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Risks and Returns of Cryptocurrency

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We establish that cryptocurrency returns are driven and can be predicted by factors that are specific to cryptocurrency markets. Cryptocurrency returns are exposed to cryptocurrency network factors but not cryptocurrency production factors. We construct the network factors to capture the user adoption of cryptocurrencies and the production factors to proxy for the costs of cryptocurrency production. Moreover, there is a strong time-series momentum effect, and proxies for investor attention strongly forecast future cryptocurrency returns. (*JEL* G12,G31)

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Cryptocurrency is a recent phenomenon that is receiving significant attention. On the one hand, it is based on a fundamentally new technology, the potential of which is not fully understood. On the other hand, at least in the current form, it fulfills similar functions as other, more traditional assets. Extensive academic attention has focused on developing theoretical models of cryptocurrencies. The theoretical literature on cryptocurrencies has suggested a number of factors that are potentially important in the valuation of cryptocurrencies. The first group of papers builds models stressing the network effect of cryptocurrency adoption (e.g., Pagnotta and Buraschi 2018; Biais et al. 2018; Cong, Li, and Wang 2019) and emphasizes the price dynamics induced by the positive externality of the network effect. The second group of papers focuses on the production side of the coins—the miners' problem (e.g., Cong, He, and Li 2018; Sockin and Xiong 2019)—and shows that the evolution of cryptocurrency prices is linked to the marginal cost of production. The third group of papers ties the movements of cryptocurrency prices to those of traditional asset classes such as fiat money

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(e.g., Athey et al. 2016; Schilling and Uhlig 2019; Jermann 2018). There is also a growing literature on the empirical regularities of cryptocurrencies. Borri (2019) shows that individual cryptocurrencies are exposed to cryptomarket tail-risks. Makarov and Schoar (2020) find that cryptocurrency markets exhibit periods of potential arbitrage opportunites across exchanges. Griffin and Shams (2020) study Bitcoin price manipulation. Our paper is the first comprehensive analysis of cryptocurrencies through the lens of empirical asset pricing. Its contribution is twofold. First, it tests the mechanisms and predictions of the existing theoretical models. Second, it establishes a set of basic asset pricing facts for this asset class, which provides a common benchmark that the current and future models of cryptocurrencies should take into consideration.

We start by constructing an index of cryptocurrency (or coin) market returns. This index is the value-weighted returns of all the coins with capitalizations of more than 1 million USD (1,707 coins in total) and covers the period of January 1, 2011, to December 31, 2018. We now describe some basic statistical properties of this index. During the sample period, the averages of the coin market returns at the daily, weekly, and monthly frequencies are 0.46%, 3.44%, and 20.44%, respectively. The daily, weekly, and monthly standard deviations of the coin market returns are 5.46%, 16.50%, and 70.80%, respectively. The coin market returns have positive skewness and kurtosis. We observe that the mean and standard deviation of the coin market returns are an order of magnitude higher than those of the stock returns during the same period. The Sharpe ratios at the daily and weekly levels are about 60% and 90% higher, and the Sharpe ratio at the monthly level is comparable to those of stocks. The returns have positive skewness increasing with the frequencies from daily to monthly. The returns experience high probabilities of extreme losses and gains. For example, an extreme loss of the daily 20% negative return on the coin market happens with a probability of 0.48%, while an extreme gain of the same size occurs with a probability of 0.89%.

We next turn to examine the relationship between the coin market returns and the main cryptocurrency-specific factors that are proposed in the theoretical literature. We formulate and investigate potential drivers and predictors for cryptocurrency returns. Specifically, we construct cryptocurrency network factors, cryptocurrency production factors, cryptocurrency momentum, proxies for average and negative investor attention, and proxies for cryptocurrency valuation ratios. For each of these factors, we aim to provide a number of possible empirical measures, as there are no canonical ways to define them in the cryptocurrency market.

We consider five measures to capture the cryptocurrency network effect. Consistent with the cryptocurrency models based on the network effect,[1] we find that the coin market returns are positively and significantly exposed to

[1] See, e.g., Cong, Li, and Wang (2019) Pagnotta and Buraschi (2018), and Biais et al. (2018).

cryptocurrency network growth. Furthermore, we show that the evolution of cryptocurrency prices not only reflects current cryptocurrency adoption but also contains information about expected future network growth.

We then study the implications of the cryptocurrency models based on the miners' production problem.[2] We construct production factors of cryptocurrency to proxy for the cost of mining and test the relationship between these production factors and cryptocurrency prices. To the first approximation, mining a cryptocurrency requires two inputs: electricity and computer power. We separately construct eight proxies for electricity costs and six proxies for computing costs. For electricity, we use time-varying and location-specific measures of the price, consumption, and generation of electricity in the United States and China (including Sichuan province, which hosts the largest mining farm in the world). For proxies of computing costs, we use the prices of Bitmain Antminer, one of the common Bitcoin mining equipments, as our primary measure. We also consider indirect measures—the stock returns of the companies that are major manufacturers of mining chips. Overall, we find that the coin market returns are not significantly exposed to the cryptocurrency production factors.

The existing theoretical models of cryptocurrencies have a number of implications for the predictability of cryptocurrency returns. Some papers argue that the evolution of cryptocurrency prices should follow a martingale, and thus cryptocurrency returns are not predictable (e.g., Schilling and Uhlig 2019). Other papers argue that, in dynamic cryptocurrency valuation models, cryptocurrency returns could potentially be predicted by momentum, investor attention, and cryptocurrency valuation ratios (e.g., Cong, Li, and Wang 2019; Sockin and Xiong 2019). We show that momentum and investor attention strongly predict future cryptocurrency cumulative returns, but cryptocurrency valuation ratios do not.

First, we show that there is a significant time-series momentum phenomenon in the cryptocurrency market. We find that the current coin market returns predict cumulative future coin market returns from one week to eight weeks ahead. For example, a one-standard-deviation increase in the current coin market returns predicts a 3.30% increase in the weekly returns over the next week. Grouping weekly returns by terciles, we find that the top terciles outperform the bottom terciles over the one- to four-week horizons. For example, at the one-week horizon, the average return of the top tercile is 8.01% per week with a t-statistic of 4.30, while the average return of the bottom tercile is only 1.10% per week with a t-statistic of 0.92. The time-series momentum results are valid both in sample and out of sample.

Second, we construct proxies for investor attention with Google searches and show that high investor attention predicts high future returns over the one-

[2] See, e.g., Cong, He, and Li (2018) and Sockin and Xiong (2019).

to six-week horizons. For example, a one-standard-deviation increase in the investor attention measure yields a 3.0% increase in the 1-week-ahead future coin market returns. At the one-week horizon, the average return of the investor attention tercile is 6.53% per week with a t-statistic of 3.82, while the average return of the bottom tercile is only 0.43% per week with a t-statistic of 0.42. Another proxy for investor attention we construct is Twitter post counts, and we reach similar results with the Twitter measure. Additionally, we construct a proxy for negative investor attention and show that relatively high negative investor attention negatively predicts future cumulative coin market returns.

Research on the equity market (e.g., Hong, Lim, and Stein 2000; Hou, Xiong, and Peng 2009) shows that there is a strong interaction between momentum and investor attention. Sockin and Xiong (2019) also show that investor attention can generate momentum in the cryptocurrency market, and in their model, the momentum effect disappears controlling for investor attention. We investigate whether there is a similar interaction between momentum and investor attention in the cryptocurrency market. We find that investor attention is high during and after periods of high coin market returns. However, in a bivariate coin market predictability regression with both variables, we show that the two effects do not subsume each other. Finally, we test whether the magnitude of the momentum effect is different during periods of high investor attention and vice versa. In contrast to the equity market, we show that there is limited interaction between cryptocurrency momentum and investor attention.

Moreover, we test whether the cryptocurrency valuation ratios similar to those in the financial markets can predict future coin market returns. In the equity market, the fundamental-to-market ratios are commonly referred to as valuation ratios and are measured as the ratio of the book value of equity to the market value of equity or some other ratio of fundamental value to market value. It is more difficult to define a similar measure of the fundamental value for cryptocurrency. In their dynamic cryptocurrency asset pricing model, Cong, Li, and Wang (2019) show that the cryptocurrency fundamental-to-value ratio, defined as the number of user adoptions over market capitalization, negatively predicts future cryptocurrency returns. Motivated by the theoretical model and studies of other financial markets, we construct six cryptocurrency valuation ratios and test the return predictability of these valuation ratios. Although the coefficient estimates are consistently negative, none of the six cryptocurrency valuation ratios predict future cumulative coin market returns significantly.

Another approach to study what cryptocurrencies represent is to examine the exposures of cryptocurrency returns to other asset classes. In other words, we assess how investors and markets value current and future prospects of cryptocurrencies. The theoretical literature and the community of cryptocurrency have proposed various narratives for what cryptocurrencies represent. Schilling and Uhlig (2019) argue that, in an endowment economy where fiat money and cryptocurrency coexist and compete, the cryptocurrency returns comove with the price evolution of the fiat money. Athey et al. (2016)

emphasize the importance of currency exchange rates on cryptocurrency prices. Another popular narrative is that cryptocurrency is “digital gold” and represents a new way to store value. Specifically, we study whether major cryptocurrencies comove with currencies, commodities, stocks, and macroeconomic factors. In contrast to these popular explanations, we find that the exposures of cryptocurrencies to these traditional assets are low. Overall, there is little evidence, in the view of the markets, behind the narrative that there are similarities between cryptocurrencies and these traditional assets.

We note several additional results. First, we acknowledge that we have a short time series and that there is much uncertainty and learning about cryptocurrencies during the sample period. We show that our main results are similar for the first half and the second half of the sample. Second, we discuss the relationship between the cryptocurrency time-series momentum and cross-sectional momentum. Third, we investigate the importance of regulative events in affecting cryptocurrency prices, and show that negative regulative events but not positive regulative events significantly affect cryptocurrency prices. Fourth, we examine the importance of speculative interests in driving cryptocurrency prices. We show that cryptocurrency returns are higher when speculative interests increase, but the coefficient estimates are only marginally significant. Fifth, we construct a direct measure of cryptocurrency investor sentiment and show that the expected coin market return is higher when investor sentiment is high. In the multivariate regressions with the sentiment, investor attention, and momentum measures, all three variables are statistically significant in predicting future cryptocurrency returns. Sixth, we test the role of beauty contests in the cryptocurrency market. Motivated by Biais and Bossaerts (1998), we use the volume-volatility ratio to capture the degree of disagreement in the cryptocurrency market and show that cryptocurrency return is high when the current volume-volatility ratio is high. Seventh, we conduct a VAR analysis with the coin market returns and the different measures of coin network growth measures. Eighth, we test the effect of production factors with an alternative specification. Lastly, we examine the subsample results based on cryptocurrency characteristics.

Our paper uses standard textbook empirical asset pricing tools and methods, the discussion of which we mostly omit for conciseness. Our findings on momentum are related to a series of papers such as Jegadeesh and Titman (1993), Moskowitz and Grinblatt (1999), Moskowitz, Ooi, and Pedersen (2012), Asness, Moskowitz, and Pedersen (2013), and Daniel and Moskowitz (2016). Da, Engelberg, and Gao (2011) use Google searches to proxy for investor attention.

Yermack (2015) is one of the first papers that brought academic attention to the field of cryptocurrency. Several recent articles document individual facts related to cryptocurrency investment. Stoffels (2017) studies cross-sectional cryptocurrency momentum. Hu, Parlour, and Rajan (2018) show that individual cryptocurrency returns correlate with Bitcoin returns. Borri (2019) shows that individual cryptocurrencies are exposed to cryptomarket tail-risks. Makarov and Schoar (2020) and Borri and Shakhnov (2018) find that cryptocurrency markets exhibit periods of potential arbitrage opportunites across exchanges. Griffin and Shams (2020) study Bitcoin price manipulation. Corbet et al. (2019) studies cryptocurrencies as a financial asset. Moreover, a number of recent papers develop models of cryptocurrencies (see, e.g., Weber 2016; Huberman, Leshno, and Moallemi 2017; Biais et al. 2018; Chiu and Koeppl 2017; Cong and He 2019; Cong, Li, and Wang 2019; Cong, He, and Li 2018; Sockin and Xiong 2019; Saleh 2018; Schilling and Uhlig 2019; Jermann 2018; Abadi and Brunnermeier 2018; Routledge and Zetlin-Jones 2018).

1. Data and Basic Characteristics

We collect trading data of all cryptocurrencies available from Coinmarketcap.com. Coinmarketcap.com is a leading source of cryptocurrency price and volume data. It aggregates information from over 200 major exchanges and provides daily data on opening, closing, high, and low prices, as well as volume and market capitalization (in dollars) for most of the cryptocurrencies.[3] For each cryptocurrency on the website, Coinmarketcap.com calculates its price by taking the volume-weighted average of all prices reported at each market. A cryptocurrency needs to meet a list of criteria to be listed, such as being traded on a public exchange with an application programming interface (API) that reports the last traded price and the last 24-hour trading volume, and having a nonzero trading volume on at least one supported exchange so that a price can be determined. Coinmarketcap.com lists both active and defunct cryptocurrencies, thus alleviating concerns about survivorship bias.

We first construct a coin market return as the value-weighted return of all the underlying coins. We use daily close prices to construct daily coin market returns. The weekly and monthly coin market returns are calculated from the daily coin market returns. We require the coins to have information on price, volume, and market capitalization. We further exclude coins with market capitalizations of less than 1,000,000 USD. For earlier years that are not covered by Coinmarketcap.com, we splice the coin market returns with Bitcoin returns from earlier years. The data of the earlier year Bitcoin returns are from CoinDeck and span from January 1, 2011, to April 29, 2013. We start from January 1, 2011, because there was not much liquidity and trading before that date. Altogether, the index of the coin market return covers the period from January 1, 2011, to December 31, 2018.

We use four primary measures to proxy for the network effect of user adoption: the number of wallet users, the number of active addresses, the number of transaction count, and the number of payment count. The data of

[3] Some coins are not tracked by the website because the coins' exchanges do not provide accessible APIs.

wallet users are from Blockchain.info. We obtain data on active addresses, transaction count, and payment count from Coinmetrics.io. We use seven primary production factors to proxy for the cost of mining: the average price of electricity in the United States, the net generation of electricity of all sectors in the United States, the total electricity consumption of all sectors in the United States, the average price of electricity in China, and the average price of electricity in Sichuan province. We obtain data on the average price of electricity in the United States, the net generation of electricity of all sectors in the United States, and the total electricity consumption of all sectors in the United States from the U.S. Energy Information Administration. We obtain data on the average price of electricity in China and the average price of electricity in Sichuan province from the National Bureau of Statistics of China and the Price Monitoring Center, NDRC. Our primary computing cost data are the prices of Bitmain Antminer. We extract the Bitmain Antminer data from Keepa.com. The data for Bitmain Antminer start from September 2015.

Google search data series are downloaded from Google. Twitter post counts for the word "Bitcoin" are downloaded from Crimson Hexagon.[4] The spot exchange rates in units of U.S. dollars per foreign currency are from the Federal Reserve Bank of St. Louis. We focus on five major currencies: Australian dollar, Canadian dollar, euro, Singaporean dollar, and U.K. pound. The spot prices of precious metals are from several sources. The gold and silver prices are from the London Bullion Market Association (LBMA). Platinum prices are from the London Platinum and Palladium Market (LPPM).

Aggregate and individual stock returns are from CRSP. Detailed SIC three-digit industry return data series are constructed using individual stock returns. Chinese stock return data are from CSMAR. We build the value-weighted aggregate Chinese stock returns and detailed CIC (China Industry Classification) industry return data series from the individual stocks. The data series of Chinese stock returns last until December 2016. The return series of the 155 anomalies are downloaded from Andrew Chen's website.[5]

We obtain data on the Fama-French three-factor, Carhart four-factor, Fama-French five-factor, and Fama-French six-factor models from Kenneth French's website. We also collect the return series of Fama-French 30 industries, Europe, Japan, AsiaExJapan, and North America from Kenneth French's website.

The macroeconomic data series are from the website of the Federal Reserve Bank of St. Louis. Nondurable consumption is defined as the sum of personal consumption expenditures: nondurable goods, and personal consumption expenditures: services.

Stock market prices, dividends, and earnings, as well as the three-month Treasury bill rates, are from Robert Shiller's website. Using these data series, we

4 We thank William Goetzmann for kindly sharing the Twitter post count data with us.

5 One of the 156 anomalies does not exist during the sample period. The database ends at December 2016.

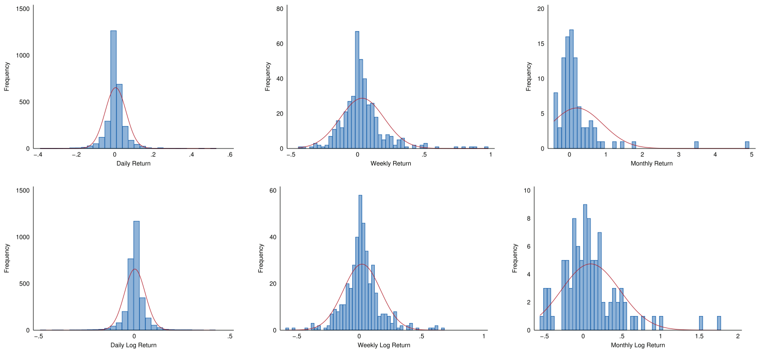

Figure 1
Coin market return distributions
This figure plots the distributions of daily, weekly, and monthly cryptocurrency returns and log returns.

construct the stock market price-to-dividend ratio (pd), price-to-earnings ratio (pe), and the relative bill rate (tbill). The relative bill rate is defined as the three-month Treasury bill rate minus its 12 month backward moving average. Credit spread (credit) is defined as the yield spread between BAA corporate bonds and AAA corporate bonds. Term spread (term) is defined as the yield spread between the 10-year Treasury and 3-month Treasury. Data series on the BAA corporate yield, AAA corporate yield, 10-year Treasury yield, and 3-month Treasury yield are from the Federal Reserve Bank of St. Louis's website.

We now document the main statistical properties of the time series for the coin market returns. Figure 1 shows the return distributions of coin market returns and coin market log returns at daily, weekly, and monthly frequencies. Figure 2 plots the price movements of the coin market compared with those of the three major cryptocurrencies. There are strong comovements across the three major cryptocurrencies. Table 1 compares the properties of the coin market returns with those of Bitcoin returns, Ethereum returns, Ripple returns, and stock market returns.

Table 1 shows the statistics of the coin market returns at the daily, weekly, and monthly frequencies compared with those of the stock market returns. Both the average and the standard deviation of the coin market returns are very high. At the daily frequency, the mean return is 0.46% and the standard deviation is 5.46%; at the weekly frequency, the mean return is 3.44% and the standard deviation is 16.50%; at the monthly frequency, the mean return is 20.44% and the standard deviation is 70.80%. Both the means and the standard deviations are an order of magnitude higher than those for the stock market returns. These facts are broadly known.

The Sharpe ratios of the coin market returns are 0.08 at the daily frequency, 0.21 at the weekly frequency, and 0.29 at the monthly frequency. At the daily and weekly frequencies, the Sharpe ratios of the coin market are about 60%

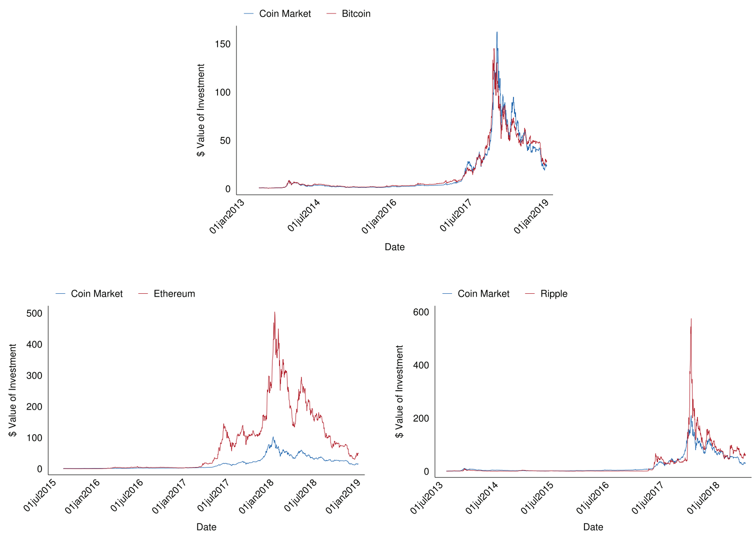

Figure 2
Cryptocurrency market returns and major coins
This figure plots the cryptocurrency market returns against Bitcoin, Ethereum, and Ripple. The figures show the value of investment over time for one dollar of investment at the starting point of the graphs. The Bitcoin graph starts at April 29, 2013. The Ethereum graph starts at August 8, 2015. The Ripple graph starts at August 5, 2013.

and 90% higher than those of the stock market for the comparable time period. At the monthly frequency, the Sharpe ratio is similar to that of the stock market for the comparable time period.

We compare the characteristics of the coin market returns to those of the Bitcoin, Ripple, and Ethereum returns. Note that the Ripple return series starts on August 4, 2013, and the Ethereum return series starts on August 7, 2015. For the Bitcoin returns, the Sharpe ratios are 0.08 at the daily frequency, 0.21 at the weekly frequency, and 0.29 at the monthly frequency. For Ethereum, the Sharpe ratios are 0.08 at the daily frequency, 0.20 at the weekly frequency, and 0.36 at the monthly frequency. The Ethereum returns have a higher mean and standard deviation than the coin market returns. For the Ripple returns, the Sharpe ratios are 0.07 at the daily frequency, 0.13 at the weekly frequency, and 0.24 at the monthly frequency. The Ripple returns have a markedly higher mean and standard deviation compared with those of the coin market returns. The Sharpe ratios of Ripple returns are lower than those of the coin market returns at all three frequencies.

The coin market returns are positively skewed at all frequencies, in contrast to the stock returns, which are negatively skewed. The skewness increases from 0.74 at the daily frequency to 1.74 at the weekly frequency, and to 4.37 at the monthly frequency. The corresponding kurtosis is 15.52 at the daily frequency, 10.22 at the weekly frequency, and 26.54 at the monthly frequency. All three of

Table 1
Summary statistics

Panel A. Summary statistics of main variables

Daily	Mean	SD	t-Stat	Sharpe	Skewness	Kurtosis	% > 0
CMKT	0.46%	5.46%	4.60	0.08	0.74	15.52	54.04
Bitcoin	0.46%	5.44%	4.66	0.08	0.82	15.56	53.61
Ethereum	0.60%	7.39%	2.86	0.08	0.27	15.98	48.63
Ripple	0.53%	7.84%	2.66	0.07	6.06	100.37	46.08
Stock	0.05%	0.95%	2.21	0.05	–0.46	7.88	54.57
Weekly	Mean	SD	t-Stat	Sharpe	Skewness	Kurtosis	% > 0
CMKT	3.44%	16.50%	4.25	0.21	1.74	10.22	57.31
Bitcoin	3.44%	16.29%	4.32	0.21	1.79	10.58	59.47
Ethereum	4.84%	24.33%	2.65	0.20	1.46	7.59	51.69
Ripple	5.72%	45.59%	2.11	0.13	7.77	80.58	46.45
Stock	0.22%	1.98%	2.28	0.11	–0.47	5.15	59.71
Monthly	Mean	SD	t-Stat	Sharpe	Skewness	Kurtosis	% > 0
CMKT	20.44%	70.80%	2.83	0.29	4.37	26.54	58.33
Bitcoin	19.64%	66.66%	2.89	0.29	4.37	26.01	58.33
Ethereum	23.27%	65.03%	2.29	0.36	1.42	4.53	48.78
Ripple	32.68%	137.29%	1.92	0.24	4.01	20.49	38.46
Stock	0.94%	3.42%	2.70	0.27	–0.42	4.07	68.75

Panel B. Extreme events of daily CMKT returns

Disasters	Counts	%	Miracles	Counts	%
< –5 %	250	8.56%	> 5 %	318	10.88%
< –10 %	85	2.91%	> 10 %	107	3.66%
< –20 %	14	0.48%	> 20 %	26	0.89%
< –30 %	3	0.10%	> 30 %	10	0.34%

This table documents the summary statistics of the coin market returns (CMKT). Panel A reports the daily, weekly, and monthly summary statistics of the coin market index and compares them with returns for Bitcoin, Ethereum, Ripple, and the stock market. The mean, standard deviation, t-statistics, Sharpe ratio, skewness, kurtosis, and the percentage of obervations that are positive are reported. Panel B reports the percentage of extreme events based on the daily coin market index returns. The coin market returns, the Bitcoin returns, and the stock market returns are from January 1, 2011, to December 31, 2018. The Ethereum returns are from August 8, 2015, to December 31, 2018. The Ripple returns are from August 5, 2013 to December 31, 2018.

the major cryptocurrencies have positive skewness and high kurtosis. The coin market returns have high probabilities of exceptional negative and positive daily returns. For example, the probability of a –20% daily return is almost 0.5%, and the probability of a 20% daily return is almost 0.9%.

In the Internet Appendix, we also show the mean, standard deviation, and Sharpe ratios of the returns on different days of the week. In contrast to the stocks, there is no pronounced Monday effect. However, the returns are lower on Saturdays: the average Sunday coin market return is 0.28% with a Sharpe ratio of 0.05, compared with a 0.46% daily average with a Sharpe ratio of 0.08; the average Sunday Bitcoin is 0.29% with a Sharpe ratio of 0.06, compared with a 0.46% daily average with a Sharpe ratio of 0.08; the average Sunday Ethereum is 0.25% with a Sharpe ratio of 0.03, compared with a 0.60% daily average with a Sharpe ratio of 0.08; and the average Sunday Ethereum is –0.15% with a Sharpe ratio of –0.02, compared with a 0.53% daily average with a Sharpe ratio of 0.07. While the coin market and Bitcoin returns are somewhat lower on Sundays, the returns on Saturday are consistently lower.

2. Cryptocurrency-Specific Factors

The theoretical literature has proposed a number of cryptocurrency-specific factors as drivers of cryptocurrency prices and as predictors of cryptocurrency returns. In this section, we develop and investigate the implications of cryptocurrency-specific factors. We first construct cryptocurrency network and production factors. We find that the coin market returns are strongly exposed to the network factors but not the production factors. Then, we test if cryptocurrency returns are predictable by studying whether different cryptocurrency-specific factors can predict future coin market returns. We consider momentum, proxies for investor attention, and proxies for cryptocurrency valuation ratios. All of these variables are specific to the cryptocurrency markets. We find that momentum and proxies for investor attention can account for future coin market returns, and thus strongly reject the notion that cryptocurrency prices are a martingale.

2.1 Network factors

The theoretical literature on cryptocurrency has emphasized the importance of network factors in the valuation of cryptocurrencies (e.g., Cong, Li, and Wang 2019; Sockin and Xiong 2019; Pagnotta and Buraschi 2018; Biais et al. 2018). In particular, the network effect of user adoption can potentially play a central role in the valuation of cryptocurrencies. Because users' adoption of cryptocurrencies generates positive network externality, cryptocurrency prices respond to user adoptions. Hence, variations in user adoptions of the cryptocurrency network could contribute to movements in cryptocurrency prices.

We construct network factors of cryptocurrency and test whether these factors can account for variations in cryptocurrency prices. We use four measures to proxy for the network effect: the number of wallet users, the number of active addresses, the number of transaction count, and the number of payment count.[6] Thus, we measure cryptocurrency network growth using the wallet user growth, active address growth, transaction count growth, and payment count growth. We also construct a composite measure by taking the first principal component of the four primary measures, which we denote as $PC^{network}$. Panel A of Table 2 reports the correlation across the network factors we consider. The four primary measures correlate with each other positively, with correlations ranging from 0.17 to 0.77. The first principal component of the four demand factors strongly correlates with all four of the primary measures. The first principal component has correlations of 0.45, 0.88, 0.88, and 0.90 with the wallet user growth measure, the active address growth measure, the transaction count growth measure, and the payment count growth measure, respectively.

[6] Because Bitcoin is by far the largest and well-known cryptocurrency available, we use Bitcoin network data. The tests in the paper use coin market returns; in the Internet Appendix, we show that our results are qualitatively similar using Bitcoin returns.

Table 2
Cryptocurrency return loadings to network factors

Panel A. Correlation of network factors

	Δuser	Δaddress	Δtrans	Δpayment
Δuser	1.00	0.35	0.17	0.27
Δaddress		1.00	0.68	0.67
Δtrans			1.00	0.77
Δpayment				1.00
$PC^{network}$	0.45	0.88	0.88	0.90

Panel B. Network factor exposures

	(1)	(2)	(3)	(4)	(5)
Δuser	1.40*				
	(1.98)				
Δaddress		1.86***			
		(5.34)			
Δtran			0.68**		
			(2.14)		
Δpayment				0.95***	
				(3.42)	
$PC^{network}$					0.09***
					(4.25)
R^2	0.05	0.30	0.10	0.18	0.19

This table reports the factor loadings of the coin market returns on the network factors. The network factors include wallet user growth, active address growth, transaction count growth, payment count growth, and the first principal component of the four primary measures. Panel A shows the correlation matrix of the variables. Panel B reports the loadings of the coin market returns on the network factors. The standard t-statistic is reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics. The data frequency is monthly.

We regress the coin market returns on each of the four measures of changes in the cryptocurrency network and the composite measure. Panel B of Table 2 presents the results using the network factors. The coin market returns positively correlate with all four of the individual cryptocurrency network factors and the composite measure. The coefficient on the wallet user growth measure is significant at the 10% level, and the three other coefficients are significant at the 1% level. The R^2s range from 5% for the wallet user growth measure to 30% for the active address growth measure. The R^2s using the composite measure is 19%. Consistent with the theoretical models, these results suggest that the network factors that measure the network effect of user adoptions are important drivers of cryptocurrency prices.

Moreover, in a dynamic cryptocurrency pricing model with the network effect, cryptocurrency prices not only reflect current cryptocurrency adoption but also contain information about expected future network growth—a key mechanism of Cong, Li, and Wang (2019). We test this model implication by examining whether current coin market returns contain information about future cryptocurrency network growth. In particular, we predict cumulative future cryptocurrency adoption growth over different horizons using current coin market returns. We investigate cumulative future cryptocurrency adoption growth from one-month to eight-month horizons. We use cumulative wallet

Table 3
Predicting future network growth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Δuser				
cmkt	0.13***	0.21***	0.28***	0.32***	0.35***	0.36***	0.39**	0.44**
	(4.09)	(3.55)	(3.37)	(3.25)	(2.99)	(2.67)	(2.44)	(2.30)
Cons	0.09***	0.19***	0.28***	0.36***	0.45***	0.53***	0.61***	0.68***
	(7.39)	(6.25)	(5.51)	(5.00)	(4.66)	(4.40)	(4.23)	(4.12)
R^2	0.20	0.15	0.12	0.10	0.08	0.06	0.06	0.06
				Δaddress				
cmkt	0.24***	0.31*	0.29*	0.26	0.22	0.15	0.17	0.15
	(2.94)	(1.94)	(1.79)	(1.54)	(1.25)	(0.94)	(1.24)	(1.20)
Cons	0.04**	0.09***	0.14***	0.20***	0.25***	0.29***	0.33***	0.37***
	(2.61)	(2.78)	(2.85)	(3.15)	(3.54)	(3.98)	(4.24)	(4.36)
R^2	0.26	0.15	0.08	0.05	0.03	0.01	0.02	0.02
				Δtrans				
cmkt	0.14	0.15	0.04	0.04	0.05	−0.02	−0.05	−0.14
	(1.59)	(0.91)	(0.24)	(0.21)	(0.27)	(−0.10)	(−0.35)	(−0.90)
Cons	0.05**	0.10***	0.16***	0.22***	0.26***	0.30***	0.35***	0.40***
	(2.37)	(2.79)	(2.93)	(3.10)	(3.33)	(3.54)	(3.56)	(3.55)
R^2	0.07	0.03	0.00	0.00	0.00	0.00	0.00	0.01
				Δpayment				
cmkt	0.25**	0.32*	0.27	0.23	0.23	0.12	0.11	0.06
	(2.60)	(1.78)	(1.37)	(1.10)	(1.06)	(0.64)	(0.61)	(0.38)
Cons	0.04*	0.09**	0.15**	0.21**	0.26***	0.31***	0.34***	0.38***
	(1.79)	(2.11)	(2.33)	(2.57)	(2.85)	(3.13)	(3.22)	(3.22)
R^2	0.17	0.10	0.05	0.02	0.02	0.01	0.00	0.00

This table reports the results of predicting cumulative future coin network growth with coin market returns. The network factors include wallet user growth, active address growth, transaction count growth, and payment count growth. Data are monthly. The t-statistics are reported in parentheses and are Newey-West adjusted with $n-1$ lags. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels. The data frequency is weekly.

user growth, active address growth, transaction count growth, and payment count growth to capture cryptocurrency adoption growth.

Consistent with the prediction that cryptocurrency returns reflect expected future cryptocurrency adoptions, we find that coin market returns positively predict future cryptocurrency adoption growth as shown in Table 3. Specifically, coin market returns positively and statistically significantly predict cumulative wallet user growth at all the horizons. Coin market returns positively and statistically significantly predict cumulative active address growth and cumulative payment count growth for the first three periods and two periods, respectively, and cease to be significant afterward. The coin market returns positively predict cumulative transaction count growth for the first five periods, but the predictability is not statistically significant. The only exception is the transaction growth measure: there is an insignificant, negative effect on transaction growth over the long horizons. A possible explanation for the negative effect is congestion, as it becomes very expensive to transact in Bitcoin when there is congestion, which deters many of the smaller transactions that would have occurred otherwise (e.g., Easley, O'Hara, and Basu 2019).

2.2 Production factors

Several papers have argued that the costs of mining are essential for the infrastructure and security of cryptocurrencies (e.g., Sockin and Xiong 2019; Abadi and Brunnermeier 2018; Cong, He, and Li 2018). Notably, Sockin and Xiong (2019) show that, in a general equilibrium model with cryptocurrency production, the prices of the cryptocurrency are intimately linked to the marginal cost of mining.

We construct production factors of cryptocurrency to proxy for the cost of mining and test the relationship between these production factors and cryptocurrency prices. To the first approximation, mining a cryptocurrency requires two inputs: electricity and computer power. We separately construct proxies for electricity costs and computing costs. We first discuss our proxies for electricity costs. For electricity, we use seven primary measures. Three of the seven primary measures are U.S.-related: (i) average price of electricity in the United States, (ii) net generation of electricity of all sectors in the United States, and (iii) total electricity consumption of all sectors in the United States. The other four measures are China-related: (i) average price of electricity in China, (ii) electricity generation in China, (iii) average price of electricity in Sichuan province, and (iv) electricity generation in Sichuan province. We include the China proxies, because electricity supply is location specific and because China is considered to have the largest coin-mining operation among all countries.[7] We include Sichuan province proxies because Sichuan province hosts the largest mining farm in the world. Similarly, we also construct a composite measure as the first principal component of these seven primary measures. We denote the composite measure as PC^{elec}.

Panel A of Table 4 presents the correlation matrix of the electricity factors. Except for the two electricity price measures in China, the other five primary measures positively and strongly correlate with one another. Electricity prices in China are under strict government control. Unsurprisingly, they have low correlations with other electricity measures. The first principal component of the seven electricity factors strongly and positively correlates with most of the seven primary factors. The correlations are 0.76, 0.93, 0.88, 0.71, and 0.77 with the U.S. electricity price growth measure, the net U.S. generation growth measure, the U.S. electricity consumption growth measure, the China generation growth measure, and the Sichuan generation growth measure, respectively. The correlation between the first principal component and the China electricity price growth measure is –0.15, and the correlation between the first principal component and the Sichuan electricity price growth measure is 0.18. Panel B of Table 4 presents the electricity factor results for the coin market returns. Somewhat surprisingly, the coin market returns are not statistically

[7] See Jasper Pickering and Fraser Moore, "How China Become a Haven for People Looking to Cash in on the Bitcoin Gold Rush," *Business Insider,* December 12, 2017.

Table 4
Cryptocurrency return loadings to electricity factors

Panel A. correlation of electricity factors

Δ	P^{US}	Gen^{US}	Con^{US}	P^{CN}	P^{SC}	Gen^{CN}	Gen^{SC}
P^{US}	1.00	0.60	0.59	−0.09	0.16	0.25	0.63
Gen^{US}		1.00	0.93	−0.13	0.11	0.64	0.55
Con^{US}			1.00	−0.13	0.15	0.51	0.48
P^{CN}				1.00	−0.00	−0.06	−0.01
P^{SC}					1.00	0.06	0.04
Gen^{CN}						1.00	0.55
Gen^{SC}							1.00
PC^{elec}	0.76	0.93	0.88	−0.15	0.18	0.71	0.77

Panel B. Electricity factor exposures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
P^{US}	−1.06 (−0.34)							
Gen^{US}		0.30 (0.38)						
Con^{US}			0.17 (0.31)					
P^{CN}				−7.39 (−0.72)				
P^{SC}					3.24 (0.50)			
Gen^{CN}						0.11 (0.12)		
Gen^{SC}							−0.60 (−1.16)	
PC^{elec}								−0.00 (−0.02)
R^2	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.00

This table reports the factor loadings of the coin market returns on the production factors that relate to electricity costs. Panel A shows the correlation matrix of the production factors. Panel B reports the factor loadings of the coin market returns on the production factors. Standard t-statistics are reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics. The data frequency is monthly.

significantly exposed to any of these production factor proxies. The R^2s of these regressions are low.

For proxies of computing costs, we use as our primary measure the prices of Bitmain Antminer, a major piece of Bitcoin mining equipment. We also consider the excess stock returns of the companies that are major manufacturers of either GPU mining chips (Nvidia Corporation and Advanced Micro Devices, Inc.) or ASIC mining chips (Taiwan Semiconductor Manufacturing Company, Limited, and Advanced Semiconductor Engineering, Inc.).[8] We construct a composite measure as the first principal component of these five primary computing factors. We denote the composite measure as PC^{comp}.

[8] See Shanthi Rexaline, “The Companies Behind the Chips That Power Cryptocurrency Minning,” *Benzinga,* February 2, 2018.

Table 5
Cryptocurrency return loadings to computing factors

Panel A. Correlation of computing factors

	$\Delta P^{Antminer}$	Nvidia	AMD	TSMC	ASE
$\Delta P^{Antminer}$	1.00	−0.03	−0.15	0.00	0.09
Nvidia		1.00	0.42	0.52	0.31
AMD			1.00	0.27	0.26
TSMC				1.00	0.71
ASE					1.00
PC^{comp}	−0.03	0.74	0.59	0.87	0.78

Panel B. Computing factor exposures

	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta P^{Antminer}$	0.31*					
	(1.90)					
Nvidia		0.50				
		(0.84)				
AMD			−0.02			
			(−0.03)			
TSMC				0.03		
				(0.02)		
ASE					0.45	
					(0.47)	
PC^{comp}						0.00
						(0.04)
R^2	0.09	0.06	0.03	0.00	0.01	0.00

This table reports the factor loadings of the coin market returns on the production factors that relate to computing costs. Panel A shows the correlation matrix of the production factors. Panel B reports the factor loadings of the coin market returns on the production factors. Standard t-statistics are reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics. The data frequency is monthly.

Panel A of Table 5 presents the correlation matrix of the computing factors. Most of the pairs are positively correlated. The correlation between Antminer price growth and Nvidia return is –0.03, and the correlation between Antminer price growth and AMD return is –0.15. The first principal component is positively correlated with the four return measures and has a low correlation with the Antminer price growth measure. Panel B of Table 5 presents the computing factor results for the coin market returns. The coin market returns have insignificant loadings on the four excess return measures. The coin market returns have some loadings on the Antminer price growth measure, but they are only significant at the 10% level. The coin market returns are not significantly exposed to the first principal component.

The model of Sockin and Xiong (2019) primarily concerns utility tokens. Therefore, we conduct our analyses on production factors on Bitcoin, Ethereum, and Ripple, respectively. Because Ethereum and Ripple are utility tokens, while Bitcoin is not, we expect to find that Ethereum and Ripple load significantly on the production factors. We show the results in the Internet Appendix. There is some evidence that Bitcoin returns are exposed to the Bitmain Antminer price growth, but Bitcoin and Ripple returns do not load significantly on these production factors. Overall, there is limited evidence that the computing factors are important drivers of cryptocurrency returns.

Lastly, we test the lead-lag effects between the changes in production factors and cryptocurrency returns to account for possible anticipation effects. We document the results in the Internet Appendix. We show that the one-month-ahead coin market returns are not significantly exposed to most of the production factors. The only exception is the changes in the average price of electricity in the United States, but the significant level is negative and only at the 10% level. However, we find that the current coin market returns positively predict some of the future production factors. In particular, the coin market returns positively and statistically significantly predict future changes in the average price of electricity in the United States, net generation of electricity of all sectors in the United States, total electricity consumption of all sectors in the United States, electricity generation in Sichuan province, and the first principal component of the production factors. Interestingly, we find that the results are stronger for the U.S.-based measures relative to the China-based measures. This is consistent with the fact that electricity prices and generation are heavily regulated in China. These results are consistent with a potential anticipation effect of production costs in the cryptocurrency market.

2.3 Are cryptocurrency returns predictable?

In this section, we test whether the coin market returns are predictable. The existing theoretical models of cryptocurrencies provide various predictions on the predictability of cryptocurrency returns. Schilling and Uhlig (2019) argue that the evolution of cryptocurrency prices should follow a martingale, and thus cryptocurrency returns are not predictable. Other papers predict that, in dynamic cryptocurrency valuation models, cryptocurrency returns could potentially be predicted by momentum, investor attention, and cryptocurrency valuation ratios (e.g., Cong, Li, and Wang 2019; Sockin and Xiong 2019). Motivated by the existing theoretical development and empirical findings in the financial markets, we test whether the cryptocurrency returns are predictable by momentum, investor attention, and proxies for cryptocurrency valuation ratios.

2.3.1 Cryptocurrency momentum. One of the most studied asset pricing regularities is momentum (e.g., Jegadeesh and Titman 1993; Moskowitz and Grinblatt 1999). As discussed in Cong, Li, and Wang (2019), the network effect of user adoption generates a positive externality that is not immediately incorporated into cryptocurrency prices. This channel can potentially lead to a momentum effect in cryptocurrency returns. In their model, Sockin and Xiong (2019) generate momentum in the cryptocurrency market through investor attention—a mechanism similar to De Long et al. (1990).

In this section, we start by establishing that there is strong evidence of time-series momentum at various time horizons. Panel A in Table 6 documents the time-series momentum results in the regression setting. Specifically, we regress

Table 6
Time-series momentum

Panel A. Regression results

Weekly	$R_{t,t+1}$ (1)	$R_{t,t+2}$ (2)	$R_{t,t+3}$ (3)	$R_{t,t+4}$ (4)	$R_{t,t+6}$ (5)	$R_{t,t+8}$ (6)
R_t	0.20**	0.49***	0.81***	1.07***	1.55*	1.62*
	(2.53)	(2.73)	(3.01)	(2.65)	(1.94)	(1.75)
R^2	0.04	0.08	0.09	0.08	0.06	0.02

Panel B. Sorting results

Time-series momentum by groups (weekly, percentage)

Rank	R_t	$R_{t,t+1}$	t-stat	$R_{t,t+2}$	t-stat	$R_{t,t+4}$	t-stat
Low	−10.70	1.10	(0.92)	3.59	(1.69)	7.21	(1.58)
Middle	1.74	1.21	(1.34)	2.77	(1.92)	8.76	(3.43)
High	19.43	8.01	(4.30)	16.22	(4.94)	39.08	(5.30)
Diff		6.91		12.63		31.87	

Time-series momentum by groups—No lookahead (weekly, percentage)

Rank	R_t	$R_{t,t+1}$	t-stat	$R_{t,t+2}$	t-stat	$R_{t,t+4}$	t-stat
Low	−10.86	0.80	(0.63)	2.22	(1.18)	2.41	(0.90)
Middle	1.88	1.44	(1.50)	3.05	(1.94)	8.53	(3.08)
High	18.42	6.42	(3.34)	13.25	(3.91)	31.60	(4.27)
Diff		5.62		11.03		29.19	

This table reports the time-series momentum results. Panel A shows the regression results, and panel B shows the results based on grouping weekly coin market returns into terciles. The first part of panel B reports results for the whole sample. The second part of panel B uses the first two years of data to determine the tercile cutoffs and examine the out-of-sample time-series momentum performance. The t-statistics are reported in parentheses and are Newey-West adjusted with $n-1$ lags. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels. The data frequency is weekly.

cumulative future coin market returns on current coin market returns from the one-week to eight-week horizons. The current coin market returns positively and statistically significantly predict cumulative future coin market returns at all eight horizons. The results are significant at the 5% level for the one-week to five-week horizons and are significant at the 10% level from the six-week to eight-week horizons. For example, a one-standard-deviation increase in the current coin market return leads to increases in cumulative future coin market returns of 3.30%,[9] 8.09%, 13.37%, and 17.66% increases at the one-week, two-week, three-week, and four-week horizons, respectively. Specifically, the one-week-ahead weekly return is that of buying the underlying coin market index at 11:59:59 UTD Sunday and selling the underlying coin market index at 11:59:59 UTD one week later. In the Internet Appendix, we also report the results based on noncumulative returns. The current coin market returns positively and significantly predict one-week- to five-week-ahead returns. The current coin market returns positively but insignificantly predict six-week- and seven-week-ahead returns. The current coin market returns negatively

[9] The 3.30% weekly return is calculated by multiplying a one-standard-deviation increase of coin market returns (16.50%) and the coefficient estimate (0.20).

but insignificantly predict eight-week-ahead returns, suggesting some potential long-term reversal effect.

In the first part of panel B in Table 6, we estimate the magnitude of the time-series momentum by grouping weekly returns into terciles and evaluating their performance going forward. We find that the top terciles outperform the bottom terciles at the one- to four-week horizons, consistent with the time-series regression results presented earlier. For example, at the one-week horizon, the average return of the top tercile is 8.01% per week with a t-statistic of 4.30, while the average return of the bottom tercile is 1.10% per week with a t-statistic of 0.92. The difference between the top and bottom terciles is 6.91% at the one-week horizon. At the two-week horizon, the average of the cumulative coin market returns of the top tercile is 16.22%, and that of the bottom tercile is only 3.59%. The difference between the top and bottom terciles is 12.63%. In the additional results section, we restrict our sample to 2014 onward. Again, we find a strong and significant momentum effect of somewhat smaller magnitude.[10]

In the second part of panel B in Table 6, we use the first two years of data to determine the tercile cutoffs and study the out-of-sample time-series momentum performance. We find a strong and significant momentum effect for the out-of-sample tests. For example, at the one-week horizon, the average return of the top tercile is 6.42%, and that of the bottom tercile is 0.80%. The difference between the top and bottom terciles is 5.62%, which is economically large and slightly smaller than the in-sample result of 6.91%.

Additionally, we test whether the time-series momentum effect is linked to network externalities, as suggested in Cong, Li, and Wang (2019). In their dynamic cryptocurrency valuation model, the momentum effect is generated by the positive externality of the network effect that is not incorporated into cryptocurrency prices immediately. That is, their model implies that controlling for cryptocurrency adoption growth would subsume the time-series momentum effect. In Table 7, we show that there is evidence that cryptocurrency adoption growth positively predicts future coin market returns. However, controlling for cryptocurrency adoption growth does not subsume the time-series momentum effect documented presented earlier.

2.3.2 Cryptocurrency investor attention. The theoretical literature of cryptocurrencies has also suggested that investor attention could potentially be linked to future cryptocurrency returns (e.g., Sockin and Xiong 2019). In this section, we investigate the role of investor attention in predicting cryptocurrency returns. Specifically, we construct the deviation of Google searches for the word "Bitcoin" in a given week compared with the average of those in the preceding four weeks. We standardize the Google search measure to have a mean of zero and a standard deviation of one. We use Google searches for the

10 Stoffels (2017) documents that a cross-sectional momentum strategy based on 15 cryptocurrencies generates abnormal returns during the period between 2016 and 2017.

Table 7
Momentum and network effect

Weekly	$R_{t,t+1}$ (1)	$R_{t,t+2}$ (2)	$R_{t,t+3}$ (3)	$R_{t,t+4}$ (4)	$R_{t,t+6}$ (5)	$R_{t,t+8}$ (6)
R_t	0.09	0.34*	0.54**	0.64**	0.77**	0.80**
	(0.93)	(1.71)	(2.24)	(2.14)	(2.02)	(2.03)
Δuser	0.64	0.92	1.25	1.63	2.78	4.22
	(1.63)	(1.50)	(1.37)	(1.56)	(1.57)	(1.29)
R^2	0.03	0.06	0.07	0.05	0.04	0.03
R_t	0.17**	0.42**	0.73***	0.98**	1.45*	1.47*
	(2.21)	(2.49)	(2.89)	(2.56)	(1.88)	(1.67)
Δaddress	0.21*	0.49*	0.53*	0.60*	0.66	1.07*
	(1.90)	(1.96)	(1.73)	(1.93)	(1.53)	(1.90)
R^2	0.05	0.10	0.10	0.09	0.06	0.02
R_t	0.19**	0.47***	0.81***	1.09***	1.57*	1.60*
	(2.46)	(2.67)	(3.01)	(2.62)	(1.92)	(1.68)
Δtrans	0.04	0.13	−0.04	−0.20	−0.21	0.08
	(0.43)	(0.74)	(−0.16)	(−0.62)	(−0.34)	(0.11)
R^2	0.04	0.08	0.09	0.08	0.06	0.02
R_t	0.20**	0.48***	0.79***	1.06***	1.52*	1.58*
	(2.55)	(2.65)	(2.95)	(2.59)	(1.91)	(1.70)
Δpayment	−0.01	0.06	0.06	0.02	0.14	0.21
	(−0.35)	(0.72)	(0.54)	(0.21)	(0.84)	(0.93)
R^2	0.04	0.08	0.09	0.08	0.06	0.02

This table reports the results that compare coin market return predictability of momentum and network effect. The table reports the results of predicting cumulative future coin market returns with current coin market returns and each of the network factors. The Newey-West adjusted t-statistics with $n-1$ lags are reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels. The data frequency is weekly.

word "Bitcoin" to proxy for investor attention of the cryptocurrency market because Bitcoin is by far the largest and most visible cryptocurrency available. In panel A of Table 8, we report the results of regressing cumulative future coin market returns from one-week to eight-week horizons on the Google search measure. The Google search measure statistically significantly predicts the one-week to six-week ahead cumulative coin market returns at the 5% level. The coefficient estimates of the seven-week and eight-week horizons are positive but are no longer statistically significant. A one-standard-deviation increase in searches leads to increases in weekly returns of about 3% for the one-week ahead cumulative coin market returns and about 5% for the two-week-ahead cumulative coin market returns.[11] In the Internet Appendix, we also report results based on noncumulative returns. The current coin market returns positively and significantly predict one-week- to four-week-ahead returns. The current coin market returns positively but insignificantly predict five-week-ahead returns. The current coin market returns negatively but insignificantly predict six-, seven-, and eight-week-ahead returns.

In the first part of panel B in Table 8, we investigate the return predictability of the Google search measures by grouping them into terciles and evaluating

[11] Wang and Vergne (2017) use the level of newspaper mentions of Bitcoin to proxy for the "buzz" of Bitcoin. They document that high "buzz" predicts low Bitcoin returns in the future. Mai et al. (2016) use the level of Twitter post counts to predict Bitcoin returns.

Table 8
Google searches

Panel A. Regression results

Weekly	$R_{t,t+1}$ (1)	$R_{t,t+2}$ (2)	$R_{t,t+3}$ (3)	$R_{t,t+4}$ (4)	$R_{t,t+6}$ (5)	$R_{t,t+8}$ (6)
$Google_t$	0.03***	0.05***	0.07***	0.10***	0.09**	0.07
	(3.92)	(4.33)	(4.23)	(3.99)	(1.98)	(1.30)
R^2	0.03	0.04	0.03	0.02	0.01	0.00

Panel B. Sorting results

Google searches by groups (weekly, percentage)

Rank	Google	$R_{t,t+1}$	t-stat	$R_{t,t+2}$	t-stat	$R_{t,t+4}$	t-stat
Low	−0.45	0.43	(0.42)	0.02	(0.01)	0.10	(0.04)
Middle	−0.02	2.55	(2.03)	6.79	(2.73)	19.77	(3.11)
High	0.48	6.53	(3.82)	13.95	(4.89)	32.05	(5.47)
Diff		6.09		13.93		31.95	

Google searches by groups—No lookahead (weekly, percentage)

Rank	Google	$R_{t,t+1}$	t-stat	$R_{t,t+2}$	t-stat	$R_{t,t+4}$	t-stat
Low	−0.45	0.70	(0.68)	1.06	(0.70)	1.98	(0.78)
Middle	−0.01	1.15	(1.12)	2.13	(1.35)	4.90	(1.89)
High	0.59	6.12	(3.56)	13.75	(4.58)	32.65	(5.20)
Diff		5.42		12.69		30.67	

This table reports the time-series Google search results. Panel A shows the regression results, and panel B shows the results based on grouping weekly coin market returns into terciles. The first part of panel B reports results for the whole sample. The second part of panel B uses the first two years of data to determine the tercile cutoffs and examine the out-of-sample time-series performance. The Google search measure is constructed as the Google search data for the word "Bitcoin" minus its average of the previous four weeks, and then normalized to have a mean of zero and a standard deviation of one. The t-statistics are reported in parentheses and are Newey-West adjusted with $n-1$ lags. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels. The data frequency is weekly.

their performance going forward. Consistent with the regression results, we find that the top tercile outperforms the bottom tercile in terms of cumulative coin market returns at the one- to four-week-ahead horizons. For example, at the one-week horizon, the average return of the top tercile is 6.53% per week with a t-statistic of 3.82, while the average return of the bottom tercile is 0.43% per week with a t-statistic of 0.42. The difference between the top and bottom terciles is 6.09% at the one-week horizon. At the two-week horizon, the average of the cumulative coin market returns of the top tercile is 13.95% with a t-statistic of 4.89, and that of the bottom tercile is only 0.02% with a t-statistic of 0.01. The difference between the top and bottom terciles is 13.93%. In the additional results section, we restrict our sample to 2014 onward and find similar return predictive power of the Google search measures.

In the second part of panel B in Table 8, we use the first two years of data to determine the tercile cutoffs and study the out-of-sample effect of investor attention, and we find a strong positive investor attention effect as well. For example, at the one-week horizon, the average return of the top tercile is 6.12%, and that of the bottom tercile is 0.70%. The difference between the top and the bottom terciles is 5.42%, which is economically large and slightly smaller than the in-sample estimate of 6.09%.

Table 9
Bitcoin hack

Panel A. Regression results

Weekly	$R_{t,t+1}$ (1)	$R_{t,t+2}$ (2)	$R_{t,t+3}$ (3)	$R_{t,t+4}$ (4)	$R_{t,t+6}$ (5)	$R_{t,t+8}$ (6)
$Hack_t$	−0.02***	−0.05***	−0.08**	−0.11**	−0.20*	−0.32
	(−3.05)	(−2.93)	(−2.39)	(−2.02)	(−1.67)	(−1.45)
R^2	0.02	0.03	0.03	0.03	0.04	0.03

Panel B. Sorting results

Bitcoin hack by groups (weekly, percentage)

Rank	Hack	$R_{t,t+1}$	t-stat	$R_{t,t+2}$	t-stat	$R_{t,t+4}$	t-stat
Low	−0.98	6.39	(3.29)	14.38	(4.13)	31.99	(4.24)
Middle	−0.07	2.89	(2.71)	4.69	(2.61)	14.08	(3.45)
High	1.27	0.60	(0.80)	2.88	(2.74)	7.72	(3.45)
Diff		−5.79		−11.50		−24.27	

Bitcoin hack by groups—No lookahead (weekly, percentage)

Rank	Hack	$R_{t,t+1}$	t-stat	$R_{t,t+2}$	t-stat	$R_{t,t+4}$	t-stat
Low	−1.33	8.59	(2.47)	18.31	(2.05)	46.97	(3.33)
Middle	−0.68	5.06	(2.93)	10.72	(3.74)	21.20	(3.59)
High	0.71	0.99	(1.55)	2.19	(2.05)	7.62	(3.85)
Diff		−7.60		−16.12		−39.35	

This table reports the time-series Bitcoin hack results. Panel A reports the regression results, and panel B reports the sorting results. The Bitcoin hack measure is constructed as the ratio between Google searches for the phrase "Bitcoin hack" and searches for the word "Bitcoin," and then normalized to have a mean of zero and a standard deviation of one. Results are based on weekly data. The t-statistics are reported in parentheses and are Newey-West adjusted with $n-1$ lags. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels. The data frequency is weekly.

2.3.3 Negative investor attention. We have shown that unconditionally investor attention positively predicts cryptocurrency returns. However, not all investor attention is positive. For example, in their model, Sockin and Xiong (2019) differentiate positive investor attention and negative investor attention, and show that negative investor attention is followed by cryptocurrency price depreciation in the future.

In this section, we investigate whether negative investor attention predicts cryptocurrency returns. We construct a ratio between Google searches for the phrase "Bitcoin hack" and searches for the word "Bitcoin" to proxy for negative investor attention. We standardize the measure to have a mean of zero and a standard deviation of one. Panel A of Table 9 shows the results of the predictive regressions. The ratio negatively and significantly predicts one- to six-week-ahead cumulative coin market returns. For example, a one-standard-deviation increase in the ratio leads to a 2% decrease of coin market returns in the next week. Panel B of Table 9 reports the in-sample and out-of-sample return predictability of the negative investor attention measures by grouping them into terciles and evaluating their performance going forward. Consistent with the regression results, we find strong negative return predictability results of the negative investor attention measures.

Another way to see the results on the investor attention is that our measures of investor attentions proxy for speculative interest and sentiment in cryptocurrencies. Positive investor sentiment is followed by cryptocurrency price appreciation, and negative investor sentiment is followed by depreciation. We further investigate these issues in Section 4.

2.3.4 Interaction between momentum and attention. We have shown that there are strong effects of time-series momentum and investor attention in the cryptocurrency market. The equity market research (e.g., Hong, Lim, and Stein 2000; Hou, Xiong, and Peng 2009) shows that there is a strong relationship between momentum and investor attention. It is possible that these two results capture the same underlying phenomenon. For example, Sockin and Xiong (2019) propose a potential channel to generate momentum. In their model, momentum arises because users have incorrect expectations about future prices—a mechanism similar to De Long et al. (1990). Their model suggests that cryptocurrency momentum and investor attention could potentially arise from the same underlying mechanism. The cryptocurrency momentum and investor attention results could also interact with each other. For example, the cryptocurrency time-series momentum effect may be weaker at times of high investor attention, because there is little information leakage at times of high investor attention.

First, we show that the current investor attention of cryptocurrencies is indeed associated with current and past coin market performance. We regress the current deviation in the Google searches on the contemporaneous and the coin market returns of the previous four weeks. Table 10 documents the results. We find that the deviations in Google searches are positively and significantly associated with contemporaneous and the previous week's coin market returns. The Google search measures do not significantly correlate with past coin market returns beyond one week. Intuitively, these results suggest that investor attention is elevated after superior cryptocurrency market performance.

We further test the interaction between the time-series momentum and the investor attention phenomena. The results are reported in Table 11. In the first test of Table 11, we regress cumulative future coin market returns on current coin market returns and Google search measures. We find that the coefficients to the current coin market returns are significant for all the horizons, and the coefficients to the Google search measures are significant from the one-week to the five-week horizons. The magnitudes of the coefficients are similar to the standalone estimates. For example, the one-week-ahead coefficients under the univariate regressions are 0.20 and 0.03 for the current coin market returns and the Google search measures, respectively, while they are 0.18 and 0.03 under the bivariate regressions. These results show that the time-series momentum and the investor attention results do not subsume each other.

In the second test of Table 11, we test the performance of the time-series momentum result when investor attention is high. We construct an indicator

Table 10
Google searches and past returns

Regression results

Weekly	$Google_t$ (1)	$Google_t$ (2)	$Google_t$ (3)	$Google_t$ (4)	$Google_t$ (5)
R_t	0.01***	0.01**	0.01**	0.01**	0.01**
	(2.80)	(2.21)	(2.14)	(2.27)	(2.25)
	[2.77]	[2.14]	[1.96]	[1.96]	[2.25]
R_{t-1}		0.01***	0.01***	0.01***	0.01***
		(2.78)	(2.71)	(2.85)	(2.93)
		[2.47]	[2.34]	[2.34]	[2.42]
R_{t-2}			0.00	0.00	0.00
			(0.14)	(0.27)	(0.40)
			[0.09]	[0.09]	[0.18]
R_{t-3}				−0.00	−0.00
				(−1.01)	(−0.90)
				[−1.04]	[−0.94]
R_{t-4}					−0.00
					(−0.75)
					[−0.94]
R^2	0.02	0.04	0.04	0.04	0.04

This table reports the relationships between the Google search measure and past coin market returns. The Google search measure is constructed as the Google search data for the word "Bitcoin" minus its average of the previous four weeks, and then normalized to have a mean of zero and a standard deviation of one. The standard t-statistic is reported in parentheses, and the bootstrapped t-statistic is reported in brackets. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics. The data frequency is weekly.

variable, $1_{\{Google>0\}}$, that equals one if the current Google search measure is above the sample mean and zero otherwise. We regress the cumulative future coin market returns from one-week to eight-week horizons to the current coin market return, the indicator variable, and the interaction term. The interaction term is not significant at any of the eight horizons, suggesting that the magnitude of the time-series momentum effect is similar for high and low investor attention periods. In the third test of Table 11, we test the performance of the investor attention result when the current coin market return is high. We construct an indicator variable, $1_{\{R>0\}}$, that equals one if the current coin market return is positive and zero otherwise. We regress the cumulative future coin market returns from one-week to eight-week horizons to current Google search measure, the indicator variable, and the interaction term. The interaction term is not significant at any of the eight horizons, suggesting that the magnitude of the investor attention effect is similar for high and low coin market return periods.

Furthermore, we study the cross-section of time-series momentum for high- and low-attention coins. We collect Google attention data for the 10 largest cryptocurrencies from the beginning of 2014 to the end of 2018. The sample period is shorter for this analysis, because before 2014, there are very few cryptocurrencies and the data for alternative coins are hard to get. The list of coins is Bitcoin, Ethereum, Ripple, Litecoin, Tether, Bitcoin-Cash, Tezos, Binance-coin, Monero, and Cardano. At a given point in time, we group the existing coins into two subsamples based on the Google attention data—a group

Table 11
Interaction between momentum and attention

Weekly	$R_{t,t+1}$ (1)	$R_{t,t+2}$ (2)	$R_{t,t+3}$ (3)	$R_{t,t+4}$ (4)	$R_{t,t+6}$ (5)	$R_{t,t+8}$ (6)
R_t	0.18**	0.45**	0.74***	0.99**	1.49*	1.58*
	(2.28)	(2.48)	(2.74)	(2.41)	(1.82)	(1.67)
$Google_t$	0.03***	0.05***	0.06***	0.08***	0.07	0.05
	(3.48)	(3.46)	(3.28)	(3.28)	(1.46)	(0.88)
R^2	0.07	0.11	0.11	0.09	0.06	0.02
R_t	0.20**	0.55*	0.88*	1.16*	2.33	2.84
	(2.01)	(1.81)	(1.88)	(1.65)	(1.52)	(1.44)
$1_{\{Google>0\}}$	0.05***	0.10***	0.14**	0.20**	0.22	0.13
	(2.67)	(2.90)	(2.54)	(2.34)	(1.31)	(0.50)
$R_t \times 1_{\{Google>0\}}$	−0.04	−0.20	−0.27	−0.36	−1.68	−2.43
	(−0.29)	(−0.56)	(−0.51)	(−0.49)	(−1.14)	(−1.24)
R^2	0.06	0.10	0.11	0.10	0.07	0.03
$Google_t$	0.04***	0.08***	0.09***	0.08**	0.09	0.15
	(3.34)	(4.25)	(4.12)	(2.29)	(1.33)	(1.60)
$1_{\{R>0\}}$	0.04***	0.07**	0.14***	0.19***	0.24**	0.18
	(2.72)	(2.42)	(2.97)	(2.77)	(2.06)	(1.10)
$Google_t \times 1_{\{R>0\}}$	−0.01	−0.03	−0.03	0.01	−0.00	−0.10
	(−0.77)	(−1.35)	(−1.31)	(0.35)	(−0.03)	(−1.20)
R^2	0.05	0.06	0.05	0.05	0.02	0.00

This table reports the predictive regressions of future cumulative coin market returns on momentum, attention, and the interaction of the two. The indicator variable $1_{\{Google>0\}}$ equals one if the current Google search measure is above the sample mean and zero otherwise. The indicator variable $1_{\{R>0\}}$ equals one if the current coin market return is positive and zero otherwise. Results are based on weekly returns. The Newey-West adjusted t-statistics with $n-1$ lags are reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels. The data frequency is weekly.

of high-attention coins and a group of low-attention coins. We construct the value-weighted returns of the high-attention group and the low-attention group, separately, and test the time-series momentum strategy effect in each subgroup.

We regress the future cumulative returns on current returns for each of the subsamples and report the results in the Internet Appendix. We find that in this sample, the time-series momentum effect is stronger for the relatively low-attention coins. In particular, the coefficient estimates for both the high-attention and the low-attention subgroups are positive, suggesting that there are time-series momentum effects for both groups. However, the coefficient estimates for the high-attention subgroup is not statistically significant, while the coefficient estimates for the low-attention subgroup is statistically significant up to six weeks out. The magnitudes of the coefficient estimates are also much larger for the low-attention subgroup relative to the high-attention subgroup. The results are consistent with the “underreaction” mechanism of momentum.

2.3.5 Cryptocurrency valuation ratio. Additionally, we test whether the cryptocurrency valuation ratios similar to those in the financial markets can predict future coin market returns. In the equity market, the fundamental-to-market ratios are commonly referred to as valuation ratios and are measured as the ratio of the book value to the market value of equity or some other fundamental value to market value (e.g., dividend-to-price; earnings-to-price).

Another value measure used in the literature that has been shown to correlate highly with fundamental-to-market value is the negative of the long-term cumulative past returns (e.g., De Bondt and Thaler 1985, 1987; Fama and French 1996; and Moskowitz 2015). It is more difficult to define a similar measure of fundamental value for cryptocurrency. However, in their dynamic cryptocurrency asset pricing model, Cong, Li, and Wang (2019) argue that the cryptocurrency fundamental-to-value ratio can be defined as the number of user adoptions over market capitalization, which negatively predicts future cryptocurrency returns.

The market value of cryptocurrency is readily available. However, there is no direct measure of fundamental value for the cryptocurrencies. In its essence, value is a measure of the gap between the market value and the fundamental value of an asset. Because of the lack of a standard "book" value measure of the cryptocurrency market, we use an array of different proxies to capture the idea of fundamental value. We proxy the fundamental-to-market ratio by a number of value measures motivated by the finance literature. The first one is the long-term past performance measure: the negative of the past 100-week cumulative coin market return. The other four measures aim to proxy the cryptocurrency fundamental-to-market value directly: the user-to-market ratio, the address-to-market ratio, the transaction-to-market ratio, and the payment-to-market ratio. The idea of these four measures is to use some measures of the "book" value of the underlying cryptocurrency market and scale by the current market capitalization. The user base of the cryptocurrency market seems to capture the concept of "book" value in the financial markets. This is consistent with the theoretical literature of the cryptocurrency market that emphasizes the notion of the network effect, which can be proxied by the current user base of the cryptocurrencies. On the other hand, the market value of the cryptocurrency provides a market assessment of the current value of the complete cryptocurrency infrastructure. Therefore, the user base-to-market value measure can capture the notion of fundamental-to-market ratio in the financial markets. In panel A of Table 12, we report the correlations across the different valuation ratios in the cryptocurrency market. The five primary measures are highly correlated with one another, with correlations ranging from 0.73 to 0.91. The first principal component measure for the five fundamental-to-market ratios has correlations of 0.91, 0.91, 0.96, 0.93, and 0.93 with the long-term past returns, the wallet user-to-market ratio, the active address-to-market ratio, the transaction-to-market ratio, and the payment-to-market ratio, respectively.

We regress the coin market returns on the lagged cryptocurrency fundamental-to-market ratios, and the results are reported in panel B of Table 12. We document the regression results from one-week to eight-week horizons. Although the coefficient estimates are consistently negative, none of the five standalone fundamental-to-market ratios predict future coin market returns significantly over any horizon. The principal component measure also fails

Table 12
Cryptocurrency valuation ratio

Panel A. Correlation of fundamental-to-market ratios

	Past100	User	Add	Trans	Pay
Past100	1.00	0.90	0.81	0.74	0.78
User/MCAP		1.00	0.85	0.73	0.74
Add/MCAP			1.00	0.91	0.89
Trans/MCAP				1.00	0.90
Pay/MCAP					1.00
PC	0.91	0.91	0.96	0.93	0.93

Panel B. Predictive regressions

	$R_{t,t+1}$ (1)	$R_{t,t+2}$ (2)	$R_{t,t+3}$ (3)	$R_{t,t+4}$ (4)	$R_{t,t+6}$ (5)	$R_{t,t+8}$ (6)
Past100	−0.00	−0.00	−0.00	−0.01	0.00	0.01
	(−0.05)	(−0.17)	(−0.17)	(−0.15)	(0.01)	(0.16)
R^2	0.00	0.00	0.00	0.00	0.00	0.00
User/MCAP	−0.01	−0.01	−0.01	−0.02	−0.02	−0.00
	(−0.71)	(−0.68)	(−0.59)	(−0.49)	(−0.31)	(−0.06)
R^2	0.00	0.00	0.00	0.00	0.00	0.00
Add/MCAP	−0.01	−0.02	−0.03	−0.05	−0.10	−0.13
	(−1.01)	(−1.12)	(−1.21)	(−1.23)	(−1.12)	(−0.96)
R^2	0.00	0.00	0.01	0.01	0.01	0.01
Trans/MCAP	−0.01	−0.02	−0.03	−0.05	−0.07	−0.09
	(−0.78)	(−0.88)	(−0.91)	(−0.87)	(−0.65)	(−0.50)
R^2	0.00	0.00	0.01	0.01	0.01	0.01
Pay/MCAP	−0.01	−0.03	−0.05	−0.08	−0.13	−0.19
	(−1.39)	(−1.59)	(−1.51)	(−1.42)	(−1.19)	(−1.01)
R^2	0.01	0.01	0.02	0.02	0.02	0.02
PC	0.00	0.00	0.01	0.01	0.02	0.03
	(0.81)	(0.59)	(0.49)	(0.45)	(0.62)	(0.79)
R^2	0.00	0.00	0.00	0.00	0.00	0.01

This table reports the predictive regressions of coin market returns on proxies for cryptocurrency market fundamental-to-market ratio. The proxies for cryptocurrency valuation ratio include the (negative) past 100-week cumulative coin market returns, the user-to-market ratio, the address-to-market ratio, the transaction-to-market ratio, payment-to-market ratio, and the first principal component of the previous five proxies. The ratios are estimated using the cointegration method. Results are based on weekly returns. The Newey-West adjusted t-statistics with $n-1$ lags are reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels. The data frequency is weekly.

to predict future coin market returns over these horizons. Overall, there is a very weak relationship between the future coin market returns and the current cryptocurrency fundamental-to-value ratio.

3. Exposures to Other Assets

Both the cryptocurrency literature and the community have debated the nature of cryptocurrencies. For example, Schilling and Uhlig (2019) show that, in an endowment economy with both fiat money and cryptocurrency, the evolution of cryptocurrency prices is linked to that of the fiat money. Athey et al. (2016) emphasize the importance of fiat money risks of cryptocurrencies. The cryptocurrency community has proposed that cryptocurrencies are “digital gold” and serve the purpose of the traditional precious metal commodity. Moreover, Schilling and Uhlig (2019) argue that cryptocurrency returns can have exposure to macroeconomic risks such as monetary policies. In this section, we evaluate these claims by examining the relationship between cryptocurrency returns and traditional asset returns such as currency, commodity, and equity.

3.1 Currency and commodity factor loadings

In an endowment economy where fiat money and cryptocurrency coexist and compete with each other, Schilling and Uhlig (2019) show that the evolution of cryptocurrency prices is correlated with the that of the fiat money prices. Athey et al. (2016) also emphasize the importance of fiat money risks of cryptocurrencies. We test this prediction by investigating the cryptocurrency exposures to traditional currencies. Columns (1) to (6) of Table 13 show the coin market returns' exposures to the traditional currency returns. For currency returns, we consider five major currencies: Australian dollar, Canadian dollar, euro, Singaporean dollar, and U.K. pound. The exposures of the coin market returns to these major currencies are not statistically significant, and the alpha estimates barely change. We further test cryptocurrency exposures on currency factors as in Lustig, Roussanov, and Verdelhan (2011) instead of individual major currency returns.[12] Columns (7) to (9) of Table 13 report the coin market returns' exposures to these currency factors. Consistent with the results on individual currency returns, we find that the coin market returns do not have significant exposures to the currency factors. We conclude that there is no consistent evidence of systematic currency exposures in cryptocurrencies.

Another popular narrative around cryptocurrencies is that cryptocurrencies serve the same purpose as traditional precious metal commodities. That is, cryptocurrencies are "digital gold." If the investors of cryptocurrencies hold this belief, we would expect to find that the returns of cryptocurrencies comove with the returns of the traditional precious metal commodities. We test the precious metal commodity exposures of the coin market returns and report the results in Table 14. For precious metal commodities, we consider gold, platinum, and silver. The exposures of the coin market return to these three major commodities are not statistically significant. Overall, we conclude that there is no consistent evidence of systematic precious metal commodity exposures in cryptocurrencies.

3.2 Equity factor loadings

We document the common stock factor exposures of the coin market returns in the Internet Appendix. For the equity risk factors, we choose the Capital Asset Pricing Model (CAPM), Fama-French three-factor, Carhart four-factor,

[12] We thank Nicola Borri for providing us with the up-to-date currency factors.

Table 13
Currency loadings of coin market returns

CMKT	(1)	(2)	(3)	(4)	(5)	(6)
ALPHA	21.01***	21.33***	20.98***	20.73***	21.23***	21.09***
	(2.88)	(2.90)	(2.91)	(2.87)	(2.94)	(2.80)
	[2.56]	[2.53]	[2.43]	[2.53]	[2.46]	[2.45]
AUSTRALIA	1.69					−1.24
	(0.72)					(−0.28)
	[0.54]					[−0.32]
CANADA		2.95				0.42
		(0.71)				(0.09)
		[0.95]				[0.12]
EURO			3.73			1.65
			(1.24)			(0.36)
			[1.21]			[0.47]
SINGAPORE				4.45		2.38
				(1.04)		(0.27)
				[0.95]		[0.35]
UK					4.21	2.90
					(1.40)	(0.72)
					[1.13]	[0.55]
R^2	0.01	0.01	0.02	0.01	0.02	0.02

CMKT	(7)	(8)	(9)
ALPHA	23.16***	21.28***	22.14***
	(3.02)	(2.71)	(2.79)
	[3.15]	[2.67]	[2.87]
DOLLAR	4.35		3.92
	(1.00)		(0.88)
	[0.78]		[0.68]
CARRY		3.17	2.47
		(0.72)	(0.55)
		[1.39]	[1.02]
R^2	0.01	0.01	0.01

This table reports the factor loadings of the coin market returns on returns of different currencies and currency factors. The currencies include Australian dollar, Canadian dollar, euro, Singapore dollar, and U.K. pound. The currency factors are based on Lustig, Roussanov, and Verdelhan (2011). The returns are in percentage. The results are based on monthly returns. The standard t-statistic is reported in parentheses, and the bootstrapped t-statistic is reproted in brackets. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics. The data frequency is monthly.

Fama-French five-factor, and Fama-French six-factor models.[13] The alphas for all of the considered models are statistically significant. The average return of the period is 20.44% per month. The CAPM-adjusted alpha decreases to 17.53% per month—a reduction of about 14%. The CAPM beta is large at 3.15 but not statistically significant. The betas are statistically significant at the 10% level only for the five-factor and six-factor models. The corresponding alphas are 15.32% and 15.00% per month for the five-factor model and six-factor model, respectively. The exposures to the other factors are not statistically significant. The exposures to the SMB (small-minus-big) factor are negative but not stable across the specifications: the magnitude of the coefficient decreases when five-factor and six-factor models are considered. The exposures to the

[13] The Fama-French three-factor model is based on Fama and French (1993) and Fama and French (1996). The Carhart four-factor model is based on Carhart (1997). The Fama-French five-factor model is based on Fama and French (2016). The Fama-French six-factor model is based on Fama and French (2017).

Table 14
Commodity loadings of coin market returns

CMKT	(1)	(2)	(3)	(4)
ALPHA	20.40**	19.83***	20.52**	20.24***
	(2.81)	(2.69)	(2.83)	(2.70)
	[2.37]	[4.31]	[2.55]	[4.62]
GOLD	−0.53			−2.55
	(−0.35)			(−0.91)
	[−0.26]			[−1.06]
PLATINUM		−0.02		−0.14
		(−0.02)		(−0.07)
		[−0.02]		[−0.07]
SILVER			0.34	1.54
			(0.41)	(1.10)
			[0.25]	[0.59]
R^2	0.00	0.00	0.00	0.01

This table reports the factor loadings of the coin market returns on returns of different precious metal commodities. The commodities include gold, platinum, and silver. Returns are in percentage. The standard t-statistic is reported in parentheses and the bootstrapped t-statistic is reproted in brackets. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics. The data frequency is monthly.

HML (high-minus-low) factor are negative and have consistent magnitudes and signs; this suggests that the coin market returns may comove more with growth rather than with value firms. The exposures to the RMW (robust-minus-weak) factor are positive and are estimated slightly more accurately than other statistically not significant factors; this suggests that the coin market returns comove more with high-profit rather than low-profit firms. The point estimates on the MOM (momentum) and CMA (conservative-minus-aggressive) factors are very inaccurate.[14]

3.2.1 Exploring the factor zoo. The finance literature has documented more than a hundred factors for predicting the cross-section of stock returns (see e.g., summarizes in Feng, Giglio, and Xiu 2017 and Chen and Velikov 2017). To investigate whether any of those factors may be important in pricing cryptocurrencies, we estimate the loadings of the 155 common factors from Andrew Chen's website. One caveat is that this data set ends at the end of 2016 and thus does not cover the most recent return experiences. We report the results in the Internet Appendix due to the large number of factors. We find that only four out of the 155 factors are significant, but those four factors do not form any discernible patterns.

3.3 Macroeconomic factors

We further examine the macroeconomic factor exposures of the coin market returns. For macroeconomic factors, we consider the nondurable consumption growth, durable consumption growth, industrial production growth, and

[14] Stoffels (2017) and Gilbert and Loi (2018) examine cryptocurrency loadings on the CAPM and Fama-French three-factor models.

personal income growth. We document the results in the Internet Appendix. We find that the coin market returns do not significantly load on these macroeconomic factors. We further investigate the three major cryptocurrencies individually. For Bitcoin and Ripple, all of the exposures are not statistically significant. For Ethereum, notably, the durable consumption growth factor has a significant loading.

4. Additional Results

4.1 Short sample

We have eight years of coin market return data spanning from the beginning of 2011 to the end of 2018. The short sample is a potential barrier to study cryptocurrency that we cannot avoid. Moreover, there is a great deal of uncertainty and learning about cryptocurrencies during the period. As argued by Pástor and Veronesi (2003), it takes time for investors to fully learn and understand emerging technologies, which can lead to price bubbles.

One approach we take to partially address these concerns is to break the sample into two halves and check whether our results are stable for these subsamples. During the first half of the sample, there are considerably more uncertainty and learning about cryptocurrency as an asset class. We document these results in the Internet Appendix. We find that the directions of all of the results are the same for the first and second halves of the sample. The magnitudes of the results are also comparable between the two subsamples. There is potentially still a lot of uncertainty and learning about cryptocurrencies today, but the assumption we need for the subsample tests is relatively mild: the uncertainty has decreased from the first half of the sample to the second half of the sample. The analysis on the volatility of the coin market returns also supports this assumption. We find that the standard deviation of coin market returns decreased significantly from the first half to the second half of the sample period. The figure in the Internet Appendix shows a significant decrease in the volatility of the coin market returns over time.

4.2 Time-series momentum and cross-sectional momentum

We study the relationship between time-series momentum and cross-sectional momentum. It is difficult to directly compare the time-series momentum and cross-section momentum results. The time-series momentum is a phenomenon on the aggregate coin market returns, while the cross-sectional momentum results are neutral in terms of the aggregate performance of the coin market. We use two different methods to test the relationships between the time-series momentum and the cross-sectional momentum results. In the first method, we use coin market returns to predict the cross-sectional cryptocurrency momentum. This approach gives us a sense about whether the cross-sectional momentum effect is stronger when the time-series momentum is on a positive trajectory. We report the results in the Internet Appendix. The coin market returns do not significantly predict future cumulative cross-sectional momentum returns. This result suggests that the profitable periods of the cryptocurrency time-series momentum and cross-sectional momentum are different.

In the second method, we follow the approach similar to Moskowitz, Ooi, and Pedersen (2012) and construct a portfolio version of the time-series momentum. For our set of instruments, we use one of the following: largest three coins, largest five coins, and largest ten coins. For each instrument and month, we consider whether the excess return over the past three weeks is positive or negative and go long the instrument if positive and short if negative. We hold the position for one week, so there is no overlapping sample. The unadjusted excess returns are positive and significant at the 1% level for all three of the specifications. The economic magnitudes of the excess returns are large, ranging from 3.17% for the top three coins to 4.62% for the top ten coins. Controlling for the coin market returns, the economic magnitudes of the excess returns barely change. Controlling for the cryptocurrency cross-sectional momentum as constructed in Liu, Tsyvinski, and Wu (2019), the magnitudes of the spreads decrease but remain highly statistically significant. It is not surprising that the magnitudes of the spreads decrease after controlling for the cross-sectional momentum because the excess returns of the strategy contain information about the cross-sectional momentum by construction. However, there is additional information coming from the construction similar to Moskowitz, Ooi, and Pedersen (2012), which is evidenced by the fact that the magnitudes of the spreads remain positive and statistically significant after controlling for the cross-sectional momentum. Finally, we also test whether the strategies contain information above and beyond the cryptocurrency three-factor model in Liu, Tsyvinski, and Wu (2019). After controlling for the three-factor model, the magnitudes of the spreads further decrease but still remain positive and significant at the 5% level for the top five and top ten coins and at the 10% level for the top three coins.

4.3 Regulations

A potentially important determinant of cryptocurrency valuation is regulations. To test whether cryptocurrency regulations are important determinants of cryptocurrency valuations, we follow the method of Auer and Claessens (2018) and Shanaev et al. (2019) and determine 120 regulative events. We further categorize these regulative events into positive and negative events based on Auer and Claessens (2018). We document the list of regulative events and the results in the Internet Appendix. We find that the contemporaneous cryptocurrency returns are lower during the days of regulative events. However, we find that the cryptocurrency returns respond to negative regulative events but not to positive regulative events.

4.4 Speculative interest and sentiment

In this section, we test whether speculation and investor sentiment may be important drivers of cryptocurrency prices. We extract the speculative shares of cryptocurrency usage from Coindesk.com. We test whether the cryptocurrency returns strongly respond to the contemporaneous and expectations of future speculative share growth. We further control for the network growth rates as discussed earlier to examine whether the results of network effects are driven by variations in speculative interests. We document the results on speculative interests in the Internet Appendix. We find some evidence that the cryptocurrency returns positively load on the contemporaneous speculative share growth, but the coefficient estimates are not significant. In the bivariate regressions, we show that the loadings of the cryptocurrency returns to the contemporaneous network growth remain positive and statistically significant. Furthermore, we show that the coin market returns positively forecast future speculative share growth. The coefficients are significant at the three-month and eight-month horizons. These results show that current coin market returns also contain information about expectations of future speculative share growth.

To test the effect of sentiment, we construct a measure that is directly aimed to capture investor sentiment.[15] The measure of cryptocurrency sentiment is defined as the log ratio between the count of positive and the count of negative phrases of cryptocurrencies in Google searches. The positive and negative phrases are described in the corresponding table in the Internet Appendix. Therefore, when the measure is high, investor sentiment is more positive and vice versa. We test whether the sentiment measure predicts future cryptocurrency returns, and compare that to the measures of investor attention and momentum. We find that the sentiment measure positively and significantly predicts future cryptocurrency returns. However, this result is distinct from the investor attention and cryptocurrency momentum results. All three variables are statistically significant in predicting future cryptocurrency returns in the multivariate regressions.

4.5 Beauty contests

One potential theoretical explanation of high volatility in financial markets may be that they are represented by the Keynesian beauty contest model. In this section, we aim to test the role of beauty contests in the cryptocurrency markets. We need a time-varying measure of the degrees of disagreement among the cryptocurrency investors. Ideally, we would like to have the expectations of individual cryptocurrency investors. Practically, this is not feasible due to data limitation at this time. We take a different route and measure the dispersion of investor expectations using the ratio between cryptocurrency volume and return volatility. This choice is motivated by Biais and Bossaerts (1998),

[15] Chen et al. (2019) classify cryptocurrency-related positive and negative words of StockTwits and Reddit.

who show theoretically that the volume-volatility ratio summarizes the degree of disagreement among the investors and discriminates between genuine disagreement and mere Bayesian learning with agreeing agents. We test empirically whether the coin market returns respond to the volume-volatility ratio contemporaneously and whether the volume-volatility ratio predicts future coin market returns. We summarize these results in the Internet Appendix. We find that the coin market return is higher when the current volume-volatility ratio is higher. This result is consistent with the idea that investors tend to bid the price up when there is a lot of disagreement in the cryptocurrency market. The flip side is that the volume-volatility ratio does not predict future cumulative coin market returns over any horizon.

4.6 VAR analysis

One concern about the network factor analysis is that the contemporaneous correlations between the network size/activity factors and coin market returns might be mechanical and not truly capture the value of network externalities. To address the concern, we conduct a bivariate VAR analysis with the coin market returns and different coin network growth measures. The results are documented in the Internet Appendix.

To differentiate the network effects from the potential mechanical effects, we examine how changes in the network factors affect valuations in the future—that is, what is the cumulative permanent return associated with a shock to network size/activity factors. The bottom-left graph of each panel shows the associated impulse response function. We find that a shock to the wallet user growth, active address growth, and transaction count growth factors positively predict the coin market returns in the future and that there is not any reversal effect. The effects tend to concentrate on the first couple of weeks. In particular, the wallet user growth and active address growth factors positively and statistically significantly predict coin market returns in the future. The payment count growth measure is the only exception, but the point estimate is not significant. In terms of the cumulative effect, the cumulative return responses to one standard deviation of network factor shock are about 4% based on the changes in wallet user growth, about 2% based on the active address growth, and about 0.45% based on the transaction count growth.

Moreover, there is a bidirectional relationship between the network factors and the cryptocurrency returns. Consistent with the results in Table 3 in the paper, the VAR shows that the coin market returns positively and significantly predict future network growth based on all four specifications. The top-right graph of each panel shows the associated impulse response function. In the bivariate VAR framework, the approach accounts for this bidirectional effect, that returns may affect trading decisions and therefore affect the network size. Additionally, the bivariate VAR again reveals a coin market momentum effect in all four specifications. The top-left graph of each panel shows the associated impulse response function. The VAR approach also helps account for the momentum effect in the cumulative effect of network size/activity factors on the valuation of cryptocurrencies. Overall, the VAR suggests some evidence that a positive shock to the network size/activity factors leads to a permanent increase in the valuations of the coin market in the future. In terms of the timing of the effects, the impulse response functions suggest that it can take a few weeks for the impulse responses to decay to zero.

4.7 Additional production factor test

When the electricity price increases, the return to mining should decrease. However, the reduction in the return to mining would force some miners to exit, which leads to a higher probability of any given miner receiving the reward plus fees and a reduction of the difficulty of the cryptographic puzzles. These two effects would endogenously restore the profitability of the mining. Therefore, the shocks to electricity prices or computing power do not necessarily affect the marginal cost of mining because a change in these costs would affect the profitability of miners, causing an adjustment in the number of miners and therefore an adjustment in the required computing effort to restore profitability (e.g., Easley, O'Hara, and Basu 2019).

To address this effect, we include another set of tests. We regress the coin market returns on the number of Bitcoins given as a block reward, controlling for the price of Bitcoins and the fees paid. The rationale of the test is the following: the price of Bitcoin is endogenous, the fees paid could be endogenous as they are driven by network usage, but the number of Bitcoins given as a block reward is exogenous and deterministically changes through time according to the Bitcoin protocol. Therefore, the exogenous variation, controlling for the price of Bitcoin and the fees, could be used to identify the effects of mining costs.

Column (1) of the table documents the baseline specification. The coefficient of interest is in the changes of the number of Bitcoins given as a block reward, or $\Delta Gen\ Coin$. We find that, although the coefficient estimate is positive, it is not statistically significant. Column (2) uses next-month changes of the number of Bitcoins given as a block reward to test any anticipation effect. The point estimate is again positive but not statistically significant. Column (3) includes both the current and next-month changes in the number of Bitcoins given as a block reward as the independent variables, and both coefficient estimates are not significant. Columns (4) to (6) repeat the exercises of columns (1) to (3) but include the first principal component of the production factor, and the results are similar. Columns (7) to (12) repeat the exercises but control for the level of fees instead of changes in fees. We find that the coefficient estimates of $\Delta Gen\ Coin$ and $\Delta Gen\ Coin_{+1}$ are not statistically significant, consistent with results in columns (1) to (6).

Easley, O'Hara, and Basu (2019) argue that fee is not the only endogenous variable in the mining process, and that the confirmation time is also endogenously determined as a function of miner competition. Therefore, we also control for the confirmation time in our analysis and examine the results. Columns (13) to (24) report the results controlling for the confirmation time. In particular, columns (13) to (18) control for the changes of confirmation time, and columns (19) to (24) control for the level of confirmation time. We find that the coefficient estimates of $\Delta Gen\ Coin$ and $\Delta Gen\ Coin_{+1}$ remain statistically insignificant. Overall, we do not find a significant effect of the exogenous variation in the number of Bitcoins given as a block reward, controlling for the price of Bitcoin and the fees, on the cryptocurrency valuations.

4.8 Subsample by cryptocurrency characteristics

In this section, we consider a number of cryptocurrency characteristics: (i) whether the cryptocurrency is based on Proof-of-Work (PoW) or Proof-of-Stake (PoS), (ii) whether the cryptocurrency is minable, (iii) whether the cryptocurrency is built on an Ethereum blockchain, (iv) whether the cryptocurrency is a stable coin, and (v) whether the cryptocurrency is a smart contract. Based on each characteristic, we form a value-weighted portfolio of all the underlying cryptocurrencies. In the untabulated results, we look at the loadings of returns for each subgroup on the network factors, production factors, currency factors, commodity factors, equity factors, and macroeconomic factors.

First, we examine the loadings on the network factors. We find that the returns for the subgroups generally load positively on the network factors. Based on the first principal component of the four primary measures, we show that the returns of all six subgroups load positively on the network factors. In particular, the returns of PoW, minable coins, Ethereum blockchain coins, and stable coins positively and statistically significantly expose to the first principal component. On the other hand, the returns of PoS and smart contract coins do not statistically significantly expose to the first principal component. Then, we turn to the loadings on the production factors. We find that the returns for most of the subgroups do not significantly load on the production factors. We conclude that the factor exposures of the subgroup returns are largely consistent with the aggregate coin market returns. Lastly, we turn to the loadings of the returns for subgroups on the currency, commodity, equity, and macroeconomic factors. In general, we find that the returns of the subgroups have low exposures to these factor models. We conclude that the factor exposures of the subgroup returns are largely consistent with the aggregate coin market returns.

5. Conclusion

We find that cryptocurrency returns strongly respond to cryptocurrency network factors, as suggested by the theoretical literature. However, our empirical results do not support the notion that the evolution of cryptocurrency prices is linked to cryptocurrency production factors. At the same time, the returns of cryptocurrency can be predicted by two factors specific to its markets:

momentum and investor attention. In contrast to the equity market, we show that the momentum result and the investor attention result are distinct phenomena and that there is only limited interaction between them. Moreover, cryptocurrency returns have low exposures to traditional asset classes such as currencies, commodities, and stocks, and to macroeconomic factors.

References

Abadi, J., and M. Brunnermeier. 2018. Blockchain economics. Working Paper, Princeton University.

Asness, C., T. J. Moskowitz, and L. H. Pedersen. 2013. Value and momentum everywhere. *Journal of Finance* 68:929–985.

Athey, S., I. Parashkevov, V. Sarukkai, and J. Xia. 2016. Bitcoin pricing, adoption, and usage: Theory and evidence. Working Paper, Stanford University.

Auer, R., and S. Claessens. 2018. Regulating cryptocurrencies: Assessing market reactions. *BIS Quarterly Review* 51–65.

Biais, B., C. Bisiere, M. Bouvard, C. Casamatta, A. J. Menkveld. 2018. Equilibrium bitcoin pricing. Working Paper, Toulouse School of Economics.

Biais, B., and P. Bossaerts. 1998. Asset prices and trading volume in a beauty contest. *Review of Economic Studies* 65:307–340.

Bianchi, D. 2017. Cryptocurrencies as an asset class: An empirical assessment. Working Paper, Warwick University.

Borri, N. 2019. Conditional tail-risk in cryptocurrency markets. *Journal of Empirical Finance* 50:1–19.

Borri, N., and K. Shakhnov. 2018. Cryptomarket discounts. Working Paper, LUISS University.

Carhart, M. M. 1997. On persistence in mutual fund performance. *Journal of Finance* 52:57–87.

Chen, A., and M. Velikov. 2017. Accounting for the anomaly zoo: A trading cost perspective. Working Paper, Penn State University.

Chen, C. Y., R. Despres, L. Guo, and T. Renault. 2019. What makes cryptocurrencies special? Investor sentiment and return predictability during the bubble. Working Paper.

Chiu, J., and T. V. Koeppl. 2017. The economics of cryptocurrencies–bitcoin and beyond. Working Paper, QueenâŁ™s University.

Cong, L. W., and Z. He. 2019. Blockchain disruption and smart contracts. *Review of Financial Studies* 32:1754–1797.

Cong, L. W., Z. He, and J. Li. 2018. Decentralized mining in centralized pools. Working Paper, University of Chicago.

Cong, L. W., Y. Li, and N. Wang. 2019. Tokenomics: Dynamic adoption and valuation. Working Paper, Columbia University.

Corbet, S., B. M. Lucey, A. Urquhart, and L. Yarovaya. 2019. Cryptocurrencies as a financial asset: A systematic analysis. *International Review of Financial Analysis* 62:182–199.

Da, Z., J. Engelberg, and P. Gao. 2011. In search of attention. *Journal of Finance* 66:1461–1499.

Daniel, K., and T. J. Moskowitz. 2016. Momentum crashes. *Journal of Financial Economics* 122:221–247.

De Long, J. B., A. Shleifer, L. H. Summers, and R. J. Waldmann. 1990. Noise trader risk in financial markets. *Journal of Political Economy* 98:703–738.

De Bondt, W. F., and R. Thaler. 1985. Does the stock market overreact? *Journal of Finance* 40:793–805.

———. 1987. Further evidence on investor overreaction and stock market seasonality. *The Journal of Finance* 42:557–581.

Easley, D., M. O'Hara, and S. Basu. 2019. From mining to markets: The evolution of bitcoin transaction fees. *Journal of Financial Economics* 134:91–109.

Fama, E. F., and K. R. French. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33:3–56.

———. 1996. Multifactor explanations of asset pricing anomalies. *Journal of Finance* 51:55–84.

———. 2016. Dissecting anomalies with a five-factor model. *Review of Financial Studies* 29:69–103.

———. 2017. Choosing factors. Working Paper, University of Chicago.

Feng, G., S. Giglio, and D. Xiu. 2017. Taming the factor zoo. Working Paper, University of Chicago.

Gilbert, S., and H. Loi. 2018. Digital currency risk. *International Journal of Economics and Finance* 10:108.

Griffin, J. M., and A. Shams. 2020. Is bitcoin really un-tethered? *Journal of Finance* 52:57–87.

Hong, H., T. Lim, and J. C. Stein. 2000. Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. *Journal of Finance* 55:265–295.

Hou, K., W. Xiong, and L. Peng. 2009. A tale of two anomalies: The implications of investor attention for price and earnings momentum. Working Paper, Princeton University.

Hu, A., C. A. Parlour, and U. Rajan. 2018. Cryptocurrencies: Stylized facts on a new investible instrument. Working Paper, University of California, Berkeley.

Huberman, G., J. D. Leshno, and C. C. Moallemi. 2017. Monopoly without a monopolist: An economic analysis of the bitcoin payment system. Working Paper, University of Chicago.

Jegadeesh, N., and S. Titman. 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance* 48:65–91.

Jermann, U. J. 2018. Bitcoin and Cagan's model of hyperinflation. Working Paper, University of Pennsylvania.

Liu, Y., A. Tsyvinski, and X. Wu. 2019. Common Risk Factors in Cryptocurrency. Working Paper, Yale University.

Lustig, H., N. Roussanov, and A. Verdelhan. 2011. Common risk factors in currency markets. *Review of Financial Studies* 24:3731–3777.

Mai, F., Q. Bai, Z. Shan, X. S. Wang, and R. Chiang. 2016. The impacts of social media on Bitcoin performance. Working Paper, University of Cincinnati.

Makarov, I., and A. Schoar. 2020. Trading and arbitrage in cryptocurrency markets. *Journal of Financial Economics* 135:293–319.

Moskowitz, T. J. 2015. Asset pricing and sports betting. Working Paper, Yale University.

Moskowitz, T. J., and M. Grinblatt. 1999. Do industries explain momentum? *Journal of Finance* 54:1249–1290.

Moskowitz, T. J., Y. H. Ooi, and L. H. Pedersen. 2012. Time series momentum. *Journal of Financial Economics* 104:228–250.

Pagnotta, E., and A. Buraschi. 2018. An equilibrium valuation of bitcoin and decentralized network assets. Working Paper, Imperial College Business School.

Pástor, L. and P. Veronesi. 2003. Stock valuation and learning about profitability. *Journal of Finance* 58:1749–1789.

Routledge, B., and A. Zetlin-Jones. 2018. Currency stability using blockchain technology. Working Paper, Carnegie Mellon University.

Saleh, F. 2018. Blockchain without waste: Proof-of-stake. Working Paper, McGill University.

Schilling, L., and H. Uhlig. 2019. Some simple bitcoin economics. *Journal of Monetary Economics* 106:16–26.

Shanaev, S., S. Sharma, A. Shuraeva, and B. Ghimire. 2019. Taming the blockchain beast? Regulatory implications for the cryptocurrency market. Working Paper, University of London.

Sockin, M., and W. Xiong. 2019. A model of cryptocurrencies. Working Paper, Princeton University.

Stoffels, J. 2017. Asset pricing of cryptocurrencies and momentum based patterns. Working Paper, Erasmus School of Economics.

Wang, S., and J. Vergne. 2017. Buzz factor or innovation potential: What explains cryptocurrencies' returns? *PloS One* 12.

Weber, W. E. 2016. A Bitcoin standard: Lessons from the gold standard. Working Paper, Bank of Canada.

Yermack, D. 2015. Is Bitcoin a real currency? An economic appraisal. In *Handbook of Digital Currency,* ed. D. L. K. Chuen, 31–43. Amsterdam: Elsevier.