Cryptocurrencies: Stylized Facts on a New Investible Instrument

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Abstract

We present stylized facts on the asset pricing properties of cryptocurrencies: summary statistics on cryptocurrency return properties and measures of common variation for secondary market returns on 222 digital coins. In our sample, secondary market returns of all other currencies are strongly correlated with Bitcoin returns. We also provide some investment characteristics of a sample of 64 initial coin offerings (ICOs).

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1 Introduction

Cryptocurrencies are a new class of investible instruments and can even be included in individual retirement accounts. As of November 2017, the total market capitalization of cryptocurrencies reached over $300 billion, with Bitcoin, Ether, and Ripple being the most prominent. Briefly, cryptocurrencies or tokens are digital assets issued in return for remuneration in the form of fiat money or other cryptocurrencies. Various exchanges exist in which they can be traded for other cryptocurrencies or fiat money. The convertibility of these digital assets to fiat money means they can be incorporated into any portfolio and viewed as any other asset class, even though their exact legal definition is still unsettled. While brokerage, trading, and even financial derivatives for these currencies are beginning to flourish and receive widespread attention, little research has been done on the asset pricing properties of this new instrument class.

In this paper, we document some stylized facts about cryptocurrency returns. Besides the novelty of this investment vehicle, cryptocurrencies provide an interesting benchmark because they are effectively unregulated. Specifically, prior to the SEC crowdfunding regulations, there was no restriction in the U.S. on who could introduce a cryptocurrency. Further, trading is also unregulated, so prices must also reflect uncertainty associated with the viability of an exchange. By contrast, most other data series examine assets that were issued in the context of some regulatory framework; such data are therefore truncated by the minimum requirements of either exchange listing, or adherence to GAAP or other such requirements.

Both the returns and volatilities that we document are high. In addition, we show that cryptocurrencies, in aggregate, carry a common source of systematic risk correlated with Bitcoin returns. This has important implications for portfolio diversification and risk assessment. We also document the performance of Initial Coin Offerings and compare them to IPOs. Interestingly, an economic implication of the ICO market is that the initial returns to IPOs may be puzzlingly low.

This paper contributes to an emerging literature on the pricing of Bitcoin, and the larger question of the economic value of cryptocurrencies. A number of papers are concerned with explaining valuation and pricing of Bitcoin from economic first principles. Athey et al. (2016) evaluate a model of adoption with Bitcoin prices up to 2015 and concludes that adoption cannot explain prices. Yermack (2013). Ciaian et al. (2016) use an econometric approach to show macro-financials do not explain Bitcoin prices. Gandal and Halaburda (2014) suggest a network effect is present that characterizes competition between different cryptocurrencies, and explain Bitcoin's early dominant position.

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In related work, Elendner et al. (2016) provide a brief history of altcoins and document secondary market return properties for Bitcoin and altcoins over the period April 2014 through July 2016. They also consider the pairwise correlations of the top ten cryptocurrencies by market capitalization as of July 2016, and show the representation of principal components in the returns of each of these currencies. They find that Bitcoin is not represented in the first principal component, but is instead represented in the later ones. In contrast, we demonstrate that Bitcoin returns have a high correlation with the first principal component of altcoin returns, so that Bitcoin may indeed be thought of as a factor that drives cryptocurrency returns.

Various authors have investigated the properties of ICOs and cryptocurrencies, including Lyandres et al. (2019) who reflect on the similarities between cryptocurrencies and other securities, Bourveau et al. (2019) who investigate information provision on Initial Coin Offerings, while Lee et al. (2019) considers information aggregation. Finally, Howell et al. (forthcoming) provide detailed analyses of ICO markets.

A related strand of literature addresses market efficiency in cryptocurrencies, which is characterized by a high degree of decentralization in trading and in issuances. Kroeger and Sarkar (2017), for example, show the law of one price is often violated for Bitcoin, and relate this to the microstructure of Bitcoin trading. In a similar vein, Gandal et al. (2018) exhibit price manipulation in the Bitcoin market, likely by a single trader. We take the prices (and hence the return patterns) of alternative cryptocurrencies (altcoins) as given, and document a number of stylized facts.

The remainder of this article is organized as follows. Section 1.1 discusses the market mechanisms of initial coin offerings and trading. Section 2 gives an account of the data sources. Section 3 documents returns to ICOs and compares them to the literature on IPOs. Section 4 discusses the return distributions of cryptocurrencies, and their correlation with other assets. Section 5 discusses the possible benchmark to evaluate returns. Section 6 concludes.

1.1 Cryptocurrencies: Coins and Tokens

Bitcoin is one of the earliest and well-known crypto-currencies, and the first to use a *blockchain* to record and decentralize the ledger of ownership and transactions and through it solve the "double-spend" problem. There are two categories of tradable cryptocurrencies alternative to Bitcoin: coins and tokens. These are sometimes referred to as altcoins (so called because they are coins that are alternative to Bitcoin), While the nomenclature is not standardized,

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there often are technological and use-differences between coins and tokens. Coins typically have their own blockchains, whereas tokens are issued on some underlying platform, often one that enables smart contracts. For example, the altcoin, Litecoin, is recorded on a variation of Bitcoin technology, others such as b-cash use new software implemented as a *fork* on a pre-existing transaction ledger.[1] Coins are used mainly as media of exchange or stores of value, akin to non-digital currencies. Prominent coins other than Bitcoin include Ether and Ripple.[2] Tokens are typically used in a manner akin to coupons or vouchers on specific sites for specific purposes and are often used as a reward or funding mechanism.

The issuing process of most coins and tokens is determined by the underlying software, and hence by the developers. For example, new Bitcoins are released slowly according to a pre-specified formula, and are distributed to computing nodes ("miners") as a reward for verifying transactions in their decentralized ledgers. Auroracoin was distributed freely in equal amounts to all the residents of Iceland. Tokens are issued through Initial Token Sales (ITS), more commonly known as Initial Coin Offerings (ICOs). In such a sale, a firm wishing to embark on a project raises money for the project through an ICO. One kind of token is a utility token: If the firm is successful at carrying out the project, the token allows the holder to consume some good or service delivered by the project. For example, in September 2017, Filecoin raised $257 million in an ICO to provide a cloud storage device that uses unused hard drive space. Token holders will be able to purchase storage space on the device when it is ready. A second kind is a securities token, with a sub-case being an equity token, in which the token-holder receives future cash flows from a successful project.[3]

While there is no standardized process, the following steps usually occur in issuing an ICO. First, the ICO is publicized on a number of aggregators (including, for example, 99bitcoins.com, icowatchlist.com and icoalert.com). These aggregators then direct participants to a *white paper* which details the purpose of the offering and use of underlying funds, and provides a homepage where the ICO takes place. There is no standard format, size or length. The ICO homepage provides a bidding mechanism (usually, a fixed price take-it-or-leave it offer) for tokens, although this is also not standardized. Second, participants deliver cryptocurrencies such as Bitcoin or Ether to a designated address, and receive the tokens in exchange. Some offerings last for a few minutes, and others last for several months. For long-duration ICOs, the prices of tokens may increase during the ICO period. The tokens can be traded on a secondary market, sometimes before the ICO is complete. We note, that

[1] The Bitcoin block chain, in this specific case.

[2] "Ether" is often used synonymously with "Ethereum" to refer to the currency, although the latter more correctly describes the entire platform.

[3] For our period of analysis, most coins are not securities.

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in as much as the same coins such as BitCoin and Ether are used in ICOs, these coins could also be viewed as incorporating an option to participate in subsequent ICOs. We touch on the implications of this in Section 5 below.

Secondary market trading of both Bitcoin and altcoins (both coins and tokens) is active, on various platforms in various jurisdictions. Typically, trading occurs 24 hours per day and every day of the year, on one of many electronic exchanges. Most exchanges take the form of an open electronic limit order book (similar to such books in equity markets), but without centralized regulation, market limits, or order size rules. As of November 2017, prominent exchanges include Bitfinex, Kraken, and GDAX. Most of the trade in altcoins occurs against Ethereum or Bitcoin, but also sometimes (and increasingly) against US dollars or fiat currency backed realcoins such as tethers. Some exchanges provide methods for direct deposits and withdrawals from bank accounts. Many exchanges also offer purchases using credit cards, albeit with high fees. Some exchanges, such as Poloniex, offer margin trading, which requires posting cryptocurrencies as collateral and allows for the possibility of shorting. We emphasize that these markets are unregulated. The altcoin exchanges themselves bear both default and "malfeasance" risk. This observation is consistent with the finding of Kroeger and Sarkar (2017), who note price differences in Bitcoin across various exchanges.

The contrast to equity trading in the US is striking. Secondary market trades in public equities are highly regulated, with the SEC, other regulators, and exchanges themselves imposing restrictions both on firms (with respect to disclosures to investors, for example) and on investors (including, for example, margin requirements).

In spite, or perhaps because of this, as of November 2017, several asset management funds, including hedge funds, have spawned to invest in diversified offerings of cryptocurrencies and ICOs. A few of these are similar to common investment management organizations, including in the use of managers and management, exit, and performance fees. Their focuses may differ, and they often target specific return characteristics or specific classes of cryptocurrencies. Organizations such as the CME and CBOE have additionally implemented cryptocurrency futures on a cash-settled basis, which provides further channels for shorting and for participants to apply expertise in financial engineering.

2 Data Sources

We consider two sets of data. First, we obtain secondary market price data from CoinMarketCap[4] over the time period 2013–2017. This website publishes live prices from all of the

[4] https://www.coinmarketcap.com

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major cryptocurrency exchanges. It also records historical daily data, with prices calculated as a weighted average of prices across the different exchanges. The data include daily open, high, low, closing prices, trading volume, and market capitalization. As trading occurs round the clock, the closing prices are collected at 23:59 UTC daily, including during weekends and US public holidays. At the time of data collection, no historical data API was provided, so we hand-collected the historical prices.

As of November 23, 2017, CoinMarketCap lists a total of 1,324 cryptocurrencies, including Bitcoin, Ether and other altcoins. By comparison, the number of currencies issued by sovereign governments is around 180. We keep a currency in our data set if (i) we have are at least one year's worth of data (ii) as of November 23, 2017, it has a market capitalization of at least $1 million. Due to the unregulated and decentralized nature of blockchain development, many coins exist that have little legitimacy, and the $1 million cutoff ensures the market has allocated sufficient capital to the coins we consider. This leaves us with secondary market information on 222 cryptocurrencies.

A limitation of the data source is that it relies on the assumption that information aggregated from multiple exchanges yields a good summary indication of cryptocurrency prices. However, as Kroeger and Sarkar (2017) demonstrate persistent violations of the law of one price for Bitcoin, this may turn out to be a poor assumption. Thus for our results to be meaningful, a necessary assumption is that such violations do not affect the correlations we demonstrate.

Table 10 (Tables 11) in the data appendix; provide summary statistics for the top 50 coins (tokens), by market capitalization, respectively. For coins, these include the market leader Bitcoin, as well as the well known coins Ethereum, Ripple, Dash, Litecoin, and Monero. The coins are generally older, and have much larger market capitalizations than; the tokens. The daily mean return on both is high compared to other asset classes, with prices moving by several percent per day. The total market capitalization of these cryptocurrencies sums to about $250 billion on November 23, 2017.

Second, we examine a data set consisting of 64 ICOs. The ICO data is also hand-collected from individual application white papers available as of August 2017, and are the largest by market capitalization. The ICOs were issued over the period 2013–2017, when the market had little or no regulation. The dataset includes the name of the application, the token abbreviation, the duration and time of the ICO, the total amount of funds raised, token supply, as well as average price during the ICO. We present this information for illustrative purposes. We note that many ICOs fail, or fail shortly after issuance.[5]

[5]The site `deadcoins.com` presents a (partial) list of failed ICOs.

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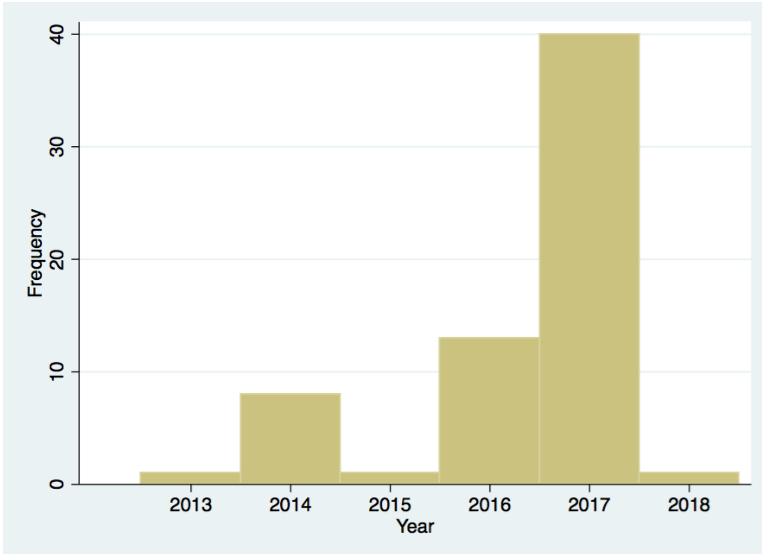

This histogram shows the number of ICOs in the data, by year.

Figure 1: Number of ICOs in data, by year

3 ICO returns

In Table 1, we display some illustrative, summary statistics on the amount raised in, and the returns from investing in ICOs. The median ICO raised about $6.4 million, but there is considerable skewness, with the mean being approximately equal to the 75th percentile, and the standard deviation about twice as high as the mean.

This skewness is exhibited in the returns as well. The ICO returns are calculated under the assumption that tokens were purchased at the average offering price in the ICO, and sold in the secondary market at the end of the first trading day, the first week, and the first month as the case may be. The first-day return has a median of 115%; that is, the median token more than doubles in value on the first trading day. It continues to climb in value over the first month, adding a further 29% in value.

The secondary market returns are also skewed. These returns are computed assuming that tokens were purchased at the end of the first trading day, and sold at the end of the first week or the first month, as the case may be. The median returns here are negative; −10.3% for the first week and −16.1% for the first month.[6] Nevertheless, the presence of some large returns allows the mean return over the first month to be a healthy 46.3%.

[6]Note that we have about 25% more observations on secondary market returns, relative to ICO returns, which helps to explain why the median return in the former case is negative whereas in the latter case the median return from first day to first month appears positive.

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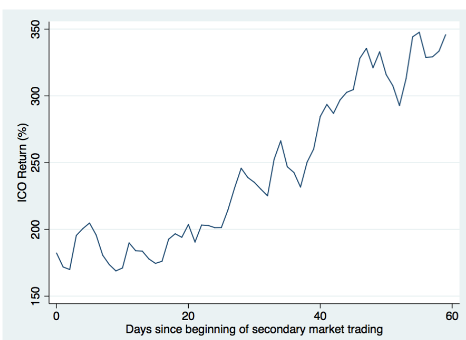
	No. Obs.	Mean	Std. Dev.	Min	p25	p50	p75	Max
Funds Raised ($ m)	64	16.36	31.81	0.006	2.45	6.39	15.41	185.0
ICO Returns (%) :								
First Day	51	4,746	31,652	-46.5	32.3	115	375	226,300
First Week	50	2,815	18,319	-54.6	17.7	94.8	277	129,733
First Month	51	19,999	140,818	-78.4	7.06	144	368	1,005,917
Secondary Mkt Returns (%):								
First Week	64	1.75	58.4	-94.3	-31.4	-10.3	28	274
First Month	64	46.3	191	-94	-57.8	-16.1	49.6	1,091

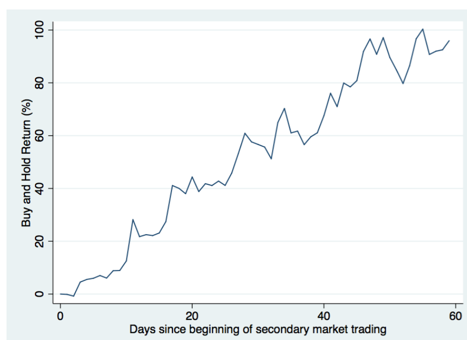
This table shows the amounts raised and the returns to investing in ICOs. The ICO returns assume that tokens are purchased at the average offering price in the ICO and sold in the secondary market. Secondary market returns are based on purchase and sale in the secondary market.

Table 1: Initial Coin Offerings: Summary Statistics

These data contain some large outlier returns, with first trading day returns above 1000%. We exclude these outliers to give a more reasonable graphical representation of the returns. Figure 2a depicts the mean percentage return of participating directly in a token offering, versus the returns of only trading in the secondary market (Figure 2b). These suggest tokens are issued at steep discounts to secondary market trading.



(a) Mean Return from ICO Participation



(b) Mean Return from Secondary Market Participation

Figure 2: Mean Return from ICO and Secondary Market Purchase of Tokens, with Large Outliers Removed

To the extent that ICOs are used to raise money for projects and firms, points of comparison for returns include IPO returns and venture capital (VC) returns. As with IPOs, in an ICO an investor purchases a claim (in this case a token) directly from a firm, and can

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then trade it with other investors in a secondary market.

While the process for ICOs and the subsequent trading of altcoins parallel that of publicly traded equity, there are some important differences. First, there is uncertainty over whether ICO tokens are in fact securities. The legal definition of a security is somewhat broad. In the SEC v. W. J. Howey Co. (1946), the US Supreme Court ruled that parts of a citrus grove coupled with a servicing contract constituted a security. It further defined an investment contract to be a "contract, transaction or scheme whereby a person invests his money in a common enterprise and is led to expect profits solely from the efforts of the promoter or a third party." [7] Many ICOs have been specifically designed to fail the Howey test. That said, recent communications from the SEC suggest regulators are taking a closer look at this market.[8] To all intents and purposes, the altcoins issued in our same were unregulated.

Second, the amounts raised in an ICO are typically much smaller than those raised in an IPO. The median amount raised in an IPO in the U.S. in 2016 was $94.5 million, compared to the $6.4 million we report for ICOs in Table 1.[9]

Third, ICO tokens are sometimes issued over a month or two. While the IPO process in all can take several months, the issuance of shares in an IPO typically happens at a point of time (although with greenshoe options and the like, the number of shares issued can vary from the number in the initial announcement).

There were 98 IPOs in the U.S. in 2016, with a mean first-day return of 12.1%, and mean return to the end of the year of 26.5%. Turning to 2017, data available from Nasdaq show that across 89 IPOs issued from March 2017 onward, the maximum first-day return was 52.2% and the minimum was -26.0%.[10] Negative first-day returns were relatively rare. Thus, in the cross-section IPO returns appear to be significantly less volatile than ICO returns. Of course, the assets that are subject to IPOs have been carefully selected by founders, investment banks and exchanges.

Given both the small amounts raised in the typical ICO and the fact that ICOs typically relate to early-stage projects, another point of comparison is investments in venture capital. However, here too there are important differences. VC investments are illiquid, and often need to be held for several years before they can be sold. In contrast, ICOs are sometimes tradable in the secondary market even before the ICO is complete. A recent Cambridge

[7] For a detailed discussion of this complex issue see chapter 2 of Rosenblum (2003)

[8] A recent statement by Chairman Jay Clayton `https://www.sec.gov/news/public-statement/statement-clayton-2017-12-11`

[9] The information we report on 2016 IPOs is from "2017 IPO Report," by Wilmer, Cutler, Pickering, Hale, and Dorr, LLP, available at `https://www.wilmerhale.com/uploadedFiles/Shared_Content/Editorial/Publications/Documents/2017-WilmerHale-IPO-Report.pdf`

[10] See `https://www.nasdaq.com/markets/ipos/performance.aspx`

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Associates Report[11] shows that over the period 2011 through 2016, the annual return on a VC index often in the 20-25% range. Of course, the latter return is a return on a portfolio, and so not directly comparable to the individual ICO returns we exhibit in Table 1.

4 Cyrptocurrency Return Characteristics

4.1 Summary Returns

Summary statistics for secondary market returns on cryptocurrencies are given in Table 2. The calculations apply the filters described in the previous section, which leave 222 cryptocurrencies. In addition, returns are winsorized at the 1% level so that large outliers leave the distributions interpretable. For each cryptocurrency, we compute the mean daily return, the variance of daily returns, and the daily turnover (defined as the market capitalization as of November 23, 2017, divided by the mean daily dollar volume) over a one-year period ending on November 23, 2017. We also compute the market capitalization as of the ending date. The table reports summary statistics on the cross-sectional distribution across the 222 cryptocurrencies. The mean daily return for this sample is a remarkable 2.53%, with a median of 1.8%.

	Mean	SD	Min	p25	p50	p75	Max
Mean Daily Return (%)	2.53	2.65	-0.276	1.18	1.8	2.7	19.7
St. Dev of Daily Returns (%)	17.9	11.1	0.77	11	14.6	20.3	69.9
Daily Turnover	0.0358	0.0474	0.0004	0.0072	0.0236	0.0482	0.479
Market Capitalization ($ m)	951.0	9,553.5	1.0	3.3	8.7	36.8	137,444.0
Observations	222						

Table 2: Secondary Market Information on Cryptocurrencies: Summary Statistics

Notice that in Figure 3, we show the log of dollar volume and market capitalization. We do this because of the skewness in the data. Indeed, Figure 3a shows that mean daily returns roughly follow a power law distribution, with a significant amount of daily returns as high as 5-10% per day, but with most falling around 1-2% per day. Log market capitalizations show an even greater degree of skewness.

[11] "U.S. Venture Capital 2016 Q3," available at
https://www.cambridgeassociates.com/benchmark/u-s-venture-capital-2016-q3/

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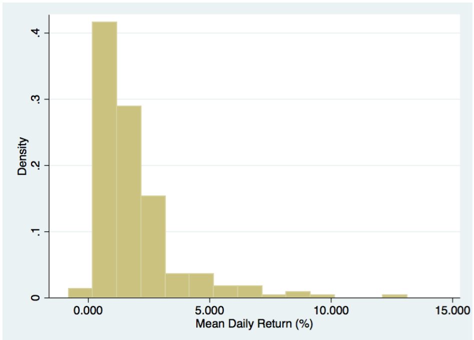
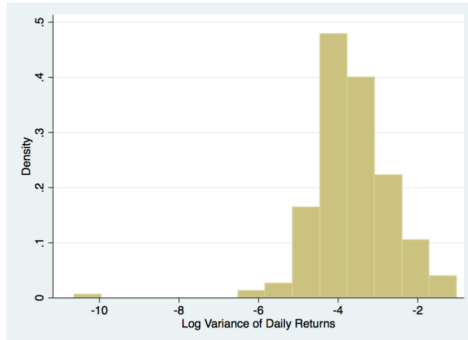
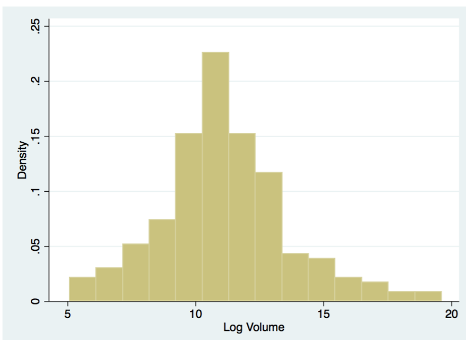


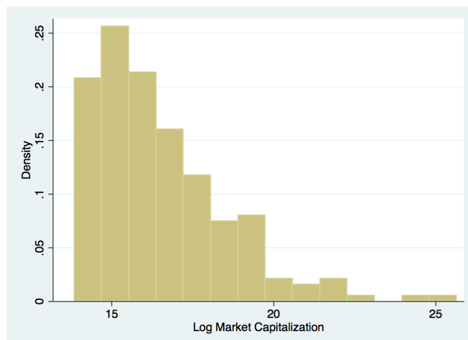
(a) Histogram of mean daily returns.



(b) Histogram of log variance of daily returns



(c) Histogram of log volume



(d) Histogram of log market capitalization

Figure 3: Cross-sectional Distribution across 222 Cryptocurrencies

4.2 BitCoin Returns

Bitcoin returns displays basic time-series econometric properties that are similar to stock prices. Table 3 shows that, at both the daily and monthly frequencies, we can confidently reject a unit root for returns, but not for prices. Table 4 shows this in regression form. With no constant, one-period lagged returns do not predict next period returns at either the daily or monthly frequencies.

4.3 Market portfolio returns

Bessembinder (2017) documents that approximately 60% of public US stocks earn less than the average monthly T-bill return over their life. However, as is well-known, a diversified portfolio of US stocks earns well in excess of the risk-free rate. Although most cryptocurrencies have a positive excess return over our sample period (the monthly T-bill rate is well less than 1% over most of the period), it is nevertheless useful to look at a return on a diversified portfolio of cryptocurrencies.

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Frequency/Price	Dickey-Fuller Test Statistic	No. of Obs.	p-value
Daily Return	-41.09	1,669	0.000
Monthly Return	-7.10	55	0.000
Daily Price	4.35	1,669	1.000
Monthly Price	4.28	55	1.000

This table calculates the Dickey-Fuller test statistics to test for unit roots in the Bitcoin return series. Test statistics were calculated separately for daily and monthly returns and prices. These series include a trend.

Table 3: Dickey-Fuller Tests of Unit Root for Bitcoin Returns and Prices

Frequency	Coef.	Std. Err	t-statistic	No. of Obs.	R^2
Daily	0.001	0.053	0.02	1,669	0.00
Monthly	-0.137	0.132	-1.04	55	0.02

This table presents coefficients for regressions of Bitcoin returns on a one-period lag of themselves. No constant is included in the regressions.

Table 4: One-Period Lagged Bitcoin Return Predictability Regressions

Figure 4 compares the value of $100 invested in an equally-weighted and market capitalization-weighted (or value-weighted) portfolio of cryptocurrencies over a three-year period. Weights for the value-weighted portfolio are based on market capitalizations as of November 23, 2014. To be included in the portfolio at November 23, 2014, we consider only cryptocurrencies with daily value traded greater than $100. This leaves 37 cryptocurrencies. As shown, the equally-weighted portfolio outperforms the value-weighted portfolio, due to the currency exposures aside from Bitcoin. A three-year investment held in such portfolios would lead to a 31-fold and 22-fold increase in the initial investment value, respectively. Nonetheless, there is a clear degree of co-variation among the two portfolios.

To examine the risk-return tradeoff, we plot the efficient frontier of daily returns for a two-year horizon. For this exercise, we consider only the top 50 cryptocurrencies by daily turnover as of November 23, 2015. The global minimum variance portfolio has a daily volatility of 3.22% and a daily mean return of 0.68%. This implies an annualized Sharpe ratio of 4.02, assuming 365 trading days in a year. The minimum variance portfolio is 56% weighted in Bitcoin. The weight on Bitcoin decreases as one increases the portfolio volatility along the frontier. Notice, that daily turnover is measured as as an average over the period of November 2015-2017, however the market caps use November 23, 2015.

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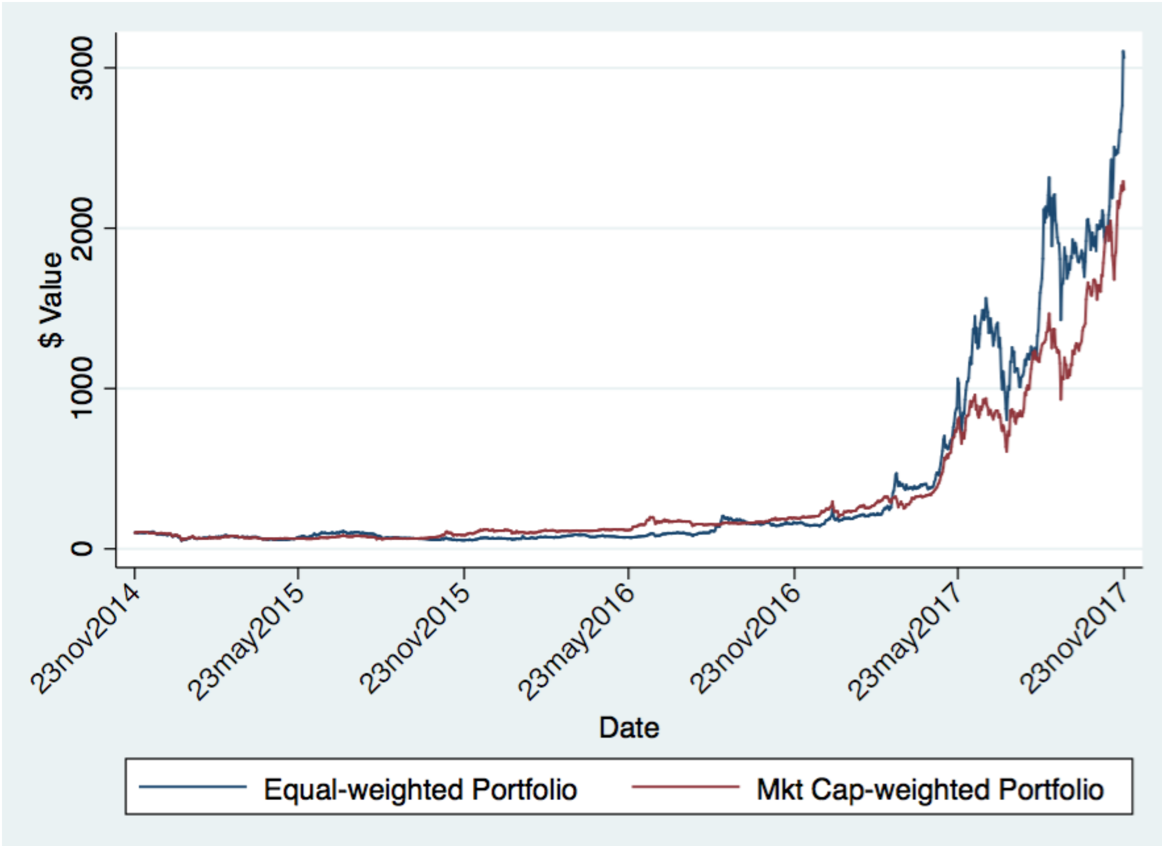

This plot considers the change in the value of $100 if invested into an equally-weighted portfolio and a market-capitalization weighted portfolio on November 23, 2014. These portfolios consist of all tradable cryptocurrencies in the data. To be considered tradable, we require the daily value traded to be greater than $100. The total size of the portfolio is 37 currencies. Approximately 89% of the market-capitalization weighted portfolio consists of Bitcoin.

Figure 4: Value of $100 Invested in Diversified Cryptocurrency Portfolio

4.4 Cross-Asset Correlations

In an effort to understand sources of common variation, we now consider the correlations of various cryptocurrencies with other assets. Correlations between return series are derived for each cryptocurrency except Bitcoin and (i) Bitcoin returns, (ii) gold returns[12], and (iii) S&P 500 Excess Return, at both daily and monthly frequencies. We report features of the cross-sectional distribution of the correlation coefficients across the 221 altcoins in Table 5.

The only asset for which cross-correlations are noticeably above zero is Bitcoin. The histograms for daily correlations are given in Figures 6a through 6c, where the distribution

[12]Gold prices are calculated as the London Bullion Market 3PM London Time Gold Fixing Price.

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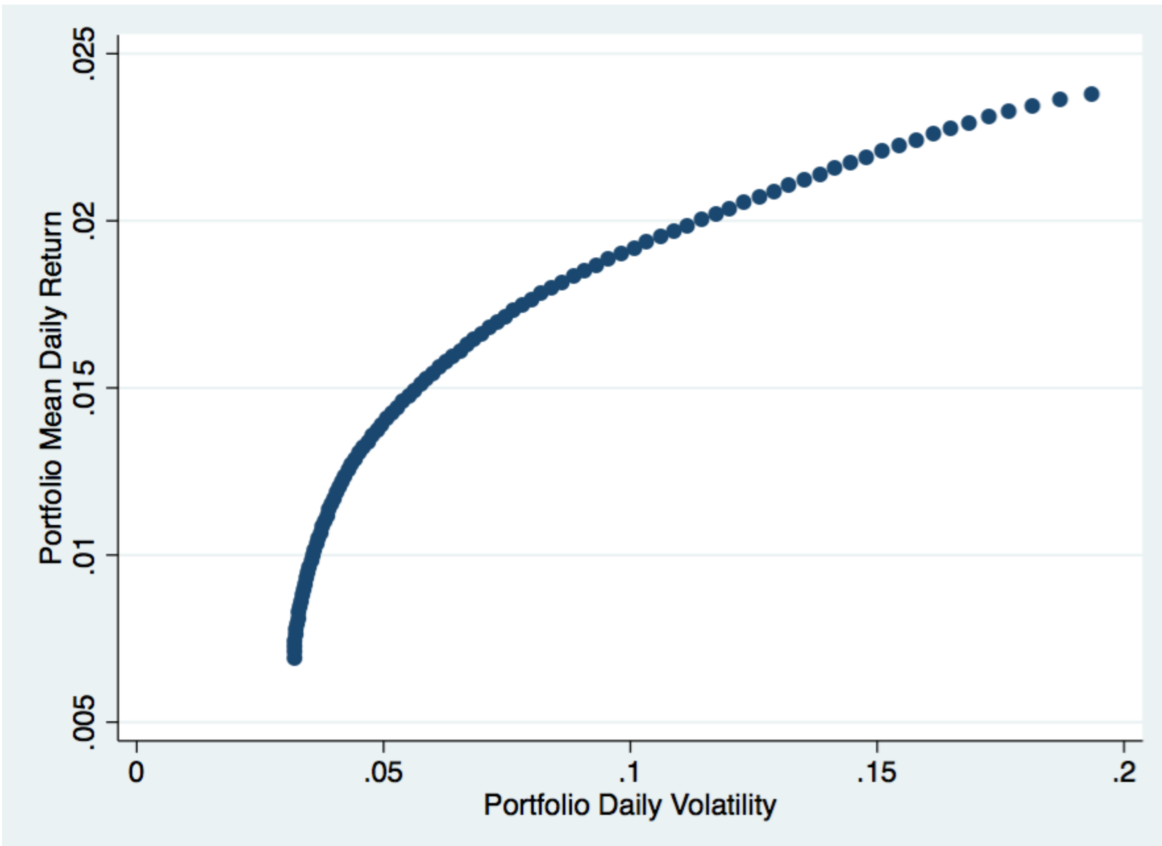

This plot considers 50 portfolios on an efficient frontier of the top 50 cryptocurrencies by turnover, as of November 23, 2015, with market capitalizations of at least $1 million. Portfolio weights were required to be weakly positive. The global minimum variance portfolio is 56% weighted in Bitcoin.

Figure 5: Efficient Frontier of Daily Returns

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Correlation With:	Mean	SD	Min	p25	p50	p75	Max
Bitcoin	0.174	0.113	-0.123	0.0926	0.177	0.251	0.645
Gold	0.0193	0.0474	-0.145	-0.0081	0.0146	0.0408	0.223
S&P 500 Excess Return	0.0045	0.0468	-0.224	-0.0184	0.0034	0.03	0.152
Observations	221						

Correlation With:	Mean	SD	Min	p25	p50	p75	Max
Bitcoin	0.21	0.29	-0.382	0.0057	0.18	0.363	0.949
Gold	0.0611	0.186	-0.456	-0.0657	0.047	0.156	0.688
S&P 500 Excess Return	-0.0166	0.189	-0.671	-0.106	0.0179	0.0863	0.527
Observations	221						

This table shows summary statistics for altcoin correlation coefficients with Bitcoin, Gold, and the S&P500 Excess Return. There are 221 observations as Bitcoin is excluded. The top part of the table shows daily correlations, and the bottom part shows monthly correlations.

Table 5: Daily (top) and Monthly (bottom) Altcoin Correlations with Other Assets

for Bitcoin correlations show many observations demonstrating high correlations between 0.30 and 0.50.

Table 6 lists currencies with the highest (positive, in our sample) correlations, and those that exhibit the lowest correlations, at monthly frequencies. The top 10 most correlated cryptocurrencies are mostly coins. Coins that exhibit highest positive correlation tend to be ones with a longer history, and include some coins with high turnover and high market capitalization. These correlations are very close to one, which may suggest some source of systematic risk. Coins that exhibit correlations closest to zero tend to be for certain gaming-specific purposes, such as NoLimitCoin, a coin dedicated to fantasy sports, or GameCredits, a universal coin for various other types of gaming transactions.

These high correlations explain the high apparent co-movement between the equally-weighted and market capitalization-weighted portfolio in Figure 4, where the latter portfolio is weighted 89% in Bitcoin. Since Bitcoin is a much smaller fraction of the equally-weighted portfolio, if there were no correlation between Bitcoin and non-Bitcoin cryptocurrencies, comovement between the two portfolio returns would be much less.

To show that aggregate altcoin returns are related to Bitcoin returns, we form equally-weighted and value-weighted portfolios on November 24, 2015, excluding Bitcoin, and regress the daily portfolio returns on Bitcoin daily returns. These results are presented in Table 9. These regressions show a strong relationship between aggregate altcoin returns and Bitcoin.

What is the source of this strong correlation with Bitcoin? One possible explanation is

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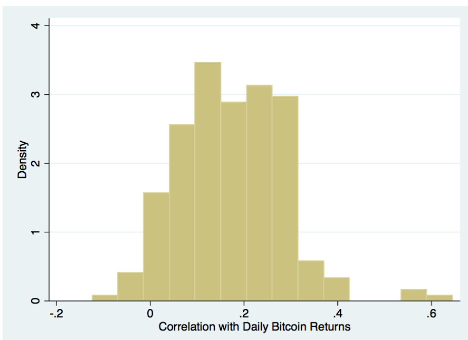
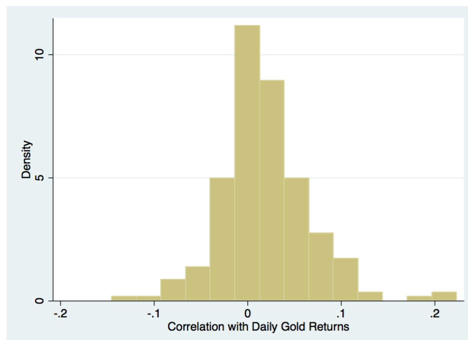
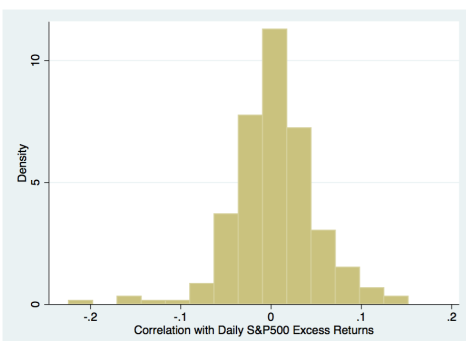


(a) Correlations with Daily Bitcoin returns.



(b) Correlations with Daily Gold returns.



(c) Correlations with Daily S&P500 excess returns.

Figure 6: The pairwise correlation coefficients are calculated from daily returns from the first price of every month to the next.

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Name	**Symbol**	**Corr.**	**Type**	**Turnover**
MaidSafeCoin	MAID	0.53	Token	0.0014
Auroracoin	AUR	0.50	Coin	0.0029
Waves	WAVES	0.48	Coin	0.0244
Ardor	ARDR	0.46	Token	0.0014
Peercoin	PPC	0.45	Coin	0.0187
Xaurum	XAUR	0.44	Token	0.5016
Augur	REP	0.43	Token	0.1729
Litecoin	LTC	0.43	Coin	1.0301
Monero	XMR	0.43	Coin	0.5640
Namecoin	NMC	0.43	Coin	0.0271
Pandacoin	PND	0.03	Coin	0.0000
Zoin	ZOI	0.03	Coin	0.0007
Fastcoin	FST	0.03	Coin	0.0000
ECC	ECC	0.03	Coin	0.0000
E-Dinar Coin	EDR	0.02	Coin	0.0218
NewYorkCoin	NYC	0.02	Coin	0.0000
FedoraCoin	TIPS	0.02	Coin	0.0000
Circuits of Value	COVAL	0.01	Token	0.0000
Cryptonite	XCN	0.00	Coin	0.0008
HTMLCOIN	HTML5	-0.03	Coin	0.0000

This table shows the top 10 most correlated and top 10 least correlated coins with Bitcoin. Correlations are calculated at the daily frequency using one year's worth of data from November 24, 2016 to November 23, 2017.

Table 6: Top 10 Highest and Lowest Correlation Coins versus Bitcoin, Based on Daily Returns

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	(1) Return (Eq. Weight)	(2) Return (Mkt. Weight)	(3) Return (Eq. Weight)	(4) Return (Mkt. Weight)	(5) Return (Eq. Weight)	(6) Return (Mkt. Weight)
Bitcoin Return	0.790***	0.530***				
	(0.0609)	(0.0776)				
Bitcoin Weekday Ret.			0.747***	0.618***	0.732***	0.611***
			(0.0832)	(0.0894)	(0.0852)	(0.0905)
Gold Return					0.687	0.359
					(0.587)	(0.288)
S&P 500 Excess Ret.					-0.391	-0.0175
					(0.362)	(0.268)
Constant	0.006**	0.006***	0.007***	0.007***	0.007***	0.006***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
R-squared	0.24	0.17	0.22	0.20	0.23	0.20
N	484	484	484	484	484	484

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows two-year daily return regressions of portfolios formed with altcoins on Bitcoin returns. Both portfolios are formed as of November 24, 2015 and exclude Bitcoin. Both portfolios include 117 altcoins. Weekday returns exclude cryptocurrency prices that fall on Saturday or Sunday. Standard errors adjusted for heteroskedasticity.

Table 7: Regressions of Altcoin Portfolio Daily Returns on Bitcoin Daily Returns

that many altcoins do not trade directly against fiat currencies, but against Bitcoin itself. Purchasing any of these altcoins thus may require purchases in Bitcoin, which may drive the common price movement.

4.5 Principal Component Analysis

Another way to show the strong relationship of altcoin returns with Bitcoin is to consider the first principal component of their returns, and examine its correlation with Bitcoin. Table 8 gives the first five components from PCA results for daily and monthly returns. To make sure a sufficiently complete time series is included, we restrict the universe of cryptocurrencies in this analysis to coins for which at least two years worth of price history are available. The first principal component explains 11.4% of daily returns, while the first principal component for monthly returns explains 31.7% of daily returns. For both these frequencies, the first principal component is closely related to Bitcoin returns, as demonstrated by Figures 7c and 7d. The correlation of the first principal component with Bitcoin has a magnitude 0.689 for daily returns and 0.456 for monthly returns.

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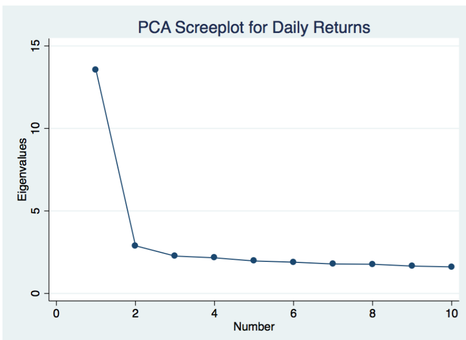
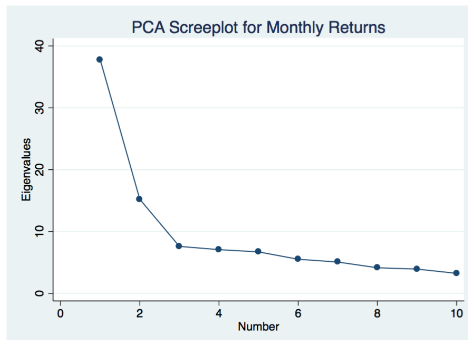
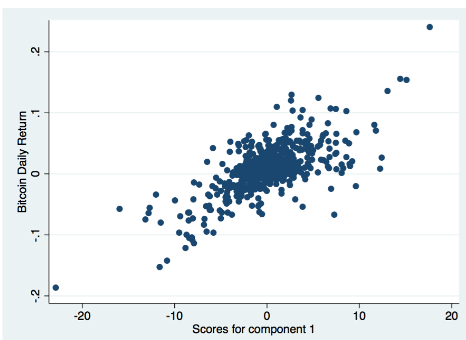


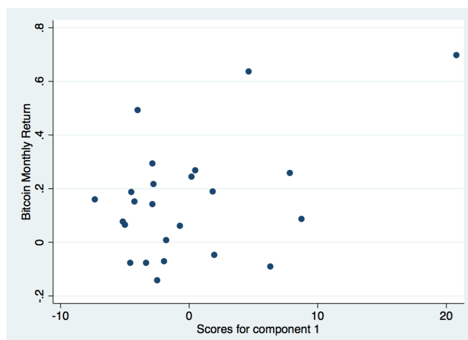
(a) Screeplot of PCA for daily returns



(b) Screeplot of PCA for weekly returns



(c) Plot of Daily Bitcoin Returns vs. First Principal Component Scores



(d) Plot of Monthly Bitcoin Returns vs. First Principal Component Scores

Figure 7: Figure 7a shows a screeplot for the daily PCA, of the principal component number against its eigenvalue. The first principal component explains 11.4% of daily return variation, while Figure 7b illustrates this monthly. The first principal component explains 31.7% of monthly return variation. Figure 7c shows a scatterplot of the scores of the first principal component from the daily PCA against daily Bitcoin returns, while the last figure shows a scatterplot of the scores of the first principal component from the monthly PCA against monthly Bitcoin returns.

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Daily Returns				
Component	**Eigenvalue**	**Difference**	**Proportion** (%)	**Cumulative** (%)
Component 1	13.535	10.648	11.4	11.4
Component 2	2.886	0.624	2.4	13.8
Component 3	2.262	0.103	1.9	15.7
Component 4	2.159	0.193	1.8	17.5
Component 5	1.965	0.072	1.7	19.2
Observations				724

Monthly Returns				
Component	**Eigenvalue**	**Difference**	**Proportion** (%)	**Cumulative** (%)
Component 1	37.753	22.545	0.317	31.7
Component 2	15.208	7.611	0.128	44.5
Component 3	7.597	0.525	0.064	50.9
Component 4	7.072	0.363	0.059	56.8
Component 5	6.708	1.195	0.056	62.5
Observations				24

This table shows results for the first five principal components for daily and monthly returns. We limit the analysis to only currencies that have at least two years worth of time series data.

Table 8: Principal Component Analysis of Cryptocurrency Returns

4.6 Relationship Between Bitcoin, Gold, and S&P 500 Returns

In Table 9, we report the results of regressing daily (monthly) Bitcoin returns on the excess return of the S&P 500 and the return of gold. Both at the daily and monthly levels, the beta of Bitcoin with respect to the S&P 500 and to gold is not significantly different from zero at the 10% level. In the monthly regression, the coefficient on the excess return of the S&P 500 is relatively large in magnitude, but has a p-value of only approximately 22.8%.

5 Evaluating Coin Returns

We have provided information about cryptocurrency returns. A natural question is what is the source of their value? A number of recent papers build models to value cryptocurrencies such as Bitcoin based on its use in transactions (see, for example, Athey et al. (2016), Schilling and Uhlig (2018), Sockin and Xiong (2018)) or to value tokens issued in ICOs based on their use as a store of value (Cong et al. (2018)), or on information produced during the ICO

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(a) Daily Returns

	Bitcoin	Bitcoin
S&P 500 Excess Ret.	-0.112	
	(-0.54)	
Gold		0.056
		(0.34)
Constant	0.005***	0.005***
	(3.10)	(3.08)
R-squared	-0.00	-0.00
N	1,114	1,114

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Monthly Returns

	Bitcoin	Bitcoin
S&P 500 Excess Ret.	3.811	
	(1.22)	
Gold		-1.130
		(-0.60)
Constant	0.121	0.147*
	(1.35)	(1.67)
R-squared	0.01	-0.01
N	55	55

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows the results of regressions of Bitcoin returns on S&P excess returns and gold returns. t-statistics are in parentheses. Panel (a) shows the results using daily returns for all three variables, and panel (b) using monthly returns.

Table 9: Regressions of Bitcoin Returns on Gold Returns and S&P Excess Returns

process (Catalini and Gans (2018) and Li and Mann (2018)). Although a full-blown model to value cryptocurrencies or tokens is beyond the scope of our paper, we outline below some thoughts on valuation in this sector.

First observe, that the basic finance approach of discounting cash flows at the appropriate risk adjusted rate is frequently not applicable to cryptocurrencies, as they are frequently designed not to be claims to cash flows to eschew regulation. For investment purposes, of course, the ability to resale is sufficient to include in a portfolio. However, consider what the possible sources of value are. In what follows, we consider different ways in which cryptocurrencies could be valued as investment securities. Determining which one is appropriate requires a structural estimation and is beyond the scope of this paper. However, for completeness, we include some of the possibilities.

(i) Simple Discounted Cash flow Analysis: In as much as there is a liquid market for coins, they may be valued as any other financial security. Specifically, if other assets that have a similar riskiness have an expected return of Er_t at time t, the price of a coin at time t should be

$$P_t = \frac{E_t P_{t+1}}{1 + Er_t}.$$

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This naturally implies an empirical proxy for the (unobserved) expected return of

$$1 + r_t \quad = \quad \frac{P_{t+1}}{P_t} + \epsilon_t,$$

where the independence of the error term stems from the unbiased expectations.

(ii) Utility Tokens: In addition to being a store of value (in the sense that it can be sold), most coins have a use component, denote this by ν. Suppose that a fraction α of a coin is required to use it. If the personal discount rate is δ, then we have

$$P_t \quad = \quad \max\left[\frac{E_t P_{t+1}}{1 + Er_t}\ , (1-\alpha)\frac{E_t P_{t+1}}{1 + Er_t} + \frac{E\nu_{t+1}}{1+\delta_t}\right].$$

Clearly, the empirical proxy, $\frac{P_{t+1}}{P_t}$ will systematically underestimate the expected return.

This formulation, similar to a convenience yield in commodities, depends on the specific implementation of the coin. Further note, that in many cases the use value (convenience yield) could exhibit a network externality. Specifically, the value to a user of owning the coin is increasing in the distribution of ownership of the coin, i.e., on how many people join the network. In this case, variables such as volume should be correlated with the estimation error induced by using $\frac{P_{t+1}}{P_t}$.

The use value above could possibly include the option to invest in a subsequent ICO. The value of the latter could be correlated with the current token's underlying price. Such valuation exercises are, of course, complex. Further, the use value could be part of a claim to a network product. Recall, traded tokens can be used to encourage agents to visit or participate in a website or venture. Thus, purchasing a coin can also be viewed as a commitment to purchase the underlying product. (Equivalent to requiring anyone buying a new iphone to buy an apple stock.) Because of this, sequential trade in a token, can imply an increase in the value of the underlying enterprise. To see this, consider a simple framework in which a monopolist owns all the underlying tokens in a particular ICO. The monopolist believes the value of the enterprise will eventually lie between $[0, 1]$. Suppose, for simplicity that the value is directly equal to the adoption rate, and so lies between $[0, 1]$. Further, suppose the monopolist owner has diffuse priors on the eventual adoption of her enterprise. Consider a sequence of discrete trades at which she sells one token, after each trade, her expected valuation will increase, and the support of her posterior will shrink. If she has mean variance preferences, her valuation will rise, both because of the higher expected value, but also because the risk

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adjustment has fallen. In short, her valuation increases. Of course, the solution to a dynamic trading game with network effects and risk aversion is beyond the scope of this paper, especially if the monopolist strategically sets the price.

6 Conclusion

In this paper, we provide summary statistics for returns of over 200 cryptocurrencies. We provide data for both the universe of currencies and for those involved in initial coin offerings. There is a large degree of skewness and volatility in the population of returns. A principal risk factor is the return of Bitcoin itself, which is highly correlated with many altcoins. This is demonstrable through examining simple correlations with Bitcoin returns at the daily and monthly frequencies, as well as through a principal component analysis. The existence of this risk factor has implications for asset management and regulation in cryptocurrencies.

Finally, observe, because there is currently little or no regulation around coins, they are not comparable to listed equities in which there are both stringent disclosure requirements and listing requirements. Indeed, the listing requirements for all exchanges mean the analogy between ICOs and IPOs is literally semantic.

The more relevant comparison group is probably venture capital. However, even in this case, a notable difference is that given the structure of the VC industry, the supply of capital is restricted, whereas in principle it is less so in the ICO model. We would thus expect the observed distribution of projects (coins) to be different. Cochrane (2005) estimates the risk and return characteristics of venture capital investments. He observes that data are only available if the firms invested in obtain new financing, go public, or are acquired. Without adjusting for the selection bias, he obtains mean log returns of 108%. These are associated with very high volatilities and thus high arithmetic returns.

In prior years, traditional finance theories have avoided explanations of the cryptocurrency landscape due to its decentralized nature, volatility, and high technological barrier. However, the entry of institutional market participants such as ICO issuers, asset managers, and traditional derivatives exchanges in this area suggest that the time is right for a financial treatment of this topic. Revelations in this paper may help introduce finance to this new class of assets by summoning traditional financial concepts.

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7 Data Appendix

Table 10: Top 50 Cryptocurrencies (Coins) by Market Capitalization

Symbol	Coin Name	Avg Daily Turnover	Avg Daily Volume ($ '000s)	Mkt Cap ($ mil)	Mean Return (%)	Series Start	Series End	Obs.
BTC	Bitcoin	0.0111	326,173.060	137,444.00	0.338	28apr2013	23nov2017	1671
ETH	Ethereum	0.0243	221,308.170	36,577.30	0.959	07aug2015	23nov2017	840
BCH	Bitcoin Cash	0.0749	740,494.560	21,899.40	1.996	23jul2017	23nov2017	124
XRP	Ripple	0.0078	29,743.270	9,230.52	0.521	04aug2013	23nov2017	1573
DASH	Dash	0.0181	10,074.678	4,447.48	0.867	14feb2014	23nov2017	1379
LTC	Litecoin	0.0430	50,727.574	3,882.95	0.410	28apr2013	23nov2017	1671
XMR	Monero	0.0268	7,826.890	2,555.95	0.691	21may2014	23nov2017	1283
MIOTA	IOTA	0.0133	21,311.869	2,494.42	0.733	13jun2017	23nov2017	164
NEO	NEO	0.0501	27,985.730	2,329.20	1.759	09sep2016	23nov2017	441
XEM	NEM	0.0054	2,251.155	1,837.21	1.090	01apr2015	23nov2017	968
ETC	Ethereum Classic	0.0664	61,146.016	1,760.67	0.919	24jul2016	23nov2017	488
QTUM	Qtum	0.1074	59,804.188	1,047.38	1.104	24may2017	23nov2017	184
LSK	Lisk	0.0278	5,333.186	997.92	1.381	06apr2016	23nov2017	597
ZEC	Zcash	0.1324	20,666.154	855.65	0.189	29oct2016	23nov2017	391
XLM	Stellar Lumens	0.0222	3,972.991	755.91	0.589	05aug2014	23nov2017	1207
ADA	Cardano	0.0096	8,181.512	739.96	0.637	01oct2017	23nov2017	54
HSR	Hshare	0.1446	22,418.451	702.92	1.338	20aug2017	23nov2017	96
BCC	BitConnect	0.0152	5,144.708	639.91	2.979	20jan2017	23nov2017	308
WAVES	Waves	0.0090	2,324.414	529.43	0.677	02jun2016	23nov2017	540
STRAT	Stratis	0.0233	5,501.349	367.88	1.827	12aug2016	23nov2017	469
BTS	BitShares	0.0311	7,248.575	355.84	0.506	21jul2014	23nov2017	1222
ARK	Ark	0.0195	2,321.125	304.62	2.690	22mar2017	23nov2017	247
BCN	Bytecoin	0.0036	514.262	283.90	0.851	17jun2014	23nov2017	1256
KMD	Komodo	0.0090	1,424.306	252.31	1.928	05feb2017	23nov2017	292
DCR	Decred	0.0131	686.052	250.98	1.008	10feb2016	23nov2017	653
STEEM	Steem	0.0074	1,313.143	246.29	0.772	18apr2016	23nov2017	585
DOGE	Dogecoin	0.0240	2,100.000	203.82	0.444	15dec2013	23nov2017	1440
MONA	MonaCoin	0.0050	296.762	199.31	0.653	20mar2014	23nov2017	1345
FCT	Factom	0.0386	1,870.721	198.87	1.082	06oct2015	23nov2017	780
VTC	Vertcoin	0.0336	799.934	170.45	0.961	20jan2014	23nov2017	1404
PIVX	PIVX	0.0163	469.936	170.08	2.144	13feb2016	23nov2017	650
SC	Siacoin	0.0345	3,112.306	168.73	1.263	26aug2015	23nov2017	821
GBYTE	Byteball Bytes	0.0054	544.795	162.86	1.674	27dec2016	23nov2017	332
BTCD	BitcoinDark	0.0085	99.553	144.09	0.920	16jul2014	23nov2017	1227
XZC	ZCoin	0.0644	1,060.964	134.38	2.129	06oct2016	23nov2017	414
ETP	Metaverse ETP	0.0632	3,447.782	134.34	0.737	05jun2017	23nov2017	172
GAME	GameCredits	0.0138	551.179	127.35	2.352	01sep2014	23nov2017	1180
NXT	Nxt	0.0412	1,601.074	126.35	0.588	04dec2013	23nov2017	1451
SYS	Syscoin	0.0189	533.261	122.48	0.969	20aug2014	23nov2017	1192
PURA	Pura	0.0143	63.409	111.72	5.677	27mar2015	23nov2017	973
GXS	GXShares	0.0204	6,860.774	111.69	0.390	25jun2017	23nov2017	152
BLOCK	Blocknet	0.0041	47.425	106.72	1.589	01nov2014	23nov2017	1119
LKK	Lykke	0.0096	239.586	94.00	0.638	14nov2016	23nov2017	375
B3	B3Coin	0.0196	46.103	93.69	4.555	03sep2016	23nov2017	447
DGB	DigiByte	0.0346	2,098.686	91.24	0.715	06feb2014	23nov2017	1387
XVG	Verge	0.0216	562.986	82.27	2.336	25oct2014	23nov2017	1126
VEN	VeChain	0.0141	1,491.588	72.61	1.224	22aug2017	23nov2017	94
CNX	Cryptonex	0.0019	140.362	69.03	-0.303	07oct2017	23nov2017	48
PART	Particl	0.0047	280.182	65.91	0.525	20jul2017	23nov2017	127
ZEN	ZenCash	0.0440	1,142.268	61.00	1.437	01jun2017	23nov2017	176

Data collected from CoinMarketCap as of November 23, 2017. Daily returns are calculated from daily closing times at 11:59 UTC. Only currencies with market capitalization greater than $1 million as of November 23, 2017 were retained. Average turnover and mean return are calculated from all prices available, and market capitalization calculated for November 23, 2017. Returns are winsorized at the 1% level.

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Table 11: Top 50 Cryptocurrencies (Tokens) by Market Capitalization

Symbol	Coin Name	Avg Daily Turnover	Avg Daily Volume ($ '000s)	Mkt Cap ($ mil)	Mean Return (%)	Series Start	Series End	Obs.
EOS	EOS	0.0783	38,106.645	929.84	1.247	01jul2017	23nov2017	146
OMG	OmiseGO	0.0735	46,753.898	814.28	2.938	14jul2017	23nov2017	133
USDT	Tether	0.2689	39,268.586	674.06	0.001	25feb2015	23nov2017	1003
PPT	Populous	0.0045	663.878	417.12	2.412	11jul2017	23nov2017	136
POWR	Power Ledger	0.3447	36,249.355	297.01	15.706	01nov2017	23nov2017	23
ARDR	Ardor	0.0112	1,279.812	295.37	0.873	23jul2016	23nov2017	489
REP	Augur	0.0110	1,193.035	276.16	0.850	27oct2015	23nov2017	759
PAY	TenX	0.0334	8,848.668	198.18	1.204	27jun2017	23nov2017	150
RDN	Raiden Network Token	0.0462	5,246.636	196.15	10.845	08nov2017	23nov2017	16
MAID	MaidSafeCoin	0.0075	622.911	192.91	0.495	28apr2014	23nov2017	1306
GNT	Golem	0.0213	3,892.432	192.90	1.307	18nov2016	23nov2017	371
VERI	Veritaseum	0.0032	680.210	187.70	2.515	08jun2017	23nov2017	169
GAS	Gas	0.0205	1,474.337	182.28	3.225	06jul2017	23nov2017	141
SALT	SALT	0.0353	5,158.009	179.84	0.368	29sep2017	23nov2017	56
AE	Aeternity	0.0078	381.590	169.02	2.375	01jun2017	23nov2017	176
BATa	Basic Attention Token	0.0199	3,656.435	166.95	0.482	01jun2017	23nov2017	176
BNB	Binance Coin	0.0813	11,608.214	159.47	3.352	25jul2017	23nov2017	122
DGD	DigixDAO	0.0035	258.896	152.49	0.581	18apr2016	23nov2017	585
TRX	TRON	0.0118	1,247.613	151.66	1.450	13sep2017	23nov2017	72
KNCa	Kyber Network	0.0196	3,720.485	149.48	-0.607	24sep2017	23nov2017	61
ICNa	Iconomi	0.0085	870.732	147.20	1.179	30sep2016	23nov2017	420
ETHOS	Ethos	0.0180	984.004	128.14	4.123	18jul2017	23nov2017	129
SNT	Status	0.0563	9,788.998	123.13	0.365	28jun2017	23nov2017	149
BTMa	Bytom	0.0504	4,896.432	116.09	1.023	08aug2017	23nov2017	108
WTC	Walton	0.1157	10,692.261	116.03	3.519	27aug2017	23nov2017	89
ZRX	0x	0.0282	3,745.922	114.44	0.501	16aug2017	23nov2017	100
QSP	Quantstamp	0.5502	64,070.031	110.64	41.937	21nov2017	23nov2017	3
CVC	Civic	0.0384	4,777.549	104.83	1.072	17jul2017	23nov2017	130
FUN	FunFair	0.0152	1,194.093	94.59	1.505	27jun2017	23nov2017	150
BNT	Bancor	0.0332	3,002.473	91.58	-0.445	18jun2017	23nov2017	159
MTL	Metal	0.0328	3,362.694	85.02	1.488	09jul2017	23nov2017	138
ATM	ATMChain	0.0141	1,102.007	83.47	1.561	04oct2017	23nov2017	51
GNO	Gnosis	0.0120	2,007.348	79.74	0.415	01may2017	23nov2017	207
SNGLS	SingularDTV	0.0050	397.903	78.43	1.083	03oct2016	23nov2017	417
STORJ	Storj	0.0507	3,148.219	77.56	1.271	02jul2017	23nov2017	145
MGO	MobileGo	0.0068	448.975	63.36	-0.194	11jun2017	23nov2017	166
ADX	AdEx	0.1949	5,525.782	62.02	2.566	01jul2017	23nov2017	146
EDG	Edgeless	0.0279	1,220.744	60.12	2.246	30mar2017	23nov2017	239
LINK	ChainLink	0.0460	4,428.780	59.38	0.473	20sep2017	23nov2017	65
ANT	Aragon	0.0108	745.394	58.75	0.539	18may2017	23nov2017	190
PPP	PayPie	0.0054	161.859	58.56	4.133	10oct2017	23nov2017	45
RCNa	Ripio Credit Network	0.1197	4,484.943	55.74	2.751	26oct2017	23nov2017	29
MCO	Monaco	0.0848	6,825.059	52.86	2.202	03jul2017	23nov2017	144
LRC	Loopring	0.0267	1,210.805	50.36	1.928	30aug2017	23nov2017	86
DATA	Streamr DATAcoin	0.0246	1,603.112	50.22	1.095	03nov2017	23nov2017	21
QRL	Quantum Resistant Ledger	0.0198	712.308	49.92	0.808	10jun2017	23nov2017	167
ZSC	Zeusshield	0.0141	401.114	48.74	0.694	13oct2017	23nov2017	42
KIN	Kin	0.0020	118.557	48.24	-0.575	27sep2017	23nov2017	58
RLC	iExec RLC	0.0100	453.400	46.14	0.886	20apr2017	23nov2017	218
WINGS	Wings	0.0154	419.200	45.51	2.032	11jan2017	23nov2017	317

Data collected from CoinMarketCap as of November 23, 2017. Daily returns are calculated from daily closing times at 11:59 UTC. Only currencies with market capitalization greater than $1 million as of November 23, 2017 were retained. Average turnover and mean return are calculated from all prices available, and market capitalization calculated for November 23, 2017. Returns are winsorized at the 1% level.

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