Blockchain characteristics and cryptocurrency returns

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May, 2023

Abstract

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Keywords: Hashrate, Network, Factor Analysis, GMM, Rolling Estimation.
JEL Classification: E4, G12, G15

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Introduction

Cryptocurrencies are an emerging new asset class and it has been unclear what factors determine their prices and returns. Theory suggests that blockchain characteristics such as network size and computing power are key determinants of prices (Pagnotta and Buraschi, 2018; Biais et al., 2022; Pagnotta, 2022; Prat and Walter, 2021). However, there is little empirical work on the importance of blockchain characteristics on price dynamics.[1] Motivated by this gap in the empirical literature, we focus on network size and computing power and examine if these blockchain characteristics can explain cryptocurrency returns.

We formulate two hypotheses based on existing theoretical models. First, we conjecture that the prices of individual cryptocurrencies should be positively related to their network size and computing power. Aggregate network size and computing power should be important for explaining cryptocurrency returns because they reflect the state of the cryptocurrency market. Specifically, aggregate network size captures the general adoption levels of cryptocurrencies as it reflects the number of unique active addresses transacting on the blockchain. Aggregate computing power proxies for the resources expended on mining and relates to the reliability and security of cryptocurrency blockchains. The evolution of these two factors should offer important information about the state of the cryptocurrency market.

Analogous to established fiat currencies that are accepted by numerous entities for transactions, a large network is indicative of greater adoption of the cryptocurrency (Biais et al., 2019). A large number of unique blockchain users is also suggestive of enhanced liquidity of the respective cryptocurrency. Further, a larger network attracts developers to build applications for the cryptocurrency's blockchain, which increases the usability of the currency.

Computing power is a key characteristic of Proof-of-Work (PoW) blockchains, which is

[1] Exceptions include Liu and Tsyvinski (2020) who proxy for Bitcoin mining activity using the price of Bitmain's mining hardware and the cost of electricity in the U.S. and China. In contrast, we use hashrates because they are available for all Proof-of-Work cryptocurrencies and are measured at the daily level, thereby providing better information about aggregate mining activity at a high-frequency level. Biais et al. (2022) focus on Bitcoin and highlight the importance of transaction benefits and network security. Pagnotta (2022) finds that the prices of Bitcoin, Ethereum, and Litecoin are positively related to their hashrates.

measured in hashes with one hash referring to one function being solved by a computer. In essence, computing power is a measure of the real resources such as mining equipment and energy expended on confirming transactions on the blockchain (Prat and Walter, 2021). Computing power should relate to prices because it affects the reliability and security of the blockchain and high computing power indicates that miners are expending greater resources to efficiently and securely record transactions. For instance, Blockchain.com shows the time-trend in Bitcoin's hashrate, which has increased rapidly over the past decade.[2]

We collect data on network size (number of *unique* addresses transacting on a blockchain) and computing power (hashrates) for 18 baseline currencies.[3] We select these 18 currencies because they are among the largest currencies at the beginning of our sample period with reliable data on network size and computing power. We begin our empirical analysis by examining the relationship between prices, network size, and computing power at the cryptocurrency-level. Theory predicts that the price of a mineable cryptocurrency is jointly determined in equilibrium with its network and computing power (Pagnotta and Buraschi, 2018; Biais et al., 2022; Pagnotta, 2022; Prat and Walter, 2021). Therefore, there should be a cointegrating relationship among them. We estimate this relationship for the baseline currencies using the dynamic ordinary least squares (DOLS) methodology (Stock and Watson, 1993; Lettau and Ludvigson, 2001; Lustig and Van Nieuwerburgh, 2005). We find that for most of the 11 Proof-of-Work (PoW) cryptocurrencies, there is a significant long-term positive trend between prices, network size, and computing power. For six of the seven non-PoW cryptocurrencies, there is a significant long-term trend between prices and network size.

For our second set of tests, we examine whether aggregate network size and computing power can explain cryptocurrency returns. To construct the two blockchain-based measures, we aggregate the growth rates in network and computing power across the 18 cryptocurrencies. Specifically, the factors are the average weekly growth rates of network size ($gNET$)

[2] See `https://www.blockchain.com/explorer/charts/hash-rate` .

[3] Of these 18 cryptocurrencies, 11 use Proof-of-Work (PoW) consensus mechanisms that rely on mining (using computing power) to secure and operate the blockchain. They are Bitcoin, Ethereum, Litecoin, Dash, Dogecoin, Ethereum Classic, Decred, Digibyte, Vertcoin, Zcash, and Monero. The other seven, Ripple, Stellar, Lisk, NEM, Augur, Maidsafecoin, and Waves, are non-PoW cryptocurrencies and they do not have computing power because they are not mineable and rely on other blockchain consensus mechanisms.

and computing power (gCP) of the 18 cryptocurrencies. These two factors are also orthogonal to each other mitigating multicollinearity. Following existing studies (Shen et al., 2020; Liu and Tsyvinski, 2020; Liu et al., 2022; Cong et al., 2021), we also consider three cryptocurrency return-based factors related to market returns, size, and momentum. We use the Generalized Method of Moments (GMM) estimation procedures following Fama and MacBeth (1973) and Cochrane (2005) (see Appendix B for further details).

Our analysis shows that the two blockchain-based factors, $gNET$ and gCP, have positive and significant coefficients on cryptocurrency returns in single-factor models. Between the two factors, the estimates for $gNET$ are stronger than that of gCP. Specifically, in the full-sample estimation, the two blockchain factors together explain about 83% of the cross-sectional variation in expected returns for the set of the 18 cryptocurrencies. This fit is comparable to the cross-sectional fit (68%) of a model with the return-based factors (i.e., market, size, and momentum). Using Fama-Macbeth (FMB) estimation procedures, we examine the cross-sectional fit of the factor models across time. We find that the models that include the $gNET$ and gCP factors always have either a similar or a higher cross-sectional fit than a three-factor model with the market, size, and momentum factors. Moreover, a model comprising $gNET$, gCP, along with the three return-based factors exhibits the strongest fit, which suggests that incorporating blockchain-based factors can improve model fit.

We conclude our analysis with some additional tests. First, to ensure that Bitcoin's fundamentals are not driving the significance of the blockchain-based factors, we construct versions of the factors that *exclude* Bitcoin's blockchain measures. Second, we expand our sample of 18 test cryptocurrencies with an additional 36 currencies. We select these 36 currencies because they have returns data for our entire sample period from a reputable U.S.-based cryptocurrency exchange. Additionally, we control for sentiment-based factors such as weekly trading volume, Reddit posts, Google Searches, and geopolitical uncertainty. In these robustness tests, we find that the blockchain factors have positive coefficients.

Our findings are consistent with existing models for cryptocurrency prices. Pagnotta and Buraschi (2018) link cryptocurrency prices to blockchain trustworthiness, defined as the absence of fraud and protection from cyber-attacks. Biais et al. (2022) build a model connecting the fundamental value of cryptocurrencies to transactional benefits. Sockin and Xiong (2023) note that the "trustless" nature of decentralized networks contributes to their value. Pagnotta (2022) develops a model where the price of proof-of-work currencies is related to their blockchain security, proxied by hashrates, and Prat and Walter (2021) note the importance of hashrate levels for Bitcoin pricing. Following theoretical work, we capture blockchain security with computing power and transaction benefits using network size.

Our findings have implications for investors and policy makers. For investors, our study highlights the importance of blockchain fundamentals as cryptocurrency prices are related to hashrates and unique active addresses. From a policy perspective, the link between cryptocurrency prices and blockchain production and usage factors is consistent with regulatory views of some cryptocurrencies such as Bitcoin as digital commodities (CoinDesk, 2022).

Our work also makes several contributions to the literature. We are the first to use aggregate blockchain characteristics when examining cryptocurrency returns across a broad sample of cryptocurrencies. For large cryptocurrencies, like Bitcoin, research has also documented significant price differences across exchanges (Kroeger and Sarkar, 2017; Makarov and Schoar, 2020; Borri and Shakhnov, 2022). In related work, Shen et al. (2020) and Liu et al. (2022) argue that cryptocurrency returns can be explained by a cryptocurrency market factor, a size factor, and a momentum factor. We complement these studies by supplementing market-based models with blockchain-based factors.

Relatedly, Yermack (2017) argues that blockchain usage improves corporate governance. Abadi and Brunnermeier (2018) study record-keeping via distributed ledgers and Schilling and Uhlig (2019) study the monetary policy implications of Bitcoin's production. Biais et al. (2019) and Prat and Walter (2021) analyze the equilibrium behavior of miners. Cong and He (2019) highlight how blockchains allow for efficient execution of contracts and Chiu and Koeppl (2019) argue that blockchains improve the settlement of securities. Easley et al. (2019) show that transaction fees paid to miners become more important as more blocks are being mined and Huberman et al. (2021) examine the economics of Bitcoin's transaction fee structure. Foley et al. (2019) examine illegal transactions on Bitcoin and Griffin and Shams (2020) discuss manipulation in bitcoin markets. Howell et al. (2019) and Gan et al. (2021) study initial coin offerings while Cong et al. (2020) relate the value of cryptocurrency tokens to their transactional demand. Cong et al. (2020) highlight the high energy costs of proof-of-work blockchains and Alsabah and Capponi (2020) study proof-of-work protocols to find that the mining industry has moved towards centralization as opposed to decentralization. Lastly, Härdle et al. (2020) provide a general overview of cryptocurrencies.[4]

1 Data Description and Summary Statistics

This section describes the data and the main variables used in our tests. For completeness, we provide a detailed description of the main variables in Table A1 of the Appendix.

1.1 Balanced Panel Approach

For our empirical analysis, we use a balanced-panel approach because there is large non-random turnover in the universe of cryptocurrencies. For example, currencies with small capitalization rates disappear as developers abandon the project, miners do not secure their blockchains, or users stop using them.[5] Additionally, many cryptocurrencies are only introduced to capitalize on market upswings and then simply disappear. Li et al. (2021) document approximately 500 'pump-and-dump' schemes that arose during late 2017 when the cryptocurrency market was growing at a rapid rate. This non-random turnover creates

[4]In other related work, Chod et al. (2020) and Cui et al. (2020) examine how blockchains can improve supply-chains. Tsoukalas and Falk (2020) study the optimality of token-weighted voting. Iyengar et al. (2020) analyze the welfare implications of blockchain adoption while Irresberger et al. (2020), John et al. (2020), Roşu and Saleh (2021), and Saleh (2021) study Proof-of-Stake blockchains. Our work also complements theoretical (Weber, 2016; Athey et al., 2016; Routledge et al., 2018; Jermann, 2021), empirical (Wang and Vergne, 2017; Stoffels, 2017; Mai et al., 2018; Auer and Claessens, 2018; Borri, 2019; Hu et al., 2019), and other work on cryptocurrencies (Corbet et al., 2019; Shanaev et al., 2020). For an overview of the literature on cryptocurrencies and fintech in general see Allen et al. (2022).

[5]For example, the website 99bitcoins documents that there are currently over 1,500 'dead coins' for a variety of reasons with the most common one being an inactive development team. See https://99bitcoins.com/deadcoins/.

biases in unbalanced panel data sets that cannot be easily addressed econometrically.[6]

Additionally, there have been many instances of currencies being delisted due to fraud or persistent hacks. For example, Bitcoin Gold was delisted from the Bittrex exchange on September 14th, 2018 after a blockchain hack on that led to over $18 million in Bitcoin Gold being transferred from user accounts to malicious addresses.[7] An unbalanced panel that would include all traded currencies at any given point in time would include hacked or fraudulent cryptocurrencies, thus deteriorating the quality of the sample. To ensure high data quality and to avoid the econometric complexities of unbalanced panels, we opt for the balanced-panel approach, which does not create biases in standard asset pricing tests.

Our sample starts on 1/6/2017 because many cryptocurrencies with reliable data on blockchain characteristics have been introduced by then and ends on 5/28/2021. One concern with the balanced panel approach is that the sample may only include large currencies or currencies listed for a long time-period, which can induce a survivorship bias. However, this is not the case with our sample since we select the baseline currencies based on blockchain data availability at the beginning of the sample and not based on their return performance over our sample period. We also highlight that our sample does not only include large cryptocurrencies. To the contrary, our sample consists of cryptocurrencies that have significantly dropped in capitalization ranks over the sample period. For instance, Maidsafecoin, which was ranked 9th as of January 6th, 2017 (the first week of our sample), was ranked 147th as of May 28th, 2021, the last day of our sample. Vertcoin, which was ranked 76th as of January 6th, 2017, was ranked around 500 as of May 28th, 2021.[8]

1.2 Data sources

We obtain our data from three sources. The first one is Coin Metrics Pro data from which we collect prices and blockchain characteristics (unique active addresses and hashrates) for

[6]See Fitzgerald et al. (1998), Hirano et al. (2001), and Baltagi (2008) for proposed remedies to sample attrition.

[7]See https://cointelegraph.com/news/why-bitcoin-gold-got-delisted-from-bittrex.

[8]See https://coinmarketcap.com/historical/20170106/ and https://coinmarketcap.com/historical/20210528/.

18 cryptocurrencies, which form our baseline sample.[9] We use Coin Metrics because, to the best of our knowledge, it provides the highest quality data on blockchain characteristics. In particular, it collects this data in real time from the blockchains by setting up blockchain nodes. Further, Coin Metrics only reports price data from the most reputable cryptocurrency exchanges, and uses 35 criteria to filter out illiquid or unreliable exchanges.

The exchanges from which Coin Metrics obtains price data are similar to those in Makarov and Schoar (2020)[10]. Examples of these exchanges are Coinbase, Kraken, and Bittrex. Exchanges like CoinBene, OkEX, IDAX, Exrates, and BitForex, which have been found to report suspicious volume data, are excluded from Coin Metrics' data reporting.[11] Because of the strict criteria imposed, Coin Metrics reports data for a smaller sample of currencies compared to other data providers. Nevertheless, because of its high-quality data standards, Coin Metrics data have been used by many studies.[12]

Our second source of data is the Bittrex cryptocurrency exchange from which we collect prices for 36 additional cryptocurrencies used in our robustness tests. Our decision to use data from Bittrex is not arbitrary as we base our sample on the cryptocurrency market conditions in January 2017. At that time, Bittrex was the U.S. exchange with the widest offering of cryptocurrencies. In particular, in January 2017, the start date of our sample, Bittrex listed over 100 other cryptocurrencies excluding our 18 baseline ones, of which 36 were still present as of the last day of our sample. For comparison, in January 2017, Coinbase and Gemini, only listed the top three and top five cryptocurrencies, respectively.

Additionally, Bittrex has been listed as one of the trusted exchanges by Bitwise in their report to the SEC regarding inflated and wash trading volumes on exchanges.[13] Since fake trading was especially prevalent between 2013 and 2017 (e.g., see Amiram et al. (2020),

[9] The authors had access to Coin Metrics Pro only until May 28th of 2021. For completeness, we download Coin Metrics' Community Network freely available data from `https://coinmetrics.io/community-network-data/` until January 31st, 2023. Reliable and complete data is only available for 11 out of the 18 currencies, for which we present the results in Appendix Table A5.

[10] Makarov and Schoar (2020) use data from Kaiko, another institutional-grade data provider.

[11] See Bitwise's report to the SEC at https://static.bitwiseinvestments.com/Research/Bitwise-Asset-Management-Analysis-of-Real-Bitcoin-Trade-Volume.pdf.

[12] For example, Chaim and Laurini (2018), Valdeolmillos et al. (2019), Conlon and McGee (2020), Irresberger et al. (2020), and Filippou et al. (2021).

[13] See the list provided by Bitwise Asset Management at https://www.bitcointradevolume.com/.

Figure 11), using a reputable exchange mitigates concerns of data quality. Bittrex is also included in the Kaiko data used by Makarov and Schoar (2020). Lastly, we gather market capitalization data on the cryptocurrencies obtained from Bittrex using Coinmarketcap.com, which has been previously used by Amiram et al. (2020), Shen et al. (2020), Liu and Tsyvinski (2020), and Liu et al. (2022), for our illustration in Figure 1.

1.3 Baseline Cryptocurrencies

Our main empirical analysis is conducted using 18 baseline currencies, which consist of both mineable and non-mineable cryptocurrencies. The mineable, or Proof-of-Work (PoW), cryptocurrencies are Bitcoin, Ethereum, Litecoin, Dash, Dogecoin, Ethereum Classic, Digibyte, Decred, Vertcoin, ZCash, and Monero.[14] The non-mineable currencies are Ripple, Stellar, Lisk, NEM, Augur, Maidsafecoin, and Waves. The non-mineable currencies rely on distributed ledger technology paired with consensus mechanisms such as the Byzantine fault tolerance (BFT) or the Proof-of-Stake (PoS) frameworks.

We select the above currencies based on blockchain data availability and market capitalization rates at the beginning of our sample from Coin Metrics Pro. These 18 currencies constitute approximately 97% of the cryptocurrency market in the first week of our sample and an average of 82% over our entire sample period (see Figure 1). Given their size, reliable blockchain data, and consistent presence in the market, the evolution of their blockchain characteristics is a reliable indicator of the state of the cryptocurrency market.

1.4 Blockchain Characteristics

Our empirical analysis focuses on network size and computing power as they are key properties of a blockchain. We measure network size with the number of *unique* active addresses transacting on a blockchain. We obtain this data from Coin Metrics, which does not double

[14] While Dash and Decred rely on a mix of Proof-of-Work and Proof-of-Stake (i.e., hybrid model), we classify them as Proof-of-Work for parsimony.

count active addresses with multiple transactions on a given day.[15] The number of unique active addresses is not a perfect measure of adoption since a portion of active addresses arises from multiple transactions meant to obfuscate the movements of funds. Nevertheless, we use it because it is available for all the baseline 18 currencies except Monero.

Beside network size, we also focus on computing power, which affects the reliability and security of of Proof-of-Work blockchains. Computing power is measured in hashes and we obtain hashrate data for the 11 mineable currencies. Further, a blockchain can be hacked if rogue miners amass a significant share of the existing computing power, which is improbable for cryptocurrencies with high computing power (Kroll et al., 2013; Eyal and Sirer, 2018). Computing power is also a sufficient statistic for the resources expended on operating a blockchain. For example, De Vries (2018) and Saleh (2021) note that the annual energy consumption of the computational resources spent on mining Bitcoin is comparable to that used by countries such as Austria and Ireland. Data limitations also dictate the use of hashrates as a cost-of-production proxy. Specifically, detailed data on the total resources expended by miners (e.g., electricity, hardware costs) is only available for Bitcoin.[16] However, accurate hashrate data is available for all the mineable currencies in our sample.

We note that these blockchain characteristics capture long-term trends in the cryptocurrency industry. Computing power represents fixed capital investment in cryptocurrency mining, effectively serving as a long-term factor in that it doesn't generally exhibit sudden spikes upward but rather regular growth.[17] Similarly, network usage is also a long-run factor as it represents adoption of cryptocurrencies, which while exhibiting greater volatility than computing power, is inherently reflective of broader trends in the cryptocurrency industry.

For both network size and computing power, we construct weekly network growth rates. They are the first differences of the log-unique active addresses and log-hashrates between

[15] We do not use the network size of Monero because it masks transactions across multiple addresses, which dilutes and hides the true address count (Narayanan et al., 2016).

[16] See the Cambridge Bitcoin Electricity Consumption Index at https://cbeci.org/index.

[17] One exception is in May of 2021, when the People's Republic of China banned Bitcoin mining, which led to a large sudden drop in Bitcoin mining, which eventually recovered over the next six months as miners moved to other jurisdictions such as Mongolia and Kazakhastan (De Vries et al., 2022; CBECI, 2023). We highlight that while significant drops in hashrate have been observed, significant spikes upward have not at the weekly-level.

consecutive Fridays. As in Liu and Tsyvinski (2020), we winsorize these first differences at the 1% and 99% levels.

2 Cryptocurrency-Level DOLS Evidence

We begin our empirical analysis with cryptocurrency-level cointegration tests in the baseline sample of the 18 baseline currencies. These tests are based on the theoretical prediction that cryptocurency prices are related to the blockchain's computing power and network size.[18]

2.1 DOLS Regression Methodology

Estimating the relation between cryptocurrency prices, network, and computing power is challenging since these variables are jointly determined in equilibrium and are all non-stationary processes.[19] Thus, using ordinary least squares would lead to spurious regression results (e.g., Phillips (1986)). Instead, we use cointegration analysis, which we implement with the dynamic ordinary least squares (DOLS) of Stock and Watson (1993).[20]

To implement DOLS, we assume that there is a linear cointegrating relationship between log prices (P), log network (NET), and log computing power (CP). As in Lustig and Van Nieuwerburgh (2005), we impose the restriction that the cointegrating relationship eliminates any deterministic trends. This set up implies the following DOLS regression:

$$P_t = \alpha + \beta_{NET} NET_t + \beta_{CP} CP_t + \sum_{\tau=-k}^{k} \beta_{NET,\tau} \Delta NET_{t+\tau} + \sum_{\tau=-k}^{k} \beta_{CP,\tau} \Delta CP_{t+\tau} + \delta \cdot t + \epsilon_t. \quad (1)$$

[18]The summary statistics for log prices, network, and computing power of the baseline currencies are reported in Panel A of Table A2.

[19]In unreported results, we implement the augmented Dickey and Fuller (1979) (ADF) test using eight lags and find that the prices, network size, and computing power of the 18 baseline currencies are unit-root (non-stationary) processes in most instances. Similarly, the Kwiatkowski et al. (1992) (KPSS) test also suggests that prices, network, and computing power are non-stationary using eight lags while when applying the Phillips and Perron (1988) (PP), we find that that prices and computing power are non-stationary, while network size exhibits a stationary process.

[20]In the asset pricing literature, Lettau and Ludvigson (2001) employ DOLS to estimate the relationship of aggregate consumption with income and wealth. Lustig and Van Nieuwerburgh (2005) use DOLS to show that U.S. housing wealth is related to aggregate U.S. income. We acknowledge that even though our time-series for each cryptocurrency is small, 230 weeks in total, cointegration analysis in such sample sample sizes is consistent with prior literature. For example, Lettau and Ludvigson (2001) conduct their cointegration analysis using quarterly data between 1952 to 1998 for a total of 184 quarters.

ΔNET and ΔCP are the first differences of NET and CP, respectively. Stock and Watson (1993) show that under mild conditions, the ordinary least squares estimates of β_{CP} and β_{NET} from regression (1) are not affected by endogeneity. Intuitively, endogeneity creates feedback loops between prices, NET, and CP. Controlling for the first differences of NET and CP accounts for these loops. We caveat that the DOLS methodology does not mitigate endogeneity, but rather provides estimates of CP and NET that are free of endogeneity bias while acknowledging that there exists an endogeneous relationship between prices, computing power, and network. In essence, DOLS allows us to relate the magnitude of movements in prices to the magnitude of movements in computing power and network.

For non-PoW cryptocurrencies, we assume that there is a linear cointegrating relationship between log prices (P) and log network (NET). In this case, the DOLS regression only controls for first-differences in NET. In the DOLS estimation, we use two leads and two lags for the first differences in equation (1) (i.e., $k = 2$). The results are similar when using up to four leads and lags. We compute the t-statistics of the estimated parameters with robust Newey-West standard errors corrected for autocorrelation. Further, we normalize all log variables (log prices, log network size, and log computing power) by subtracting their respective sample means and dividing by their sample standard deviations. The normalization allows for the comparison of the estimates of NET and CP within and across currencies.

2.2 DOLS Regression Estimates

We report the DOLS results for the 11 PoW cryptocurrencies in Table 1. The results confirm the predictions of existing theoretical models (e.g., Biais et al. (2022), Pagnotta (2022)), which suggest that cryptocurrency prices are positively related to network size and computing power, and hence, β_{NET} and β_{CP} should be positive. Specifically, the majority of the coefficients on network size are positive and statistically significant. The only negative estimate for β_{NET} is the one for Dash. We also find that the majority of estimates for computing power are positive and statistically significant, with Dogecoin having the only negative β_{CP} estimate, which is consistent with Dogecoin's returns being driven by sentiment and mania (Shahzad et al., 2022). In terms of magnitude, we find that Bitcoin, Ethereum, and Monero (BTC, ETH, and XMR, respectively) exhibit the strongest movement with their computing power in columns (1), (2), and (11). Additionally, the positive coefficients on ΔCP_{t+1} and ΔCP_{t+2} suggest that increases in prices attract miners.

We report the DOLS results for the seven non-PoW cryptocurrencies in Table 2. We find that the coefficients on NET are statistically significant at the 5% level for all non-PoW cryptocurrencies with the exception of NEM. Ripple (XRP) and Lisk (LSK) exhibit the strongest comovement with their network. Interestingly, for many cryptocurrencies in both Tables 1 and 2, we find positive coefficients on ΔNET_{t+1} and ΔNET_{t+2}, which suggests that increases in price also translate to higher usage, further corroborating the endogenous cointegrating relationship exhibited by prices, network, and computing power. Collectively, the DOLS results provide evidence that, on average, there is a common positive long-run trend between cryptocurrency prices and blockchain fundamentals for each cryptocurrency.

3 Variable Construction and Description

Given the importance of network size and computing power at the cryptocurrency-level, it is reasonable to expect that aggregate network size may reflect market-level blockchain adoption levels and that aggregate computing power may reflect market-level blockchain security and efficiency. Accordingly, network size and computing power should have information that is relevant for cryptocurrency returns.

3.1 Cryptocurrency Returns Data

The cross-sectional tests use weekly cryptocurrency returns computed from daily prices. For the 18 baseline currencies, we obtain USD-denominated daily prices from Coin Metrics, which collects prices from exchanges worldwide and weights them by the trading volume of each exchange. We use the daily prices to compute weekly returns by cumulating the daily returns of 7-day periods ending on Fridays. We use weekly returns to mitigate any day-of-the-week effects (e.g., Biais et al. (2022)) and problems with outliers. We set the end of the 7-day period to Friday following convention in the weekly Fama-French factors.

We report descriptive statistics of the returns of the 18 baseline assets in Table 3. According to the statistics, these cryptocurrencies earn positive average returns and exhibit significant return fluctuations as their standard deviations are larger than their respective means and medians. For example, DOGE exhibits the strongest weekly returns (0.077), but is ranked fourth in NET growth rate (0.011), and 6th out of 11th in CP growth, further affirming our DOLS results in Table 1 about the weak relation between CP and price for Dogecoin. Ethereum exhibits the strongest network growth on a weekly basis relative to other PoW cryptocurrencies, which is consistent with its rise as the second most valuable currency. Amongst non-mineable currencies, we see that NEM, Augur, and Maidsafecoin (XEM, REP, and MAID, respectively) exhibit negative growth in NET, which is consistent with the reduction in their prominence across our sample period.

To verify that their returns are not extremely correlated, in Table A3 of the Appendix, we report the correlations among the returns of the 18 baseline cryptocurrencies. These correlations are not excessively high ranging from 0.38 to 0.70.

3.2 Blockchain-Based Asset Pricing Factors

Our blockchain factors are equal-weighted averages of the growth rates of network size and computing power of the 18 baseline currencies. For the network factor, we compute the average growth in network size (ΔNET) of 17 out of the 18 cryptocurrencies (excluding Monero), denoted $gNET$. For the computing power factor, we calculate the average growth in computing power (ΔCP) of the 11 PoW currencies with computing power, denoted gCP. We report the average ΔNET and ΔCP of each baseline currency in Table 3.

We use equal-weighted averages to ensure that the factors are not dominated by the largest currencies. In contrast, value-weighted averages would result in factors that primarily capture the NET and CP growth of Bitcoin and Ethereum, which dominate the market in terms of capitalization. For example, Bitcoin and Ethereum together account for 91% of the aggregate cryptocurrency market capitalization in the first week of our sample in January 2017 and consistently occupy approximately 70% of the aggregate cryptocurrency market. To examine whether our results are affected by Bitcoin's network size and computing power, we construct two additional blockchain factors. These factors are averages of the growth rates in the two blockchain characteristics of 17 baseline currencies excluding the network size and computing power of Bitcoin, denoted $gNET \setminus BTC$ and $gCP \setminus BTC$, respectively.

3.3 Cryptocurrency Return-Based Factors

In our cross-sectional analysis, we also consider three cryptocurrency return-based factors suggested by the existing literature (e.g., Shen et al. (2020), Liu and Tsyvinski (2020), and Liu et al. (2022)). The first one is a value-weighted cryptocurrency market factor ($CMkt(18)$). The second return-based factor is a cryptocurrency size factor ($CSize(18)$) constructed following Liu et al. (2022), and the third one is a cryptocurrency momentum factor ($CMom(18)$) constructed following Jegadeesh and Titman (1993). We construct these factors with the sample of 18 baseline cryptocurrencies detailed in Table A1.

3.4 Descriptive Statistics and Correlations

Table 4 reports summary statistics and correlations for the asset pricing factors. In the case of the blockchain-based factors, $gNET$ and gCP, the average weekly growth of aggregate network size is 0.007 and its standard deviation is 0.150. The average weekly growth of aggregate computing power is 0.025 and its standard deviation is 0.054. We also find that $gNET$ is orthogonal to gCP with a correlation of effectively zero.

The fact that network size and computing power are endogenous economic variables does not invalidate our asset pricing tests (see Appendix B). Our testing framework is very similar to that of consumption-based or investment-based asset pricing, where equilibrium variables like consumption or investments are taken as given. Then, the asset pricing tests examine whether the observed values of consumption or investments fit the cross-section of equity returns. With regards to our study, both theoretical models (Pagnotta and Buraschi, 2018;

Biais et al., 2022; Pagnotta, 2022) and our DOLS results imply a positive relation among prices, network size, and computing power.

4 Empirical Analysis

In this section we present the findings of our asset pricing tests. The methodological framework for this analysis is detailed in Appendix B.

4.1 Full-Sample Estimation Results

We estimate the GMM system of equations with the 18 baseline currencies. The asset pricing factors in these tests are the network ($gNET$) and computing power ($gNET$) factors, and their Bitcoin-free versions ($gNET \setminus BTC$ and $gCP \setminus BTC$). We also consider the market ($CMkt(18)$), cryptocurrency size ($CSize(18)$), and cryptocurrency momentum ($CMoM(18)$) factors. We tabulate the results in Table 5.[21]

According to the results for the single-factor models in columns (1) to (4), the two blockchain-based factors have positive coefficients (i.e., prices of risk). We also find that the network factors (i.e., $gNET$ and $gNET \setminus BTC$) have larger and more significant coefficients than the computing power factors (i.e., gCP and $gCP \setminus BTC$). In terms of model fit, the single-factor models suggest that the network factors explain substantially more cross-sectional variation in expected cryptocurrency returns than the computing power factors. For example, the fit of the single-factor model with $gNET$ is about 83%. We report results for the two-factor models with the blockchain factors in columns (5) and (6) of Table 5. We find that the network factor has positive and significant risk prices. The computing power factor has positive but insignificant risk prices whne including the network factor.

We report the results with the cryptocurrency return-based factors (market, size, momentum) in columns (7) and (8). These results show that only the market factor has significant

[21]In untabulated results, we run cross-sectional tests of expected cryptocurrency returns on the betas from the three- and five-factor Fama-French models (Fama and French, 1993, 2015). Consistent with existing results (e.g., Liu et al. (2022)), we find no statistically significant relation between the traditional equity-based factors (market, value, size, momentum, investment, profitability) and cryptocurrency expected returns.

price-of-risk estimates. Moreover, the return-based models explain less variation in expected cryptocurrency returns than the single factor model with the network factor alone. Finally, the five-factor models that combine all factors in columns (9) and (10) confirm that the most significant factors are the network factors and the market factor. We visualize the fit of the models in Figure 2, which plots the theoretically-implied expected returns against sample average returns. We observe that the blockchain-based factors can explain the cross-section of cryptocurrencies at least as well as the three return-generated factors.

There are several reasons why we find that network size is more important for returns than computing power. Biais et al. (2019) suggest that investment in Bitcoin's computing power is excessive as new miners increase the computing requirements for mining the next block while Cong et al. (2020) note that the rise of large industrial mining pools led to an arms race between miners translating to excessive energy consumption in Bitcoin mining. Additionally, Pagnotta (2022) argues that blockchain security is a concave function of hashrates in that significant increases in computing power only marginally enhance security after a point.

Also, investment in computing power is generally irreversible (Prat and Walter, 2021) and non-transferable across cryptocurrencies. For example, mining Bitcoin is done by hardware geared to exclusively solve the $SHA-256$ algorithm. The costly and irreversible nature of computing power creates an incentive for existing miners to provide a constant flow of computing power and be less sensitive to market conditions. Thus, changes in computing power may have less impact on prices and returns.

4.2 Fama-MacBeth Estimation Results

We tabulate the results of rolling FMB regressions in Table 6. For rolling-FMB regressions, we run 75 regressions in total across the total 230 weeks of our sample, with each regression comprising 156 weeks of the sample.[22] Consistent with the full-sample results, the risk-price estimates of $gNET$ and gCP are positive. The risk-price of $gNET$ is also higher than that

[22]For instance, the first regression comprises weeks 1-156, the second regression comprises weeks 2-157, and the last (75th) regression comprises weeks 75-230.

of gCP in the two-factor models. From the return-based factors, the market factor $CMkt$ is the only one that has statistically significantly price-of-risk estimates. In terms of model fit, the two-factor models with the blockchain-based factors explain a significant portion of the variation in expected returns (about 58%). Their fit is marginally better than that of the three-factor model with the $CMkt$, $CSize$, and $CMoM$ factors (about 54%). This finding is important since we are comparing two fundamentals-based factors, which have economic foundations, against three return-generated factors.

We further examine the fit of the various models in Figure 3. The figure plots the theoretically-implied expected returns against sample average returns, averaged across the 75 rolling regressions. The figure confirms that the two blockchain-based factors can explain the cross-section of cryptocurrencies at least as well as the three return-generated factors.

4.3 Time-Variation in Model Fit

The rolling FMB tests allow us to assess the evolution of the fit of the various asset pricing models over our sample. Specifically, in Figure 4 we plot the time series of R^2's from the 75 cross-sectional rolling regressions. The figure shows that across time the explanatory power of the blockchain-based factors is similar to that of the return-based factors. Further, the model with the blockchain-based factors generally exhibits higher R^2's than the three-factor model with $CMkt$, $CSize$, and $CMoM$. Since January 2021, the blockchain-based and return-based models exhibit similar cross-sectional performance. Overall, according to Figures 4 and A2, the fit of the blockchain two-factor model in the rolling regressions is at least as good, if not better, as that of the return-based three-factor model. Our findings are also consistent with El Montasser et al. (2022) who highlight that cryptocurrency markets are inefficient during the same late-2020 time period when our model fit is lower while noting that these markets are becoming more efficient as the industry matures.

4.4 Additional Cryptocurrencies

Our DOLS and cross-sectional tests are based on a sample of 18 cryptocurrencies. In our final test, we examine whether our main findings extend to a larger sample of currencies that includes an additional set of 36 currencies, for a total of 54 cryptocurrencies.

We report the list of the additional cryptocurrencies in Panel B of Table A2 of the Appendix. To identify the additional 36 currencies, we searched for cryptocurrencies listed on the Bittrex exchange with reliable return data for the entire period from 1/6/2017 to 5/28/2021. We offer summary statistics for the additional 36 currencies in Panel B of Table A2 in the Appendix. These statistics show that the additional test assets differ a lot in terms of average returns and return volatilities.

The blockchain characteristics of the 36 additional currencies are not included in the derivation of the blockchain-based factors for two reasons. First, even though we have reliable price data for the 36 additional currencies through Bittrex, we do not not have accurate blockchain data for these currencies.[23] Second, using test assets whose blockchain characteristics are not in the blockchain-based factors, alleviates endogeneity concerns. We note that for our tests in the extended sample, we construct return-generated factors based on the 54 cryptocurrencies (i.e., $CMkt(54)$, $CSize(54)$, and $CMom(54)$) since return data are available for all cryptocurrencies in this sample.[24]

We run the full-sample cross-sectional regressions using the 54 cryptocurrencies and report the results in Panel A of Table 7. We find that in single-factor models, $gNET$ and gCP have positive and statistically significant risk prices. In the multi-factor models, the most significant factors are network ($gNET$) and market ($CMkt(54)$).

We report the estimation results using the FMB procedure in Panel B of Table 7. We find that in the single-factor models, the blockchain-based factors have positive and statistically

[23]We note that it is difficult to obtain vetted historical data on blockchain characteristics. For example, Irresberger et al. (2020) use Coin Metrics data and focus on 27 cryptocurrencies. However, a number of those 27 did not have data as of January 6th, 2017, which is the first day of our sample.

[24]For most currencies on Bittrex, we obtain their BTC-denominated prices, which we multiply by Bitcoin's U.S.D. value for the same day-end to obtain their USD-equivalent price. We supplement the Bittrex price data with market capitalization data from Coinmarketcap.com for constructing the size factor.

significant risk-price estimates. Only the risk prices of the network factor are statistically significant in the two-factor models. The two-factor blockchain-based models exhibit similar cross-sectional fit (about 43-44%) to the model with the three return-based factors (about 48%). Graphical evidence in Figure A1 of the Appendix shows that the expected returns predicted by the blockchain-based factors line up with the sample average returns as well as the expected returns predicted by the return-based factors. Overall, incorporating blockchain-based factors can improve model fit as a model with all five factors ($gNET$, gCP, $CMkt(54)$, $CSize(54)$, and $CMoM(54)$) exhibits a 57.8% fit.

In Figure A2 of the Appendix, we present the evolution of the fit of various models in the sample of 54 cryptocurrencies. Panel A depicts the fit of models with either $gNET$ or $CMkt(54)$. Panel B depicts the fit of the model with $gNET$ and gCP and the model with $CMkt(54)$, $CSize(54)$, and $CMoM(54)$. According to Panel A, the network factor ($gNET$) exhibits a higher R^2 than the market factor. Further, Panel B shows that the fit of the two blockchain-based factors is comparable to that of the return-based factors.

4.5 Additional Sensitivity Analysis

To mitigate concerns regarding omitted variables, we conduct additional tests controlling for trading volume ($\Delta TradingVolume$), Google searches ($\Delta GoogleSearches$), Reddit posts ($\Delta RedditPosts$), and geopolitical uncertainty ($\Delta GEPU$) in Table A4.[25] We find that while these sentiment-based factors are significant in column (1), the blockchain-based factors retain their significance when controlling for sentiment in columns (2) and (3). Further, we split the sample into the first and second half in columns (4)-(7) and find that our model fit is stronger in the first half consistent with the evidence in Figure 4. Figure 4 finds a significant drop around late 2020 and early 2021 in the explanatory power of gCP and $gNET$ as the cryptocurrency market grew approximately 250% from \$400 billion to a high of approximately \$1.4 trillion in February, 2021, which was not particularly driven by

[25] We do not conduct cross-sectional tests as the sentiment-based factors are not true asset pricing factors, but rather weekly time-series variables (detailed in Table A1).

underlying growth in fundamentals.

Lastly, we expand our sample to January 31st, 2023, to mitigate concerns regarding whether our findings extend outside our sample period and present regression results in Table A5. We find that $gNET$ and gCP along with their Bitcoin-free versions are significant in this extended sample.[26]

5 Conclusion

In the cryptocurrency market, miners expend real resources to generate the computing power required to secure and operate the blockchain. Also, a large network of users enhances the usefulness of the cryptocurrency as a medium of exchange. Therefore cryptocurrency prices should be related to the computing power and network size of their blockchains. First, we run DOLS regressions and show that prices are positively related to network size and computing power at the cryptocurrency-level. Next, our cross-sectional results indicate that blockchain-based factors using network and computing power have significant explanatory power for cryptocurrency returns at the market-level.

Our findings have implications for investors and policy makers. From an investor perspective, we highlight the importance of blockchain fundamentals in constructing returns models, and note that they can improve standard market-based models. From a policy perspective, the finding that cryptocurrency prices are related to their underlying production (i.e., mining) and usage (network) is suggestive of some cryptocurrencies behaving like digital commodities enabling users to pay for blockspace to conduct transactions.

Our paper is an important step towards better understanding cryptocurrency prices. In particular, we are the first to provide cross-sectional evidence that expected cryptocurrency returns are related to aggregate network size and computing power. At the same time, we also highlight several limitations of our study such as the small number of currencies examined and the inherent endogeneity of blockchain-based factors in explaining prices.

[26] We do not conduct cross-sectional tests due to the small number of baseline currencies (11) with available data in this extended sample.

Figure 1: Market Capitalization Coverage of our Sample

This figure plots the weekly percentage of the market capitalization of our sample of 18 baseline cryptocurrencies relative to the aggregate market capitalization of all cryptocurrencies as derived from coinmarketcap.com. The 18 baseline cryptocurrencies are Bitcoin, Ethereum, Litecoin, Dash, Dogecoin, Etereum Classic, Digibyte, Decred, Vertcoin, ZCash, Monero, Ripple, Stellar, Lisk, NEM, Augur, Maidsafecoin, and Waves. On average, our sample of 18 base cryptocurrencies with consistent data on blockchain characteristics from Coinmetrics account for 82% of the aggregate cryptocurrency market with a maximum coverage of 99.3% towards the beginning of our sample period. The list of all 18 baseline cryptocurrencies is presented in Panel A of Table A2. The sample period is from 1/6/2017 to 5/28/2021.

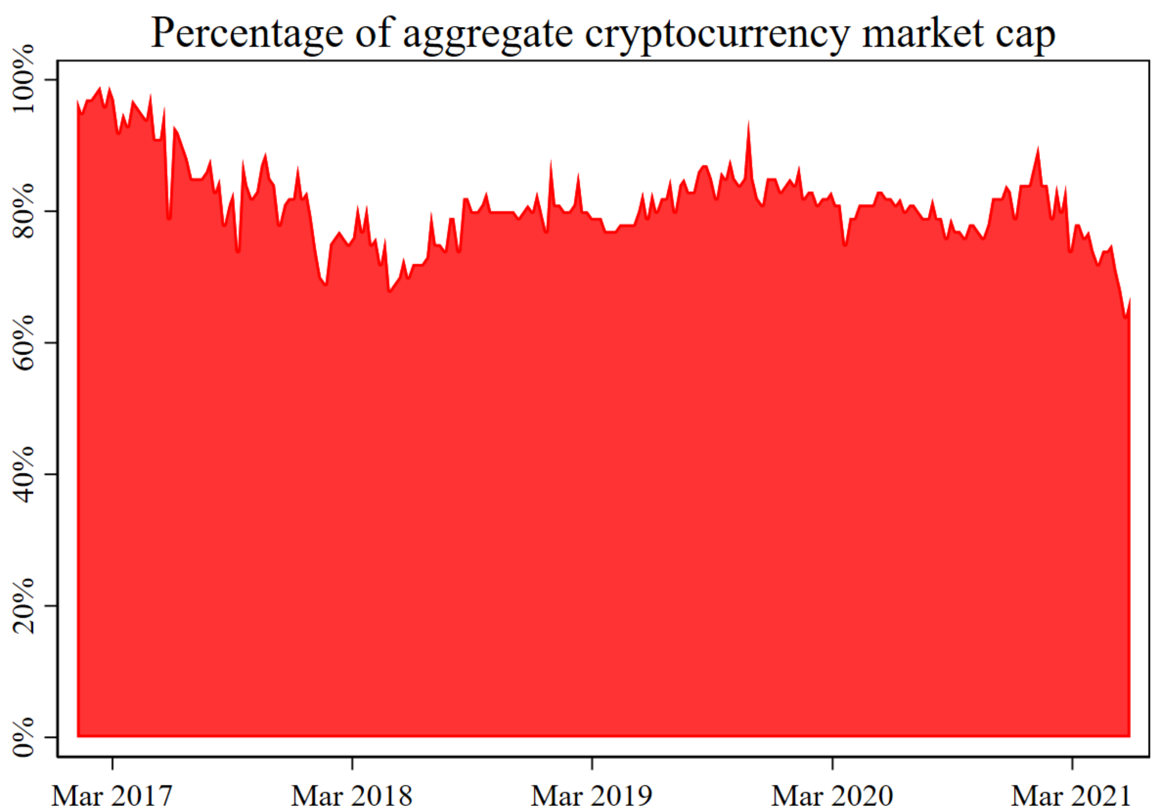


Figure 2: Fitted and Sample Average Cryptocurrency Returns: Full Sample

The figure presents fitted expected and average returns from the full-sample cross-sectional regressions of cryptocurrency expected returns on full-sample factor betas. For each cross-sectional regression, we compute the fitted expected returns, i.e., factor betas × risk prices ($\beta' \times \lambda$), and the sample average returns for the 18 cryptocurrencies in our baseline sample. In Figure A, fitted expected returns are generated based on a model in which the asset pricing factor is the growth in network, $gNET$. In Figure B, the factor is the growth in computing power, gCP, and in Figure C, the asset pricing factors are $gNET$ and gCP. In Figure D, the asset pricing factor is the cryptocurrency market factor ($CMkt(18)$). In Figure E, the factors are the market ($CMkt(18)$), the size factor ($CSize(18)$), and the momentum factor ($CMom(18)$) from the sample of 18 cryptocurrencies. In Figure F, fitted expected returns are generated from a model that pools all five factors together. R^2 is the cross-sectional R^2. The estimation of the models is based on the GMM approach described in Section 5 and the estimation results are reported in Table 5. The sample runs from 1/6/2017 to 5/28/2021.

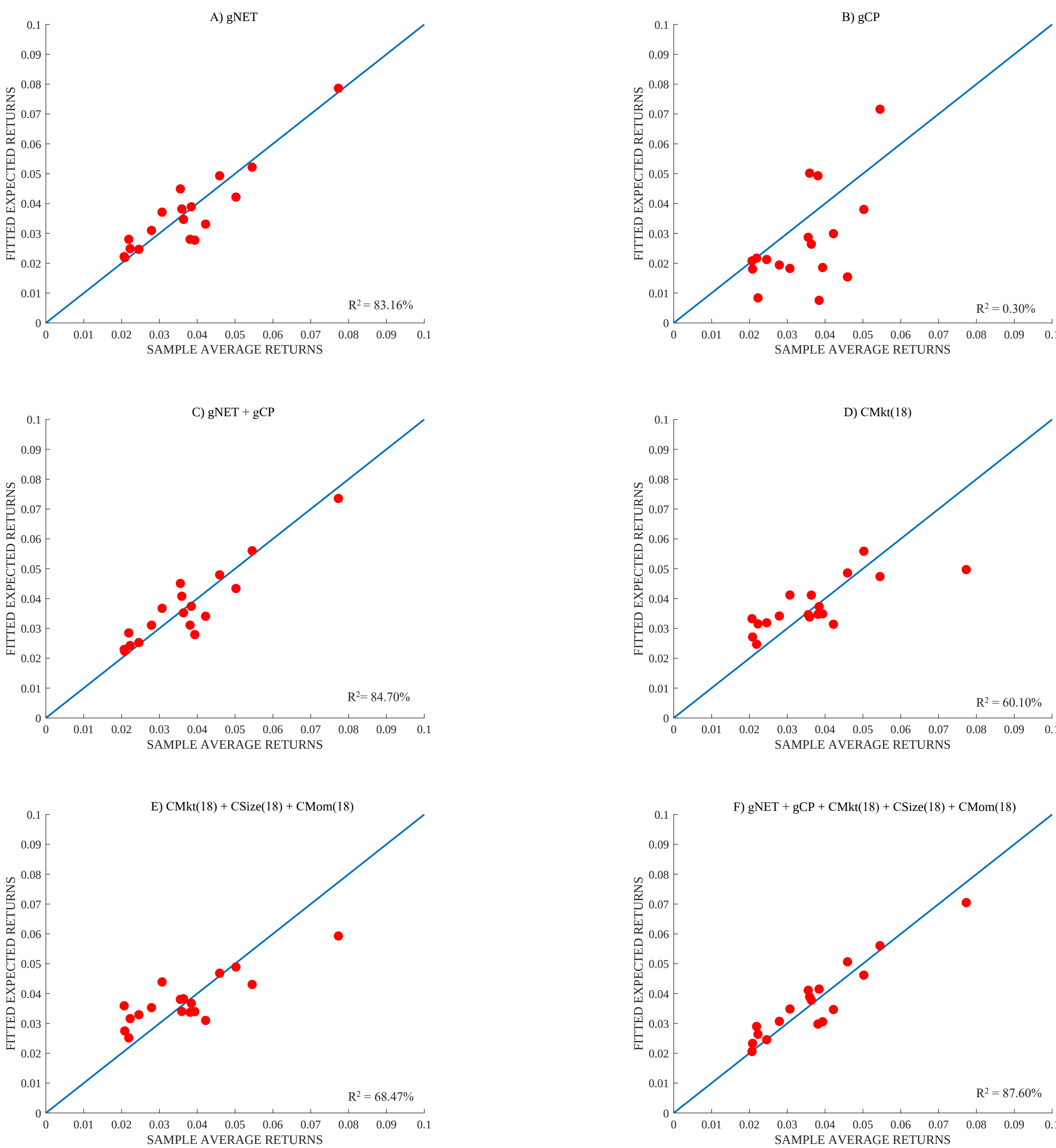


Figure 3: Fitted and Sample Average Cryptocurrency Returns: Rolling Regressions

The figure presents fitted expected and average returns from the rolling Fama-MacBeth regressions of expected cryptocurrency returns on factor betas. For each rolling regression, we compute the fitted expected returns, i.e., factor betas × risk prices ($\beta' \times \lambda$), and the sample average returns at the weekly frequency for the 18 cryptocurrencies in our baseline sample. In the graph, we plot the mean of the fitted and average returns from the 75 cross-sectional rolling regressions. In Figure A, fitted expected returns are generated based on a model in which the asset pricing factor is the growth in network, $gNET$. In Figure B, the factor is the growth in computing power, gCP, and in Figure C, the factors are $gNET$ and gCP. In Figure D, the asset pricing factor is the cryptocurrency market ($CMkt(18)$). In Figure E, the factors are the market ($CMkt(18)$), the size factor ($CSize(18)$), and the momentum factor ($CMom(18)$) from the sample of 18 cryptocurrencies. In Figure F, fitted expected returns are generated from a model that pools all five factors together. Average R^2 is the time series average of the cross-sectional R^2's. The estimation of the models is based on the GMM approach described in Section 5 and the estimation results are reported in Table 6. The sample runs from 1/6/2017 to 5/28/2021.

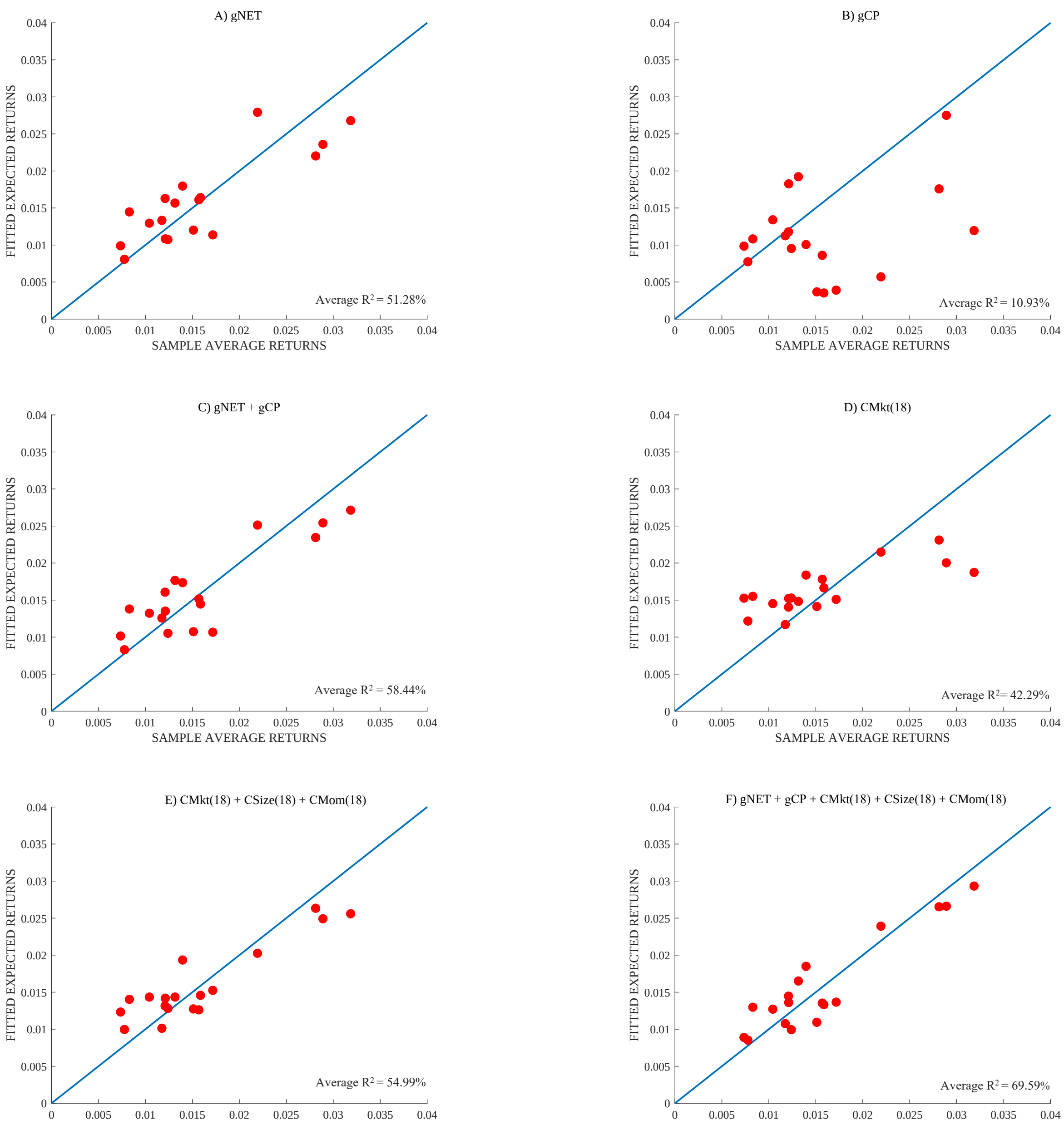
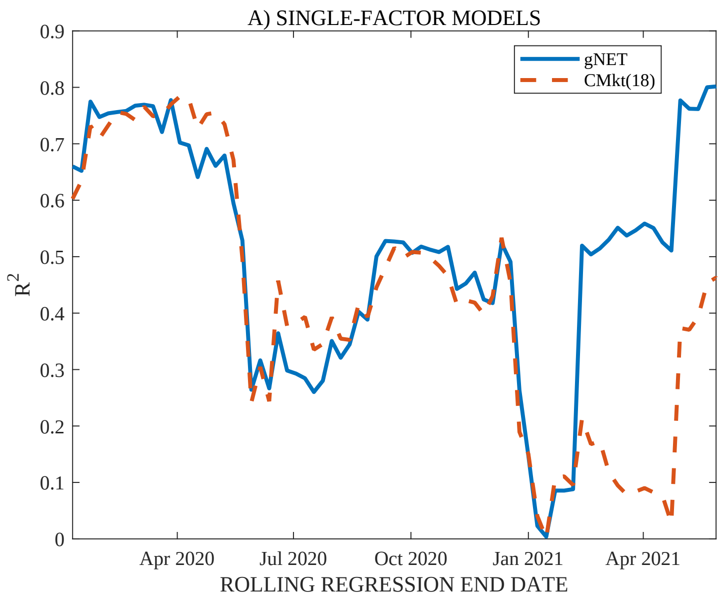


Figure 4: Cross-Sectional R^2's from Rolling Fama-MacBeth Regressions

The figure plots the time series of the cross-sectional R^2's for the rolling Fama-MacBeth regressions of expected cryptocurrency returns on factor betas. The rolling window is 156 weeks and it is updated weekly for a total of 75 regressions. The test assets are the baseline 18 cryptocurrencies from Panel A of Table A2. Figure A shows the time series of R^2's of single-factor models. Figure B presents results for multi-factor models. $gNET$ and gCP are the blockchain-based factors for network and computing power growth. $CMkt(18)$, $CSize(18)$, and $CMom(18)$ are respectively the return-based market, size, and momentum factors from the baseline sample of 18 cryptocurrencies. The sample period is from 1/6/2017 to 5/28/2021.



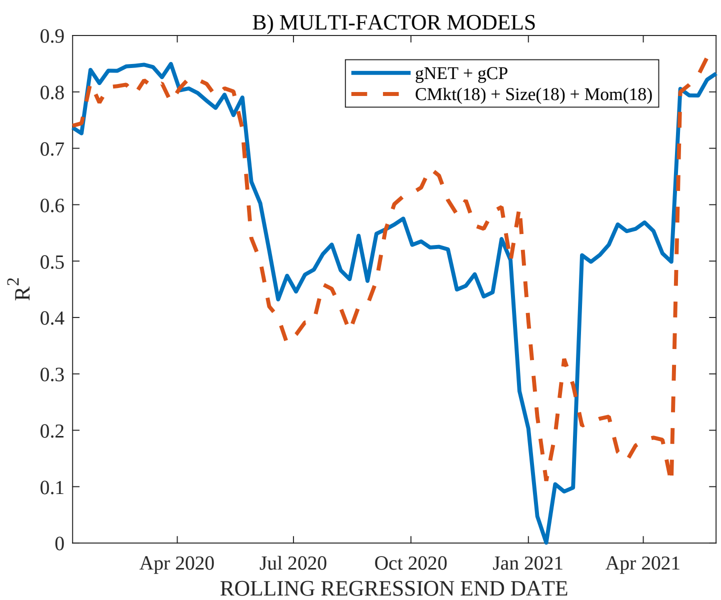


Table 1: Cointegrating Relation between Prices, Network Size, and Computing Power: Proof-of-Work Cryptocurrencies

This table reports estimates of the cointegrating relation between cryptocurrency prices (Price), network size (NET), and computing power (CP) for the 11 proof-of-work (PoW) cryptocurrencies in our baseline sample of 18 cryptocurrencies. The PoW cryptocurrencies are Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Dash (DASH), Dogecoin (DOGE), Ethereum Classic (ETC), Decred (DCR), Digibyte (DGB), Vertcoin (VTC), ZCash (ZEC), and Monero (XMR). The cointegrating relation is $\text{Price}_t = \alpha + \beta_{NET} \times \text{NET}_t + \beta_{CP} \times \text{CP}_t + \delta_t$ and it is estimated with the dynamic ordinary least squares (DOLS) methodology of Stock and Watson (1993) using equation (1) with two leads and lags of the first differences in NET and CP. The superscripts ***, **, and * indicate significant estimates at the 0.01, 0.05, and 0.10 level, respectively. The t-statistics, reported in parenthesis, are based on Newey-West standard errors with a bandwidth of 8. The sample runs from 1/6/2017 to 5/28/2021.

	BTC (1)	*ETH* (2)	*LTC* (3)	*DASH* (4)	*DOGE* (5)	*ETC* (6)	*DCR* (7)	*DGB* (8)	*VTC* (9)	*ZEC* (10)	*XMR* (11)
NET_t	0.72***	0.30*	0.85***	−0.21	0.95***	−0.57***	0.86**	0.30	1.11***	0.87***	
	(9.75)	(1.75)	(11.93)	(−0.60)	(3.19)	(−5.38)	(2.25)	(1.43)	(15.65)	(12.33)	
CP_t	1.20***	1.07***	0.27***	0.85***	−0.39	0.95***	0.82	0.96***	0.43***	0.27	1.24***
	(4.68)	(5.28)	(2.89)	(4.30)	(−1.21)	(6.45)	(1.47)	(5.84)	(7.70)	(1.38)	(6.21)
ΔNET_{t+2}	0.11	0.46***	0.26**	−0.68***	0.11	−0.11*	0.04	0.03	0.10	0.49***	
	(0.32)	(2.96)	(2.12)	(−3.38)	(0.70)	(−1.65)	(0.14)	(0.79)	(1.04)	(3.48)	
ΔNET_{t+1}	0.63	0.54***	0.44***	−0.92***	0.35	−0.19**	0.04	0.09	0.24**	0.67***	
	(1.27)	(2.66)	(2.61)	(−3.06)	(1.53)	(−1.96)	(0.08)	(1.27)	(2.31)	(4.12)	
ΔNET_t	−2.30***	0.35	−0.40***	−0.45	−1.23***	0.27**	−1.53**	−0.24	−0.45***	−0.27	
	(−4.32)	(1.56)	(−3.11)	(−0.79)	(−2.87)	(2.36)	(−2.12)	(−1.27)	(−2.90)	(−1.48)	
ΔNET_{t-1}	−1.60***	0.23	−0.27**	−0.29	−0.84***	0.19**	−1.15**	−0.16	−0.28***	−0.11	
	(−3.47)	(1.25)	(−2.22)	(−0.67)	(−2.64)	(1.98)	(−2.11)	(−1.29)	(−2.74)	(−0.64)	
ΔNET_{t-2}	−0.87***	0.17	−0.10	−0.17	−0.53**	0.08	−0.61**	−0.08	−0.13*	0.03	
	(−2.83)	(1.24)	(−1.09)	(−0.64)	(−2.22)	(1.30)	(−2.08)	(−1.23)	(−1.67)	(0.20)	
ΔCP_{t+2}	0.35*	3.06***	0.32	0.52	0.22	0.64**	0.73**	0.14	0.03	0.23	0.56
	(1.91)	(6.04)	(1.24)	(1.33)	(0.55)	(2.03)	(2.00)	(0.91)	(0.28)	(0.79)	(1.49)
ΔCP_{t+1}	0.55**	3.73***	0.48	0.63**	0.33	0.92**	0.76*	0.31**	−0.02	0.51	0.86*
	(2.02)	(7.29)	(1.50)	(2.01)	(0.74)	(2.31)	(1.77)	(2.34)	(−0.13)	(1.47)	(1.84)
ΔCP_t	−0.27	2.88***	0.58*	0.40	0.63*	0.15	0.54	0.21	0.00	0.86**	−0.40
	(−0.83)	(6.06)	(1.91)	(1.21)	(1.70)	(0.35)	(1.40)	(1.53)	(0.02)	(2.57)	(−0.83)
ΔCP_{t-1}	−0.10	3.13***	0.55	0.80**	0.82**	0.33	0.90**	0.18	0.02	0.88***	−0.42
	(−0.32)	(7.41)	(1.61)	(2.52)	(2.28)	(0.74)	(2.56)	(1.32)	(0.19)	(2.77)	(−0.83)
ΔCP_{t-2}	0.11	3.19***	0.34	0.73**	0.52	0.07	0.58*	0.20	0.01	0.49*	−0.41
	(0.53)	(5.96)	(1.04)	(2.02)	(1.56)	(0.20)	(1.80)	(1.25)	(0.13)	(1.77)	(−0.94)
δ_t	−0.01***	−0.00***	−0.00**	−0.01*	0.00*	−0.00	−0.01	−0.00	0.00***	−0.01*	−0.01***
	(−2.73)	(−4.38)	(−2.06)	(−1.70)	(1.76)	(−1.55)	(−1.41)	(−1.48)	(4.72)	(−1.81)	(−3.87)
α	1.42***	0.15	0.26	1.12	−0.56**	0.28	1.63	0.42	−0.47***	0.63*	1.28***
	(2.84)	(1.06)	(1.54)	(1.60)	(−2.21)	(1.13)	(1.36)	(1.58)	(−3.56)	(1.74)	(3.90)

Table 2: Cointegrating Relation between Prices and Network Size: Non-Proof-of-Work Cryptocurrencies

This table reports estimates of the cointegrating relation between cryptocurrency prices (Price) and network size (NET) for the seven non-proof-of-work (non-PoW) cryptocurrencies in our baseline sample of 18 cryptocurrencies. The non-PoW cryptocurrencies are Ripple (XRP), Stellar (XLM), Lisk (LSK), NEM (XEM), Augur (REP), MaidSafeCoin (MAID), and Waves (WAVES). The cointegrating relation is $\text{Price}_t = \alpha + \beta_{NET} \times \text{NET}_t + \delta_t$ and it is estimated with the dynamic ordinary least squares (DOLS) methodology of Stock and Watson (1993) using equation (1) with two leads and lags of the first differences of NET. The superscripts ***, **, and * indicate significant estimates at the 0.01, 0.05, and 0.10 level, respectively. The t-statistics, reported in parenthesis, are based on Newey-West standard errors with a bandwidth of 8. The sample runs from 1/6/2017 to 5/28/2021.

	XRP (1)	*XLM* (2)	*LSK* (3)	*XEM* (4)	*REP* (5)	*MAID* (6)	*WAVES* (7)
NET_t	0.86***	0.79***	1.18***	0.08	0.55***	0.80***	0.44**
	(4.91)	(5.24)	(13.71)	(0.34)	(2.68)	(2.63)	(2.23)
ΔNET_{t+2}	0.11	0.12	0.20***	−0.02	−0.26*	0.05	0.01
	(0.76)	(1.44)	(2.95)	(−0.11)	(−1.70)	(0.47)	(0.20)
ΔNET_{t+1}	0.42*	0.19*	0.46***	0.02	−0.30	0.14	0.06
	(1.70)	(1.76)	(4.21)	(0.08)	(−1.29)	(0.77)	(0.57)
ΔNET_t	−0.71***	−0.13	−1.15***	−0.02	−0.82***	−0.40**	−0.19
	(−3.41)	(−1.08)	(−11.58)	(−0.07)	(−3.17)	(−2.00)	(−1.59)
ΔNET_{t-1}	−0.47***	−0.04	−0.76***	0.03	−0.53**	−0.27	−0.17*
	(−2.95)	(−0.34)	(−9.68)	(0.11)	(−2.46)	(−1.63)	(−1.69)
ΔNET_{t-2}	−0.27**	−0.02	−0.41***	0.06	−0.27**	−0.16	−0.09
	(−2.31)	(−0.27)	(−7.87)	(0.32)	(−2.07)	(−1.52)	(−1.43)
δ_t	−0.00	−0.00	0.00***	0.00	0.00	0.00	0.00
	(−0.19)	(−0.37)	(3.97)	(0.06)	(0.99)	(0.82)	(1.44)
α	0.04	0.10	−0.54***	−0.00	−0.30	−0.47	−0.47
	(0.21)	(0.32)	(−3.36)	(−0.01)	(−0.95)	(−0.87)	(−0.30)

Table 3: Descriptive Statistics: Cryptocurrency Returns, Network, and Computing Power Growth

The table reports descriptive statistics for the weekly returns and the weekly growth rates in network (NET) and computing power (CP) of the 18 cryptocurrencies in our baseline sample, which consists of 11 proof-of-work (PoW) cryptocurrencies and 7 non-PoW cryptocurrencies. The PoW cryptocurrencies are Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Dash (DASH), Dogecoin (DOGE), Ethereum Classic (ETC), Decred (DCR), Digibyte (DGB), Vertcoin (VTC), ZCash (ZEC), and Monero (XMR). The non-PoW cryptocurrencies are Ripple (XRP), Stellar (XLM), Lisk (LSK), NEM (XEM), Augur (REP), MaidSafeCoin (MAID), and Waves (WAVES). Weekly returns are the cumulative daily returns of seven-day periods ending on Fridays. Weekly growth rates of network and computing power are the first differences of the Friday log values of unique active addresses and hashrates, respectively. The statistics for the growth rates in network do not include Monero (XMR), whose true active addresses count is not available as it is a privacy-focused currency. The sample period is from 1/6/2017 to 5/28/2021.

	Returns			**NET Growth Rate**			**CP growth rate**			N
	Mean	Median	St. Dev.	Mean	Median	St. Dev.	Mean	Median	St. Dev.	
				Proof-of-Work Cryptocurrencies						
BTC	0.022	0.017	0.115	0.003	0.005	0.094	0.018	0.014	0.123	230
ETH	0.038	0.019	0.177	0.016	0.008	0.135	0.021	0.020	0.046	230
LTC	0.031	0.008	0.188	0.011	0.003	0.213	0.018	0.017	0.087	230
DASH	0.028	0.001	0.190	0.007	0.007	0.260	0.032	0.022	0.120	230
DOGE	0.077	−0.003	0.501	0.011	0.017	0.267	0.021	0.028	0.085	230
ETC	0.036	0.003	0.236	0.002	−0.004	0.651	0.015	−0.003	0.122	230
DCR	0.042	0.010	0.199	0.008	−0.006	0.251	0.045	0.037	0.152	230
DGB	0.055	0.002	0.296	−0.005	−0.012	0.254	0.028	0.005	0.178	230
VTC	0.038	−0.006	0.259	0.002	−0.022	0.274	0.035	0.012	0.217	230
ZEC	0.021	−0.003	0.184	0.004	0.003	0.152	0.020	0.017	0.079	230
XMR	0.025	0.019	0.162				0.025	0.019	0.096	230
				Non-Proof-of-Work Cryptocurrencies						
XRP	0.046	−0.014	0.266	0.004	−0.012	0.310				230
XLM	0.050	−0.004	0.301	0.022	0.028	0.618				230
LSK	0.036	−0.008	0.238	0.001	0.014	0.469				230
XEM	0.036	−0.010	0.219	−0.005	0.004	0.403				230
REP	0.022	0.001	0.171	−0.001	−0.016	0.467				230
MAID	0.021	0.017	0.169	−0.003	−0.006	0.587				230
WAVES	0.039	0.001	0.219	0.023	0.001	0.822				230

Table 4: Descriptive Statistics and Correlations of Asset Pricing Factors

The table reports descriptive statistics of the cryptocurrency asset pricing factors used in our empirical analysis. The blockchain-based factors are the aggregate growth in network size ($gNET$) and computing power (gCP) across the 18 baseline cryptocurrencies. $gNET \setminus BTC$ and $gCP \setminus BTC$ are the resulting blockchain-based without Bitcoin's network and computing power. The cryptocurrency market-based factors include the value-weighted market return ($CMkt(18)$), a cryptocurrency size factor ($CSize(18)$), and a cryptocurrency momentum factor ($CMom(18)$) constructed from the 18 baseline cryptocurrencies used in our main empirical analysis. $CMkt(54)$, $CSize(54)$, and $CMom(54)$ are the market, size, and momentum factors in the extended sample of 54 cryptocurrencies used in our robustness tests. We also report summary statistics and correlations for the return of Bitcoin (BTC). The sample of 18 and the additional 36 cryptocurrencies (total 54) are listed in Panels A and B of Table A2, respectively. Details on the construction of the variables are provided in Table A1 of the Appendix. The sample period is from 1/6/2017 to 5/28/2021.

	Mean	SD	$gNET$	gCP	$gNET \setminus BTC$	$gCP \setminus BTC$	$CMkt(18)$	$CSize(18)$	$CMom(18)$	$CMkt(54)$	$CSize(54)$	$CMom(54)$
$gNET$	0.007	0.150	1.00									
gCP	0.025	0.054	−0.00	1.00								
$gNET \setminus BTC$	0.008	0.158	1.00***	−0.01	1.00							
$gCP \setminus BTC$	0.025	0.056	−0.02	0.98***	−0.02	1.00						
$CMkt(18)$	0.024	0.118	0.39***	0.13***	0.38***	0.12***	1.00					
$CSize(18)$	0.006	0.142	−0.08***	0.33***	−0.08***	0.33***	−0.16***	1.00				
$CMom(18)$	0.019	0.128	0.07***	0.17***	0.07***	0.17***	0.19***	0.35***	1.00			
$CMkt(54)$	0.024	0.119	0.39***	0.13***	0.38***	0.12***	1.00***	−0.16***	0.19***	1.00		
$CSize(54)$	0.025	0.126	−0.10***	0.34***	−0.11***	0.33***	−0.03**	0.53***	0.25***	−0.03*	1.00	
$CMom(54)$	−0.002	0.097	0.15***	0.03*	0.16***	0.05***	0.10***	0.03*	0.39***	0.10***	0.01	1.00
BTC	0.022	0.115	0.33***	0.12***	0.32***	0.11***	0.91***	−0.07***	0.14***	0.91***	0.01	0.13***

Table 5: Full-Sample Cross-Sectional Regressions of Expected Returns on Factor Betas

The table reports results from cross-sectional regressions of expected cryptocurrency returns on factor betas. The cross-sectional regressions are jointly estimated with the time series regressions for the full-sample factor betas (untabulated) over the entire sample period via the first-stage GMM system of equation (5). The table reports the estimated cross-sectional risk prices for the corresponding factor betas. The test assets are the 18 cryptocurrencies listed in Panel A of Table A2. The blockchain-based factors are $gNET$, gCP, and $gNET \setminus BTC$, and $gCP \setminus BTC$. The cryptocurrency return-based factors are the value-weighted return of the 18 cryptocurrencies ($CMkt(18)$), a cryptocurrency size factor ($CSize(18)$), and a cryptocurrency momentum factor ($CMom(18)$). The superscripts ***, **, and * indicate significant price of risk estimates at the 0.01, 0.05, and 0.10 level, respectively. We also report the χ^2-statistic, degrees of freedom (dof), and p-value for the test that all moment conditions in the GMM system are jointly zero. Finally, the R^2 and $RMSE$ are the cross-sectional R^2's and the root-mean-square-error, respectively. The sample runs from 1/6/2017 to 5/28/2021.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$gNET$	0.098***				0.092***				0.100***	
	(4.59)				(4.26)				(3.14)	
gCP		0.033***			0.003				−0.002	
		(3.83)			(0.47)				(−0.32)	
$gNET \setminus BTC$			0.103***			0.096***				0.104***
			(4.62)			(4.27)				(3.14)
$gCP \setminus BTC$				0.034***		0.002				−0.002
				(3.88)		(0.43)				(−0.28)
$CMkt(18)$							0.035***	0.035***	0.032***	0.031***
							(3.84)	(3.89)	(3.70)	(3.63)
$CSize(18)$								−0.009	−0.004	−0.004
								(−0.78)	(−0.42)	(−0.41)
$CMom(18)$								−0.002	0.015	0.015
								(−0.19)	(1.16)	(1.17)
χ^2	4.10	14.60	3.84	15.05	4.26	4.12	10.40	10.63	3.61	7.11
dof	17	17	17	17	16	16	17	15	13	13
p	0.99	0.62	0.99	0.59	0.99	0.99	0.88	0.77	0.99	0.89
R^2	83.16%	0.30%	83.29%	0.70%	84.70%	85.13%	60.10%	68.47%	87.60%	88.22%
RMSE	0.58%	2.45%	0.58%	2.37%	0.54%	0.54%	0.92%	0.86%	0.49%	0.48%

Table 6: Fama-MacBeth Regressions of Expected Returns on Factor Betas

The table reports results from rolling Fama-MacBeth regressions of expected cryptocurrency returns on factor betas. The cross-sectional regressions are jointly estimated with the time series regressions for the rolling factor betas (untabulated) via the first-stage GMM system of equation (5). The table reports time series averages of the estimated cross-sectional risk prices for the corresponding factor betas. The rolling time window is 156 weeks and it is updated every week leading to 75 regressions. The test assets are the 18 cryptocurrencies listed in Panel A of Table A2. The blockchain-based factors are $gNET$, gCP, and $gNET \setminus BTC$, and $gCP \setminus BTC$. The cryptocurrency return-based factors are the value-weighted return of the 18 cryptocurrencies ($CMkt(18)$), a cryptocurrency size factor ($CSize(18)$), and a cryptocurrency momentum factor ($CMom(18)$). The superscripts ***, **, and * indicate significant price of risk estimates at the 0.01, 0.05, and 0.10 level, respectively. The t-statistics of the average estimates in parenthesis are adjusted for autocorrelation with the Petersen (2009) correction. We also report the time series averages of the χ^2-statistic, degrees of freedom (dof), and p-value for the test that all moment conditions in the GMM system are jointly zero. The average R^2 and average $RMSE$ are the time series averages of the cross-sectional R^2's and the root-mean-square-error, respectively. The sample runs from 1/6/2017 to 5/28/2021.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$gNET$	0.067^{***}				0.059^{***}				0.044^{**}	
	(3.07)				(3.04)				(2.03)	
gCP		0.015^{*}			0.001				0.000	
		(1.90)			(0.26)				(0.04)	
$gNET \setminus BTC$			0.072^{***}			0.063^{***}				0.047^{**}
			(3.13)			(3.12)				(2.06)
$gCP \setminus BTC$				0.015^{*}		0.000				0.000
				(1.94)		(0.10)				(0.01)
$CMkt(18)$							0.015^{**}	0.04^{**}	0.013^{**}	0.013^{**}
							(1.97)	(2.09)	(2.32)	(2.34)
$CSize(18)$								-0.001	-0.000	-0.000
								(-0.22)	(-0.21)	(-0.21)
$CMom(18)$								0.015	0.011	0.011
								(1.30)	(1.22)	(1.23)
Average χ^2	8.62	11.48	8.68	11.43	8.55	8.63	9.49	8.09	6.73	76.86
dof	17	17	17	17	16	16	17	15	13	13
Average p	0.92	0.82	0.92	0.82	0.90	0.89	0.90	0.89	0.89	0.88
Average R^2	51.28%	10.93%	51.42%	24.22%	58.44%	58.62%	42.29%	54.99%	69.59%	70.01%
Average RMSE	0.63%	1.10%	0.63%	1.13%	0.57%	0.57%	0.77%	0.59%	0.46%	0.46%

Table 7: Full-Sample and Fama-MacBeth Regressions of Expected Returns on Factor Betas: 54 Cryptocurrencies

The table reports results from full sample and rolling Fama-MacBeth regressions of expected cryptocurrency returns on factor betas. Panel A reports results for full sample regressions and Panel B presents rolling Fama-MacBeth regressions. The cross-sectional regressions of expected returns on factor betas are jointly estimated with the time series regressions for the factor betas (untabulated) via the first-stage GMM system of equation (5). The table reports time series averages of the estimated cross-sectional risk prices for the corresponding factor betas. The rolling time window is 156 weeks and it is updated every week leading to 75 regressions. The test assets are the 54 cryptocurrencies listed in Table A2. The blockchain-based factors (gCP, $gNET$, $gCP \setminus BTC$, $gNET \setminus BTC$) are derived from the sample of 18 cryptocurrencies in Panel A of Table A2 due to data availability. The return-based cryptocurrency factors ($CMkt(54)$, $CSize(54)$, $CMom(54)$) are derived from the sample of 54 cryptocurrencies. The superscripts ***, **, and * indicate significant price of risk estimates at the 0.01, 0.05, and 0.10 level, respectively. In Panel B, the t-statistics of the average estimates in parenthesis are adjusted for autocorrelation with the Petersen (2009) correction. In Panel B, we also report the time series averages of the χ^2-statistic, degrees of freedom (dof), and p-value for the test that all moment conditions in the GMM system are jointly zero. The average R^2 and average $RMSE$ are the time series averages of the cross-sectional R^2's and the root-mean-square-error, respectively. The sample runs from 1/6/2017 to 5/28/2021.

Panel A: Full-Sample Cross-Sectional Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$gNET$	0.111***				0.077***				0.048**	
	(5.13)				(3.71)				(2.09)	
gCP		0.033***			0.013**				0.002	
		(4.62)			(2.20)				(0.32)	
$gNET \setminus BTC$			0.117***			0.077***				0.050**
			(5.15)			(3.55)				(2.07)
$gCP \setminus BTC$				0.034***		0.013**				0.002
				(4.68)		(2.24)				(0.33)
$CMkt(54)$							0.039***	0.032***	0.032***	0.032***
							(4.08)	(3.65)	(3.64)	(3.61)
$CSize(54)$								0.016*	0.012	0.012
								(1.77)	(1.41)	(1.39)
$CMom(54)$								0.009	0.005	0.005
								(1.03)	(0.63)	(0.63)
χ^2	49.65	44.71	49.12	47.11	43.82	45.27	47.87	46.63	42.82	42.66
dof	53	53	53	53	52	52	53	51	49	49
p	0.60	0.78	0.70	0.79	0.78	0.73	0.67	0.64	0.72	0.72
R^2	41.89%	20.90%	41.62%	23.66%	52.02%	52.74%	27.06%	58.01%	66.59%	66.76%
RMSE	1.57%	2.12%	1.59%	2.04%	1.27%	1.27%	1.37%	1.04%	0.93%	0.93%

Panel B: Fama-MacBeth Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$gNET$	0.071***				0.058***				0.031***	
	(2.70)				(3.63)				(5.10)	
gCP		0.015**			0.003				0.001	
		(2.31)			(0.84)				(0.30)	
$gNET \setminus BTC$			0.076***			0.059***				0.032***
			(2.74)			(3.71)				(4.57)
$gCP \setminus BTC$				0.017**		0.004				0.001
				(2.36)		(0.89)				(0.42)
$CMkt(54)$							0.017*	0.012*	0.013*	0.013*
							(1.65)	(1.66)	(1.82)	(1.79)
$CSize(54)$								0.008	0.005	0.005
								(1.15)	(0.76)	(0.74)
$CMom(54)$								0.007	0.007	0.007
								(0.90)	(1.06)	(1.06)
Average χ^2	49.69	43.30	49.67	43.29	44.90	44.02	39.51	39.55	38.93	38.60
dof	53	53	53	53	52	52	53	51	49	49
Average p	0.59	0.78	0.59	0.79	0.71	0.74	0.86	0.80	0.78	0.80
Average R^2	41.97%	15.07%	42.05%	17.39%	43.46%	44.13%	31.99%	47.65%	57.83%	57.86%
Average RMSE	1.11%	1.50%	1.12%	1.47%	1.04%	1.03%	1.20%	0.95%	0.86%	0.86%

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Appendix A: Supplemental Figures and Tables

Figure A1: Fitted and Sample Average Cryptocurrency Returns: Rolling Regressions with 54 Cryptocurrencies

The figure presents fitted expected and average returns from rolling Fama-MacBeth regressions of various factor models. For each regression, we compute the fitted expected returns and the sample average returns at the weekly frequency for the 54 cryptocurrencies from Table A2. We plot the mean of the fitted and average returns from the 75 cross-sectional rolling regressions. In Figure A (B), the factor is $gNET$ (gCP). In Figure C, the factors are $gNET$ and gCP. In Figure D and E the factors are $CMkt(54)$, and $CMkt(54)$, $CSize(54)$, and $CMom(54)$, respectively. In Figure F, the factors are all five factors. Average R^2 is the time-series average of the cross-sectional R^2's. We use the GMM estimation approach described in Section 5 and the estimation results are in Panel B of Table 7. The sample runs from 1/6/2017 to 5/28/2021.

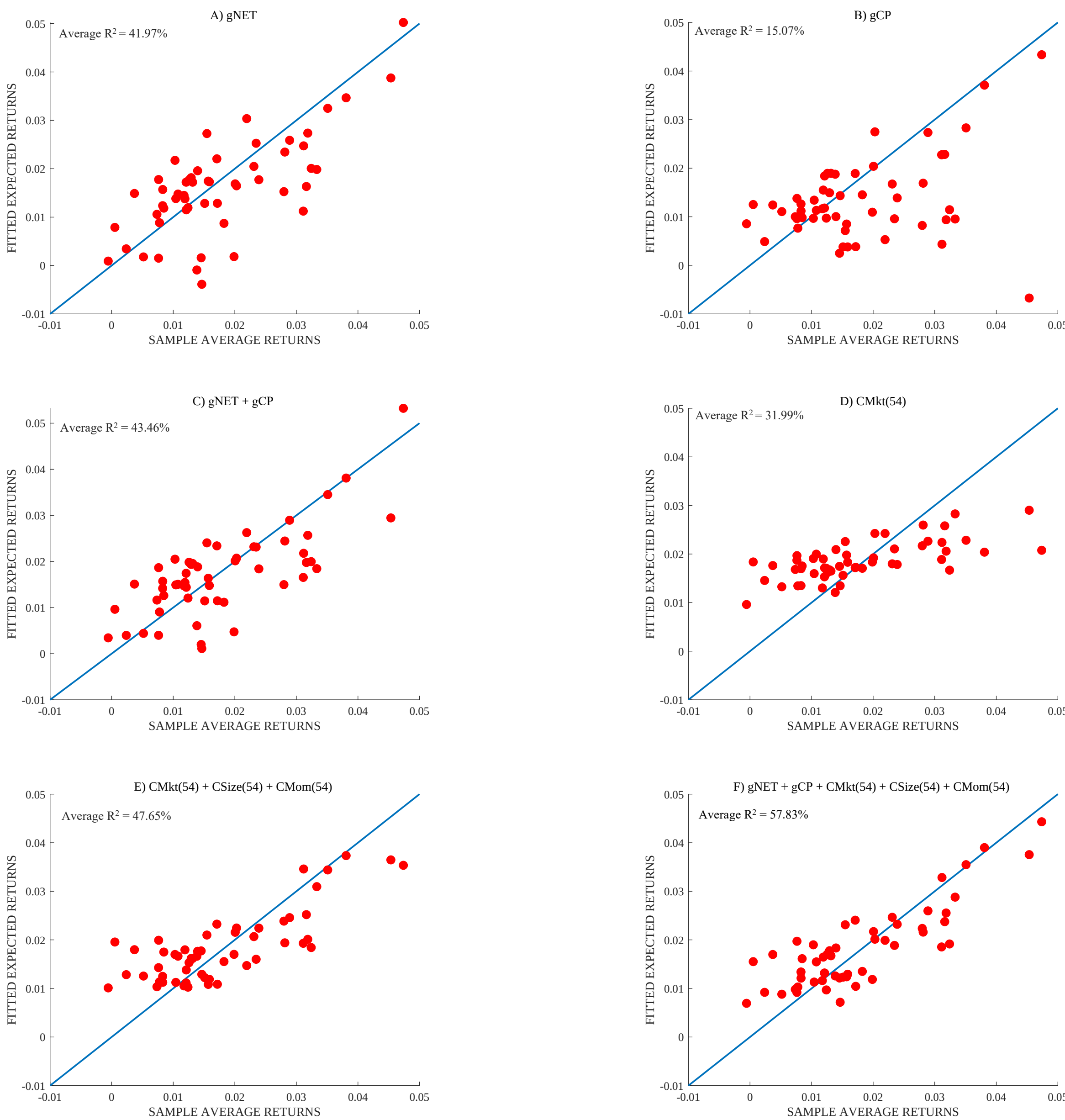
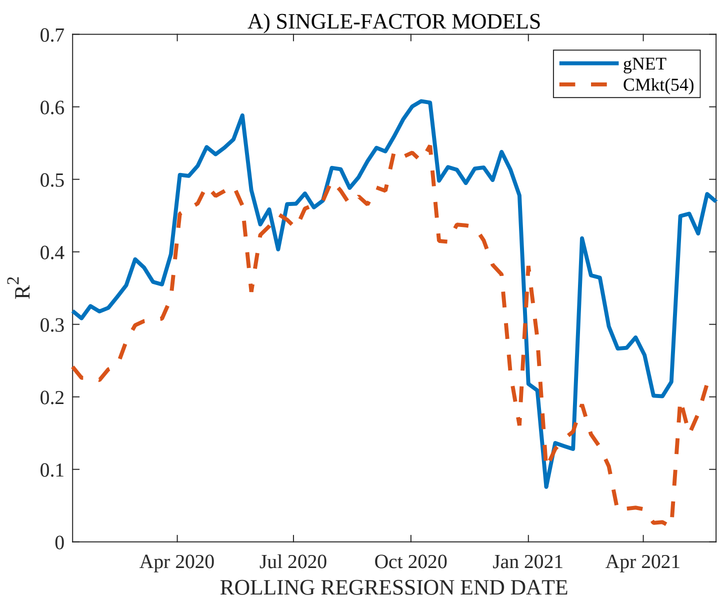


Figure A2: Cross-Sectional R^2's from Rolling Fama-MacBeth Regressions: 54 Cryptocurrencies

The figure plots the time series of the cross-sectional R^2's for the rolling Fama-MacBeth regressions of expected cryptocurrency returns on factor betas. The rolling window is 156 weeks and it is updated weekly for a total of 75 regressions. The test assets are the 54 cryptocurrencies from Table A2. Figure A shows the time series for the R^2's of single-factor models and Figure B presents results for multi-factor models. $gNET$ and gCP are the blockchain-based factors for network and computing power growth. $CMkt(54)$, $CSize(54)$, and $CMom(54)$ are respectively the return-based factors for the market, size, and momentum from the sample of 54 cryptocurrencies. The sample period is from 1/6/2017 to 5/28/2021.



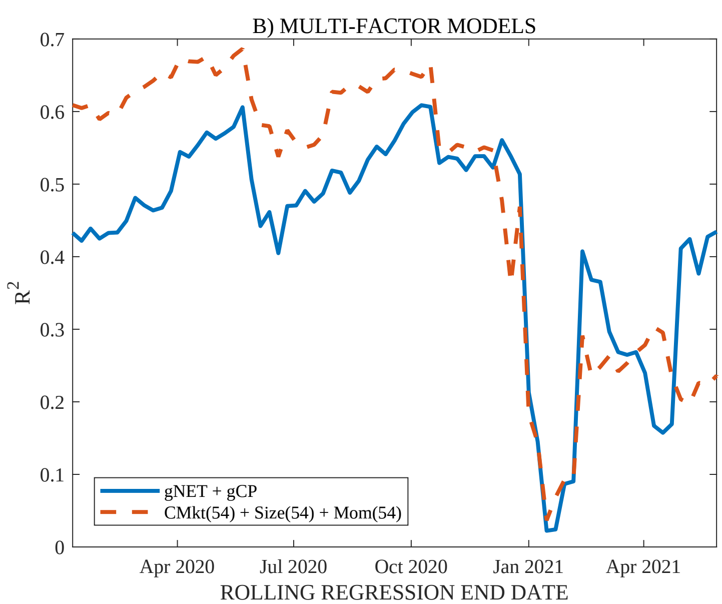


Table A1: Variable Descriptions

This table presents detailed descriptions of the main variables used in our analysis.

Variable	Description
	Cryptocurrency Variables
$Return$	Weekly returns based on cumulative daily returns of seven-day periods ending on Fridays.
$Price$	Natural logarithm of price as of Friday. The price is the fixed closing price at midnight UTC time on Friday. It is denominated in U.S. dollars. Daily prices for the 18 baseline cryptocurrencies are from Coin Metrics fixing/reference rate service. Daily prices for the 36 additional cryptocurrencies are obtained from the Bittrex exchange, which is U.S.-based and listed as a trusted exchange according to a Bitwise report to the SEC.
NET	Natural logarithm of *unique* active addresses on the blockchain as of Friday. Unique active addresses are the number of addresses from (or to) which transactions are conducted on the blockchain. The daily active address count is from Coin Metrics, which gathers data directly from the cryptocurrencies' blockchains. We do not collect network data for Monero (XMR) because the true active addresses count on Monero's blockchain is not available as it is a privacy-focused cryptocurrency.
ΔNET	Weekly first differences of NET.
CP	Natural logarithm of the hashrate value as of Friday. The hashrate values are obtained from Coin Metrics, which gathers data directly from the cryptocurrencies' blockchains. For Digibyte (DGB) and Decred (DCR), we multiply the average difficulty of mining blocks with the number of blocks mined that day. Hashrate data for Ripple (XRP), Stellar (XLM), Lisk (LSK), NEM (XEM), Augur (REP), MaidSafeCoin (MAID), and Waves (WAVES) are not available as these currencies are non-mineable, i.e., they do not use a Proof-of-Work consensus mechanism that relies on computing power to support the blockchain.
ΔCP	Weekly first differences of CP.
	Cryptocurrency Blockchain-based Factors
$gNET$	Equal-weighted average of the weekly growth rates of network size (ΔNET) for 17 of the 18 baseline cryptocurrencies excluding Monero (XMR).
gCP	Equal-weighted average of the weekly growth rates of computing power (ΔCP) for 11 of the 18 baseline Proof-of-Work consensus cryptocurrencies excluding Ripple (XRP), Stellar (XLM), Lisk (LSK), NEM (XEM), Augur (REP), MaidSafeCoin (MAID), and Waves (WAVES).
$gNET \setminus BTC$	Equal-weighted average of the weekly growth rates of network size (ΔNET) for 16 of the 18 baseline cryptocurrencies excluding Bitcoin (BTC) and Monero (XMR).
$gCP \setminus BTC$	Equal-weighted average of the weekly growth rates of computing power (ΔCP) for ten of the 18 baseline Proof-of-Work consensus cryptocurrencies excluding Bitcoin (BTC), Ripple (XRP), Stellar (XLM), Lisk (LSK), NEM (XEM), Augur (REP), MaidSafeCoin (MAID), and Waves (WAVES).

Table A1: Variable Descriptions (continued)

Variable	Description
	Cryptocurrency Market-Based Factors
CMkt(18)	Value-weighted returns of the 18 baseline cryptocurrencies listed in Panel A of Table A2 using the market capitalization rates as of the previous week. Sample period: 1/6/2017 - 5/28/2021 (230 weeks).
CMkt(54)	Value-weighted returns of the 54 cryptocurrencies listed in Panel A (18 baseline) and Panel B (36 additional) of Table A2 using the market capitalization rates as of the previous week. Sample period: 1/6/2017 - 5/28/2021.
CSize(18)	The difference between the average returns of the smallest 6 out of the 18 baseline cryptocurrencies by market capitalization as of the prior week and the average returns of the largest 6 out of the 18 baseline cryptocurrencies by market capitalization as of the prior week. Sample period: 1/6/2017 - 5/28/2021.
CSize(54)	The difference between the average returns of the smallest 18 out of the 54 cryptocurrencies by market capitalization as of the prior week and the average returns of the largest 18 out of the 54 baseline cryptocurrencies by market capitalization as of the prior week. Sample period: 1/6/2017 - 5/28/2021.
CMom(18)	Average of the contemporaneous returns of 6 of the 18 baseline cryptocurrencies with the highest returns (winners) in the prior week minus the average of the contemporaneous returns of 6 of the 18 baseline cryptocurrencies with the lowest returns (losers) in the prior week. Sample period: 1/6/2017 - 5/28/2021.
CMom(54)	Average of the contemporaneous returns of 18 of the 54 cryptocurrencies with the highest returns (winners) in the prior week minus the average of the contemporaneous returns of 18 of the 54 baseline cryptocurrencies with the lowest returns (losers) in the prior week. Sample period: 1/6/2017 - 5/28/2021.
	Cryptocurrency Sentiment-Based Factors
$\Delta TradingVolume$	First difference in the natural log of the weekly total units traded (bought and sold) multiplied by the average of last week's price. This sum, is based on units traded each week for Bitcoin and Ethereum. The volume data are provided by Coinmetrics.io and includes trades from a set of cryptocurrency exchanges that is almost identical to the exchanges used in Makarov and Schoar (2020).
$\Delta GoogleSearches$	First differences of the natural log of the weekly average values of worldwide Google searches downloaded from Google Trends for Bitcoin, Ethereum, and Cryptocurrency. The Google searches are scaled into an index with the maximum value reported as 100 in the data.
$\Delta RedditPosts$	First differences of the natural log of the weekly sum of the number of *new* Reddit posts on the subreddits of Bitcoin, Ethereum, and a general cryptocurrency subreddit ('r/Cryptocurrency'). The data are obtained by parsing Reddit's public API.
$\Delta GEPU$	Monthly values of the global economic policy uncertainty index (GEPU) constructed by Davis (2016) and obtained from https://www.policyuncertainty.com/global_monthly.html.

Table A2: Descriptive Statistics for Sample Cryptocurrencies

This table presents descriptive statistics for the cryptocurrencies in our sample. We report averages for the log of network size (NET), log of computing power (CP), prices in USD, log-prices, market capitalization rates (in millions USD), and cryptocurrency returns. We also report the standard deviation of returns. In Panel A, we report these statistics for the baseline sample of 18 cryptocurrencies, which consist of 11 Proof-of-Work (PoW) cryptocurrencies and 7 non-PoW cryptocurrencies. The 11 PoW cryptocurrencies are Bitcoin, Ethereum, Litecoin, Dash, Dogecoin, Ethereum Classic, Decred, Digibyte, Vertcoin, ZCash, and Monero. While Dash and Decred are considered as hybrid PoS/PoW cryptocurrencies, we classify them as PoW cryptocurrencies for parsimony. The seven non-PoW cryptocurrencies are Ripple, Stellar, Lisk, NEM, Augur, Maidsafecoin, and Waves. Related statistics for the set of 36 additional cryptocurrencies are reported in Panel B. The samples in Panels A and B are from 1/6/2017 to 5/28/2021.

Panel A: 18 Baseline Cryptocurrencies							
	Averages						St. Dev.
	NET	*CP*	*Price*	*Ln(Price)*	*MktCap (millions)*	*Ret*	*Ret*
11 Proof-of-Work Cryptocurrencies							
Bitcoin	13.6	31.3	11,307.59	8.91	204,483	0.022	0.11
Ethereum	12.5	18.8	457.45	5.59	49,392	0.038	0.18
Litecoin	11.3	18.6	82.89	4.09	5,062	0.031	0.19
Dash	11.0	20.8	191.67	4.89	1,604	0.028	0.19
Dogecoin	10.9	18.4	0.02	−5.77	2,273	0.077	0.50
EthereumClassic	10.2	1.9	11.76	2.13	1,290	0.036	0.24
Decred	9.6	6.4	41.54	3.30	406	0.042	0.20
Digibyte	9.2	6.5	0.02	−4.32	276	0.055	0.30
Vertcoin	7.0	13.4	0.92	−0.80	41	0.038	0.26
Zcash	10.3	0.3	135.57	4.58	666	0.021	0.18
Monero		6.2	112.12	4.44	1,871	0.025	0.16
7 Non-Proof-of-Work Cryptocurrencies							
Ripple	9.0		0.39	−0.32	39,198	0.046	0.27
Stellar	9.6		0.15	−2.51	15,678	0.050	0.30
Lisk	6.5		3.78	0.68	467	0.036	0.24
NEM	7.6		0.17	−2.32	1,538	0.036	0.22
Augur	5.6		21.10	2.86	232	0.022	0.17
Maidsafecoin	3.5		0.27	−0.54	124	0.021	0.17
Waves	8.9		3.94	0.87	394	0.039	0.22
Average					18,055	0.04	0.23

Panel B: 36 Additional Cryptocurrencies					
	Averages				St. Dev.
	Price	*Ln(Price)*	*MktCap (millions)*	*Ret*	*Ret*
Aeon	0.86	−0.65	13	0.04	0.27
Ardor	0.16	−2.37	161	0.03	0.20
Bitshares	0.06	−3.22	236	0.03	0.24
Burst	0.01	−5.16	17	0.05	0.30
Curecoin	0.13	−2.38	3	0.02	0.22
Einsteinium	0.13	−2.75	30	0.06	0.33
Exclusivecoin	0.38	−0.81	2	0.06	0.38
Expanse	0.78	−0.54	7	0.02	0.24
FLO	0.05	−3.19	8	0.04	0.24
Gamecredits	0.68	−0.60	46	0.03	0.26
Geocoin	0.72	−0.93	2	0.05	0.41
Groestlcoin	0.40	−0.48	29	0.06	0.31
I/O Coin	0.66	−0.34	11	0.02	0.22
Memetic	0.09	−3.49	2	0.07	0.53
Monacoin	1.84	0.10	113	0.07	0.57
Monetary Unit	0.05	−4.07	6	0.04	0.29
Navcoin	0.44	−0.43	28	0.04	0.41
NEO	24.86	2.49	1,663	0.05	0.27
Gulden	0.04	−3.67	17	0.02	0.20
Nexus	0.89	−0.73	51	0.04	0.29
OkCash	0.08	−3.16	6	0.03	0.25
Pinkcoin	0.01	−5.46	3	0.04	0.28
PIVX	1.55	−0.26	89	0.05	0.30
Reddcoin	0.00	−6.62	72	0.07	0.49
SteemDollars	1.92	0.30	230	0.05	0.55
Salus	17.70	2.43	16	0.05	0.31
Sphere	0.94	−0.15	4	0.06	0.42
STEEM	0.84	−0.80	13	0.03	0.23
Syscoin	0.14	−2.60	77	0.04	0.23
Validity	2.17	0.22	8	0.04	0.31
Viacoin	0.78	−0.82	18	0.04	0.23
Vericoin	0.20	−2.30	6	0.03	0.22
DigitalNote	0.00	−6.57	24	0.07	0.41
Myriad	0.00	−6.25	5	0.04	0.27
Stealth	0.14	−2.48	4	0.06	0.42
Verge	0.02	−5.17	248	0.09	0.51
Average			91	0.04	0.32

Table A3: Correlations between Fundamentals-based Factors and Cryptocurrency Returns

This table reports cross-correlations of the aggregate network and computing power growth factors ($gNET$, gCP, $gNET \setminus BTC$, and $gCP \setminus BTC$) with the weekly returns of the 18 baseline cryptocurrencies from Panel A of Table A2. We also report their cross-correlations with the average return of the extended sample of 36 cryptocurrencies (*AvgRet(36)*), which comprises the 36 additional cryptocurrencies from Panel B of Table A2. The sample period begins on 1/6/2017 and ends on 5/28/2021.

	$gNET$	gCP	$gNET \setminus BTC$	$gCP \setminus BTC$	BTC	ETH	LTC	$DASH$	$DOGE$	ETC	DCR	DGB	VTC	ZEC	XMR	XRP	XLM	LSK	XEM	REP	$MAID$	$WAVES$
$gNET$	1.00																					
gCP	−0.00	1.00																				
$gNET \setminus BTC$	1.00	−0.01	1.00																			
$gCP \setminus BTC$	−0.02	0.98	−0.02	1.00																		
BTC	0.33	0.12	0.32	0.11	1.00																	
ETH	0.34	0.07	0.33	0.06	0.51	1.00																
LTC	0.30	0.16	0.30	0.16	0.62	0.51	1.00															
$DASH$	0.25	0.17	0.25	0.17	0.49	0.65	0.51	1.00														
$DOGE$	0.24	−0.02	0.24	−0.00	0.24	0.26	0.30	0.27	1.00													
ETC	0.29	0.20	0.29	0.20	0.38	0.52	0.49	0.57	0.43	1.00												
DCR	0.25	0.24	0.26	0.26	0.43	0.51	0.46	0.47	0.28	0.31	1.00											
DGB	0.27	0.39	0.27	0.39	0.40	0.47	0.32	0.37	0.27	0.34	0.40	1.00										
VTC	0.16	0.31	0.16	0.33	0.39	0.35	0.35	0.36	0.12	0.21	0.42	0.36	1.00									
ZEC	0.18	0.18	0.18	0.19	0.47	0.66	0.54	0.73	0.31	0.66	0.44	0.45	0.31	1.00								
XMR	0.23	0.21	0.23	0.24	0.57	0.59	0.51	0.71	0.26	0.46	0.45	0.41	0.50	0.61	1.00							
XRP	0.28	0.09	0.28	0.09	0.33	0.39	0.64	0.30	0.27	0.29	0.35	0.40	0.26	0.39	0.35	1.00						
XLM	0.21	0.21	0.21	0.20	0.43	0.35	0.41	0.28	0.24	0.27	0.29	0.35	0.38	0.31	0.33	0.61	1.00					
LSK	0.24	0.34	0.24	0.36	0.35	0.49	0.41	0.51	0.19	0.48	0.50	0.49	0.55	0.55	0.63	0.35	0.27	1.00				
XEM	0.24	0.20	0.24	0.20	0.51	0.43	0.38	0.41	0.22	0.28	0.41	0.45	0.30	0.39	0.46	0.43	0.56	0.39	1.00			
REP	0.25	0.21	0.25	0.22	0.37	0.52	0.38	0.54	0.17	0.40	0.44	0.40	0.31	0.56	0.55	0.34	0.25	0.57	0.37	1.00		
$MAID$	0.20	0.17	0.19	0.17	0.49	0.37	0.39	0.34	0.18	0.23	0.39	0.38	0.34	0.34	0.44	0.27	0.27	0.40	0.34	0.33	1.00	
$WAVES$	0.19	0.14	0.19	0.13	0.41	0.49	0.48	0.35	0.15	0.37	0.39	0.46	0.34	0.40	0.48	0.45	0.32	0.47	0.38	0.36	0.25	1.00
AvgRet(36)	0.28	0.37	0.28	0.37	0.63	0.56	0.56	0.51	0.38	0.40	0.62	0.68	0.58	0.56	0.59	0.55	0.49	0.70	0.62	0.58	0.53	0.53

Table A4: Additional Analysis: Robustness to Sentiment-based Factors

The table reports results from regression analysis controlling for sentiment-based factors such as trading volume ($\Delta TradingVolume$), Google searches ($\Delta GoogleSearches$), Reddit posts ($\Delta RedditPosts$), and geopolitical uncertainty ($\Delta GEPU$). The test assets are the 18 cryptocurrencies listed in Panel A of Table A2. The blockchain-based factors are $gNET$ and gCP. The cryptocurrency return-based factors are the value-weighted return of the 18 cryptocurrencies ($CMkt(18)$), a cryptocurrency size factor ($CSize(18)$), and a cryptocurrency momentum factor ($CMom(18)$). The superscripts ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 level, respectively. The sample runs from 1/6/2017 to 5/28/2021. The first half of the sample spans 1/6/2017 to 3/15/2019 in columns (4) and (5) and the second half spans from 3/22/2019 to 5/28/2021 in columns (6) and (7).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Full Sample		First Half		Second Half	
$gNET$		0.34***	0.05	0.43***	0.06	0.29***	0.03
		(5.74)	(1.41)	(3.77)	(1.02)	(4.38)	(0.91)
gCP		0.73***	0.41***	0.99***	0.49***	0.46	0.25*
		(3.68)	(3.67)	(4.06)	(3.16)	(1.50)	(1.81)
$\Delta TradingVolume$	0.05*	0.02	0.03	-0.03	-0.01	0.06	0.05*
	(1.80)	(0.86)	(1.42)	(-0.96)	(-0.41)	(1.64)	(1.91)
$\Delta GoogleSearches$	0.02**	0.01	-0.00	0.01	0.00	0.00	-0.01
	(2.05)	(1.54)	(-0.84)	(1.39)	(0.37)	(0.34)	(-1.49)
$\Delta RedditPosts$	0.02	0.01	0.00	0.05**	-0.00	0.00	0.01
	(1.50)	(1.12)	(0.22)	(2.53)	(-0.39)	(0.15)	(1.32)
$\Delta GEPU$	-0.41*	-0.28	-0.09	-0.21	0.18	-0.31	-0.28**
	(-1.69)	(-1.34)	(-0.92)	(-0.70)	(1.27)	(-0.98)	(-2.32)
$CMkt(18)$			1.04***		1.04***		1.00***
			(23.49)		(15.40)		(18.80)
$CSize(18)$			0.12		0.23**		0.02
			(1.05)		(2.08)		(0.19)
$CMom(18)$			-0.10		0.02		-0.27**
			(-1.07)		(0.24)		(-2.12)
Adjusted R^2	.02	.09	.28	.14	.34	.07	.24
Observations	4,140	4,140	4,140	2,070	2,070	2,070	2,070
Currencies	18	18	18	18	18	18	18
Weeks	230	230	230	115	115	115	115

Table A5: Additional Analysis: Extended Sample

The table reports results from regression analysis using the blockchain-based factors (gCP, $gNET$, $gCP \setminus BTC$, $gNET \setminus BTC$), which are are derived from 11 cryptocurrencies namely Bitcoin, Dash, Digibyte, Dogecoin, Ethereum, Litecoin, Maidsafecoin, Vertcoin, NEM, Monero, and Ripple due to consistent data availability between 1/6/2017 and 1/31/2023. The return-based cryptocurrency factors ($CMkt(11)$, $CSize(11)$, $CMom(11)$) are derived from the sample of 11 cryptocurrencies. The superscripts ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 level, respectively. The sample runs from 1/6/2017 to 1/31/2023.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$gNET$	0.30***				0.28***				0.05**	
	(10.95)				(10.52)				(2.01)	
gCP		0.72***			0.68***				0.12**	
		(12.27)			(11.88)				(2.20)	
$gCP \setminus BTC$			0.12***			0.11***				0.03***
			(12.88)			(12.75)				(3.10)
$gNET \setminus BTC$				0.03***		0.03***				0.01**
				(10.74)		(10.59)				(2.38)
$CMkt(11)$							1.07***	1.07***	1.04***	1.03***
							(37.23)	(37.41)	(33.91)	(33.81)
$CSize(11)$								0.23***	0.21***	0.19***
								(9.31)	(7.57)	(7.11)
$CMom(11)$								0.00	-0.01	-0.01
								(0.03)	(-0.23)	(-0.40)
Adjusted R^2	.03	.04	.05	.03	.07	.07	.28	.30	.30	.30
Observations	3,531	3,531	3,531	3,531	3,531	3,531	3,531	3,531	3,531	3,531
Currencies	11	11	11	11	11	11	11	11	11	11
Weeks	321	321	321	321	321	321	321	321	321	321

Appendix B

Asset Pricing: Estimation Framework

In this section we describe the methodology of the asset pricing tests.

Stochastic Discount Factor

We frame our tests within the stochastic discount factor (SDF) paradigm. Under general conditions, there exists an SDF M_t, which can price the returns of any asset i, $R_{i,t}$. That is,

$$\mathbb{E}\big[R_{i,t}M_t\big] = 1. \tag{1}$$

This pricing relationship dates back to Rubinstein (1976), Lucas (1978), Ross (1978), Harrison and Kreps (1979), and Hansen and Richard (1987). Tirole (1985) also finds a similar SDF representation when pricing fiat money. Biais et al. (2022) extend the model of Tirole (1985) to include a cryptocurrency. Moreover, the pricing equation (1) implies that the theoretical expected returns are related to the covariances between returns and the SDF:

$$\mathbb{E}\big[R_{i,t}\big] = \big(1 - Cov(R_{i,t}, M_t)\big)/\mathbb{E}\big[M_t\big]. \tag{2}$$

The functional form of the SDF is dictated by investor preferences. It also depends on investor portfolio and consumption decisions, and it reflects the evolution of the marginal utility of total wealth. Since preferences for cryptocurrency investors are unobservable, we cannot pin down the functional form of M_t and directly estimate the pricing equation (2). Therefore, we follow Cochrane (2005, 2011) and assume that M_t is a linear function of observable factors. Cochrane suggests that the factors should be aggregate economic indicators that affect the portfolio decisions and total wealth of investors. Specifically, M_t is defined as

$$M_t = 1 - (f_t - \mathbb{E}[f_t])'\gamma, \tag{3}$$

where f_t are factors centered around their means and γ is the vector of SDF parameters.

The linear SDF in equation (3) implies that the pricing model (2) is:

$$\mathbb{E}\big[R_{i,t}\big] = 1 + \beta_i'\lambda. \tag{4}$$

Above, β_i' $\big(= \mathbb{E}\big[R_{i,t}(f_t - \mathbb{E}[f_t])'\big]\mathbb{E}\big[(f_t - \mathbb{E}[f_t])(f_t - \mathbb{E}[f_t])'\big]^{-1}\big)$ is the vector of factor betas for cryptocurrency i and λ $\big(= \mathbb{E}\big[(f_t - \mathbb{E}[f_t])(f_t - \mathbb{E}[f_t])'\big]\gamma\big)$ is the vector of risk prices. We use the standard linear-beta representation of the stochastic discount factor in equation (4) in cross-sectional regressions of expected returns on factor betas.

Cross-Sectional Pricing Model of Expected Returns

The pricing equation (4) is the basis of our empirical tests. In our set up, the factors f_t capture the overall economic conditions in the cryptocurrency market as well as the wealth of the marginal cryptocurrency investor.

Hence, in this setting, investors require high premia for cryptocurrencies whose returns are positively correlated with aggregate network and computing power growth. That is, cryptocurrencies whose returns covary positively with the aggregate blockchain characteristics are considered risky cryptocurrencies. These risky cryptocurrencies should earn high average returns to entice investors to include them in their portfolios. The relation between risk premia and covariances with blockchain-based factors should hold for mineable and non-mineable currencies, even if the latter do not require the consumption of computing power for mining. As long as aggregate computing power affects the overall wealth of cryptocurrency investors, the SDF paradigm predicts that aggregate computing power should impact the risk premia of all currencies, even the non-mineable ones.[27]

[27] This is a reasonable assumption because developments in mining and blockchain technology have positive externalities for non-PoWs. For example, developments in Bitcoin or Ethereum allow for batches of transactions using Layer-2 solutions or on other non-mineable cryptocurrencies such as ERC-20 tokens that transact on Ethereum's blockchain to be more securely aggregated. Therefore, the growth in computing power of a PoW can improve the transaction benefits of non-PoWs, which ultimately increases their value.

Full-Sample and Fama-MacBeth Cross-Sectional Tests

In our asset pricing tests, we estimate equation (4) in the cross-section of cryptocurrency returns. We conduct two sets of cross-sectional tests. First, similar to Lettau and Ludvigson (2001), we use the full sample to estimate a single cross-sectional regression of expected returns on estimated betas. Second, we follow Fama and MacBeth (1973) (FMB), who estimate rolling regressions and allow for the risk-return trade-off to evolve across time. The FMB approach is appropriate for our analysis because the cryptocurrency market is relatively new and constantly evolving. The FMB approach can account for changes in market conditions by allowing the factor betas and prices of risk to vary over time.

We focus on cross-sectional tests because they can identify if an asset pricing factor is spurious. For example, Daniel and Titman (1997) suggest that the covariance structure of returns with true asset pricing factors should line up with the average returns of the test assets and result in high cross-sectional fit. In contrast, spurious asset pricing factors can have significant beta estimates in time-series factor regressions while having poor fit in the cross-section of expected returns (Daniel and Titman (1997); Lewellen et al. (2010)). Cross-sectional tests also provide estimates for the risk prices of the blockchain-based factors. This allows for direct tests of theoretical models of cryptocurrency prices (Biais et al., 2019, 2022), which imply positive risk prices for the blockchain factors. For the aforementioned reasons, cross-sectional tests are superior to time-series tests based on factor models.

Estimation Methodology

To implement the cross-sectional tests, we use the following GMM system from Cochrane (2005):

$$\begin{bmatrix} I_{N(K+1)} & 0_{N(K+1)\times N} \\ 0_{K\times N(K+1)} & \beta' \end{bmatrix} \times \begin{bmatrix} \mathbb{E}\big[R_t - \alpha - \beta(f_t - E[f_t])\big] \\ \mathbb{E}\big[\big(R_t - \alpha - \beta(f_t - E[f_t])\big) \otimes (f_t - E[f_t])\big] \\ \mathbb{E}\big[R_t - 1 - \beta\lambda\big] \end{bmatrix} = A \times g_T = 0. \quad (5)$$

Above, N is the number of cryptocurrency test assets and K $(K < N)$ is the number of factors. The matrix A is a $\big(N(K+1)+K\big) \times N(K+2)$ weighting matrix and g_T is the $N(K+2) \times 1$ vector of moment conditions, which are functions of α, β, and λ. The vector α is the $N \times 1$ vector of time series alphas, β is the $N \times K$ matrix of time series betas, and λ is the vector of the K risk prices.

The first two sets of moments in g_T estimate the time-series alphas and betas, respectively. The last set of moments runs the cross-sectional regression of expected returns on factor betas to estimate the prices of risk. The GMM system is over-identified since the first $N \times (K+1)$ conditions exactly identify the N time series alphas and the $N \times K$ time series betas, while the final N moments identify the K prices of risk.

For the full-sample unconditional tests, we run the system in equation (5) once using the full time series sample. For the FMB estimation, we use a rolling time window of 156 weeks, i.e., approximately three years. The window is updated weekly resulting in 75 cross-sectional regressions. The estimation window is long enough to provide reliable estimates of the factor exposures while allowing us to estimate a sufficiently large number of cross-sectional regressions.

The rolling estimation yields a time series of risk estimates λ_t. We follow Fama and MacBeth (1973) and report the time-series averages of the cross-sectional price-of-risk estimates, $\bar{\lambda}$. We also calculate the variance of the average risk price following Petersen (2009):

$$Var(\bar{\lambda}) = \frac{Var(\lambda_t)}{n} + \frac{(n-1)Cov(\lambda_t, \lambda_{t-1})}{n}. \tag{6}$$

This correction accounts for serial correlation in the λ estimates.

In their original implementation, Fama and MacBeth (1973) first run OLS time-series regressions of test assets on factors to obtain the β's. Next, they separately estimate cross-sectional OLS regressions of average returns on factor betas to identify the λ's. Instead, following Cochrane (2005), we adopt the GMM approach of equation (5) because it *simultaneously* estimates the time-series and cross-sectional regressions and accounts for the fact that the β's, i.e., the independent variables in the cross-sectional regressions, are generated regressors.