	0.13
MAID	MaidSafeCoin	-0.21	0.14
MANA	Decentraland	0.33	0.17
MKR	Maker	0.02	0.12
NEO	Neo	-0.63	0.12
OMG	OMG Network	-1.14	0.14
PAY	TenX	-1.73	0.13
POWR	Power Ledger	-0.43	0.13
PPT	Populous	-2.70	0.17
REP	Augur	-1.17	0.13
SNT	Status	-0.48	0.13
XEM	NEM	-1.06	0.12
XTM	Stellar	0.02	0.12
XRP	Ripple	0.15	0.13
ZRX	Ox	-0.24	0.14

The table groups the 40 cryptocurrencies used in the out-of-sample analysis by their consensus mechanism: Proof of Work (PoW) or Non Mineable Currencies (NMCs). It reports each asset's ticker, name, mean weekly return (in percentage), and the standard deviation of weekly returns. The OOS data sample covers the period from January 5, 2018 to April 25, 2025 and includes 382 weekly observations. Among these, there are exceptions due to data availability: ANT is available only until 2024-10-04, MAID until 2025-01-17, PPT until 2022-09-09, VTC until 2023-12-08, WTC is available only until 2024-06-14, and DRGN starts from January 19, 2018. Note: Dash is listed under PoW, though it includes masternodes. Given the many hybrid cases in cryptocurrency design, the classification into NMCs should be viewed as a broad and general one, as the underlying definitions can vary across platforms and consensus models. For this reason, we deliberately avoid using the PoS label and opt instead for the more general NMC category.

#### 4.1. Factor construction

Due to the non-tradable nature of blockchain characteristics, direct aggregation of such data to form an asset pricing factor is unfeasible. As a result, these characteristics must be "projected" onto cryptocurrency returns. In fact, even if direct aggregation were possible, comparison would still be problematic because different blockchains employ distinct algorithms for calculating metrics such as computational power and active user counts. By projecting these blockchain characteristics onto cryptocurrency returns, we make these factors tradable in the market, thus enabling the empirical testing of the hypotheses derived earlier (see [Barillas and Shanken, 2017](#)).

To construct the factors we follow [Bhambhwani et al. \(2019\)](#), which was inspired by [Lettau and Ludvigson \(2001\)](#), who pioneered this methodology to estimate the impact of consumption growth rates on the stock market. To define the factors, it is important to construct a FMPs for each characteristic. This process involves projecting the growth rate of each characteristic onto the returns of the test cryptocurrencies, effectively creating a portfolio that replicates as closely as possible (in a linear sense) the dynamics of the

underlying factor. For instance, picking the case of the users variable of ETH to illustrate our methodology, Eq. (17) describes the relationship between Users of ETH ( $US_{ETH,t}$ ) and the price changes of other cryptocurrencies:

$$\Delta US_{ETH,t,t-\tau} = \beta_1 \Delta Price_{BTC,t,t-\tau} + \beta_2 \Delta Price_{XMR,t,t-\tau} + \beta_3 \Delta Price_{LTC,t,t-\tau} + \beta_4 \Delta Price_{DASH,t,t-\tau} \quad (17)$$

Here, the return of the analyzed cryptocurrency (ETH) is omitted to avoid spurious effects. After obtaining the exposures of ETH Users to the price changes of each of the other factor-driving cryptocurrencies, the estimated coefficients are turned into weights by simple standardization:

$$\begin{aligned} W_{BTC} &= \frac{\beta_1}{\beta_1 + \beta_2 + \beta_3 + \beta_4} \\ W_{XMR} &= \frac{\beta_2}{\beta_1 + \beta_2 + \beta_3 + \beta_4} \\ W_{LTC} &= \frac{\beta_3}{\beta_1 + \beta_2 + \beta_3 + \beta_4} \\ W_{DASH} &= \frac{\beta_4}{\beta_1 + \beta_2 + \beta_3 + \beta_4} = 1 - W_{BTC} - W_{XMR} - W_{LTC}. \end{aligned}$$

The FMP for ETH's Users is then created by applying these weights to the price changes of all other cryptocurrencies, as shown in Eq. (18):

$$FMP_{US_{ETH}} = W_{BTC} \times \Delta Price_{BTC,t,t-\tau} + W_{XMR} \times \Delta Price_{XMR,t,t-\tau} + W_{LTC} \times \Delta Price_{LTC,t,t-\tau} + W_{DASH} \times \Delta Price_{DASH,t,t-\tau} \quad (18)$$

We repeat this process for all cryptocurrencies, generating an FMP for each characteristic (users, computational power and Google Trends) and cryptocurrency.<sup>15</sup> Once all FMPs are obtained, the aggregate factor is derived as shown in Eqs. (19a), (19b), and (19c):

$$UsersF_t = w_{BTC,t} \times FMP_{US_{BTC,t}} + w_{XMR,t} \times FMP_{US_{XMR,t}} + w_{LTC,t} \times FMP_{US_{LTC,t}} + w_{DASH,t} \times FMP_{US_{DASH,t}} \quad (19a)$$

$$HashrateF_t = w_{BTC,t} \times FMP_{HR_{BTC,t}} + w_{ETH,t} \times FMP_{HR_{ETH,t}} + w_{LTC,t} \times FMP_{HR_{LTC,t}} + w_{DASH,t} \times FMP_{HR_{DASH,t}} \quad (19b)$$

$$SentimentF_t = w_{BTC,t} \times FMP_{GOO_{BTC,t}} + w_{XMR,t} \times FMP_{GOO_{XMR,t}} + w_{LTC,t} \times FMP_{GOO_{LTC,t}} + w_{DASH,t} \times FMP_{GOO_{DASH,t}} + w_{ETH,t} \times FMP_{GOO_{ETH,t}} \quad (19c)$$

In these equations, the weights  $w_{BTC,t}$ ,  $w_{XMR,t}$ ,  $w_{LTC,t}$ ,  $w_{DASH,t}$ ,  $w_{ETH,t}$  are determined by the relative market capitalizations of each cryptocurrency. The same process is applied to the all the characteristics, with Bitcoin's blockchain data excluded from factors unrelated to BTC. This approach allows us to evaluate whether the results remain consistent and robust even when the significant influence of Bitcoin, which has dominated the digital currency market over most of our sample, is removed from the analysis.

#### 4.1.1. Pro-cyclicality of the factors

To assess the pro-cyclicality of our factors, we adopt the view in Cochrane (2005), who characterizes pro-cyclical factors as tradable factors that earn a positive risk premium. A positive risk premium indicates that these factors tend to generate higher returns when market conditions are favorable and marginal utility is low, while yielding lower returns during unfavorable market conditions when marginal utility is high. Moreover, assets with a positive risk premium should exhibit a positive exposure to pro-cyclical factors, further reinforcing their alignment with favorable market conditions. Building on these premises, an initial test examines whether the factors exhibit a positive risk premium, as shown by the summary statistics in Table 2.

As one would expect, in Panel (a) of Table 2, all pairs of cryptocurrency return series are positively correlated, with coefficients ranging between 0.52 to 0.70. Even though this is not indicated in the table, all pairwise Pearson correlation coefficients are statistically significant at standard levels. In Panel (b) of Table 2, all the factor-mimicking portfolios imply a positive and relatively large weekly Sharpe ratio, ranging from 0.02 for the sentiment factor to the large 0.30 obtained for momentum. Visibly, the different factors imply heterogeneous total risk, as measured by their return sample standard deviation. This narrows the range of the Sharpe ratios to plausible levels.

To estimate the exposure of cryptocurrency returns to the factors, we employ standard OLS regressions. The first regression does not involve the factors that we have constructed as the cryptocurrency returns were simply regressed against the return of BTC and the momentum factor, as illustrated in Eq. (20):

$$Return_{Crypto,t} = \alpha + w_{BTC} Return_{BTC,t} + w_{MOM} MOM_t + \epsilon_t \quad (20)$$

<sup>15</sup> In constructing the factors, we exclude the weights of ETH in the case of the hashrate factor and XMR as far as the user factor is concerned. As discussed earlier, hashrate data for ETH is no longer available after its transition to Proof-of-Stake in 2022. In the case of Monero, it was unfortunately not possible to recover the number of users since its blockchain is designed to obfuscate public user addresses, preventing accurate user count.

**Table 2**  
Summary statistics and correlations.

Panel (a): Correlations between cryptocurrency returns					
	BTC	ETH	XMR	LTC	DASH
BTC	<b>1.00</b>				
ETH	<b>0.60</b>	<b>1.00</b>			
XMR	<b>0.56</b>	<b>0.61</b>	<b>1.00</b>		
LTC	<b>0.70</b>	<b>0.54</b>	<b>0.59</b>	<b>1.00</b>	
DASH	<b>0.56</b>	<b>0.53</b>	<b>0.59</b>	<b>0.52</b>	<b>1.00</b>

Panel (b): Summary statistics of the factor mimicking portfolio returns			
Factors	Mean	Standard deviation	Sharpe ratio
Momentum	4.81	15.91	0.30
User Factor	0.74	6.76	0.11
Hashrate Factor	0.74	6.76	0.11
Google Factor	0.56	15.62	0.04
User Factor Ex-BTC	0.93	8.17	0.11
Hashrate Factor Ex-BTC	0.54	5.85	0.09
Google Factor Ex-BTC	0.21	12.79	0.02

Panel (c): Pairwise correlations between factors									
	Bitcoin	Momentum	User Factor	Hashrate Factor	Google Factor	User Factor Ex-BTC	Hashrate Factor Ex-BTC	Google Factor Ex-BTC	
Bitcoin	<b>1</b>								
Momentum	<b>0.08</b>	<b>1</b>							
User Factor	<b>0.57</b>	0.01	<b>1</b>						
Hashrate Factor	<b>0.71</b>	<b>0.22</b>	<b>0.71</b>	<b>1</b>					
Google Factor	<b>0.74</b>	<b>0.21</b>	<b>0.68</b>	<b>0.97</b>	<b>1</b>				
User Factor Ex-BTC	<b>0.82</b>	<b>0.19</b>	<b>0.75</b>	<b>0.94</b>	<b>0.91</b>	<b>1</b>			
Hashrate Factor Ex-BTC	<b>0.83</b>	<b>0.21</b>	<b>0.72</b>	<b>0.97</b>	<b>0.96</b>	<b>0.98</b>	<b>1</b>		
Google Factor Ex-BTC	<b>0.48</b>	0.03	<b>0.92</b>	<b>0.65</b>	<b>0.55</b>	<b>0.73</b>	<b>0.65</b>	<b>1</b>	

Panel (a) shows the correlations for the weekly returns of the cryptocurrencies used for the construction of the factors: Bitcoin (BTC), Ethereum (ETH), Monero (XMR), Litecoin (LTC), and Dash. Panel (b) reports descriptive statistics (mean, standard deviation, Sharpe ratio) for the seven factor mimicking portfolios. Panel (c) presents the pairwise correlations of the weekly returns of the factors used in the in-sample regression analysis. The sample covers the period from August 21, 2015 to April 25, 2025 and includes 505 weekly observations. Significant coefficients based on a 5% test are boldfaced.

In addition, we analyze an additional model in which each of the fundamental factors developed earlier are incorporated into a classical three-factor model one at the time:

$$Return_{Crypto,t} = \alpha + w_{BTC} Return_{BTC,t} + w_{MOM} MOM_t + w_{Factor} Factor_t + \epsilon_t \tag{21}$$

Finally, given Bitcoin’s central role in the cryptocurrency space, we apply a robustness test by alternatively estimating the three-factor models to the case in which the fundamental characteristics are constructed without including BTC returns (the case to be labeled "Ex-BTC Factors"). The results of these tests are presented in Section 5.1 below.

#### 4.2. Out-of-sample analysis

Before presenting our key forecasting results, we provide a concise overview of the predictive model and of the statistical measures of forecast accuracy employed. Section 4.3 outlines the methodology used for portfolio sorting and construction based on earlier measures of realized predictive performance.

A predictive regression model can be described as:

$$r_{t+1} = \alpha_i + \beta_i x_{i,t} + e_{t+1}, \tag{22}$$

where  $r_{t+1}$  denotes the return of the cryptocurrency at time  $t + 1$ , and  $x_{i,t}$  represents one of the characteristic factors with which future returns of the crypto asset are predicted. It should be emphasized that the predictor is measured at time  $t$ , which in our application corresponds to one week before the target variable. Following the approach in Welch and Goyal (2008), we only compute one-step-ahead point forecasts. To estimate the parameters by standard OLS, the sample is recursively expanded to include the most recent data, adopting what amounts to an expanding window estimation approach.

The predictive accuracy of the various factors/models is then assessed relative to a benchmark commonly adopted in the literature, defined by the simple (recursive) mean  $\bar{r}_t = \sum_{j=1}^t r_j$ .<sup>16</sup> This benchmark is obtained when Eq. (22) collapses to become a regression only including the constant and with no predictors. Intuitively, if a model’s prediction of the future return  $\hat{r}_{t+1}$  performs better than the benchmark  $\bar{r}_{t+1}$ , it can be inferred that  $x_{i,t}$  contains valuable information for predicting the returns of a cryptocurrency. Importantly, our OOS testing design does not involve a two-step procedure (e.g., estimating time-series betas followed by cross-sectional regressions), but rather a direct recursive estimation of the predictive regression for each cryptocurrency.

<sup>16</sup> The most commonly used benchmarks in the literature are the simple historical average and the last available (“no-change in price”) data point, which in this case would consist of a zero return forecast for returns, see, e.g., He et al. (2023).

The first metric which we employ to evaluate predictive performance is the  $R_{OS}^2$ :

$$R_{OS}^2 = 1 - \frac{\sum_{k=q_0+1}^q (r_{m+k} - \hat{r}_{m+k})^2}{\sum_{k=q_0+1}^q (r_{m+k} - \bar{r}_{m+k})^2} \quad (23)$$

This predictive accuracy indicator, originally introduced by [Campbell and Thompson \(2008\)](#), compares the predictions of a model,  $\hat{r}_{t+1}$ , with those of the benchmark,  $\bar{r}_{t+1}$ . When  $R_{OS}^2 > 0$ , the model outperforms the benchmark. To test the significance of the results, we rely on the classical equal predictive accuracy test developed by [Diebold and Mariano \(2002\)](#) and [West \(1996\)](#).<sup>17</sup> In fact, albeit with reference to US equity data, [Campbell and Thompson \(2008\)](#) have shown that even a marginally positive  $R_{OS}^2$  – such as 0.5% for monthly data and 1% for quarterly data – can yield significant economic gains to a mean–variance investor. In our application that uses weekly data, even smaller  $R_{OS}^2$  coefficients of 10–20 basis points may therefore be of economic relevance.

One of the main limitations of the  $R_{OS}^2$  is its inability to account for an investor's risk aversion. To address this shortcoming, we introduce an additional metric to evaluate a model's validity: the CER. The CER is obtained by computing the average utility of an investor who uses a given forecasting model to allocate wealth dynamically across assets, and comparing it to the utility derived from following a benchmark strategy based on the historical mean. Indeed, the CER represents the constant, risk-free rate of return that would make an investor indifferent between investing on the basis of the forecasting model and the benchmark. This metric allows for a more exhaustive assessment of economic value, incorporating both expected returns and risk.

Specifically, at each date  $t$  we (i) form a *one-step-ahead* forecast of excess returns and (ii) update second moments using rolling windows, then (iii) choose portfolio weights that will be held from  $t$  to  $t+1$ . The steps are as follows:

- Obtain  $\hat{\mu}_{t+1|t} \in \mathbb{R}^N$ : model-implied forecast of excess returns for  $t+1$  given  $I_t$ ;
- Estimate  $\hat{\Sigma}_t \in \mathbb{R}^{N \times N}$ : conditional covariance matrix of returns estimated at  $t$  (rolling window of length  $W=40$  weeks, as in [Rapach et al., 2010](#));
- Compute the  $w_t \in \mathbb{R}^N$ : portfolio weights chosen at  $t$  and applied over  $[t, t+1]$  assuming a coefficient of relative risk aversion of  $\gamma > 0$ .

Given quadratic utility  $U_t(w) = w^\top \hat{\mu}_{t+1|t} - \frac{\gamma}{2} w^\top \hat{\Sigma}_t w$ , the unconstrained mean–variance optimal portfolio is

$$w_t = \frac{1}{\gamma} \hat{\Sigma}_t^{-1} \hat{\mu}_{t+1|t}. \quad (24)$$

Given the weights chosen at  $t$ , realized excess returns  $r_{t+1} \in \mathbb{R}^N$ , and *ex-ante* risk  $\hat{\Sigma}_t$ , the period utility realized at  $t+1$  is

$$\hat{v}_{t+1} = w_t^\top r_{t+1} - \frac{\gamma}{2} w_t^\top \hat{\Sigma}_t w_t, \quad (25)$$

and the sample average over the OOS window  $\mathcal{T}$  is  $\bar{v} \equiv \mathcal{T}^{-1} \sum_{t \in \mathcal{T}} \hat{v}_{t+1}$ . We define the *certainty-equivalent return* (CER) of a strategy  $S$  as the constant per-period excess return  $CER_S$  that makes an investor indifferent between receiving  $CER_S$  with zero variance each period and following  $S$ . Under quadratic utility, this is

$$CER_S = \bar{R}_{p,S} - \frac{\gamma}{2} Var(R_{p,S}), \quad (26)$$

where  $R_{p,S,t+1} \equiv w_{S,t}^\top r_{t+1}$  is the portfolio excess return. At each  $t$  in the OOS period, we report the difference  $\Delta CER \equiv CER_{\text{model}} - CER_{\text{benchmark}}$  and annualize it by multiplying by 52 (weekly data). In particular, at each  $t$  in the OOS we iterate on the loop of forecasting mean returns, estimating  $\hat{\Sigma}_t$  from a  $W=40$ -week rolling window, computing optimal mean–variance portfolio weights, and recording  $R_{p,t+1} = w_t^\top r_{t+1}$  and  $\hat{v}_{t+1}$  as in (25). Finally, compute  $CER_{\text{model}}$ ,  $CER_{\text{benchmark}}$ , and  $\Delta CER$ . This recursive design is repeated for each predictive model. A higher CER indicates a greater willingness to pay for access to the predictive strategy, capturing its economic value beyond simple statistical fit. As such, the CER complements  $R_{OS}^2$  by providing an investor-relevant measure of performance, as emphasized in [Marquering and Verbeek \(2004\)](#), [Campbell and Thompson \(2008\)](#), [Welch and Goyal \(2008\)](#), and [Wachter and Warusawitharana \(2009\)](#).

### 4.3. Portfolios and significance tests

As regards the construction of a static investment strategy, we aim to leverage on the heterogeneous predictability of alternative cryptocurrencies. Building on the predictability scores obtained in previous analyses, cryptocurrencies can be classified and hence sorted in portfolios according to their realized forecasting accuracy, as measured by  $R_{OS}^2$  or certainty equivalent returns.

To assess whether any predictability uncovered earlier can generate economic value to an investor, over and beyond the results of the mean–variance asset allocation exercise applied according to the steps explained earlier, we construct 16 portfolios from the full test set of 40 cryptocurrencies examined in this paper. These portfolios correspond to eight different predictors—namely, the three fundamental factors (User, Hashrate, and Google sentiment), their versions excluding Bitcoin data, as well as Bitcoin and Momentum as standalone predictors. For each of these predictors, we evaluate performance using both  $R_{OS}^2$  and the CER, resulting in a total of 16 portfolios.

<sup>17</sup> It is well known that [Diebold and Mariano \(2002\)](#) and [West \(1996\)](#)'s statistics may lead to erroneous conclusions when one compares predictions from nested linear models. Yet, this case never occurs in our application.

Once the cryptocurrencies are ranked according to their cumulative out-of-sample forecasting performance up to a certain month in the OOS period, we construct long-short portfolios by going long in the 20 cryptocurrencies with predictability measures above the median and shorting the 20 below the median. This procedure is repeated every month, ensuring that the composition of the portfolios dynamically reflects the most up-to-date predictive performance of each model. Because each predictive factor originates a different sequence of sortings and hence long-short strategies, the OOS results shall depend and be informative on each of the factors taken in isolation from the others.

## 5. Empirical results

In Section 5.1, we first present and analyze the results of the in-sample regressions. The transition from a two-factor model, which includes BTC and momentum, to a three-factor model, where the fundamental factors are introduced individually (Tables 3 and 4), is examined in detail.

In Section 5.2, we focus on the OOS analysis. As a preliminary step, we show the cumulative forecast errors for BTC, ETH, LTC, and DASH, the four cryptocurrencies with the longest available history (Figs. 4 and 5). We then present the results for the OOS estimation of the full cross-section of 40 cryptocurrencies (Table 5). This analysis evaluates the predictive performance of the models compared to the benchmark approach based on the simple average. Finally, Table 6 presents the results of the backtesting performed on the investment strategies that exploit the possibility to build long-short portfolios based on the relative back-tested predictability.

### 5.1. In-sample results

In the case of the two-factor model, in which past Bitcoin returns and the returns on the momentum factor mimicking portfolio explain the returns of the four baseline cryptocurrencies, each of them exhibits a positive, significant exposure to Bitcoin's return, with coefficients ranging from 0.87 in the case of Dash to 0.98 in the case of Litecoin. However, Panel (a) of Table 3 shows that the estimated exposure to the momentum factor is much lower, with coefficients ranging from 0.02 for Dash to 0.14 for Monero, even though four out of five coefficients are statistically significant. The  $R^2$  of these regressions implies an overall explanatory power that goes from a minimum of 0.32 for Dash to a maximum of 0.5 for Litecoin. The table suggests that Bitcoin returns serve as a meaningful common "market portfolio" factor in describing cryptocurrency returns, while the findings concerning the momentum factor align with those in Liu and Tsyvinski (2021).

Panels (b), (c), and (d) of Table 3 show the findings obtained by the three-factor models, in which cryptocurrency returns are regressed on Bitcoin, momentum, and each of the three fundamental factor mimicking portfolio returns (Users, Hashrate, and Google, taken one at the time). Broadly similar results emerge across these richer models: all cryptocurrency return series display positive, precisely estimated exposures to each fundamental factor. Additionally, the sign of the estimated loading on Bitcoin returns shifts across models: in the two-factor model, such an estimated beta turns out to be positive across all cryptocurrencies, while in the three-factor models, it becomes negative and it is generally statistically significant. For example, Panel (b) shows negative BTC exposures for all cryptocurrency return series, ranging from  $-0.26$  for DASH to  $-0.40$  for both ETH and XMR. Comparing  $R^2$  coefficients across models, reveals a much higher explanatory power expressed by the three-factor model vs. the two-factor model.

Panel (c) of Table 2 integrates the information in Table 3 by showing the estimated pairwise correlations among the factor mimicking portfolios. BTC is found to be strongly correlated with the fundamental factors, ranging from 0.74 in the case of the Google factor to 0.57 for the User factor, possibly explaining why BTC sensitivity coefficients change signs in the three-factor models vs. the two-factor one; i.e., this could be as a result of the considerable collinearity characterizing BTC returns vs. the remaining factors.<sup>18</sup>

We test the robustness of these in-sample results by building three-factor models that use versions of the factor-mimicking portfolios that exclude BTC from their construction, to allow BTC to play a role only through its returns to be included in the regressions. Table 4 reports the corresponding results, which align closely with those in Table 3. As in the previous table, all cryptocurrency return series display positive and precisely estimated exposures to each fundamental factor, confirming the robustness of their explanatory role across model specifications.

### 5.2. Out-of-sample results

The OOS tests examine predictive accuracy by comparing whether the factors we have created in Section 3 can forecast cryptocurrency returns more effectively than a simple recursive average does. Beginning with the model in Eq. (22), a battery of statistics (e.g., the OOS  $R^2$ , the CER, the cumulative forecast error) are calculated to compare these results with the benchmark. Results are organized in two displays: Panel (a) of Table 5 presents results for the fundamental factors while Panel (b) shows findings when the Ex-BTC factors are used. Because we use each of them in isolation from the others, we present the main findings in a separate panel, one per each factor.

<sup>18</sup> A few additional pairs of factors are characterized by large correlations, for instance the User and HashRate and sentiment factors, but it is crucial to note that the returns on these factor mimicking portfolios are never used jointly in the prediction models. Of course, one expects to find large correlations between factor returns computed using all cryptocurrencies and those ex-bitcoin data but we note a few instances of small and statistically insignificant correlations.

**Table 3**  
In-sample analysis results.

	BTC	ETH	XMR	LTC	DASH
<i>Panel (a): 2-Factor Model</i>					
Alpha (%)	<b>0.95</b> (2.62)	0.54 (0.12)	0.45 (-1.03)	<b>-0.91</b> (-2.48)	-0.69 (-1.48)
BTC Beta		<b>0.90</b> (16.47)	<b>0.83</b> (15.27)	<b>0.98</b> (21.73)	<b>0.87</b> (15.26)
Momentum Beta	0.04 (1.84)	<b>0.09</b> (3.32)	<b>0.14</b> (15.27)	<b>0.08</b> (3.58)	0.02 (0.57)
R-square	<b>0.01</b>	<b>0.37</b>	<b>0.35</b>	<b>0.50</b>	<b>0.32</b>
<i>Panel (b): 3-Factor Model Including the User Factor</i>					
Alpha (%)	<b>0.57</b> (2.85)	0.47 (1.47)	0.04 (-0.12)	-0.50 (-1.84)	-0.23 (-0.63)
BTC Beta		<b>-0.40</b> (-5.57)	-0.05 (-0.56)	<b>-0.78</b> (-1.87)	<b>-0.26</b> (-3.45)
Momentum Beta	<b>-0.05</b> (-3.80)	-0.02 (-1.12)	0.03 (1.56)	-0.01 (0.56)	<b>-0.08</b> (-3.44)
User Factor	<b>0.82</b> (33.59)	<b>1.54</b> (22.32)	<b>1.46</b> (20.50)	<b>1.23</b> (20.88)	<b>1.34</b> (16.29)
R-square	<b>0.70</b>	<b>0.68</b>	<b>0.65</b>	<b>0.73</b>	<b>0.55</b>
<i>Panel (c): 3-Factor Model Including the Hashrate Factor</i>					
Alpha (%)	<b>0.62</b> (2.98)	0.58 (2.15)	-0.11 (-0.28)	-1.71 (-1.80)	0.18 (0.48)
BTC Beta		<b>2.00</b> (29.75)	<b>1.09</b> (14.19)	<b>1.47</b> (23.01)	<b>0.96</b> (15.93)
Momentum Beta	-0.04 (2.79)	0.01 (0.75)	<b>0.08</b> (3.35)	0.00 (0.26)	-0.04 (-1.95)
Hashrate Factor	<b>0.96</b> (31.98)	<b>2.00</b> (29.75)	<b>0.99</b> (14.19)	<b>0.68</b> (23.01)	<b>0.96</b> (15.93)
R-square	<b>0.67</b>	<b>0.77</b>	<b>0.48</b>	<b>0.76</b>	<b>0.48</b>
<i>Panel (d): 3-Factor Model Including the Google Factor</i>					
Alpha (%)	<b>0.86</b> (2.69)	0.21 (0.78)	-0.49 (-1.12)	<b>0.81</b> (-2.36)	-0.47 (-1.28)
BTC Beta		<b>0.38</b> (9.75)	<b>0.91</b> (14.76)	<b>0.77</b> (16.25)	<b>0.44</b> (8.65)
Momentum Beta	0.03 (1.71)	<b>0.09</b> (5.60)	<b>0.14</b> (5.16)	<b>0.08</b> (3.94)	0.02 (0.87)
Google Factor	<b>0.24</b> (12.20)	<b>0.54</b> (28.24)	<b>-0.08</b> (-2.65)	<b>0.21</b> (8.99)	<b>0.44</b> (17.28)
R-square	<b>0.23</b>	<b>0.76</b>	<b>0.36</b>	<b>0.57</b>	<b>0.57</b>

The table presents the estimates of the regressions of the weekly return time series of cryptocurrencies on two- and three-factor models. The cryptocurrencies analyzed are: Bitcoin (BTC), Ethereum (ETH), Monero (XMR), Litecoin (LTC), and DASH. In panel (a), the results of the regressions on a two-factor model, which includes the return of BTC and the momentum factor, are shown. In panels (b)–(d), the estimates of the regressions on a three-factor model are presented, which, compared to the previous model, respectively add the User Factor (b), Hashrate Factor (c), and Google Factor (d). The sample covers the period from August 21, 2015 to April 25, 2025 and includes 505 weekly observations. The HAC *t*-statistics for the respective statistics are reported in parentheses. Coefficients in bold are statistically significant at the 5% level. The R-squared statistics are boldfaced when the corresponding F-test of overall model significance rejects the null hypothesis.

As a preliminary step, we perform a focused analysis on a subset of cryptocurrencies – BTC, ETH, LTC, and DASH – which offer the longest available time series. Figs. 4 and 5 visually represent prediction accuracy across models for these four assets. The goal is to show the difference between the prediction errors of each three-factor predictive regression and that of the benchmark. The cumulative forecast errors are computed over the full sample, from August 21, 2015 to April 25, 2025, to include 505 weekly observations. In the plots, the first row concerns the prediction errors derived from using raw fundamentals and momentum to forecast cryptocurrency returns, while the remaining six plots concern the forecasting power of factor mimicking portfolios formed on the basis of Users, HashRate, and Google sentiment, built either using BTC data or omitting BTC.<sup>19</sup>

In the plots, the curve represents the cumulative difference in forecast errors between the predictive regression model and the benchmark. When the curve is positioned above the zero line, this indicates that the predictive model has generated smaller cumulative forecast errors and is therefore outperforming the benchmark. When the curve is below the zero line, the opposite holds: the predictive model has produced larger cumulative forecast errors and is underperforming. The slope of the curve also conveys useful information. If the curve is rising, this means that the predictive model is improving relative to the benchmark in that period, even if the curve may still lie below zero. Conversely, if the curve is declining, this signals that the predictive model is deteriorating in relative terms and is losing ground compared to the benchmark. In this way, the vertical position of the curve shows the level of relative performance, while its slope shows how that relative performance evolves over time.

<sup>19</sup> The momentum factor is by definition a mimicking portfolio.

**Table 4**  
In-sample analysis results when BTC is excluded from the construction of factor mimicking portfolios.

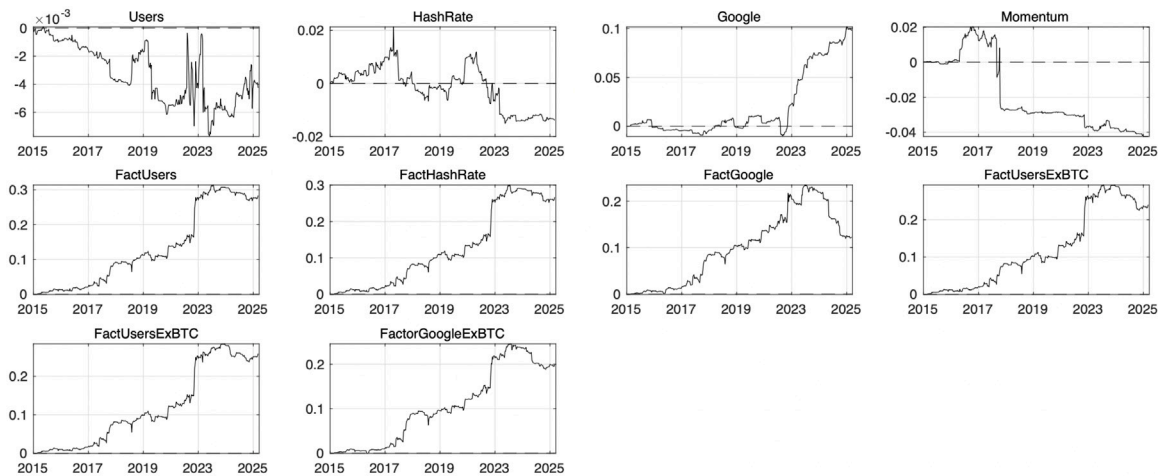
	BTC	ETH	XMR	LTC	DASH
<i>Panel (a): 3-Factor Model with User Factor ex-BTC</i>					
Alpha (%)	<b>0.69</b> (2.71)	0.35 (1.20)	-0.05 (-0.17)	<b>-0.71</b> (-2.17)	-0.36 (-0.93)
BTC Beta		<b>-0.05</b> (-0.93)	<b>-0.12</b> (2.47)	<b>0.50</b> (8.73)	0.03 (0.51)
Momentum Beta	<b>-0.04</b> (-2.41)	-0.02 (-0.95)	0.03 (1.74)	0.03 (1.26)	<b>-0.08</b> (3.54)
Factor User Beta	<b>0.70</b> (22.91)	<b>1.29</b> (25.94)	<b>1.30</b> (26.68)	<b>0.66</b> (11.80)	<b>1.14</b> (18.55)
R-square	<b>0.51</b>	<b>0.73</b>	<b>0.73</b>	<b>0.61</b>	<b>0.60</b>
<i>Panel (b): 3-Factor Model with Hashrate Factor ex-BTC</i>					
Alpha (%)	<b>0.81</b> (2.40)	0.40 (1.03)	0.03 (1.26)	-0.51 (-1.65)	-0.05 (-0.17)
BTC Beta		<b>0.22</b> (3.12)	<b>-0.31</b> (-7.30)	<b>0.36</b> (6.54)	-0.09 (-1.47)
Momentum Beta	0.04 (1.80)	0.02 (0.91)	0.02 (1.72)	0.2 (0.96)	<b>-0.08</b> (-3.80)
Hashrate Beta	<b>0.15</b> (8.26)	<b>1.25</b> (13.20)	<b>2.09</b> (36.47)	<b>1.13</b> (14.97)	<b>1.76</b> (20.09)
R-square	<b>0.13</b>	<b>0.53</b>	<b>0.82</b>	<b>0.65</b>	<b>0.63</b>
<i>Panel (c): 3-Factor Model with Google Factor ex-BTC</i>					
Alpha (%)	<b>0.9</b> (3.01)	0.32 (0.87)	-0.4 (0.96)	<b>-0.65</b> (-2.02)	-0.12 (-0.49)
BTC Beta		<b>0.41</b> (7.52)	<b>0.79</b> (12.01)	<b>0.64</b> (13.29)	<b>0.12</b> (3.23)
Momentum Beta	0.04 (2.12)	<b>0.11</b> (34.81)	<b>0.14</b> (5.19)	<b>0.09</b> (4.68)	<b>0.04</b> (2.74)
Google Factor Beta	<b>0.35</b> (15.58)	<b>0.52</b> (15.77)	0.04 (0.92)	<b>0.36</b> (12.41)	<b>0.80</b> (35.16)
R-square	<b>0.33</b>	<b>0.58</b>	<b>0.36</b>	<b>0.62</b>	<b>0.80</b>

The table presents the estimates of the regressions of the weekly return time series of cryptocurrencies on three-factor models, with the Factor variable constructed excluding BTC. The cryptocurrencies analyzed are Bitcoin (BTC), Ethereum (ETH), Monero (XMR), Litecoin (LTC), and DASH. In panels a, b, and c, the estimates for the models with the respective factors are presented: User Factor Ex-BTC (a), Hashrate Ex-BTC (b), Google Factor Ex-BTC (c). The sample covers the period from August 21, 2015 to April 25, 2025 and includes 505 weekly observations. The HAC *t*-statistics for the respective statistics are reported in parentheses. Coefficients in bold are statistically significant at the 5% level. The R-squared statistics are boldfaced when the corresponding F-test of overall model significance rejects the null hypothesis.

In Figs. 4 and 5, the four panels reveal that across all plots, fundamental-based predictive models consistently outperform the benchmark, with curves lying above zero and trending upward, especially between 2020 and 2023. Moreover, the factor mimicking portfolios do visibly better than the raw factors in the first row; in contrast, the momentum-based model shows some limited predictive power only at the beginning of the sample, but fails to outperform the benchmark throughout the rest of the period, with a steadily declining curve lying below zero. Specifically, the Hashrate Factor proves to be the most stable and effective signal across the board, with solid results for all cryptocurrencies. The increased effectiveness of the fundamental characteristics when they are represented by composite mimicking factors may relate to Rapach et al. (2010)'s findings, who demonstrated that combining predictions reduces forecast volatility, yielding better outcomes in an equity context.<sup>20</sup> In general, all plots show that including or excluding BTC data in the construction of predictive mimicking portfolios makes little to no difference across cryptocurrencies. Moreover, by the end of our OOS period, most of the factor mimicking portfolio predictors provide a cumulative predictive accuracy spread in the order of 10–60 percent for all cryptocurrencies. The largest cumulative improvements vs. the historical mean are obtained for DASH (when both the User and Google Factor score an almost 60 percent improvement). To comment on the differences across cryptocurrencies, one should focus on how the raw variables diverge, as they are the only components that consistently differ across assets, for example, the raw Users variable displays erratic or even negative predictive power across most assets – especially for BTC and ETH – while the corresponding factor-mimicking portfolio consistently improves forecast performance, highlighting the added value of cross-sectional aggregation. The Google sentiment signal shows improved predictive performance from 2023 onward for BTC, ETH, and LTC, while it remains consistently below zero for DASH throughout the sample period.

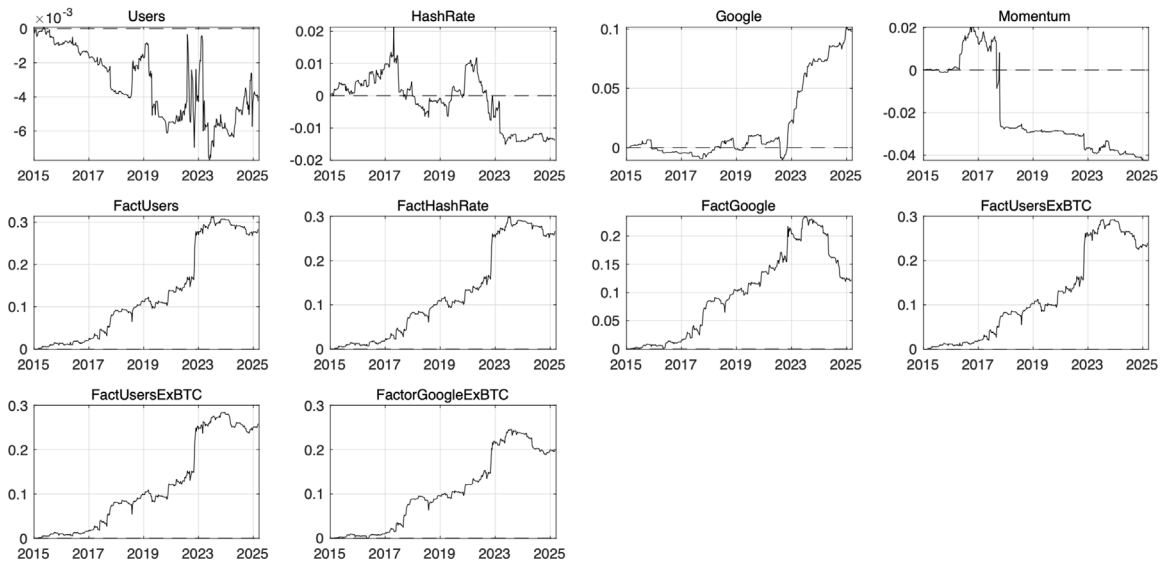
Building on the visual intuition offered by Figs. 4 and 5, we proceed to analyze the findings presented in Table 5 for our full cross-section of 40 cryptocurrencies. Yet, the sample expands to 40 cryptocurrencies in the cross-sectional dimension, at the expense

<sup>20</sup> Rapach et al. (2010) combined forecasts ex post; thus, predictions were estimated for each model and subsequently combined, all models sharing the objective of predicting the equity market risk premium. In this paper, however, factors are calculated by combining fundamental characteristics across various cryptocurrencies ex ante.



(a) Bitcoin

With reference to Bitcoin returns, the charts represent the difference between the prediction error of the historical mean and the prediction error of a predictive factor regression that uses as a forecast instrument the variable indicated in correspondence to the plot. The sample covers the period from August 21, 2015 to April 25, 2025 and includes 505 weekly observations.



(b) Ethereum

With reference to Ethereum returns, the charts represent the difference between the prediction error of the historical mean and the prediction error of a predictive factor regression that uses as a forecast instrument the variable indicated in correspondence to the plot. The sample covers the period from August 21, 2015 to April 25, 2025 and includes 505 weekly observations.

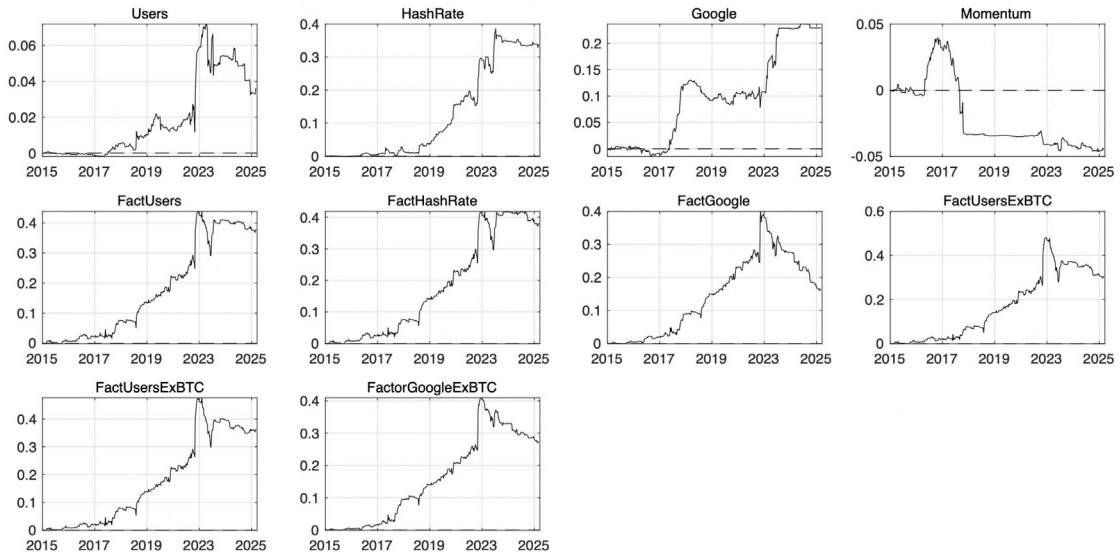
Fig. 4. Cumulative prediction errors.

of time-series length, which is restricted to the January 2018–April 2025 period. The estimation window for model parameters remains 382 weeks (i.e., 5 years), implying that the out-of-sample period spans from January 2020 to April 2025.<sup>21</sup>

In the table, we report the  $R^2_{OS}$ , with the associated  $p$ -value calculated using the method in Diebold and Mariano (2002).<sup>22</sup> Panel (a) of Table 5 predominantly displays positive  $R^2_{OS}$  values, indicating that for most factor mimicking predictors, the corresponding predictive regression generally provides stronger OOS accuracy than a simple average. The predictive power of network size and

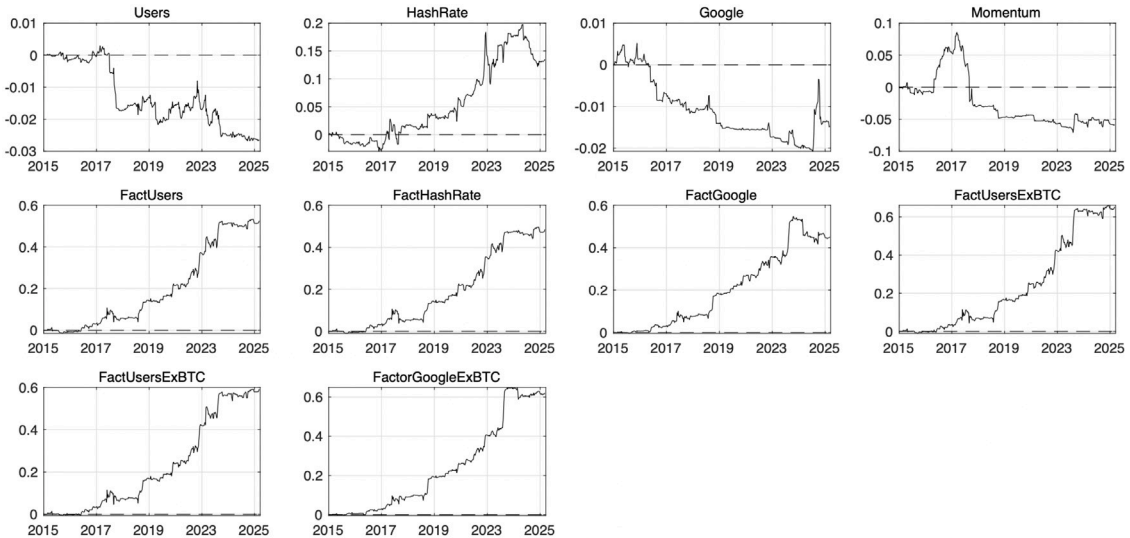
<sup>21</sup> There are exceptions due to data availability: ANT is available only until 2024-10-04, MAID until 2025-01-17, PPT until 2022-09-09, VTC until 2023-12-08, WTC is available only until 2024-06-14, and DRGN starts on January 19, 2018.

<sup>22</sup> The null hypothesis  $R^2_{OS} \leq 0$  is tested against the alternative hypothesis  $R^2_{OS} > 0$  using a t-ratio test statistic, in which the estimated standard error is HAC-adjusted.



(a) Litecoin

With reference to Litecoin returns, the charts represent the difference between the prediction error of the historical mean and the prediction error of a predictive factor regression that uses as a forecast instrument the variable indicated in correspondence to the plot. The sample covers the period from August 21, 2015 to April 25, 2025 and includes 505 weekly observations.



(b) Dash

With reference to Dash returns, the charts represent the difference between the prediction error of the historical mean and the prediction error of a predictive factor regression that uses as a forecast instrument the variable indicated in correspondence to the plot. The sample covers the period from August 21, 2015 to April 25, 2025 and includes 505 weekly observations.

Fig. 5. Cumulative prediction errors.

computing power extends beyond PoW cryptocurrencies, suggesting that these fundamentals capture market-wide risk dimensions. This is consistent with the notion that investors may undervalue assets that perform well in procyclical conditions, regardless of their consensus mechanism. All fundamental factors are equally successful (the null of a non positive  $R^2_{OS}$  can be rejected 27, 25, and 32 times out of 40, respectively), but on average rather successful as in 60–80 percent of the cases the  $R^2_{OS}$  turns out to be significant while under the null this should occur only 5 percent of the time. Interestingly, although the edge was initially small, the results suggest that Google sentiment has become a more reliable predictor over time. In fact, by the end of our OOS period, it outperforms both User and HashRate fundamentals in terms of the number of significant out-of-sample  $R^2_{OS}$  values. It is also notable that when one predictor tends to work for a given ticker, this extends to all predictors. This suggests that it may be the

**Table 5**  
Out-of-sample (OOS) predictive results.

Ticker	Panel (a): OOS predictive results for a cross-section of cryptocurrencies								
	User Factor			Hashrate Factor			Google Factor		
	OOS $R^2$	p-value	OOS CER ( $\gamma = 3$ )	OOS $R^2$	p-value	OOS CER ( $\gamma = 3$ )	OOS $R^2$	p-value	OOS CER ( $\gamma = 3$ )
	<b>Proof of Work (PoW)</b>								
BTC	<b>5.72</b>	0.00	0.36	<b>5.16</b>	0.00	0.34	<b>2.72</b>	0.00	0.27
BTG	<b>4.62</b>	0.00	0.08	<b>4.67</b>	0.00	0.07	<b>4.25</b>	0.00	0.08
DASH	<b>5.99</b>	0.00	0.09	<b>5.92</b>	0.00	0.07	<b>5.72</b>	0.00	0.01
DCR	<b>4.49</b>	0.00	0.41	<b>3.93</b>	0.00	0.38	<b>4.26</b>	0.00	0.36
DGB	<b>6.51</b>	0.00	0.28	<b>6.21</b>	0.00	0.29	<b>6.48</b>	0.00	0.12
DOGE	<b>2.52</b>	0.01	0.20	<b>2.88</b>	0.00	0.18	<b>2.24</b>	0.00	0.20
ETC	<b>5.93</b>	0.00	0.28	<b>4.67</b>	0.00	0.32	<b>4.80</b>	0.00	0.30
ETH	<b>5.06</b>	0.00	0.39	<b>5.40</b>	0.00	0.43	<b>3.57</b>	0.00	0.48
LTC	<b>4.88</b>	0.01	0.35	<b>4.80</b>	0.00	0.33	<b>3.10</b>	0.01	0.21
VTC	2.52	0.06	0.05	2.28	0.07	0.06	0.13	0.21	0.00
WTC	0.03	0.13	-0.15	0.05	0.10	-0.10	-0.52	0.10	-0.10
XVG	<b>5.57</b>	0.00	0.18	<b>5.57</b>	0.00	0.20	<b>5.60</b>	4.84	0.12
ZEC	<b>2.39</b>	0.03	0.09	<b>2.68</b>	0.03	0.10	<b>1.90</b>	0.02	-0.02
	<b>Non Mineable Currencies (NMCs)</b>								
ADA	<b>8.17</b>	0.00	0.56	<b>8.25</b>	0.00	0.55	<b>10.42</b>	0.00	0.55
ANT	-3.26	0.65	0.02	-3.43	0.62	0.05	-3.71	0.60	0.04
BAT	1.32	0.05	0.16	<b>1.30</b>	0.05	0.14	<b>2.72</b>	0.00	0.17
CVC	0.30	0.14	0.13	0.66	0.10	0.15	<b>1.36</b>	0.04	0.19
DRGN	<b>1.26</b>	0.05	-0.04	1.02	0.17	-0.04	1.62	0.06	0.01
ELF	0.33	0.06	0.08	0.14	0.06	0.06	<b>2.60</b>	0.00	0.19
FUN	<b>1.51</b>	0.03	0.18	<b>1.57</b>	0.02	0.17	<b>1.47</b>	0.01	0.11
GAS	<b>2.77</b>	0.02	-0.16	<b>1.24</b>	0.03	-0.20	<b>2.38</b>	0.02	-0.18
GNO	<b>3.93</b>	0.00	0.31	<b>4.10</b>	0.00	0.28	<b>3.52</b>	0.00	0.28
GNT	-1.06	0.16	0.12	-1.60	0.19	0.13	<b>0.67</b>	0.05	0.19
KNC	0.21	0.13	0.07	-0.04	0.12	0.06	-0.47	0.10	0.06
LEND	<b>1.92</b>	0.02	0.22	<b>2.40</b>	0.00	0.40	<b>4.39</b>	0.27	0.00
LINK	<b>0.73</b>	0.01	0.33	<b>0.24</b>	0.01	0.27	<b>1.78</b>	0.00	0.28
MAID	-0.70	0.53	-0.05	-0.75	0.58	-0.07	-0.85	0.67	-0.07
MANA	<b>1.47</b>	0.02	0.22	<b>1.87</b>	0.01	0.26	<b>2.75</b>	0.00	0.24
MKR	1.10	0.06	0.02	<b>2.13</b>	0.05	0.06	<b>2.27</b>	0.03	0.06
NEO	<b>8.13</b>	0.00	0.36	<b>7.53</b>	0.00	0.29	<b>7.46</b>	0.00	0.34
OMG	-0.30	0.09	0.05	-0.18	0.70	0.06	<b>1.08</b>	0.03	0.07
PAY	<b>1.85</b>	0.05	0.02	1.56	0.05	0.01	<b>1.32</b>	0.03	0.02
POWR	<b>1.20</b>	0.05	0.09	0.80	0.06	0.08	<b>1.86</b>	0.01	0.18
PPT	1.08	0.12	0.03	1.19	0.12	0.02	0.88	0.15	-0.01
REP	-0.15	0.17	-0.09	-0.32	0.17	-0.10	0.10	0.06	0.10
SNT	<b>3.36</b>	0.01	0.21	<b>3.48</b>	0.01	0.21	<b>4.18</b>	0.00	0.19
XEM	<b>1.72</b>	0.03	0.06	<b>1.02</b>	0.05	0.01	<b>3.66</b>	0.01	0.05
XLM	<b>5.66</b>	0.00	0.08	<b>6.50</b>	0.00	0.09	<b>6.22</b>	0.00	0.01
XRP	<b>2.61</b>	0.02	0.12	2.97	0.06	0.14	<b>2.44</b>	0.00	0.17
ZRX	<b>3.72</b>	0.00	0.18	<b>3.92</b>	0.00	0.17	<b>5.37</b>	0.00	0.16
	<b>Average</b>								
	2.63	0.07	0.15	2.54	0.09	0.15	2.79	0.18	0.14
	<b>Average (ex BTC, DASH, ETH, LTC)</b>								
	2.32	0.08	0.13	2.24	0.10	0.13	2.68	0.20	0.12

(continued on next page)

time series of cryptocurrency returns that contains pockets of predictability and this may be picked up both by fundamental and by sentiment-driven forecasting. Regarding the CER results, these are overwhelmingly positive in 35 out of 40 tickers, both for the fundamental predictors and for Google sentiment. This implies that, across all predictors, factor-mimicking-based predictability is never wealth-destroying in risk-adjusted terms, and thus carries some economic value.

This suggests that, even after accounting for investors' risk aversion, the forecasts derived from fundamental-based models – including Google sentiment – consistently yield economically meaningful gains. In other words, the positive CER values indicate that these strategies not only improve predictive accuracy, but also translate into improved risk-adjusted performance, reinforcing their relevance to portfolio allocation.

In a summary, the average OOS R-squared are 2.63, 2.54, and 2.79 percent. To further strengthen the genuine nature of the OOS evidence, we compute the  $R_{OOS}^2$  averages excluding the cryptocurrencies used in the construction of the factors (BTC, DASH, ETH, LTC). As expected, the resulting averages are somewhat lower, but the overall results remain consistent, supporting the robustness of our findings. Although the differences are small, these results support the idea that sentiment-driven information – possibly capturing investor attention and expectations – can be just as valuable as standard fundamentals like user base and hashrate in forecasting cryptocurrency returns. Similarly, the CER values are remarkably homogeneous across predictors, with averages of 15%, 15%, and 14%, confirming a comparable degree of economic value across all factor types.

Table 5 (continued).

Ticker	Panel (b): OOS predictive results when the factor predictors are Ex-BTC								
	User Factor Ex-BTC			Hashrate Factor Ex-BTC			Google Factor Ex-BTC		
	OOS $R^2$	p-value	OOS CER ( $\gamma = 3$ )	OOS $R^2$	p-value	OOS CER ( $\gamma = 3$ )	OOS $R^2$	p-value	OOS CER ( $\gamma = 3$ )
	<b>Proof of Work (PoW)</b>								
BTC	<b>4.06</b>	0.00	0.27	<b>3.16</b>	0.00	0.31	<b>0.89</b>	0.00	0.40
BTG	<b>4.30</b>	0.00	0.04	<b>3.63</b>	0.00	0.04	<b>2.96</b>	0.00	0.07
DASH	<b>4.82</b>	0.01	0.04	<b>4.42</b>	0.01	0.07	<b>4.31</b>	0.00	0.08
DCR	<b>3.54</b>	0.01	0.33	<b>3.67</b>	0.01	0.36	<b>4.82</b>	0.00	0.46
DGB	<b>5.54</b>	0.00	0.19	<b>5.41</b>	0.00	0.18	<b>6.12</b>	0.00	0.17
DOGE	<b>2.53</b>	0.01	0.23	<b>2.25</b>	0.01	0.26	<b>1.34</b>	0.02	0.28
ETC	<b>4.80</b>	0.00	0.24	<b>3.82</b>	0.00	0.23	<b>1.40</b>	0.01	0.34
LTC	<b>3.69</b>	0.01	0.24	<b>3.42</b>	0.01	0.30	<b>1.83</b>	0.07	0.33
VTC	2.55	0.06	0.02	2.39	0.07	0.01	-1.00	0.22	-0.07
WTC	-0.48	0.17	-0.12	-0.80	0.21	-0.18	-1.10	0.19	-0.17
XVG	<b>4.40</b>	0.00	0.10	<b>4.70</b>	0.00	0.10	<b>5.53</b>	0.00	0.10
ZEC	1.28	0.06	0.10	0.39	0.08	0.07	<b>-0.78</b>	0.05	0.07
	<b>Non Mineable Currencies (NMCs)</b>								
ADA	<b>7.37</b>	0.00	0.52	<b>7.05</b>	0.00	0.54	<b>9.65</b>	0.00	0.62
ANT	-3.86	0.73	-0.04	-4.50	0.78	-0.08	-4.93	0.75	-0.02
BAT	0.73	0.09	0.09	0.22	0.11	0.12	<b>1.48</b>	0.02	0.20
CVC	-0.45	0.27	0.08	-1.06	0.34	0.07	-0.27	0.14	0.14
DRGN	1.17	0.06	-0.04	<b>1.35</b>	0.05	-0.04	<b>2.23</b>	0.03	0.01
ELF	0.10	0.06	0.07	-0.38	0.07	0.08	<b>2.01</b>	0.00	0.20
ETH	<b>4.11</b>	0.00	0.36	<b>2.20</b>	0.00	0.36	<b>-0.07</b>	0.00	0.52
FUN	<b>0.97</b>	0.05	0.11	0.55	0.09	0.10	0.56	0.07	0.10
GAS	<b>2.84</b>	0.04	-0.17	<b>3.20</b>	0.05	-0.16	<b>4.41</b>	0.03	-0.12
GNO	<b>3.30</b>	0.00	0.30	<b>2.05</b>	0.00	0.29	<b>1.08</b>	0.00	0.31
GNT	-1.06	0.19	0.06	-1.40	0.17	0.04	<b>0.50</b>	0.05	0.23
KNC	0.15	0.14	0.05	-0.56	0.20	0.03	-1.45	0.24	0.06
LEND	<b>2.09</b>	0.02	0.16	<b>1.10</b>	0.05	0.15	<b>2.38</b>	0.01	0.34
LINK	<b>0.64</b>	0.01	0.29	<b>-0.79</b>	0.02	0.31	<b>-0.27</b>	0.02	0.31
MAID	-0.77	0.58	-0.07	-1.17	0.63	-0.06	-1.62	0.67	-0.05
MANA	<b>1.02</b>	0.04	0.18	0.54	0.07	0.18	<b>1.42</b>	0.01	0.24
MKR	0.12	0.08	0.09	-0.71	0.10	0.16	<b>-0.24</b>	0.04	0.21
NEO	<b>7.02</b>	0.00	0.32	<b>6.39</b>	0.00	0.32	<b>6.81</b>	0.00	0.41
OMG	-0.70	0.15	0.02	-2.00	0.24	-0.03	-1.45	0.18	-0.01
PAY	<b>1.69</b>	0.05	0.01	<b>1.90</b>	0.04	0.04	<b>2.16</b>	0.01	0.05
POWR	0.66	0.08	0.04	0.76	0.06	0.04	<b>2.41</b>	0.00	0.02
PPT	0.62	0.17	-0.02	0.27	0.22	-0.01	0.26	0.23	-0.01
REP	-0.17	0.18	-0.09	-0.62	0.23	-0.12	-0.85	0.11	0.00
SNT	<b>2.46</b>	0.03	0.15	<b>2.06</b>	0.04	0.16	<b>3.02</b>	0.01	0.20
XEM	<b>1.73</b>	0.04	0.12	<b>1.66</b>	0.04	0.11	<b>4.55</b>	0.01	0.11
XTM	<b>3.86</b>	0.01	0.06	<b>2.88</b>	0.01	0.05	<b>3.06</b>	0.01	-0.12
XRP	<b>2.44</b>	0.01	0.18	<b>1.98</b>	0.03	0.17	<b>2.83</b>	0.02	0.04
ZRX	<b>3.24</b>	0.01	0.16	<b>2.74</b>	0.01	0.14	4.16	0.92	0.00
	<b>Average</b>								
	2.06	0.09	0.12	1.55	0.10	0.12	1.75	0.10	0.15
	<b>Average (ex BTC, DASH, ETH, LTC)</b>								
	1.82	0.09	0.10	1.36	0.11	0.10	1.76	0.11	0.13

Notes: Panel (a) reports OOS predictive results for the User, Hashrate, and Google factors; Panel (b) reports OOS results when factors are constructed ex-BTC. For each cryptocurrency we report the out-of-sample  $R^2$ , the associated  $p$ -value, and the annualized certainty equivalent return (CER) for a mean-variance investor with risk aversion  $\gamma = 3$ . Boldface indicates  $R^2$  significant at the 5% level. The evaluation period is January 5, 2018–April 25, 2025 (382 weekly observations). Exceptions due to data availability: ANT until 2024-10-04, MAID until 2025-01-17, PPT until 2022-09-09, VTC until 2023-12-08, WTC until 2024-06-14, and DRGN starting on 2018-01-19.

Interestingly, the Hashrate factor, which is typically expected to be more relevant to PoW cryptocurrencies – given their reliance on mining activity – also appears to be highly effective in forecasting returns of NMC coins. For instance, among NMC assets, ADA exhibits an out-of-sample  $R^2_{OS}$  as high as 8.17, a value that exceeds the  $R^2_{OS}$  obtained for any PoW cryptocurrency for the same predictive factor. This finding is particularly notable, as PoS systems do not rely on hashrate in the same operational sense as PoW, thus suggesting that the Hashrate factor may be capturing broader aspects of market activity, attention, or investor behavior that are informative even outside its natural domain.

Similar patterns and qualitative results can be observed in Panel (b) of 5 when the recursive OOS backtesting involves the Ex-BTC factors. For instance, with reference to the HashRate factor, the number of significant  $R^2_{OS}$  coefficients slightly declines from 27, 25, and 32 out of 40 to 24, 23, and 28 when moving from the baseline version of Panel (a) to the Ex-BTC version of Panel (b), for the User, HashRate, and Sentiment factors, respectively. The average  $R^2_{OS}$  coefficients across cryptocurrencies are indeed 2.06 ( $p$ -value 0.09), 1.55 ( $p$ -value 0.10), and 1.75 ( $p$ -value 0.10) percent. Analogously, the average  $R^2_{OS}$  coefficients across cryptocurrencies are 2.06 ( $p$ -value 0.09), 1.55 ( $p$ -value 0.10), and 1.75 ( $p$ -value 0.10) percent. These values are slightly lower than those obtained in

**Table 6**  
Results of backtesting the investment portfolio strategies.

Portfolio sorting criterion	Weekly return	Weekly sharperatio	Weekly % alpha	p-value
Bitcoin OOS R-square	-0.15	-0.05	-0.15	0.38
Bitcoin OOS CER	0.42	0.12	<b>0.42</b>	0.02
Momentum OOS R-square	-0.06	-0.02	-0.06	0.73
Momentum OOS CER	-0.14	-0.06	-0.14	0.38
Google Sent. Factor OOS R-square	0.30	0.10	<b>0.30</b>	0.05
Google Sent. Factor OOS CER	0.73	0.27	<b>0.73</b>	0.00
User Factor OOS R-square	0.19	0.05	0.21	0.37
User Factor OOS CER	0.77	0.24	<b>0.77</b>	0.00
Hashrate Factor OOS R-square	0.32	0.08	0.32	0.12
Hashrate Factor OOS CER	0.79	0.24	<b>0.78</b>	0.00
Google Sent. Factor Ex-BTC OOS R-square	-0.13	-0.04	-0.13	0.42
Google Sent. Factor Ex-BTC OOS CER	0.78	0.26	<b>0.78</b>	0.00
User Factor Ex-BTC OOS R-square	0.34	0.09	0.33	0.08
User Factor Ex-BTC OOS CER	0.70	0.20	<b>0.69</b>	0.00
Hashrate Factor Ex-BTC OOS R-square	0.09	0.02	0.08	0.67
Hashrate Factor Ex-BTC OOS CER	0.83	0.25	<b>0.82</b>	0.00

The table reports the weekly returns, Sharpe ratios, estimated alphas, and the related alpha  $p$ -value for portfolio strategies based on a long-short investment rule on cryptocurrencies that can be better predicted. The alpha is calculated by regressing the various portfolios against the CMBI10 benchmark. The data sample covers the period from January 5, 2018 to April 25, 2025 and includes 382 weekly observations. Specifically, the portfolio buys the 20 cryptocurrencies that can be better predicted and sells the cryptocurrencies that are predicted worse within the sample. Significant statistics based on a 5% size test are boldfaced.

the baseline specification that includes BTC, which is understandable given the dominant role that Bitcoin plays in shaping the dynamics of the overall cryptocurrency market. In this case, however, the sentiment-based factor fails to outperform the others in terms of predictive accuracy, as its average  $R_{OS}^2$  is lower than that of the User factor, which is the best-performing predictor in the Ex-BTC setting.

We close this Section on OOS predictability by exploring the economic value of a novel portfolio sorting strategy based on the results in Table 5. Table 6 reports the average weekly return, the Sharpe ratio, and the realized portfolio alpha of a strategy that involves the systematic shorting of poorly predictable (e.g., characterized by a low or negative partial, recursive OOS squared) cryptocurrencies and buying those with strong predictive accuracy, consistently with prior findings. The alpha of the strategy is estimated in a regression in which systematic risk is captured by the returns of the CMBI portfolio (specifically CMBI10 index), also to avoid redundancy with respect to the other data used in factor construction and earlier tests.

The strategies based on sorts that rely on the most successful factor mimicking predictors, especially those based on their CER, lead to excellent total as well as risk-adjusted performances. For instance, ranking cryptocurrencies on the basis of their Users recursive OOS CER yields a long-short portfolio which gives as much as 0.77 percent per week, with a weekly Sharpe ratio of 0.24 and highly significant alpha of 0.77 percent. More generally, Table 6 shows that in the case of nine strategies out of 16, sorting on the basis of realized OOS CER leads to stronger performance vs. a  $R_{OS}^2$ -led sorting, highlighting the importance of considering risk preferences when constructing cryptocurrency portfolios. Interestingly, the significant weekly alphas are quite close in magnitude to the corresponding portfolio returns, suggesting that the benchmark factor (CMBI) does not fully account for the performance of these strategies and that a substantial portion of the return can be attributed to the predictive signals embedded in our sorting criteria. Finally, the large Sharpe ratios and average abnormal returns obtained from this long-short strategy based on fundamental blockchain-based predictability suggest the possibility that technological features such as the power and network spread of blockchains may have become pervasive enough to affect the vary nature of the fundamental pricing measure characterizing the financial markets.

## 6. Robustness analysis

To evaluate the robustness of our main findings, we conduct a set of additional analyses that extend and validate our baseline results along multiple dimensions.

First, we estimate alternative in-sample regressions in which the baseline momentum factor is replaced with a set of well-established control variables. In particular, we include: (i) the CMBI10 benchmark index, (ii) a crypto-size factor, and (iii) a crypto-value factor. The construction of the latter two variables is detailed in the next subsection. Due to data availability constraints, the regression that includes the CMBI index starts on January 16, 2017. This exercise enables us to verify whether the forecasting power of our fundamental and sentiment-based predictors is affected by controlling for standard sources of return variation in crypto markets. By doing so, we aim to mitigate concerns about omitted variable bias and to test whether our predictors contribute incremental information beyond traditional market-wide and valuation-related proxies.

Second, we estimate a joint predictive regression model that includes all three proposed factors – user activity, hashrate, and Google sentiment – simultaneously. This specification allows us to assess the relative importance of each predictor and to verify

whether their forecasting power holds when controlling for the others. We also implement a model combination framework à la Rapach et al. (2010) by aggregating forecasts from each of the three factors. The resulting combined model achieves higher average out-of-sample  $R^2$  performance compared to models based on individual predictors alone. Furthermore, when sorting cryptocurrencies based on the forecasted returns from the combined model, the resulting long-short portfolio delivers positive and statistically significant alpha, confirming the economic value of the combination.

Third, we extend our portfolio evaluation by controlling for multiple sources of risk. Specifically, we augment the alpha regressions of our sorted portfolios by including not only the CMBI benchmark, but also the crypto-size, crypto-value, and momentum factors. This multifactor adjustment confirms the robustness of our main results: portfolio strategies based on forecast accuracy continue to exhibit positive and statistically significant alpha.

Finally, we experiment with an alternative sorting approach. Within the high predictability bucket, we sort cryptocurrencies by their predicted returns and construct long-short portfolios by going long on the 10 cryptocurrencies with the highest forecasts and short on the 10 with the lowest. This approach focuses on the directional predictive signal within the high- $R^2$  group. The resulting long-short portfolio continues to exhibit strong economic performance, with average returns and Sharpe ratios similar to those obtained in the previous sorting exercise.

### 6.1. Construction of size and value factors

We construct weekly factor-mimicking portfolios to capture size and value effects in cryptocurrency returns, in the spirit of Fama and French (1993) and Liu and Tsyvinski (2021), but adapted to the crypto asset class.

*Size factor.* On each week  $t$ , we rank the five cryptocurrencies in our in-sample period based on their market capitalization. We then compute the average weekly return of the two cryptocurrencies with the smallest market capitalization ( $R_t^{\text{Small}}$ ) and the two with the largest capitalization ( $R_t^{\text{Big}}$ ). The size factor (SMB) is then given by:

$$\text{SMB}_t = R_t^{\text{Small}} - R_t^{\text{Big}}$$

*Value factor.* To proxy for the relative valuation of cryptocurrencies, we compute a weekly “cap-to-users” ratio for each coin (excluding Monero, which does not report user statistics):

$$\text{ValueRatio}_{i,t} = \frac{\text{MarketCap}_{i,t}}{\text{Users}_{i,t}}$$

We rank cryptocurrencies based on this ratio. A low ratio indicates a “cheap” crypto (value), while a high ratio indicates an “expensive” one (growth). We compute the average return of the two cryptocurrencies with the lowest ValueRatio ( $R_t^{\text{Value}}$ ) and the two with the highest ratio ( $R_t^{\text{Growth}}$ ). The value factor is defined as:

$$\text{Value}_t = R_t^{\text{Value}} - R_t^{\text{Growth}}$$

This spread reflects the return differential between undervalued and overvalued cryptocurrencies based on user-adjusted capitalization.

### 6.2. Detailed results

To save space, Tables A2, A3, and A4 are reported in the Online Appendix and present the results of the in-sample analysis where the momentum factor is replaced, respectively, by the CMBI10 index, the crypto-size factor, and the crypto-value factor. As shown in these tables, the coefficients of the fundamental and sentiment-based predictors remain positive and statistically significant.<sup>23</sup>

Table 7 presents the results of the in-sample analysis when all three factors – User, Hashrate, and Google sentiment – are included simultaneously in the regression. In this way, we can also assess the relative importance and contribution of each factor while controlling for the others. In this specification, some differences emerge: for instance, the User Factor appears positively significant only for BTC and LTC, the Hashrate Factor is relevant for BTC, while the Google Factor remains significant for ETH and DASH. Overall, the model’s fit improves compared to the baseline specifications where the factors are included individually.

Table 8 presents the results from a forecast combination strategy where we average the predictions from the three individual factors. The combined forecasts yield a higher average out-of-sample  $R^2_{\text{OOS}}$  compared to the individual models, confirming the benefits of forecast aggregation. While we adopt this strategy primarily as a robustness check, the improvement in predictive performance suggests that forecast combination may offer a stable and informative benchmark in cryptocurrency return prediction. Specifically, whereas the average  $R^2_{\text{OOS}}$  in Table 5 was 2.63 for the User Factor, 2.54 for the Hashrate Factor, and 2.79 for the Google Factor, the combination strategy results in an improved average  $R^2_{\text{OOS}}$  of 3.13.<sup>24</sup>

<sup>23</sup> In the Online Appendix (Table A5), we also added an additional robustness check in which we have combined, in the in-sample analysis, our three proposed factors (User, Hashrate, Google) jointly with standard crypto controls (CMBI, size, value, and momentum).

<sup>24</sup> We also provide a robustness check that includes an out-of-sample estimation based on standard crypto-market predictors, i.e., a combined forecast using market, size, value, and momentum cryptocurrency factors. This analysis confirms the relevance of conventional factors in addition to the novel ones introduced in this paper and is reported in Table A6 of the Online Appendix. Yet, in no way the CERs obtained from our fundamental (plus Google attention scores) can be entirely imputed to the traditional crypto factors only.

**Table 7**  
In-sample analysis results with all the three factors.

	BTC	ETH	XMR	LTC	DASH
<i>3-Factors Model Including all the three Factors</i>					
Alpha (%)	0.35 (1.83)	<b>0.52</b> (2.33)	<b>-0.36</b> (-2.06)	<b>-0.49</b> (-2.03)	<b>-0.65</b> (-3.03)
User Factor	<b>0.72</b> (3.71)	<b>-0.33</b> (4.98)	<b>-3.45</b> (-19.61)	<b>2.18</b> (9.01)	<b>-5.61</b> (25.90)
Hashrate Factor	<b>0.34</b> (2.27)	<b>-0.08</b> (-0.45)	<b>4.26</b> (31.88)	<b>-0.45</b> (-2.44)	<b>4.86</b> (29.58)
Google Factor	<b>-0.10</b> (-4.89)	<b>0.33</b> (13.65)	<b>-0.20</b> (-10.63)	<b>-0.14</b> (-2.44)	<b>0.69</b> (29.85)
R-square	<b>0.82</b>	<b>0.70</b>	<b>0.89</b>	<b>0.77</b>	<b>0.84</b>

The table presents the estimates of the regressions of the weekly return time series of cryptocurrencies on three Factors Model. The cryptocurrencies analyzed are: Bitcoin (BTC), Ethereum (ETH), Monero (XMR), Litecoin (LTC), and DASH. The sample is August 21, 2015–April 25, 2025 and includes 505 weekly observations. HAC *t*-statistics are reported in parentheses. Coefficients in bold are statistically significant at the 5% level. The R-squared statistics are boldfaced when the corresponding F-test of overall model significance rejects the null hypothesis.

In addition, when we implement portfolio sorting based on the combined model following the same methodology described in Section 4.3, Table 9 (Panel (a)) shows that the resulting long-short portfolios deliver positive average returns and statistically significant alphas. These results reinforce the idea that combining signals from multiple predictors not only enhances forecast accuracy, but also translates into meaningful economic value for investors. The significance of the alpha indicates that the strategy consistently exploits predictable patterns in returns that are not captured by traditional benchmarks. Finally, rather than ranking cryptocurrencies according to overall OOS forecasting accuracy, we restrict the sample to the subset of cryptocurrencies whose  $R^2_{OOS}$  exceeds the median value, now selecting the top 10 for long and bottom 10 for short positions. The resulting portfolio still generates significant alpha, as shown in Panel (b).

As last step, we obtain significant alphas not only from regressions on the CMBI benchmark return, but also when controlling for additional multifactor exposures to crypto momentum, size, and value, as reported in Table 10.

## 7. Conclusion

The objective of this paper is to investigate the predictability of cryptocurrency returns, structuring the analysis into two distinct steps. Firstly, we examine the contemporaneous relationships between fundamental and sentiment factors and cryptocurrency returns, what we refer to as the in-sample analysis. Secondly, we introduce a novel approach based on the investigation of the behavior of fundamental factors as predictors of cryptocurrency returns. Additionally, we develop and assess the realized recursive performance of spread portfolios that invest in cryptocurrencies with higher predictability while shorting those with lower predictability. The strong results obtained by such long-short strategies emphasize the economic value of the predictive power of blockchain fundamentals and sentiment indicators in the cryptocurrency markets.

In the in-sample analysis, we construct three factor-mimicking portfolios – based on active users (Users), computational power (HashRate), and the Google Trends index – using the returns of the cryptocurrencies themselves as basis assets. These factors are grounded in key blockchain characteristics, modeling insights, and are evaluated for their explanatory power. The results confirm their effectiveness in accounting for cryptocurrency return variation, in line with previous studies such as Bhambhawani et al. (2023). Notably, even when considered individually, the fundamental factors consistently outperform a naïve historical average benchmark.

In the OOS analysis, the factor-mimicking portfolio predictors generate substantial cumulative forecast improvements for cryptocurrency returns, with excess performance gains ranging between 10 and 60 percent by the end of the OOS period. Across a cross section of 40 cryptocurrencies, the OOS predictive performance is predominantly positive, and sentiment-based predictors show particularly strong forecast power. Their economic value, as captured by the CER, is remarkable: in many cases, CER estimates exceed 20% and are consistently above the risk-free rate, signaling considerable gains in risk-adjusted terms. In addition, our findings emphasize that blockchain-based predictors retain significant predictive value even for non-mineable cryptocurrencies, confirming their status as systematic risk factors beyond the confines of PoW protocols. We also report that the estimated alphas obtained from the long-short portfolios that reflect relative predictability, records a significant increase when the individual cryptocurrencies are ranked according to their certainty equivalent, as opposed to those obtained by sorting them by  $R^2$ . This further stresses the importance of incorporating risk-adjusted metrics, such as the CER, in the assessment of predictive performance. These results may support a view of cryptocurrencies as digital commodities that require substantial computational power and electricity for their creation, akin to the extraction of physical commodities, like gold.<sup>25</sup> Overall, our findings are robust to alternative empirical choices and validation strategies.

<sup>25</sup> Recently, the Commodity Futures Trading Commission (CFTC) has asserted its jurisdiction over the derivatives written on Bitcoin by classifying it as a commodity, thereby overseeing its derivatives and related financial products.

**Table 8**  
OOS predictive results from combining all factors. (User + Hashrate + Google).

Ticker	OOS R-square	OOS CER ( $\gamma = 3$ )
<b>Proof of Work (PoW)</b>		
BTC	<b>5.02</b>	0.41
BTG	<b>4.89</b>	0.08
DASH	<b>6.42</b>	0.06
DCR	<b>4.60</b>	0.40
DGB	<b>6.89</b>	0.26
DOGE	<b>2.67</b>	0.22
ETC	<b>5.70</b>	0.32
ETH	<b>5.77</b>	0.46
LTC	<b>4.68</b>	0.32
VTC	2.52	0.04
XVG	<b>5.51</b>	0.17
ZEC	<b>2.87</b>	0.09
<b>Non Mineable Currencies (NMCs)</b>		
ADA	<b>9.65</b>	0.57
ANT	-3.28	0.03
BAT	<b>2.09</b>	0.17
CVC	0.96	0.16
DRGN	<b>1.40</b>	-0.02
ELF	<b>1.39</b>	0.12
FUN	<b>1.69</b>	0.15
GAS	<b>2.72</b>	-0.17
GNO	<b>4.36</b>	0.32
GNT	-0.35	0.16
KNC	-0.15	0.06
LEND	<b>3.21</b>	0.31
LINK	<b>1.66</b>	0.35
MAID	-0.73	-0.07
MANA	<b>2.22</b>	0.28
MKR	<b>2.32</b>	0.06
NEO	<b>8.51</b>	0.34
OMG	0.49	0.07
PAY	<b>1.68</b>	0.01
POWR	<b>1.69</b>	0.01
PPT	1.11	0.01
REP	0.08	-0.06
SNT	<b>3.97</b>	0.22
WTC	<b>3.89</b>	0.12
XEM	<b>2.48</b>	0.05
XLM	<b>6.64</b>	0.08
XRP	<b>3.41</b>	0.16
ZRX	<b>4.72</b>	0.19
<b>Average</b>	<b>3.13</b>	<b>0.16</b>
<b>Average (ex BTC, DASH, ETH, LTC)</b>	<b>2.87</b>	<b>0.15</b>

The table presents out-of-sample predictive performance based on a forecast combination strategy that averages the predictions from the three individual models using the User, Hashrate, and Google Sentiment factors. For each cryptocurrency, we report the out-of-sample  $R^2$  and the annualized certainty equivalent return (CER) for a mean-variance investor with risk aversion  $\gamma = 3$ . Boldface indicates  $R^2$  values that are significant at the 5% level. The evaluation period spans from January 5, 2018 to April 25, 2025, covering 382 weekly observations. Exceptions due to data availability are noted as follows: ANT is available until 2024-10-04, MAID until 2025-01-17, PPT until 2022-09-09, VTC until 2023-12-08, WTC until 2024-06-14, and DRGN starts from January 19, 2018.

Our paper leaves open several avenues of future exploration. First, we believe that constructing fundamental factors based on alternative blockchain characteristics, such as network value to transaction (NTV, the ratio between a cryptocurrency's market capitalization and its transaction activity, the total value of all on-chain transactions, see [Sakkas and Urquhart, 2024](#)) may warrant consideration. This is especially relevant given the market shift towards blockchains that deviate from the PoW Work mechanism, which is a necessary condition to perform hashrate calculation, in favor of more energy-efficient consensus algorithms, such as PoS. The results of our study also suggest that investors and researchers should consider directly (e.g., within a recursive sorting framework applied to different cryptocurrencies, as we do) incorporating risk-adjusted metrics, such as the CER, in addition to traditional predictive measures, like the OOS  $R^2$ , when assessing the potential of cryptocurrency investment. These considerations could provide a more robust framework for forecasting returns, especially as the cryptocurrency market evolves and becomes increasingly complex. Finally, we believe that there is considerable potential in providing an extension of the analysis to a broader range of cryptocurrencies, with the goal of developing more general fundamental factors, although such an extension may only become feasible in the coming years as the market continues to mature.

**Table 9**  
Backtesting results of portfolio strategies.

Portfolio sorting criterion	Weekly return (%)	Sharpe ratio	Weekly % alpha	p-value
<i>Panel (a): Combining all factors (User + Hashrate + Google)</i>				
OOS $R^2$	0.12	0.35	0.12	0.49
OOS CER	0.82	0.28	<b>0.82</b>	0.00
<i>Panel (b): Predictability-Based Forecast Sorting (High <math>R^2</math> subset)</i>				
User Factor	0.09	1.71	<b>0.09</b>	0.00
Hashrate Factor	0.09	1.73	<b>0.09</b>	0.00
Google Sentiment Factor	0.09	1.89	<b>0.09</b>	0.00
Combined Factors	0.10	1.82	<b>0.09</b>	0.00

Panel (a) reports weekly returns, Sharpe ratios, estimated alphas, and p-values for portfolio strategies based on a long-short investment rule on cryptocurrencies that are better predicted versus worse predicted. Panel (b) reports analogous statistics for portfolios sorted on forecasted returns ( $\hat{r}_{i,t+1}$ ) within the subset of cryptocurrencies with out-of-sample  $R^2$  above the median, selecting the top 10 for long and the bottom 10 for short positions. Alphas are estimated against the CMB110 benchmark. The evaluation period is January 5, 2018–April 25, 2025 (382 weekly observations). Significant statistics at the 5% level are boldfaced.

**Table 10**  
Weekly alpha and p-value of long-short portfolios. multifactor controls.

Portfolio sorting criterion	Weekly % alpha	p-value
Factors Combined OOS R-square	<b>0.67</b>	0.00
Factors Combined OOS CER	0.18	0.32
Bitcoin OOS R-square	0.00	0.78
Bitcoin OOS CER	<b>0.36</b>	0.05
Momentum OOS R-square	-0.14	0.44
Momentum OOS CER	-0.10	0.47
Google Sent. Factor OOS R-square	<b>0.33</b>	0.04
Google Sent. Factor OOS CER	<b>0.58</b>	0.00
User Factor OOS R-square	0.17	0.42
User Factor OOS CER	<b>0.55</b>	0.00
Hashrate Factor OOS R-square	0.30	0.15
Hashrate Factor OOS CER	<b>0.59</b>	0.00

The table reports weekly alphas and the corresponding p-values for long-short portfolio strategies sorted by out-of-sample predictability metrics. The alpha is estimated from regressions on the CMB110 benchmark return while controlling for additional multifactor exposures to crypto momentum, size, and value. The data sample spans from January 5, 2018 to April 25, 2025. Significant alphas at the 5% level are boldfaced.

## CRedit authorship contribution statement

**Massimo Guidolin:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization. **Serena Ionta:** Visualization, Software, Investigation, Formal analysis, Data curation.

## Appendix A. Supplementary data

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.intfin.2026.102285>. The Appendix contains additional tables and figures, as well as the derivation of the theoretical framework supporting the empirical analysis.

## Data availability

Data will be made available on request.

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