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JEL Classification: E4, G12, G15

Keywords: Hashrate, network, Factor Analysis, GMM, Rolling Estimation

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November 25, 2021

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Introduction

Cryptocurrencies are an emerging new asset class and it has been unclear what factors determine their prices and returns. On the one hand, most empirical research focuses on the influence of investor sentiment and other non-fundamental factors.[1] On the other hand, theory suggests that blockchain characteristics such as network size and computing power are key determinants of prices.[2] However, there is little empirical work on the importance of blockchain characteristics on price dynamics.[3] Motivated by this gap in the empirical literature, we focus on the network size and computing power and examine if these blockchain characteristics can explain the dynamics of cryptocurrency prices and the cross-sectional variation in expected cryptocurrency returns.

We formulate two hypotheses based on existing theoretical models (Pagnotta and Buraschi, 2018; Biais et al., 2020; Pagnotta, 2021). First, we conjecture that the prices of individual cryptocurrencies should be positively related to their network size and computing power. In extension, aggregate network size and computing power should be important asset pricing factors because they reflect the state of the cryptocurrency market. Specifically, aggregate network size should capture the general adoption levels of cryptocurrencies. Aggregate computing power should proxy for the cumulative resources expended on mining and relates to the overall reliability and security of cryptocurrency blockchains. Therefore, the evolution of these two factors should offer important information about the state of the cryptocurrency market and should affect the expected cryptocurrency returns.

Our sample period is from 1/6/2017 to 5/28/2021. The sample starts in 2017 since

[1]See Griffin and Shams (2020), Makarov and Schoar (2020), and Liu, Tsyvinski, and Wu (2021).

[2]See Pagnotta and Buraschi (2018), Biais, Bisiere, Bouvard, and Casamatta (2019), Biais, Bisiere, Bouvard, Casamatta, and Menkveld (2020), Cong, Li, and Wang (2020), and Pagnotta (2021).

[3]Exceptions include Liu and Tsyvinski (2020) who show that over the 2011 to 2018 period, Bitcoin's network comoves with average cryptocurrency returns while variables related to Bitcoin's mining do not. Liu and Tsyvinski (2020) 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 very high-frequency level. Biais et al. (2020) focus on Bitcoin and highlight the importance of transaction benefits and network security. Pagnotta (2021) finds that the prices of Bitcoin, Ethereum, and Litecoin are positively related to their hashrates.

many important cryptocurrencies were introduced around that time. For this period, we collect data on computing power (hashrates) and network size (number of *unique* addresses transacting on a blockchain) for 18 baseline currencies.[4] 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 theoretical relationship between cryptocurrency prices, network size, and computing power at the cryptocurrency-level. In particular, 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., 2020; Pagnotta, 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 asset pricing factors based on aggregate network size and computing power can explain the cross-section of expected cryptocurrency returns. To construct the two blockchain-based factors, we aggregate the growth rates in network and computing power across the 18 cryptocurrencies in our baseline sample. Specifically, the factors are the average weekly growth rates of network size ($gNET$) and computing power (gCP) of the 18 baseline currencies. Following existing studies (Shen, Urquhart, and Wang, 2020; Liu and Tsyvinski, 2020; Liu et al., 2021), we also consider three cryptocurrency return-based factors related to market returns, size, and momentum. The test assets are the 18 baseline currencies.

[4]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.

We structure the asset pricing tests around the stochastic discount factor paradigm (Cochrane 2005, 2011) and estimate cross-sectional regressions of expected cryptocurrency returns. We focus cross-sectional tests because they can identify spurious factors. For example, Daniel and Titman (1997) suggest that spurious factors are characterized by significant beta estimates in time-series factor regressions but poor fit in the cross-section of expected returns. Cross-sectional tests also provide estimates for the risk prices of the blockchain-based factors. This allows for direct tests of cryptocurrency models (Biais et al., 2019, 2020), which imply positive risk prices for the blockchain factors.

We implement the cross-sectional asset pricing tests with two different methodologies. First, we follow Lettau and Ludvigson (2001) and estimate unconditional full-sample regressions. Second, because the cryptocurrency market has been evolving, we also adopt the rolling-window estimation approach of Fama and MacBeth (1973) (FMB). In both cases, the cross-sectional regressions are estimated with the Generalized Method of Moments (GMM). We use the GMM methodology because it estimates factor betas from time-series regressions and *simultaneously* runs the cross-sectional regressions. In the FMB estimation, we set the rolling window to 156 weeks (i.e., approximately three years). From the rolling cross-sectional regressions, we obtain a time series of estimated prices of risk. As in Fama and MacBeth (1973), we focus on the average prices of risk.

The estimation shows that the two blockchain-based factors $gNET$ and gCP have positive and significant risk prices in single-factor models. Between the two factors, the risk prices for $gNET$ are larger. In two-factor models with both blockchain-based factors, the risk-price estimates for $gNET$ is positive and significant while that of gCP is positive but insignificant. The estimation also shows that expected cryptocurrency returns are significantly related to the blockchain-based factor betas. 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 pricing kernel with the return-based cryptocurrency market, size, and momentum factors.

In the FMB estimation, the average fit of all models is lower compared to the full-sample estimation results. However, we still find that, on average, the fit of the two-factor model with $gNET$ and gCP is comparable to the fit of the model with the three return-generated factors. The FMB results also allow us to 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 the three-factor model with the market, size, and momentum factors.

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. To mitigate issues of endogeneity, the blockchain characteristics of the 36 additional currencies are not included in the $gNET$ and gCP factors. In both robustness tests, we find that in two-factor models with the blockchain factors, these factors have positive risk prices. They also explain a similar portion of the cross-sectional variation in expected returns as do models with the three cryptocurrency return-based factors (i.e., market, size and momentum).

Our work makes several contributions to the literature. We are the first to use aggregate blockchain characteristics in cross-sectional asset pricing tests and show that they are related to cryptocurrency returns. To the contrary, many existing studies suggest that cryptocurrency returns are driven by investor sentiment (e.g., Cheah and Fry (2015)). This evidence is consistent with Griffin and Shams (2020), who note that Bitcoin is susceptible to manipulation while also serving as a barometer for the cryptocurrency market. For large cryptocurrencies, like Bitcoin, research has also documented significant price differences across exchanges (Kroeger and Sarkar, 2017; Borri and Shakhnov, 2019; Makarov and Schoar, 2020). To expand on prior work, we consider a larger set of currencies (54 in total) and examine whether aggregate blockchain factors are related to their average returns.

In related work, Shen et al. (2020) and Liu et al. (2021) argue that cryptocurrency returns can be explained by factors related to a cryptocurrency market portfolio, a size factor, and a momentum factor. These factors are return-generated and are perceptible to the criticisms of Cochrane (2011) and Harvey, Liu, and Zhu (2016) about the lack of economic interpretation of return-generated factors. In contrast, we use asset pricing factors based on blockchain fundamentals drawn from theoretical models (e.g., Biais et al. (2020), Pagnotta (2021)).

Further, Liu and Tsyvinski (2020) show that cryptocurrency returns are affected by Bitcoin's network but not by proxies related to Bitcoin's production. Their main production proxies are the cost of electricity in the U.S. and China, and the prices of Bitmain Antminer, a Bitcoin mining hardware. Instead, we use hashrates to capture the resources expended for mining. Hashrates are available for all mineable currencies and are advocated by theoretical models as an important measure of blockchain security (e.g., Pagnotta (2021); Prat and Walter (2021)). Further, Liu and Tsyvinski (2020) mostly focus on time-series factor regressions whereas we estimate GMM cross-sectional regressions that better assess the ability of factors to fit the cross-section of expected returns.

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, and network externalities, captured by the number of users. Biais et al. (2020) build a model connecting the fundamental value of cryptocurrencies to transactional benefits and the risk of a hack. They estimate their model with a structural econometric approach using data on Bitcoin. Sockin and Xiong (2020) note that the "trustless" nature of decentralized networks contributes to their value. Pagnotta (2021) develops a model where the price of proof-of-work currencies is related to their blockchain security, which can be captured by their hashrates. Following this theoretical work, we capture blockchain trustworthiness and security with computing power and transaction benefits using the size of the network.

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, O'Hara, and Basu (2019) show that transaction fees paid to miners become more important as more blocks are being mined and Huberman, Leshno, and Moallemi (2021) examine the economics of Bitcoin's transaction fee structure. Foley, Karlsen, and Putniņš (2019) find that before 2013 many of Bitcoin's transactions were related to illegal activities. Howell, Niessner, and Yermack (2019) and Gan, Tsoukalas, and Netessine (2021) study initial coin offerings. Cong et al. (2020) relate the value of cryptocurrency tokens to their transactional demand.

Cong, He, and Li (2020) highlight the high energy costs of proof-of-work blockchains. Alsabah and Capponi (2020) study proof-of-work protocols and find that the mining industry has moved towards centralization as opposed to decentralization. Lastly, Härdle, Harvey, and Reule (2020) provide a general overview of cryptocurrencies. The above studies mostly focus on micro-level aspects of the cryptocurrency market. In contrast, we adopt a more aggregate approach and examine the determination of the cross-section of cryptocurrency expected returns using aggregate blockchain-based factors.[5]

The rest of the paper is organized as follows. Section 1 describes the data. Section 2 presents the cointegration analysis. Section 3 describes the test assets and factors used in the asset pricing tests. Sections 4 and 5 respectively present the methodology and findings of the asset pricing cross-sectional analysis. Section 6 concludes the paper.

[5] In other related work, Chod, Trichakis, Tsoukalas, Aspegren, and Weber (2020) and Cui, Gaur, and Liu (2020) examine how blockchains can improve supply-chains. Tsoukalas and Falk (2020) study the optimality of token-weighted voting. Iyengar, Saleh, Sethuraman, and Wang (2020) analyze the welfare implications of blockchain adoption while Irresberger, John, and Saleh (2020), John, Rivera, and Saleh (2020), Roşu and Saleh (2021), and Saleh (2021) study Proof-of-Stake blockchains. Our work also complements theoretical (Weber, 2016; Athey, Parashkevov, Sarukkai, and Xia, 2016; Jermann, 2021; Routledge, Zetlin-Jones, et al., 2018), empirical (Wang and Vergne, 2017; Stoffels, 2017; Mai, Shan, Bai, Wang, and Chiang, 2018; Auer and Claessens, 2018; Borri, 2019; Hu, Parlour, and Rajan, 2019), and other work on cryptocurrencies (Corbet, Lucey, Urquhart, and Yarovaya, 2019; Shanaev, Sharma, Ghimire, and Shuraeva, 2020).

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 sample. The sample starts on 1/6/2017 because many important cryptocurrencies with reliable data on blockchain characteristics have been introduced by then. The sample ends on 5/28/2021.

We adopt the balanced-panel approach because in the cryptocurrency market 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.[6] Additionally, many cryptocurrencies are only introduced to capitalize on market upswings and then simply disappear. For example, Li, Shin, and Wang (2021) document approximately 500 cryptocurrency 'pump-and-dump' schemes that arose during late 2017 and early 2018 when the cryptocurrency market was growing at a rapid rate. This non-random turnover creates biases in unbalanced panel data sets that cannot be easily addressed econometrically.[7]

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 hack on its blockchain that led to over $18 million in Bitcoin Gold being withdrawn from user accounts to malicious addresses.[8] An unbalanced panel that would include all traded currencies at any given point in time would include such hacked or fraudulent cryptocurrencies, thus deteriorating the quality of the sample. To ensure high

[6] 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/.

[7] See Fitzgerald, Gottschalk, and Moffitt (1998), Hirano, Imbens, Ridder, and Rubin (2001), and Baltagi (2008) for proposed remedies to sample attrition.

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

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.

Nevertheless, a 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.[9]

1.2 Data sources

We obtain our data from three sources. The first one is Coin Metrics from which we collect prices and blockchain characteristics (unique active addresses and hashrates) for 18 cryptocurrencies, which form our baseline sample. 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

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

[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.

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 May 28th, 2021, the last day of our sample. For comparison, in January 2017, Coinbase and Gemini, two other major U.S.-based crypto-exchanges, only listed the top three and top five cryptocurrencies.

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, Lyandres, and Rabetti (2020), 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. (2021).

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,

[12]Chaim and Laurini (2018), Valdeolmillos, Mezquita, González-Briones, Prieto, and Corchado (2019), Conlon and McGee (2020), Irresberger et al. (2020), and Filippou, Rapach, and Thimsen (2021).

[13]See the list provided by Bitwise Asset Management at https://www.bitcointradevolume.com/ and a list by FTX, a cryptocurrency derivatives exchange, at https://ftx.com/volume-monitor.

Decred, Vertcoin, ZCash, and Monero.[14] The non-mineable currencies are Ripple, Stellar, Lisk, NEM, Augur, Maidsafecoin, and Waves. These 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. Specifically, we use the Coin Metrics database because, to the best of our knowledge, it includes the highest quality blockchain data. Then, we select the largest currencies for which Coin Metrics provides blockchain characteristics for our entire sample period (1/6/2017 to 5/28/2021). 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

The core of our empirical analysis focus on the network size and computing power of a blockchain because of the key properties of these two blockchain measures. Specifically, network size is related to the number of users of the blockchain. Analogous to established fiat currencies, which are accepted by a large number of entities as a means of transaction, a large network indicates greater adoption of the cryptocurrency. A large number of unique blockchain users also suggests enhanced liquidity of the respective cryptocurrency.

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 count active addresses with multiple transactions on a given day.[15] The number of unique active addresses is not a perfect measure of cryptocurrency adoption since a portion of active addresses arises

[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.

[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, Bonneau, Felten, Miller, and Goldfeder, 2016).

from multiple transactions meant to obfuscate the movements of funds. Nevertheless, we use it because it is available for all the baseline currencies except Monero.

Beside network size, we also focus on computing power. Computing power is measured in hashes. We obtain the hashrate data for the 11 mineable currencies in our sample from Coin Metrics. Computing power is important because it affects the reliability and security of the blockchains of Proof-of-Work currencies. For instance, when computing power is high, miners are expending plentiful resources to efficiently and securely record transactions. Further, a blockchain can be hacked if rogue miners amass more than 51% of the existing computing power. This is highly improbable for cryptocurrencies with high computing power (Kroll, Davey, and Felten, 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 many cryptocurrencies including all the mineable currencies in our sample.

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 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

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

cryptocurency prices are related to the blockchain's computing power and network size (e.g., Pagnotta and Buraschi (2018), Biais et al. (2020), Pagnotta (2021)).[17]

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.[18] 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).[19]

To implement the DOLS, we assume that for PoW currencies 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:

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

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. 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

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

[18] In unreported results, we implement the augmented Dickey and Fuller (1979) test and find that the prices, network size, and computing power of the 18 baseline currencies are unit-root processes.

[19] 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.

(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 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. (2020), Pagnotta (2021)), 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 the network size 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.

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. 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 Asset Pricing: Test Assets and Factors

The DOLS analysis shows that network size and computing power are important determinants of cryptocurrency prices. This evidence provides micro-foundations for the asset pricing analysis. Specifically, 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 reliability and security of blockchains. Accordingly, aggregate network size and computing power should have information that is relevant for expected cryptocurrency returns. In this section, we discuss the data and factors used in the asset pricing tests.

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. (2020)) and problems with outliers. We set the end of the 7-day period to Friday following the Friday 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. To verify that our test assets 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 cross-sectional tests are centered around asset pricing factors based on blockchain network size and computing power. These blockchain factors are equal-weighted averages of the growth rates of network size and computing power of the 18 baseline currencies. In particular, for the network factor, we compute the average growth in network size (ΔNET) of 17 out of the 18 cryptocurrencies (excluding Monero). For the computing power factor, we calculate the average growth in computing power (ΔCP) of the 11 PoW currencies with computing power. We denote the average growth in network size and computing power by $gNET$ and gCP, respectively. For completeness, 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 further 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 the 17 baseline currencies excluding the network size and computing power of Bitcoin. We denote the factors that exclude Bitcoin's network and computing power growth by $gCP \setminus BTC$ and $gNET \setminus BTC$, 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. (2021)). 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. (2021), and the third one is a cryptocurrency momentum factor ($CMom(18)$) constructed following Jegadeesh and Titman (1993). Detailed definitions of these factors are in Table A1 of the Appendix. We construct these factors with the sample of 18 baseline cryptocurrencies.

3.4 Factor 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.

4 Asset Pricing: Estimation Framework

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

4.1 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,

$$\mathbb{E}\big[R_{i,t}M_t\big] = 1. \tag{2}$$

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. (2020) extend the model of Tirole (1985) to include a cryptocurrency. Moreover, the pricing equation (2) implies that the theoretical expected returns are related to the covariances between returns and the SDF:

$$\mathbb{E}\big[R_{i,t}\big] = \big(1 - Cov(R_{i,t}, M_t)\big)/\mathbb{E}\big[M_t\big]. \tag{3}$$

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 (3). 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

$$M_t = 1 - (f_t - \mathbb{E}[f_t])'\gamma, \tag{4}$$

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

The linear SDF in equation (4) implies that the pricing model (3) is:

$$\mathbb{E}\big[R_{i,t}\big] = 1 + \beta_i'\lambda. \tag{5}$$

Above, β_i' $\left(= \mathbb{E}\big[R_{i,t}(f_t - \mathbb{E}[f_t])'\big]\mathbb{E}\big[(f_t - \mathbb{E}[f_t])(f_t - \mathbb{E}[f_t])'\big]^{-1}\right)$ is the vector of factor betas for cryptocurrency i and λ $\left(= \mathbb{E}\big[(f_t - \mathbb{E}[f_t])(f_t - \mathbb{E}[f_t])'\big]\gamma\right)$ is the vector of risk prices. We use the standard linear-beta representation of the stochastic discount factor in equation (5) in cross-sectional regressions of expected returns on factor betas.

4.2 Cross-Sectional Pricing Model of Expected Returns

The pricing equation (5) 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. We argue that aggregate computing power and aggregate network growth rates should affect the wealth of the marginal cryptocurrency investor because theoretical models (Pagnotta and Buraschi, 2018; Biais et al., 2020; Pagnotta, 2021) predict a positive relation among prices, network size, and computing power. This positive theoretical relation is also strongly supported by our DOLS results.

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.[20]

[20]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

We also note that the fact that network size and computing power are endogenous economic variables does not invalidate our asset pricing tests. Our testing framework is very similar to that of consumption-based or investment-based asset pricing models, 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 can fit the cross-section of equity returns. In our case, instead of consumption or investment, the economic variables of interest are the blockchain network size and computing power.

4.3 Full-Sample and Fama-MacBeth Cross-Sectional Tests

In our asset pricing tests, we estimate equation (5) 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, Nagel, and Shanken (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, 2020), which imply positive risk prices for the blockchain factors. For the

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.

aforementioned reasons, cross-sectional tests are superior to time-series tests based on factor models.

4.4 Estimation Methodology

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

$$\begin{bmatrix} I_{N(K+1)} & 0_{N(K+1)\times N} \\ 0_{K\times N(K+1)} & \beta' \end{bmatrix} \times \begin{bmatrix} \mathbb{E}\big[R_t - \alpha - \beta(f_t - E[f_t])\big] \\ \mathbb{E}\big[\big(R_t - \alpha - \beta(f_t - E[f_t])\big) \otimes (f_t - E[f_t])\big] \\ \mathbb{E}\big[R_t - 1 - \beta\lambda\big] \end{bmatrix} = A \times g_T = 0. \quad (6)$$

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 (6) 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):

$$Var(\bar{\lambda}) = \frac{Var(\lambda_t)}{n} + \frac{(n-1)Cov(\lambda_t, \lambda_{t-1})}{n}. \tag{7}$$

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 (6) 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.

5 Asset Pricing: Findings of Cross-Sectional Tests

In this section we present the findings of our asset pricing tests.

5.1 Full-Sample Estimation Results

We estimate the GMM system of equation (6) 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 estimate one- and two-factor models with the blockchain-based factors, one- and three-factor models with the return-based factors, and five-factor models with all the 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 prices of risk. We also find that the network factors

[21] In untabulated results, we run cross-sectional tests of expected cryptocurrency returns on the betas from the equity-based three- and five-factor Fama-French models (Fama and French, 1993, 2015). Consistent with existing results (e.g., Liu et al. (2021)), we find no statistically significant relation between the traditional equity-based factors (market, value, size, momentum, investment, profitability) and cryptocurrency expected returns.

(i.e., $gNET$ and $gNET \setminus BTC$) have larger and more significant risk prices than the computing power factors (i.e., gCP and $gCP \setminus BTC$). These findings corroborate the theoretical results in Pagnotta (2018) and Pagnotta and Buraschi (2018) regarding the positive relation between cryptocurrency prices and the two blockchain fundamentals. These results are also consistent with our previous DOLS results regarding the positive cointegration between prices, network, and computing power at the cryptocurrency-level.

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%. The fit of the model with gCP is almost zero.

We report results for the two-factor models with the blockchain factors in columns (5) and (6) of Table 5. Consistent with the results from the single-factor models, we find that the network factor has positive and significant risk prices. The computing power factor has positive but insignificant risk prices.

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 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. The figure plots the theoretically-implied expected returns against sample average returns. The figure confirms that the blockchain-based factors can explain the cross-section of cryptocurrencies at least as well as the three return-generated factors.

5.2 Fama-MacBeth Estimation Results

We tabulate the results of the rolling FMB regressions in Table 6. Consistent with the full-sample results, the risk-price estimates of the $gNET$ and gCP are positive. The risk-price of $gNET$ is also higher than that 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 full economic interpretation, 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.

5.3 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, in the post July 2019 subsample, the model with the blockchain-based factors 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 Figure 4, the fit of the blockchain two-factor model in every rolling regression is at least as good, if not better, as that of the return-based three-factor model.

5.4 Network Size Versus Computing Power

The asset pricing tests suggest that network size is more important for the cross-section of expected returns than computing power. There are several reasons that can explain this finding. To begin with, Biais et al. (2019) suggest that investment in computing power is excessive as new miners increase the computing requirements for mining the next block. For example, in the case of Bitcoin, 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 (2021) argues that blockchain security is a concave function of hashrates. Therefore, when computing power reaches a certain high level, increases in computing power marginally enhance blockchain security. In this case, changes in computing power should have a minimal impact on prices and returns.

The cost structure of mining also contributes to computing power becoming less important, especially after it surpasses a certain high level. Specifically, Pagnotta (2021) highlights that miners' investment costs are convex due to the upward adjustments in mining difficulty upon entry of new miners. 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 of Bitcoin, which cannot be reconfigured to mine other currencies. Similarly, Ethereum relies on the *Ethash* algorithm that is generally solved using graphic processing units (GPUs).[22] 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 thereby muting the effect of computing power on cryptocurrency prices.

In contrast, there are no theoretical arguments that increases in the number of users transacting on a blockchain become less relevant after a certain point. Additionally, as the cryptocurrency market has grown the ease of accessing exchanges and transacting on a blockchain has been increasing allowing users to easily enter and exit the cryptocurrency market. Similarly, switching across blockchains has become relatively easy through the use of exchanges or cryptocurrency swap markets. Therefore, network growth can be very sensitive to market conditions and adoption-related events (e.g., Biais et al. (2020)).

Overall, as theory suggests, computing power is an important characteristic of PoW cryptocurrencies that affects their price levels. This prediction is supported by our DOLS results. However, the impact of computing power on returns can be weak due to the irreversibility

[22] See a list of Bitcoin mining hardware at https://www.buybitcoinworldwide.com/mining/hardware/ and a list of top Ethereum mining GPUs at https://beincrypto.com/learn/ethereum-mining-rig/.

of investments in mining equipment. Moreover, when computing power reaches a certain high level, changes in computing power have a minimal impact on blockchain security. However, network growth is more responsive to market changes and, regardless of the size of the network, changes in the number of users should have a strong impact on prices and returns.

5.5 More Test Assets

Our main analysis, DOLS and cross-sectional tests, is 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 the 18 baseline cryptocurrencies and an additional set of 36 currencies, for a total of 54 test assets.

5.5.1 Additional Test Assets

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.[23] 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.[24] 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

[23]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.

[24]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 that have historical blockchain data. However, a number of those 27 did not have data as of January 6th, 2017, which is the first day of our sample.

on the 54 cryptocurrencies (i.e., $CMkt(54)$, $CSize(54)$, and $CMom(54)$) since return data are available for all cryptocurrencies in this sample.

5.5.2 Results from the Extended Sample

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 the single-factor models with the blockchain-based factors, $gNET$ and gCP have positive and statistically significant risk prices. In the multi-factor models, the most significant factors are network and market.

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 significant risk-price estimates. Only the risk prices of the network factor are statistically significant in the two-factor models. Also, 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.

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. Interestingly, in the post-April 2021 sample, the models with the blockchain-based factors outperform the models with return-based factors in terms of cross-sectional fit.

6 Conclusion

The main hypothesis of this paper is that blockchain measures affect the prices and returns of cryptocurrencies. We examine this hypothesis using the blockchain characteristics of 18 cryptocurrencies. First, we run DOLS regressions and show that cryptocurrency prices are positively related to network size and computing power. This finding at the cryptocurrency-level confirms the intuition of the existing theoretical literature on the relation between cryptocurrency prices and blockchain fundamentals (e.g., Pagnotta and Buraschi (2018), Biais et al. (2020), Pagnotta (2021)).

Next, we aggregate network and computing power growth rates across cryptocurrencies to create two blockchain-based asset pricing factors, network ($gNET$) and computing power (gCP), which we use in standard asset pricing tests in the cross-section of cryptocurrency expected returns. Our cross-sectional results indicate that the two blockchain-based factors have positive prices of risk and high explanatory power for the cross-section of expected cryptocurrency returns. Additionally, the ability of the two blockchain-based factors to explain average cryptocurrency returns is at least as good as that of models with return-generated factors such market, size, and momentum.

Overall, 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. As the cryptocurrency market further matures additional asset pricing factors might become relevant. Our analysis can serve as a tool for studying these additional factors.

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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.

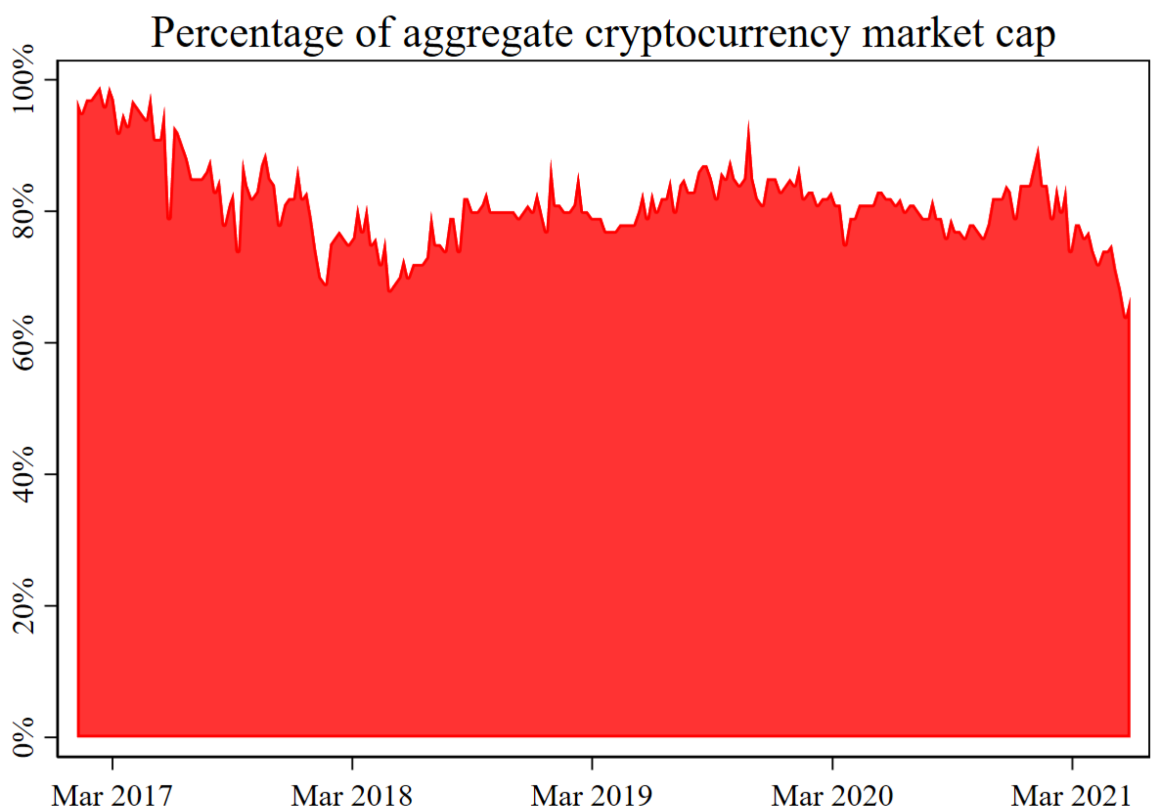

Figure 2: Fitted and Sample Average Cryptocurrency Returns: Full Sample

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 4.3 and the estimation results are reported in Table 5. The sample runs from 1/6/2017 to 5/28/2021.

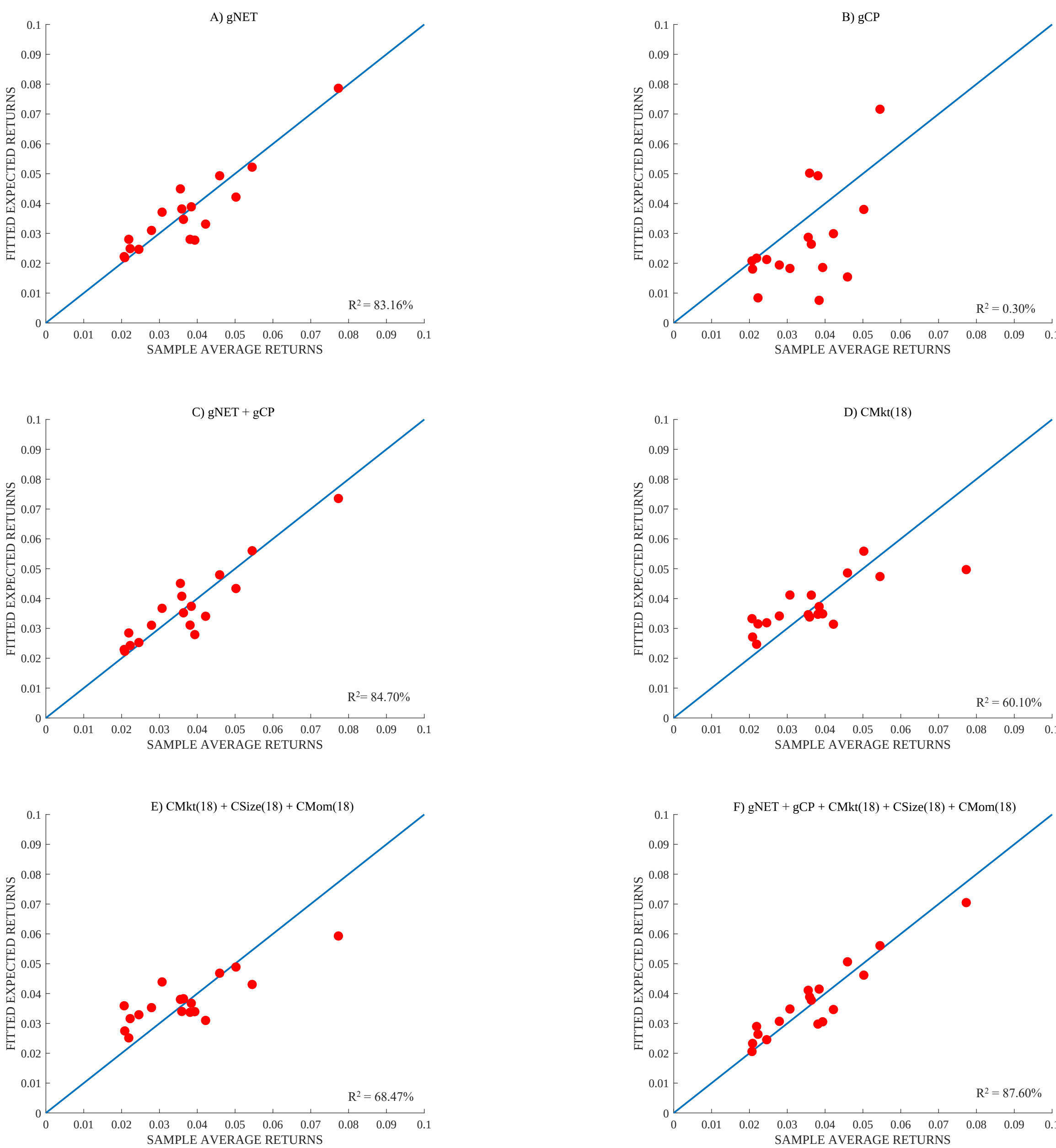

Figure 3: Fitted and Sample Average Cryptocurrency Returns: Rolling Regressions

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 4.3 and the estimation results are reported in Table 6. The sample runs from 1/6/2017 to 5/28/2021.

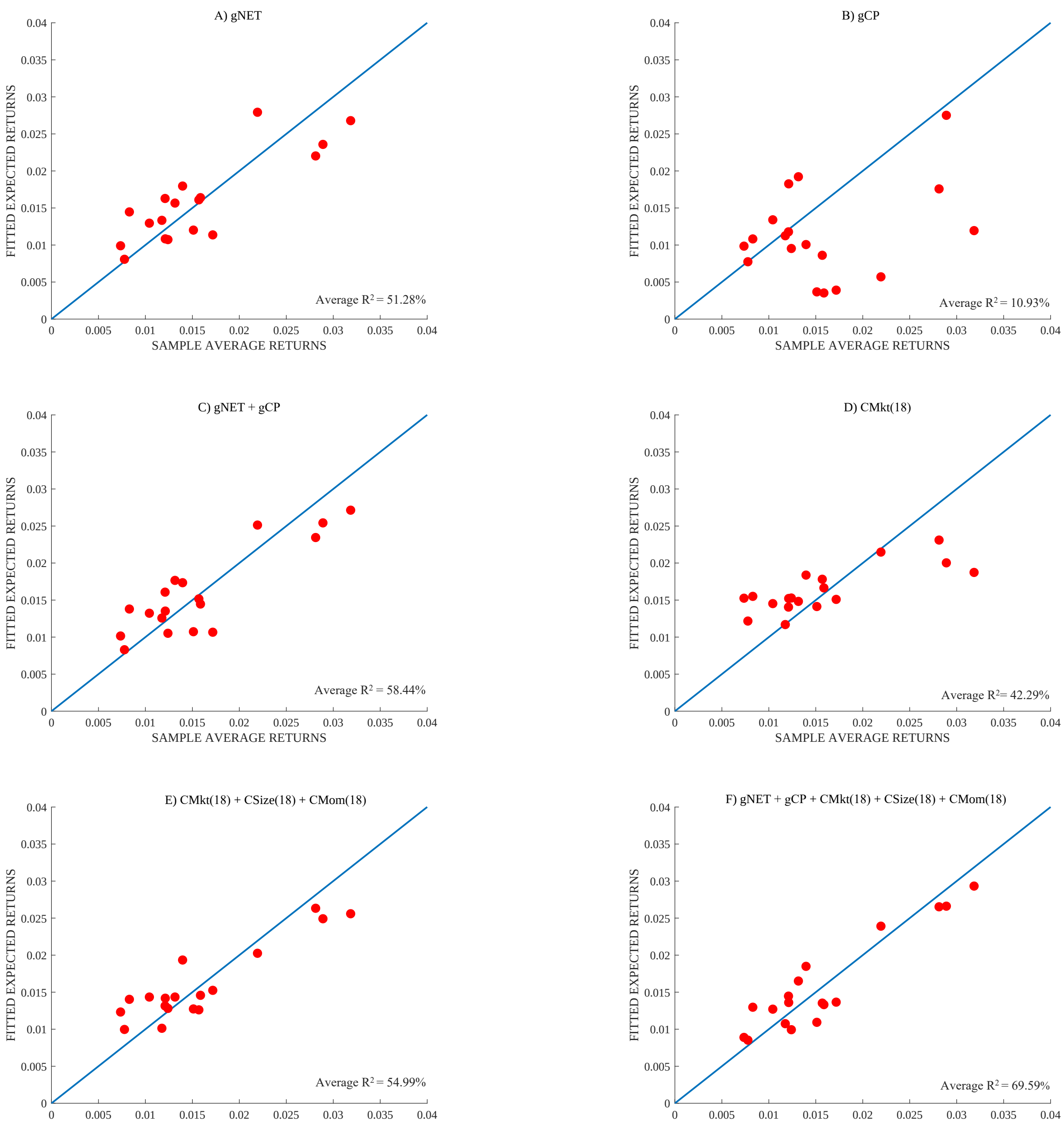

Figure 4: Cross-Sectional R^2's from Rolling Fama-MacBeth Regressions

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.

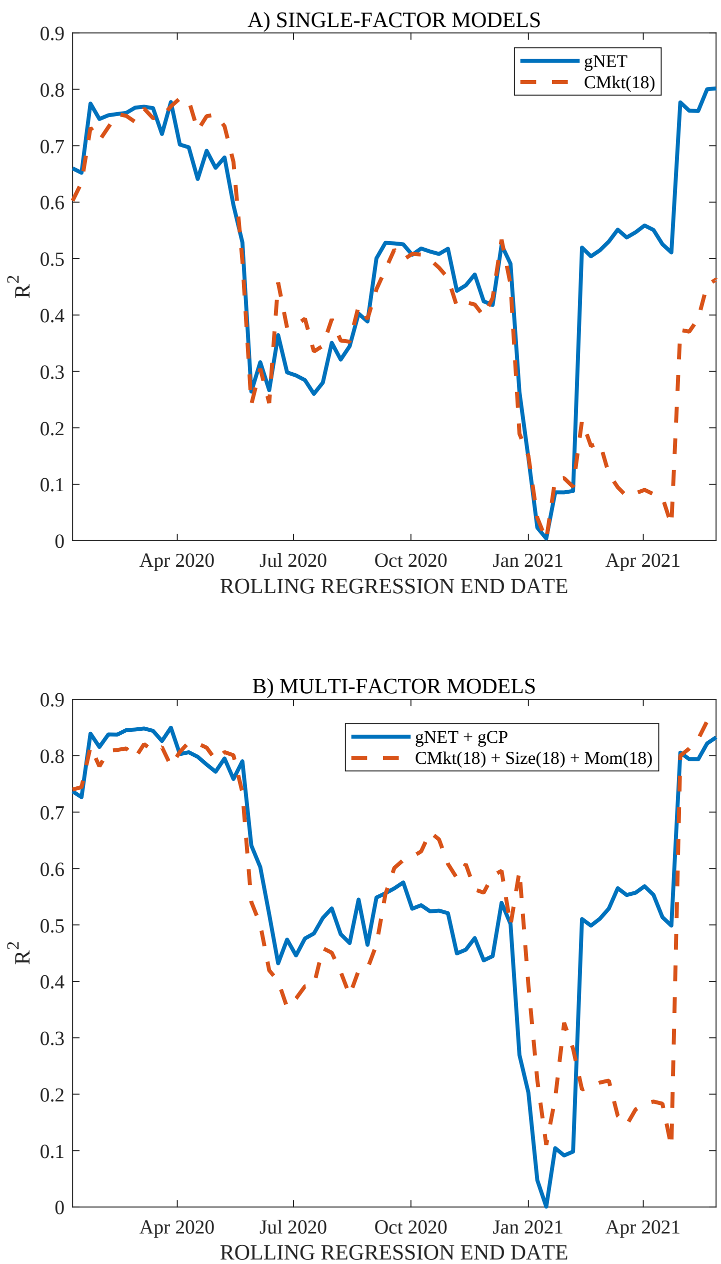

Table 1: Cointegrating Relation between Prices, Network Size, and Computing Power: Proof-of-Work Cryptocurrencies

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*** (9.75)	0.30* (1.75)	0.85*** (11.93)	−0.21 (−0.60)	0.95*** (3.19)	−0.57*** (−5.38)	0.86** (2.25)	0.30 (1.43)	1.11*** (15.65)	0.87*** (12.33)	
CP_t	1.20*** (4.68)	1.07*** (5.28)	0.27*** (2.89)	0.85*** (4.30)	−0.39 (−1.21)	0.95*** (6.45)	0.82 (1.47)	0.96*** (5.84)	0.43*** (7.70)	0.27 (1.38)	1.24*** (6.21)
ΔNET_{t+2}	0.11 (0.32)	0.46*** (2.96)	0.26** (2.12)	−0.68*** (−3.38)	0.11 (0.70)	−0.11* (−1.65)	0.04 (0.14)	0.03 (0.79)	0.10 (1.04)	0.49*** (3.48)	
ΔNET_{t+1}	0.63 (1.27)	0.54*** (2.66)	0.44*** (2.61)	−0.92*** (−3.06)	0.35 (1.53)	−0.19** (−1.96)	0.04 (0.08)	0.09 (1.27)	0.24** (2.31)	0.67*** (4.12)	
ΔNET_t	−2.30*** (−4.32)	0.35 (1.56)	−0.40*** (−3.11)	−0.45 (−0.79)	−1.23*** (−2.87)	0.27** (2.36)	−1.53** (−2.12)	−0.24 (−1.27)	−0.45*** (−2.90)	−0.27 (−1.48)	
ΔNET_{t-1}	−1.60*** (−3.47)	0.23 (1.25)	−0.27** (−2.22)	−0.29 (−0.67)	−0.84*** (−2.64)	0.19** (1.98)	−1.15** (−2.11)	−0.16 (−1.29)	−0.28*** (−2.74)	−0.11 (−0.64)	
ΔNET_{t-2}	−0.87*** (−2.83)	0.17 (1.24)	−0.10 (−1.09)	−0.17 (−0.64)	−0.53** (−2.22)	0.08 (1.30)	−0.61** (−2.08)	−0.08 (−1.23)	−0.13* (−1.67)	0.03 (0.20)	
ΔCP_{t+2}	0.35* (1.91)	3.06*** (6.04)	0.32 (1.24)	0.52 (1.33)	0.22 (0.55)	0.64** (2.03)	0.73** (2.00)	0.14 (0.91)	0.03 (0.28)	0.23 (0.79)	0.56 (1.49)
ΔCP_{t+1}	0.55** (2.02)	3.73*** (7.29)	0.48 (1.50)	0.63** (2.01)	0.33 (0.74)	0.92** (2.31)	0.76* (1.77)	0.31** (2.34)	−0.02 (−0.13)	0.51 (1.47)	0.86* (1.84)
ΔCP_t	−0.27 (−0.83)	2.88*** (6.06)	0.58* (1.91)	0.40 (1.21)	0.63* (1.70)	0.15 (0.35)	0.54 (1.40)	0.21 (1.53)	0.00 (0.02)	0.86** (2.57)	−0.40 (−0.83)
ΔCP_{t-1}	−0.10 (−0.32)	3.13*** (7.41)	0.55 (1.61)	0.80** (2.52)	0.82** (2.28)	0.33 (0.74)	0.90** (2.56)	0.18 (1.32)	0.02 (0.19)	0.88*** (2.77)	−0.42 (−0.83)
ΔCP_{t-2}	0.11 (0.53)	3.19*** (5.96)	0.34 (1.04)	0.73** (2.02)	0.52 (1.56)	0.07 (0.20)	0.58* (1.80)	0.20 (1.25)	0.01 (0.13)	0.49* (1.77)	−0.41 (−0.94)
δ_t	−0.01*** (−2.73)	−0.00*** (−4.38)	−0.00** (−2.06)	−0.01* (−1.70)	0.00* (1.76)	−0.00 (−1.55)	−0.01 (−1.41)	−0.00 (−1.48)	0.00*** (4.72)	−0.01* (−1.81)	−0.01*** (−3.87)
α	1.42*** (2.84)	0.15 (1.06)	0.26 (1.54)	1.12 (1.60)	−0.56** (−2.21)	0.28 (1.13)	1.63 (1.36)	0.42 (1.58)	−0.47*** (−3.56)	0.63* (1.74)	1.28*** (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 (6). 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 (6). 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 (6). 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: 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 4.3 and the estimation results are in Panel B of Table 7. The sample runs from 1/6/2017 to 5/28/2021.

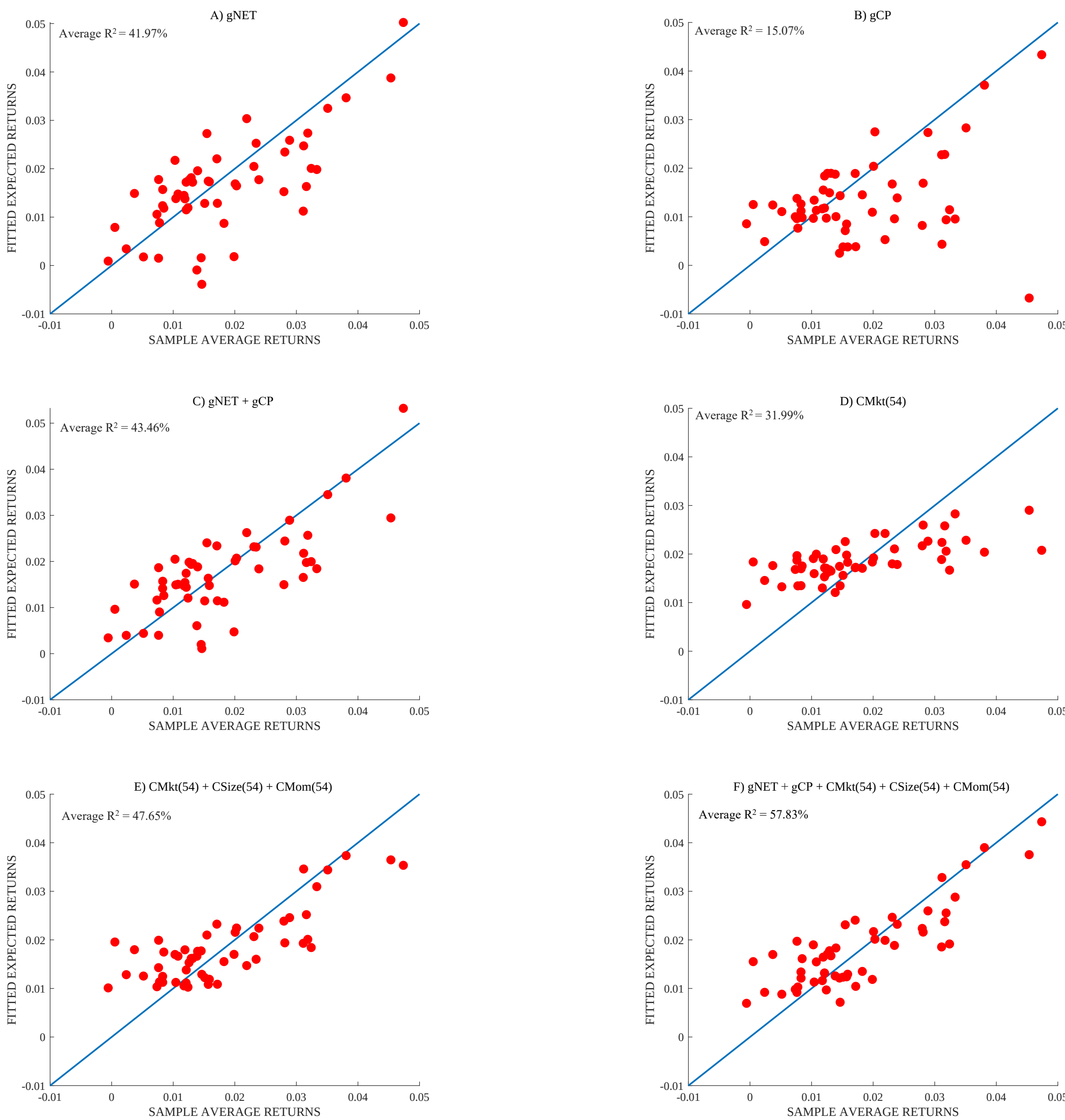
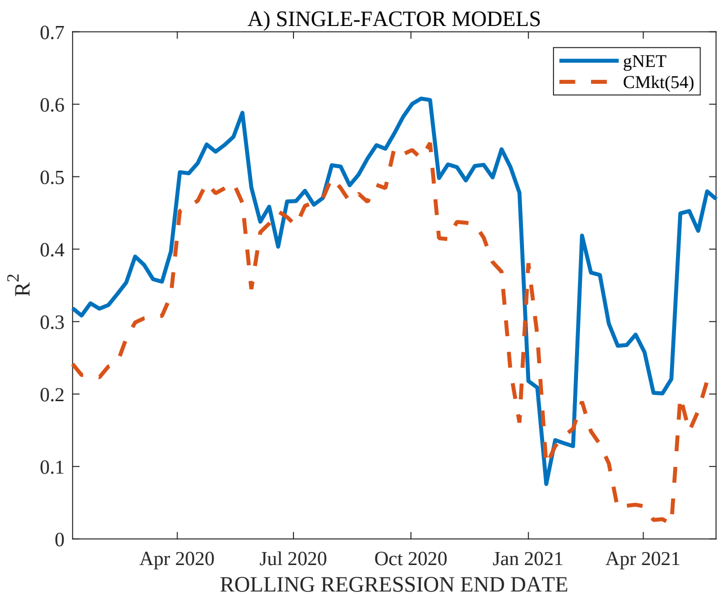


Figure A2: Cross-Sectional R^2's from Rolling Fama-MacBeth Regressions: 54 Cryptocurrencies

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.



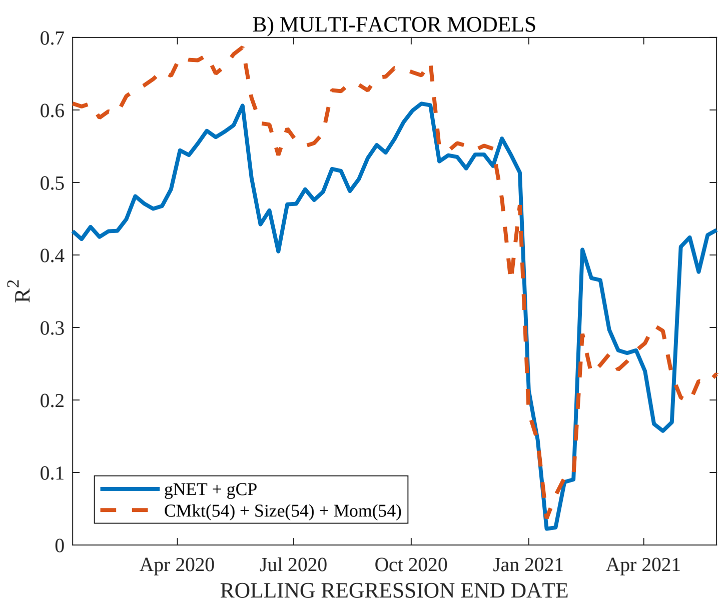


Table A1: Variable Descriptions

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.

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