Do Fundamentals Drive Cryptocurrency Prices?

Siddharth M. Bhambhwani*

Stefanos Delikouras†

George M. Korniotis‡

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Abstract

We examine if two fundamental blockchain characteristics affect cryptocurrency prices. They are computing power (hashrate) and network (number of users), which are related to blockchain trustworthiness and transaction benefits. We find a significant long-run relationship between these characteristics and the prices of prominent cryptocurrencies. We also document that cryptocurrency returns are exposed to fundamental-based risk factors related to aggregate computing power and network, even after controlling for Bitcoin return and cryptocurrency momentum. In out-of-sample tests, the computing power and network factors can explain the return variation of a broad set of cryptocurrencies, whose fundamentals are not included in the factors.

Keywords: Bitcoin, Ethereum, Litecoin, Monero, Dash, Hashrate, Computing Power, Network, Cointegration, Asset Pricing Factors

JEL Classification: E4, G12, G15

*Siddharth M. Bhambhwani, Hong Kong University of Science and Technology, email: acsidd@ust.hk

†Stefanos Delikouras, University of Miami, email: sdelikouras@bus.miami.edu

‡George M. Korniotis, University of Miami and CEPR, email: gkorniotis@bus.miami.edu

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Introduction

Identifying the determinants of asset prices is an important question in finance. Traditional asset pricing theories argue that fundamentals, like earnings, should determine equity prices (Gordon, 1959; Campbell and Shiller, 1988). In contrast, behavioral theories suggest that investor sentiment forces prices to deviate from fundamentals (Shiller, 1981; Baker and Wurgler, 2006; Stambaugh, Yu, and Yuan, 2012). Pástor and Veronesi (2003, 2006) argue that price run-ups can arise when future profitability is uncertain with prices eventually tracing fundamentals. Similarly, Bartram and Grinblatt (2018) show that even if prices deviate from their estimates of fair value, they eventually converge to fundamentals.

However, studying the impact of fundamental factors on equity prices is challenging because fundamentals are often difficult to measure and vary significantly across firms. For instance, fundamental firm characteristics like reputation and goodwill are unobservable, while the fundamentals of a technology firm, for example, are different from those of a hotel chain. The diversity in firm fundamentals might be the reason for the plethora of asset pricing factors (Cochrane, 2011). Many factors are based on fundamentals like investments and profitability (Fama and French, 2015; Hou, Xue, and Zhang, 2015) and others capture behavioral phenomena like investor inattention and mispricing (Hirshleifer and Jiang, Hirshleifer and Jiang; Daniel, Hirshleifer, and Sun, 2017; Stambaugh and Yuan, 2017).

Unlike public firms, cryptocurrencies have common fundamentals. Specifically, theory suggests that the computing power and network size of blockchains determine cryptocurrency values. These blockchain measures capture the trustworthiness and transaction benefits of a blockchain (Pagnotta and Buraschi, 2018; Biais, Bisiere, Bouvard, Casamatta, and Menkveld, 2018). Despite the robust theoretical predictions that cryptocurrency values are determined by fundamentals, there is almost no related empirical work.

In this paper, we fill the gap in the literature and carefully examine if cryptocurrency prices are empirically related to computing power and network size. We refer to these two blockchain measures as cryptocurrency fundamentals and offer two sets of novel findings.

First, we show that in the long run, the prices of cryptocurrencies depend on their computing power and network. Second, we construct asset pricing factors related to aggregate computing power and aggregate network and show that they can explain the time series variation of cryptocurrency returns. Our factor analysis is quite extensive, goes beyond Bitcoin, and it includes a total of 39 cryptocurrencies. Further, we explicitly recognize that factors like investor-sentiment that are unrelated to fundamentals may affect cryptocurrency returns. In our asset pricing tests we account for these effects by controlling for Bitcoin returns and cryptocurrency momentum.

We analyze the relationship between prices and fundamentals using five prominent cryptocurrencies that rely on miners to produce and secure the underlying blockchain. These are Bitcoin, Ethereum, Litecoin, Monero, and Dash. We focus on these cryptocurrencies because they are among the oldest and most established cryptocurrencies. As such they have reliable data on prices and fundamentals for a relative long time period. Specifically, we collect daily prices from August 7th, 2015 to June 28th, 2019 and aggregate them to the weekly frequency. We focus on the weekly frequency following Biais et al. (2018) to mitigate the impact of day-of-the-week effects. In our asset pricing factor tests, we also consider an extended sample of 34 cryptocurrencies. For the additional 34 cryptocurrencies, we are able to collect price data from March 31st, 2017 to June 28th, 2019.

We also gather information on network and computing power for each of the five main cryptocurrencies. We measure network by the number of unique users that transact on the blockchain. Computing power is measured in terahashes and it is directly related to the resources expended by miners creating blocks in the blockchain. These resources are electricity consumption, purchases of hardware and software as well as the cost of setting up mining farms. Even if we cannot measure these costs directly, computing power is a sufficient statistic of the resources spent on cryptocurrency mining. For example, Saleh (2018) suggests a positive relationship between computing power and electricity consumption. Additionally, we compare our computing power measure (i.e., hashrate) to the Cambridge Bitcoin Energy Consumption Index (CBECI), which takes into account the cost of producing Bitcoin vis-à-vis the efficiency of mining equipment and the costs of running mining facilities. We find that our hashrate measure is highly correlated with the CBECI.

Our empirical analysis starts with tests at the cryptocurrency level. Specifically, for each of the five baseline currencies, we examine if prices are related to computing power and network. Because these three variables are non-stationary, OLS regressions of prices on the two blockchain fundamentals are spurious (Phillips, 1986). Therefore, we estimate the corresponding (cointegration) relationship using the dynamic ordinary least squares (DOLS) of Stock and Watson (1993). The DOLS methodology has been used in the asset pricing literature because it accounts for the endogeneity of economic variables that are jointly determined in equilibrium. For example, Lettau and Ludvigson (2001) use DOLS to estimate the relation between consumption, income, and wealth, while Lustig and Van Nieuwerburgh (2005) use DOLS to estimate the trend of U.S. housing wealth with income.

We estimate full-sample and rolling DOLS regressions. The full-sample results show that there is strong cointegrating relationship between prices, computing power, and network. In particular, the cointegration parameters related to fundamentals are positive and statistically significant for all cryptocurrencies. The results from the rolling DOLS regressions show that cryptocurrencies face periods when prices deviate from fundamentals. The average duration of the price-deviation episodes are from 6 to 11 weeks. The existence of these price-deviation episodes is consistent with prior work showing that factors, which are not necessarily related to blockchain fundamentals, may affect cryptocurrency returns (e.g., Makarov and Schoar (2019)).

Next, we examine the asset pricing ability of the blockchain fundamentals. For this analysis, we follow the asset pricing literature and estimate factor regressions. The DOLS results suggest that prices are, on average, related to computing power and network, but in some periods prices deviate from fundamentals. We therefore create one set of factors related to fundamentals and a second one aiming to capture deviations from fundamentals.

Motivated by the existing results for equity markets, we conjecture that price deviations from fundamentals are related to investor sentiment trading (e.g., Baker and Wurgler (2006)). We consider two investor-sentiment factors. The first one is a cryptocurrency momentum factor, which we calculate following Jegadeesh and Titman (1993). We consider cryptocurrency momentum because momentum effects have been linked to investor psychology (e.g., see Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999)).

The second factor is Bitcoin. We conjecture that Bitcoin is susceptible to sentiment trading because it is the most traded cryptocurrency. Thus, it can capture periods when trading forces that are unrelated to fundamentals are strong. Also, from a completely different perspective, Bitcoin is the largest cryptocurrency in terms of market capitalization and it can be used as a proxy for cryptocurrency market-wide risk. Whether Bitcoin captures investor sentiment or is a proxy for systematic cryptocurrency risk, it is important that we include it in our empirical factor models.

We use the aforementioned crypto-momentum and Bitcoin factors to estimate a baseline 2-factor model. We find that the Bitcoin factor is statistically significant for Ethereum, Litecoin, Monero, and Dash, with betas ranging from 0.76 to 0.96. For the cryptocurrency momentum factor, we find significant exposures for Monero, Litecoin, and Dash.

Next, we examine whether cryptocurrency returns are exposed to aggregate factors based on blockchain fundamentals. Constructing these factors is not straightforward since blockchain measures are not in the same units and cannot be summed across cryptocurrencies. For example, computing power is not comparable across cryptocurrencies that use different hashing algorithms. To address this issue, we project the blockchain measures on the space of cryptocurrency returns using the factor-mimicking-portfolio (FMP) methodology (Knez, Litterman, and Scheinkman, 1994; Lamont, 2001; Vassalou, 2003). Specifically, for each cryptocurrency, we project its computing power and network growth rates on the space of cryptocurrency returns. We then aggregate these factor-mimicking portfolios to obtain market-wide fundamental factors related to computing power and network.

We test two predictions to show that the fundamental factors are procyclical asset pricing factors. Cochrane (2005) suggests that procyclical factors should indicate "good" and "bad" times for investors and should carry a positive risk premium. For cryptocurrency investors, "good" times are when aggregate computing power and network size are high because, as suggested by existing theories and our DOLS results, this is when prices are typically high. Consistent with our intuition, we find that the fundamental factors earn positive risk premia and have reasonable Sharpe ratios. For example, the Sharpe ratio of the computing power factor is 0.197. For the same period, the Sharpe ratio of the U.S. stock market is 0.124.

Our second prediction is that if the computing power and network factors are procyclical, then the exposures (betas) of cryptocurrency returns to these factors should be positive because cryptocurrencies earn high average returns. To test this hypothesis, we estimate three distinct 3-factor models. These models include the two factors from the baseline model, i.e., the Bitcoin return and the cryptocurrency momentum factor, combined with either the computing power factor, the network factor, or a cumulative factor. The cumulative factor is based on the singular value decomposition (SVD) of the two fundamental factors.

We find that the 3-factor models perform better than the 2-factor one. For Ethereum, for example, the adjusted R^2 rises from 20% in the 2-factor model to 67% in the 3-factor model with computing power. Cryptocurrency returns are also exposed to the fundamental factors since we estimate statistically significant positive betas ranging from 0.48 to 1.19 (0.72 to 1.44) for the aggregate computing power (network) factor. Further, in the presence of the fundamental factors, the Bitcoin and momentum betas become less significant.

Finally, we show that our results are robust to changes to our methodology. Our first robustness test is motivated by that fact that if the fundamentals-based factors are true sources of cryptocurrency risk, they should price the returns of any cryptocurrency. We test this hypothesis with a set of 34 cryptocurrencies that *excludes* the five baseline currencies. This is an out-of-sample test because the fundamentals of the new cryptocurrencies are excluded from the construction of the fundamental factors. We estimate pooled and currency-specific OLS regressions with the fundamental factors controlling for the momentum factor and the Bitcoin return. The estimation results show that the new cryptocurrencies have statistically positive exposures to the aggregate computing power and network factors. We find almost identical results when we control for the Ethereum return as opposed to the Bitcoin return.

The out-of-sample results indicate that the pricing ability of the two fundamental factors is neither mechanical nor is an artifact of the way we construct them.

In the next robustness test, we examine the effect of Bitcoin on our findings. Given that Bitcoin is the largest cryptocurrency, the significance of the computing power and network factors may be driven by Bitcoin's dominance. We therefore compute new aggregate computing power and network factors that are based on FMP regressions that *exclude* Bitcoin from the basis assets. Also, the new factors *exclude* the factor mimicking portfolios related to the fundamentals of Bitcoin. We find that the explanatory power of the new Bitcoin-free factors for cryptocurrency returns remains strong both in- and out-of-sample.

In the final robustness test, we expand the number of basis assets in the factor-mimicking-portfolio (FMP) regressions that we use to create the fundamental factors. Specifically, we add the 34 out-of-sample cryptocurrency returns so that each FMP regression has 38 basis assets. The new factors are computed for the time period for which the out-of-sample cryptocurrency data are available (i.e., March 31st, 2017 to June 28th, 2019). We find that the exposures of cryptocurrency returns on the new factors are still positive and significant.

Overall, our empirical findings contribute to the nascent literature on cryptocurrencies. Pagnotta and Buraschi (2018) provide a theory linking cryptocurrency prices to computing power, which reflects the network's trustworthiness, and the number of users, which captures network externalities. Biais et al. (2018) propose an overlapping generations model where the fundamental value of cryptocurrencies depends on transactional benefits. Abadi and Brunnermeier (2018) highlight that decentralized ledgers can become unstable because new ledgers can fork off (i.e., split off) an existing blockchain. Sockin and Xiong (2018) note that the "trustless" aspect of decentralized networks is a key innovation of blockchain technology, which also contributes to the value of the blockchain. We confirm the prediction of these theoretical papers that computing resources and network size affect prices.

One open question in the literature is identifying the asset pricing factors that drive cryptocurrency prices. Baur, Hong, and Lee (2018) find that Bitcoin is uncorrelated to other assets like equity, bonds, or commodities. Liu and Tsyvinski (2018) show that cryptocurrencies are exposed to momentum, captured by lagged cryptocurrency returns, and investor attention, captured by Google searches and Twitter activity. Liu, Tsyvinski, and Wu (2019) reach similar conclusions highlighting the importance of a cryptocurrency-based size factor.

We complement these papers in several ways. First, our factors are based on theoretical predictions that highlight the importance of blockchain characteristics. Specifically, we use computing power and network size because theoretical models relate these characteristics to the trustworthiness and transactional benefits of a blockchain. Second, instead of using long-short trading strategies, we estimate the proposed fundamentals-based asset pricing models at the cryptocurrency-level using five prominent cryptocurrencies. More importantly, we conduct an out-of-sample estimation using an extended set of 34 cryptocurrencies.

Overall, our results are related to the asset pricing literature. Pástor and Veronesi (2003, 2006) argue that valuation uncertainty leads to equity price run-ups. Similarly, the increase in cryptocurrency prices in late 2017 could be related to potentially disruptive capabilities of the blockchain technology (Catalini and Gans, 2016). Daniel et al. (2017) propose behavioral factors for explaining equity returns. We also consider a behaviorally-oriented factor, namely, cryptocurrency momentum. Finally, Harvey, Liu, and Zhu (2016) argue that the statistical significance of new factors should be high because of data mining. Following their conclusions, we conduct both in-sample and out-of-sample tests and show that the statistical significance of the fundamentals-based cryptocurrency factors clears their proposed hurdles.

The rest of the paper is organized as follows. Section 1 reviews cryptocurrencies, the literature, and presents our hypothesis. Section 2 describes our data and presents summary statistics. Section 3 presents our long-term analysis. Section 4 reports our factor analysis while Section 5 reports our out-of-sample factor analysis. Section 6 concludes the paper.

1. Background and Literature Review

We preface our analysis with a brief discussion on cryptocurrencies, computing power, and network. We also provide a brief literature review and present our central hypothesis.

1.1. Cryptocurrencies and Blockchain

There are two types of cryptocurrencies: mineable and non-mineable ones. In our main analysis we focus on five prominent mineable cryptocurrencies, namely Bitcoin, Ethereum, Monero, Litecoin, and Dash. Mineable cryptocurrencies are rewards to solving a cryptographic algorithm via a process known as mining. The miner that first solves the cryptographic algorithm generates a block and receives a reward. The block reward is in units of the respective cryptocurrency. In the process of mining blocks, miners verify transaction records into that block, which is then added (i.e., chained) to the prior block, thereby forming the blockchain (Nakamoto, 2008; Narayanan, Bonneau, Felten, Miller, and Goldfeder, 2016). By verifying transactions, miners also receive a fee for each transaction they record in the block.

Contrary to mineable cryptocurrencies, the distribution and creation of non-mineable cryptocurrencies (NMCs) is decided ex-ante and is generally based on the protocol of their founders. Cong, Li, and Wang (2018) discuss the economics of non-mineable currencies, which they refer to as "tokens." We exclude NMCs from our main analysis because the absence of mining activity implies that they do not have a measure of computing power. However, we use NMCs in our out-of-sample robustness tests presented in Section 5.1.

1.2. Computing Power

An important characteristic of blockchains of mineable cryptocurrencies is computing power. Computing power is measured in hashes, with one hash referring to one function solved by a computer. Saleh (2018) argues that computing power is related to the resources expended to maintain the blockchain. Specifically, he reports that Bitcoin and Ethereum, which have the highest computing powers of all cryptocurrencies, "collectively consume more energy on an annual basis than all but 69 countries individually." Unfortunately, there is no data available for the energy consumption of most cryptocurrencies. Thus, we use computing power as a proxy for overall resources spent on crypto-mining, including electricity.

Computing power is important because it facilitates the fast and secure record-keeping of transactions. For example, a rogue miner needs more than 50% of the existing computing power of a cryptocurrency to hijack its blockchain and record transactions to her private benefit. This is currently impossible for cryptocurrencies with high computing power like Bitcoin (Kroll, Davey, and Felten, Kroll et al.; Eyal and Sirer, 2018).

1.3. Network

The other characteristic of blockchains, which is as important as computing power, is the size of the cryptocurrency network. Network is the number of unique active users that that transact the cryptocurrency, whose unique address is publicly available on the blockchain . Analogous to established fiat currencies that have a large number of entities willing to accept them for transactions, a large network is indicative of greater adoption of the cryptocurrency. A large number of unique blockchain users is also suggestive of enhanced liquidity of the respective cryptocurrency. Moreover, a large network attracts developers to build applications for the cryptocurrency's blockchain, which increase the usability of the currency. For example, cryptocurrencies with large networks such as Bitcoin and Ethereum have a multitude of Android, iOS, and Windows wallet applications.

1.4. Literature Review

Despite the significance of computing power and network size for the efficient functioning of blockchains, the existing literature has not carefully studied how they relate to cryptocurrency prices. Instead, many studies have focused on whether cryptocurrencies are real currencies. Yermack (2015) argues that Bitcoin is not yet a proper currency because it is not a widespread medium of exchange or unit of account. He concludes that Bitcoin is a speculative asset due to its high price volatility relative to other currencies. Selgin (2015) and Baur et al. (2018) argue that Bitcoin combines features of fiat and commodity currencies. More recently, Pagano and Sedunov (2019) posit that Bitcoin is a true form of money in recent years as more vendors accept it as medium of exchange.

One hurdle with using cryptocurrencies as media of exchange or store of value is that their secondary markets are underdeveloped. For example, Auer and Claessens (2018) argue that because of market segmentation, regulatory news in a jurisdiction affects the prices of cryptocurrencies traded in that jurisdiction. Makarov and Schoar (2019) study the prices of Bitcoin, Ethereum, and Ripple across different exchanges. They find that sometimes prices differ across exchanges for weeks, which imply large arbitrage profits. Such arbitrage profits can lead to persistent price run-ups or jumps as documented by Cheah and Fry (2015), who find that during July 2010 to July 2014 Bitcoin went through a number of "bubble-like" periods. Cheah and Fry (2015) conclude that Bitcoin has zero fundamental value and its price is driven by investor sentiment.

Another concern with cryptocurrencies is their use for illegal transactions. The extent to which cryptocurrencies, and Bitcoin in particular, is used for illicit activities is only based on approximations and it varies significantly across studies. Foley, Karlsen, and Putniņš (2019) estimate that over the 2009 to 2017 period about 46% of Bitcoin's trading volume was related to illegal activities. They also find that the portion of illegal activity started decreasing in 2013 with a substantial decrease in 2015. Consistent with Foley et al. (2019), Fanusie and Robinson (2018) find that over the 2013 to 2016 period less than 1% of Bitcoin transactions entering conversion services (i.e., services exchanging cryptocurrencies for fiat money) can be linked to money laundering.

Overall, in recent years, the use of Bitcoin for illegal activities have been decreasing. Therefore, if the value of Bitcoin were mainly determined by its use by criminals, its prices should have been decreasing. The drop in its price should have been especially strong after the major Bitcoin seizures by authorities in 2013, which demonstrated that Bitcoin transactions are traceable.[1]. In contrast, the price of Bitcoin kept increasing after 2013 and all through 2017, suggesting that facilitating illicit activities is not the main driver of its value in recent years.

Despite the concerns related to cryptocurrencies, cryptocurrencies have facilitated the

[1]On October 1, 2013, the FBI seized the Bitcoins of Ross William Ulbricht, the founder of Silk Road. On October 2, 2013, it seized the Bitcoins kept in the Silk Road escrow accounts

introduction of the blockchain technology in our economic life, which constitutes a significant innovation. Yermack (2017) highlights that blockchain usage can improve corporate governance. Cong and He (2019) emphasize that blockchain technology can lead to executing contracts automatically. Chiu and Koeppl (2019) show that the blockchain technology improves the settlement of securities.

An important open issue is the relation of the nascent cryptocurrency market with other financial markets as well as identifying the asset pricing factors that drive cryptocurrency expected returns. Baur et al. (2018) find that Bitcoin is uncorrelated to equity, bonds, and commodities. Liu and Tsyvinski (2018) show that Bitcoin, Ripple, and Ethereum are unrelated to equity, bonds, currencies, and precious metals markets. They also find that cryptocurrencies are not exposed to existing financial factors but instead, they are exposed to two cryptocurrency-specific factors. These factors are momentum, which is captured by lagged cryptocurrency returns, and investor attention, which is measured by Google searches and Twitter activity. Liu et al. (2019) reach similar conclusions for a much larger set of cryptocurrencies while highlighting the importance of a cryptocurrency-based size factor. Bianchi (2018) also finds strong momentum effects in Bitcoin returns.

Existing theoretical work studies the fundamental value of currencies in decentralized financial networks. Pagnotta and Buraschi (2018) show that the fundamental values of mineable cryptocurrencies should depend on consumer preferences (i.e., aversion to risk and censorship) and usefulness of the currency (captured by trust and adoption levels). Trust is related to the absence of fraud, resistance to censorship, and protection from cyber-attacks and it is related to the computing power devoted to the currency. Biais et al. (2018) highlight the importance of transactional benefits for cryptocurrency values, which are related to the number of cryptocurrency users.

Finally, there is important work focusing on microstructure issues. For instance, Easley, O'Hara, and Basu (2018) explore the role of transaction fees paid to miners for the evolution of the Bitcoin market. They argue that transaction fees are important to keep the blockchain viable as more and more blocks are being mined. Abadi and Brunnermeier (2018) study the theoretical problem of whether record-keeping is better arranged through distributed ledgers than through a traditional centralized institution.[2]

1.5. Testable Hypotheses

We form two testable hypotheses following the prior theoretical literature. First, at the individual cryptocurrency level, we examine whether prices are related to computing power and network size. Based on the existing theoretical models, we expect that, on average, there should be a positive relation between prices, computing power, and network size. Given the recent empirical evidence (e.g., Corbet, Lucey, and Yarovaya (2018), Liu and Tsyvinski (2018), Makarov and Schoar (2019)), we also expect that there might be periods where prices deviate from the relationship with the two blockchain fundamentals.

Second, at the cryptocurrency market level, we examine whether aggregate measures of blockchain fundamentals capture sources of systematic risk. Given the strong theoretical relation between cryptocurrency prices and fundamentals, the aggregate factors related to computing power and network should be able to explain cryptocurrency returns. We test this conjecture with traditional factor analysis inspired by the asset pricing literature.

2. Data and Descriptive Statistics

In this section, we describe our data sources and sample summary statistics. For completeness, we also provide descriptions of the main variables in Table A1 of the Appendix.

2.1. Cryptocurrency Price Data

In our main analysis, we focus on Bitcoin, Ethereum, Litecoin, Monero, and Dash, which have dominated the market in terms of capitalization. For instance, they account for 70%

[2]The importance of computing power, adoption levels, and transaction fees for the proper functioning of a blockchain is also highlighted in Houy (2014), Malinova and Park (2017), Tinn (2017), Huberman, Leshno, and Moallemi (2017), Cong et al. (2018), Li, Ma, and Chang (2018), Prat and Walter (2018), Chiu and Koeppl (2019), Cong and He (2019), and Iyidogan (2019).

to 95% of the aggregate cryptocurrency market when including NMCs and over 98% when excluding them (see Table 1). Because these 5 currencies are among the oldest and most established one, we can collect a relative large sample of prices and blockchain measures.

We use daily price from Coinmetrics.io. Coinmetrics.io obtains prices from liquid cryptocurrency exchanges and weighs them by the trading volume of each exchange. We use this volume-weighted price. Coinmetrics.io uses data from 22 established exchanges out of the approximately 260 exchanges currently operating.[3] To filter out illiquid or unreliable exchanges, Coinmetrics.io uses 35 criteria that exchanges must meet in order for their prices to be included in the volume-weighted aggregation.[4] The prices are quoted in U.S. Dollars.

The daily prices are as of 00:00 UTC time of the following day (i.e., Friday's prices are recorded as of 00:00 UTC Saturday). We compute weekly returns by averaging the daily log prices over a 7-day period, and taking the first difference of the weekly averages. The 7-day period ends on Friday similar to the Friday convention in the weekly Fama-French factors. We repeat our analysis using various ending days for our 7-day period, such as Sunday or Monday, and find qualitatively very similar results. We use 7-day intervals that include weekends because cryptocurrency exchanges run around the clock. We average prices across the 7-day period to mitigate any day-of-the-week effects and the problems with outliers.

2.2. Computing Power and Network Data

Our proxies for cryptocurrency fundamentals are computing power and network, which are also provided by Coinmetrics.io. Computing power is measured in terahashes (1 terahash = 10^{12} hashes). Network measures the number of unique active addresses transacting on the blockchain. Addresses that conduct multiple transactions are not double-counted. We are unable to gather the number of active addresses for Monero because this cryptocurrency uses ring signatures to mask transactions across multiple addresses obfuscating the true address

[3] Please see https://coinmarketcap.com/rankings/exchanges/3 for a non-exhaustive list of exchanges

[4] Bitwise presented a report to the SEC that 95% of volume on some exchanges was faked (https://www.sec.gov/comments/sr-nysearca-2019-01/srnysearca201901-5164833-183434.pdf). Examples of suspicious exchanges were CoinBene, OkEX, IDAX, LBank, Exrates, and BitForex. The Coinmetrics.io data does not include any of these exchanges.

count (Narayanan et al., 2016). Based on the daily blockchain measure, we construct weekly growth rates using the same approach as with weekly cryptocurrency returns.

2.3. Validation of the Computing Power Measure

We argue that computing power, measured by the hashrate, is a sufficient statistic for the resources expended to maintain a blockchain. We can not use a direct measure of resources because it is unavailable for almost all cryptocurrencies. However, we validate our computing power measure by comparing it to the energy cost indices of Bitcoin and Ethereum. For Bitcoin, in untabulated results, we find a 99% correlation of its hashrate with the Cambridge Bitcoin Energy Consumption Index (CBECI).[5] We also validate the computing power measure for Ethereum's hashrate using data from Digiconomist's Ethereum Energy Consumption Index. In untabulated results, we find a 89.53% correlation between the Digiconomist index and our hashrate measure.[6] These results suggest that computing power captures the real resources expended on powering the blockchain.

2.4. Descriptive Statistics

As described above, our main variables are the weekly growth rates of prices, computer power, and network. We report their descriptive statistics in Table 2 and Table A2 in the Appendix for the period August 7th, 2015 to June 28th, 2019. As we see in Panel A of Table 2, all five cryptocurrencies have positive average returns. Also, they demonstrate significant return fluctuations as their standard deviations are substantially larger than their respective means. For example, the standard deviation of Ethereum is 5.59 times larger than its mean. This finding is not surprising since cryptocurrencies are a new asset class. For instance, Pástor and Veronesi (2003) find that the return volatilities of young firms are much greater than

[5]The high correlation is not surprising since the research examining the costs of mining, including the CBECI, relies on the hashrate as a key parameter to proxy some costs related to the cost of producing Bitcoin. For the full methodology of CBECI, please visit https://www.cbeci.org/methodology/.

[6]We are only able to obtain data from May 2017 onwards for the Ethereum Energy Consumption Index. Please see the graph of Ethereum's energy consumption at https://digiconomist.net/ethereum-energy-consumption. The methodology follows from De Vries (2018). In untabulated results, we also find a 98% correlation between Bitcoin's hashrate and Digiconomists's Bitcoin Energy Consumption Index.

their average returns. Similarly, the computing power growth (Panel B) and average network growth (Panel C) have standard deviations that are greater than their respective averages. Overall, these descriptive statistics confirm the prior literature that cryptocurrencies have high volatility in prices and fundamentals.

Finally, in Table A2 in the Appendix, we report the correlation estimates across the five cryptocurrencies. We find that the five cryptocurrencies are positively correlated. However, the magnitude of these correlations, which ranges from 0.33 to 0.63, is weaker than those of standard equity portfolios used in asset pricing tests. For instance, the cross-correlations (untabulated) of the weekly returns for the six Fama-French portfolios sorted on size and book-to-market range from 0.74 to 0.96 over the same sample period.

3. Prices and Fundamentals in the Long-Term

In this section, we estimate the relationship between cryptocurrency prices and fundamentals. We find that the price of a cryptocurrency is typically high when its computing power and network are also high. This finding enables us to claim in Section 4 that aggregate computer power and aggregate network are procyclical risk factors that indicate "good" and "bad" times for cryptocurrency investors. Without this cryptocurrency-level "micro" evidence, we cannot claim that the aggregate blockchain measures are procyclical risk factors.

3.1. Graphical Analysis of Prices and Fundamentals

We begin by plotting the price of Bitcoin, Ethereum, and Monero along with their computing power (network) in Figure 1 (Figure 2). We present the graphs for Litecoin and Dash in Figures A1 and A2 of the Appendix, respectively. In these figures, we normalize each time series by subtracting their means and dividing by their standard deviations.

Overall, we observe a positive relation between prices and fundamentals. However, sometimes prices deviate from the trend with fundamentals. For example, according to Panel A of Figure 1, after September 2017 the price of Bitcoin rises above the trend with computing power. From late 2018 onward, the price of Bitcoin moves below the trend and eventually retraces back to the trend with computing power in early 2019. In the case of Ethereum (Panel B of Figure 2), the trend in prices falls below the trend in network size during the later months of 2018 and retraces back towards the common trend in mid 2019.

3.2. Evidence of Non-Stationarity

The graphical evidence suggests that cryptocurrency prices are related to computing power and network. The graphs also suggest that these three variables might be non-stationary. Therefore, we test for units roots with the augmented Dickey and Fuller (1979) (ADF) test. For the ADF test, we use a regression that includes a constant, a linear time trend, and four lags. In untabulated tests, we find that the inference of the ADF test is robust to using up to eight lags and no linear time trend in the ADF regression.

We report the ADF test statistic as well as descriptive statistics for the log-levels of prices, computing power, and network size in Table A3 of the Appendix. Given the size of our time series sample, the ADF test statistic would imply a rejection of the null hypothesis of a unit root at the 5% significance level if its value were lower than -3.55. According to Table A3, our estimated ADF test statistics range from -3.017 to $+0.262$ suggesting that the time series of prices and fundamentals are non-stationary.

3.3. Evidence of Cointegration

Based on the evidence of non-stationarity, we cannot estimate the relationship between prices and fundamentals with ordinary least squares because such regressions would be spurious (e.g., Phillips (1986)). Instead, we proceed with cointegration analysis. Following Lettau and Ludvigson (2001) and Lustig and Van Nieuwerburgh (2005), we determine the number of cointegrating relationships with the Johansen test (Johansen, 1988, 1991). According to the Johansen trace statistics, in untabulated results, we find that there is only one cointegrating relationship between price, computing power, and network for all five cryptocurrencies.

3.4. Dynamic Ordinary Least Squares Methodology

Since there is only one cointegrating relationship, we can use the dynamic ordinary least squares (DOLS) of Stock and Watson (1993) to estimate it. The DOLS provides a consistent estimate of the cointegrating vector when regressors are endogeneous and jointly determined in equilibrium. Lettau and Ludvigson (2001) use DOLS to estimate the trend of aggregate consumption with income and wealth. For instance, Lustig and Van Nieuwerburgh (2005) use DOLS to estimate the relationship between U.S. housing wealth and income.

We apply the DOLS methodology as follows. Theory predicts that there is a positive relationship between prices and blockchain fundamentals. We take this prediction to the data and assume that empirically there is a linear cointegrating relationship between log prices ($Price$), log computing power (CP), and log network (NET). As in Lustig and Van Nieuwerburgh (2005), we impose the restriction that the cointegrating vector eliminates any deterministic trends. This set up implies the following empirical linear model:

$$Price_t \ = \ \alpha \ + \ \delta \times t \ + \ \beta_{CP} \times CP_t \ + \ \beta_{NET} \times NET_t \ + \ e_t. \tag{1}$$

Above, e_t is a white noise process implying that deviations from the relationship between $Price$, CP, and NET are temporary.

Since CP and NET are endogenous, they are correlated with e_t in equation (1) and the OLS estimates of β_{CP} and β_{NET} are biased. The way to resolve the endogeneity problem in the Stock and Watson (1993) framework is to project e_t onto the first difference of CP (ΔCP) and NET (ΔNET) and obtain the following linear projection for e_t:

$$e_t \ = \ \sum_{\tau=-k}^{k} \beta_{CP,\tau} \times \Delta CP_{t+\tau} \ + \ \sum_{\tau=-k}^{k} \beta_{NET,\tau} \times \Delta NET_{t+\tau} \ + \ \epsilon_t. \tag{2}$$

In equation (2), the new error term ϵ_t is orthogonal to e_t. Finally, we combine equations (1) and (2) to derive the DOLS regression:

$$\begin{aligned} Price_t \ &= \ \alpha \ + \ \delta \times t \ + \ \beta_{CP} \times CP_t \ + \ \beta_{NET} \times NET_t \ + \ \sum_{\tau=-k}^{k} \beta_{CP,\tau} \times \Delta CP_{t+\tau} \quad (3) \\ &+ \ \sum_{\tau=-k}^{k} \beta_{NET,\tau} \Delta NET_{t+\tau} + \epsilon_t. \end{aligned}$$

Stock and Watson (1993) show that under mild conditions, the ordinary least squares estimates of β_{CP} and β_{NET} from the DOLS regression (3) are not affected by endogeneity because all the right-hand-side variables in equation 3 are orthogonal to ϵ_t. For parsimony, we use one lead and one lag for the first differences of the right-hand-side variables in equation (3). The estimation results are similar when using up to 3 leads and 3 lags. From the estimation results, we focus on the estimates of β_{CP} and β_{NET}. We compute their t-statistics with robust Newey-West standard errors corrected for autocorrelation. The length of the autocorrelation is determined by automatic bandwidth selection.

3.5. Full Sample DOLS Estimation

We present the results of the DOLS estimation for our full sample in Table 3. According to our findings, cryptocurrency prices are positively related to fundamentals. In particular, the cointegration parameters for computing power and network are positive and statistically significant for all five cryptocurrencies with the exception of the computing power estimate of β_{CP} for Litecoin (column (4) of Panel A).

For instance, in the case of Bitcoin (column (1) in Panel A), the cointegration parameter for computing power (β_{CP}) is positive and significant (estimate = 1.298; t-statistic = 5.88). Similarly, the cointegration parameter for computing power for Ethereum (column (2) in Panel A) is also positive and significant (estimate = 0.912; t-statistic = 3.53). The currency with the strongest relationship with its computing power is Monero with a cointegration parameter of 1.526 (t-statistic = 11.25).

The cointegration parameters for network (β_{NET}) are also positive and significant for all currencies. For example, in the case of Bitcoin, the cointegration parameter estimate is 1.802 (t-statistics = 3.76). In the case of Ethereum, the cointegration parameter estimate is 0.612 (t-statistics = 2.20). Overall, the results in Panel A of Table 3 provide evidence that in the long-run, cryptocurrency prices share the same trend with blockchain fundamentals.

3.6. Rolling DOLS Estimation

Prior research suggests that there might exist periods when prices deviate from fundamentals (e.g., Makarov and Schoar (2019)). To identify these periods, we estimate rolling DOLS regressions. From the rolling regressions, we focus on the statistical significance of the β_{CP} and β_{NET} parameter estimates. In particular, we identify periods during which the estimates of β_{CP} and β_{NET} are either statistically insignificant (i.e., $-2 \leq t$-statistic < 2) or inconsistent with economic theories (i.e., t-statistic < -2). We call these periods price-deviation episodes. We also examine the severity of these price deviations, by calculating the average number of weeks that prices deviate from fundamentals

We estimate 180 rolling DOLS regressions across the 202 weeks using 20-week windows. We report the number and the average length of the price-deviation episodes for computing power (network) in Panel B (C) of Table 3. We find that cryptocurrencies experience between 6 to 9 and 8 to 11 episodes during which prices deviate from the trend with computing power and network, respectively. In the case of Bitcoin, for example, we count 6 and 9 such episodes where its price is unrelated to computing power and network size, respectively. We also find that the average duration of these episodes is about 22 weeks for computing power and only 6.44 weeks for network.

Overall, the DOLS estimates suggest that in the long-run cryptocurrency prices share a common trend with their blockchain fundamentals. Temporarily, however, the strength of this relationship may weaken.

4. Aggregate Fundamentals as Asset Pricing Factors

In this section, we conduct standard asset pricing tests shifting our attention from individual cryptocurrencies to the aggregate cryptocurrency market.

4.1. Testable Predictions: Procyclical Factors

Our asset pricing tests are based on the hypothesis that computing power and network size are procyclical asset pricing factors. This hypothesis follows from the existing theoretical models and our DOLS results.

Specifically, theoretical models (e.g., Pagnotta and Buraschi (2018)) suggest that cryptocurrency prices are high when the trustworthiness and transaction benefits of the currency are also high. Thus, at the aggregate level, when the overall trustworthiness and transaction benefits are high, prices of most currencies should also be high. These periods are good times for cryptocurrency investors because the value of their cryptocurrency wealth is high. The DOLS analysis from Section 3.5 confirms these theoretical insights since we find that good times in the cryptocurrency market, i.e., periods of high prices, are associated with larger values for computing power and network size. Based on this evidence, computing power and network should be procyclical cryptocurrency factors.

We test whether the two fundamental factors are procyclical following the intuition in Cochrane (2005). To begin with, procyclical asset pricing factors that are also traded assets (e.g., Fama and French (2015)) should carry positive risk premia because they deliver high (low) returns during good times when marginal utility of wealth is low (high). Further, assets that earn positive risk premia should have positive exposures to procyclical asset pricing factors. Based on this intuition, we first examine whether the aggregate computing power and network carry positive risk premia. Second, since cryptocurrencies earn large and positive risk premia (see Table 2), we test whether their betas with respect to the procyclical fundamental factors are positive.

4.2. Construction of Fundamental-Based Cryptocurrency Factors

We follow the asset pricing literature and construct *return*-based fundamental factors. Similar to consumption growth (e.g., Lettau and Ludvigson (2001)), computing power, and network are non-traded factors. Therefore, we use the factor-mimicking-portfolio methodology to project them on the space of cryptocurrency returns. This is similar to creating factor-mimicking portfolios for macroeconomic factors such as U.S. consumption growth or U.S. GDP growth (e.g., see Knez et al. (1994) and Vassalou (2003)).

Projecting the blockchain measures on returns serves two purposes. First, because the fundamentals of each cryptocurrency are now expressed in "return" units, we can aggregate them across currencies. To the contrary, raw values of blockchain measures of different cryptocurrencies cannot be summed since, according to Table A4 in the Appendix, they use different hashing algorithms. Second, the return-based cryptocurrency factors allow us to test the two predictions implied by the asset pricing analysis. Specifically, we can test whether computing power and network are procyclical factors that command positive risk premia and whether cryptocurrencies with large positive expected returns have positive exposures to these procyclical factors.

To construct the factor-mimicking portfolios (FMPs), we project the growth rate of computing power and network of the five currencies on the returns of the other four currencies. We exclude the respective cryptocurrency when calculating its projection on cryptocurrency returns to avoid mechanical correlations between the cryptocurrency returns and the corresponding factor. For example, in the case of computing power, we estimate OLS regressions of the changes in log computing power of each cryptocurrency on the returns of the other four cryptocurrencies. We normalize the OLS estimates and calculate portfolio weights for the four cryptocurrencies. We compute the FMP of computing power by multiplying the OLS-based weights with the returns of the respective four cryptocurrencies.

We repeat this procedure for each of the five cryptocurrencies. We then calculate the aggregate computing power factor as the rank-weighted average of the computing power FMPs. The weights are based on ranks created using the market capitalization rates of the five cryptocurrencies in the prior period.[7] We denote the aggregate computing power factor

[7] To construct the rank-based weights, we rank the five cryptocurrencies by market capitalization. We assign ranks 1 to 5 to the cryptocurrency with the lowest to highest market capitalization. We transform ranks into the respective weights 1/15, 2/15, 3/15, 4/15, and 5/15. We find qualitatively similar results when using weights based on actual market capitalization rates. However, to avoid mechanical correlations between market capitalization rates and cryptocurrency returns, we use the rank-weighted approach.

by ACP. We follow a similar procedure for the aggregate network factor where we exclude Monero due to unreliable network data. We denote the aggregate network factor by $ANET$. Finally, we construct a cumulative fundamentals factor by combining the ACP and $ANET$ factors using the singular value decomposition (SVD) methodology.

Once concern with our FMP methodology is that we are only using 4 basis assets in the FMP regressions. As a robustness test, in Section 5.4, we increase the number of basis assets to include 34 additional cryptocurrencies. After computing these new fundamental factors, we repeat our asset pricing tests, and find similar results compared to the results with the original factors. In our main analysis, we maintain the original factors because we can compute them for a longer time period (August 7th, 2015 to June 28th, 2019). The sample with the additional currencies is much shorter and starts from March 31st, 2017.

4.3. Investor-Sentiment Cryptocurrency Factors

The results from our rolling DOLS regressions suggest that factors other than fundamentals may influence cryptocurrency prices causing them to deviate from the trend with computing power and network. To account for this finding in our asset pricing tests, we consider two factors which we conjecture are related to investor sentiment.

The first one is the Bitcoin return, which we denote by $\Delta Price(BTC)$. Bitcoin is the most important cryptocurrency since it constitutes about 51% to 84% of the aggregate market capitalization inclusive of NMCs (see Table 1). Because of its popularity and high trading volume, we posit that it is susceptible to sentiment trading. Therefore, as a factor, the return of Bitcoin may be able to capture the trading forces that create short-term deviations between prices and fundamentals.

Although we classify Bitcoin as an investor-sentiment factor, we acknowledge that because of its large market capitalization, it can also be considered a proxy for cryptocurrency market-wide risk. According to the results in Liu et al. (2019) (see Table 1 and Figure 1 in Liu et al. (2019)), the return on Bitcoin exhibits very similar statistical properties to the overall cryptocurrency market. Whether Bitcoin captures investor sentiment or systematic risk, it is important to include it as a separate factor in our empirical analysis.

Our second investor-sentiment factor captures momentum effects. We construct a cryptocurrency momentum factor following Jegadeesh and Titman (1993). Specifically, our momentum factor is the difference between the contemporaneous return of the cryptocurrency with highest return (winner) in the prior period and the contemporaneous return of the cryptocurrency with lowest return (loser) in the prior period. We exclude Bitcoin from the momentum factor because we include its return as a separate factor. We include the cryptocurrency momentum factor in our empirical analysis because the asset pricing literature has shown that momentum effects can be attributed to investor psychology (e.g., see Barberis et al. (1998), Daniel et al. (1998), and Hong and Stein (1999)). Liu and Tsyvinski (2018) also examine momentum effects using the lagged returns of each cryptocurrency and Liu et al. (2019) construct momentum factors similar to ours.

4.4. Summary Statistics of Cryptocurrency Factors

Table 4 reports summary statistics for the cryptocurrency factors. We also include summary statistics for the returns of the U.S. stock market and the 30-day Treasury bill obtained from Kenneth French's data library. We use the summary statistics to test our first asset pricing hypothesis. Namely, if aggregate computing power and network factors are meaningful procyclical risk factors for cryptocurrency markets then they should earn positive risk premia. Consistent with this hypothesis, we find that the three fundamentals-based risk factors have a positive risk premium over the return of the 30-day Treasury bill.[8] In particular, the average weekly returns of the ACP, $ANET$, and the SVD factors are 2.27%, 2.06%, and 1.45%, respectively. In the same period, the return for the 30-day Treasury bill was 0.020%.

The cryptocurrency factors not only have high average returns, but they also have high standard deviations compared to the U.S. equity market. However, their Sharpe ratios are comparable to that of the U.S. stock market. For example, the Sharpe ratio of the ACP

[8] In the absence of a "risk-free" asset for the cryptocurrency market, we follow the asset pricing literature and use the 30-day Treasury bill returns to compute risk premia.

factor is 0.197 while the Sharpe ratios of the $ANET$ and SVD factors are 0.218 and 0.206, respectively. Comparatively, the Sharpe ratio of the U.S. equity market is 0.124. Overall, the cryptocurrency factors reflect the high reward/high risk trade-off of this market.

An important question is how correlated these factors are to each other. We report their correlations in Panel A of Table A5 in the Appendix. We find that the momentum factor has the lowest correlation with the other factors. The return of Bitcoin is correlated with the ACP and $ANET$ factors with correlation coefficients ranging from 0.617 to 0.762. The highest correlation is between ACP and $ANET$ with a correlation coefficient of 0.96. We also run some factor-spanning tests that confirm that ACP and $ANET$ seem to have similar information.[9]

The high correlation between the ACP and $ANET$ factors might be related to the small number of basis assets in the FMP regressions. In our robustness analysis in Section 5.4, we increase the number of basis assets using newer cryptocurrencies, for which we have data from March 31st, 2017 to on June 28th, 2019, and find that the correlation between ACP and $ANET$ decreases. We maintain the original factors in our main analysis because we can compute them for a longer time period (August 7th, 2015 to June 28th, 2019).

4.5. Factor Analysis with Bitcoin and Crypto-Momentum

To provide a benchmark for the explanatory power of the fundamental blockchain factors, we estimate a baseline 2-factor model with the Bitcoin return and cryptocurrency momentum. We estimate the 2-factor model for the five cryptocurrencies using ordinary least squares (OLS). When Bitcoin is the test asset, we exclude the Bitcoin return as a factor. We report the estimation results in Panel A of Table 5. We find that Ethereum, Monero, Litecoin, and Dash are significantly exposed to Bitcoin with Bitcoin betas ranging from 0.76 to 0.96.

The estimates of the cryptocurrency momentum betas ($CryptoMom$) are also statistically

[9] For the spanning tests, we follow Huberman and Kandel (1987) and Hou, Mo, Xue, and Zhang (2018) and project each factor on the another one and test if the alphas from the spanning regressions are significant. We report these results in Panel B of Table A5 in the Appendix. Since both alphas are statistically insignificant, the spanning test reveals that the two factors render each other redundant. However, it seems that the $ANET$ factor possesses marginally more explanatory power than the ACP factor.

significant in 3 out of 5 instances and range from 0.03 to 0.32. In terms of explanatory power, we find that the 2-factor model with Bitcoin return and cryptocurrency momentum can explain between 20% to 41% of the time series variation in cryptocurrency returns. Overall, the evidence in Panel A of Table 5 suggest that Bitcoin is a significant factor for cryptocurrencies. Consistent with Liu and Tsyvinski (2018) and Liu et al. (2019), we also find that momentum is an important phenomenon in the cryptocurrency market.

4.6. Factor Analysis with Computing Power and Network Size

Next, we test if cryptocurrency returns have positive exposures to the fundamental factors. The ACP and $ANET$ are procyclical factors and their betas should be positive because all cryptocurrencies in our sample earn large, positive average returns in excess of the risk-free rate. We estimate the risk exposures to the fundamental factors using various 3-factor models that include either the ACP or the $ANET$ or the cumulative SVD factors.[10] We do not include all the factors in one factor model because they are highly correlated (Please see Table A5 in the appendix).

4.7. Computing Power Factor

We examine the asset pricing ability of computing power by estimating a 3-factor model with the ACP factor termed the ACP model. We present the estimation results in Panel B of Table 5. We find that the exposures to the ACP factor are positive and statistically significant for all cryptocurrencies. For example, for Bitcoin and Ethereum, the estimated betas are 0.48 (t-statistic = 11.13) and 1.19 (t-statistic = 17.06), respectively.

When we introduce the ACP factor to the model, the exposures of the five cryptocurrencies to the Bitcoin and cryptocurrency momentum factors become less significant. For example, the Bitcoin beta for Ethereum decreases from 0.76 in the 2-factor specification of

[10] In untabulated results, we estimate 8-factor specifications that include the Fama and French (2015) five factors and the factors from our 3-factor model. The results are identical to the ones reported here since the equity-based Fama-French factors have no explanatory power in our cryptocurrency sample (e.g., Liu and Tsyvinski (2018)).

Panel A to −0.19 in the 3-factor ACP model of Panel B. Similarly, the Bitcoin betas for Monero, Litecoin, and Dash, respectively, decrease from 0.88, 0.96, and 0.66 in the 2-factor model to 0.40, 0.38, and −0.02 in the ACP model.

Given that the ACP factor is statistically significant, the explanatory power of the 3-factor ACP model is also higher than that of the 2-factor specification. Specifically, there is a significant increase in the adjusted R^2's reported in Panel B for the ACP model compared to those in Panel A for the 2-factor model (Bitcoin and crypto-momentum). For example, in the case of Ethereum, the adjusted R^2 increases from 20% in Panel A to 67% in Panel B of Table 5. Similarly, for Monero and Litecoin, the adjusted R^2's increase from 36% and 41% in Panel A to 48% and 64% in Panel B, respectively.

4.8. Network Factor

Next, we estimate a 3-factor model that includes the aggregate network factor ($ANET$). We refer to this specification as the ANET model and present its estimation results in Panel C of Table 5. Similar to the ACP factor, we find that all cryptocurrencies have positive and statistically significant exposures to the $ANET$ factor. We also find that the explanatory power of the 3-factor ANET model is higher than that of the 2-factor model. In the case of Ethereum, for example, the introduction of the $ANET$ factor increases the fit of the asset pricing model from 20% in Panel A to 51% in Panel C of Table 5. Further, including the $ANET$ factor in the model decreases the significance of the exposures of the four cryptocurrencies to the Bitcoin factor.

4.9. Cumulative SVD Factor

We combine the ACP and $ANET$ factors into a single factor using the singular value decomposition (SVD) methodology. We denote the cumulative factor with *SVD*. The SVD procedure is similar to the principal component analysis (PCA). We use the SVD factor because it preserves the mean of the computing power and network factors. In contrast, as shown in Wang (2017), PCA factors have zero mean thus inflating alphas in factor regressions. For completeness, we present the results of a 3-factor model using the PCA of the aggregate computing power and network factors in Table A6 of the Appendix.

We estimate a 3-factor specification with the SVD factor and refer to it as the SVD model. We report its estimation results in Panel D of Table 5 and find that all cryptocurrencies have positive and statistically significant exposures to the *SVD* factor. The explanatory power of the 3-factor model with the SVD factor is also higher than that of the 2-factor model with the Bitcoin and crypto-momentum factors alone. Overall, the evidence in Table 5 demonstrates that the returns of individual cryptocurrencies are exposed to the aggregate fundamental factors of the cryptocurrency market.

5. Robustness Analysis

In this section, we conduct additional tests to examine the robustness of our main results.

5.1. Out-of-Sample Tests

Our conjecture is that the computing power and network factors proxy for the trustworthiness and transaction benefits of the cryptocurrency market. Hence, they should constitute sources of risk for all cryptocurrencies and not just the ones in the baseline sample. Thus, we explore their out-of-sample pricing power with a set of cryptocurrencies that does *not* include the five baseline currencies. The new set of currencies includes mineables and non-mineable currencies (NMCs). The distribution and creation of NMCs is generally decided ex-ante and does not require any computing power spent on mining.

We include NMCs in our analysis to strengthen the evidence that computing power and network are procyclical factors. Our conjecture is that the marginal cryptocurrency investor should under-value cryptocurrencies, mineable or non-mineable, that pay well during good times, i.e., during times when aggregate computing power, network, and cryptocurrency wealth (prices) are high. Hence, we should to find a positive relation between the computing power factor and the price of NMCs even though these currencies do not rely on mining.

5.1.1. Out-of-Sample Cryptocurrencies

For the out-of-sample analysis, we rely on 34 cryptocurrencies for which we could obtain a balanced panel for a relatively long time series. We report the list of the out-of-sample cryptocurrencies in Table A7 of the Appendix. The extended set of cryptocurrencies includes 16 mineable and 18 non-mineable cryptocurrencies. Some of the more prominent cryptocurrencies included in this sample are Ripple, Stellar, Zcash, and Dogecoin.

We extract our sample of cryptocurrencies from Bittrex, which is one of the largest and most liquid cryptocurrency exchanges in the U.S.A. This sample begins on March 31st, 2017 and ends on June 28th, 2019. We use the daily prices from Bittrex, which we convert from Bitcoin units into U.S. dollars. We compute weekly returns as with the baseline currencies. We report the average and standard deviation of the returns of the 34 cryptocurrencies in the last two columns of Table A7. According to these statistics, the risk-return profiles of the currencies are very diverse and span a wide spectrum of reward-to-risk ratios.

5.1.2. Pooled OLS Regressions

Using the out-of-sample cryptocurrencies, we estimate pooled OLS regressions of four models. We first estimate a 2-factor model using the Bitcoin return and cryptocurrency momentum. Next, we estimate 3-factor models by including either the ACP, $ANET$, or SVD factor. To account for time series dependence and heteroscedasticity in the error terms, we follow Petersen (2009) and double-cluster the standard errors by currency and week. The advantage of the pooled OLS regression with clustered standard errors is that it provides estimates of the average exposures to each factor as well as properly calculated standard errors.

We report the estimation results of the 2-factor model in column (1) of Table 6. We find a strong exposure of the 34 cryptocurrencies to Bitcoin with a statistically significant beta of 1.02 (t-statistic = 9.05). However, the cryptocurrency momentum is not very important in the new sample, which includes a lot of small cryptocurrencies. This finding is consistent with Liu et al. (2019), who show that momentum effects are weaker for smaller cryptocurrencies.

Next, we examine the exposures of the cryptocurrencies to the fundamental factors by estimating 3-factor models. In these models, we include either the ACP, or the $ANET$, or the SVD factors. We report the results in columns (2) to (4) of Table 6. We find that the returns of the 34 cryptocurrencies are significantly exposed to the fundamental factors. The exposures to Bitcoin are also muted in the 3-factor models. For example, in column (3), we show that embedding the network factor into the 2-factor model reduces the magnitude of the Bitcoin beta from 1.02 to 0.17 and its t-statistic from 9.16 to 0.82.

Further, the adjusted R^2's of the 3-factor models exceed that of the 2-factor model. For instance, the 3-factor model with ACP increases the explanatory power of the 2-factor model from 25% to 34%. In untabulated tests, we find that single-factor models with either the ACP, $ANET$, or SVD factors have adjusted R^2's ranging around 32%. This finding suggests that the fundamentals factors alone provide greater explanatory power than Bitcoin.

5.1.3. Beta Estimates for Out-of-Sample Cryptocurrencies

We also estimate time series factor regressions for each cryptocurrency. Our goal is to examine whether the statistical significance of the fundamental betas in the pooled regressions is driven by specific currencies. For this analysis, we estimate the 3-factor ACP, ANET, and SVD models for each cryptocurrency and tabulate the betas and t-statistics related to the ACP, $ANET$, and SVD factors. We report the results in Table A8 of the Appendix.

We find that all 34 currencies have positive and significant factor betas with a few exceptions. In particular, the ACP, $ANET$, and SVD betas are statistically insignificant for 3 currencies: Groestlcoin, Monacoin, and Spherecoin. The fact that the ACP factor loads positively and significantly for all but 1 non-mineable cryptocurrency (Spherecoin) is important. Non-mineable cryptocurrencies have no computing power and there is no possibility of a mechanical correlation between their returns and the ACP factor. Therefore, the statistical significance of the ACP beta can only be attributed to the validity of ACP as a procyclical risk factor in the cryptocurrency market

5.1.4. Gibbons-Ross-Shanken Statistic

We further examine the efficiency of the asset pricing models in the sample of the 34 cryptocurrencies using the Gibbons, Ross, and Shanken (1989) (GRS) test for time series alphas. We compute the GRS statistic for the factor models in Table 6. For each currency, we estimate time series factor regressions and obtain a total of 34 alphas for each model, which are then used to compute the GRS statistics reported in Table 6. We find that the GRS test statistic for the 2-factor model is 1.29 and it is statistically insignificant (p-value = 0.16). Nevertheless, the GRS statistic decreases greatly in the 3-factor models. For example, the GRS is 0.22 (0.34, 0.26) in the specification with the ACP ($ANET$, SVD) factor.

Overall, the out-of-sample analysis provides evidence that the broader cryptocurrency market is exposed to the risks captured by the aggregate computing power and network factors. Further, the out-of-sample analysis alleviates any concerns that the significance of the two fundamental factors is created mechanically because they are projections on the return space of the five baseline cryptocurrencies.

5.2. Robustness to Bitcoin's Dominance

Bitcoin has consistently dominated the cryptocurrency market since its inception. Hence, our results could be driven by the inclusion of Bitcoin's computing power and network in the two fundamentals-based factors. We address this concern and derive aggregate computing power and network factors by *excluding* Bitcoin's returns from the construction of the factor-mimicking-portfolios (FMPs) of the other cryptocurrencies. We also *exclude* Bitcoin's own factor-mimicking portfolio from the construction of the aggregate computing power and network factors (ACP and $ANET$). We denote these alternative Bitcoin-free factors by $ACP \setminus BTC$ and $ANET \setminus BTC$. Similar to the main tests in Panels B and C of Table 5, we run time series regressions with the five baseline cryptocurrencies and present the results in Table A9 of the Appendix.

We find that the Bitcoin-free fundamental factors have similar explanatory power to the original factors. For Ethereum for example, we estimate a statistically significant positive beta of 1.13 for the $ACP \setminus BTC$ factor along with an adjusted R^2 of 55%. This R^2 is higher than the R^2 of the 2-factor model with Bitcoin return and crypto-momentum that we report in Panel A of Table 5.

Lastly, we estimate new 3-factor models with the $ACP \setminus BTC$ and $ANET \setminus BTC$ factors in the extended set of 34 cryptocurrencies, and present the results in Table A10. We find that the out-of-sample results are robust to excluding Bitcoin from the construction of the fundamentals-based factors. For example, the loading for the $ANET \setminus BTC$ factor is positive and statistically significant (beta estimate = 0.84; t-statistic = 5.45). This estimate is qualitatively similar to the $ANET$ beta of 0.94 (t-statistic = 4.45) in column (4) of Table 6. Furthermore, the adjusted R^2 in Table A10 is 33%, which is very similar to the one reported in Table 6. Overall, excluding Bitcoin from the construction of aggregate computing power and network factors does not affect our results.

5.3. Controlling for Ethereum's Return

In our next test, we examine the robustness of our out-of-sample results to the return of Ethereum. The intuition behind this robustness check is that the out-of-sample cryptocurrencies are relatively new and emerged around late 2016 and early 2017. Therefore, their returns may be more closely tied to the returns of younger prominant cryptocurrencies, like Ethereum, as opposed to the returns of Bitcoin, which appeared in 2009. Therefore, we re-run the analysis in Table 6 by replacing the return of Bitcoin with the return of Ethereum ($\Delta Price(ETH)$). We report the new results in Table A11 of the Appendix.

We find that the new betas of the ACP, $ANET$, and SVD factors remain positive and statistically significant. Also, the 3-factor models possess greater explanatory power than the 2-factor specification with the return of Ethereum and crypto-momentum. Overall, the results in Tables 6 and A11 suggest that controlling for Bitcoin or Ethereum does not affect the asset pricing ability of the fundamental factors.

5.4. Fundamental Factors with Many Basis Assets

A final issue we address is the number of cryptocurrency returns used to form the factor mimicking portfolios (FMP) for computing power and network growth. In our baseline analysis, the growth rates of the fundamentals of a cryptocurrency are projected on the returns of the other 4 cryptocurrencies. Because of the small number of basis assets, the ACP and $ANET$ factors might be reflecting the return behavior of the few basis assets and not the behavior of the growth in aggregate fundamentals.

We address this concern by expanding the number of basis assets in the FMP regressions. In particular, we estimate the FMP regressions using the returns of 4 baseline cryptocurrencies and the returns of the 34 out-of-sample cryptocurrencies. That is, each FMP regression has 38 basis assets. We denote the new factors as $ACP(38)$, $ACP(38)$, and $SVD(38)$ (please see Table A1 in the Appendix for a detailed description of these factors). We compute the new factors for the period from March 31st, 2017 to June 28th, 2019.

The summary statistics in Table A12 show that the new factors have higher average returns and standard deviations compared to the original ACP and $ANET$ factors. However they have similar Sharpe ratios. Also, the correlation between $ACP(38)$ and $ACP(38)$ is only 0.10 and it is substantially lower compared to the correlation between ACP and ACP, which is 0.98. Overall, the descriptive statistics suggest that the new factors are more volatile probably because they use the newer out-of-sample cryptocurrencies, which are less stable than the 5 baseline, more established, cryptocurrencies. However, the $ACP(38)$ and $ACP(38)$ factors are not correlated, so we can use them together in our asset pricing tests.

We repeat the analysis in Section 5.1.2 and estimate pooled OLS regressions of the returns of the 34 out-of-sample cryptocurrencies on the $ACP(38)$, $ACP(38)$, and $SVD(38)$ factors. We report the new estimation results in Table A13 in the Appendix. Consistent with our previous results, we find that the betas of the new factors are positive. Albeit statistically significant, their t-statistics are lower compared to those reported in Table 6 for the ACP, ACP, and SVD factors. This result is not surprising since the new factors are more volatile compared to the original ones (Please see the standard deviations reported in Table A12 in the Appendix). Overall, the new evidence suggests that the pricing power of the fundamental factors is not driven by the number of the basis assets in the FMP regressions.

6. Conclusion

The core hypothesis of this paper is that cryptocurrencies have an intrinsic value related to their blockchain's computing power and network adoption. This hypothesis is motivated by the fact that miners expend real resources to generate the computing power required to secure and operate the blockchain. Further, an optimally performing blockchain serves as a medium for transactions and attracts users, developers, and intermediaries, thereby leading to an increase in the cryptocurrency's network size.

We examine our core hypothesis with Bitcoin, Ethereum, Litecoin, Monero, and Dash. We use DOLS regressions and find that there is a positive and statistically significant relationship among price, computing power, and network size. Next, we use factor analysis and show that aggregate computing power and network constitute risk factors in the cryptocurrency market. The exposure of the various cryptocurrencies to these factors are economically and statistically significant even after controlling for the pricing effects of Bitcoin and cryptocurrency momentum. In out-of-sample tests, we also find that the computing power and network factors price the returns of an extended set of 34 cryptocurrencies. These out-of-sample results reinforce our conjecture that the two fundamental factors proxy for systematic risks in the cryptocurrency market.

More broadly, our paper serves as an important step towards better understanding cryptocurrency prices. In particular, we are the first to provide concrete evidence that computing power and network size are empirically related to cryptocurrency prices and can be used to construct asset pricing factors. Undeniably, other important factors might surface as the cryptocurrency market matures. For example, regulation risk and political risk may also become important for cryptocurrency returns. Our analysis could serve as a tool for identifying these additional factors.

Figure 1: Price and Computing Power of Bitcoin, Ethereum, and Monero

This figure plots weekly averages of the daily log price and log computing power (log hashrate) for Bitcoin, Ethereum, and Monero over the sample period from 8/7/2015 to 6/28/2019. We normalize prices and computing power by subtracting the mean and dividing by the standard deviation of each time series.

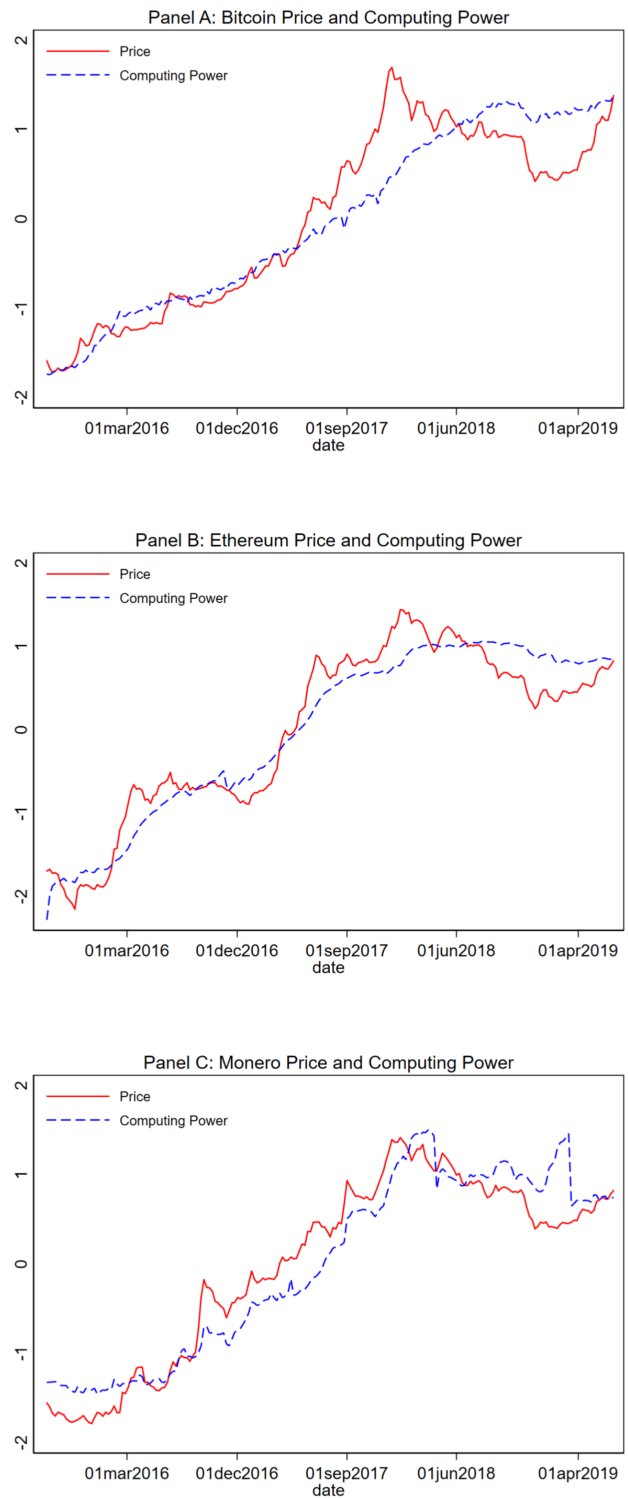

Figure 2: Price and Network Size of Bitcoin and Ethereum

This figure plots weekly averages of the daily log price and log network size (log of unique active addresses) for Bitcoin and Ethereum over the sample period from 8/7/2015 to 6/28/2019. We normalize prices and network size by subtracting the mean and dividing by the standard deviation of each time series.

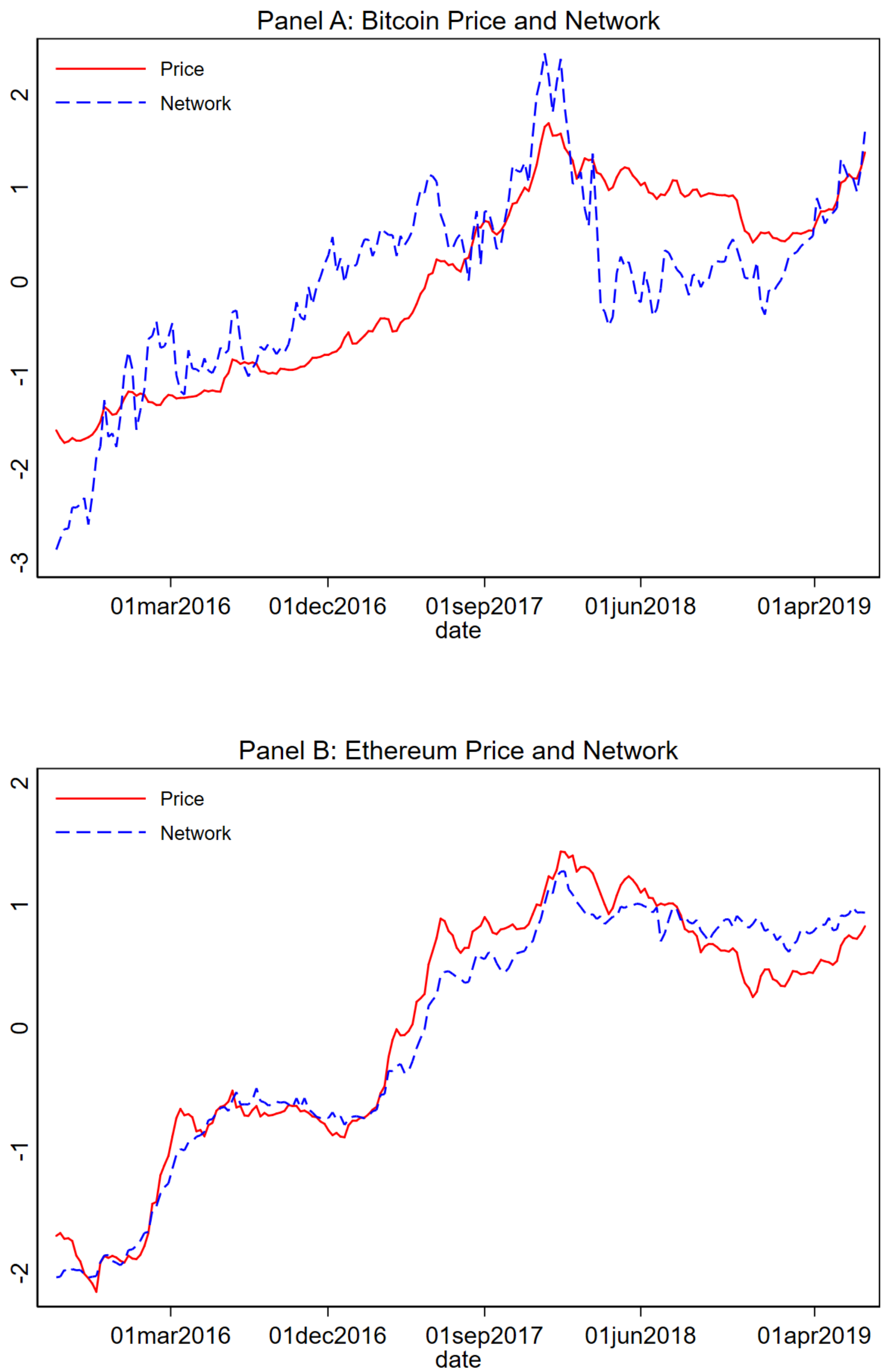

Table 1: Cryptocurrency Market Capitalizations

In this table, we report the market capitalization (in millions U.S.D.) of the five cryptocurrencies used in our empirical analysis: Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Dash (DSH), and Monero (XMR). We obtain weekly snapshots from Coinmarketcap.com on the weeks ending in 8/30/2015, 9/4/2016, 9/3/2017, and 9/2/2018 using the Historical Snapshots Index. Rank is the rank of each cryptocurrency in terms of capitalization. Market percentage is the ratio of the capitalization of each cryptocurrency over the total capitalization of the top-15 cryptocurrencies. The total capitalization of the top-15 cryptocurrencies accounts for 95% of the market capitalization of all cryptocurrencies during our sample, which runs from 8/7/2017 to 6/28/2019.

In U.S.D. Millions	**BTC**	**ETH**	**LTC**	**DSH**	**XMR**	**Sum**
August 30th, 2015						
Market Capitalization	$3,346	$89	$121	$15	$4	$3,575
Rank	1	4	3	5	15	
Market Percentage	84%	2%	3%	0.4%	0.1%	90%
September 4th, 2016						
Market Capitalization	$9,491	$972	$186	$74	$148	$10,871
Rank	1	2	4	8	5	
Market Percentage	82%	8%	2%	1%	1%	95%
September 3rd, 2017						
Market Capitalization	$76,620	$33,307	$4,203	$2,717	$1,897	$118,744
Rank	1	2	5	9	7	
Market Percentage	51%	22%	3%	2%	1%	80%
September 2nd, 2018						
Market Capitalization	$125,427	$29,942	$3,815	$1,972	$1,762	$162,920
Rank	1	2	7	11	12	
Market Percentage	60%	14%	2%	1%	1%	78%

Table 2: Descriptive Statistics: Growth in Prices, Computing Power, and Network

This table reports descriptive statistics for the weekly growth rates in prices ($\Delta Price$), computing power (ΔCP), and network (ΔNET) of the five cryptocurrencies in our sample: Bitcoin (BTC), Ethereum (ETH), Monero (XMR), Litecoin (LTC), and Dash (DSH). Weekly growth rates are the first differences of the weekly averages of the respective daily log values. In Panel A, we present the growth rates in prices. In Panel B, we report the growth rates in computing power, and in Panel C, we show the growth rates in network. Our sample period begins on 8/7/2015 and ends on 6/28/2019.

Panel A: Price	Mean	Median	St. Dev.	Obs.
$\Delta Price(BTC)$	0.019	0.010	0.087	202
$\Delta Price(ETH)$	0.027	0.009	0.151	202
$\Delta Price(XMR)$	0.017	0.005	0.131	202
$\Delta Price(LTC)$	0.025	-0.001	0.154	202
$\Delta Price(DSH)$	0.020	0.007	0.127	202
Panel B: Computing power	Mean	Median	St. Dev.	Obs.
$\Delta CP(BTC)$	0.025	0.031	0.061	202
$\Delta CP(ETH)$	0.035	0.037	0.080	202
$\Delta CP(XMR)$	0.029	0.021	0.076	202
$\Delta CP(LTC)$	0.016	0.018	0.139	202
$\Delta CP(DSH)$	0.054	0.030	0.128	202
Panel C: Network	Mean	Median	St. Dev.	Obs.
$\Delta NET(BTC)$	0.006	0.007	0.067	202
$\Delta NET(ETH)$	0.027	0.018	0.409	202
$\Delta NET(LTC)$	0.011	0.002	0.129	202
$\Delta NET(DSH)$	0.013	0.009	0.159	202

Table 3: Dynamic Ordinary Least Squares Regressions

This table reports estimates of the cointegrating relationship among cryptocurrency prices (Price), computing power (CP), and network (NET) for the five cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), Monero (XMR), Litecoin (LTC), and Dash (DSH). The cointegrating relationship is defined as $\text{Price}_t = \alpha + \delta \times t + \beta_{CP} \times \text{CP}_t + \beta_{NET} \times \text{NET}_t$. The main parameters of interest are the estimates of β_{CP} and β_{NET}. To estimate these prameters, we apply the dynamic ordinary least squares (DOLS) specification of Stock and Watson (1993) to our sample that runs from 8/7/2015 to 6/28/2019. In Panel A, we report the cointegration parameters for computing power and network along with their respective Newey-West corrected t-statistics. In Panel B (C), we report the number of periods in which cryptocurrency prices deviate from the cointegrating relation with computing power (network) along with the average duration of such periods. We estimate price deviations using 180 rolling DOLS regressions with 20-week windows across the 202 weeks in our sample.

	(1) BTC	(2) ETH	(3) XMR	(4) LTC	(5) DSH
Panel A: Cointegration Parameters					
β_{CP}	1.298***	0.912***	1.526***	−0.031	0.445***
t-statistic	5.88	3.53	11.25	−0.28	3.04
β_{NET}	1.802***	0.612***		1.372***	1.874***
t-statistic	3.76	2.20		10.45	2.89
Panel B: Price deviations from CP					
Num of price-deviation episodes ($t < 2$)	6	6	8	9	8
Average duration of episodes (weeks)	22	11.83	7.75	11.22	12.50
Panel C: Price deviations from NET					
Num of price-deviation episodes ($t < 2$)	9	8		8	11
Average duration of episodes (weeks)	6.44	6.00		10.50	5.00

Table 4: Factor Analysis: Descriptive Statistics

This table reports the descriptive statistics of the asset pricing factors used in our empirical analysis. These factors are the return of Bitcoin ($\Delta Price(BTC)$), the cryptocurrency momentum factor ($CryptoMom$), the aggregate computing power factor (ACP), the aggregate network factor ($ANET$), the singular value decomposition of the two factors (SVD), the return of the U.S. equity market, and the risk free rate. Details on the construction of $CryptoMom$, ACP, $ANET$, and SVD are provided in Table A1 of the Appendix. The sample period runs from 8/7/2015 to 6/28/2019.

	Mean	St. Dev.	Sharpe Ratio	Obs.
$\Delta Price(BTC)$	1.922	8.641	0.220	201
$CryptoMom$	5.581	15.857	0.351	201
ACP	2.271	11.446	0.197	201
$ANET$	2.060	9.341	0.218	201
SVD	1.447	6.921	0.206	201
Equity market return	0.256	1.904	0.124	201
Risk-free rate	0.020	0.016		201

Table 5: Factor Analysis: 3-Factor Models with Fundamental Factors

This table reports estimates from time series regressions of the weekly returns of the five baseline cryptocurrencies on three asset pricing factors. The cryptocurrencies are Bitcoin (BTC), Ethereum (ETH), Monero (XMR), Litecoin (LTC), and Dash (DSH). In Panel A, the 2-factor asset pricing model includes the return of Bitcoin ($\Delta Price(BTC)$) and the cryptocurrency momentum factor ($CryptoMom$). In Panel B (C), we add the aggregate computing power factor ,ACP (aggregate network factor $ANET$), to the 2-factor specification. In Panel D, we include the SVD factor to the 2-factor specification. t-statistics are in parentheses. The superscripts ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 level, respectively. The sample is from 8/7/2015 to 6/28/2019 and consists of 201 weekly observations.

	(1)	(2)	(3)	(4)	(5)
Panel A: 2-factor	BTC	ETH	XMR	LTC	DSH
$\Delta Price(BTC)$		0.76^{***}	0.88^{***}	0.96^{***}	0.66^{***}
		(6.85)	(8.73)	(11.59)	(7.23)
$CryptoMom$	0.03	0.10	0.32^{***}	0.09^{**}	0.11^{**}
	(0.86)	(1.63)	(5.76)	(2.09)	(2.21)
α ($\times 100$)	1.74^{***}	0.67	-0.85	-0.60	0.16
	(2.68)	(0.65)	(-0.91)	(-0.78)	(0.18)
Adjusted R^2	-.0013	.20	.36	.41	.22
Panel B: 3-factor ACP	BTC	ETH	XMR	LTC	DSH
$\Delta Price(BTC)$		-0.19^{**}	0.40^{***}	0.38^{***}	-0.02
		(-2.14)	(3.43)	(4.63)	(-0.19)
$CryptoMom$	-0.04	-0.06	0.24^{***}	-0.00	-0.00
	(-1.43)	(-1.57)	(4.59)	(-0.08)	(-0.11)
ACP	0.48^{***}	1.19^{***}	0.60^{***}	0.72^{***}	0.85^{***}
	(11.13)	(17.06)	(6.65)	(11.31)	(12.52)
α ($\times 100$)	1.08^{**}	0.70	-0.84	-0.58	0.18
	(2.11)	(1.06)	(-0.99)	(-0.97)	(0.28)
Adjusted R^2	.38	.67	.48	.64	.56
Panel C: 3-factor ANET	BTC	ETH	XMR	LTC	DSH
$\Delta Price(BTC)$		-0.41^{***}	0.29^{*}	0.01	-0.47^{***}
		(-3.00)	(1.95)	(0.07)	(-4.88)
$CryptoMom$	-0.04^{*}	-0.02	0.26^{***}	0.00	-0.00
	(-1.75)	(-0.33)	(4.89)	(0.02)	(-0.04)
$ANET$	0.72^{***}	1.44^{***}	0.73^{***}	1.17^{***}	1.39^{***}
	(16.81)	(11.24)	(5.24)	(13.17)	(15.27)
α ($\times 100$)	0.68	0.61	-0.88	-0.65	0.10
	(1.63)	(0.75)	(-1.00)	(-1.15)	(0.17)
Adjusted R^2	.59	.51	.44	.69	.64
Panel D: 3-factor SVD	BTC	ETH	XMR	LTC	DSH
$\Delta Price(BTC)$		-0.31^{***}	0.34^{***}	0.24^{***}	-0.18^{**}
		(-2.92)	(2.69)	(2.82)	(-2.02)
$CryptoMom$	-0.05	-0.05	0.24^{***}	-0.00	-0.01
	(-1.62)	(-1.11)	(4.69)	(-0.10)	(-0.14)
$SVD(ACP,ANET)$	0.87^{***}	1.99^{***}	1.00^{***}	1.33^{***}	1.57^{***}
	(13.25)	(14.81)	(6.20)	(12.09)	(13.61)
α ($\times 100$)	0.92^{*}	0.66	-0.85	-0.60	0.15
	(1.93)	(0.93)	(-1.00)	(-1.03)	(0.25)
Adjusted R^2	.47	.62	.46	.66	.60

Table 6: Factor Analysis: Out-of-Sample Cryptocurrencies

This table reports estimates from pooled OLS regressions of weekly cryptocurrency returns ($\Delta Price$) on our asset pricing factors. The test assets are the 34 cryptocurrencies described in Table A7 of the Appendix. In column (1), the 2-factor asset pricing model includes the return of Bitcoin ($\Delta Price(BTC)$) and the cryptocurrency momentum factor ($CryptoMom$). The 3-factor models in columns (2), (3), and (4) additionally include the aggregate computing power factor (ACP), the aggregate network factor ($ANET$), and the singular value decomposition of the computing power and network factors (SVD), respectively. Standard errors are double-clustered by week and currency. t-statistics are in parentheses. The superscripts ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 level, respectively. We also report the Gibbons et al. (1989) (GRS) test statistics for the efficiency of the factor models along with the respective p values. The GRS statistic is based on cryptocurrency-level alphas estimated from time series regressions for each currency. The sample runs from 3/31/2017 to 6/28/2019 and consists of 118 weekly observations.

	(1)	(2)	(3)	(4)
	2-factor	3-factor ACP	3-factor ANET	3-factor SVD
$\Delta Price(BTC)$	1.02^{***}	0.35^{**}	0.17	0.27
	(9.05)	(2.20)	(0.82)	(1.55)
$CryptoMom$	0.12^{*}	−0.01	0.02	−0.00
	(1.74)	(−0.18)	(0.26)	(−0.03)
ACP		0.71^{***}		
		(5.27)		
$ANET$			0.94^{***}	
			(4.54)	
SVD				1.22^{***}
				(5.01)
α ($\times 100$)	−0.82	−0.21	−0.40	−0.28
	(−0.86)	(−0.27)	(−0.49)	(−0.35)
Adjusted R^2	0.25	0.34	0.32	0.33
GRS Statistic	1.29	0.22	0.34	0.26
p-value	0.16	1.00	1.00	1.00
Cryptocurrencies	34	34	34	34
Observations	4,012	4,012	4,012	4,012

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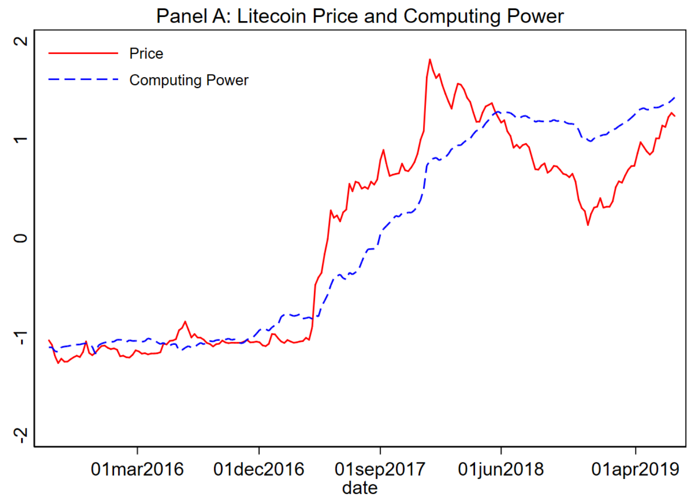
Appendix

Figure A1: Price and Computing Power of Litecoin and Dash

This figure plots weekly averages of the daily log price and log computing power (log hashrate) for Litecoin and Dash over the sample period from 8/7/2015 to 6/28/2019. We normalize prices and computing power by subtracting the mean and dividing by the standard deviation of the respective time series.



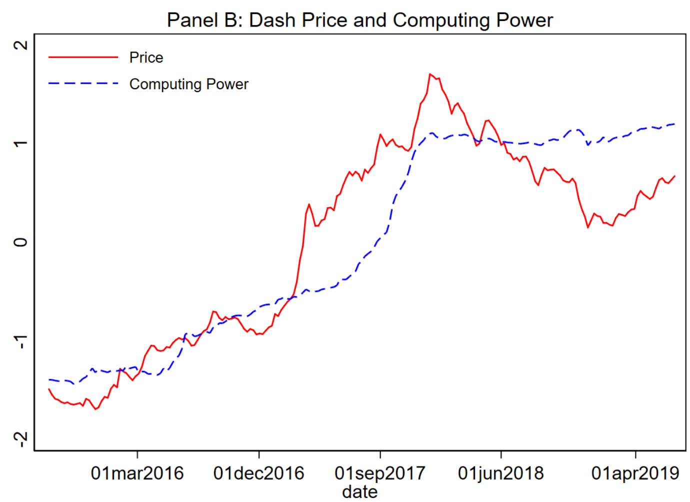


Figure A2: Price and Network of Litecoin and Dash

This figure plots weekly averages of the daily log price and log network (log addresses) of Litecoin and Dash over the sample period from 8/7/2015 to 6/28/2019. We normalize prices and network size by subtracting the mean and dividing by the standard deviation of the respective time series.

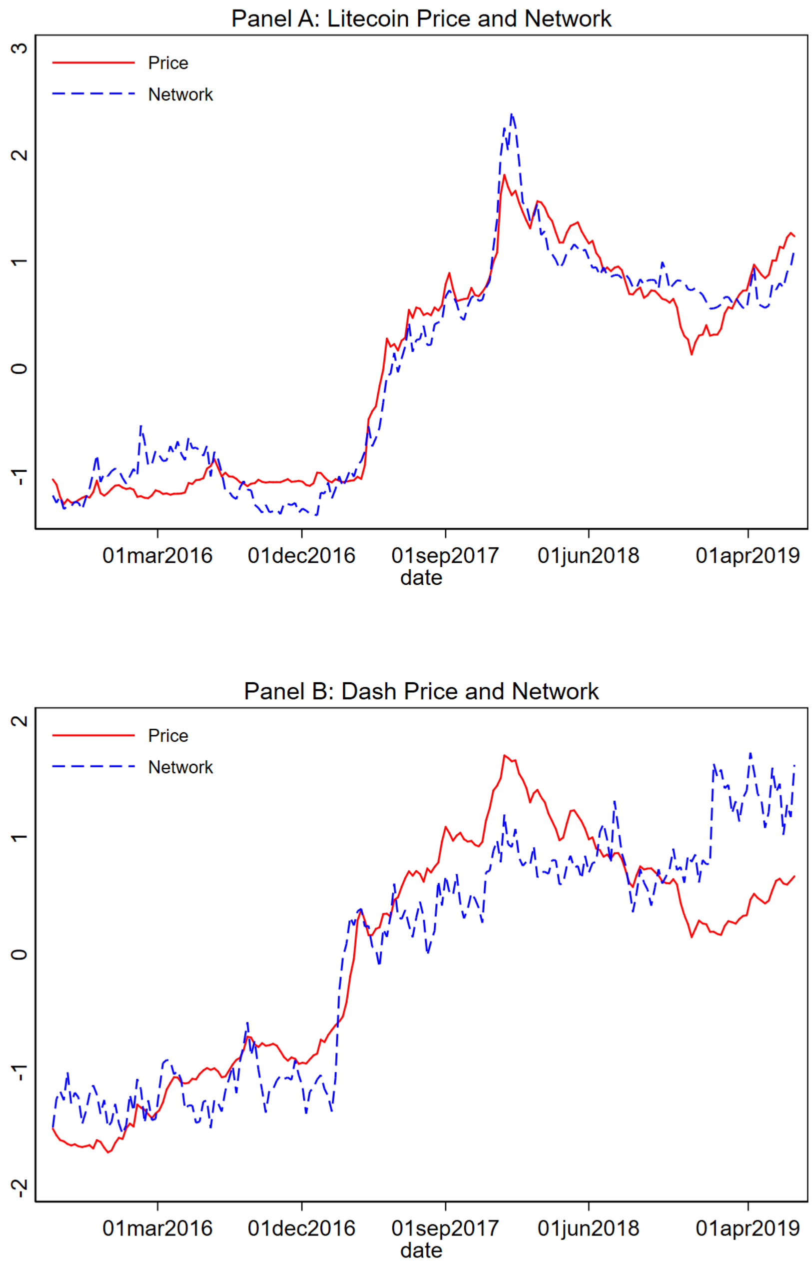


Table A1: Variable Descriptions

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

Variable	Description
	Cryptocurrency Variables
Price	Average of daily log prices over the 7-day period ending on Friday. The daily price is the fixed closing price at midnight UTC of the current day denominated in U.S. dollars. The daily prices are from Coinmetrics.io's fixing/reference rate service.
CP	Average of daily log hashrate over the 7-day period ending on Friday. The daily hasharate is the mean difficulty of finding a new block multiplied by the number of blocks mined on that day. For example, if 100 blocks of Bitcoin were mined on a particular day and each block required an average of 5 TH to mine, the computing power value would be 500$\times$ 10^{12} hashes (1 TH = 10^{12} *hashes*).
NET	Average of daily log *unique* active addresses over the 7-day period ending on Friday. The daily addresses are the sum of unique addresses that were active in the network (either as a recipient or originator of a ledger change) that day. Unique active addresses are the number of addresses from (or to) which transactions are conducted on the cryptocurrency's respective blockchain. Network data for Monero are not available.
	Cryptocurrency Asset Pricing Factors
CryptoMom	Contemporaneous return of the cryptocurrency with the highest return (winner) in the prior period less the contemporaneous return of the cryptocurrency with the lowest return (loser) in the prior period, excluding Bitcoin. We exclude Bitcoin from the calculation of cyrptocurrency momentum because the contemporaneous return of Bitcoin is included in our factor analysis as a separate factor.
ACP	Rank-weighted return of the factor-mimicking portfolios for the growth rate of computing power (log hashes) for each of the five baseline cryptocurrencies (i.e., BTC, ETH, LTC, DSH, XMR). We compute ACP as follows. First, we construct factor-mimicking portfolios for the growth rate in computing power for each currency. For example, in the case of Ethereum, we regress the change in the CP of Ethereum on the returns of the other cryptocurrencies: **A:** $\Delta CP_{ETH,t,t-\tau} = \beta_1 \times \Delta Price_{BTC,t,t-\tau} + \beta_2 \times \Delta Price_{XMR,t,t-\tau} + \beta_3 \times \Delta Price_{LTC,t,t-\tau} + \beta_4 \times \Delta Price_{DSH,t,t-\tau}$ Then, we calculate factor-mimicking portfolio weights using the coefficients from the regression **A** above. That is, **B:** $W_{BTC} = \beta_1/(\beta_1+\beta_2+\beta_3+\beta_4)$; $W_{XMR} = \beta_2/(\beta_1+\beta_2+\beta_3+\beta_4)$ $W_{LTC} = \beta_3/(\beta_1+\beta_2+\beta_3+\beta_4)$; $W_{DSH} = \beta_4/(\beta_4+\beta_2+\beta_3+\beta_4)$ Next, we create a factor-mimicking portfolio (FMP) of the growth in computing power of Ethereum by multiplying the returns of the other cryptocurrencies with the respective factor-mimicking portfolio weights obtained from the expression **B** above: **C:** $FMP\ CP\ (ETH) = W_{BTC} \times \Delta Price_{BTC,t,t-\tau} + W_{XMR} \times \Delta Price_{XMR,t,t-\tau} + W_{LTC} \times \Delta Price_{LTC,t,t-\tau} + W_{DSH} \times \Delta Price_{DSH,t,t-\tau}$ We perform steps **A**, **B**, and **C** for the five baseline cryptocurrencies.

Table A1: Variable Descriptions (continued)

Variable	Description
	In the final step, we create an aggregate rank-weighted return of the computing power factor mimicking portfolios, which we denote as ACP: **D:** $ACP_t = w_{eth} \times FMP\,CP\,(ETH)_t + w_{btc} \times FMP\,CP\,(BTC)_t + w_{xmr} \times FMP\,CP\,(XMR)_t + w_{ltc} \times FMP\,CP\,(LTC)_t + w_{dsh} \times FMP\,CP\,(DSH)_t$ Above, w_{eth} is the prior period rank-weighted market capitalization of Ethereum with respect to Bitcoin, Monero, Litecoin, and Dash. To calculate the rank weights, we first rank the five cryptocurrencies by market capitalization. Then, we assign ranks 1 to 5 to the five cryptocurrencies based on their ascending market capitalization. Finally, we transform the ranks 1, 2, 3, 4, and 5 into the respective weights: 1/15, 2/15, 3/15, 4/15, and 5/15.
$ANET$	Rank-weighted return of the factor-mimicking portfolios of the growth rate in network (log addresses) for four baseline cryptocurrencies (i.e., BTC, ETH, LTC, DSH). The methodology for calculating the $ANET$ factor is identical to that for the ACP factor. Monero (XMR) is not included in the network factor because network data are not available for this currency.
SVD	Singular value decomposition of the ACP and $ANET$ factors. SVD is extracted from the reduced-form singular value decomposition of the $m \times n$ (201×2) matrix $\mathbf{A}$, which combines the time series of ACP and $ANET$. In particular, we decompose $\mathbf{A}$ into: $\mathbf{A} = \mathbf{U}\,\mathbf{v}\,\mathbf{W}^{\mathrm{T}}$, where $\mathbf{U}$ is an $m \times n$ (201×2) matrix, $\mathbf{v}$ is a diagonal $n \times n$ (2×2) matrix consisting of the two singular values, and $\mathbf{W}$ is an $n \times n$ (2×2) matrix consisting of the two eigenvectors. The singular values are 2.12 and 0.28. The first eigenvector values of the $\mathbf{W}$ matrix are 0.78 and 0.63 and the second eigenvector values are -0.63 and 0.78. The cumulative factor SVD is the first column vector of $\mathbf{U}$.
PCA	First principal component of the ACP and $ANET$ factors.
	Bitcoin-Free Fundamental Factors
$ACP \setminus BTC$	Calculated similar to ACP above, however we exclude the return of Bitcoin ($\Delta Price(BTC)$) from the construction of the factor mimicking portfolios for the other 4 baseline cryptocurrencies and *also exclude* Bitcoin's FMP ($FMP\ CP\ (BTC)$) from the construction of ACP.
$ANET \setminus BTC$	Calculated similar to $ANET$ above, however we exclude the return of Bitcoin ($\Delta Price(BTC)$) from the construction of the factor mimicking portfolios for the other 4 baseline cryptocurrencies and *also exclude* Bitcoin's FMP ($FMP\ NET\ (BTC)$) from the construction of $ANET$.
	Factors based on a Large Set of Cryptocurrencies
$ACP(38)$	Rank-weighted return of the factor-mimicking portfolios of the growth rate in computing power (log hashes) of each of the five baseline cryptocurrencies (i.e., BTC, ETH, XMR, LTC, and DSH). The factor is calculated similar to ACP. The only difference is that we are projecting the computing power growth of each baseline cryptocurrency on the returns of other 4 baseline cryptocurrencies and the returns of the 34 out-of-sample cryptocurrencies. Similar to ACP, the return a cryptocurrency is excluded from the factor-mimicking portfolio of its own computer power growth.

Table A1: Variable Descriptions (continued)

Variable	Description
$ANET(38)$	Rank-weighted return of the factor-mimicking portfolios of the growth rate in network (log addresses) of each of four baseline cryptocurrencies (i.e., BTC, ETH, LTC, and DSH). The methodology for calculating the $ANET(38)$ factor is identical to that of the $ACP(38)$ factor. In particular, we form the factor mimicking portfolios of the network growth of a cryptocurrency by projecting it on the returns of other 4 baseline cryptocurrencies and the returns of the 34 out-of-sample cryptocurrencies. Similar to $ANET$, the return of a cryptocurrency is excluded from the factor-mimicking portfolio of its own network growth. Monero (XMR) is not included in the network factor because network data are not available for this currency.
$SVD(38)$	Singular value decomposition of the $ACP(38)$ and $ANET(38)$ factors. SVD is extracted from the reduced-form singular value decomposition of the $m \times n$ (118×2) matrix $\mathbf{A}$, which combines the time series of ACP and $ANET$. In particular, we decompose $\mathbf{A}$ into: $\mathbf{A} = \mathbf{U}\ \mathbf{v}\ \mathbf{W}^{\mathrm{T}}$, where $\mathbf{U}$ is an $m \times n$ (118×2) matrix, $\mathbf{v}$ is a diagonal $n \times n$ (2×2) matrix consisting of the two singular values, and $\mathbf{W}$ is an $n \times n$ (2×2) matrix consisting of the two eigenvectors. The singular values are 2.40 and 1.86. The first eigenvector values of the $\mathbf{W}$ matrix are 0.97 and 0.24 and the second eigenvector values are -0.24 and 0.97. The cumulative factor *SVD(38)* is the first column vector of $\mathbf{U}$.

Table A2: Cross-correlations of Cryptocurrency Returns

This table reports correlations for the weekly growth rates in prices ($\Delta Price$) between the five cryptocurrencies in our sample: Bitcoin (BTC), Ethereum (ETH), Monero (XMR), Litecoin (LTC), and Dash (DSH). Weekly growth rates are the first differences of the weekly averages of the respective daily log values. Our sample period begins on 8/7/2015 and ends on 6/28/2019. All correlations are significant at the 0.01 level.

	$\Delta Price(BTC)$	$\Delta Price(ETH)$	$\Delta Price(XMR)$	$\Delta Price(LTC)$	$\Delta Price(DSH)$
$\Delta Price(BTC)$	1				
$\Delta Price(ETH)$	0.44	1			
$\Delta Price(XMR)$	0.52	0.47	1		
$\Delta Price(LTC)$	0.64	0.37	0.46	1	
$\Delta Price(DSH)$	0.46	0.58	0.54	0.38	1

Table A3: Descriptive Statistics for Prices, Computing Power, and Network

This table presents descriptive statistics for the weekly averages of the daily log price, computing power, and network for the five cryptocurrencies used in our analysis: Bitcoin (Panel A), Ethereum (Panel B), Monero (Panel C), Litecoin (Panel D), and Dash (Panel E). The table also includes the augmented Dickey and Fuller (1979) (ADF) test statistics calculated from ADF regressions that include a constant, a linear trend, and four lags for the time series of prices, computing power, and network. A test statistic below −3.55 implies a rejection of the null hypothesis that the time series process has a unit root.

	Mean	Median	St. Dev.	ADF	Obs.
Panel A: Bitcoin					
$Ln(Price)$	7.598	7.899	1.267	−1.377	203
$Ln(CP)$	32.491	32.389	1.611	−0.749	203
$Ln(NET)$	13.305	13.342	0.275	−2.399	203
Panel B: Ethereum					
$Ln(Price)$	3.947	4.809	2.157	−1.323	203
$Ln(CP)$	42.087	43.181	2.267	0.262	203
$Ln(NET)$	11.059	11.929	1.832	−1.474	203
Panel C: Monero					
$Ln(Price)$	2.901	3.785	2.165	−0.939	203
$Ln(CP)$	29.799	29.991	1.528	−1.168	203
Panel D: Litecoin					
$Ln(Price)$	2.969	3.444	1.530	−1.591	203
$Ln(CP)$	19.621	19.072	2.291	−1.720	203
$Ln(NET)$	10.543	10.818	0.989	−1.820	203
Panel E: Dash					
$Ln(Price)$	3.897	4.437	1.856	−0.830	203
$Ln(CP)$	19.981	19.177	4.184	−1.505	203
$Ln(NET)$	10.098	10.376	0.829	−3.017	203

Table A4: Cryptocurrency Hashing Algorithims and Inception Dates

This table reports the hashing algorithms and inception dates of the five baseline cryptocurrencies in our sample. The hashing algorithm is the basis of the cryptographic tasks that miners need to solve in order to create the blockchain.

Currency	Name	Hashing Algorithm	Inception
BTC	Bitcoin	SHA-256	01/03/2009
LTC	Litecoin	Scrypt	10/07/2011
DSH	Dash	X11	01/18/2014
XMR	Monero	CryptoNight	04/18/2014
ETH	Ethereum	EthHash	07/30/2015

Table A5: Factor Correlations and Spanning Test

Panel A reports cross-correlations for the cryptocurrency-based asset pricing factors which are the return of bitcoin ($\Delta P(BTC)$), the cryptocurrency momentum factor ($CryptoMom$), the aggregate computing power factor (ACP), the aggregate network factor ($ANET$), and the singular value decomposition of ACP and $ANET$ (SVD). In Panel B, we report the results of a factor-spanning test, where we regress ACP on $ANET$ and vice versa in columns (1) and (2), respectively.

Panel A: Correlations	$\Delta Price(BTC)$	*CryptoMom*	ACP	$ANET$	*SVD(ACP,ANET)*
$\Delta Price(BTC)$	1				
CryptoMom	0.06	1			
ACP	0.62***	0.22***	1		
$ANET$	0.76***	0.18***	0.96***	1	
SVD	0.68***	0.21***	0.99***	0.99***	1

Panel B: Spanning Test	(1) ACP	(2) ANET
$ANET$	1.18***	
	(50.07)	
ACP		0.79***
		(50.07)
$\alpha(\times 100)$	−0.16	0.28
	(−0.70)	(1.51)
Adjusted R^2	.93	.93
Observations	201	201

Table A6: Factor Analysiss: 3-Factor Model with Principal Component Factor

This table presents the estimates from time series regressions of cryptocurrency returns on a 3-factor model. The three factors are the return of Bitcoin, the cryptocurrency momentum factor, and the first principal component of the aggregate computing power and network factors (PCA). t-statistics are in parentheses. The superscripts ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 level, respectively. The sample period runs from 8/7/2015 to 6/28/2019.

	(1)	(2)	(3)	(4)	(5)
	BTC	ETH	XMR	LTC	DSH
$\Delta Price(BTC)$		-0.33^{***}	0.33^{**}	0.21^{**}	-0.23^{**}
		(-3.02)	(2.53)	(2.35)	(-2.50)
$CryptoMom$	-0.05^{*}	-0.04	0.24^{***}	-0.00	-0.01
	(-1.66)	(-0.98)	(4.72)	(-0.09)	(-0.14)
PCA	0.04^{***}	0.10^{***}	0.05^{***}	0.07^{***}	0.08^{***}
	(13.82)	(14.22)	(6.06)	(12.29)	(13.90)
α ($\times 100$)	1.74^{***}	0.67	-0.85	-0.60	0.16
	(2.68)	(0.65)	(-0.91)	(-0.78)	(0.18)
Adjusted R^2	.49	.60	.46	.67	.61
Observations	201	201	201	201	201

Table A7: List of Out-of-Sample Cryptocurrencies

This table lists the 34 cryptocurrencies used in the out-of-sample analysis of Section 5.1. Panel A (Panel B) presents the alphabetical list of the mineable (non-mineable) cryptocurrencies. The table also reports the average and standard deviation of their weekly returns. The data are obtained from the Bittrex exchange and the sample period runs from 3/31/2017 to 6/28/2019.

Name	Ticker	Mean($\Delta Price$)	St. Dev.($\Delta Price$)
Panel A: Mineable Cryptocurrencies			
Decred	DCR	0.01	0.14
Digibyte	DGB	0.03	0.27
Dogecoin	DOG	0.02	0.20
FLO	FLO	0.02	0.22
EthereumClassic	ETC	0.01	0.15
Groestlcoin	GRS	0.04	0.25
Lisk	LSK	0.02	0.19
Monacoin	MON	0.04	0.23
Syscoin	SYS	0.01	0.19
Viacoin	VIA	0.02	0.19
Vericoin	VRC	0.01	0.18
Vertcoin	VTC	0.02	0.19
WAVES	WAV	0.02	0.18
Verge	XVG	0.05	0.34
Zcoin	XZC	0.01	0.16
ZCash	ZEC	0.00	0.15
Panel B: Non-mineable Cryptocurrencies			
ARK	ARK	0.02	0.21
Augur	REP	0.01	0.15
Factom	FCT	0.00	0.17
Komodo	KMD	0.02	0.19
Melon	MLN	− 0.02	0.18
NEO	NEO	0.04	0.24
Nexus	NXS	0.00	0.20
NXT	NXT	0.01	0.21
PIVX	PIV	0.00	0.17
Reddcoin	RDD	0.04	0.31
Spherecoin	SPHR	0.02	0.24
SHIFT	SHI	0.01	0.20
STEEM	STE	0.01	0.19
SteemDollars	SBD	0.00	0.19
Stratis	STR	0.02	0.22
NEM	XEM	0.02	0.18
Stellar	XLM	0.03	0.25
Ripple	XRP	0.03	0.23

Table A8: Factor Analysis: Time Series Regressions in Out-of-Sample Cryptocurrencies

This table reports the beta estimates and respective t-statistics for the aggregate computing power factor (ACP), the aggregate network factor ($ANET$), and the cumulative fundamental factor (SVD) from time series regressions using three distinct 3-factor models that include the Bitcoin return, the cryptocurrency momentum factor, and either the computing power (ACP), network ($ANET$), or cumulative fundamental factor (SVD). The estimates for the Bitcoin and momentum factors are not reported. The test assets are the 34 cryptocurrencies used in the out-of-sample analysis of Section 5.1. The superscripts ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 level, respectively. Panel A (Panel B) presents the results for the mineable (non-mineable) cryptocurrencies. The data are obtained from the Bittrex exchange and the sample period runs from 3/31/2017 to 6/28/2019.

Panel A: Mineable Cryptocurrencies

Model:		**3-factor ACP**		**3-factor ANET**		**3-factor SVD**	
Name	Ticker	ACP	$t(ACP)$	$ANET$	$t(ANET)$	SVD	$t(SVD)$
Decred	DCR	0.75***	(6.71)	0.95***	(5.71)	1.27***	(6.38)
Digibyte	DGB	0.85***	(3.50)	1.04***	(2.96)	1.41***	(3.32)
Dogecoin	DOG	0.82***	(5.16)	1.19***	(5.24)	1.45***	(5.23)
EthereumClassic	ETC	0.72***	(6.80)	0.92***	(5.86)	1.22***	(6.50)
FLO	FLO	0.60***	(2.84)	0.74***	(2.44)	1.00***	(2.71)
Groestlcoin	GRS	0.11	(0.44)	0.21	(0.58)	0.22	(0.49)
Lisk	LSK	1.13***	(7.94)	1.47***	(6.86)	1.93***	(7.60)
Monacoin	MON	0.11	(0.52)	0.26	(0.84)	0.24	(0.64)
Syscoin	SYS	0.91***	(6.10)	1.17***	(5.34)	1.54***	(5.86)
Viacoin	VIA	0.73***	(4.38)	0.89***	(3.66)	1.21***	(4.14)
Vericoin	VRC	0.75***	(5.19)	0.92***	(4.32)	1.25***	(4.90)
Vertcoin	VTC	0.48***	(2.89)	0.62***	(2.60)	0.81***	(2.80)
WAVES	WAV	0.58***	(4.04)	0.79***	(3.82)	1.00***	(3.99)
Verge	XVG	1.23***	(3.75)	1.67***	(3.52)	2.13***	(3.69)
Zcoin	XZC	0.70***	(5.02)	0.97***	(4.83)	1.22***	(4.99)
ZCash	ZEC	0.80***	(8.12)	1.01***	(6.75)	1.35***	(7.66)

Panel B: Non-mineable Cryptocurrencies

Model:		**3-factor ACP**		**3-factor ANET**		**3-factor SVD**	
Name	Ticker	ACP	$t(ACP)$	$ANET$	$t(ANET)$	SVD	$t(SVD)$
ARK	ARK	0.70***	(3.73)	0.91***	(3.34)	1.19***	(3.61)
Factom	FCT	0.68***	(4.41)	0.96***	(4.35)	1.19***	(4.42)
Komodo	KMD	0.82***	(4.94)	1.06***	(4.38)	1.39***	(4.77)
Melon	MLN	0.63***	(4.23)	0.74***	(3.36)	1.04***	(3.93)
NEO	NEO	0.94***	(4.41)	1.20***	(3.85)	1.59***	(4.23)
Nexus	NXS	0.88***	(5.10)	1.12***	(4.40)	1.49***	(4.88)
NXT	NXT	0.61***	(3.42)	0.94***	(3.72)	1.10***	(3.55)
PIVX	PIV	0.75***	(4.75)	0.99***	(4.31)	1.28***	(4.62)
Reddcoin	RDD	0.70***	(2.48)	0.78***	(1.91)	1.13***	(2.28)
Augur	REP	0.73***	(5.97)	0.93***	(5.19)	1.23***	(5.72)
SteemDollars	SBD	0.38***	(2.38)	0.69***	(3.09)	0.73***	(2.65)
SHIFT	SHI	0.78***	(4.57)	0.99***	(3.98)	1.32***	(4.38)
Spherecoin	SPHR	0.24	(1.01)	0.29	(0.84)	0.40	(0.95)
STEEM	STE	0.84***	(5.64)	1.09***	(4.97)	1.43***	(5.43)
Stratis	STR	0.75***	(4.50)	0.89***	(3.64)	1.24***	(4.21)
NEM	XEM	0.83***	(6.30)	1.15***	(6.07)	1.44***	(6.26)
Stellar	XLM	0.67***	(3.06)	0.94***	(2.96)	1.17***	(3.04)
Ripple	XRP	1.01***	(5.11)	1.38***	(4.81)	1.75***	(5.04)

Table A9: Factor Analysis: 3-Factor Model with Bitcoin-Free Fundamental Factors

This table reports estimates from time series regressions of weekly cryptocurrency returns on three factors. The cryptocurrencies are Bitcoin (BTC), Ethereum (ETH), Monero (XMR), Litecoin (LTC), and Dash (DSH). The first two factors in the asset pricing model are the the return of Bitcoin ($\Delta Price(BTC)$), and the cryptocurrency momentum factor ($CryptoMom$). The third factor is the aggregate computing power factor, $ACP \setminus BTC$, or the aggregate network factor, $ANET \setminus BTC$, calculated excluding Bitcoin blockchain characteristics and Bitcoin returns from the factor mimicking portfolios. t-statistics are in parentheses. The superscripts ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 level, respectively. The sample is from 8/7/2015 to 6/28/2019.

	(1)	(2)	(3)	(4)	(5)
Panel A: 3-factor ACP	BTC	ETH	XMR	LTC	DSH
$\Delta Price(BTC)$		-0.16	0.06	0.55^{***}	-0.25^{***}
		(-1.43)	(0.57)	(5.46)	(-3.47)
$CryptoMom$	-0.08^{**}	-0.10^{**}	0.14^{***}	0.01	-0.08^{***}
	(-2.52)	(-2.03)	(3.31)	(0.28)	(-2.72)
$ACP \setminus BTC$	0.54^{***}	1.13^{***}	1.03^{***}	0.52^{***}	1.13^{***}
	(12.17)	(12.50)	(12.60)	(6.28)	(19.32)
α ($\times$100)	1.07^{**}	0.84	-0.70	-0.52	0.32
	(2.17)	(1.09)	(-1.01)	(-0.75)	(0.65)
Adjusted R^2	.43	.55	.65	.51	.73
Panel B: 3-factor ANET	BTC	ETH	XMR	LTC	DSH
$\Delta Price(BTC)$		-0.15	0.47^{***}	0.52^{***}	-0.20^{***}
		(-1.44)	(3.86)	(5.55)	(-3.00)
$CryptoMom$	-0.04	-0.03	0.26^{***}	0.04	-0.01
	(-1.27)	(-0.71)	(4.96)	(0.92)	(-0.44)
$ANET \setminus BTC$	0.55^{***}	1.27^{***}	0.59^{***}	0.63^{***}	1.22^{***}
	(11.18)	(14.30)	(5.53)	(7.64)	(20.97)
α ($\times$100)	0.97^{*}	0.45	-0.96	-0.71	-0.06
	(1.89)	(0.62)	(-1.10)	(-1.06)	(-0.12)
Adjusted R^2	.38	.61	.45	.55	.76

Table A10: Out-of-Sample Cryptocurrencies and Bitcoin-Free Fundamental Factors

This table reports estimates from pooled OLS regressions of weekly cryptocurrency returns ($\Delta Price$) on three asset pricing factors. The test assets are the 34 cryptocurrencies described in Table A7 of the Appendix. The first two factors in the asset pricing model are the return of Bitcoin ($\Delta Price(BTC)$) and the cryptocurrency momentum factor ($CryptoMom$). The third factor is the aggregate computing power factor, $ACP \setminus BTC$, or the aggregate network factor, $ANET \setminus BTC$, calculated excluding Bitcoin blockchain characteristics and Bitcoin returns from the factor mimicking portfolios. Standard errors are double-clustered by week and currency. t-statistics are in parentheses. The superscripts ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 level, respectively. We also report the Gibbons et al. (1989) (GRS) test statistics along with the respective p values. The GRS statistic is based on currency-level alphas estimated from time series regressions for each currency. The sample runs from 3/31/2017 to 6/28/2019.

	(1) 3-factor ACP	(2) 3-factor ANET
$\Delta Price(BTC)$	0.26	0.31*
	(1.48)	(1.90)
$CryptoMom$	−0.02	0.01
	(−0.23)	(0.15)
$ACP \setminus BTC$	0.81***	
	(5.53)	
$ANET \setminus BTC$		0.84***
		(5.45)
α ($\times$100)	0.11	−0.18
	(0.13)	(−0.23)
Adjusted R^2	0.34	0.33
GRS Statistic	0.158	.178
p-value	1.00	1.00
Cryptocurrencies	34	34
Observations	4,012	4,012

Table A11: Factor Analysis: Out-of-Sample Cryptocurrencies and Ethereum

This table reports estimates from pooled OLS regressions of weekly cryptocurrency returns ($\Delta Price$) on three asset pricing factors. The test assets are the 34 cryptocurrencies described in Table A7 of the Appendix. In column (1), the factors in the asset pricing model are the return of Ethereum ($\Delta Price(ETH)$) and the cryptocurrency momentum factor ($CryptoMom$). The 3-factor models in columns (2), (3), and (4) additionally include the aggregate computing power factor (ACP), the aggregate network factor ($ANET$), and the singular value decomposition of the computing power and network factors (SVD), respectively. Standard errors are double-clustered by week and currency. t-statistics are in parentheses. The superscripts ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 level, respectively. We also report the Gibbons et al. (1989) (GRS) test statistics along with the respective p values. The GRS statistic is based on currency-level alphas estimated from time series regressions for each currency. The sample runs from 3/31/2017 to 6/28/2019 and consists of 118 weekly observations.

	(1) 2-factor	(2) 3-factor ACP	(3) 3-factor ANET	(4) 3-factor SVD
$\Delta Price(ETH)$	0.77***	0.27**	0.33***	0.28**
	(9.57)	(2.16)	(3.02)	(2.38)
$CryptoMom$	0.04	−0.03	−0.00	−0.02
	(0.34)	(−0.35)	(−0.01)	(−0.23)
ACP		0.67***		
		(4.66)		
$ANET$			0.74***	
			(4.87)	
SVD				1.08***
				(4.76)
α ($\times$100)	0.30	0.20	−0.15	0.04
	(0.35)	(0.27)	(−0.21)	(0.06)
Adjusted R^2	0.28	0.33	0.34	0.34
GRS Statistic	1.02	0.20	0.29	0.24
p-value	0.45	1.00	1.00	1.00
Cryptocurrencies	34	34	34	34
Observations	4,012	4,012	4,012	4,012

Table A12: Descriptive Statistics and Cross-correlations of Factors using Out-of-sample returns

This table reports descriptive statistics and cross-correlations for various factors. These factors are the aggregate computing power factor (*ACP(38)*) constructed by projecting the computing power of the baseline cryptocurrencies on the returns of 38 cryptocurrencies, the aggregate network factor (*ANET(38)*) constructed by projecting the network of the baseline cryptocurrencies on the returns of 38 cryptocurrencies, and the singular value decomposition of these two factors (*SVD(38)*). The other factors are the original aggregate computing power factor (ACP), the original aggregate network factor ($ANET$), their singular value decomposition (SVD), the return of Bitcoin ($\Delta Pr(BTC)$), and the cryptocurrency momentum factor (*CryptoMom*). Details on the construction of the factors are provided in Table A1 of the Appendix. The sample period runs from 3/31/2017 to 6/28/2019 and consists of 118 weekly observations. The superscripts ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 level, respectively.

	Mean	SD	SharpeRatio	*ACP(38)*	*ANET(38)*	*SVD(38)*	$ANET$	ACP	SVD	$\Delta Pr(BTC)$
ACP(38)	2.98	21.76	0.14	1						
ANET(38)	2.54	17.34	0.15	0.10	1					
SVD(38)	1.46	9.13	0.16	0.98***	0.29***	1				
$ANET$	1.90	11.15	0.17	0.33***	0.71***	0.46***	1			
ACP	1.89	13.17	0.14	0.41***	0.67***	0.52***	0.98***	1		
SVD	1.26	8.12	0.15	0.38***	0.69***	0.50***	0.99***	0.996***	1	
$\Delta Pr(BTC)$	2.05	10.07	0.20	0.16*	0.71***	0.29***	0.84***	0.74***	0.78***	1
CryptoMom	4.58	13.21	0.35	0.16*	0.19**	0.19**	0.22**	0.25***	0.25***	0.12

Table A13: Factor Analysis with the $ACP(38)$ and $ANET(38)$ Factors

This table reports estimates from pooled OLS regressions of weekly cryptocurrency returns ($\Delta Price$). The test assets are the 34 cryptocurrencies described in Table A7 of the Appendix. In column (1), the factors are the return of Bitcoin ($\Delta Price(BTC)$) and the cryptocurrency momentum factor ($CryptoMom$). In column (2), we add the aggregate computing power factor ($ACP(38)$) and the aggregate network factor ($ANET(38)$). In column (3), we add the singular value decomposition of $ACP(38)$ and $ANET(38)$, denoted as $SVD(38)$. Standard errors are double-clustered by week and currency. t-statistics are in parentheses. The superscripts ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 level, respectively. We also report the Gibbons et al. (1989) (GRS) test statistics for the efficiency of the factor models along with the respective p values. The GRS statistic is based on cryptocurrency-level alphas estimated from time series regressions for each currency. The sample runs from 3/31/2017 to 6/28/2019 and consists of 118 weekly observations.

	(1)	(2)	(3)
	2-factor	4-factor	SVD
$\Delta Price(BTC)$	1.02^{***}	0.76^{***}	0.91^{***}
	(9.05)	(5.50)	(7.95)
CryptoMom	0.12^{*}	0.05	0.07
	(1.74)	(0.84)	(1.06)
ACP(38)		0.18^{***}	
		(3.13)	
ANET(38)		0.17^{*}	
		(1.82)	
SVD(38)			0.45^{***}
			(3.11)
α ($\times$100)	-0.82	-0.74	-1.03
	(-0.86)	(-1.14)	(-1.22)
Average R^2	0.25	0.29	0.29
GRS Statistic	1.29	1.15	1.56
p-value	0.16	0.33	0.07
Cryptocurrencies	34	34	34
Observations	4,012	4,012	4,012