

Predictability of bitcoin returns

July 2020

Abstract

This paper comprehensively examines the performance of a host of popular variables to predict Bitcoin returns. We show that time-series momentum, economic policy uncertainty, and financial uncertainty outperform other predictors in all in-sample, out-of-sample, and asset allocation tests. Bitcoin returns have no exposure to common stock and bond market factors but rather are affected by Bitcoin-specific and external uncertainty factors.

JEL Classification: C5; G1

Keywords: Bitcoin; Return predictability; Forecasting; Time-series momentum; Certainty equivalent return

Introduction

“One of the earliest and most enduring questions of financial econometrics is whether financial asset prices are forecastable. Indeed, modern financial economics is firmly rooted in early attempts to ‘beat the market’, an endeavour that is still of current interest, discussed and debated in journal articles, conferences, and cocktail parties” (Campbell et al., 1997, p.27).

In line with such efforts, this paper aims to identify Bitcoin return predictors using approaches by Welch and Goyal (2008), Rapach and Zhou (2013), and Rapach et al. (2016). Among the financial asset classes, Bitcoin has emerged as the most popular digital financial asset and has attracted wide interest from market participants and researchers (An and Rau, 2019; Momtaz, 2019; Shi and Shi, 2019). It has also been broadly used as an alternative to traditional currencies to facilitate trade among criminals, fraudsters, and money launderers (Ju et al., 2016). However, Bitcoin has been increasingly used to speculate rather than transact; the recent fact that 73% of Bitcoin is held in dormant accounts supports this view (Böhme et al., 2015; Weber, 2016).

As with any other currency, speculative investors in Bitcoin require reliable predictors to identify arbitrage opportunities, and few studies to the best of our knowledge have attempted to identify such factors. This could be linked to the supposition that Bitcoin returns may be highly volatile (Baek and Elbeck, 2015), with such price behaviours detached from economic fundamentals (Koutmos, 2018b). In contrast to stocks and bonds as the most speculated financial assets, Bitcoin yields no dividends or interest to investors. The absence of observable fundamental value leaves the investor with little choice but to disproportionately rely on alternative market information. Detzel et al. (2020) demonstrate that Bitcoin returns are predictable by 1- to 20-week moving averages of daily prices. Atsalakis et al. (2019) propose

a hybrid neuro-fuzzy model to forecast the daily price of Bitcoin. However, no comprehensive study has explored Bitcoin returns' predictability using a group of popular predictors.

Our findings are particularly notable given that traders and investors have relied on alternative approaches, such as technical analyses, as no fundamental valuation technique is yet available to the Bitcoin market (Balcilar et al., 2017). We fill this gap and fully investigate what forces drive Bitcoin prices and help investors' asset allocations by employing a standard framework (Welch and Goyal, 2008; Rapach and Zhou, 2013; Rapach et al., 2016) and model excess Bitcoin returns to the Bitcoin market and external market factors. Specifically, we examine a 'zoo' of 33 predictors to demonstrate that the time-series momentum scaled by volatility (*TSM_{SV}*), economic policy uncertainty (*PU*), and financial uncertainty (*FU*) are the strongest predictors of Bitcoin returns in in-sample, out-of-sample, and asset allocation tests.

We achieve our objective by classifying potential predictors—as suggested by previous literature as factors that can predict Bitcoin returns—into five broad categories: Bitcoin market (Koutmos, 2018b), stock market, bond market, sentiment, and external uncertainty predictors (Demir et al., 2018; Karalevicius et al., 2018). Our findings suggest that time-series momentum, economic policy uncertainty, and financial uncertainty variables are useful predictors of Bitcoin returns. Further, we demonstrate the economic benefits from applying specific predictors in delivering significant portfolio advantages to Bitcoin investors, based on the certainty equivalent return.

The paper provides four important contributions. First, we offer unprecedented breadth in our efforts to identify the potential predictors of Bitcoin returns, which are crucial for portfolio management purposes. This is timely, as the specific use of Bitcoin in wider portfolio management strategies has been shown to provide hedging benefits (Atsalakis et al., 2019; Kajtazi and Moro, 2018); however, Bitcoin markets are typically characterised by crashes (Fry and Cheah, 2016), excessive volatility (Katsiampa, 2017), and positive returns when the

fundamental value is shown to be zero (Cheah and Fry, 2015). Second, we propose several market predictors not widely explored in Bitcoin literature that may help to predict Bitcoin returns. Additionally, we explore the relative strength of other market predictors that have been suggested as potential predictors of Bitcoin returns. These include the trading volume (Koutmos, 2018a), returns' volatility (Bouri et al., 2016), risk exposure (Borri, 2019), serial dependence (Cheah et al., 2018), liquidity, and crashes (Donier and Bouchand, 2015). Third, we explore the relative strength of sentiment and uncertainty as predictors of Bitcoin returns, as suggested by previous studies (Demir et al., 2018; Karalevicius et al., 2018). Finally, we demonstrate the economic value of return predictability using our identified factors to predict Bitcoin returns within an asset allocation context.

Our study is relevant in both academia and practice. First, researchers can use our findings as benchmarks for Bitcoin return predictability. For example, the performance of new proposed factors in future studies can be compared with that of time-series momentum, economic policy uncertainty, and financial uncertainty factors. Many factors here can also be used to study other Bitcoin price features (e.g. volatility). This is because various funds—such as Crypto Fund AG—are often established to expose investors to cryptocurrencies. Investors can use the time-series momentum, economic policy uncertainty, and financial uncertainty to form trading strategies, as these are identified as strong predictors of Bitcoin movements under various tests. However, caution should be exercised by investors in 'real-time' trading, as many predictors exhibit promising in-sample performance but do not survive out-of-sample tests, as we demonstrate. The certainty equivalent return (CER) gain can be interpreted as a portfolio management fee that investors would be willing to pay to obtain the regression forecast instead of using the historical average (Rapach and Zhou, 2013). Thus, fund managers can consider the high CER gains from the time-series momentum to decide what fees to charge investors.

The rest of this paper is organised as follows: Section 2 maps the literature related to our study. Section 3 discusses the data and methodology. Section 4 presents the empirical results of in-sample and out-of-sample testing, while Section 5 analyses the asset allocations. Section 6 reports our robustness tests, and Section 7 concludes by outlining the implications of the current work and future research directions.

Related literature

Our study closely relates to the growing body of research on identifying the determinants of Bitcoin price formation. Only very limited research has directly explored the predictors of Bitcoin returns and investigated the predictors that can offer profitable trading strategies. For example, Balcilar et al. (2017) discover that Bitcoin's volume serves as a suitable predictor. Garcia and Schweitzer (2015) reveal that social media data, such as Twitter activity and search engine volume, provide additional predictive power. Jang and Lee (2017) argue that Bitcoin block size and mining rate may create profitable trading strategies. Given the lack of fundamental valuation techniques to quantify Bitcoin's intrinsic value, market participants have to heavily rely on alternative tools to predict Bitcoin prices, such as technical analyses. Specifically, Detzel et al. (2020) demonstrate that trading strategies based on moving averages generate substantial excess returns. Adcock and Gradojevic (2019) observe that Bitcoin returns are characterised by predictive local non-linear trends based on artificial neural networks, while Atsalakis et al. (2019) propose a hybrid neuro-fuzzy model to forecast Bitcoin's daily prices: this model substantially outperforms a naive buy-and-hold strategy.

More generally, this paper also relates to prior studies on time variations in Bitcoin risk premiums that can be classified into two broad categories. One stream of literature uses Bitcoin's own market information to examine its market fluctuations. For example, Donier and

Bouchaud (2015) verify that liquidity well-indicates future Bitcoin market crashes. Bouri et al. (2016) investigate Bitcoin returns and volatility behaviours before and after the severe crash of 2013 and document a serial correlation in Bitcoin returns. Koutmos (2018a; 2018b) extend our understanding of Bitcoin price behaviours by examining the impacts of the Bitcoin market microstructure—including trading volumes, transaction fees, and market capitalisation—on Bitcoin returns. Urquhart (2018), Corbet et al. (2019), and Shen et al. (2019) highlight investor attention's role in Bitcoin returns and volatility. However, these studies are all explanatory in nature, and focus on specific factors' influence. In contrast, our paper attempts to identify the potential predictors of Bitcoin returns.

Another stream of literature reasons that Bitcoin serves as an ideal hedge asset to provide diversification benefits to investors, as the Bitcoin market is not directly exposed to shocks from other financial markets. Dyhrberg (2016) explores the relationship between Bitcoin and the federal funds' rate, the dollar-to-pound exchange rate, and the Financial Times Stock Exchange index to indicate that Bitcoin can be used in the short-term as a hedge against equity indices and the US dollar. Bouri et al. (2017a) use a dynamic conditional correlation model to examine whether Bitcoin can act as a hedge for traditional assets, including stock indices, bonds, oil, or gold. Their results indicate that it can be used for diversification, but not as a perfect hedge tool. Bouri et al. (2017b) further argue that Bitcoin can be used as a hedge asset against global uncertainty. Demir et al. (2018) find that Bitcoin could serve as a hedging tool against political uncertainty. While they use the Bayesian graphical structural vector autoregressive model to examine the relationship between Bitcoin returns and political uncertainty (Demir et al., 2018), we focus on the predictive power of Bitcoin returns using both in-sample and out-of-sample tests.

Data and methodology

Data characteristics and econometrics framework

We collect daily high, low and closing Bitcoin prices, as well as volume from 13 October 2011 to 1 January 2019 from bitcoincharts.com. We also employ five groups of predictors to examine the underlying drivers of Bitcoin returns: Bitcoin market, stock market, bond market, sentiment, and uncertainty predictors. The Bitcoin market variables include the bid-ask spread, systematic risk, and idiosyncratic volatility, among others, which capture the market's unique characteristics. The stock and bond market variables include common equity and bond predictors, as in prior studies. Finally, as the Bitcoin market exhibits highly volatile price movements and is subject to external market uncertainty, we include variables capturing investor sentiment and market uncertainty towards Bitcoin returns. The different market variables in our estimation allow us to explore the role of each in Bitcoin returns' predictability and better understand its exposure to different markets. The predictors we use in each of these categories are listed in Panels A, B, C, D, and E of Table 1, respectively.

[Insert Table 1 here]

We use the following predictive regression model proposed by Welch and Goyal (2008), Rapach and Zhou (2013), and Rapach et al. (2016):

$$RET_{t,t+h} = \alpha + \beta x_t + \varepsilon_{t,t+h}, \quad (1)$$

where $RET_{t,t+h} = \frac{1}{h}(RET_{t+1} + \dots + RET_{t+h})$: RET_t is the Bitcoin log excess return for day t , x_t is the predictor variable, h is the forecast horizon, and β is interpreted as a measure of how significant x_t is in predicting the Bitcoin return. If β takes a value of 0.5, a one-standard-deviation move in the predictor associated with the β would result in a 50-basis point change

in Bitcoin's returns for the following day. Rapach et al. (2016) argue that a monthly in-sample R^2 statistic of approximately 0.5% represents an economically meaningful degree of return predictability. Thus, we adopt this benchmark for our h -day horizons.

We are interested in testing the significance of β in Equation (1). As the statistical inferences in this equation are subject to the Stambaugh (1999) bias,¹ we compute a wild bootstrapped p -value to test $H_0 : \beta = 0$ against $H_A : \beta > 0$ in Equation (1) following Rapach et al. (2016). Further, the in-sample prediction may overstate the β related to a particular predictor in real-time (Welch and Goyal, 2008). Consequently, after we detect strong in-sample evidence that a predictor is statistically significant, we further assess Bitcoin return predictability in an out-of-sample forecast environment (Campbell and Thompson, 2008).

A significant out-of-sample performance strongly supports predictability, as it is less likely to be subject to in-sample data mining or biased standard errors. If the out-of-sample forecast evaluation begins from time m , we use all available data up to time $t = (m - h)$ to estimate the predictive regression parameters to produce the first out-of-sample forecast at time m . Subsequently, a recursive forecast procedure is applied to any future time until $(T - h)$, where T represents the sample size.

Specifically, the day $(t + 1)$ out-of-sample Bitcoin risk-premium forecast is based on an individual predictor variable in Equation (1) and data through day t , and is given by

$$RET_{t,t+h} = \hat{\alpha}_t + \hat{\beta}_t x_t, \quad (2)$$

where $\hat{\alpha}_t$ and $\hat{\beta}_t$ are the ordinary least-squares (OLS) estimates of α and β in Eq. (1), respectively, based on data from the beginning of the sample through day t . We compare the

¹ Stambaugh (1999) indicates that coefficients in such predictive regressions as Equation (1) exhibit a finite sample bias, and a normal t -test could be misleading when the predictors are highly persistent.

forecasts given in Equation (2) to the historical average forecast, which is the average excess return from the beginning of the sample through day t . Following Welch and Goyal (2008), we assume the constant expected excess return model β is zero in Equation (1), which implies that returns are unpredictable. As suggested by Welch and Goyal (2008), the historical average forecast serves as a stringent out-of-sample benchmark, as the individual variables' predictive regression forecasts generally fail to outperform historical average forecasts.

We follow Campbell and Thompson (2008) in evaluating our predictors' out-of-sample performance relative to the updated historical average using the following out-of-sample R^2 statistic (R_{OS}^2)

$$R_{OS}^2 = 1 - \frac{\sum_{t-m}^{T-h} (RET_{t+h} - RET_{t+h})^2}{\sum_{t-m}^{T-h} (RET_{t+h} - \overline{RET}_{t+h})^2}, \quad (3)$$

where RET_{t+h} is the actual daily Bitcoin excess return, RET_{t+h} is the forecast Bitcoin return from the predictive regression in Equation (1), and \overline{RET}_{t+h} is the historical average benchmark. The out-of-sample R^2 gauges the predictive forecast's improvement over the historical average forecast in terms of the mean squared forecast error (MSFE). When $R_{OS}^2 > 0$, our predictive forecast outperforms the historical average forecast. We test the statistical significance of R_{OS}^2 by the MSFE-adjusted statistic (Clark and West, 2007). This tests the null hypothesis that the historical average MSFE is less than or equal to the predictive regression MSFE, against the alternative hypothesis that the historical average MSFE is greater than the predictive regression MSFE or $H_0 : R_{OS}^2 \leq 0$ against $H_A : R_{OS}^2 > 0$.² The R_{OS}^2 indicates the extent to which a predictor would have been useful for investors if used in 'real-time' over certain historical periods.

² The forecast evaluation period begins on 29 May 2014, or the 901st observation in our sample.

Asset allocation

We then use the out-of-sample Bitcoin returns from the predictive regression in Equation (1) within the mean-variance framework (Campbell and Thompson, 2008; Ferreira and Santa-Clara, 2011; Rapach and Zhou, 2013) to evaluate the economic value gained from employing each of the predictors. Profit- or utility-based metrics directly measure the value of forecasts to economic agents. Return forecasts in this framework are used as ad hoc trading rules based on investors' optimal utility decisions (Leitch and Tanner, 1991; Rapach and Zhou, 2013). Specifically, we assume that an investor is willing to allocate all their wealth between Bitcoin and risk-free assets in the following manner:

$$w_t = \frac{1}{\gamma} \frac{RET_{t+1}}{\hat{\sigma}_{t+1}^2}, \quad (4)$$

where w_t is the share of Bitcoin that a mean-variance investor would allocate to their portfolio during the subsequent day, γ is the relative risk-aversion coefficient, RET_{t+1} is the out-of-sample return from the predictive regression estimated in Equation (2), and $\hat{\sigma}_{t+1}^2$ is the out-of-sample return variance. Campbell and Thompson (2008) suggest that a 120-day moving window is appropriate for generating a volatility forecast for past returns. The w_t value is restricted to a range from 0.0 to 1.0.³

We assess the benefits of using predictive regression forecasts instead of the respective benchmark mean-excess return forecasts by using the certainty equivalent return (CER), defined as the difference between the CER value obtained from using the predictive regression forecast for asset allocation and that obtained from the benchmark mean forecast. The CER measure is

³ The forecast evaluation period for the out-of-sample estimation also begins on 29 May 2014.

$$CER = \bar{R}_P - 0.5\gamma\sigma_P^2, \quad (5)$$

where \bar{R}_P and σ_P^2 are the mean and variance of the portfolio return over the forecast evaluation period, respectively. We then annualise the CER gain, which can be interpreted as the fee that investors would be willing to pay to obtain the forecast instead of using the historical average.⁴ This approach allows us to directly measure the economic value of return predictability. Additionally, we analyse the economic value of return predictability at longer horizons by assuming that the investor rebalances at the same frequency as the forecast horizon. For the 28-day horizon—or at the end of the 28-day holding period—the investor employs a predictive regression or prevailing mean forecast of the excess return over the next 28-day holding period and allocation rule, given by Equation (4), to determine the Bitcoin weight for the next holding period. The forecast returns that serve as the input for Equation (3) are obtained from the predictive regression as in Equation (2). The prevailing mean forecast is the average excess returns from the beginning of the sample through day t . The investor repeats this process at the end of each holding period and determines the new weight. The codes to implement in-sample, out-of-sample, and asset allocation tests are similar to those used in prior studies.⁵

Empirical results

Table 2 provides the summary statistics of the Bitcoin returns ($Return_t$) and predictors of interest. The daily returns for Bitcoin have a mean of 0.38%, a median of 0.22%, and a standard deviation of 4.69%. The high standard deviation associated with Bitcoin returns, which implies

⁴ A utility gain of 2% or more in the predictive model is typically considered economically significant (Rapach and Zhou, 2013).

⁵ See <http://apps.olin.wustl.edu/faculty/zhou/>.

substantial fluctuations in Bitcoin prices, is consistent with prior studies (Cheah and Fry, 2015; Fry and Cheah, 2016; Katsiampa, 2017).

[Insert Table 2 here]

In-sample predictability

Table 3 presents the results from the in-sample test using the predictive OLS regression in Equation (1) across various time horizons. We ensure that we only select those predictors with strong in-sample evidence by setting a benchmark with two criteria. First, the estimated coefficient of the predictor(s) must be statistically significant. Second, the in-sample, R^2 statistic must be greater than 0.5% since a monthly statistic of 0.5% indicates an economically meaningful degree of return predictability (Campbell and Thompson, 2008 and Rapach et al., 2016). Four predictors based on these criteria exceed the benchmark across all h -day horizons. These include two predictors of market characteristics, the Bitcoin crash dummy (BD) and the time-series momentum scaled by volatility ($TSMSV$; see Panel A in Table 3); and two uncertainty predictors, the Economic Policy Uncertainty Index (PU) and the Financial Uncertainty (FU ; see Panel E in Table 3).

[Insert Table 3 here]

At the one-week horizon, our momentum predictor ($TSMSV$) has the largest $\hat{\beta}$ estimate (0.32); in other words, a one-standard deviation increase in $TSMSV$ leads to a 32-basis point increase in the next day's Bitcoin excess returns.⁷ It is noteworthy that, by scaling the volatility, the adjusted time-series momentum predictor $TSMSV$ substantially outperforms TSM . This may result from dramatic Bitcoin market fluctuations. We remove the impact of volatility to

⁷ We standardize each predictor to have a standard deviation of one and report returns in percentage in Table 3.

discover that the time-series momentum predictor could be employed by the investor to formulate a profitable portfolio strategy.⁸ Further, excess Bitcoin returns are associated with changes in the *PU* and *FU* ($\hat{\beta} = 0.17$ and $\hat{\beta} = 0.26$, respectively). The results are consistent with Demir et al. (2018), indicating that external uncertainty factors display a strong predictive ability. Additionally, the other four measurements of market uncertainty—*VIX*, *VXD*, *VXN*, and *VXO*—are all significant. This result further supports the argument that external uncertainty factors have significant forecasting ability. Finally, the Bitcoin crash dummy also exhibits significant predictive power on returns with a $\hat{\beta}$ estimate of (0.27).

At the two-, three-, and four-week horizons, *BD*, *TSMSV*, *PU*, and *FU* all display substantially stronger predictive power than other popular predictors; specifically, their estimators at the four-week horizon are 0.19, 0.26, 0.21, and 0.25, respectively. The R^2 statistics further support our estimation results. The four significant predictors are well above the 0.5% threshold. Regarding the Bitcoin hedging ability over a longer time frame, we find that the predictability of *VIX*, *VXD*, *VXN*, and *VXO* significantly decreases, while that of *PU* and *FU* remains significant. These findings imply that Bitcoin can be predicted by the policy-related economic uncertainty and financial market's uncertainty.

Clearly, many predictors are omitted as a result of either the lack of statistical significance in $\hat{\beta}$ or having an $R^2 \leq 0.5\%$. However, this finding is as anticipated, as Rapach et al. (2016) reveal that only few predictors of aggregate stock returns display strong predictive power. However, in-sample forecasts could be subject to the Stambaugh bias (Busetti and Marcucci, 2013), and thus, it is essential to assess Bitcoin returns' out-of-sample predictability.

⁸ Our result is consistent with Kim et al. (2016), demonstrating that the scaled time-series momentum delivers a large, significant alpha for a diversified portfolio of international futures contracts.

Out-of-sample predictability

According to Welch and Goyal (2008), in-sample predictability can occur as a result of overfitting, while out-of-sample forecasting is a more stringent test of return predictability. Therefore, the remaining analysis focus more on our out-of-sample results. Table 4 presents the out-of-sample R^2 (R_{OS}^2) and Clark and West's (2007) MSFE-adjusted statistics for the out-of-sample return predictability across h -day horizons. We select those predictors that have positive R_{OS}^2 values and statistically significant Clark and West (2007) test. For the four in-sample predictors (BD , $TSMSV$, PU , and FU) with a positive $\hat{\beta}$ and in-sample $R^2 > 0.5\%$, we find that only three predictors ($TSMSV$, PU , and FU) exhibit a positive R_{OS}^2 , and the Clark and West (2007) test results are statistically significant for all h -day horizons. Further, BD has positive R_{OS}^2 values and the Clark and West (2007) test results are statistically significant for both the 7- and 14-day horizons; however, it fails to outperform the prevailing mean benchmark in terms of the MSFE at the 21- and 28-day horizons.⁹

The strong performance of $TSMSV$ is consistent with prior studies, which reveal that Bitcoin returns are highly volatile (Baek and Elbeck, 2015; Detzel et al., 2020). Substantial economic gains are also achieved by considering the risk of momentum (Barroso and Santa-Clara, 2015). Further, Moreira and Tyler (2017) find that volatility-managed portfolios—which take low weights during high volatility periods and high weights during low-volatility periods—generate large utility gains. From this perspective, our $TSMSV$ scales momentum down when volatility is low and up when volatility is high, which ultimately contributes to improve predictability.

⁹ While the R_{OS}^2 of BD is negative at the 21- and 28-day horizons, the Clark and West (2007) test statistic is significant. This is similar to Neely et al. (2014) which shows that certain macroeconomic predictors have negative R_{OS}^2 values and significant test statistics.

The uncertainty predictors *PU* and *FU* appear to perform as well as the *TSMSV* in terms of R_{OS}^2 statistics. Specifically, *FU* outperforms all other predictors with the largest R_{OS}^2 statistic of 7.92% at the 28-days horizon, confirming our in-sample test findings. These results suggest that the predictive regression forecasts based on these three factors produce a substantially smaller MSFE and outperform the benchmark.

It is noteworthy that our paper's decreased number of predictors is consistent with Rapach et al. (2016). Of the four in-sample predictors of aggregate stock returns, they discover that only short interest could be used as an out-of-sample predictor—and this was arguably the strongest known predictor of aggregate stock returns. It is argued that the substantial decrease in the number of predictors could be linked to the fact that highly persistent predictors can generate spuriously high in-sample return predictability (Campbell and Yogo, 2006; Ferson et al., 2003).

[Insert Table 4 here]

Asset allocation

This section measures the economic value of predictors' forecast ability using an asset allocation framework. Table 5 reports the out-of-sample CER gains. We annualise these and assume a relative risk aversion coefficient of 5.¹⁰ Given the high time-varying volatile nature of Bitcoin returns, their predictability is rather limited across the longer horizons (Bouri et al., 2016). Therefore, we focus our results on the 7- and 14-day horizons, and demonstrate that the

¹⁰ The magnitude can be different when the relative risk aversion coefficient varies. However, the patterns remain qualitatively similar. For example, the CER gains of *BD* decrease when the relative risk aversion coefficient increases.

BD, *TSMSV*, *PU*, and *FU* predictors produce out-of-sample CER gains. The *TSMSV* has CER gains of 21.06% for the 7-day horizon and 16.84% for the 14-day horizon, with *BD*, *PU*, and *FU* predictors also generating positive CER gains for both. However, we note that CER gains significantly decrease beyond the 14-day horizon for *PU* and *FU*, while only *BD* and *TSMSV* continuously provide positive CER gains. Therefore, the *PU* and *FU* information provides limited economic value for risk-averse investors with longer investment horizons.

[Insert Table 5 here]

Recent studies highlight transaction costs' role in trading strategies' profits (Novy-Marx, 2014; Patton and Weller, 2019). Thus, we examine the CER after considering transaction costs, and proxy for such costs by estimating $TC = (bid - ask) / ((bid + ask) / 2)$ following Amihud and Mendelson (1986). We obtain the bid and ask spread data from Bitcoinity.org,¹¹ following Dyhrberg et al. (2018).¹² As the bid-ask data begins on 6 November 2012, we replace the earlier missing values of transaction costs (*TC*) with the mean of *TC* over the sample period, to avoid losing information. The mean Bitcoin transaction cost is 0.183%, which is consistent with the transaction costs ranging from 0.1% to 0.3% as advised by Detzel et al. (2020).

We adjust transaction costs by subtracting them from the Bitcoin returns, following Novy-Marx and Velikov (2016). Specifically, the transaction costs are the product of turnover and transaction costs, where turnover is the absolute change in portfolio weight from day $(t - 1)$ to t . For example, if the return is 0.0424 on a particular day, the transaction cost is 0.003 and the turnover is 0.8 or specifically, the portfolio weight is 0.1 on day $(t - 1)$ and 0.9 on day t and the return net of the transaction cost is 0.040. Subsequently, we use this to estimate the CER:

¹¹ See data.bitcoinity.org for details.

¹²We obtain similar results when we use 0.1% and 0.3% as transaction costs. Detzel et al. (2020) suggest that the transaction costs of Bitcoin range from 0.1% to 0.3%.

the CER under transaction costs is $CER = \bar{R}_p - TC - 0.5\gamma\sigma_p^2$, where $\bar{R}_p - TC$ is the mean of the portfolio return net of transaction costs over the forecast evaluation periods.

[Insert Table 6 here]

We adjust transaction costs to the CER and our results in Table 6 remain materially unchanged. However, an issue exists with implementing the trading strategies issue. Investors can be exposed to long wait times to execute their orders and must attach fees to facilitate their trades (Easley et al., 2019). Therefore, our results should be interpreted with caution.

Robustness test addressing time-varying market return volatility

6.1 Addressing time-varying market return volatility

Prior studies indicate that time-varying market return volatility creates substantial heteroscedasticity in time-series return predictability regressions. As documented by Hafner (2018), such cryptocurrencies as Bitcoin exhibit strong time-varying volatility. The typical approach in addressing this heteroscedasticity involves adjusting the OLS regressions with White's (1980) heteroscedasticity-consistent standard errors. However, Johannes et al. (2014) and Westerlund and Narayan (2015) indicate that incorporating return heteroscedasticity into point estimates and standard errors under the generalised least squares estimate could result in a more efficient estimator with less noise and more power in finite samples. Therefore, following Johnson (2019), we apply the weighted least-squares method using the *ex-ante* variance (WLS-EV) to address the estimation inefficiency due to the Bitcoin market time-varying volatility. Specifically, we estimate volatility as

$$RV\hat{\sigma}_d^2 = \hat{\alpha} + \hat{\beta}_1 RV_d + \hat{\beta}_2 RV_{d-11} \quad , \quad (6)$$

where $\hat{\alpha}$, $\hat{\beta}_1$ and $\hat{\beta}_2$ are the estimated coefficients in a regression of RV_{d+1} on RV_d , RV_d and RV_{d-1} ; RV_d is the realised variance of five-minute log Bitcoin returns.

Table 7 reports the results of out-of-sample tests based on the weighted least squares using *ex ante* variance (WLS-EV). We find that three main predictors (*TSMSV*, *PU*, and *FU*), which we identified in our previous tests, all have a positive out-of-sample R_{OS}^2 and the Clark and West (2007) test is statistically significant for all h -day horizons. The results suggest that our results are robust to the alternative estimation method after accounting for the Bitcoin market's time-varying volatility.

[Insert Table 7 here]

6.2 Persistent and temporal stability

As indicated by Neely et al. (2014) and Rapach et al. (2016), many popular return predictors are highly persistent. This raises the concern that the t-statistic will be inflated for our coefficient, which is known as the Stambaugh (1999) bias. We address this by using the IVX-Wald statistic developed by Kostakis et al. (2015) to test $H_0: \beta = 0$ against $H_A: \beta \neq 0$. This powerful Wald's test is robust to the regressor's degree of persistence, whether unit root, local-to-unit root, near stationary or stationary. Table 8 presents these test results. The IVX-Wald statistics for *TSMSV*, *PU*, and *FU* are significant across all horizons, indicating that our predictors' predictive power is not compromised. Overall, our results after accounting for the predictors' persistence of predictors demonstrate that the IVX-Wald test further supports our prior findings.

[Insert Table 8 here]

Structural instability can leave a long, non-stationary impact on time-series variables, resulting in inaccurate inferences regarding the parameters' overall stability. It is well known that Bitcoin prices can significantly fluctuate; we address this concern by testing general persistent time variations in regression coefficients, as developed by Elliott and Müller (2006). Their test is asymptotically efficient for a variety of breaking processes. More importantly, Paye and Timmermann (2006) confirm that the test has excellent finite sample properties for predictive regressions with highly persistent predictors. Specifically, we use Elliott and Müller's (2006) qLL statistic to test $H_0 : \beta_t = \beta$ for all t . None of the qLL statistics are significant at any horizon for the estimate coefficient. For example, Table 9 reports that the qLL statistics for $TSMSV$ are -2.97, -3.71, -4.62, and -4.31 at one, two, three, and four weeks, respectively, which do not surpass Elliott and Müller's (2006) critical values.¹³ Overall, we find no evidence that the predictive ability of $TSMSV$, PU , and FU changes during our sample period.

[Insert Table 9 here]

6.3 Density forecast

Our out-of-sample test uses the root mean squared forecast errors (RMSE) to measure our predictors' accuracy. However, the RMSE criterion only accounts for the mean return's precision. In other words, the point forecast exhibits difficulty in providing reliable quantitative information about forecast densities and contains no description of the associated uncertainty (Tay and Wallis, 2000). As indicated by Amisano and Giacomini (2007), a density forecast can represent a complete characterisation of the uncertainty associated with the forecast. Specifically, we follow Cenesizoglu and Timmermann (2012), and use a constant mean and volatility model to create a simple no-predictability benchmark

¹³ See Table 1 of Elliott and Müller (2006) for the critical values.

$$RET_{t+1} = \beta_0 + \varepsilon_{t+1}, \quad \varepsilon_{t+1} \sim N(0, \sigma^2), \quad (7)$$

where RET_{t+1} is the excess Bitcoin return. We use Amisano and Giacomini's (2007) weighted likelihood ratio test statistic to evaluate the individual density forecast's predictive accuracy relative to the forecast implied by the prevailing mean and variance (PMV) model. The test statistic is computed as

$$t = \frac{\overline{WLR}_P}{\hat{\sigma}_P / \sqrt{P}}, \quad (8)$$

where $\overline{WLR}_P = P^{-1} \sum_{t=0}^{P-1} WLR_{t+1}$ is the average weighted likelihood ratio using P out-of-sample observations, and $\hat{\sigma}_P$ is an estimator of its variance. The weighted likelihood ratio WLR_{t+1} is calculated as the weighted average difference between the log scores of an individual model and the PMV model:

$$WLR_{t+h} = w(\overline{RET}_{t+h}) (\log f_{t+h|t}(RET_{t+h}) - \log f_{t+h|t}^{PMV}(RET_{t+h})), \quad (9)$$

where $w(\overline{RET}_{t+h})$ is a weight function evaluated at the standardised return at time $(t+h)$, while $f_{t+h|t}(RET_{t+h})$ and $f_{t+h|t}^{PMV}(RET_{t+h})$ are the predictive densities of the individual and PMV models, respectively. We then follow Cenesizoglu and Timmermann's (2012) work to set the weight to one and focus on the full distribution.

[Insert Table 10 here]

Table 10 reports the results of the weighted likelihood ratio test for our sample period. Positive values imply that the predictive model generates more accurate density forecasts than the PMV model, while negative values indicate that the PMV model is relatively superior. We find significant, positive values of the weighted likelihood ratio for all three previously identified

predictors, which indicates that the model using *TSMSV*, *PU*, and *FU* produces more accurate density forecasts than the PMV model.

Conclusion

The paper presents the results of a first attempt at identifying the potential predictors of Bitcoin returns, following the approaches established by Welch and Goyal (2008), Rapach and Zhou (2013), and Rapach et al. (2016). We find that some Bitcoin market and uncertainty predictors are the primary drivers of Bitcoin returns.

These results have several important implications, the first of which applies for investors and speculators in Bitcoin markets: identifying appropriate predictors will enable them to identify Bitcoin mispricing and undertake arbitrage through market timing. This will also allow them to either switch asset classes or move in and out of the market at appropriate times. Additionally, an investor or speculator can realise economic gains if time-series momentum (*TSMSV*), economic policy uncertainty (*PU*), and financial uncertainty (*FU*) are considered during the asset allocation processes in portfolio management.

The second implication involves policy-makers and regulators. Although such markets are largely unregulated at present, they can use the predictors identified here if they do attempt such regulation, to facilitate a detection of bubbles emerging in Bitcoin markets. This will enable the introduction of ‘cooling’ measures to halt or inhibit trading in an orderly fashion, consequently protecting non-speculative users from unnecessary financial losses.

Future research in this area might compare different methods for selecting appropriate predictors, explore the use of macroeconomic factors for capturing changes in the wider economy, or consider the inclusion of structural breaks and other major events.

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Table 1: Determinants of Bitcoin returns

Variable	Definition and Source	Explanation and Data Source
Panel A: Bitcoin Market Characteristics Predictors		
<i>BA</i>	Bid-ask spread measure	<p>Corwin and Schultz (2012), $BA = \frac{2(e^\kappa - 1)}{1 + e^\kappa}$ where $\kappa = \frac{\sqrt{2\tau} - \sqrt{\tau}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma}{3 - 2\sqrt{2}}}$, $\tau = E \left\{ \sum_{j=0}^1 \left[\ln \left(\frac{H_{t+j}^O}{L_{t+j}^O} \right) \right]^2 \right\}$,</p> <p>$\gamma = \left[\ln \left(\frac{H_{t,t+j}^O}{L_{t,t+j}^O} \right) \right]^2$, where H_t^O (L_t^O) is the observed high (low) Bitcoin price for day t, and $H_{t,t+j}^O$ ($L_{t,t+j}^O$) is the observed high (low) Bitcoin price over two days t and $t + 1$. We estimate the innovation (u_t) BA as the residual of the following AR(2) model (using innovation, u_t, is due to the persistency of liquidity, e.g., Pástor and Stambaugh 2003) $liq_t = \alpha_0 + \alpha_1 liq_{t-1} + \alpha_2 liq_{t-2} + u_t$, where liq_t is the liquidity measure of BA in day t.</p>
<i>BD</i>	Crash dummy	<p>This dummy variable accounts for the crash behaviour of Bitcoin price. This variable takes a value of 1 if on that day there is a price crash and 0 otherwise. The crash date is identified using Investoo.com</p> <p>(https://www.techstars.com/content/startup-digest/history-major-bitcoin-crashes/)</p>
<i>BETA</i>	Systematic risk	<p>Coefficient from regressing daily excess Bitcoin return on the excess market return (<i>MKTRF</i>) over the prior 12 days.</p>
<i>DV</i>	Dollar volume measure of Bitcoin	<p>Daily dollar volume in Bitcoin market averaged over the prior 12 days (Brennan et al., 1998). We estimate the innovation (u_t) DV as the residual of the following AR(2) model (using innovation, u_t, is due to the persistency of liquidity, e.g., Pástor and Stambaugh 2003) $liq_t = \alpha_0 + \alpha_1 liq_{t-1} + \alpha_2 liq_{t-2} + u_t$, where liq_t is the liquidity measure of DV in day t.</p>
<i>ISK</i>	Idiosyncratic skewness	<p>Skewness of residuals from regressing daily excess Bitcoin return on the Fama-French three-factor model over the prior 12 days.</p>

<i>IVOL</i>	Idiosyncratic volatility	Standard deviation of residuals from regressing daily excess Bitcoin return on the Fama-French three-factor model over the prior 12 days.
<i>RV</i>	Price impact measure	Daily absolute-return-to-dollar-volume ratio averaged over the prior 12 days, We estimate the innovation (u_t) <i>RV</i> as the residual of the following AR (2) model (using innovation, u_t , is due to the persistency of liquidity, e.g., Pástor and Stambaugh 2003). $liq_t = \alpha_0 + \alpha_1 liq_{t-1} + \alpha_2 liq_{t-2} + u_t$, where liq_t is the liquidity measure of <i>RV</i> in day t.
<i>SK</i>	Skewness of return	Skewness of daily Bitcoin return over the prior 12 days.
<i>TEUSD</i>	Transaction fees paid to miners	The total value of all transaction fees paid to miners (Easley et al., 2019). We obtain transaction fee data from https://www.blockchain.com . We estimate the innovation (u_t) <i>TEUSE</i> as the residual of the following AR(2) model (using innovation, u_t , is due to the persistency of <i>TEUSE</i>) $TEUSE_t = \alpha_0 + \alpha_1 TEUSE_{t-1} + \alpha_2 TEUSE_{t-2} + u_t$, where $TEUSE_t$ is the transaction fees measure of <i>TEUSE</i> in day t.
<i>TSM</i>	Time-series Momentum	Compound daily excess Bitcoin return over the prior 12 days (Moskowitz et al., 2012).
<i>TSMSV</i>	Scaled <i>TSM</i> by volatility	<i>TSM</i> scaled by <i>VOL</i> (Moskowitz et al., 2012).
<i>VOL</i>	Volatility of return	Standard deviation of daily Bitcoin returns over the prior 12 days.
<i>VOLG</i>	Volatility of return from GARCH (1,1)	Volatility of Bitcoin return estimated from GARCH (1,1) (Cheah et al., 2018).

Panel B: Stock Market Predictors

<i>CMA</i>	Investment factor	Kenneth French's website.
<i>HML</i>	Book-to-market factor	Kenneth French's website.
<i>MKTRF</i>	Daily excess market returns	Kenneth French's website.
<i>RMW</i>	Profitability factor	Kenneth French's website.

<i>SMB</i>	Size factor	Kenneth French's website.
<i>UMD</i>	Momentum factor	Kenneth French's website.

Panel C: Bond Market Predictors

<i>JUNK</i>	The junk spread	Defined as the spread between Moody's Baa and Aaa corporate bond yields as in Keim and Stambaugh (1986).
<i>RF</i>	Treasury bill rate	Kenneth French's website.
<i>TERM</i>	The term spread	Defined as the spread of the ten-year and a one-year Treasury bond yield as in Fama and French (1989).

Panel D: Sentiment Predictors

BBS	US Investor Sentiment Bull-Bear Spread	AII Investor Sentiment Survey.
GSI	Google Trend Search Index for Bitcoin	Google Trends for the keyword "Bitcoin" (https://trends.google.com/trends/explore?q=bitcoin&geo=US).
TMAX	The daily high temperature recorded at the Central Park weather station in New York	Following Novy-Marx (2014) we obtain the weather data from The National Climatic Data Center (NCDC).

Panel E: External Uncertainty Predictors

PU	Economic Policy Uncertainty Index	Economic policy uncertainty website, http://www.policyuncertainty.com/ (Baker et al.,2016).
FU	Financial Uncertainty	Following Jurado et al. (2015), we obtain the data from Sydney Ludvigson's website.
MU	Macro Uncertainty	Following Jurado et al. (2015), we obtain the data from Sydney Ludvigson's website.
RU	Real Uncertainty	Following Jurado et al. (2015), we obtain the data from Sydney Ludvigson's website.
VIX	CBOE S&P500 Volatility Index	Wharton Research Data Services.
VXD	CBOE DJIA Volatility Index	Wharton Research Data Services.
VXN	CBOE NASDAQ Volatility Index	Wharton Research Data Services.

Table 2: Summary Statistics

This table reports descriptive statistics for the key variables. Detailed variable definitions are available in Table 1.

	Mean	Standard Deviation	Minimum	Median	Maximum
<i>Return(%)</i>	0.38	4.69	-48.52	0.22	40.14
<i>Panel A: Bitcoin Market Characteristics Predictors</i>					
<i>BA</i>	-0.01	1.14	-14.79	-0.08	16.26
<i>BD</i>	0.19	0.40	0.00	0.00	1.00
<i>BETA</i>	-0.18	3.18	-19.72	-0.12	35.73
<i>DV</i>	0.00	2.78	-47.85	-0.08	42.42
<i>ISK</i>	0.03	0.70	-2.75	0.05	2.08
<i>IVOL</i>	0.03	0.02	0.00	0.03	0.19
<i>RV</i>	0.00	0.00	-0.01	0.00	0.01
<i>SK</i>	0.00	0.87	-2.91	-0.02	2.70
<i>TEUSD</i>	0.08	27.81	-348.86	-1.13	482.47
<i>TSM</i>	0.05	0.20	-0.50	0.02	1.59
<i>TSMSV</i>	1.51	4.44	-9.66	0.71	22.31
<i>VOL</i>	0.04	0.03	0.00	0.03	0.26
<i>VOLG</i>	0.00	0.01	0.00	0.00	0.10
<i>Panel B: Stock Market Predictors</i>					
<i>CMA</i>	0.00	0.31	-1.32	0.00	1.97
<i>HML</i>	-0.01	0.47	-1.69	-0.03	2.38
<i>MKTRF</i>	0.05	0.84	-4.03	0.07	5.06
<i>RMW</i>	0.00	0.31	-1.58	-0.01	1.63
<i>SMB</i>	0.01	0.48	-1.63	0.00	2.52
<i>UMD</i>	0.00	0.67	-3.13	0.04	3.64
<i>Panel C: Bond Market Predictors</i>					
<i>JUNK</i>	0.94	0.25	0.53	0.90	1.54
<i>RF</i>	0.00	0.00	0.00	0.00	0.01
<i>TERM</i>	1.56	0.67	0.06	1.60	2.91
<i>Panel D: Sentiment Predictors</i>					
<i>BBS</i>	0.06	0.13	-0.35	0.06	0.44
<i>GSI</i>	161.58	240.65	3.04	77.26	3260.00
<i>TMAX</i>	63.11	18.26	13.00	64.00	100.00
<i>Panel E: Uncertainty Predictors</i>					
<i>PU</i>	98.19	57.77	3.32	84.95	586.55
<i>FU</i>	0.81	0.09	0.68	0.79	1.16
<i>MU</i>	0.61	0.03	0.55	0.60	0.69
<i>RU</i>	0.61	0.02	0.59	0.61	0.66
<i>VIX</i>	15.30	4.14	9.14	14.26	40.74
<i>VXD</i>	14.78	3.67	7.58	13.88	34.51
<i>VXN</i>	17.54	4.32	10.31	16.48	42.95
<i>VXO</i>	14.76	4.61	6.32	13.83	37.66
<i>PCA</i>	-0.03	2.32	-4.25	-0.39	10.60

Table 3: In-sample Predictive Regression Estimation Results

The table reports the ordinary least squares estimate of β and R^2 statistic for the predictive regression model: $RET_{t,t+h} = \alpha + \beta x_t + \varepsilon_{t,t+h}$, where $RET_{t,t+h} = (1/h)(RET_{t+1} + \dots + RET_{t+h})$, RET_t is the Bitcoin log excess return (%) for day t, and x_t is a predictor variable. See Table 1 for the variable definitions of 33 predictors and their principal component. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, based on one sided wild bootstrapped p -value. In order to provide comparable results, we standardize each predictor so the standard deviation is one for all predictors. We also take all the negative of *BD*, *BETA*, *ISK*, *TEUSD*, *CMA*, *HML*, *SMB*, *RF*, *BBS*, *GSI*, *FU*, *MU*, *RU*, *VIX*, *VXD*, *VXN* and *VXO* to facilitate comparisons across predictors.

	<i>h</i> = 7 days			<i>h</i> = 14 days			<i>h</i> = 21 days			<i>h</i> = 28 days		
	$\hat{\beta}$	<i>t</i> -stat	R^2 (%)	$\hat{\beta}$	<i>t</i> -stat	R^2 (%)	$\hat{\beta}$	<i>t</i> -stat	R^2 (%)	$\hat{\beta}$	<i>t</i> -stat	R^2 (%)
Panel A: Bitcoin Market Characteristics Predictors												
<i>BA</i>	0.12	2.12**	0.44	0.08	2.26***	0.33	0.04	1.94*	0.13	0.05	2.16**	0.22
<i>BD</i>	0.27	4.03***	2.16	0.22	3.64***	2.86	0.21	3.72***	3.5	0.19	3.33***	3.5
<i>BETA</i>	0.11	1.33	0.38	0.07	0.93	0.25	0.01	0.18	0.01	0	0.02	0
<i>DV</i>	0.06	1.24	0.11	0.04	1.55	0.11	0.02	0.98	0.03	0.02	0.92	0.03
<i>ISK</i>	0.03	0.4	0.03	0.03	0.48	0.05	0.08	1.43	0.52	0.1	1.93*	0.94
<i>IVOL</i>	0.13	1.17	0.53	0.05	0.59	0.12	0.01	0.2	0.01	0.01	0.19	0.01
<i>RV</i>	0.06	2.47*	0.11	0.01	0.84	0.01	0.03	1.58	0.06	0	0.4	0
<i>SK</i>	0.07	1.12	0.14	0.11	2.1*	0.68	0.08	1.56	0.54	0.05	0.96	0.24
<i>TEUSD</i>	0.05	1.47	0.07	0.02	0.92	0.03	0.01	0.37	0.01	0.01	0.47	0.01
<i>TSM</i>	0.21	1.11	1.4	0.25	1.82	3.61	0.18	1.61	2.62	0.14	1.41	1.96
<i>TSMSV</i>	0.32	2.53**	3.2	0.34	3.37***	6.82	0.3	3.29***	6.93	0.26	2.92***	6.44
<i>VOL</i>	0.14	1.25	0.57	0.06	0.78	0.19	0.02	0.35	0.04	0.01	0.09	0
<i>VOLG</i>	0.22	1.96	1.43	0.09	1.12	0.45	0.05	1.13	0.22	0.04	0.97	0.13
Panel B: Stock Market Predictors												
<i>CMA</i>	0.04	0.9	0.04	0.03	0.85	0.04	0.02	0.74	0.03	0.02	0.65	0.03
<i>HML</i>	0.06	1.49	0.11	0.02	0.7	0.02	0.02	0.8	0.03	0.02	0.96	0.04
<i>MKTRF</i>	0.06	1.53	0.12	0.05	1.54	0.14	0.05	1.96*	0.19	0.05	2.01*	0.24
<i>RMW</i>	0.06	1.31	0.09	0.04	1.35	0.1	0.05	1.77*	0.18	0.05	1.85*	0.25
<i>SMB</i>	0.08	1.77*	0.2	0.02	0.61	0.02	0.02	0.77	0.04	0.01	0.5	0.01

<i>UMD</i>	0.06	1.44	0.11	0.03	1.02	0.05	0.03	1.28	0.06	0.02	0.74	0.02
<i>Panel C: Bond Market Predictors</i>												
<i>JUNK</i>	0.01	0.08	0	0.01	0.18	0.01	0.01	0.13	0.01	0.01	0.1	0.01
<i>RF</i>	0.15	1.96*	0.65	0.14	1.84	1.15	0.15	1.84	1.62	0.15	1.82	1.96
<i>TERM</i>	0.09	1.02	0.25	0.09	0.96	0.5	0.09	0.92	0.67	0.09	0.88	0.77
<i>Panel D: Sentiment Predictors</i>												
<i>BBS</i>	0.07	0.94	0.17	0.05	0.57	0.12	0.04	0.52	0.16	0.05	0.58	0.24
<i>GSI</i>	0.06	0.62	0.11	0.1	1.21	0.56	0.13	1.76	1.42	0.13	1.82	1.79
<i>TMAX</i>	0.01	0.17	0	0.01	0.15	0.01	0	0.01	0	0	0.02	0
<i>Panel E: Uncertainty Predictors</i>												
<i>PU</i>	0.17	2.98***	0.88	0.18	3.38***	1.79	0.19	3.63***	2.94	0.21	3.56***	4.33
<i>FU</i>	0.26	3.48***	2.01	0.25	3.21***	3.44	0.25	2.96**	4.39	0.25	3.01**	5.35
<i>MU</i>	0.03	0.49	0.04	0.03	0.47	0.07	0.03	0.39	0.08	0.03	0.31	0.06
<i>RU</i>	0.08	1.13	0.18	0.08	1.31	0.39	0.08	1.26	0.48	0.07	1.14	0.5
<i>VIX</i>	0.14	1.92*	0.6	0.12	1.67	0.81	0.09	1.29	0.7	0.08	1.18	0.66
<i>VXD</i>	0.18	2.4**	0.96	0.15	2.2*	1.39	0.13	1.8	1.37	0.12	1.65	1.33
<i>VXN</i>	0.21	2.86***	1.32	0.18	2.5**	1.9	0.15	1.94	1.7	0.13	1.69	1.53
<i>VXO</i>	0.16	2.3**	0.77	0.12	1.79	0.89	0.1	1.36	0.81	0.09	1.21	0.76
<i>PCA</i>	0.18	2.22**	1	0.16	1.95	1.41	0.13	1.54	1.26	0.11	1.35	1.14

Table 4: Out-of-Sample Test Results

The table reports the proportional reduction in mean squared forecast error (MSFE) at the h -day horizon for a predictive regression forecast of the Bitcoin log excess return based on the predictor variable in the first column vis-à-vis the prevailing mean benchmark forecast, where statistical significance is based on the Clark and West (2007) statistic for testing the null hypothesis that the prevailing mean MSFE is less than or equal to the predictive regression MSFE, against the alternative hypothesis that the prevailing mean MSFE is greater than the predictive regression MSFE. See Table 1 for the variable definitions of 33 predictors and their principal component. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	$h = 7$ days		$h = 14$ days		$h = 21$ days		$h = 28$ days	
	R_{OS}^2 (%)	CW-stat	R_{OS}^2 (%)	CW-stat	R_{OS}^2 (%)	CW-stat	R_{OS}^2 (%)	CW-stat
Panel A: Bitcoin Market Characteristics Predictors								
<i>BA</i>	0.23	2.94 ***	-0.34	1.12	-0.39	-0.60	-0.15	0.73
<i>BD</i>	0.49	2.49 ***	0.15	2.11 ***	-1.80	1.72**	-3.18	1.42*
<i>BETA</i>	0.07	0.93	-0.35	-0.53	-2.30	-2.11	-2.42	-1.72
<i>DV</i>	-0.87	0.51	-0.34	0.56	-1.31	-0.31	-1.11	-0.36
<i>ISK</i>	-0.71	-0.42	-0.55	-2.28	-0.20	0.61	-0.18	1.38
<i>IVOL</i>	0.52	1.38	-0.33	-0.49	-2.13	-3.39	-3.34	-2.95
<i>RV</i>	0.10	2.58 ***	-0.18	-2.78	-0.48	-3.26	-0.31	-1.85
<i>SK</i>	0.01	0.19	0.37	1.23	0.08	0.62	-0.24	-0.37
<i>TEUS</i>								
<i>D</i>	0.07	1.24	-0.27	-0.41	-0.68	-1.95	-0.62	-1.27
<i>TSM</i>	0.87	1.53 *	2.41	2.03 ***	2.07	1.95 **	1.50	1.85 **
<i>TSMSV</i>	1.67	2.76 ***	2.56	2.93 ***	1.85	2.71 ***	1.63	2.50 ***
<i>VOL</i>	0.47	1.41 *	-0.09	0.16	-1.52	-2.82	-2.68	-2.99
<i>VOLG</i>	0.74	2.18 ***	0.44	1.41	0.01	0.16	-0.16	-0.51
Panel B: Stock Market Predictors								
<i>CMA</i>	-0.01	0.17	-0.21	-1.21	-0.57	-1.95	-0.53	-1.36
<i>HML</i>	-0.28	0.03	-0.40	-1.72	-0.46	-2.72	-0.55	-2.08
<i>MKTR</i>								
<i>F</i>	-0.81	-0.22	-0.82	0.20	-1.06	0.08	-0.58	0.48
<i>RMW</i>	0.13	1.09	-0.27	0.28	-0.37	-0.19	-0.69	0.23

<i>SMB</i>	0.29	1.57*	-0.28	-1.24	-0.53	-2.01	-0.59	-1.79
<i>UMD</i>	-0.26	0.15	-0.62	-1.59	-0.90	-1.88	-1.24	-2.54
<i>Panel C: Bond Market Predictors</i>								
<i>JUNK</i>	-0.39	-0.62	-1.07	-0.97	-1.92	-1.51	-2.51	-1.74
<i>RF</i>	-1.72	0.12	-4.32	-0.06	-6.51	-0.11	-7.74	-0.03
<i>TERM</i>	-0.24	0.06	-0.87	-0.27	-1.67	-0.46	-2.00	-0.43
<i>Panel D: Sentiment Predictors</i>								
<i>BBS</i>	0.07	0.59	-0.64	-1.60	-1.48	-2.22	-1.34	-1.63
<i>GSI</i>	-3.90	-0.09	-8.78	-0.83	-13.09	-0.70	-18.18	-0.79
<i>TMAX</i>	-0.46	0.05	-1.02	-0.39	-1.74	-0.94	-2.02	-1.15
<i>Panel E: Uncertainty Predictors</i>								
<i>PU</i>	0.87	2.91 ***	0.86	2.58 ***	1.63	2.71 ***	1.87	2.74 ***
<i>FU</i>	2.81	2.95 ***	4.64	2.66 ***	6.20	2.40 ***	7.92	2.31 ***
<i>MU</i>	-0.42	-0.34	-1.10	-0.60	-2.05	-0.92	-2.64	-0.95
<i>RU</i>	-0.42	0.66	-1.15	0.53	-2.03	0.34	-2.50	0.31
<i>VIX</i>	-1.77	-0.02	-2.64	-0.31	-2.13	-0.61	-2.05	-0.82
<i>VXD</i>	-1.11	0.88	-1.53	0.64	-0.67	0.44	-0.25	0.31
<i>VXN</i>	-0.47	1.34 *	-0.45	1.11	0.04	0.72	-0.24	0.33
<i>VXO</i>	-1.19	0.48	-1.84	-0.05	-1.56	-0.39	-1.80	-0.66
<i>PCA</i>	-0.18	1.12	-0.20	0.83	-0.06	0.46	-0.32	0.15

Table 5: Out-of-Sample CER Gains

The table reports the certainty equivalent return (CER) gain (in percent) for a mean-variance investor with relative risk aversion coefficient of five who allocates between Bitcoin and T-bills using a predictive regression excess return forecast based on the predictor variable in the first column relative to the prevailing mean benchmark forecast. See Table 1 for the variable definitions of 33 predictors and their principal component. The weight is constrained to lie between 0 and 1. The forecast horizon and rebalancing frequency coincide and are given by h .

	$h = 7 \text{ days}$	$h = 14 \text{ days}$	$h = 21 \text{ days}$	$h = 28 \text{ days}$
Panel A: Bitcoin Market Characteristics Predictors				
<i>BA</i>	5.45	-0.48	-0.14	5.54
<i>BD</i>	27.82	27.10	4.80	17.04
<i>BETA</i>	4.11	-0.67	2.36	-4.48
<i>DV</i>	-7.05	-5.39	-4.22	-4.92
<i>ISK</i>	-2.74	-0.24	0.94	-2.08
<i>IVOL</i>	10.76	4.48	-1.91	-0.44
<i>RV</i>	0.14	-0.05	-0.11	0.02
<i>SK</i>	-0.11	5.74	1.57	-0.77
<i>TEUSD</i>	-3.20	-1.24	-4.34	-4.27
<i>TSM</i>	9.41	9.58	-3.95	0.73
<i>TSMSV</i>	21.06	16.84	20.15	10.51
<i>VOL</i>	13.45	5.67	-2.33	-0.69
<i>VOLG</i>	12.75	2.67	1.14	0.64
Panel B: Stock Market Predictors				
<i>CMA</i>	1.36	0.37	1.61	0.63
<i>HML</i>	-1.59	-0.42	0.27	-0.29
<i>MKTRF</i>	11.30	1.50	-1.44	-0.21
<i>RMW</i>	1.53	-0.40	3.99	-2.44
<i>SMB</i>	0.70	-0.26	2.22	0.24
<i>UMD</i>	6.84	0.68	-2.35	-0.78
Panel C: Bond Market Predictors				

<i>JUNK</i>	-1.41	-2.10	-4.17	-2.75
<i>RF</i>	1.76	-2.46	-11.05	1.53
<i>TERM</i>	5.03	8.18	10.82	5.98
<i>Panel D: Sentiment Predictors</i>				
<i>BBS</i>	1.98	-1.13	2.03	2.07
<i>GSI</i>	-4.84	-11.61	-0.97	7.43
<i>TMAX</i>	3.33	1.77	5.41	1.11
<i>Panel E: Uncertainty Predictors</i>				
<i>PU</i>	13.49	9.75	-17.73	-1.59
<i>FU</i>	24.57	9.51	-3.85	8.14
<i>MU</i>	0.84	-4.20	-10.78	-5.63
<i>RU</i>	3.58	-1.45	-4.66	-2.02
<i>VIX</i>	9.91	3.65	-15.76	-7.83
<i>VXD</i>	16.30	2.95	-9.60	-1.87
<i>VXN</i>	22.14	16.55	2.34	2.94
<i>VXO</i>	12.06	0.01	-12.82	-8.60
<i>PCA</i>	19.11	6.72	-4.34	0.39

Table 6: Out-of-Sample CER Gains including Transaction Fees. See Table 1 for the variable definitions of 33 predictors and their principal component.

	<i>h = 7 days</i>	<i>h = 14 days</i>	<i>h = 21 days</i>	<i>h = 28 days</i>
<i>Panel A: Bitcoin Market Characteristics Predictors</i>				
<i>BA</i>	4.84	-0.80	-0.39	5.28
<i>BD</i>	27.66	26.90	4.60	16.95
<i>BETA</i>	3.41	-0.87	2.19	-4.66
<i>DV</i>	-7.74	-5.73	-4.45	-5.12
<i>ISK</i>	-3.22	-0.43	0.70	-2.35
<i>IVOL</i>	10.25	4.26	-2.07	-0.60
<i>RV</i>	-0.05	-0.24	-0.27	-0.14
<i>SK</i>	-0.34	5.45	1.39	-0.93
<i>TEUSD</i>	-3.54	-1.44	-4.49	-4.43
<i>TSM</i>	7.97	8.76	-4.40	0.35
<i>TSMSL</i>	18.91	15.70	19.27	9.89
<i>VOL</i>	12.85	5.41	-2.50	-0.85
<i>VOLG</i>	12.29	2.42	0.97	0.46
<i>Panel B: Stock Market Predictors</i>				
<i>CMA</i>	1.13	0.18	1.36	0.42
<i>HML</i>	-2.09	-0.60	0.07	-0.46
<i>MKTRF</i>	10.34	1.08	-1.64	-0.38
<i>RMW</i>	1.09	-0.70	3.73	-2.65
<i>SMB</i>	0.06	-0.47	2.04	0.05
<i>UMD</i>	6.27	0.47	-2.52	-0.95

<i>Panel C: Bond Market Predictors</i>				
<i>JUNK</i>	-1.59	-2.24	-4.31	-2.91
<i>RF</i>	1.39	-2.74	-11.27	1.31
<i>TERM</i>	4.85	7.98	10.64	5.79
<i>Panel D: Sentiment Predictors</i>				
<i>BBS</i>	1.71	-1.34	1.83	1.87
<i>GSI</i>	-5.14	-11.90	-1.26	7.21
<i>TMAX</i>	2.97	1.51	5.23	0.91
<i>Panel E: Uncertainty Predictors</i>				
<i>PU</i>	12.43	9.19	-18.13	-1.93
<i>FUH</i>	24.33	9.29	-4.09	7.92
<i>MUH</i>	0.60	-4.45	-10.96	-5.81
<i>RUH</i>	3.32	-1.68	-4.83	-2.19
<i>VIX</i>	9.23	3.25	-16.05	-8.04
<i>VXD</i>	15.69	2.61	-9.91	-2.15
<i>VXN</i>	21.49	16.18	2.03	2.66
<i>VXO</i>	11.46	-0.32	-13.11	-8.81
<i>PCA</i>	18.62	6.45	-4.63	0.13

Table 7: Out-of-Sample Test Results based on Weighted Least Squares using Ex Ante Variance (WLS-EV)

See Table 1 for the variable definitions of 33 predictors and their principal component.

	<i>h</i> = 7 days		<i>h</i> = 14 days		<i>h</i> = 21 days		<i>h</i> = 28 days	
	R_{OS}^2 (%)	CW-stat	R_{OS}^2 (%)	CW-stat	R_{OS}^2 (%)	CW-stat	R_{OS}^2 (%)	CW-stat
<i>Panel A: Bitcoin Market Characteristics Predictors</i>								
<i>BA</i>	0.85	3.96 ***	0.38	2.13 ***	0.03	0.65	-0.10	0.36
<i>BD</i>	1.64	2.95***	1.07	2.44 ***	-0.79	1.93 **	-2.90	1.55 *
<i>BETA</i>	0.58	1.99 ***	-0.91	-0.69	-2.81	-1.21	-2.64	-1.21
<i>DV</i>	-0.20	1.25	0.03	1.35 *	-0.73	0.45	-0.96	0.06
<i>ISK</i>	0.36	1.46 *	0.08	0.53	0.33	1.21	0.09	1.66 *
<i>IVOL</i>	0.57	2.00 ***	-0.43	-1.03	-1.99	-2.63	-3.24	-2.39
<i>RV</i>	0.85	3.32***	0.54	2.11 ***	0.10	0.46	-0.03	-0.01
<i>SK</i>	0.79	2.29 ***	1.15	1.96 **	0.68	1.34 *	0.12	0.48
<i>TEUSD</i>	0.86	3.51 ***	0.53	2.16 ***	0.07	0.49	-0.15	-0.25
<i>TSM</i>	0.37	1.73 ***	2.05	2.08 ***	1.80	1.99 ***	0.74	1.79*
<i>TSM SV</i>	1.25	2.98***	2.81	3.07 ***	2.01	2.81 ***	1.49	2.57***
<i>VOL</i>	0.60	2.10 ***	-0.18	-0.15	-1.40	-2.21	-2.56	-2.48
<i>VOLG</i>	0.88	3.09 ***	0.49	1.82 **	0.14	0.60	-0.12	-0.17
<i>Panel B: Stock Market Predictors</i>								
<i>CMA</i>	0.76	2.41 ***	0.51	1.67 **	0.19	0.92	-0.13	0.13
<i>HML</i>	0.59	2.30 ***	0.33	1.36 *	0.11	0.56	-0.21	-0.44
<i>MKTRF</i>	-0.14	1.34 *	-0.20	1.31 *	-0.68	0.92	-0.49	0.84
<i>RMW</i>	0.94	3.29 ***	0.45	2.11 ***	0.21	1.31 *	-0.27	0.83
<i>SMB</i>	0.96	3.45***	0.43	1.58 *	0.05	0.31	-0.22	-0.43
<i>UMD</i>	0.70	2.78 ***	0.29	1.19	-0.13	-0.01	-0.81	-1.43
<i>Panel C: Bond Market Predictors</i>								
<i>JUNK</i>	0.31	1.11	-0.41	0.30	-1.50	-0.62	-2.60	-1.48
<i>RF</i>	-0.76	0.62	-4.06	0.08	-7.91	-0.16	-9.52	-0.07

<i>TERM</i>	0.23	0.76	-0.76	-0.04	-2.32	-0.53	-2.57	-0.55
<i>Panel D: Uncertainty and Sentiment Predictors</i>								
<i>BBS</i>	0.59	2.11 ***	0.07	0.46	-0.36	-0.29	-0.54	-0.25
<i>GSI</i>	-3.71	0.28	-10.26	-0.26	-16.25	-0.33	-21.51	-0.45
<i>TMAX</i>	0.14	0.95	-0.54	-0.01	-1.45	-0.79	-2.02	-1.19
<i>Panel E: Uncertainty Predictors</i>								
<i>PU</i>	1.51	3.38 ***	1.47	2.83 ***	2.17	2.83 ***	2.35	2.80 ***
<i>FU</i>	3.31	3.08 ***	4.74	2.67 ***	5.99	2.42 ***	7.29	2.31 ***
<i>MU</i>	0.11	0.84	-0.81	-0.35	-2.02	-0.90	-2.66	-0.93
<i>RU</i>	0.38	1.75***	-0.32	1.11	-1.59	0.72	-2.33	0.52
<i>VIX</i>	-0.36	0.45	-1.29	-0.28	-1.82	-0.76	-2.32	-1.09
<i>VXD</i>	0.23	1.29*	-0.25	0.76	-0.42	0.42	-0.60	0.13
<i>VXN</i>	0.71	1.72 **	0.58	1.25	0.13	0.70	-0.68	0.13
<i>VXO</i>	0.08	0.93	-0.80	-0.02	-1.44	-0.54	-2.17	-0.94
<i>PCA</i>	0.69	1.53 *	0.34	0.87	-0.19	0.33	-0.85	-0.11

Table 8: Predictive Regressions via the Instrumental Variable (IVX) Approach

The table presents the results of univariate predictive regressions models, as the IVX-Wald refers to the Wald statistic. See Table 1 for the variable definitions of 33 predictors and their principal component.

	<i>h</i> = 7 days		<i>h</i> = 14 days		<i>h</i> = 21 days		<i>h</i> = 28 days	
	IVX-Wald	<i>p</i> -value	IVX-Wald	<i>p</i> -value	IVX-Wald	<i>p</i> -value	IVX-Wald	<i>p</i> -value
<i>Panel A: Bitcoin Market Characteristics Predictors</i>								
<i>BA</i>	10.61	0	8.71	0	4.7	0.03	8.11	0
<i>BD</i>	6.63	0.01	4.54	0.03	4.11	0.04	3.33	0.07
<i>BETA</i>	2.77	0.1	1.62	0.2	0.4	0.53	0.22	0.64
<i>DV</i>	2.84	0.09	3.09	0.08	1.02	0.31	1.24	0.27
<i>ISK</i>	0.64	0.43	0.01	0.94	0.58	0.45	1.44	0.23
<i>IVOL</i>	1.07	0.3	0.01	0.93	0.09	0.77	0.35	0.55
<i>RV</i>	2.6	0.11	0.18	0.67	2.22	0.14	0.05	0.83
<i>SK</i>	0.21	0.65	1.33	0.25	0.77	0.38	0.14	0.71
<i>TEUSD</i>	3.22	0.07	1.99	0.16	0.44	0.51	0.86	0.35
<i>TSM</i>	6.09	0.01	9.21	0	6.07	0.01	4.41	0.04
<i>TSMSV</i>	14.1	0	18.63	0	16.36	0	14.1	0
<i>VOL</i>	1.46	0.23	0.12	0.73	0.01	0.94	0.17	0.68
<i>VOLG</i>	7.08	0.01	1.13	0.29	0.35	0.56	0.13	0.72
<i>Panel B: Stock Market Predictors</i>								
<i>CMA</i>	0.05	0.82	0	0.96	0.06	0.81	0.11	0.74
<i>HML</i>	0.02	0.9	0.8	0.37	0.95	0.33	0.89	0.35
<i>MKTRF</i>	2.16	0.14	2.79	0.09	3.94	0.05	5.1	0.02
<i>RMW</i>	0.33	0.56	0.15	0.7	0.37	0.54	0.6	0.44
<i>SMB</i>	3.44	0.06	0.65	0.42	1.03	0.31	0.64	0.42
<i>UMD</i>	0.22	0.64	0.04	0.85	0.06	0.8	0.35	0.55

<i>Panel C: Bond Market Predictors</i>								
<i>JUNK</i>	0.69	0.41	0.59	0.44	0.67	0.41	0.68	0.41
<i>RF</i>	2.16	0.14	1.93	0.16	1.95	0.16	1.88	0.17
<i>TERM</i>	0.82	0.36	0.86	0.35	0.84	0.36	0.78	0.38
<i>Panel D: Sentiment Predictors</i>								
<i>BBS</i>	0.47	0.49	0.14	0.71	0.14	0.71	0.22	0.64
<i>GSI</i>	0.09	0.77	0.62	0.43	1.54	0.21	1.66	0.2
<i>TMAX</i>	0.05	0.83	0.04	0.83	0.01	0.93	0	0.95
<i>Panel E: Uncertainty Predictors</i>								
<i>PU</i>	4.06	0.04	5.25	0.02	7.32	0.01	9.82	0
<i>FU</i>	9.3	0	9	0	8.89	0	8.94	0
<i>MU</i>	0.69	0.41	0.7	0.4	0.64	0.42	0.53	0.47
<i>RU</i>	0.63	0.43	0.71	0.4	0.65	0.42	0.55	0.46
<i>VIX</i>	6.34	0.01	5.94	0.01	5.35	0.02	5.17	0.02
<i>VXD</i>	6.83	0.01	6.35	0.01	5.77	0.02	5.4	0.02
<i>VXN</i>	7.81	0.01	7.04	0.01	5.84	0.02	5.1	0.02
<i>VXO</i>	6.84	0.01	5.69	0.02	5.09	0.02	4.78	0.03
<i>PCA</i>	6.82	0.01	6.08	0.01	5.07	0.02	4.47	0.03

Table 9: Predictive Regression Structural Stability Test.

This table presents the Elliott and Müller (2006) qLL statistic for the predictive regression model. The qLL statistic is for testing the null hypothesis that the intercept and slope coefficients are constant. The 10%, 5%, and 1% critical values for the qLL statistics are -12.80, -14.32, and -17.57, respectively (Elliott and Müller, 2006). See Table 1 for the variable definitions of 33 predictors and their principal component.

	<u>$h = 7$ days</u>	<u>$h = 14$ days</u>	<u>$h = 21$ days</u>	<u>$h = 28$ days</u>
	qLL statistics	qLL statistics	qLL statistics	qLL statistics
Panel A: Bitcoin Market Characteristics Predictors				
<i>BA</i>	-1.92	-6.23	-5.79	-3.05
<i>BD</i>	-5.48	-6.25	-8.76	-10.29
<i>BETA</i>	-2.34	-3.73	-4.72	-4.16
<i>DV</i>	-1.07	-1.77	-3.22	-1.48
<i>ISK</i>	-4.44	-3.09	-3.91	-4.79
<i>IVOL</i>	-3.56	-3.42	-2.79	-3.27
<i>RV</i>	-0.77	-0.73	-0.75	-1.15
<i>SK</i>	-4.13	-3.66	-4.35	-4.3
<i>TEUSD</i>	-1.21	-1.55	-1.63	-1.38
<i>TSM</i>	-2.25	-1.08	-1.08	-1.28
<i>TSMSV</i>	-2.97	-3.71	-4.62	-4.31
<i>VOL</i>	-3.73	-3.23	-2.3	-2.8
<i>VOLG</i>	-1.57	-0.7	-1.02	-1.43
Panel B: Stock Market Predictors				
<i>CMA</i>	-2.86	-2.17	-5.95	-6.33
<i>HML</i>	-3.01	-2.13	-3.65	-3.75
<i>MKTRF</i>	-7.07	-10.66	-11.79	-8.57
<i>RMW</i>	-2.27	-3.2	-3.81	-4.82
<i>SMB</i>	-4.09	-5.75	-3.91	-2.54

<i>UMD</i>	-5.95	-4.37	-4.96	-9.44
<i>Panel C: Bond Market Predictors</i>				
<i>JUNK</i>	-5.23	-5.04	-4.85	-4.83
<i>RF</i>	-7.7	-7.81	-7.84	-7.92
<i>TERM</i>	-10.29	-8.41	-8	-7.78
<i>Panel D: Sentiment Predictors</i>				
<i>BBS</i>	-7.05	-7.61	-7.1	-5.5
<i>GSI</i>	-4.01	-4.63	-5.01	-4.97
<i>TMAX</i>	-11.88	-9.06	-7.89	-7.15
<i>VIX</i>	-5.48	-5.49	-5.82	-5.92
<i>VXD</i>	-5.98	-5.86	-6.04	-6.47
<i>VXN</i>	-6.49	-6.46	-7.06	-7.68
<i>VXO</i>	-5.58	-5.5	-6.1	-6.17
<i>Panel E: Uncertainty Predictors</i>				
<i>PU</i>	-7.65	-9.88	-8.87	-9.89
<i>FU</i>	-2.85	-2.67	-2.54	-2.49
<i>MU</i>	-5.43	-5.09	-4.86	-4.86
<i>RU</i>	-5.94	-7.76	-8.32	-8.66
<i>VIX</i>	-5.48	-5.49	-5.82	-5.92
<i>VXD</i>	-5.98	-5.86	-6.04	-6.47
<i>VXN</i>	-6.49	-6.46	-7.06	-7.68
<i>VXO</i>	-5.58	-5.5	-6.1	-6.17
<i>PCA</i>	-5.46	-5.46	-5.92	-6.29

Table 10: Density Forecast

This table presents the weighted likelihood ratio test statistic of Amisano and Giacomini (2007) for pairwise comparison of the performance of two density forecasts. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. See Table 1 for the variable definitions of 33 predictors and their principal component.

	<i>h</i> = 7 days		<i>h</i> = 14 days		<i>h</i> = 21 days		<i>h</i> = 28 days		
	weighted likelihood ratio	<i>t</i> -stat	weighted likelihood ratio	<i>t</i> -stat	weighted likelihood ratio	<i>t</i> -stat	weighted likelihood ratio	<i>t</i> -stat	
<i>Panel A: Bitcoin Market Characteristics Predictors</i>									
<i>BA</i>	0.16	1.66*	0.04	0.38	0.04	0.58	0.09	1.09	
<i>BD</i>	0.71	2.19**	0.83	2.17**	0.57	1.29	0.17	0.32	
<i>BETA</i>	0.08	0.58	-0.07	-0.99	-0.55	-4.99	-0.62	-4.72	
<i>DV</i>	-0.25	-1.21	-0.03	-0.2	-0.26	-1.1	-0.26	-1.15	
<i>ISK</i>	-0.19	-1.99	-0.11	-4.08	0.15	1.17	0.26	1.3	
<i>IVOL</i>	0.23	2.04**	-0.04	-0.77	-0.42	-12.43	-0.71	-11.93	
<i>RV</i>	0.04	16.57***	0	-5.75	0	0.61	0	-12.05	
<i>SK</i>	0	0.08	0.28	2.33**	0.21	2.27**	0.04	0.8	
<i>TEUSD</i>	0.01	0.1	-0.04	-0.36	-0.09	-0.85	-0.1	-0.78	
<i>TSM</i>	0.57	2.56**	1.6	4.43***	1.31	4.91***	0.96	4.25***	
<i>TSMSV</i>	1.28	3.46***	2.61	4.66***	2.55	4.68***	2.32	4.48***	
<i>VOL</i>	0.24	1.97**	0.03	0.38	-0.28	-8.31	-0.57	-13.18	
<i>VOLG</i>	0.56	6.44***	0.25	4.91***	0.14	4.46***	0.06	2.78***	
<i>Panel B: Stock Market Predictors</i>									
<i>CMA</i>	-0.02	-0.42	-0.02	-0.49	-0.04	-1	-0.07	-1.66	
<i>HML</i>	-0.04	-0.54	-0.05	-1.29	-0.01	-0.52	-0.05	-2.07	
<i>MKTRF</i>	-0.15	-1.45	-0.11	-0.96	-0.09	-0.75	-0.01	-0.06	

<i>RMW</i>	0.03	0.43	0	-0.03	0.05	0.61	-0.02	-0.13
<i>SMB</i>	0.1	1.12	-0.03	-0.8	-0.03	-0.7	-0.07	-1.75
<i>UMD</i>	-0.04	-0.56	-0.09	-1.72	-0.09	-1.51	-0.2	-3.38

Panel C: Bond Market Predictors

<i>JUNK</i>	-0.12	-2.53	-0.26	-3.69	-0.42	-5.52	-0.59	-7.52
<i>RF</i>	-0.54	-1.71	-1.38	-2.75	-2.09	-3.36	-2.65	-3.53
<i>TERM</i>	-0.08	-0.68	-0.21	-1.35	-0.38	-2.08	-0.53	-2.43

Panel D: Sentiment Predictors

<i>BBS</i>	0.02	0.49	-0.14	-3.37	-0.28	-5.3	-0.27	-4.3
<i>GSI</i>	-1.26	-2.5	-2.77	-4.17	-3.91	-5.78	-5.65	-6.85
<i>TMAX</i>	-0.14	-1.52	-0.26	-2.38	-0.4	-3.78	-0.51	-4.82

Panel E: Uncertainty Predictors

<i>PU</i>	0.41	2.42**	0.69	2.35**	1.23	3.04***	1.64	3.32***
<i>FU</i>	1.06	2.74***	1.84	3.77***	2.46	4.73***	3.11	5.41***
<i>MU</i>	-0.11	-1.75	-0.23	-2.48	-0.4	-3.73	-0.58	-4.77
<i>RU</i>	-0.06	-0.58	-0.15	-0.96	-0.28	-1.61	-0.44	-2.27
<i>VIX</i>	-0.24	-1.15	-0.39	-1.6	-0.28	-1.59	-0.33	-2.28
<i>VXD</i>	0	-0.01	0.04	0.15	0.26	1.33	0.29	1.82*
<i>VXN</i>	0.24	1.02	0.42	1.63	0.5	2.69***	0.33	2.27**
<i>VXO</i>	-0.07	-0.34	-0.19	-0.86	-0.15	-0.89	-0.29	-2.01
<i>PCA</i>	0.21	1.05	0.33	1.51	0.32	2.06	0.16	1.26