Bitcoin: Predictability and Profitability via Technical Analysis*

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Abstract

We document that Bitcoin returns, while unpredictable by macroeconomic variables, are predictable by 1- to 20-week moving averages (MAs) of daily prices, both in- and out-of-sample. Trading strategies based on MAs generate substantial alpha, utility and Sharpe ratios gains, and significantly reduce the severity of drawdowns relative to a buy-and-hold position in Bitcoin, which already has a Sharpe ratio of 1.8. We explain these facts with a novel equilibrium model that demonstrates, with uncertainty about growth in fundamentals, rational learning by investors with different priors yields predictability of returns by MAs.

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I. Introduction

Bitcoin is one of the most speculative assets in the history of finance. Its rapid price increase surprised even the most optimistic of market observers and early investors. One dollar invested in Bitcoin on July 18, 2010 grew to $70,970 by June 30, 2018, after hitting a peak value of $214,922. The same investment in the S&P500 stock index, which experienced relatively strong performance by historical standards, grew to only $2.55 over the same period. Moreover, Bitcoin is only the first digital coin in the rapidly growing cryptocurrency market that has a capitalization exceeding $800 billion at the end of 2017. Bitcoin's dramatic price growth accompanies similarly dramatic volatility. For example, Bitcoin experienced three large drawdowns averaging 30% in 2017 alone. Few, if any, measurable fundamentals explain Bitcoin's explosive price growth and high volatility. In this paper, we address two natural asset pricing questions: what explains the dynamics of Bitcoin prices and are Bitcoin returns predictable?

Presumably, the value of Bitcoin depends on some form of convenience yield, i.e., the benefit from its roles as a medium of exchange and a store of value. However, unlike more established government-backed currencies, Bitcoin's current and expected future convenience yield is a highly uncertain and randomly evolving quantity investors must learn about. Further, unlike other common financial assets such as stocks, bonds, and currencies, Bitcoin lacks universally accepted value-relevant fundamentals such as dividends, interest payments, and accounting statements. Given this lack of fundamentals, one naturally suspects that Bitcoin investors rely heavily on technical indicators such as the path of prices and volume to infer value-relevant information.

We formalize this intuition by providing a novel rational continuous-time equilibrium model that justifies the use of common technical analysis strategies in trading financial assets.[1] In the model, investors with different priors learn about the latent growth rate of Bitcoin's convenience yield. In contrast to other traded assets, investors in our model can only learn from past prices and convenience yields; they do not have access to other value-relevant signals. We show that, in this setting, moving-average trading rules are optimal, moving averages predict returns, and price drift exists (i.e., a higher expected return after a rise in the Bitcoin price). Different from Han et al.

[1]Empirically, Brock et al. (1992) and Lo et al. (2000), among others, show that trading based on technical indicators, especially the moving averages of prices, can be profitable in the stock market. Schwager (1989) and Lo and Hasanhodzic (2009) further provide insightful comments about the effectiveness of technical strategies from top practitioners.

(2016), our model does not assume some investors use exogenously given technical trading rules. In contrast, in the theoretical literature on technical analysis, our model is the first equilibrium model with endogenous technical traders. Our model also differs from prior rational models that generate time series momentum-style price drift. For example, in the model of Banerjee et al. (2009), the existence of price drift relies on differences in higher-order beliefs, and in the model of Cochrane et al. (2008), this drift requires existence of multiple risky assets.[2]

Consistent with our model, we find that daily Bitcoin returns are predictable in-sample by ratios of current (log) price to its 1- to 20-week moving averages (MAs). The model also predicts that this predictability becomes stronger when uncertainty decreases as investors learn about the dynamics of the latent growth of the convenience yield. Consistent with this prediction, we find both a negative interaction between the price-to-MA and return variance (uncertainty) in return-forecasting regressions, as well as a downward trend in variance over time. Since in-sample predictive regressions can overstate the significance of predictability to investors in real time (e.g., Goyal and Welch, 2008)], we assess out-of-sample predictability. To incorporate information across horizons, we apply out-of-sample mean-combination forecasts (e.g., Rapach et al., 2010). We find positively and statistically significant out-of-sample R^2s for most MA horizons and the mean forecasts. For comparison, we test whether Bitcoin returns are predictable by the VIX, Treasury bill rate, term spread, and the default spread, which are common predictors of stock returns. These variables fail to predict Bitcoin returns both in- and out-of-sample.

To assess the economic significance of Bitcoin-return predictability to investors, we form a trading strategy that goes long Bitcoin when the price is above the MA, and long cash otherwise. We find that these trading strategies significantly outperform the buy-and-hold benchmark, increasing Sharpe ratios by 0.2 to 0.6 per year from 1.8. The alphas and mean-variance utility gains are also large for most MA horizons. Moreover, average returns on Bitcoin on days when the MA signals indicate a long Bitcoin position are at least 18 times as large as those when the signals indicate investment in cash. These results are similar across both halves of the sample. The same strategies with various MA horizons also outperform the buy-and-hold benchmark when applied to other two

[2]Under various imperfect market conditions, Treynor and Ferguson (1985), Brown and Jennings (1989), Hong and Stein (1999), Chiarella et al. (2006), Cespa and Vives (2012), Edmans et al. (2015), Han et al. (2016), among others, show that past stock prices can predict future prices. These results imply that technical indicators, which are functions of past prices, can represent useful trading signals. Different from these models, investors in our model can only rely on past prices and they dynamically update their beliefs.

other cryptocurrencies, Ripple and Ethereum, Bitcoin's two largest competitors.

While our model is motivated by Bitcoin, it should also apply to other assets that lack value-relevant fundamentals.[3] Hence, to further test our model, we consider the NASDAQ portfolio during a ten-year window (1996–2005) that includes the dot.com boom-and-bust of the early 2000's. In this period, many emerging technologies associated with the internet and other communication advances introduced fundamentals that at the time were difficult to assess, much like those of Bitcoin. Many NASDAQ companies possessed no earnings (or negative earnings) for years before they became viable, and other company's innovations never proved valuable and eventually failed. We show that our technical trading strategies applied to the NASDAQ outperform the buy-and-hold benchmark in this ten-year window. This outperformance largely derives from avoiding the length and severity of the major NASDAQ drawdowns during this period. For similar reasons as those motivating our NASDAQ analysis, our model should also apply to individual young internet stocks during the tech boom before they had relatively informative fundamentals. During the five-year window around the peak of the tech boom (1998–2002), we find that the average MA strategy increases Sharpe ratios for almost all stocks in the Morgan Stanley Internet Index, which included many representative tech firms of the time (e.g., EBay and Amazon). These results demonstrate wider applicability of our model to other emerging assets characterized by fundamentals that are difficult to value besides Bitcoin and other cryptocurrencies.

Our model provides a testable economic implication in addition to the predictability of Bitcoin returns by MAs of prices. Specifically, in our model, trading results from variation across MA horizon indicators. Consistent with this implication, we show that proxies for disagreement across horizons and total turnover implied by the MA signals are significantly and positively associated with trading volume. Hence, overall, our results demonstrate that Bitcoin returns are predictable by MAs of different horizons, investors can profit from this predictability, and Bitcoin's trading volume is explained by differing MA trading signals across horizons.

[3]If one extends the model in this paper to include other fundamental signals, the traders would still use MAs as a signal to trade. The less precise the fundamental signal, the more weight traders would place on the price-to-MAs as a trading signal. Thus, the MA-based trading strategies should be relatively more successful in assets with noisier fundamentals, such as stocks of young firms that have yet to have reliable earnings information.

A. Related Literature

Our paper contributes to the growing literature on the economics of cryptocurrencies and the associated blockchain technology. Unlike our paper, relatively few papers in this vein study the asset pricing properties of Bitcoin. Using the Cagan model of hyperinflation, Jermann (2018) empirically examines the relative contribution of shocks to volume and velocity on variation in Bitcoin's price. Jermann finds that most of the variation in Bitcoin's price is attributable to volume shocks, consistent with stochastic adoption dominating technology innovations. Dwyer (2015) explains how cryptocurrencies can have positive value given limited supply. Athey et al. (2016), Bolt and van Oordt (2016), and Pagnotta and Buraschi (2018) all provide models in which the value of cryptocurrencies depends on some combination of (i) usage and the degree of adoption, (ii) the scarcity of Bitcoin, and (iii) the value of anonymity.

Our model differs from those used by prior studies in at least two important respects. First, our model does not require Bitcoin to be interpreted as a currency per se. We do not directly specify currency-related determinants of its value (e.g. (i)–(iii) above). Rather, we model the flow of utility-providing benefits as a random state variable, which we call a "convenience yield", but admits a more general interpretation. This generality is important because some market participants argue that Bitcoin is better thought of as a speculative asset than a currency (e.g., Yermack, 2013). For example Bitcoin's high volatility eliminates its use a store of value, a defining feature of money. Second, the papers cited above all assume full-information, however, our model features learning. This feature is critical given the lack of agreement on what determines the value of Bitcoin.[4] The learning aspect of our model also helps us to answer novel questions relative to the prior studies such as: what predicts Bitcoin returns?

Relative to asset pricing inquiries, such as ours, most of the literature on the economics of Bitcoin seeks to identify problems, implementation issues, and uses of cryptocurrencies. Böhme et al. (2015) discuss the virtual currency's potential to disrupt existing payment systems and perhaps even monetary systems. Harvey (2017) describes immense possibilities for the future for Bitcoin and its underlying blockchain technology. Balvers and McDonald (2018) describe conditions and practical steps necessary for using blockchain technology as a global currency. Easley et al.

[4]In a Bloomberg interview on December 4, 2013, Alan Greenspan stated: "You have to really stretch your imagination to infer what the intrinsic value of Bitcoin is. I haven't been able to do it. Maybe somebody else can."

(2017) provide a model of Bitcoin trading fees. Yermack (2017) discusses use of Blockchain for trading equities and the corresponding governance implications. Gandal et al. (2018) and Griffin and Shams (2018) document Bitcoin price manipulation. Biais et al. (2018) model the reliability of the Blockchain mechanism. Catalini and Gans (2017) discuss how blockchain technology will shape the rate and direction of innovation. Chiu and Koeppl (2017) study the optimal design of cryptocurrencies and assess quantitatively how well such currencies can support bilateral trade. Cong and He (2018) model the impact of blockchain technology on information environments. Fernández-Villaverde and Sanches (2017) model competition among privately issued currencies. Foley et al. (2018) document that a large portion of Bitcoin transactions represent illegal activity. Huberman et al. (2017) model fees and self-propagation mechanism of the Bitcoin payment system. Malinova and Park (2017) model the use of blockchain in trading financial assets. Saleh (2017) examines economic viability of blockchain price-formation mechanism. Prat and Walter (2016) show theoretically and empirically that Bitcoin prices forecast Bitcoin production.

The rest of the paper is organized as follows. Section II introduces the model and discusses its implications. Section III provides the data and summary statistics. Section IV reports the main empirical results, and Section V concludes.

II. The Model

Moving averages of prices have been widely used in practice for forecasting and trading risky assets such as stocks. However, to the best of our knowledge, no rational equilibrium model justifies such practice.[5] In this section, we develop the first rational continuous-time equilibrium model that provides a theoretical foundation for using the moving averages of prices for forecasting and trading risky assets including cryptocurrencies such as Bitcoin.

In the model, there is one risky asset ("Bitcoin") with one unit of net supply and one risk-free asset with zero net supply that investors can continuously trade.

Assumption 1. Each unit of Bitcoin provides a stream of convenience yield δ_t, where

$$\frac{d\delta_t}{\delta_t} = X_t dt + \sigma_\delta dZ_{1t}, \tag{1}$$

[5] In contrast to our model, Han et. al. (2016) exogenously assume there are some investors who use moving average rules in trading.

$$dX_t = \lambda(\bar{X} - X_t)dt + \rho\sigma_X dZ_{1t} + \sqrt{1-\rho^2}\sigma_X dZ_{2t}, \tag{2}$$

where $\sigma_\delta > 0$, $\lambda > 0$, $\bar{X} > 0$, $\sigma_X > 0$, and $\rho \in [-1, 1]$ are all known constants and (Z_{1t}, Z_{2t}) is a two-dimensional standard Brownian motion, and the expected growth rate X_t is an unobservable state variable.

While Bitcoin does not provide any cash flows, it can offer some benefit, which we call "convenience yield", to its owners. For example, holding Bitcoin can facilitate certain transactions, can reduce hyper-inflation risk caused by political turmoil, and can serve as a digital gold to store value. As a result, investors trade it to trade off convenience yield and risks. For risky assets like stocks and bonds, the convenience yield can represent dividend stream or interest paid to their owners. The unobservable state variable X_t is a catch-all variable for whatever state variable affects the convenience yield of an asset. For example, for Bitcoin, the state variable may capture the aggregate effect of the stringency of government regulations, the likelihood of hyper-inflation in some countries, the popularity of competing cryptocurrencies, and the related technology (e.g., block-chain update speed) advancement.

There is one main difference between cryptocurrencies like Bitcoin and more typical financial assets like stocks. For most stocks, investors observe not only stock prices but also other information about the stock such as information related to accounting, corporate policy, and key executives. Therefore, if we were to model typical stocks, another signal about the state variable X_t would be important. It is in this sense that our model is specific to cryptocurrencies like Bitcoin because in our model the only source of information about the value of Bitcoin is from market price process.[6] This difference between cryptocurrencies like Bitcoin and typical stocks suggests that the moving average methods are likely more important for the former than for the latter. For example, for stocks, if the additional signal is less noisy than past prices, then MA signals would be less useful.

On the investors, we make the assumptions below.

Assumption 2. There are two types of investors who differ by their priors about the state variable

[6] One can easily extend this model to include an additional "fundamental" signal so that it better fits typical stocks. Such an extension is available from the authors. In this extension, the traders would still use MAs as a signal to trade. The less precise the fundamental signal, the more weight traders would place on the price-to-MAs as a trading signal.

X_t and possibly initial endowment of Bitcoin.[7] Type i investor is endowed with $\eta_i \in (0,1)$ units of Bitcoin with $\eta_1 + \eta_2 = 1$ and has a prior that X_0 is normally distributed with mean $M^i(0)$ and variance $V^i(0)$, $i = 1, 2$.

Assumption 3. All investors have log preferences over the convenience yield provided by Bitcoin with discount rate β until time T. Specifically, the investor's expected utility is

$$E \int_0^T e^{-\beta t} \log C_t^i dt,$$

where C_t^i denotes the convenience yield received by a Type i investor from owning Bitcoin.

Denote by $\mathcal{F}_t$ the filtration at time t generated by the Bitcoin price process $\{B_s\}$ and the prior $(M^i(0), V^i(0))$ for all $s \le t$ and $i = 1, 2$. Further let $M_t^i \equiv E[X_t | \mathcal{F}_t^i]$ be the conditional expectation of X_t.

Both Bitcoin prices and the locally risk-free interest rate r_t are to be determined in equilibrium. We conjecture and later verify that the Bitcoin price B_t satisfies

$$\frac{dB_t}{B_t} = (\mu_t^i B_t - \delta_t)dt + \sigma_\delta B_t d\hat{Z}_{1t}^i, \tag{3}$$

where μ_t^i is an adapted stochastic process to be determined in equilibrium and $\hat{Z}_{1t}^i$ is an innovation process.

With Assumptions 1-3, we have

Proposition 1: In an economy defined by *Assumption 1-3*, there exists an equilibrium, in which

$$dB_t = ((\beta + M_t^i)B_t - \delta_t)dt + \sigma_\delta B_t d\hat{Z}_{1t}^i, \tag{4}$$

the fraction of wealth invested in the Bitcoin by Investor 1 is

$$1 + \frac{\alpha_t}{1 + \alpha_t} \frac{M_t^1 - M_t^2}{\sigma_\delta^2}, \tag{5}$$

[7] Since investors can continuously observe δ_t, they can directly calculate the volatility σ_δ and therefore there is no disagreement about the volatility.

and by Investor 2 is

$$1 - \frac{1}{1+\alpha_t} \frac{M_t^1 - M_t^2}{\sigma_\delta^2}, \tag{6}$$

where

$$M_t^i = h^i(t) + f^i(0,t) \log \frac{B_t}{B_0} + (f^i(t,t) - f^i(0,t)) \left(\log B_t - \frac{\int_0^t g^i(u,t) \log B_u du}{\int_0^t g^i(u,t) du} \right) \tag{7}$$

is the ith investor's conditional expectation of X_t, $h^i(.)$, $f^i(.,.)$, and $g^i(.,.)$ are as defined in the Appendix for $i = 1, 2$, and α_t is as defined in (A.8), denoting the ratio of the marginal utility of type 1 investor to that of type 2 investor. In addition, if

$$V^i(0) \leq \rho \sigma_X \sigma_\delta + \frac{\sigma_X^2}{\lambda}, \tag{8}$$

then

$$g^i(u,t) > 0, \quad f^i(t,t) - f^i(0,t) > 0, \forall u > 0, t > 0. \tag{9}$$

Proof. See the Appendix.

There are three important implications of Proposition 1. First, under Condition (8),[8] the Bitcoin return is predictable by the moving averages, because with $g^i(u,t) > 0$,

$$\frac{\int_0^t g^i(u,t) \log B_u du}{\int_0^t g^i(u,t) du}$$

is simply a weighted moving average of the log prices of Bitcoin. In addition, because $f^i(t,t) - f^i(0,t) > 0$ under Condition (8), the expected return increases as the difference between the current log price and the moving average increases.

The second implication is that the optimal trading strategy is a linear function of the MAs. In our model setting, investors trade with each other due to their differences in beliefs. Because of the lack of other information, investors can only rely on past prices and use MA signals to extract information from the market. As a result, their optimal trading strategies are functions of the MAs. As far as we know, this is the first rational equilibrium model that justifies the usage of MAs for

[8]It can be shown that in Condition (8), $\rho \sigma_X \sigma_\delta + \frac{\sigma_X^2}{\lambda}$ is strictly above the steady-state level of the conditional variance $V^i(t)$ and as time passes the conditional variance $V^i(t)$ monotonically converges to the steady-state level. Therefore, after a certain period of time, Condition (8) is always satisfied.

trading risky assets.

The third implication is that after an increase in the current price, the expected return over the next instant goes up (see Equation (A.12) satisfied M_t^i in the Appendix), which is consistent with the exhibition of price drift (time series return momentum), as defined in Banerjee et al. (2009). Intuitively, as price increases, investors increase their estimate of the expected growth rate of the convenience yield and thus the instantaneous expected return increases. Different from Banerjee et al. (2009), the price drift in our model does not stem from difference in higher-order beliefs. Different from Cochrane et al. (2008), the price drift in our model does not require multiple risky assets with positive net supply.

III. Data

Bitcoin trades continuously on multiple exchanges around the world. We obtain daily Bitcoin prices from the news and research site Coindesk.com, which is frequently cited in professional publications such as the *Wall Street Journal*, over the sample period July 18, 2010 (first day available) through June 30, 2018. Starting July 1, 2013, Coindesk reports a Bitcoin price equal to the average of those listed on large high-volume exchanges. Prior to July 2013, Coindesk reported the price from Mt. Gox, an exchange that handled most of the trading volume in Bitcoin at the time.[9] We also obtain data on two other cryptocurrencies, Ripple (XRP) and Ethereum (ETH), from coinmarketcap.com. These two currencies are the largest competitors to Bitcoin by market cap, but are only available over shorter samples (August 4, 2013–June 30, 2018 for XRP, and August 8, 2015–June 30, 2018 for ETH).

We obtain the daily risk-free rate and market excess return (MKT) from the website of Kenneth French. To measure the risk-free rate on weekends, we use the most recently available one-day risk-free rate. The average risk free rate over this time (see below) is multiple orders of magnitude smaller than the average Bitcoin return over this time so our risk-free rate assumptions can not have an economically meaningful impact on our results. We obtain daily prices and total returns on the NASDAQ composite index, Gold, and the Barclay's aggregate bond market index from Bloomberg. We obtain daily levels of the S&P500 index, VIX, 3-month and 10-year Treasury

[9]For details on the history of the Bitcoin market, see Eha (2017).

yields ($BILL$ and LTY, respectively), and Moody's BAA- and AAA-bond index yields (BAA and AAA, respectively) from the St. Louis Federal Reserve Bank website over the sample period July 18, 2010–June 30, 2018. We define $TERM = LTY - BILL$ and $DEF = BAA - AAA$. VIX, $BILL$, $TERM$, and DEF are commonly used returns predictors and among the few available at the daily frequency (e.g., Ang and Bekaert, 2007; Goyal and Welch, 2008; Brogaard and Detzel, 2015).

Figure 1 depicts the time-series of \$1 invested in Bitcoin or the S&P500 at the beginning of our sample period. Over the sample, \$1 investment in the S&P500 increased to about \$2.6. Over the same period, \$1 invested in Bitcoin grew to \$70,970.1! Table 1 presents summary statistics for our main variables of interest. Panel A shows that Bitcoin earns an annualized daily excess return of 193.2% and a Sharpe ratio of 1.8 with an annualized volatility of 106.2%. In contrast, MKT has a much lower average return and volatility over the period of 13.7% and 14.8%, respectively. Although far less than the Sharpe ratio of Bitcoin, the resulting MKT Sharpe ratio of 0.92 is relatively high by historical standards.

Panel B presents summary statistics for several benchmark return predictor variables used in the next section. All four are highly persistent, with an autoregressive coefficient of 0.95–1.0. Moreover, Augmented Dickey-Fuller tests fail to reject the null that any of the return predictors except VIX contain a unit root.

IV. Empirical results

In this section, we test the prediction from the model in Section II that short-horizon returns on Bitcoin are predictable by moving averages of price and, as a result, technical analysis strategies based on Bitcoin prices should out-perform the buy-and-hold Bitcoin strategy.

A. In-sample predictability

Motivated by Eqs. (4) and (7), we test the predictability of one-day Bitcoin returns using the difference between the log price of Bitcoin and the moving average of these log prices. For empirical work, we make two simplifications to the moving averages in Eq. (7). First, due to the difficulties of estimating the exact functionals, we assume equal-weighting in the moving averages (instead of the g^i-based weights). Second, following Brock et al. (1992), Lo et al. (2000), Han et al. (2013), Neely et al. (2014), and Han et al. (2016), we specify fixed time horizons of L =1, 2, 4, 10, and 20 weeks for the moving averages even though these horizons are endogenous in our model.

Specifically, letting B_t denote the price of Bitcoin on day t, we define:

$$b_t = log(B_t), \tag{10}$$

and the moving averages by:

$$ma_t(L) = \left(\frac{1}{n \cdot L}\right) \sum_{l=0}^{n \cdot L-1} b_{t-l}, \tag{11}$$

where n denotes the number of days per week in L weeks. Bitcoin trades 7 days per week, however stock returns and the macro predictors are only available on the 5 business days. Hence, for tests using the latter predictors, we use $n = 5$. For tests using only Bitcoin returns and moving averages, we use 7-day-per-week observations ($n = 7$).[10] The log price to moving average ratios, denoted $pma_t(L)$, serve as our central predictor of interest in empirical tests and are defined as:

$$pma_t(L) = p_t - ma_t(L). \tag{12}$$

Under condition (8), which is guaranteed to hold after enough time passes, the $pma(L)$ should positively predict Bitcoin returns over short time horizons. Table 2 evaluates in-sample predictive regressions of the form:

$$r_{t+1} = a + b' X_t + \varepsilon_{t+1}, \tag{13}$$

where r_{t+1} denotes the return on Bitcoin on day $t + 1$. To facilitate comparison with predictability by $BILL$, $TERM$, DEF, and VIX, we use 5-day "business" weeks throughout the table. Columns (1)–(5) of Panel A present results with $X_t = pma_t(L)$ for each L. The $pma_t(L)$ significantly predict r_{t+1} for all L with the positive sign predicted by our model. The moving averages of different horizons will mechanically be highly correlated with each other. Hence, to test whether different horizons' $pma(L)$ contain non-redundant predictive information, column (6) presents results in which the predictors are the first three principal components of the $pma(L)$, denoted

[10] To be clear, using 5-day (7-day) per week observations, the moving average horizons for L =1, 2, 4, 10, and 20 weeks are, respectively, 5, 10, 20, 50, and 100 (7, 14, 28, 70, and 140) days.

$X_t = (PC1_t,\ PC2_t,\ PC3_t)'$. The second and third principal components each load with at least marginal significance and the adjusted R^2 is roughly three to four times as high as the specifications in columns (1)–(5). Hence, it appears the set of all *pma*'s contain at least two distinct predictive signals, consistent with our multi-agent model.

Panel B presents predictive regressions of the form Eq. (13) using the common "macro" return predictors $X_t = VIX_t,\ BILL_t,\ TERM_t$, or DEF_t. Columns (1)–(5) show that none of these variables significantly predict Bitcoin returns in Eq. (13) either individually or jointly. Moreover, column (6), which uses predictors $X_t = (VIX_t,\ BILL_t,\ TERM_t,\ DEF_t,\ PC1_t,\ PC2_t,\ PC3_t)'$, shows that the macro return predictors do not subsume the predictive power of the *pma*.

Condition (8) will hold after enough time elapses with probability one as agents learn and posterior variance decreases. However, at times when the variance of the conditional expectation is relatively high, the predictive coefficient (analogous to the $f^i(t,t) - f^i(0,t)$ in Eq. (7)) on the $pma_t(L)$ should be relatively low. When this variance is high enough to violate condition (8), which is most likely to happen at the beginning of the sample, the predictive coefficient will even become negative. To test these patterns, we proxy for variance of the state variable using a measure of the conditional variance of the Bitcoin return. Specifically, we use the exponentially weighted moving average variance of Bitcoin returns, denoted σ_t^2.[11]

Table 3 presents predictive regressions of the form:

$$r_{t+1} = a + b \cdot pma_t(L) + c \cdot \sigma_t^2 + d \cdot pma_t(L) \cdot \sigma_t^2 + \varepsilon_{t+1}. \tag{14}$$

For these regressions, we use the whole sample period 12/06/2010–06/30/2018 and 7-day-per-week observations. The $pma(L)$ load significantly for all moving average horizons. Consistent with our model, the interaction terms between $pma_t(L)$ and σ_t^2 are all negative, so high variance attenuates the predictive coefficients on the $pma(L)$. Moreover, the interaction terms are significant for three of the five moving average horizons.

The top graph in Figure 2 plots the conditional variance of the Bitcoin returns over time.

[11] We use the smoothing parameter of 0.94 which is the default from RiskMetrics for computing conditional variances of daily returns. σ_t^2 is defined recursively as $\sigma_t^2 = (0.94) * \sigma_{t-1}^2 + (0.06) * r_t^2$, where r_t is the day-t return on Bitcoin. σ_0^2 is defined to be the sample variance over the first 140 days of our sample that are not used in our return-prediction tests because they are required to compute the initial 140-day moving average. In particular, the σ_t^2 is not based on any "in-sample" data used in the predictive regressions.

Consistent with the role of learning in our model, the variability of the conditional variance decreases over time. The bottom graph in Figure 2 plots the coefficient on the $pma_t(4)$ conditional on variance $(b + d \cdot \sigma_t^2)$. Consistent with our model, this coefficient is positive most of the time, especially later in the sample, however it is negative when conditional variance is high enough, early in the sample.

Overall, the in-sample predictability evidence in Tables 2 and 3 is consistent with our model. The *pma* positively predict Bitcoin returns on average. However, high conditional variance that exists before agents have a chance to "learn it away" can reverse this predictive relationship.

B. Out-of-sample predictability

It is well-established that highly persistent regressors such as VIX, $BILL$, $TERM$, and DEF can generate spuriously high in-sample return predictability (e.g., Stambaugh, 1999; Ferson et al., 2003; Campbell and Yogo, 2006). These biases and parameter instability often imply that in-sample estimates can overstate true real-time predictability, which directly impacts investors (e.g., Goyal and Welch, 2008). Hence, we next assess the out-of-sample predictability of Bitcoin returns.

Table 4 presents out-of-sample R^2 (R^2_{OS}) of forecasts from recursively estimated regressions similar to those estimated in-sample in Table 2.[12] The first five columns of Panel A report R^2_{OS} based on regressions of the form Eq. (13). For robustness, we report R^2_{OS} using several split dates between the in-sample and out-of-sample periods that include both relatively large in- and out-of-sample periods (e.g., Kelly and Pruitt, 2013). The last column (denoted MEAN), follows Rapach et al. (2010) and presents R^2_{OS} for the MEAN combination forecast, which is the simple average of the forecasts from the first five columns. Prior studies find that the MEAN combination forecasts are robust, frequently outperforming more sophisticated combination methods (that have more estimation error) in forecasting returns and other macroeconomic time-series out-of-sample (e.g., Timmermann, 2006; Rapach et al., 2010). Moreover, with diffuse priors about which MA horizon is optimal, technical traders would presumably give equal-weight to the different forecasts.

Panel A shows that several of the $pma_t(L)$ individually predict returns out-of-sample with $R^2_{OS} > 0$. Moreover, for each split date, the MEAN forecasts forecasts predict returns with at least marginal significance and R^2_{OS} of 0.83%–1.42%, which are high for the daily horizon. For compari-

[12] All out-of-sample regressions in this Table use expanding (not rolling) windows using all data available through t to make the forecast for day $t + 1$.

son, Pettenuzzo et al. (2014) find out-of-sample R^2 ranging from -0.08% to 0.55% for monthly stock returns. Panel B presents results from similar tests as Panel A, but using VIX, $BILL$, $TERM$, and DEF as predictors. Unlike the forecasts based on the pma, those based on the macro predictors generally have negative R^2_{OS}. Prior evidence show that predicting returns out-of-sample is challenging, especially at short horizons. Hence, it is already remarkable that we observe one-day out-of-sample predictability of Bitcoin returns by the pma. It should also be the case that this predictability increases with horizon. Hence, in Panel C, we present R^2_{OS} based on recursively estimated regressions of one-week (7-day) Bitcoin returns on the $pma(L)$:

$$r_{t+1,t+7} = a + b \cdot pma_t(L) + \varepsilon_{t+1,t+7}. \tag{15}$$

Consistent with prior evidence on stock and bond return predictability, Panel C shows that for each out-of-sample window and each L, the R^2_{OS} generally increase in both magnitude and significance relative to the analogous one-day-return R^2_{OS} in Panel A. The MEAN forecast, for example, has R^2_{OS} that are statistically significance and large for weekly returns. For comparison, Rapach et al. (2010) find R^2_{OS} of 1%–3.5% for quarterly stock returns. It is also worth noting that the predictability is not confined to the early part of the sample, the most recent 10% of the sample still has large and statistically significant R^2_{OS}. Overall, the out-of-sample evidence shows that the in-sample predictability of Bitcoin returns does not represent small-sample biases and evinces that investors can take advantage of Bitcoin predictability by moving averages of log prices.

C. Performance of trading strategies

The results above show that the $pma(L)$ predict Bitcoin returns with statistical significance. Next, we evaluate the associated economic significance by assessing the performance of trading strategies based on this predictability (e.g., Pesaran and Timmermann, 1995; Cochrane, 2008; Rapach et al., 2010). We define the buy indicator (buy=1) associated with each MA strategy (denoted MA(L)) as:

$$S_{L,t} = \begin{cases} 1, & \text{if } pma_t(L) > 0 \\ 0, & \text{otherwise.} \end{cases} \tag{16}$$

The return on the Bitcoin MA(L) strategy on day t is given by:

$$r_t^{MA(L)} = S_{L,t} \cdot r_t + (1 - S_{L,t}) \cdot r_{ft}, \quad (17)$$

where r_t and r_{ft} denote, respectively, the return on Bitcoin and the risk-free rate on day t. Intuitively, the trading strategy defined by Eq. (17) captures the predictability of Bitcoin by short-term trends discussed theoretically in Section II. We denote the excess return of the buy-and-hold position in Bitcoin as rx_t and the excess return on the MA strategies by $rx_t^{MA(L)}$.

Table 5 presents summary statistics for the buy-and-hold and MA strategies. Panel A, which uses the full sample (10/27/2010–6/30/2018), shows that all strategies are right-skewed and have fat tails. The Sharpe ratio of Bitcoin is 1.8, which is about four times the historical Sharpe ratio of the stock market (e.g., Cochrane, 2005). All of the MA strategies further increase this ratio to 2.0 to 2.5. Moreover, all but one of these Sharpe ratio gains are at least marginally significant using the heteroskedasticity and autocorrelation (HAC) robust test for equality of Sharpe ratios following Ledoit and Wolf (2008). The maximum drawdown of Bitcoin is 89.5%, while those of the MA strategies are all lower, ranging from 64.4% to 77.9%. Comparing Panels B and C indicates that the performance of Bitcoin was higher during the first half of the sample, although the Sharpe ratio gains of the MA strategies relative to the buy-and-hold position are similar in both subsamples.

Panel A of Figure 3 plots the cumulative value of $1 invested in Bitcoin and the MA(2) (two-week) strategy at the beginning of the sample. At the end of our sample, the $1 in Bitcoin grew to $33,617 while the $1 in the MA(2) strategy grew to approximately $148,549, a difference of about $114,932 over 7.5 years! Panel B plots the drawdowns of Bitcoin and the MA(2) strategy. As Panel B shows, the out-performance of the MA strategies relative to the buy and hold largely stems from the MA strategy having both shorter and less severe drawdowns than the buy-and-hold. For example, Bitcoin prices hit an all-time high in December 2017 at $19,343 and subsequently fell to $6,343 by the end of our sample. Panel B shows investors using the MA(2) strategy would have been spared most of the losses from this price decline.

Table 6 presents average returns of Bitcoin on days when the MA strategies indicate investment in Bitcoin (IN) and when these strategies indicate investment in Treasury bills (OUT). The results show that not only are Bitcoin returns higher on IN days, but also almost all of Bitcoin average returns accrue on these days. Moreover, this concentration of performance occurs over both halves of the sample.

Table 7 formally tests the incremental performance of MA strategies relative to the buy-and-hold. Specifically, we regress the excess returns of the MA strategies on the buy-and-hold benchmark:

$$rx_t^{MA(L)} = \alpha + \beta \cdot rx_t + \varepsilon_t. \tag{18}$$

A positive alpha indicates that access to $rx_t^{MA(L)}$ increases the maximum possible Sharpe ratio relative to that of a buy-and-hold Bitcoin position. The ultimate benefit of such increases to an investor is increased utility from a higher maximum Sharpe ratio for their whole portfolio. Thus, alpha only matters to the extent that it expands the mean-variance frontier. Intuitively, this expansion depends on the alpha relative to the residual risk investors must bear to capture it. The maximum Sharpe ratio (SR_{New}) attainable from access to rx_t and $rx_t^{MA(L)}$ is given by:

$$SR_{New} = \sqrt{\left(\frac{\alpha}{\sigma(\varepsilon_t)}\right)^2 + SR_{Old}^2}, \tag{19}$$

where SR_{Old} is the Sharpe ratio of rx_t (e.g., Bodie et al., 2014). Hence, we use the appraisal ratio $\left(\frac{\alpha}{\sigma(\varepsilon_t)}\right)$ as one measure of the benefits of technical analysis to investors.

A disadvantage of the appraisal ratio is that its effect on Sharpe ratios is nonlinear. The same appraisal ratio has a greater impact on a lesser SR_{Old} than vice versa. Thus, to further facilitate comparison across assets, we measure the percentage increase in mean-variance utility, which—for any level of risk aversion—is equal to:

$$\text{Utility gain} = \frac{SR_{New}^2 - SR_{Old}^2}{SR_{Old}^2}. \tag{20}$$

Campbell and Thompson (2008) find that timing expected returns on the stock market increases mean-variance utility by approximately 35%, providing a useful benchmark utility gain.

Panel A shows that over the entire sample period, the MA strategies earn significant α with respect to rx_t of 0.09% to 0.24% per day. These alphas lead to economically large utility gains of 19.7% to 85.5%. Panel B shows these results remain strong in the second half of the sample. With the turnovers in the Table, it would take large transaction costs of (1.38%–6.85% one-way) to eliminate the alphas of the MA strategies. These figures are large relative to actual one-way transaction costs in Bitcoin. For example, market orders on the Bitcoin exchange GDAX have fees of 0.10%–0.30% for market orders and 0% for limit orders. Even the most expensive market order fees are an order of magnitude too small to meaningfully impact the αs of the MA strategies.

A naive alternative to our discrete buy-or-sell strategies defined by Eq. (17) would be estimating mean-variance weights using our Bitcoin-return forecasts, and then testing whether the resulting strategy out-performs the buy-and-hold benchmark (e.g., Marquering and Verbeek, 2004; Campbell and Thompson, 2008; Huang et al., 2015). However, this approach has several theoretical and empirical shortcomings relative to our simple MA(L) strategies. First, the mean-variance weights assume the investor is choosing between the market return and the risk-free asset. However, Bitcoin is a poor theoretical proxy to the market portfolio of risky assets. Second, prior to 2017, investors could not short-sell Bitcoin or buy it on margin or via futures contracts. Hence, the weights on Bitcoin should be constrained between zero and one. Thus, the mean-variance-weights approach could only outperform the MA strategies by choosing optimal variation between zero and one. This in turn exacerbates the following two problems: (i) that the mean-variance weights require at least two estimated forecasts, and therefore come with substantial estimation error, and (ii) the mean-variance weights assume for tractability the mean-variance functional form of investor utility. While a common assumption, mean-variance utility is unlikely to precisely capture the behavior of a representative investor. In contrast, our discrete MA strategies are based on a directly observable out-of-sample signals and require no estimation error. They also make no assumption about the utility of underlying investors. Overall, the strong performance of our MA strategies relative to the buy-and-hold precludes the need for more sophisticated methods to demonstrate the economic significance of out-of-sample predictability by MAs.

D. Subperiods and major episodes

Despite Bitcoin's rapid increases over the past few years, its performance has been plagued by several bear markets. A Fortune magazine article (Roberts, 2017) examines the explanations behind five major Bitcoin crashes, and a more recent article (Pollack, 2017) details explanations behind the three bear market crashes of 2017. We briefly summarize the causes of these downturns from these articles as well as the more recent early 2018 meltdown, and document the performance of our technical trading strategies during these identified episodes. The evidence clearly shows that the moving average indicators relatively quickly indicated to sell Bitcoin and thus minimize large draw-downs.

An outage at Mt Gox, the prominent Bitcoin trading platform at the time in April of 2013, led to uncertainty about the platform and a collapse in Bitcoin from \$230 to \$93, a decline of nearly 60%. The MA(1), MA(2) and MA(4) declined however to \$165, \$125 and \$117, or declines of 28%, 46% and 49%, respectively. Fortune further details the second decline to overzealous US regulators in the late fall of 2013; Bitcoin fell from \$1125 to \$522, or nearly 54%. The MA(1), MA(2) and MA(4) declined however to \$900, \$603 and \$820, or declines of 20%, 46% and 27%. Third, the collapse of Mt Gox then in February 2014 lead to an additional fall from \$855 to \$598, nearly 40%. The MA(1), MA(2) and MA(4) declined however to \$900, \$603 and \$820, or declines of 20%, 46% and 27%. In all three cases, the drawdown's figure clearly illustrates that the MA predictors quickly indicated sell and hence minimize the large losses during these drawdowns.

Fortune and Cointelegraph both mentioned substantial uncertainty about the hard-fork of Bitcoin splitting into two coins (Bitcoin and Bitcoin cash) during the Summer of 2017. Bitcoin fell from \$3019 to \$1939, or approximately 56%. The MA(1), MA(2) and MA(4) declined however to \$2605, \$2417 and \$2183, or declines of 16%, 25% and 38%. The Chinese in September of 2017 then threatened to crack down on Bitcoin, contributing to fall from \$4950 to \$3003 or 27%. The MA(1), MA(2) and MA(4) declined however to \$4663, \$3581 and \$4217, or declines of 14%, 28% and 15%. Cointelegraph lastly documents a crash attributable to Bitcoin limiting its blocksize in late 2017, and prompted an exit to Bitcoin cash which increased 40%, while Bitcoin fell from \$7559 to \$5857, more than 21%. The MA(1), MA(2) and MA(4) declined to \$7147, \$6570, \$6337, or falls of 4%, 12% and 15%, respectively.

Bitcoin experienced a large downturn from \$19,343 in December 16, 2017 to \$6,387 at the end of our sample, June 30 2018. The decline of 67% began in part with a crackdown in China and Korea and fears of regulation of the U.S. that began in mid December. Similarly to the above patterns, the MA strategies indicated to sell Bitcoin and hence minimized larger losses; e.g., from 12/16/2017-6/30/2018, the MA(1), MA(2) and MA(4) lost 43%, 43% and 23%, respectively. An equal-weighted strategy lost less than 19%. Overall, in all seven episodes, the three sharp declines in 2013-2014, the three bear markets of 2017, and the recent bear market in early 2018, the MA(1), MA(2) and MA(4) decisively outperformed a buy-and-hold strategy since they relatively quickly indicated exit and hence minimized large losses.

E. Performance of trading strategies applied to other cryptocurrencies

To examine the robustness of our trading strategy performance, Table 8 presents performance results similar to those above for Ripple (XRP, Panels A and B) and Etheruem (ETH, Panels C and D), which are the two largest digital currencies by market capitalization beside Bitcoin. Panel A shows that all the MA strategies except MA(4) increase Sharpe ratios relative to the buy-and-hold strategy by up to 0.54 (from 1.05). This difference is significant for the MA(1) and MA(2) strategies and marginally significant for the equal-weighted portfolio of MA strategies (EW). Each strategy reduces the maximum drawdown of the buy-and-hold Ripple strategy by about 4.7%-32.3%. Panel B shows that the MA(1), MA(2), MA(4), and EW strategies also earn significant alphas with respect to the buy-and-hold XRP strategy, generating large utility gains (92.9%–180.1%) in the process.

Panels C and D present similar results as Panels A and D, respectively, but for strategies based on ETH instead of XRP. The ETH sample is only two and a half years long, leading to relatively low statistical power, but qualitatively similar inferences as for the Bitcoin and Ethereurm MA strategies. The MA strategies earn higher Sharpe ratios than the buy-and-hold ETH strategy. Panel C shows the ETH MA-strategy alphas are significant for three horizons (1, 2, and 4 weeks) as well as the EW strategy and the associated utility gains are economically large.

F. Comparison with NASDAQ and individual tech stocks

Over our sample, Bitcoin exhibits several substantial run-ups in prices preceding large crashes. It is therefore interesting to assess how MA strategies would help investors improve performance in prior extreme run-ups that were followed by extreme market crashes. Moreover, our equilibrium theory underlying technical analysis should apply not just to cryptocurrencies, but any asset that lacks informative fundamentals. We apply each of the MA strategies defined by Eq. (17) to the total return on the NASDAQ composite index using daily data over the sample 1996–2005, a ten year window approximately centered around the peak of the NASDAQ "bubble". During this time, fundamentals were plausibly less useful in valuing stocks in the nascent tech industry. For example, Ofek and Richardson (2003) document that during this period, aggregate earnings of internet stocks were negative and price-earnings ratios frequently exceeded 1000.

Figure 4 depicts the performance of the buy-and-hold position in NASDAQ relative to the MA(2) strategy. Panel A shows the MA(2) increases more steadily than NASDAQ, avoiding much of the latter's peaks and valleys. The MA(2) returns \$3.66 at the end of 2005 to an investor with a \$1 investment at the beginning of 1996. Conversely, a buy-and-hold investor in NASDAQ would have about half (\$1.85) of the accumulated value. Panel A shows that much of the performance gains from the MA strategy come from avoiding most of NASDAQ's large crash in the early 2000's. Panel B further shows that the MA(2) did not just avoid the largest crash, however. The strategy avoids the majority of each of the non-trivial NASDAQ drawdown before the crash as well.

Table 9 documents the performance of the MA strategies applied to the NASDAQ. Results in Panel A show that over 1996–2005, the MA(2), MA(4) and MA(10) methods possess mean returns more than four percent greater than the 7.3% of the buy-and-hold NASDAQ strategy. Further, all five methods substantially boost the NASDAQ Sharpe ratio of 0.29. For example, MA(2), MA(4) and MA(10) possess Sharpe ratios of 0.73 to 0.79. The last column documents that the MA strategies also greatly reduce the maximum drawdown of NASDAQ (77.9%) to 25.7%–45.6%.[13] Panel B of Table 9 presents the alphas, appraisal and utility gain for the NASDAQ. Results document significant alpha for MA(2) to MA(10) strategies. It also reveals high utility gains for all five strategies, ranging from 137%–688%.

Panel C presents results over a tighter window around the NASDAQ peak. A number of new internet companies entered the NASDAQ around this period, and the fundamentals of many other firms were questioned after several large earnings misstatements. The NASDAQ peaked in March 2000, and by the end of 2002 had lost 78% of its value. In contrast, the MA strategies have maximum drawdowns from 34%-43% and the equal-weighted MA strategy lost only 34% of its value—less than half the buy-and-hold position. Further, the Sharpe ratios for the MA strategies during this five year window ranged from 0.36-0.60, compared to zero for the buy-and-hold. The equal-weighted strategy generates a Sharpe ratio of 0.57 and is significantly greater than the buy-and-hold Sharpe ratio.

[13]We also applied our strategies to the NASDAQ over the past ten years, which follows the maturation of internet-based technologies and an increased understanding of fundamentals. These untabulated results show that the MA strategies no longer earn significant alpha or produce Sharpe ratio gains.

Table 10 presents the performance of technical analysis for individual technology stocks for the five years around the 2000 peak. Ofek and Richardson (2003) investigate the "dot.com mania" using daily data from internet companies identified by Morgan Stanley's index of pure internet companies. They document the difficulty of assessing fundamentals for these companies. For instance, the average PE ratio for internet companies exceeded 600, and four of the eleven industry codes possessed PE ratios exceeding 1000. Aggregate net income and EBITD were also negative across the eleven industry codes. Following Ofek and Richardson (2003), we also examine Morgan Stanley's index, which includes well-known firms such as Amazon, AOL, Ebay, Oracle and Yahoo. Results show that all five of our MA strategies and the EW strategy outperform the buy-and-hold strategy for most of the 25 stocks. An equal-weighted strategy generates an average Sharpe ratio of 0.29 across the 25 firms compared to an average buy-and-hold Sharpe of 0.02. Further, the Sharpe ratio for the equal-weighted strategy is higher for 23 of the 25 firms, losing only to AOL and Intuit. A one dollar investment in the beginning of 1998 for the equal-weighted strategy generates an impressive return of 88% compared to a loss of 42% for the buy-and-hold position. Overall, the results show that the MA strategy 'worked' for many well-known internet companies for the turbulent NASDAQ period of 1998-2002.

G. Volume implications of our model

In our model, trading is based on moving-average indicators across different horizons. Testing this refutable implication provides an opportunity to validate our model's mechanism in explaining the predictability of Bitcoin by moving averages of multiple horizons.

We test for volume generated by technical trading in two ways. First, we evaluate whether increases in total turnover implied by different MA signals also leads to higher Bitcoin volume. We measure this total turnover by the sum of the turnover generated by each moving-average buy-sell indicator $S_{L,t}$: $\sum_L |\Delta S_{L,t}|$. Second, we evaluate whether disagreement among MA buy-sell indicators $(S_{L,t})$ is associated with higher trading volume. Intuitively, if technical traders disagree, they will trade with each other. As a measure of disagreement, we use the cross-sectional standard deviation of the signed turnover implied by each MA strategy, denoted $\sigma_L(\Delta S_{L,T})$. For each measure, Table 11 presents estimations of regressions of the form:

$$\Delta \log(volume_t) = a + b \cdot X_t + c \cdot |r_t| + d \cdot \Delta \log(volume_{t-1}) + \varepsilon_t, \tag{21}$$

where the X_t denotes one or both of our two volume-inducing variables. Because large price shocks are the main empirical determinant of volume and are likely correlated with our price-based indicators, we control for the absolute value of returns (see, e.g., Karpoff, 1987). We use change in log volume as the dependent variable because the level of volume is not stationary. Volume is from coinmarketcap.com, which began reporting on 12/27/2013, so these regressions use the 12/27/2013–6/30/2018 ($n = 1,647$). In Panel A, we restrict $d = 0$. However, to avoid any possibility of results being driven by autocorrelation in volume, we do not make this restriction in Panel B.

Results in column (1) of both Panels demonstrate that increases in turnover across MA horizons lead to increases in volume, controlling for price shocks. Similarly, column (2) of each panel shows that increases in disagreement among MA traders also leads to significant increases in volume. Finally, comparing column (3) of each Panel shows that the MA-implied turnover and disagreement jointly and positively correlate with volume, however the statistical inference varies with specification.[14] Overall, the results in Table 11 are consistent with traders using MA strategies significantly impacting trading volume in Bitcoin.

V. Conclusion

Bitcoin and cryptocurrencies are increasingly attracting attention from investors and financial institutions. This has lead for instance to recent Bitcoin ETF trading by large financial institutions such as Fidelity and futures trading in the US. Yet, there is a lack of both empirical and theoretical evidence on the investment properties of Bitcoin.

Since Bitcoin has no obvious fundamentals to analyze, it is therefore a natural laboratory to use technical analysis. In this paper, we propose a new theory that suggests that moving averages of prices over different horizons should predict Bitcoin returns. Our empirical results strongly confirm this predictability. Simple real-time trading strategies that exploit this predictability significantly outperform the buy-and-hold position in Bitcoin, with increases in Sharpe ratio of 0.2–0.7. We

[14] This finding is likely not due to multicollinearity, the correlation between $\sigma_L\left(\Delta S_{L,t}\right)$ and $\Sigma_L\left(\Delta S_{L,t}\right)$ is 0.53.

show that the profitability of technical strategies relative to a buy-and-hold largely stems from their ability to exit a downward-trending market, thereby decreasing the length and severity of drawdowns. Further tests confirm the implication from our model that measures of trading activity based on the MA strategies should positively correlate with volume in the data.

Bitcoin skeptics argue that the behavior of cryptocurrency prices resembles that of the NASDAQ “bubble” around the turn of the millennium. Tech stocks during this period also resemble cryptocurrencies in the sense that they plausibly lacked easily interpreted fundamentals. Consistent with our model, we find that our MA strategies worked well applied to tech stocks during this period. Other young and undeveloped assets with noisy fundamentals will provide a natural laboratory to further test our model in the future.

Appendix: Proof of Proposition 1

In this appendix, we present the proof of Proposition 1.

First we provide the evolution equations for conditional expectation and the conditional variance. Following the standard filtering theory, $\forall i = 1, 2$, M_t^i satisfies

$$dM_t^i = \lambda(\bar{X} - M_t^i)dt + \sigma_M^i(t)d\hat{Z}_{1t}^i, \quad M_0^i = M^i(0), \tag{A.1}$$

where $\hat{Z}_{1t}^i$ is the (observable) innovation processes satisfying

$$\hat{Z}_{1t}^i = \int_0^t \frac{X_s - M_s^i}{\sigma_\delta} ds + Z_{1t},$$

$\sigma_M^i(t) = \frac{V^i(t)}{\sigma_\delta} + \rho\sigma_X$, $V^i(t) \equiv E[(X_t - M_t^i)^2|\mathcal{F}_t^i]$ is the conditional variance of X_t satisfying

$$\frac{dV^i(t)}{dt} = -2\lambda V^i(t) + \sigma_X^2 - \left(\frac{1}{\sigma_\delta}V^i(t) + \rho\sigma_X\right)^2. \tag{A.2}$$

This implies that

$$\frac{d\delta_t}{\delta_t} = M_t^i dt + \sigma_\delta d\hat{Z}_{1t}^i, \quad i = 1, 2. \tag{A.3}$$

Next we derive the optimal trading strategy and equilibrium Bitcoin price. As in Detemple (1986), Gennotte (1986), and Detemple (1991), the investor's problem is separable in inference and optimization.[15] In particular, given the initial endowment $\eta_i > 0$ and the prior $(M_i(0^-), V_i(0^-))$, Investor i's portfolio selection problem is equivalent to

$$\max_{\theta^i, C^i} E \int_0^T e^{-\beta t} \log C_t^i dt,$$

subject to

$$dW_t = r_t W_t dt + \theta_t^i(\mu_t^i - r_t)dt + \theta_t^i \sigma_\delta d\hat{Z}_{1t}^i - C_t^i dt. \tag{A.4}$$

[15] The separation principle trivially applies because the objective function is independent of the unobservable state variable (see, e.g., Fleming and Rishel (1975, Chap. 4, Sec. 11) .

Define π_t^i as the state price density for investor i. Then

$$d\pi_t^i = -r_t \pi_t^i dt - \kappa_t^i \pi_t^i d\hat{Z}_{1t}^i, \tag{A.5}$$

where κ_t^i is the price of risk perceived by investor i, i.e.,

$$\kappa_t^i = \frac{\mu_t^i - r_t}{\sigma_\delta}. \tag{A.6}$$

Using the standard dual approach (e.g., Cox and Huang, 1989) to solve Investor i's problem, we have

$$e^{-\beta t}(C_t^i)^{-1} = \xi_i \pi_t^i, \quad i = 1, 2, \tag{A.7}$$

where ξ_i is the corresponding Lagrangian multiplier. Define

$$\alpha_t = \frac{\xi_1 \pi_t^1}{\xi_2 \pi_t^2} \tag{A.8}$$

to be the ratio of the marginal utilities. Then α_t evolves as

$$d\alpha_t = -\alpha_t \mu_t^d d\hat{Z}_{1t}^1, \quad \mu_t^d = \frac{\mu_t^1 - \mu_t^2}{\sigma_\delta}, \quad \alpha_0 = \frac{\eta_2}{\eta_1}, \tag{A.9}$$

where the first equality is from Ito's lemma and the consistency condition (i.e., the Bitcoin price is the same across all investors), and the last equality follows from the budget constraints.

By market clearing condition $C_t^1 + C_t^2 = \delta_t$, we have

$$C_t^1 = \frac{\delta_t}{1+\alpha_t}, \quad C_t^2 = \frac{\alpha_t \delta_t}{1+\alpha_t},$$

$$\kappa_t^1 = \sigma_\delta + \frac{\alpha_t}{1+\alpha_t}\mu_t^d, \quad \kappa_t^2 = \sigma_\delta - \frac{1}{1+\alpha_t}\mu_t^d,$$

$$r_t = \beta + \frac{1}{1+\alpha_t}M_t^1 + \frac{\alpha_t}{1+\alpha_t}M_t^2 - \sigma_\delta^2.$$

Therefore, the fraction of wealth invested in the Bitcoin by Investor 1 is

$$\kappa_t^1/\sigma_\delta,$$

i.e.,

$$1+\frac{\alpha_t}{1+\alpha_t}\frac{\mu_t^d}{\sigma_\delta}, \tag{A.10}$$

and by Investor 2 is

$$1-\frac{1}{1+\alpha_t}\frac{\mu_t^d}{\sigma_\delta}. \tag{A.11}$$

So if $\mu_t^d > 0$, i.e., Investor 1 is more optimistic than Investor 2, then Investor 1 borrows to buy the Bitcoin, and Investor 2 sells the Bitcoin and lends.

The Bitcoin price

$$B_t = E_t^1 \int_t^T \frac{\pi_s^1}{\pi_t^1}\delta_s ds = \frac{1-e^{-\beta(T-t)}}{\beta}\delta_t,$$

which implies that

$$dB_t = ((\beta + M_t^i)B_t - \delta_t)dt + \sigma_\delta B_t d\hat{Z}_{1t}^i,$$

$$\mu_t^i = \beta + M_t^i, \text{and} \quad \mu_t^d = \frac{M_t^1 - M_t^2}{\sigma_\delta}.$$

This implies that

$$d\hat{Z}_{1t}^i = \frac{1}{\sigma_\delta}\left(d\log B_t - \left(M_t^i - \frac{\beta}{1-e^{-\beta(T-t)}} - \frac{1}{2}\sigma_\delta^2\right)dt\right).$$

Investor 1's wealth is

$$W_{1t} = E_t^1 \int_t^T \frac{\pi_s^1}{\pi_t^1} C_s^1 ds = \frac{1-e^{-\beta(T-t)}}{\beta} C_t^1 = \frac{1}{1+\alpha_t} B_t$$

and Investor 2's wealth is

$$W_{2t} = E_t^1 \int_t^T \frac{\pi_s^2}{\pi_t^2} C_s^2 ds = \frac{1-e^{-\beta(T-t)}}{\beta} C_t^2 = \frac{\alpha_t}{1+\alpha_t} B_t.$$

The number of Bitcoin Investor 1 holds is equal to

$$N_{1t} = \frac{(1+\frac{\alpha_t}{1+\alpha_t}\frac{\mu_t^d}{\sigma_\delta})W_{1t}}{B_t} = \frac{1}{1+\alpha_t}(1+\frac{\alpha_t}{1+\alpha_t}\frac{\mu_t^d}{\sigma_\delta}).$$

The number of Bitcoin Investor 2 holds is equal to

$$N_{2t} = \frac{(1 - \frac{1}{1+\alpha_t}\frac{\mu_t^d}{\sigma_\delta})W_{2t}}{B_t} = \frac{\alpha_t}{1+\alpha_t}(1 - \frac{1}{1+\alpha_t}\frac{\mu_t^d}{\sigma_\delta}).$$

We have

$$\frac{\partial N_{1t}}{\partial \alpha_t} = \frac{-(1+\alpha_t) + (1-\alpha_t)\mu_t^d/\sigma_\delta}{(1+\alpha_t)^3},$$

which is < 0 if and only if

$$\alpha_t > \frac{\mu_t^d/\sigma_\delta - 1}{\mu_t^d/\sigma_\delta + 1}.$$

Next we derive the expression of the conditional expectation M_t^i in the form of moving averages. We have

$$dM_t^i = (a^i(t) - b^i(t)M_t^i)dt + c^i(t)d\log B_t, \tag{A.12}$$

where

$$a^i(t) = \lambda\bar{X} + \left(\frac{\beta}{1 - e^{-\beta(T-t)}} + \frac{1}{2}\sigma_\delta^2\right)c^i(t),$$

$$b^i(t) = \lambda + c^i(t), \quad c^i(t) = \frac{\sigma_M^i(t)}{\sigma_\delta}.$$

Equation (A.12) implies that

$$M_t^i = h^i(t) + \int_0^t f^i(u,t)d\log B_u,$$

where

$$h^i(t) = e^{-\int_0^t b^i(s)ds}\int_0^t a^i(u)e^{\int_0^u b^i(s)ds}du,.$$

and

$$f^i(u,t) = c^i(u)e^{\int_t^u b^i(s)ds}. \tag{A.13}$$

Then by integration by parts, we have

$$
\begin{aligned}
M_t^i &= h^i(t) - f^i(0,t)\log B_0 + c^i(t)\log B_t - \int_0^t \log B_u df^i(u,t) \\
&= h^i(t) + f^i(0,t)\log \frac{B_t}{B_0} + (f^i(t,t) - f^i(0,t))\left(\log B_t - \frac{\int_0^t g^i(u,t)\log B_u du}{\int_0^t g^i(u,t)du}\right),
\end{aligned}
\tag{A.14}
$$

where

$$
g^i(u,t) = \frac{\partial f^i(u,t)}{\partial u}. \tag{A.15}
$$

We show next that if Condition (8) is satisfied, then $g^i(u,t) > 0$. To prove this, we substitute $f^i(u,t)$ in Equation (A.13) into (A.15) to obtain

$$
g^i(u,t) = \left(\frac{dc^i(u)}{du} + c^i(u)b^i(u)\right)e^{\int_t^u b^i(s)ds}, \tag{A.16}
$$

thus we need to find condition for $\frac{dc^i(u)}{du} + c^i(u)b^i(u) > 0$. Note that

$$
\frac{dc^i(t)}{dt} = -2\lambda\left(c^i(t) - \rho\frac{\sigma_X}{\sigma_\delta}\right) + \frac{\sigma_X^2}{\sigma_\delta^2} - (c^i(t))^2, \tag{A.17}
$$

and $b^i(t) = \lambda + c^i(t)$, we need to have the following condition

$$
c^i(t) < 2\rho\frac{\sigma_X}{\sigma_\delta} + \frac{\sigma_X^2}{\lambda\sigma_\delta^2}. \tag{A.18}
$$

Due to the dynamics of $c^i(t)$ given in Equation (A.17), it can be proven that at $c^i(t) = 2\rho\frac{\sigma_X}{\sigma_\delta} + \frac{\sigma_X^2}{\lambda\sigma_\delta^2}$, $\frac{dc^i(t)}{dt} < 0$. This implies that as long as

$$
c^i(0) \leq 2\rho\frac{\sigma_X}{\sigma_\delta} + \frac{\sigma_X^2}{\lambda\sigma_\delta^2}, \tag{A.19}
$$

or equivalently,

$$
V^i(0) \leq \rho\sigma_X\sigma_\delta + \frac{\sigma_X^2}{\lambda}, \tag{A.20}
$$

Condition (8) holds.

Under Condition (8), the expression

$$\frac{\int_0^t g^i(u,t)\log B_u du}{\int_0^t g^i(u,t)du} \tag{A.21}$$

is a weighted average of $\log(B_u)$ over the interval $[0,t]$. In addition, by the definition of $g^i(u,t)$, this implies that

$$f^i(t,t) - f^i(0,t) > 0$$

for any t. This completes the proof of Proposition 1.

References

Ang, A. and Bekaert, G. (2007), Stock return predictability: is it there?, *Review of Financial Studies* 20, 651–707.

Athey, S., Parashkevov, I., Sarukkai, V. and Xia, J. (2016), Bitcoin pricing, adoption, and usage: Theory and evidence. Stanford University working paper.

Balvers, R. and McDonald, B. (2018), Designing a global digital currency. Working paper.

Banerjee, S., Kaniel, R. and Kremer, I. (2009), Price drift as an outcome of differences in higher-order beliefs, *Review of Financial Studies* 22, 3707–3734.

Biais, B., Bisière, C., Bouvard, M. and Casamatta, C. (2018), The blockchain folk theorem. Toulouse School of Economics working paper.

Bodie, Z., Kane, A. and Marcus, A. J. (2014), *Investments*, 10th edn, McGraw Hill, Ohio.

Böhme, R., Christin, N., Edelman, B. and Moore, T. (2015), Bitcoin: Economics, technology, and governance, *Journal of Economic Perspectives* 29, 213238.

Bolt, W. and van Oordt, M. R. C. (2016), On the value of virtual currencies. Bank of Canada working paper.

Brock, W., Lakonishok, J. and LeBaron, B. (1992), Simple technical trading rules and the stochastic properties of stock returns, *Journal of Finance* 47, 17311764.

Brogaard, J. and Detzel, A. (2015), The asset-pricing implications of government economic policy uncertainty, *Management Science* 61, 3–18.

Brown, D. P. and Jennings, R. H. (1989), On technical analysis, *Review of Financial Studies* 2, 527551.

Campbell, J. Y. and Thompson, S. B. (2008), Predicting excess stock returns out of sample: can anything beat the historical average?, *Review of Financial Studies* 21, 1509–1531.

Campbell, J. Y. and Yogo, M. (2006), Efficient tests of stock return predictability, *Journal of Financial Economics* 81, 27–60.

Catalini, C. and Gans, J. S. (2017), Some simple economics of the blockchain. MIT working paper.

Cespa, G. and Vives, X. (2012), Dynamic trading and asset prices: Keynes vs. hayek, *Review of Economic Studies* 79, 539580.

Chiarella, C., He, X.-Z. and Hommes, C. (2006), A dynamic analysis of moving average rules, *Journal of Economic Dynamics and Control* 30, 17291753.

Chiu, J. and Koeppl, T. V. (2017), The economics of cryptocurrencies—bitcoin and beyond. Bank of Canada working paper.

Cochrane, J. H. (2005), *Asset Pricing*, Princeton University Press, Princeton, N.J.

Cochrane, J. H. (2008), The dog that did not bark: a defense of return predictability, *Review of Financial Studies* 21, 1533–1575.

Cochrane, J. H., Longstaff, F. A. and Santa-Clara, P. (2008), Two trees, *The Review of Financial Studies* 21, 347–385.

Cong, L. W. and He, Z. (2018), Blockchain disruption and smart contracts. University of Chicago working paper.

Cox, J. C. and Huang, C. (1989), Optimal consumption and portfolio policies when asset prices follow a diffusion process, *Journal of Economic Theory* 49, 33–83.

Detemple, J. B. (1986), Asset pricing in a production economy with incomplete information, *Journal of Finance* 41, 383–391.

Detemple, J. B. (1991), Further results on asset pricing with incomplete information, *Journal of Economic Dynamics and Control* 15, 425–453.

Dwyer, G. P. (2015), The economics of Bitcoin and similar private digital currencies, *Journal of Financial Stability* 17, 81–91.

Easley, D., O'Hara, M. and Basu, S. (2017), From mining to markets: The evolution of bitcoin transaction fees. Cornell University working paper.

Edmans, A., Goldstein, I. and Jiang, W. (2015), Feedback effects, asymmetric trading, and the limits to arbitrage , 105, 3766–3797.

Eha, B. P. (2017), *How Money Got Free*, Oneworld Publications Ltd, London, UK.

Fernández-Villaverde, J. and Sanches, D. (2017), Can currency competition work? University of Pennsylvania working paper.

Ferson, W. E., Sarkissian, S. and Simin, T. T. (2003), Spurious regressions in financial economics?, *Journal of Finance* 58, 1393–1413.

Foley, S., Karlsen, J. R. and Putnins, T. J. (2018), Sex, drugs, and bitcoin: How much illegal activity is financed through cryptocurrencies? Working paper.

Gandal, N., Hamrick, J., Moore, T. and Oberman, T. (2018), Price manipulation in the bitcoin ecosystem, *Journal of Monetary Economics* (forthcoming).

Gennotte, G. (1986), Optimal portfolio choice under incomplete information, *Journal of Finance* 41, 733–746.

Goyal, A. and Welch, I. (2008), A comprehensive look at the empirical performance of equity premium prediction, *Review of Financial Studies* 21, 1455–1508.

Griffin, J. M. and Shams, A. (2018), Is bitcoin really un-tethered? University of Texas working paper.

Han, Y., Yang, K. and Zhou, G. (2013), A new anomaly: The cross-sectional profitability of technical analysis, *Journal of Financial and Quantitative Analysis* 48, 1433–1461.

Han, Y., Zhou, G. and Zhu, Y. (2016), A trend factor: Any economic gains from using information over investment horizons?, *Journal of Financial Economics* 122, 352–375.

Harvey, C. R. (2017), Bitcoin myths and facts. Duke University working paper.

Hong, H. and Stein, J. C. (1999), A unified theory of underreaction, momentum trading, and overreaction in asset markets, *Journal of Finance* 54, 2143–2184.

Huang, D., Jiang, F., Tu, J. and Zhou, G. (2015), Investor sentiment aligned: A powerful predictor of stock returns, *Review of Financial Studies* 28, 791–837.

Huberman, G., Leshno, J. D. and Moallemi, C. C. (2017), Monopoly without a monopolist: An economic analysis of the bitcoin payment system. Columbia Business School working paper.

Jermann, U. J. (2018), Bitcoin and cagan's model of hyperinflation. University of Pennsylvania working paper.

Karpoff, J. M. (1987), The relation between price changes and trading volume: A survey, *Journal of Financial and Quantitative Analysis* 22, 109–126.

Kelly, B. and Pruitt, S. (2013), Market expectations in the cross-section of present values, *Journal of Finance* 68, 1721–1756.

Ledoit, O. and Wolf, M. (2008), Robust performance hypothesis testing with the sharpe ratio, *Journal of Empirical Finance* 15, 850 – 859.

Lo, A. W. and Hasanhodzic, J. (2009), The heretics of finance: Conversations with leading practitioners of technical analysis. *Bloomberg Press*.

Lo, A. W., Mamaysky, H. and Wang, J. (2000), Foundations of technical analysis: Computational algorithms, statistical inference, and empirical implementation, *Journal of Finance* 55, 1705–1770.

Malinova, K. and Park, A. (2017), Market design with blockchain technology. University of Toronto working paper.

Marquering, W. and Verbeek, M. (2004), The economic value of predicting stock index returns and volatility, *Journal of Financial and Quantitative Analysis* 39, 407–429.

Neely, C. J., Rapach, D. E., Tu, J. and Zhou, G. (2014), Forecasting the equity risk premium: The role of technical indicators, *Management Science* 60, 1772–1791.

Ofek, E. and Richardson, M. (2003), Dotcom mania: The rise and fall of internet stock prices, *The Journal of Finance* 58, 1113 – 1137.

Pagnotta, E. S. and Buraschi, A. (2018), An equilibrium valuation of bitcoin and decentralized network assets. Imperial College working paper.

Pesaran, M. H. and Timmermann, A. (1995), Predictability of stock returns: Robustness and economic significance, *Journal of Finance* 50, 1201–1228.

Pettenuzzo, D., Timmermann, A. and Valkanov, R. (2014), Forecasting stock returns under economic constraints, *Journal of Financial Economics* 114, 517 – 553.

Pollack, D. (2017), Counting costs of bitcoin's big three drops of 2017. *Cointegraph.* https://cointelegraph.com/news/counting-costs-of-bitcoins-big-three-drops-of-2017

Prat, J. and Walter, B. (2016), An equilibrium model of the market for bitcoin mining. CESifo working paper.

Rapach, D. E., Strauss, J. K. and Zhou, G. (2010), Out-of-sample equity premium prediction: combination forecasts and links to the real economy, *Review of Financial Studies* 23, 821–862.

Roberts, J. J. (2017), 5 big bitcoin crashes: What we learned. *Fortune.* http://fortune.com/2017/09/18/bitcoin-crash-history

Saleh, F. (2017), Blockchain without waste: Proof-of-stake. NYU working paper.

Schwager, J. D. (1989), *Market Wizards*, John Wiley & Sons, Hoboken, New Jersey.

Stambaugh, R. F. (1999), Predictive regressions, *Journal of Financial Economics* 54, 375–421.

Timmermann, A. (2006), Forecast combinations, in G. Elliott, C. W. J. Granger and A. Timmermann, eds, Handbook of Economic Forecasting, Vol. 1, Elsevier, North-Holland, Amsterdam, chapter 4, 135–196.

Treynor, J. L. and Ferguson, R. (1985), In defense of technical analysis, *Journal of Finance* 40, 757–773.

Yermack, D. (2013), Is bitcoin a real currency? an economic appraisal. NBER working paper.

Yermack, D. (2017), Corporate governance and blockchains, *Review of Finance* 21, 7–31.

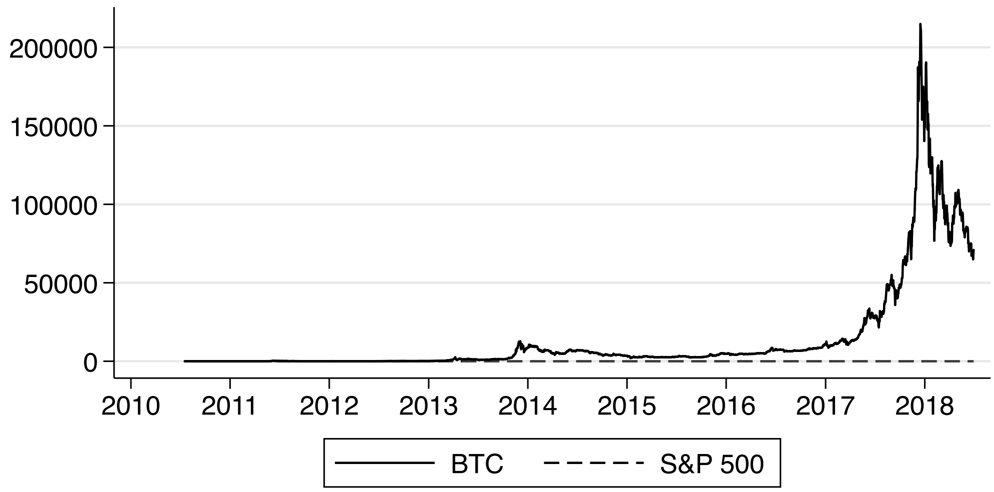


Figure 1: Dollar value of $1 invested in Bitcoin or S&P500 on 7/18/2010 through 6/30/2018.

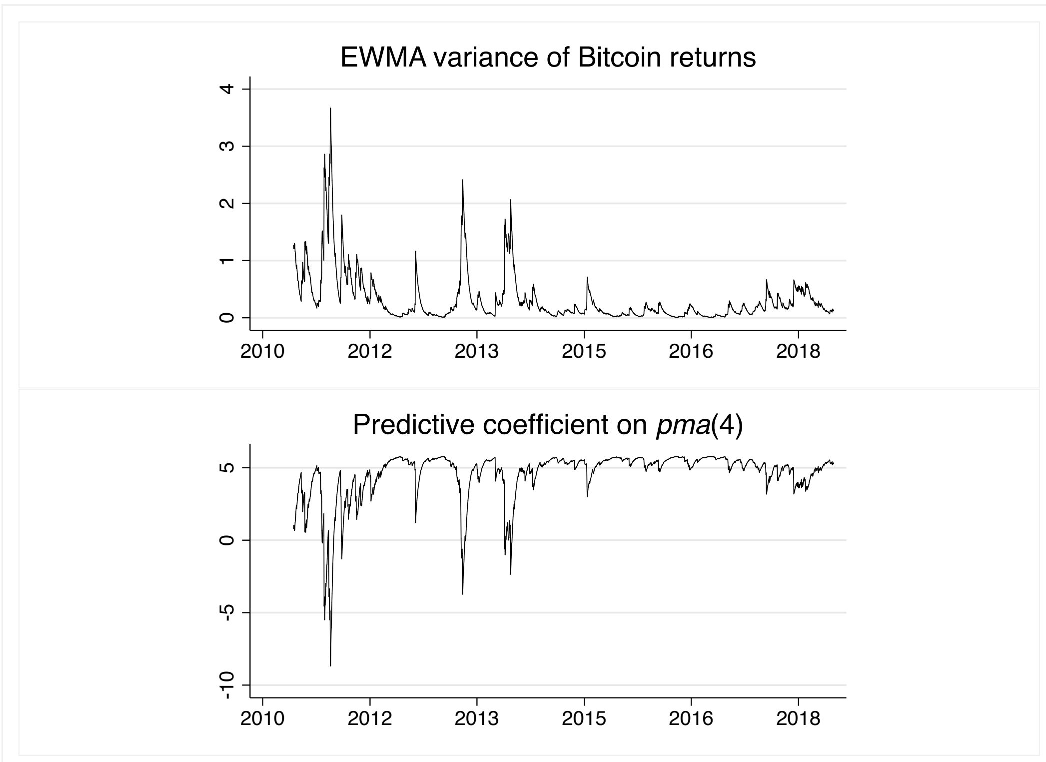
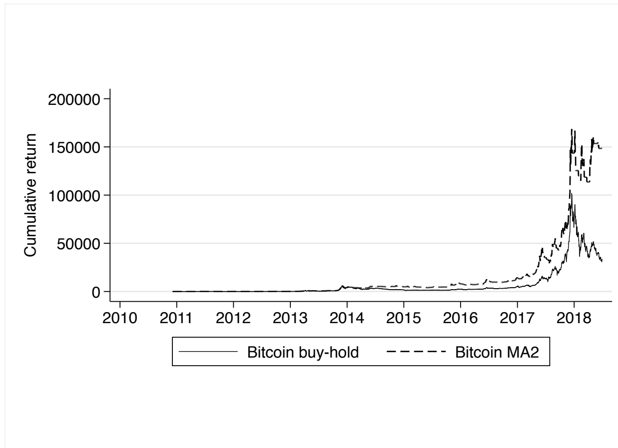


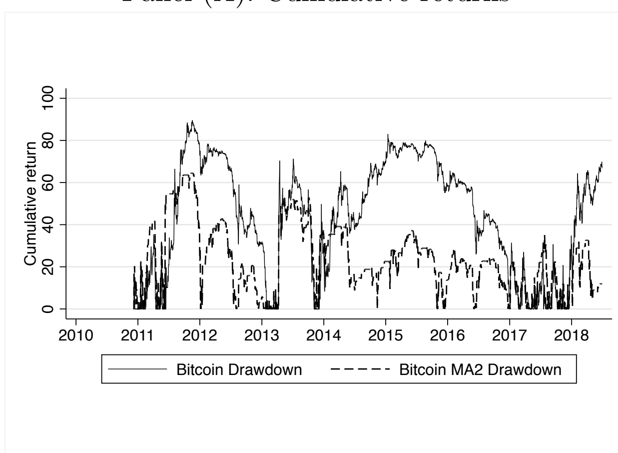
Figure 2: Conditional variance of Bitcoin returns and coefficient on $pma(4)$ conditional on variance
The top figure plots the exponentially weighted moving average variance (σ_t^2) of daily Bitcoin returns. The bottom figure depicts the predictive coefficient of $pma_t(4)$ ($b + d \cdot \sigma_t^2$) in the following regression estimated in Table 3:

$$r_{t+1} = a + b \cdot pma_t(4) + c \cdot \sigma_t^2 + d \cdot \sigma_t^2 \cdot pma_t(4) + \varepsilon_{t+1}. \quad (1)$$

The sample is 7/18/2010–6/30/2018.

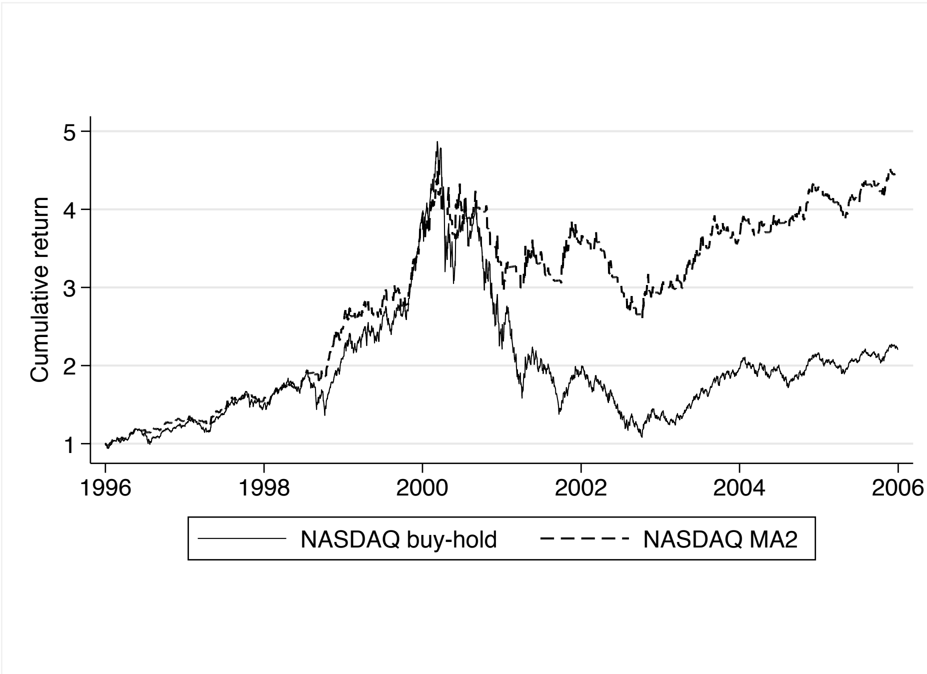


Panel (A): Cumulative returns

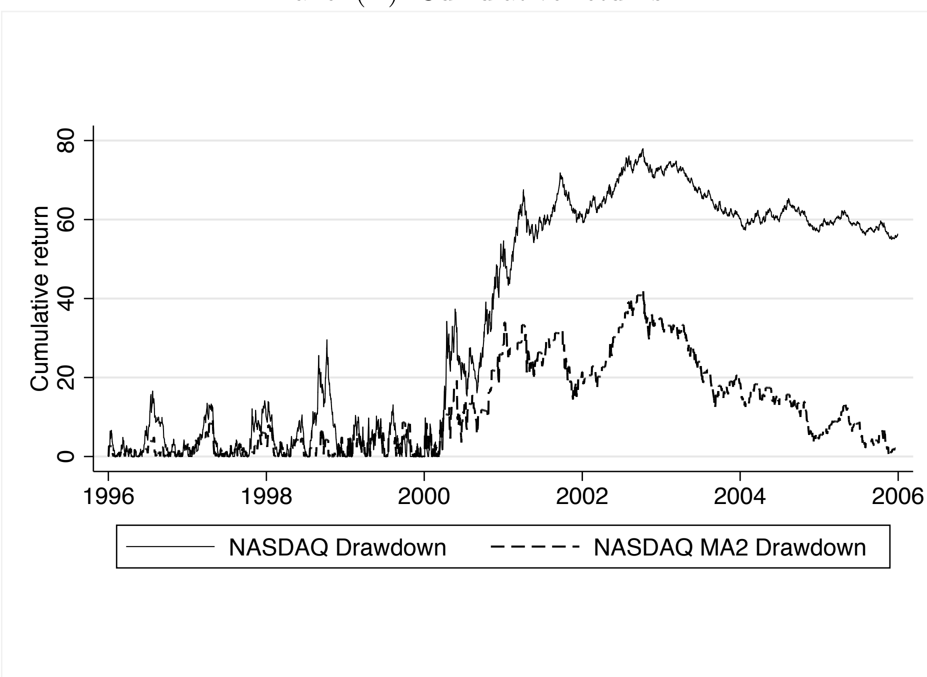


Panel (B): Drawdowns

Figure 3: Performance of investment in Bitcoin buy-and-hold and MA strategies.
Panel A presents cumulative returns to $1 invested in the buy-and-hold and MA(2) Bitcoin strategies over 7/18/2010–6/30/2018. Panel B presents drawdowns of each strategy in Panel A.



Panel (A): Cumulative returns



Panel (B): Drawdowns

Figure 4: Performance of investment in NASDAQ buy-and-hold and MA(2) strategies.
Panel A presents cumulative returns to $1 invested in the buy-and-hold and MA(2) NASDAQ strategies on 1/2/1996 through 12/30/2005. Panel B presents drawdowns of each strategy.

Table 1: Summary statistics

Panel A presents summary statistics of the returns in excess of the 1-day risk-free rate on Bitcoin (*BTC*) and the CRSP value-weighted index (*MKT*). Means, standard deviations, and Sharpe ratios are annualized. Panel B presents summary statistics of other relevant variables. AR1 denotes the first-order autoregressive coefficient and p_{df} denotes the p-value from an augmented Dickey-Fuller test for the null of a unit root. The sample period is daily from 12/06/2010–6/30/2018. Bitcoin returns trade 7 days a week and have 2,766 observations during the sample period. Other variables are available only 5 days a week and have 1,976 observations during this period.

Panel A: Returns								
	Mean(%)	SD(%)	Sharpe	Min(%)	Max(%)	Skewness	Kurtosis	AR1
BTC	193.18	106.20	1.82	-38.83	52.89	0.78	14.97	0.05
MKT	13.65	14.76	0.92	-6.97	4.97	-0.52	8.04	-0.08
Panel B: Predictor variables								
	Mean(%)	SD(%)	Min(%)	Max(%)	Skewness	Kurtosis	AR1	p_{df}
VIX	16.30	5.53	9.14	48.00	2.05	8.36	0.95	0.00
BILL	0.32	0.48	-0.02	1.91	1.92	5.61	1.00	1.00
TERM	1.99	0.61	0.87	3.60	0.45	2.50	1.00	0.89
DEF	0.95	0.25	0.53	1.54	0.62	2.33	1.00	0.31

Table 2: In-sample predictability of Bitcoin returns

This table presents estimates of predictive regressions of the form: $r_{t+1} = a + b'X_t + \epsilon_{t+1}$, where r_{t+1} denotes the return on Bitcoin on business day $t+1$. In Panel A, the predictors are the log price/moving average ratios, $pma_t(L)$, where L is the number of weeks, with 5 business days per week. We also extract the first three principal components ($PC1, PC2, or\ PC3$) from the $pma(L)$. In columns (1) to (5) of Panel B, the predictors include these principal components along with the other return predictors (VIX, $BILL$, $TERM$, and DEF). Column (6) of Panel B adds the three principal components. The sample period are business days 12/06/2010–6/30/2018 (n = 1,976). Heteroscedasticity-robust t-statistics are presented in parentheses.

Panel A: 1-Day Predictability of Bitcoin returns by log moving average/price ratios							
	(1)	(2)	(3)	(4)	(5)		(6)
$pma(1)$	0.39					$PC1_t$	-0.01
	(2.61)						(-1.46)
$pma(2)$		0.40				$PC2_t$	2.64
		(2.67)					(2.86)
$pma(4)$			0.42			$PC3_t$	-5.01
			(2.81)				(1.82)
$pma(10)$				0.46			
				(3.02)			
$pma(20)$					0.45		
					(3.00)		
Adj-R^2 (%)	0.41	0.45	0.51	0.62	0.64		1.88

Panel B: 1-Day Predictability of Bitcoin returns by log moving average/price ratios						
	(1)	(2)	(3)	(4)	(5)	(6)
VIX	-0.04				-0.05	-0.02
	(-1.33)				(-1.30)	(-0.34)
$BILL$		-0.11			0.05	0.02
		(-0.71)			(1.08)	(1.91)
$TERM$			0.34		0.34	-0.04
			(1.01)		(-0.49)	(-0.59)
DEF				-0.43	-0.75	-0.01
				(-1.68)	(-1.85)	(1.53)
$PC1$						-0.01
						(2.32)
$PC3$						2.24
						(2.50)
$PC3$						5.30
						(1.84)
Adj-R^2 (%)	0.01	0.00	0.00	0.00	0.20	1.82

Table 3: In-sample predictability of Bitcoin returns conditional on variance

This table presents estimates of predictive regressions of the form:

$$r_{t+1} = a + b \cdot pma_t(L) + c \cdot \sigma_t^2 + d \cdot pma_t(L) \cdot \sigma_t^2 + \epsilon_{t+1},$$

where r_{t+1} denotes the return on Bitcoin on day $t+1$, $pma_t(L)$ denotes the log price-to-L-week moving average ratio, and σ_t^2 denotes the exponential weighted moving average variance of Bitcoin returns. The σ_t^2 are defined recursively as $\sigma_t^2 = 0.94 \cdot \sigma_{t-1}^2 + 0.06 \cdot r_t^2$. The sample period for the regression is 12/06/2010—6/30/2018 (n=2,766 using 7-day-per week observations). The initial σ_0^2 is estimated as the sample variance of r_t over 7/28/2010–12/05/2010. Heteroskedasticity-robust t-statistics are presented in parentheses. *, **, *** denotes 10%, 5%, 1% significance levels.

	(1)	(2)	(3)	(4)	(5)
$pma_t(1)$	7.62**				
	(2.13)				
$pma_t(1) \cdot \sigma_t^2$	-5.03				
	(-1.31)				
$pma_t(2)$		7.52***			
		(3.29)			
$pma_t(2) \cdot \sigma_t^2$		-5.57**			
		(-2.07)			
$pma_t(4)$			5.81***		
			(4.01)		
$pma_t(4) \cdot \sigma_t^2$			-3.95**		
			(-2.43)		
$pma_t(10)$				2.87***	
				(3.55)	
$pma_t(10) \cdot \sigma_t^2$				-1.83**	
				(-2.08)	
$pma_t(20)$					1.26***
					(2.59)
$pma_t(20) \cdot \sigma_t^2$					-0.98
					(-1.56)
σ_t^2	1.04**	1.28***	1.50***	1.51**	1.56**
	(2.12)	(2.70)	(2.97)	(2.51)	(2.24)
Adj-R^2 (%)	0.93	1.62	2.10	1.77	1.09

Table 4: Out-of-sample predictability of Bitcoin returns

Panels A and B present R^2_{OS} (out-of-sample R^2) in percent for recursively estimated predictive regressions of the form: $r_{t+1} = a + b'X_t + \epsilon_{t+1}$, where r_{t+1} denotes day-$t+1$ return on Bitcoin. Both panels use 5-day-per week observations. In Panel A, the predictors are the $pma(L)$ and in Panel B, they are $VIX, BILL, DEF$, and $TERM$. Panel C uses the 7-day-per-week-observations and forecasts one week returns ($r_{t+1,t+7}$) using recursively estimated regressions of the form: $r_{t+1,t+7} = a + b'X_t + \epsilon_{t+1,t+7}$. T_0 denotes the in-sample period as a percentage of the total sample. The MEAN is a simple combination forecast that averages the five moving average forecasts. The sample is 12/06/2010–6/30/2018 (n=1976 in Panels A and B; n=2766 for Panel C). *,**,*** denotes 10%, 5%, 1% significance levels using the Clark-West (2007) MSFE-adjusted statistic that tests the null of equal MSFE (R^2_{OS}=0) against the competing model that has a lower MSFE (R^2_{OS}>0).

Panel A: 1-day horizon, 5-day-per-week observations						
T_0	$pma(1)$	$pma(2)$	$pma(4)$	$pma(10)$	$pma(20)$	MEAN
25%	-0.32	-0.11	0.70**	1.01**	0.72**	0.83*
50%	-0.73	-0.27	0.08	0.31**	0.86***	0.38*
90%	0.94	1.13*	1.51*	0.81	0.70	1.42*
Panel B: 1-day horizon, 5-day-per-week observations						
T_0	VIX	$BILL$	$TERM$	DEF		MEAN
25%	-0.87	-0.21	-0.27	-0.01		-0.14
50%	-1.07	0.06	-0.06	-0.03		-0.13
90%	-0.77	-0.08	-0.02	0.17		-0.10
Panel C: 1-week horizon, 7-day-per-week observations						
T_0	$pma(1)$	$pma(2)$	$pma(4)$	$pma(10)$	$pma(20)$	MEAN
25%	-0.11	0.84**	3.67**	3.71**	1.66**	3.08**
50%	1.05**	1.06**	2.38**	2.87**	4.13**	3.62**
90%	2.70**	2.32*	2.57**	1.07*	1.66**	1.92**

Table 5: Performance of Bitcoin trading strategies

This table presents summary statistics of the returns in excess of the 1-day risk-free rate on Bitcoin (BTC) and each of the MA(L) Bitcoin strategies, which take a long position in Bitcoin if $pma_t(L) > 0$, and the risk-free rate otherwise. EW denotes an equal-weighted portfolio of the individual $MA(L)$ strategies. Means, standard deviations, and Sharpe ratios are annualized. The sample period is daily from 12/06/2010—6/30/2018 (7 days per week). Panel A presents full sample results (n=2,764). Panels B and C, respectively, present results for the first (9/17/2010-8/28/2014, n=1,383) and second halves (9/18/2014-6/30/2018, n=1,383) of the sample. MDD denotes maximum drawdown. We use Ledoit and Wolf (2008) test of equality of Sharpe ratios that is robust to heteroskedasticity and serial correlation. *, **, *** denotes significance at the 10%, 5%, and 1% confidence levels, respectively.

	Mean(%)	SD(%)	Sharpe	Min(%)	Max(%)	Skewness	Kurtosis	MDD(%)
Panel A: Full-sample								
BTC	193.18	106.20	1.82	-38.83	52.89	0.78	14.97	89.48
MA(1)	196.54	79.33	2.48**	-38.83	52.89	2.12	31.47	71.65
MA(2)	187.38	79.20	2.37**	-38.83	52.89	2.07	31.27	64.43
MA(4)	187.34	82.67	2.27*	-38.83	52.89	1.63	29.21	69.66
MA(10)	195.70	88.50	2.21*	-38.83	52.89	1.59	24.99	70.28
MA(20)	188.77	94.96	1.99	-38.83	52.89	1.27	21.11	77.87
EW	191.15	78.72	2.43***	-38.83	52.89	2.09	31.31	64.60
Panel B: First-half								
BTC	288.46	129.50	2.23	-38.83	52.89	0.77	12.47	89.48
MA(1)	279.04	98.77	2.83*	-38.83	52.89	1.85	24.58	71.65
MA(2)	272.33	99.01	2.75	-38.83	52.89	1.88	24.32	64.43
MA(4)	277.63	104.11	2.67	-38.83	52.89	1.45	22.16	69.66
MA(10)	309.57	110.78	2.79**	-38.83	52.89	1.48	19.20	70.28
MA(20)	271.54	118.56	2.29*	-38.83	52.89	1.17	16.26	77.87
EW	282.02	99.41	2.84**	-38.83	52.89	1.85	23.54	64.60
Panel C: Second-half								
BTC	97.89	75.80	1.29	-21.90	25.41	0.10	8.14	69.77
MA(1)	114.03	52.90	2.16**	-11.13	25.41	1.68	16.37	32.82
MA(2)	102.43	52.02	1.97*	-11.13	22.97	1.02	12.81	37.27
MA(4)	97.05	52.81	1.84	-14.24	22.97	0.66	12.24	43.85
MA(10)	81.83	57.67	1.42	-16.73	22.97	0.13	11.34	56.33
MA(20)	106.01	62.82	1.69	-16.73	25.41	0.41	12.03	58.44
EW	100.27	49.70	2.02**	-11.13	22.97	1.00	12.10	40.05

Table 6: Returns to Bitcoin when MA strategies are invested vs not invested

This table presents average returns to Bitcoin on days when the MA(L) strategy defined in the column heading is long Bitcoin (IN) and days when the strategy is not (OUT). The sample period is daily from 12/06/2010–6/30/2018. Panel A presents full sample results (n=2,766). Panels B and C, respectively, present results for the first and second halves (n=1,383) of the sample. Units are (%/day).

	All Days	$MA(1)$	$MA(2)$	$MA(4)$	$MA(10)$	$MA(20)$
Panel A: Full sample						
OUT	0.53	-0.02	0.04	0.04	-0.02	0.04
IN		0.92	0.87	0.88	0.82	0.72
Panel B: First half						
OUT	0.79	0.07	0.11	0.07	-0.17	0.20
IN		1.25	1.25	1.3	1.27	0.96
Panel C: Second Half						
OUT	0.27	-0.10	-0.03	0.01	0.12	-0.07
IN		0.56	0.49	0.45	0.35	0.43

Table 7: Alphas of MA Bitcoin strategies relative to buy-and-hold benchmark and other asset classes

Panels A and B present regressions of the form: $rx_t^{\mathrm{MA}(L)} = \alpha + \beta_{BTC} \cdot rx_t + \epsilon_t$, where rx_t denotes the day-t buy-and-hold excess return on Bitcoin and $rx_t^{\mathrm{MA}(L)}$ denotes the excess return on the MA(L) Bitcoin strategy. Beneath each regression is the Sharpe ratio and appraisal ratio of the MA strategy as well as the utility gain from access to $rx_t^{\mathrm{MA}(L)}$ in addition to rx_t. EW denotes an equal-weighted portfolio of the MA strategies. Panel A also reports the average daily turnover (TO) of the MA strategies, the one-way transaction cost (FEE) that would be required to eliminate the alpha of the MA strategy, and the percentage of days when the return on the strategy is at least that of Bitcoin (WIN(%)). Panel A presents results for the full sample period (12/06/2010–6/30/2018, n=2,766). Panel B presents results for the second half of the sample (n=1,383). Heteroskedasticity-robust t-statistics are below point estimates in parentheses. *, **, *** denotes significance at the 10%, 5%, and 1% confidence levels, respectively.

	MA(1)	MA(2)	MA(4)	MA(10)	MA(20)	EW
Panel A: Full-sample						
β_{BTC}	0.56***	0.56***	0.61***	0.69***	0.80***	0.64***
	(15.65)	(15.52)	(17.70)	(23.02)	(34.57)	(24.08)
α(%)	0.24***	0.22***	0.19***	0.17***	0.09**	0.18***
	(4.66)	(4.21)	(3.75)	(3.37)	(2.12)	(4.71)
R^2	0.56	0.56	0.61	0.69	0.80	0.75
Appraisal	1.68	1.52	1.35	1.26	0.81	1.71
Utility gain(%)	85.53	69.39	55.45	47.84	19.70	88.15
TO(%)	17.62	10.35	6.15	2.93	1.37	7.68
FEE(%)	1.38	2.12	3.13	5.75	6.85	2.39
WIN(%)	78.80	79.85	80.07	83.21	86.32	67.33
Panel B: Second-half subsample						
	MA(1)	MA(2)	MA(4)	MA(10)	MA(20)	EW
β_{BTC}	0.49***	0.47***	0.49***	0.58***	0.69***	0.54***
	(12.84)	(12.51)	(12.76)	(14.70)	(19.56)	(19.29)
α(%)	0.18***	0.15***	0.14**	0.07	0.11**	0.13***
	(3.41)	(2.90)	(2.54)	(1.31)	(2.10)	(3.27)
R^2	0.49	0.47	0.48	0.58	0.69	0.68
Appraisal	1.75	1.49	1.31	0.67	1.10	1.69
Utility gain(%)	183.90	132.81	102.43	27.17	72.90	170.74

Table 8: Performance of trading strategies applied to Ripple and ETH

Panel A presents summary statistics of the returns in excess of the 1-day risk-free rate on Ripple (XRP) and each of the MA(L) strategies applied to Ripple. Means, standard deviations, and Sharpe ratios are annualized. MDD denotes maximum drawdown. EW denotes an equal-weighted portfolio of the MA strategies. Panel B presents regressions of the form: $rx_t^{\mathrm{MA}(L)} = \alpha + \beta_{XRP} \cdot rx_t + \epsilon_t$, where rx_t denotes the day-t buy-and-hold excess return on XRP and $rx_t^{\mathrm{MA}(L)}$ denotes the excess return on the MA(L) XRP strategy. Beneath each regression is the appraisal ratio of the MA strategy and the utility gain from access to $rx_t^{\mathrm{MA}(L)}$. In Panels A and B, the sample is 12/24/2013–6/30/2018 (n=1,650). Panels C and D, presents similar statistics as Panels A and B, respectively, but for strategies applied to Ethereum (ETH) instead of XRP. In Panels C and D, the sample is 12/28/2015–6/30/2018 (n=916). We use the Ledoit and Wolf (2008) test of equality of Sharpe ratios. Heteroskedasticity robust t-statistics are below point estimates in parentheses. *, **, *** denotes significance at the 10%, 5%, and 1% confidence levels, respectively.

Panel A: Summary Statistics for XRP strategies

	Mean(%)	SD(%)	Sharpe	Min(%)	Max(%)	Skewness	Kurtosis	MDD(%)
XRP	167.15	159.61	1.05	-46.01	179.37	7.54	141.85	90.22
MA(1)	222.36	140.17	1.59**	-46.01	179.37	10.90	234.94	77.60
MA(2)	222.98	140.98	1.58**	-46.01	179.37	10.85	230.83	72.41
MA(4)	196.70	140.42	1.40	-46.01	179.37	10.93	234.77	57.93
MA(10)	164.11	141.39	1.16	-46.01	179.37	10.76	228.61	81.63
MA(20)	135.51	143.88	0.94	-46.01	179.37	10.24	213.68	85.50
EW	188.33	136.34	1.38*	-46.01	179.37	11.86	262.17	65.72

Panel B: Strategy alphas for XRP strategies

	(1)	(2)	(3)	(4)	(5)	(6)
	MA(1)	MA(2)	MA(4)	MA(10)	MA(20)	EW
β_{XRP}	0.77***	0.78***	0.77***	0.78***	0.81***	0.79***
	(10.99)	(11.87)	(11.36)	(11.87)	(13.83)	(12.34)
α(%)	0.26***	0.25***	0.18**	0.09	-0.00	0.16**
	(3.24)	(3.20)	(2.33)	(1.15)	(-0.01)	(2.49)
R^2	0.77	0.78	0.78	0.78	0.81	0.84
Appraisal	1.40	1.41	1.01	0.50	0.00	1.06
Utility gain(%)	178.29	180.09	92.91	22.97	0.00	102.93

Table 8: (Cont'd)

Panel C: Summary Statistics for ETH strategies								
	Mean(%)	SD(%)	Sharpe	Min(%)	Max(%)	Skewness	Kurtosis	MDD(%)
ETH	334.16	132.00	2.53	-27.06	35.36	0.81	6.90	73.48
MA(1)	319.09	107.37	2.97	-27.06	35.36	1.68	12.49	42.36
MA(2)	310.48	108.48	2.86	-27.06	35.36	1.61	12.15	43.11
MA(4)	345.23	111.45	3.10*	-27.06	35.36	1.41	11.44	56.81
MA(10)	247.73	116.86	2.12	-27.06	35.36	1.10	10.13	75.23
MA(20)	302.12	122.65	2.46	-27.06	35.36	1.05	8.77	69.92
EW	304.93	107.28	2.84	-27.06	35.36	1.57	12.23	50.41

Panel D: Strategy alphas for ETH strategies						
	(1)	(2)	(3)	(4)	(5)	(6)
	MA(1)	MA(2)	MA(4)	MA(10)	MA(20)	EW
β_{ETH}	0.66***	0.67***	0.71***	0.78***	0.86***	0.74***
	(17.83)	(18.49)	(21.39)	(26.36)	(39.89)	(27.89)
$\alpha(\%)$	0.27**	0.23**	0.29***	-0.04	0.04	0.16**
	(2.55)	(2.23)	(2.90)	(-0.41)	(0.50)	(2.17)
R^2	0.66	0.67	0.71	0.78	0.86	0.82
Appraisal	1.57	1.37	1.79	0.00	0.31	1.30
Utility gain(%)	38.39	29.39	50.07	0.00	1.48	26.25

Table 9: Performance of trading strategies applied to NASDAQ over 1996–2005

Panel A presents summary statistics of the returns in excess of the 1-day risk-free rate on NASDAQ and each of the MA(L) NASDAQ strategies. Means, standard deviations, and Sharpe ratios are annualized. EW denotes an equal-weighted portfolio of the MA strategies. MDD denotes maximum drawdown. Panel B presents regressions of the form: $rx_t^{\text{MA}(L)} = \alpha + \beta_{NASDAQ} \cdot rx_t + \epsilon_t$, where rx_t denotes the day-t buy-and-hold excess return on NASDAQ and $rx_t^{\text{MA}(L)}$ denotes the excess return on the MA(L) NASDAQ strategy. Beneath each regression is the appraisal ratio of the MA strategy and the utility gain from access to $rx_t^{\text{MA}(L)}$. The sample period is 1/2/1996—12/30/2005 (n=2,519). Panel C present results similar to Panel A using over the 1998–2002 subsample (n=1,256). We use the Ledoit and Wolf (2008) test of equality of Sharpe ratios. Heteroskedasticity-robust t-statistics are below point estimates in parentheses. *, **, *** denotes significance at the 10%, 5%, and 1% confidence levels, respectively.

Panel A: Summary Statistics of NASDAQ strategies								
	Mean(%)	SD(%)	Sharpe	Min(%)	Max(%)	Skewness	Kurtosis	MDD(%)
NASDAQ	8.53	29.01	0.29	-9.69	14.15	0.19	7.14	77.93
MA(1)	9.32	18.34	0.51	-6.23	8.10	0.07	9.55	42.73
MA(2)	12.80	17.63	0.73*	-6.23	8.10	0.04	9.17	42.08
MA(4)	13.34	17.41	0.77*	-5.59	8.10	-0.07	8.36	25.66
MA(10)	13.84	17.45	0.79*	-7.66	4.92	-0.40	7.37	33.81
MA(20)	7.78	17.20	0.45	-7.66	4.28	-0.50	7.68	45.62
EW	11.42	15.09	0.76**	-5.58	4.86	-0.16	5.97	34.49

Panel B: Strategy alphas						
	(1)	(2)	(3)	(4)	(5)	(6)
	MA(1)	MA(2)	MA(4)	MA(10)	MA(20)	EW
β_{NASDAQ}	0.40***	0.37***	0.36***	0.36***	0.35***	0.37***
	(16.66)	(16.23)	(16.28)	(16.53)	(16.32)	(19.97)
α(%)	0.02	0.04**	0.04**	0.04**	0.02	0.03**
	(1.32)	(2.18)	(2.33)	(2.44)	(1.09)	(2.47)
R^2	0.40	0.37	0.36	0.36	0.35	0.50
Appraisal	0.42	0.69	0.74	0.77	0.34	0.78
Utility gain(%)	199.85	548.18	627.66	687.82	137.42	105.47

Panel C: Summary Statistics of NASDAQ strategies over 1998–2002								
	Mean(%)	SD(%)	Sharpe	Min(%)	Max(%)	Skewness	Kurtosis	MDD(%)
NASDAQ	-0.13	37.18	0.00	-9.69	14.15	0.23	5.08	77.93
MA(1)	9.62	23.07	0.42	-6.23	8.10	0.06	7.17	42.73
MA(2)	10.69	21.93	0.49*	-6.23	8.10	0.05	7.14	42.08
MA(4)	12.84	21.47	0.60*	-5.59	8.10	-0.07	6.62	25.66
MA(10)	11.89	21.12	0.56*	-7.66	4.92	-0.43	6.10	33.81
MA(20)	7.11	19.98	0.36	-7.66	4.28	-0.48	6.59	39.75
EW	10.43	18.23	0.57**	-5.58	4.86	-0.15	4.83	34.49

Table 10: Performance of trading strategies applied to stocks in Morgan Stanley Internet Index

This table presents annualized Sharpe ratios over 1998–2002 for different strategies applied to the 25 stocks that were in the Morgan Stanley internet index in the 1st quarter of 2000. The strategies include each MA(L) strategy, the equal-weighted portfolio of the MA strategies (EW), and the BH (buy-and-hold). The sample frequency is daily (n = 1,256). We also report the cumulative value of $1 invested in the EW and BH strategies at the beginning of 1998. The bottom row reports the percentage of firms where the MA strategy defined by the column outperforms the BH in terms of Sharpe ratio and portfolio performance.

	Sharpe Ratios							FV($1)	
1998-2002	MA(1)	MA(2)	MA(4)	MA(10)	MA(20)	EW	BH	EW	BH
AMZN	0.41	0.82	0.54	0.14	0.36	0.53	0.30	1.77	1.53
AOL	0.14	0.03	-0.20	-0.49	-0.50	-0.19	-0.15	0.34	0.16
ARBA	0.68	0.71	0.26	0.60	0.18	0.51	-0.21	3.23	0.06
ATHM	-0.10	-0.16	-0.32	-0.11	0.40	0.15	-0.70	0.29	0.01
COVD	-0.60	-0.16	-0.06	-0.25	-0.03	-0.28	-0.39	0.50	0.02
CNET	0.64	0.74	0.31	0.32	0.28	0.54	0.34	2.40	0.30
CSCO	0.07	0.37	0.25	0.23	0.81	0.38	0.26	1.65	1.03
DCLK	0.59	0.24	0.05	-0.61	-0.39	0.05	-0.01	0.96	0.15
EXDS	1.17	0.99	1.40	1.55	1.28	1.48	0.08	11.76	0.08
EBAY	-0.86	-0.52	-0.24	-0.41	-0.42	0.65	0.16	0.14	0.29
HLTH	0.40	0.31	0.15	-0.36	-0.51	0.04	-0.28	0.86	0.11
INAP	-0.23	0.25	0.00	-0.29	-0.26	-0.10	-0.47	0.36	0.00
INKT	0.61	0.87	0.65	0.82	0.20	0.75	-0.12	4.20	0.08
INTU	0.02	0.25	0.52	0.08	-0.19	0.16	0.63	1.00	2.82
MSFT	-0.13	0.67	0.70	0.03	0.03	0.29	0.24	1.46	1.24
ORCL	-0.11	-0.09	0.53	0.18	0.60	0.25	0.60	1.33	2.70
PCLN	0.55	0.37	0.22	-0.03	-0.05	0.26	-0.36	1.05	0.02
SCH	-0.21	-0.34	-0.22	0.08	-0.21	0.06	0.03	0.35	0.32
SCNT	0.67	0.81	0.56	0.37	0.29	0.75	0.34	2.11	1.23
SUNW	-0.32	-0.23	-0.32	0.33	-0.17	-0.18	-0.27	0.41	0.08
VERT	0.62	0.86	0.43	0.65	0.59	0.72	0.46	4.09	0.92
VIGN	0.13	-0.01	-0.02	-0.08	0.44	0.29	0.06	0.75	0.11
WCOM	-0.41	-0.54	-0.21	-0.50	-0.44	-0.21	-0.29	0.42	0.01
WEBMD	0.38	0.27	0.14	-0.18	-0.13	-0.10	-0.28	0.84	0.11
YHOO	1.04	0.81	0.60	0.43	0.80	0.83	0.42	4.51	1.21
Average	0.21	0.29	0.23	0.10	0.12	0.29	0.02	1.87	0.58
% > BH	64%	76%	60%	52%	56%	92%		88%	

Table 11: Volume and technical trading indicators

This table presents regressions of the form:

$$\Delta\log(volume)_t = a + b\cdot X_t + c\cdot|\mathrm{r_t}| + \epsilon_t,$$

$$\Delta\log(volume)_t = a + b\cdot X_t + c\cdot|\mathrm{r_t}| + \ d\cdot\Delta\log(volume)_{t-1} + \epsilon_t,$$

where $volume_t$ denotes the trading volume in Bitcoin on day t, $|r_t|$ denotes the absolute return on Bitcoin on day t, and X_t denotes one of two predictors. The second equation introduces lagged volume to accommodate for possible serial correlation. In column (1), X_t is the sum $\left(\sum_L|\Delta S_{L,t}|\right)$ of the absolute turnovers $|\Delta S_{L,t}|$ from each of the MA(L) strategies. In column (2), X_t is the cross-sectional standard deviation $\left(\sigma_L(\Delta S_{L,t})\right)$ of $\Delta S_{L,t}$, a measure of the "disagreement" among technical traders using the different MA strategies ($L = 1, 2, 4, 10$, or 20 weeks). In column (3), X_t includes $\sum_L|\Delta S_{L,t}|$ and $\sigma_L(\Delta S_{L,t})$. The sample is 12/27/2013–6/30/2018 (n=1,647). Heteroskedasticity-robust t-statistics are in parentheses.

Panel A: Determinants of Volume, without controlling for lagged volume			
	(1)	(2)	(3)
$\sum_L(\lvert\Delta S_{L,t}\rvert)$	0.03		0.07
	(4.38)		(1.47)
$\sigma_L(\Delta S_{L,t})$		0.15	0.05
		(3.65)	(3.46)
$\lvert r_t\rvert$	4.90	5.03	4.73
	(11.94)	(11.76)	(11.58)
Adj-R^2	0.17	0.16	0.17
Panel B: Determinants of Volume, controlling for lagged Volume			
	(1)	(2)	(3)
$\sum_L(\lvert\Delta S_{L,t}\rvert)$	0.03		0.04
	(3.56)		(3.85)
$\sigma_L(\Delta S_{L,t})$		0.12	0.16
		(2.78)	(1.80)
$\lvert r_t\rvert$	5.07	5.18	5.04
	(13.05)	(12.91)	(12.69)
$\Delta\log(volume)_{t-1}$	-0.23	-0.23	-0.23
	(10.13)	(-10.21)	(10.81)
Adj-R^2	0.22	0.22	0.22