Intraday return predictability in the cryptocurrency markets: momentum, reversal, or both

Zhuzhu Wen[a], Elie Bouri[b], Yahua Xu[*, c], Yang Zhao[d]

[a] *PBC School of Finance, Tsinghua University, China*

[b] *School of Business, Lebanese American University, Lebanon*

[c] *China Economics and Management Academy, Central University of Finance and Economics, China*

[d] *Chinese Academy of Finance and Development, Central University of Finance and Economics, China*

Abstract

This paper reports evidence of intraday return predictability, consisting of both intraday momentum and reversal, in the cryptocurrency market. Using high-frequency price data on Bitcoin from March 3, 2013, to May 31, 2020, it shows that the patterns of intraday return predictability change in the presence of large intraday price jumps, FOMC announcement release, liquidity levels, and the outbreak of the COVID-19. Intraday return predictability is also found in other actively traded cryptocurrencies such as Ethereum, Litecoin, and Ripple. Further analysis shows that the timing strategy based on the intraday predictors produces higher economic value than the benchmark strategy such as the always-long or the buy-and-hold. Evidence of intraday momentum can be explained in light of the theory of late-informed investors, whereas evidence of intraday reversal, which is unique to the cryptocurrency market, can be related to investors' overreaction to non-fundamental information and overconfidence bias.

Keywords: intraday return predictability; cryptocurrency markets; Bitcoin; momentum; reversal; economic value; market timing strategy

JEL classification: G1; C5; Q3; Q4

* Corresponding author: China Economics and Management Academy, Central University of Finance and Economics, No. 39 South College Road, Haidian District, 100081 Beijing, China. Email: yahua.xu@cufe.edu.cn.

1. Introduction

Being one of the most pervasive market anomalies, momentum has drawn considerable attention from academics and practitioners. The cross-sectional momentum strategy was first identified by Jegadeesh and Titman (1993), indicating that the trading strategy of buying outperforming stocks and selling underperforming stocks over the past three months to a year that can generate substantial profits in the next three months to a year.[1] Later, time-series momentum has been documented by Moskowitz et al. (2012), reflecting the persistency of stock returns over short horizons. Despite the growing body of literature on momentum (see, Kim and Suh, 2021; Li, 2020), it has almost confined to data at the monthly or weekly frequency until Gao et al. (2018) first extend the research on momentum to the intraday level in the equity market.[2] Such an extension is important given the emergence of high frequency trading that has shaped not only the way market participants trade securities but the structure of the market and the evolvement of liquidity and price discovery (OHara, 2015). Some recent empirical research has provided evidence of intraday return predictability on other conventional markets such as currency and commodity Exchange-traded-Funds (ETFs) (Elaut et al., 2018; Jin et al., 2020; Wen et al., 2020; Zhang et al., 2019), where for most cases, the first half-hour return, which contain overnight market information, significantly and positively predicts the last half-hour return of the same trading day. As possible explanations, Gao et al. (2018) draw upon the infrequent trading behavior of investors and the presence of late-informed traders who are very slow in digesting and reacting to the arrival of information.

Over the past years, cryptocurrencies, such as Bitcoin (BTC)[3], have emerged as a new asset class that continues to earn more legitimacy and acceptability in their quest to act as an

[1] Several other studies such as Griffin et al. (2003) and Grinblatt et al. (1995) confirm the cross-sectional momentum.
[2] Previous studies indicate that intraday price data have properties that are different from those of daily closing prices.
[3] Notably, Bitcoin takes the dominant role in the rapidly burgeoning cryptocurrency markets (Ferreira and Pereira, 2019; Ji et al. 2019; Wang and Ngene, 2020).

alternative to fiat currency. Their ecosystem has become wider and more integrated with business models and mainstream finance. From the perspective of investment and speculation, cryptocurrencies are now a hot investment instrument that competes with major physical commodities and conventional assets such as stocks and bonds, although their size portion in the trading volume and market capitalization of financial markets remains relatively small. The fact that cryptocurrencies are decentralized by construction make them somewhat detached from the global financial system, which has been bringing changes to the investment scene and to asset allocation and risk management decisions. Notably, cryptocurrencies differ from traditional assets in their continuous trading mechanism (i.e., they are available to trade 24 hours a day, seven days a week) and the large participation by global retail investors. Conversely, traditional assets only trade during weekdays and trading hours, and the role of institutional investors such as mutual funds on the traditional markets is very influential. Cryptocurrencies exhibit burgeoning popularity, due to their rapid price appreciation and a high ability to diversify global uncertainty (Bouri et al., 2017) and stock portfolio risk (e.g., Kajtazia and Moro, 2019; Hatemi-J et al., 2020).[4] Besides, time-series momentum has also been identified in the cryptocurrency market (e.g., Borgards, 2021; Lin et al., 2021).

From the intraday perspective, high-frequency traders are very active in the cryptocurrency market and exploit the incredible rise of computing power. Some recent studies apply intraday price data in the cryptocurrency market but limit their analysis to hedging (e.g., Meshcheryakov and Ivanov, 2020), return spillovers or volatility spillovers (Katsiampa et al., 2019; Wang and Ngene, 2020; Yousaf and Ali, 2020), risk-return relationship (Ahmed, 2020), role of algorithm trading (Petukhina et al., 2020), and market efficiency (Naeem et al., 2020). Furthermore, Wang and Ngene (2020) provide a preliminary understanding of intraday price behavior and interactions among cryptocurrencies, Bouri et al. (2021) considers the return curves of bitcoin, whereas Eross et al. (2019) focus on the intraday volume, volatility and liquidity throughout the trading day of Bitcoin. However, even though there are rising concerns about intraday return predictability and its substantial economic value, most of them are confined to the

[4] There are around 55 million cryptocurrency wallet users around the world and the cumulative market capitalization of cryptocurrencies was 237 billion U.S. dollars in 2019, according to data from Statista.

conventional assets such as equity (Gao et al., 2018; Li et al., 2021), commodities (Jin et al., 2020), foreign exchanges (Elaut et al., 2018), whereas similar discussions in the cryptocurrency market are very limited. Instead, we analyze the continuous 24-hour trading for fully explore the special trading mechanism of the cryptocurrency markets.

In this study, we address this research gap by providing a thorough analysis of the intraday return predictability in the cryptocurrency market. Notably, the Bitcoin market is ideal for examining the intraday return predictability since it takes the dominant role in the cryptocurrency markets[5], and our use of high frequency data may help uncovering crucial intraday information and essential aspects of the price process in this controversial cryptocurrency market.

We are motivated to analyze the intraday predictability patterns in the cryptocurrency market by several reasons. Firstly, unlike equities and ETFs which can only react to news release in the official trading hours during the week and the pre-market and after-hours trading sessions, Bitcoin and other leading cryptocurrencies trade continuously 24 hours per day and seven days a week globally, which make them respond to the market news in a timelier way since there is no trading break. Such an unusual feature could possibly render the intraday return predictability of Bitcoin and other cryptocurrencies dissimilar from that of conventional assets. Notably, even though the prices of both equities and cryptocurrencies are determined by supply demand as well as market fundamentals and behaviour/sentiment, the intraday volume does not necessary show a U-shaped pattern (i.e., high volume is not necessarily in the first and last hours) similar to the one shown by Gao et al. (2018) in the equity market. Motivated by the importance of the shape of intraday trading volume for intraday return predictability (e.g., Gao et al., 2018), we will look further into this issue in the cryptocurrency markets and check whether shapes of the intraday trading volume of cryptocurrency markets matter for its intraday return predictability, since the unique features of the cryptocurrency market necessitate a thorough and exhaustive analysis and might indicate that the patterns of

[5] By the middle of 2019, the relative market capitalization of BTC is around 55.8% of the global cryptocurrency market, and its absolute market capitalization is around $200 billion in the first quarter of 2019. Please refer to https://www.coinmarketcap.com, and https://www.statista.com.

intraday return predictability in the cryptocurrency market are different from those in the equity market.

Secondly, cryptocurrency markets are young and immature, attracting unexperienced young investors and speculators exhibiting irrational investment behavior, animal spirit, and the fear of missing out (Bouri et al., 2019). Furthermore, no robust fundamental models exist to calculate the value of Bitcoin. The latter may distinguish itself from other conventional assets in terms of the intraday price dynamics. The different intraday dynamics could be the driver of the different intraday return predictability pattern, which deserves an in-depth analysis.

Thirdly, in contrast to the traditional standardized investment products such as equity and commodity ETFs that are traded on standard and regulated exchanges, cryptocurrencies are traded on unregulated marketplaces (although most often they are called exchanges) that are quite similar to the over-the-counter (OTC) market that lacks appropriate legal and regulatory frameworks. This makes Bitcoin prices highly subject to speculative furies and thus to price explosivity (Bouri et al., 2019; Fry and Cheah, 2016). Accordingly, Bitcoin may exhibit distinctive intraday predictability pattern whereas Gao et al. (2018) find that in the equity market only the first and second-to-last half-hour returns positively and significantly predict the last half-hour, which arouses our interest.

Using high-frequency (hourly) data of cryptocurrency markets, this current study provides several important contributions to the existing literature. Firstly, we show that the intraday return predictability exists in the cryptocurrency market, which complements previous studies that restrict their analysis to standardized financial products such as equity and commodity ETFs (e.g., Elaut et al., 2018; Jin et al., 2020; Wen et al., 2020; Zhang et al., 2019). Notably, we find that the signs of the intraday predictors are not solely positive as those in the conventional markets, but can also be negative. Such a difference highlights the essential distinction and trading mechanism between the cryptocurrency market and the traditional standardized financial markets.

Secondly, we analyze the impacts of the intraday jump, liquidity, and FOMC announcements by splitting the sample into subsamples accordingly, and our results show that intraday return predictability patterns of the subsamples differ from each other. In fact, the intraday return predictability tends to be stronger when there is no jump, no FOMC announcement release, and low liquidity, which differs from previous findings in the conventional financial markets (Gao et al., 2018; Wen et al., 2020). Moreover, we find that the outbreak of the COVID-19 exhibits significant impacts on the intraday return predictability in the cryptocurrency market, as reflected in the changing pattern of intraday return predictability during the COVID-19 period. This finding extends previous studies regarding the effect of the pandemic on the cryptocurrency markets (Naeem et al., 2020; Shahzad et al., 2020; Yousaf and Ali, 2020).

Thirdly, we evaluate the economic implications of the findings by showing that the timing strategy based on the efficient intraday predictor generates substantially higher profits compared to the benchmark strategies. Given the ability of traders to develop a profitable trading strategy based on historical intraday returns, this interesting finding somewhat points to the inefficiency of the Bitcoin market.

Fourthly, we implement robustness checks by using other cryptocurrencies such as Ethereum (ETH), Litecoin (LTC) and Ripple (XRP), traded in different leading digital asset trading platforms, and provide evidence of intraday return predictability.

Our current work adds to the strand of literature about the intraday return predictability in conventional assets (e.g., Elaut et al., 2018; Jin et al., 2020; Wen et al., 2020; Zhang et al., 2019) by considering the understudied cryptocurrency markets. To the best of our knowledge, our current work is the first one to consider the intraday return predictability in the controversial cryptocurrency market.

The rest of this paper is structured as follows. Section 2 describes the data and Section 3 presents the methodology. Section 4 provides the empirical analysis on intraday return predictability. Section 5 provides an economic value analysis using a market timing strategy and possible economic interpretations. Section 6 conducts a robustness analysis involving leading cryptocurrencies other than Bitcoin. Section 7 provides some concluding remarks.

2. Data description

2.1. Cryptocurrency price data and other variables of interest

We consider price data on Bitcoin (BTC), the leading cryptocurrency both in terms of trading volume and market capitalization. As a new asset, BTC arouses some debates but high interest from the investors and the academic community. One distinguished feature is that BTC trades 24 hours around, which is quite different from the trading mechanism in the standardized market such as the US equity market where there is an overnight break and trading normally occurs from 9:30 to 16:00 EST. Even though the competition brought by newly introduced cryptocurrencies such as Ethereum becomes increasingly fierce, Bitcoin remains the leading cryptocurrency with a market capitalization representing 55.8% of the total market capitalization of all cryptocurrencies, followed by Ethereum (10.13%), as of June, 2019 (Wang and Ngene, 2020). Besides, Bitcoin shows dominant influences towards changes in prices of other cryptocurrencies (Ferreira and Pereira, 2019), and serves as the primary driver of interconnectedness of mostly used cryptocurrencies (Ji et al. 2019). Considering the dominance of Bitcoin, our main analysis considers the intraday return predictability in the Bitcoin market.

Our Bitcoin price data are at the 5-min frequency, covering the exchange rate of Bitcoin against the USD, downloaded from https://bitcoincharts.com/. The data are provided by Bitstamp which is one of the largest well established Bitcoin exchanges.[6] It is originally designed to be a European-focused alternative to Mt. Gox, and serves as the market leader with the equally important information share as Mt. Gox (e.g., Brandvold et al., 2015).[7] The detailed information of rapid burgeoning of Bitcoin trading can be found in Appendix A.1.

In contrast to the previous studies using the half-hour returns for the intraday prediction, we focus on hourly intraday returns computed using the 5-minute high-frequency trading prices.[8] The main reason to use hourly returns instead of half-hour returns resides in that the

[6] Bitstamp is a leading cryptocurrency exchange, located in Luxembourg, where trading between flat currency and major cryptocurrencies such as Bitcoin is allowed. Prices are given according to Greenwich Mean Time (GMT).

[7] Mr. Gox was the largest bitcoin intermediary and the world's leading bitcoin exchange, located in Tokyo, Japan, before its bankruptcy on Feb 26, 2014.

[8] According to Anderson (2000), the 5-minute frequency is the best compromise between having enough number of observations and avoiding trading noise issues.

Bitcoin market trades continuously on a 24-hour basis, whereas conventional financial markets only trades from 9:30 to 16:00, around 6.5 hours a day, and thus using half-hour intraday returns tends to produce redundant and lengthy tables. Thus, 24 hourly returns are generated per trading day, as illustrated by Eq. (1)

$$r_{i,t} = log(p_{i,t}) - log(p_{i-1,t}), i = 1, 2, \dots, 24, t = 1, 2, \dots, T, \tag{1}$$

where $p_{i,t}$ is the hourly close price at *i*s hour, $p_{0,t}$ denotes the price at 0:00 am on the trading day *t*, and *T* is the total number of the trading days of the sample.[9]

Besides, we construct related variables including trading volume, realized volatility, and Amihud (2002) ratio in each hourly interval forgetting to know the intraday dynamics of the Bitcoin market. Specifically, the realized volatility (RV) and Amihud (2002) ratio (ILLIQ) can be computed using Eq. (2) and Eq. (3), respectively.

$$RV_t = \sum_{i=1}^{T} r_i^2, \tag{2}$$

where r_i is the *i*th 5-min return, and *T* denotes the total number of the 5-min return during a trading day *t*.

$$Amihud = \frac{|r_t|}{Volume_t}, t = 1, 2, \dots, 24, \tag{3}$$

where r_t and $Volume_t$ denote the return and the trading volume in the *t*th hourly interval, respectively.

Table 1 presents the yearly descriptive statistics for the variables of interest such as return, trading volume, realized volatility, Amihud (2002) ratio, and realized jumps, from April 1, 2013 to May 1, 2021. The mean returns are negative in the year 2014 and 2018, with values of -0.01 and -0.02, respectively, and they are nonnegative in the other years. The standard deviation of returns varies a lot across the time, which reaches the highest value of 2.25 in 2013 and the lowest value of 0.52 in 2016. Although the small magnitudes of the average returns, the

[9] For the standardized financial market, the trading period normally starts from 9:30 am and ends in 16:00 pm, which leads to 13 half-hour returns in a trading day. However, the BTC market trades 24 hours a day, and thus the number of observations will be too high if we take half-hour returns.

magnitude of the minimum and maximum hourly returns are substantially larger, suggesting volatile price movements. Except in the years of 2018 and 2021, return distributions are negatively skewed with excess kurtosis, revealing leptokurtic distributions. Besides, we report the trading volume and Amihud (2002) ratio of each year, which also varies across time. Specifically, both trading volume and Amihud (2002) ratio reaches the highest value in 2013. Trading volume goes through a drastic increase from 2016 to 2017, which coincides with the large price increase in the Bitcoin market, whereas the Amihud (2002) ratio decreases sharply meanwhile. The realized volatility and jump statistics are constructed to capture the continuous and discontinuous price movements, respectively, whose mean values reach the maximum in 2013 and the relative descriptive statistics such as standard deviation, skewness, and kurtosis tend change over time. Overall, the yearly descriptive statistics demonstrate that there are large variations across the time for the behavior of the Bitcoin market.

[Insert Table 1 about here]

2.2. Intraday trading patterns

It is well known that the intraday trading volume exhibits a U-shaped pattern in the equity market (e.g., Gao et al., 2018; Zhang et al., 2019) which is linked to the normal trading hours of traditional exchanges, however, empirical evidence on intraday trading pattern in the Bitcoin market is very limited. In an interesting paper, Eross et al. (2019) who provide an analysis of intraday dynamics of the Bitcoin market and find that even though the trading volume, realized volatility, and liquidity are related to the opening of major global exchanges, the intraday trading pattern of Bitcoin market is very different due to its 24-hour and 7 days a week continuously trading mechanism.

We calculate the averages trading volume and Amihud (2002) ration in each hourly interval, shown by Fig.1 (a) and Fig.1 (b), respectively. Fig.1(a) provides the visual depiction of the intraday trading volume. In the early day, the trading volume is at a relatively low level from 1:00 a.m. to 7:00 a.m. GMT time, maybe due to the inactive trading activity during this period.

Then, the trading volume rises up continuously after 8:00 a.m. until it peaks at 15:00 p.m., consistent with the opening hours of major global exchanges, especially the European ones. After 16:00 p.m., the trading volume starts to decrease until the mid-night. Overall, the trading volume does not exhibit a U-shaped pattern, which is very different from that seen in equity market (Gao et al., 2018). One reason for the non-U shaped pattern might be related to the 24-hour continuous trading mechanism in the Bitcoin market with investors from all over the world; it subsequently follows that a U-shaped pattern in some time zones might be mixed with non- or inverse-U-shaped patterns in the other time zones (Eross et al., 2019). The other reason might be related with the absence of informed traders in the Bitcoin market that contains mostly less informed and unexperienced traders, since informed traders do not need postpone their trading, as pointed out by Elaut et al. (2018).

We also present the intraday pattern of the illiquidity measured by the Amihud measure (Amihud, 2002) which captures the price changes per unit change of the trading volume, presented by Fig.1 (b). As expected, the illiquidity level is negatively correlated with the intraday trading volume. More specifically, the illiquidity level remains relatively high from 1:00 a.m. to 7:00 a.m., and then it starts to decrease and reaches the bottom at around 16:00 p.m., which corresponds to the regular trading hours of the major equity exchanges in Europe. The illiquidity level keeps rising up thereafter. In sum, the high trading volume corresponds to the low illiquidity throughout the day in Bitcoin market. Notably, previous research further explores the predicting source of the first half-hour returns of intraday momentum in conventional financial markets, and finds that in some market such as Chinese equity market, soybean and copper markets, the open market component, namely, returns between the first half-hour trading session, is the dominant forecasting component, whereas in some other markets such as soybean meal and steel rebar, both the overnight component (i.e., return between previous days market close and next days market open) and the open market component contribute to the intraday momentum (Gao et al., 2019; Jin et al., 2020).[10]

[10] In the literature of intraday momentum, it is common to define the first half-hour return as the log return difference between 10:00 am (i.e., the end of the first half-hour trading session) and previous days market close price. Therefore, the first half-hour return contains both overnight component (i.e., return between previous days market close and next days market open) and open market component (i.e., return between market open and end of the first half-hour trading session).

[Insert Figure 1 about here]

3. Methodology

We investigate the intraday return predictability in the BTC market by checking the predictability of hourly returns earlier in the day against their counterparts later of the same trading day. Specifically, we implement both in-sample (IS) and out-of-sample (OOS) analysis as in Gao et al. (2018).

3.1. In-sample analysis

In the IS predictability analysis, we check the intraday return predictability of each hourly returns in the *i*th trading hour by regressing the hourly returns in the *j*th trading hour of the same day on it, with $i < j$, shown by Eq. (4) as follows:

$$r_{j,t} = \alpha_{i,j} + \beta_{i,j} r_{i,t} + \varepsilon_{ij,t},\ i,j = 1,2,\dots,24,\ i < j, \tag{4}$$

where $r_{j,t}$ is the *j*th hourly return on trading day *t*, and $r_{i,t}$ is the *i*th hourly return earlier on the same day. Moreover, $\alpha_{i,j}$, $\beta_{i,j}$ and $\varepsilon_{ij,t}$ are the intercept, slope, and residual terms, respectively. If the slope term $\beta_{i,j}$ is positive and significant then there is evidence of intraday return predictability, whereas if it is negative and significant there is evidence of intraday reversal.

3.2. Out-of-sample analysis

We also conduct the OOS prediction analysis by examining the robustness of the intraday predictability in the Bitcoin market, since the good IS predictability does not necessarily imply the efficient OOS prediction (Gao et al., 2018; Zhang et al., 2019; Wen et al., 2020; Welch and

Goyal, 2008).

We implement the OOS analysis by dividing the whole sample into two subsamples, where the one for IS analysis containing observations spanning from April 1, 2013 to December 31, 2016, and the one for OOS analysis containing q observations spanning from January 1, 2017 to May 1, 2021. We run the initial regression to obtain the coefficients $\hat{\alpha}_{i,j}^{p}$ and $\hat{\beta}_{i,j}^{p}$, and calculate the first forecast $\hat{r}_{j,p+1}$ by following Eq. (5),

$$\hat{r}_{j,p+1} = \hat{\alpha}_{i,j}^{p} + \hat{\beta}_{i,j}^{p} r_{i,p+1}, \tag{5}$$

where $r_{i,p+1}$ is the ith hourly return of the p+1 observation.

Regarding the OOS forecasts, we expand the estimation window by progressively adding one month of return observations each time and then run the regression Eq. (4), and thus obtain the coefficients $\hat{\alpha}_{i,j}^{p+1}$ and $\hat{\beta}_{i,j}^{p+1}$. The next forecast $\hat{r}_{j,p+2}$ is calculated as follows:

$$\hat{r}_{j,p+2} = \hat{\alpha}_{i,j}^{p+1} + \hat{\beta}_{i,j}^{p+1} r_{i,p+2}, \tag{6}$$

where the $r_{i,p+2}$ is the ith hourly return of the p+2 observations. By performing in this way recursively, we get the q OOS forecast $\hat{r}_{j}$.

Finally, we compute the OOS R-square (i.e., R_{os}^2) to assess the efficiency of the OOS predictability as in Eq. (7),

$$R_{os}^2 = 1 - \frac{\sum_{t=1}^{t=T}\left(r_{j,t} - \hat{r}_{j,t}\right)^2}{\sum_{t=1}^{t=T}\left(r_{j,t} - \bar{r}_{j,t}\right)^2}, \tag{7}$$

where $r_{j,t}$ denotes the actual hourly return, $\hat{r}_{j,t}$ is the forecasted hourly return estimated from the sample through t-1, and $\bar{r}_{j,t}$ is the historical hourly return during the same period. If the OOS R-square is positive, then the OOS predictability is superior to the historical average return (Campbell and Thompson, 2008).

4. Empirical analysis

4.1. Results of intraday return predictability

Table 2 shows the results for the efficient intraday predictability. For brevity, we only report the results showing both IS and OOS are statistically significant. Specifically, only the efficient results with the IS predictability significance level above 5% and the positive OOS R-square are reported.[11] As shown in the Table 2, The pair $r_i \sim r_j$ denotes the predictability of the ith hourly return to the jth hourly return, i.e., r_i and r_j denote the independent (i.e., intraday predictors) and the dependent variables, respectively. We can see the intraday return predictability exists pervasively. Interestingly, the predictive sign is not always positive as it is in the standardized financial (equity) markets (Gao et al., 2018), which indicates that both intraday momentum and reversals exist in the Bitcoin market. There are totally 7 pairs where the predictability is efficient for both IS and OOS analysis, for 5 of which the predictive sign is negative. Table 2 shows that the predictive coefficients are positive for the pairs $r_3 \sim r_{17}$ and $r_8 \sim r_{22}$, and negative for the pairs $r_3 \sim r_5$, $r_3 \sim r_{15}$, $r_{10} \sim r_{11}$, $r_{12} \sim r_{13}$ and $r_{22} \sim r_{23}$. To be specific, the hourly returns r_3 positively predict r_{17} with the coefficient of 0.09 and t-stat of 2.77; r_8 positively predict r_{22} with the coefficient of 0.13 and t-stat of 3.60. Notably, the above positive intraday predictors are within the regular trading hours of major exchanges. On the other hand, there are negative predictability for the pairs $r_3 \sim r_5$, $r_3 \sim r_{15}$ and $r_{12} \sim r_{13}$, at the 1% significance level, whereas for the pairs $r_{10} \sim r_{11}$ and $r_{22} \sim r_{23}$, at the 5% significance level. Notably, those negative predictors are normally outside of the regular trading hour of the major stock exchanges. In contrast, those results are quite different from the findings in the equity and commodity markets where only intraday momentum exists, that is, normally the first half-hour returns positively and efficiently predict last half-hour returns (Gao et al., 2018; Wen et al., 2020). However, due to the specific 24-hour continuous trading mechanism of the Bitcoin market, the predictors within the normal trading hours of major stock exchanges with high trading volume and liquidity tend to exhibit a positive forecasting power, whereas the predictors outside the normal trading hours tend to exhibit a negative forecasting power. In other words, both intraday momentum and reversals exist in the Bitcoin market within and outside of normal trading hours, mainly due to its 24-hour and 7 days a week continuously

[11] In unreported results, we have implemented the IS and OOS analysis, respectively, and the sizes of tables tend to be very large so we did not report them here. The specific tables are available from the authors upon requests.

trading mechanism and investors (especially retail investors) trading all over the world, which is quite different from the traditional financial assets traded on standard exchanges during regular trading hours.

[Insert Table 2 about here]

Given that the summary statistics show the presence of large price variations across the time for the behavior of the Bitcoin market, we compute the Jarque-Bera statistic for daily BTC return data from Aug 15, 2010 to May 1, 2021 and find evidence that BTC returns are not normally distributed. Therefore, we run quantile regressions. The results reported in Appendix Table A.1 show that the patterns of intraday return predictability remain the same across various quantiles, consistent with the results of the OLS regression. Therefore, using simple OLS regression is enough for our empirical analysis and provides robust results.

4.2. Impacts of intraday jump on intraday return predictability

Jumps usually measure the sudden and large infrequent movements of stock prices, and link with the discontinuous component of the realized volatility (e.g., Barndorff-Nielsen and Shephard, 2004, 2006). In a recent study, Wen et al. (2020) document the impacts of the jump on intraday predictability in the commodity markets, that is, the predictability of the first half-hour return to the last half-hour return is stronger during the days with jumps in the first half-hour interval. In this section, we conduct similar analysis to check the possible impacts of jumps on the intraday predictability in the Bitcoin market[12].

The jumps in each hourly interval are calculated following Barndorff-Nielsen and Shephard (2004, 2006) and Jiang and Oomen (2008). The detailed calculating procedure is given in the Appendix. We split all the observations into two sub-samples according to whether the jump exists in the ith hourly interval. Then, the regression (4) is applied to each sub-sample to examine the predictability of the ith hourly return (i.e., r_i) to the jth hourly return (i.e., r_j).

Table 3 presents the results for the impacts of the jumps on the intraday predictability.

[12] Ahmed (2020) considers jump variation in their analysis of the risk-return relationship in the Bitcoin market.

Panel A documents the results for the sub-sample with the existence of jumps. Only for the pair r_{12}~r_{13}, the predictability is statistically significant at the level of 5%. Panel B shows the results for the sub-sample with no jump. The predictability remains statistically significant for all pairs as in the whole sample, that is, positive intraday predictors for the pairs r_3~r_{17} and r_8~r_{22}, and negative for the pairs r_3~r_5, r_3~r_{15}, r_{10}~r_{11}, r_{12}~r_{13} and r_{22}~r_{23}. Overall, the intraday predictability pattern changes when there exist jumps. To be specific, intraday jumps tend to weaken the intraday predictability in the Bitcoin market, whereas in the equity and crude oil markets intraday momentum tends to be stronger during the high volatile period (Gao et al., 2018; Wen et al., 2020). One possible explanation for this phenomenon is that most of the traders in the cryptocurrency markets are retailers who take various and diverse responses to the market fluctuations, whereas institutional investors take a dominant role in the transactions of traditional financial assets and tend to take more consistent reactions when facing market downturns.

[Insert Table 3 about here]

4.3. Impacts of the liquidity on intraday return predictability

The liquidity plays an important role in the pattern of intraday return predictability due to the liquidity provision (Elaut et al., 2018). Gao et al. (2018) argue the twelfth half-hour return has stronger predictive power to the last half-hour return for the stocks with high Amihud (2002) ratio (less liquid). Inspired by the above stylized facts, this section investigates the impacts of the liquidity on the intraday return predictability.

We use the Amihud (2002) measure to capture the degree of illiquidity of cryptocurrencies, where the high (low) Amihud (2002) measure indicates the low (high) illiquidity. For each pair r_i~r_j, we split all the observations by the median of the Amihud (2002) measure in the ith hourly interval, thus generating the two sub-samples with high and low liquidity levels. The regression (4) is then applied to the two sub-samples respectively to examine the impacts of the liquidity on the intraday return predictability.

Table 4 provides the analysis results. Panel A shows the predictability pattern when the liquidity is high. The results show that the predictability still exists for the pairs $r_3 \sim r_{17}$, $r_{10} \sim r_{11}$ and $r_{12} \sim r_{13}$ with the predictive sign remaining the same. The predictability of the other pairs vanishes. Panel B shows the results of predictability when the liquidity is at the low level. Compared with the findings with the high liquidity level, the predictive ability of the pairs $r_{10} \sim r_{11}$ and $r_{12} \sim r_{13}$ becomes weaker. However, the predictability is significantly stronger in the other pairs. Notably, the values of the $Adj.R^2$ grows higher drastically compared with those using the whole sample as well as those when the liquidity is high. Overall, intraday return predictability tends to be stronger under the low liquidity condition in the bitcoin market, which indicates that slower information flow can cause stronger intraday momentum, and the findings are consistent with those of the traditional financial assets. This result complements previous findings considering daily data and showing that Bitcoin trading volume and price returns are somewhat related (Balcilar et al., 2017).

[Insert Table 4 about here]

4.4. Impacts of FOMC announcements on intraday return predictability

The pattern of intraday return predictability could be affected by news release. The FOMC announcement is regarded as one of the most anticipated events on the economic calendar, as the currency value could be substantially affected by the decision about the interest rates. For example, Gao et al. (2018) documents the stronger intraday predictability in the equity market on the days with FOMC announcements.[13] Additionally, Corbet et al. (2020) find that currency-based digital assets experienced idiosyncratic spillovers immediately after the FOMC announcements, and mineable digital asset such as bitcoin, is found to be more susceptible to monetary policy volatility spillovers. However, whether and how the FOMC announcements could affect the intraday return predictability in the bitcoin market remains unclear. Hence, in this section we examine the impacts of the FOMC announcements on the intraday return predictability in the bitcoin market. We divide all the daily observations into two sub-samples

[13] FOMC announcements inform people of the Federal Reserves latest decision on the monetary policy, such as the interest rates, which are normally made at 2:15 pm EST for every six weeks.

with and without FOMC announcements[14], depending on whether the announcement is released on the trading day.[15] The regression (4) is applied to the two sub-samples to investigate how the FOMC announcements affect the intraday return predictability.

Table 5 presents the analyzing results. Panel A shows the intraday return predictability when the FOMC announcements are made. The predictive coefficients are statistically significant only for the two pairs $r_8 \sim r_{22}$ and $r_{10} \sim r_{11}$ with the t-stats of 1.87 and 1.90. The rest shows nil predictability. Panel B presents the results of the intraday return predictability when there are no FOMC announcements. Compared with the return predictability during the FOMC announcements, the coefficients of all the prediction pairs are statistically significant. Additionally, the signs of each coefficient remain the same as those using the whole sample. This suggest that the intraday return predictability tends to be stronger on the days without FOMC announcements than with FOMC announcements, which is also contrary to previous findings in the traditional financial assets (e.g., Corbet et al., 2020). Such differences could be explained in light of the diverse reactions of the dominant retail and institutional investors in the cryptocurrency and traditional financial markets, respectively.

[Insert Table 5 about here]

4.5. Impacts of the COVID-19 outbreak on intraday return predictability

The outbreak of COVID-19 brings great turmoil to the financial markets. Whether and how it affects the intraday predictability in the bitcoin market is our concern. In order to analyze this question, we split the whole sample into two subsets, namely the normal period from April 1, 2013 to December 31, 2019 and the COVID-19 epidemic period from Jan 1, 2020 to May 1, 2021, and then we compare the patterns of intraday return predictability during the normal period and the COVID-19 period, by applying regression (4) to the two sub-samples.

Table 6 presents the analysis results for the impacts of the COVID-19 on the intraday return predictability. Panel A shows the results during the normal period, and Panel B shows

[14] The number of the trading days is 2945 for the whole sample, during which there are 65 FOMC announcements.
[15] FOMC releases is obtained at http://www.federalreserve.gov/monetarypolicy/fomccalendars.htm.

the results during the COVID-19 epidemic period. For the pairs $r_3 \sim r_5$, $r_{10} \sim r_{11}$, $r_{12} \sim r_{13}$ and $r_{22} \sim r_{23}$, the results show a more significant predictive power during the COVID-19 epidemic period than during the normal period. Notably, the values of $Adj.R^2$ are higher during the COVID-19 epidemic period, indicating the stronger predictive power for those pairs. For the pairs $r_3 \sim r_{15}$, $r_3 \sim r_{17}$ and $r_8 \sim r_{22}$, the predictive power diminishes and even vanishes during the COVID-19 epidemic period, even though it shows significant predictability during the normal period.

Overall, the outbreak of the COVID-19 exhibits a significant impact on the intraday return predictability in the bitcoin market, and the predictive power of each pair $r_i \sim r_j$ to the COVID-19 outbreak period is not the same, which is consistent with previous findings from the academic literature showing that intraday return predictability tends to be weaker during market downturns, which might due to the fact that retail investors in the cryptocurrency market have various interpretations during the crisis period, and thus the pattern of intraday return predictability changes or even diminishes. This also suggests that the timing strategy we take (see the below section 5) should differ between periods due to the structural break brought by the COVID-19 outbreak.

[Insert Table 6 about here]

5. Economic value and interpretations

5.1. Economic value

Till this part, we have checked the IS and OOS prediction results in the Bitcoin market and have identified the efficient intraday predictors. In this section, we aim to assess the potential economic value of the efficient intraday predictors based on the market timing strategy. For each efficient predictive pair $r_i \sim r_j$ where the *i*th hourly return r_i positively or negatively predicts the *j*th hourly return r_j, we use the hourly return r_i as the timing signal. To be specific, it takes a long (short) position at the start of the *j*th hour if the timing signal $\beta_{i,j} * r_i$ is positive (negative), and then closes it at the end of the *j*th hour. Otherwise, it takes a short (long) position at the start of the *j*th hour if the timing signal $\beta_{i,j} * r_i$ is positive (negative), and then closes it at the end of the *j*th hour. The strategy rule is illustrated as follows:

$$w(\beta_{i,j} * r_i, r_j) = \begin{cases} r_j, & \text{if } \beta_{i,j} * r_i \geq 0 \\ -r_j, & \text{if } \beta_{i,j} * r_i < 0 \end{cases}. \tag{8}$$

For the comparison with the timing strategy, we also formulate the other two benchmark strategies. One is *Always long* where it takes a long position at the start of the *j*th hour and closes it at the end of the it, regardless of the timing signal. The other one is *Buy-and-hold* where it takes a long position at the beginning of the *i*th hour and hold it until the end of the *j*th hour. The *Always long* strategy is denoted as $AL(r_j)$, and the Buy-and-hold is denoted as $BH(r_i, r_j)$.

Table 7 presents the analysis results of the market timing. The average return, standard deviation, and success rate are all in percentage. The success rate is the ratio of the number of days with non-negative return to the total number of the trading days. For the pairs $r_3 \sim r_{17}$ and $r_{10} \sim r_{11}$, the average return, the Sharpe ratio and the success rate generated by the timing strategy are inferior to that of the benchmark strategies. Nevertheless, for the other pairs, the timing strategy using the predictor as the timing signal produces the higher average return, Sharpe ratio and success rate compared with the two benchmark strategies.

Overall, apart from the predictive pairs $r_3 \sim r_{17}$ and $r_{10} \sim r_{11}$, the timing strategy using the predictor as the timing signal outperforms the benchmark strategies, i.e., *Always long* and *Buy-and-hold*. This indicates that, among the efficient predictors, the third hourly return (r_3) and tenth hourly return (r_{10}) are not effective as timing signals, but the others are able to produce the remarkable economic value in terms of the timing strategy.

[Insert Table 7 about here]

5.2. Economic interpretations

Overall, we have shown significant intraday return predictability in the Bitcoin market. The main argument drawn by Gao et al. (2018) in the equity markets regarding “the digestion of new information in the first half hour and the desire to trade in the last half hour for settlement and to avoid overnight risk" cannot serve as the base for explaining our significant results in the Bitcoin market considering its totally different trading mechanism. In fact, Gao et al. (2018) draw upon the infrequent trading behavior of investors (e.g., Bogousslavsky, 2016) through which investors delay their rebalancing trades till near the market close when liquidity is high and very similar to the high liquidity in the near market open, leading to a positive correlation between the returns in near the open and in near the market close. For Bitcoin, the first explanation is not relevant given that we have detected an almost inverted U-shaped pattern for the trading volume in the Bitcoin market due to its 24-hour continuous trading mechanism.

Another explanation given by Gao et al. (2018) evolves around the presence of traders who are very slow in digesting information and thus in reacting to the new information near the market open, which makes them trade near the market close when trading volume is high. This second explanation might be relevant to the Bitcoin market, while bearing in mind that the 24 hours trading feature in the Bitcoin market does not necessarily push traders to concentrate their trading at a particular hour but to spread their trading throughout the 24 hours. This tendency to spread trading across various trading hours can depend on the timing job duties of traders and their other activities and break time such as lunch and sleeping time (see Petukhina et al., 2020). Therefore, late-informed traders have the continuous trading space in the Bitcoin market to digest the arrival of information and react to them, which might have led to a divergence in the sign of return predictability across the various trading hours. In a different context, Xu (2017) shows that the information contained in morning and afternoon stock price movements is very different, although the author indicates that this phenomenon has not been documented before and cannot be explained by any asset pricing theory. Therefore, our findings on the Bitcoin market represent a challenge to traditional models of risk and return, which requires further examination.

Notably, the significant and negative intraday return predictability in the Bitcoin market points to intraday reversal that may be driven by price shocks (i.e., jumps), as argued by Fung et al. (2000) and Zawadowski, et al. (2006) who provide evidence of intraday reversals after large price changes for index futures. Furthermore, and given the lack of robust models to evaluate the intrinsic value of Bitcoin and the detachment of Bitcoin from fundament and economic variables, the intraday reversal results can be partially explained in light of the argument given by Savor (2012) in the stock markets. In fact, Savor (2012) indicates that no-information-based large price changes experience reversals, which is related to overreaction to non-fundamental information and to investor overconfidence bias in general given that Bitcoin traders are mostly young with an animal spirit, large cultural differences, and their information is irregular (Bouri et al., 2019) and thus trade irrationally by following some of the actions of the so-called whales. Notably, they tend to place small orders, unlike institutional investors who are very active in the stock markets, which is related to the different investor clienteles (Lou et al., 2019).

6. Robustness check

6.1. Half-hour returns

Here, we consider the intraday return predictability using hourly returns to check whether using half-hour returns generate similar patterns to those of hourly returns, given that most of the academic literature of intraday momentum mainly uses half-hour returns (e.g., Elaut et al., 2018; Gao et al., 2018; Wen et al., 2020). For brevity, Table 8 merely presents the results of the efficient predictability where the IS predictability is statistically significant and the OOS R-square is positive. The pair $r_i \sim r_j$ represents the case of the predictability of the ith half-hour return to the jth. There are totally 33 efficient pairs, of which 12 show the positive predictability indicating the presence of the intraday momentum. However, the remaining 21 pairs take on the opposite pattern. In a nutshell, the intraday return predictability using half-hour returns confirms the presence of intraday momentum and intraday reversal in the Bitcoin market.

[Insert Table 8 about here]

6.2. Intraday return predictability in other cryptocurrency markets

We conduct another robustness check that consists of considering other cryptocurrencies. To this end, we use the 5-min high frequency data of other cryptocurrencies such as ETH, LTC, and XRP.[16] As shown in Table 9, the sample periods for XRP, ETH, and LTC are from May 19, 2017, to May 1, 2021, March 9, 2016, to May 1, 2021, from May 19, 2013, to May 1, 2021, and from respectively. The results of the intraday return predictability analysis using the above three cryptocurrencies are presented in Tables 10-12. For brevity, the results for the pairs $r_i \sim r_j$ with both the efficient IS and OOS predictability are reported.

[Insert Table 9 about here]

Table 10 reports the intraday return predictability using the 5-min high frequency data of *XRP*. There are totally 13 pairs with the efficient IS and OOS predictability. Among them, seven pairs exhibit the predictive sign, i.e., $r_1 \sim r_{11}$, $r_7 \sim r_{11}$, $r_7 \sim r_{20}$, $r_8 \sim r_{22}$, $r_{11} \sim r_{20}$, $r_{12} \sim r_{24}$, $r_{14} \sim r_{22}$. The predictive coefficients are 0.07, 0.14, 0.09, 0.13, 0.08, 0.12 and 0.09, respectively. Whereas, the rest of the efficient pairs show the negative predictive pattern, i.e., $r_{11} \sim r_{13}$, $r_{12} \sim r_{21}$, $r_{14} \sim r_{21}$, $r_{15} \sim r_{20}$, $r_{16} \sim r_{18}$ and $r_{17} \sim r_{18}$, respectively.

[Insert Table 10 about here]

Regarding the intraday predictability for *ETH*, results reported in Table 11 show that among all the pairs with the efficient predictability, the predictive coefficients are positive for the pairs $r_3 \sim r_{13}$, $r_7 \sim r_{17}$, $r_8 \sim r_{22}$, $r_9 \sim r_{22}$, $r_{11} \sim r_{19}$ and $r_{12} \sim r_{24}$. The coefficients are 0.08, 0.09, 0.13, 0.07, 0.08 and 0.12, respectively. Whereas they are negative for the remaining pairs $r_1 \sim r_5$, $r_{12} \sim r_{13}$, $r_{16} \sim r_{17}$, $r_{17} \sim r_{18}$ and $r_{20} \sim r_{21}$. And the coefficients are -0.05, -0.12, -0.11, -0.07 and -0.11.

[Insert Table 11 about here]

For the case of *LTC*, the results of from Table 12 indicate the presence of 16 efficient predictive pairs. Among them, there are 8 pairs with the positive predictive sign, which are

[16] The data are extracted from www.huobi.pe/zh-cn. Huobi is one of the leading digital asset trading platforms and the second largest exchange in terms of Bitcoin trading volume till May of 2021, originally founded in China.

$r_5 \sim r_{24}$, $r_7 \sim r_{17}$, $r_7 \sim r_{24}$, $r_8 \sim r_{10}$, $r_8 \sim r_{22}$, $r_9 \sim r_{18}$, $r_{13} \sim r_{20}$ and $r_{13} \sim r_{24}$. While the rest 8 pairs whose signs of the coefficients are negative, which are $r_3 \sim r_5$, $r_4 \sim r_5$, $r_5 \sim r_6$, $r_6 \sim r_7$, $r_7 \sim r_{21}$, $r_{12} \sim r_{22}$, $r_{16} \sim r_{23}$ and $r_{22} \sim r_{23}$. The coefficients are -0.08, -0.1, -0.12, -0.19, -0.1, -0.07, -0.05 and -0.15, respectively.

[Insert Table 12 about here]

Overall, the results show the presence of significant intraday return predictability in the cryptocurrency market. The signs of the predictors' coefficients are not always positive[17], which is different from those seen in the standardized financial markets (equity and bond markets). Furthermore, the pattern of the intraday predictability is not the same among various cryptocurrency markets.

7. Conclusion

Motivated by the special trading mechanism and the inherent characteristics of the cryptocurrency market, this paper investigates the intraday return predictability patterns in the Bitcoin market. Different from the standardized financial products, Bitcoin is traded continuously 24 hours a day and 7 days a week. For brevity, we calculate the hourly returns rather the half-hour returns using the 5-min high frequency bitcoin data. The in-sample and out-of-sample predictability of every hourly returns earlier in the day to the subsequent hourly returns is analyzed. We also examine the possible impacts of the intraday jump, illiquidity and the FOMC announcements on the patterns of intraday return predictability. In addition, the potential influence of the COVID-19 epidemic on the intraday return predictability is also analyzed. Furthermore, we assess the economic value of intraday return predictability by constructing the market timing strategy using the efficient intraday predictor as the timing signal, and then compare it with that of the benchmark strategy. Some economic interpretations for the findings are also given. Finally, some robustness checks are conducted using other

[17] We also conduct the robustness check using the half-hour return, and find the similar pattern. For brevity, the results are not reported here but available from the authors upon request.

leading cryptocurrencies (e.g., Ripple, ETH and LTC) for the intraday return predictability analysis.

This paper provides several remarkable findings. First, the intraday return predictability apparently exists in the cryptocurrency market. Interestingly, the signs of the intraday predictors' coefficients are not always positive as that the negative signs can are also pervasive and points to reversals. The evidence is distinctive from the intraday return predictability documented in the previous studies where only the positive intraday predictability is identified in conventional assets (Elaut et al., 2018; Gao et al., 2018; Jin et al., 2020; Wen et al., 2020; Zhang et al., 2019). Second, we find evidence of the impacts of the intraday jump, liquidity and the FOMC announcements on the intraday return predictability. The predictive ability seems stronger when there is no jump, no FOMC announcement release, and less liquidity, which differs from the findings in the previous research (Gao et al., 2018; Wen et al., 2020). While the outbreak of the COVID-19 exhibits significant impacts on the intraday return predictability in the cryptocurrency market, the predictive power of each pair $r_i \sim r_j$ during the outbreak of the COVID-19 is not the same. It suggests that the market timing strategy we take should differ during various periods of the structural break brought by the COVID-19 pandemic. Third, in terms of the economic value, the timing strategy using the efficient predictor as the timing signal generates substantial profits relative to the benchmark strategy for most pairs $r_i \sim r_j$. Finally, using several cryptocurrencies, the results confirm the robustness of the intraday return predictability pattern in the Bitcoin market. That is, there exist both positive and negative predictive patterns in the Bitcoin market.

This paper makes important contributions to the literature by extending the intraday return predictability to the cryptocurrency market. To the best of our knowledge, it is the pioneering work examining the intraday return predictability patterns in the cryptocurrency market. We find there are both intraday momentum and reversal in the cryptocurrency market, the patterns of which can be affected by the jumps, FOMC announcements and liquidity levels. The findings are apparently distinctive from the sole existence of positive intraday return predictability in other conventional financial markets. Additionally, the outbreak of the

COVID-19 exhibits significant impacts on the intraday return predictability in the cryptocurrency market. This suggests that the timing strategy should differ during various periods due to the structural break brought by the COVID-19. By showing evidence of trading anomalies and the economic value arising from the construction of an intraday time-based trading strategy, especially during the COVID-19 outbreak, we provide evidence challenging the efficient market hypothesis, which is key to market makers and regulators (Naeem et al., 2020).

Future research can consider whether the momentum time-based trading strategy can hold in the presence of quick price rebounds or price crashes. Another line of future research can involve the examination of the impact of Bitcoin hard fork on intraday momentum and reversal.

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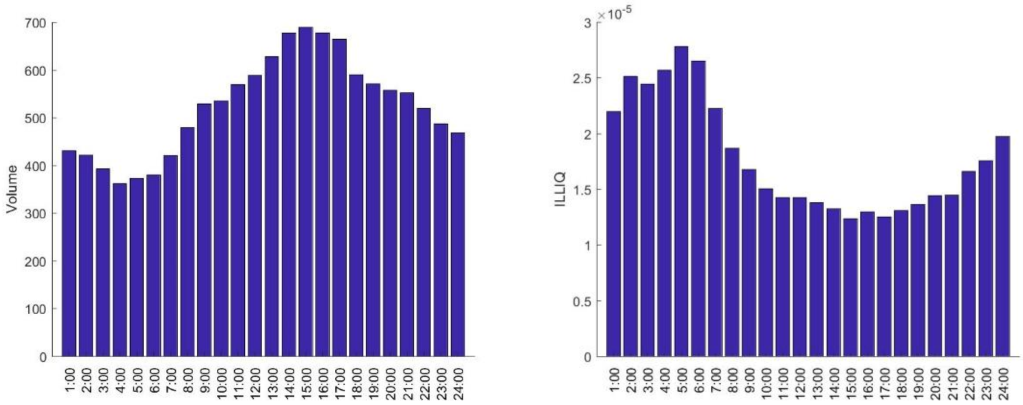
Figure 1. Intraday patterns of the trading volume and the illiquidity



（a） （b）

Notes: Fig.1(a) represents the average of the intraday trading volume in each hourly interval all over the day. Fig.1(b) shows the average of the illiquidity (i.e., Amihud ratio) in each hourly interval.

Table 1. The yearly descriptive statistics for the variables of interests

	Years	2013	2014	2015	2016	2017	2018	2019	2020	2021
Ret	Mean (%)	0.04	-0.01	0	0.01	0.03	-0.02	0.01	0.02	0.02
	Std (%)	2.25	0.95	0.77	0.52	1.11	0.99	0.8	0.78	1.06
	Min	-0.36	-0.25	-0.12	-0.13	-0.14	-0.09	-0.15	-0.16	-0.08
	Max	0.47	0.15	0.09	0.11	0.11	0.11	0.13	0.17	0.10
	Skewness	-0.96	-1.59	-1.03	-1.02	-0.77	0.19	-0.41	-1.20	0.21
	Kurtosis	84.93	75.46	32.17	76.77	15.17	14.92	49.07	88.63	10.58
Volume	Mean	714.01	625.19	692.28	246.93	583.36	490.07	375.53	366.19	504.29
	Std	1099.33	986.75	991.79	347.82	597.74	544.85	449.34	836.32	621.97
	Min	0	0	0	0.3	3.54	2.16	7.33	0	0
	Max	18546.9	22326.52	18696.33	6659.71	13968.41	7452.26	7826.85	27071.51	9346.02
	Skewness	5.41	6.7	4.6	5.89	4.62	3.78	4.47	14.84	5.64
	Kurtosis	52.1	89.31	38.97	65.6	52.83	28.25	39.02	375.82	54.50
RV ($\times 10^3$)	Mean	8.24	1.48	0.98	0.43	1.58	1.05	0.63	0.67	1.30
	Std	90.31	4.59	8.98	1.37	4.97	2.59	2.98	5.42	2.93
	Min	0	0	0	0	0	0	0	0	0
	Max	6631	267.17	777.93	67.94	242.42	68.48	153.67	363.34	96.87
	Skewness	57.28	29.47	75.44	24.56	22.79	10.13	28.06	47.17	15.50
	Kurtosis	4058.21	1425.53	6450.34	957.47	858.99	171.26	1130.89	2803.62	418.14
Amihud ($\times 10^3$)	Mean	0.3	0.18	0.12	0.22	0.15	0.14	0.16	0.22	0.20
	Std	0.89	0.29	0.28	0.46	0.16	0.17	0.19	0.31	0.18
	Min	0	0	0	0	0	0	0	0	0
	Max	31.52	12.94	16.54	16.71	3.87	5.67	3.07	19.31	1.72
	Skewness	17.28	13.29	31.64	14.62	4.65	8.87	4	27.15	2.09
	Kurtosis	447.85	435.32	1623.26	386.17	56.88	209.49	33.13	1582.46	10.55
Jump	Mean (%)	0.11	0.06	0.04	0.03	0.04	0.04	0.03	0.04	0.03
	Std (%)	0.57	0.24	0.21	0.13	0.26	0.22	0.21	0.22	0.17
	Min	0	0	0	0	0	0	0	0	0
	Max (%)	15.4	6.16	5.22	4.45	15.32	3.63	4.47	6.34	2.65
	Skewness	14.43	8.05	11.12	9.11	26.82	7.97	12.45	13.36	7.17
	Kurtosis	298.61	119.03	194.82	178.25	1326.9	79.45	193.04	270.77	64.00

Notes: This table presents the yearly descriptive statistics for the variables of interests from the year 2013 to 2021, i.e., return, trading volume, realized volatility, Amihud ratio and the intraday jump. The mean value, standard deviation, minimum value, maximum value, skewness and kurtosis of each variable are listed.

Table 2. The results for the efficient intraday predictability

	$r_3 \sim r_5$	$r_3 \sim r_{15}$	$r_3 \sim r_{17}$	$r_8 \sim r_{22}$	$r_{10} \sim r_{11}$	$r_{12} \sim r_{13}$	$r_{22} \sim r_{23}$
Coeff.	-0.1***	-0.16***	0.09***	0.13***	-0.14**	-0.10***	-0.11**
T-value	[-4.46]	[-3.50]	[2.77]	[3.60]	[-1.98]	[-2.70]	[-2.09]
$Adj.R^2$(%)	1.67	3.61	1.01	1.26	1.33	1.17	1.47

Notes: This table presents the analysis results for the efficient intraday predictability. The pair $r_i \sim r_j$ denotes the predictability of the ith hourly return to the jth hourly return, i.e., r_i and r_j denote the independent and the dependent variables, respectively. The numbers in the brackets are the Newey and West (1987) robust t-statistics. *, ** and *** denote the significance at the level of 10%, 5% and 1%, respectively.

Table 3. Impacts of the intraday jump

	$r_3 \sim r_5$	$r_3 \sim r_{15}$	$r_3 \sim r_{17}$	$r_8 \sim r_{22}$	$r_{10} \sim r_{11}$	$r_{12} \sim r_{13}$	$r_{22} \sim r_{23}$
Panel A: Jump							
Coeff.	-0.03	-0.1	0.1	0.15	0	-0.17**	-0.02
T-value	[-0.36]	[-0.77]	[1.15]	[0.99]	[0.01]	[-2.30]	[-0.21]
$Adj.R^2$(%)	-0.25	0.54	0.73	1.79	-0.33	3.03	-0.30
Panel B: No jump							
Coeff.	-0.1***	-0.17***	0.09**	0.13***	-0.17***	-0.11**	-0.11**
T-value	[-4.29]	[-3.64]	[2.45]	[3.52]	[-2.88]	[-2.57]	[-2.17]
$Adj.R^2$(%)	2.06	4.10	0.99	1.28	2.29	1.26	1.64

Notes: This table presents the impacts of the intraday jump on the intraday predictability. Panel A presents the results during the days when there exists jump in the ith hourly interval. Panel B presents the results during the days when there exists no jump in the ith hourly interval. The pair $r_i \sim r_j$ denotes the predictability of the ith hourly return to the jth hourly return, i.e., r_i and r_j denote the independent and the dependent variables, respectively. The numbers in the brackets are the Newey and West (1987) robust t-statistics. *, ** and *** denote the significance at the level of 10%, 5% and 1%, respectively.

Table 4. Impacts of the liquidity on the intraday predictability

	$r_3 \sim r_5$	$r_3 \sim r_{15}$	$r_3 \sim r_{17}$	$r_8 \sim r_{22}$	$r_{10} \sim r_{11}$	$r_{12} \sim r_{13}$	$r_{22} \sim r_{23}$
Panel A: High liquidity							
Coeff.	0.03	0.03	0.13**	0.05	-0.12**	-0.14**	0
T-value	[0.67]	[0.33]	[2.24]	[0.98]	[-2.55]	[-2.50]	[0.04]
$Adj.R^2$(%)	-0.01	-0.04	0.75	0.15	0.55	1.08	-0.07
Panel B: Low liquidity							
Coeff.	-0.12***	-0.2***	0.08**	0.16***	-0.14	-0.09*	-0.13**
T-value	[-5.96]	[-4.82]	[2.05]	[3.46]	[-1.53]	[-1.85]	[-2.09]
$Adj.R^2$(%)	5.40	8.43	1.20	1.85	1.96	1.33	3.19

Notes: This table presents the impacts of the liquidity on the intraday predictability. Panel A presents the results during the days with the high liquidity in the ith hourly interval. Panel B presents the results during the days with the low liquidity in the ith hourly interval. The pair $r_i \sim r_j$ denotes the predictability of the ith hourly return to the jth hourly return, i.e., r_i and r_j denote the independent and the dependent variables, respectively. The numbers in the brackets are the Newey and West (1987) robust t-statistics. *, ** and *** denote the significance at the level of 10%, 5% and 1%, respectively.

Table 5. Impacts of the FOMC announcements

	$r_3 \sim r_5$	$r_3 \sim r_{15}$	$r_3 \sim r_{17}$	$r_8 \sim r_{22}$	$r_{10} \sim r_{11}$	$r_{12} \sim r_{13}$	$r_{22} \sim r_{23}$
Panel A: FOMC announcements							
Coeff.	0.14	-0.01	-0.11	0.32*	0.18*	-0.19	-0.03
T-value	[0.60]	[-0.04]	[-0.42]	[1.87]	[1.90]	[-1.14]	[-1.20]
$Adj.R^2$(%)	-0.14	-1.58	-1.21	0.68	6.79	2.32	-0.96
Panel B: Non-FOMC announcements							
Coeff.	-0.1***	-0.16***	0.09***	0.13***	-0.14**	-0.1***	-0.11**
T-value	[-4.62]	[-3.55]	[2.87]	[3.48]	[-2.03]	[-2.61]	[-2.04]
$Adj.R^2$(%)	1.75	3.73	1.07	1.23	1.45	1.13	1.53

Notes: This table presents the impacts of the FOMC announcement on the intraday predictability in the bitcoin market. Panel A presents the results during the days with FOMC announcement. Panel B presents the results during the days without FOMC announcement. The pair $r_i \sim r_j$ denotes the predictability of the ith hourly return to the jth hourly return, i.e., r_i and r_j denote the independent and the dependent variables, respectively. The numbers in the brackets are the Newey and West (1987) robust t-statistics. *, ** and *** denote the significance at the level of 10%, 5% and 1%, respectively.

Table 6. The impacts of the COVID-19 outbreak on the intraday predictability

	$r_3 \sim r_5$	$r_3 \sim r_{15}$	$r_3 \sim r_{17}$	$r_8 \sim r_{22}$	$r_{10} \sim r_{11}$	$r_{12} \sim r_{13}$	$r_{22} \sim r_{23}$
Panel A: During normal period							
Coeff.	-0.09***	-0.15***	0.1***	0.13***	-0.12	-0.1**	-0.08
T-value	[-3.87]	[-2.97]	[3.11]	[3.26]	[-1.55]	[-2.29]	[-1.61]
$Adj.R^2$(%)	1.59	3.09	1.27	1.23	1.09	1.08	0.81
Panel B: During the COVID-19 outbreak							
Coeff.	-0.12***	-0.28*	0.01	0.14*	-0.24**	-0.17**	-0.35***
T-value	[-3.63]	[-1.89]	[0.21]	[1.81]	[-2.46]	[-2.41]	[-3.43]
$Adj.R^2$(%)	2.34	8.47	-0.20	1.23	3.04	1.67	15.30

Notes: This table presents the impacts of the COVID-19 outbreak on the intraday predictability. Panel A presents the results during the normal period. Panel B presents the results during the COVID-19 outbreak. The pair $r_i \sim r_j$ denotes the predictability of the ith hourly return to the jth hourly return, i.e., r_i and r_j denote the independent and the dependent variables, respectively. The numbers in the brackets are the Newey and West (1987) robust t-statistics. *, ** and *** denote the statistical significance at the level of 10%, 5% and 1%, respectively.

Table 7. Market timing

Strategy	Ave ret (%)	Std (%)	Sharpe Ratio	Skewness	Kurtosis	Success (%)
$w(r_3, r_5)$	0.02	1.41	0.01	5.83	162.02	49.69
$AL(r_5)$	-0.01	0.90	-0.02	-0.38	34.51	49.37
BH(r_3, r_5)	0.01	0.90	0.01	-1.02	34.55	
$w(r_3, r_{15})$	0.05	1.43	0.03	4.07	97.39	53.44
$AL(r_{15})$	0.02	1.03	0.02	-0.68	22.94	52.87
BH(r_3, r_{15})	0.00	1.03	0.00	0.76	22.86	
$w(r_3, r_{17})$	0.04	1.71	0.02	6.66	195.84	51.21
$AL(r_{17})$	0.01	1.09	0.01	-0.87	25.21	51.82
BH(r_3, r_{17})	0.05	1.09	0.04	0.67	25.15	
$w(r_8, r_{22})$	0.05	1.60	0.03	-1.52	64.93	54.50
$AL(r_{22})$	0.03	1.16	0.03	-4.67	169.85	53.62
BH(r_8, r_{22})	0.01	1.16	0.01	-5.16	169.22	
$w(r_{10}, r_{11})$	-0.02	1.42	-0.01	-3.17	54.59	51.85
$AL(r_{11})$	-0.03	1.14	-0.02	-4.52	80.53	52.02
BH(r_{10}, r_{11})	0.05	1.14	0.04	-1.82	81.41	
$w(r_{12}, r_{13})$	0.04	1.35	0.03	0.77	36.76	53.89
$AL(r_{13})$	0.02	0.99	0.02	0.52	28.03	53.48
BH(r_{12}, r_{13})	0.01	0.99	0.01	-0.08	28.07	
$w(r_{22}, r_{23})$	0.09	1.44	0.06	-0.31	118.22	54.43
$AL(r_{23})$	0.05	1.01	0.05	1.31	48.27	53.75
BH(r_{22}, r_{23})	0.04	1.01	0.04	-1.20	48.61	

Notes: This paper shows the results of the market timing. We use the product of the coefficient $\beta_{i,j}$ and r_i (i.e., $\beta_{i,j} * r_i$) as the timing signal. To be specific, it takes a long (short) position at the start of the *j*th hour if the timing signal $\beta_{i,j} * r_i$ is positive (negative), and then closes it at the end of the *j*th hour. Otherwise, it takes a short (long) position at the start of the *j*th hour if the timing signal $\beta_{i,j} * r_i$ is positive (negative), and then closes it at the end of the *j*th hour. For the comparison, the benchmark strategy *Always long* denoted as $AL(r_j)$ means it buys at the beginning of the *j*th hour and sells at the end of it, regardless of the timing signal. $BH(r_i, r_j)$ means it takes a long position at the beginning of the *i*th hour and hold until the end of the *j*th hour. The table summarizes the average return, standard deviation, Sharpe ratio, skewness, kurtosis, and success rate.

Table 8. The efficient intraday predictability using half-hour returns

	$r_1 \sim r_8$	$r_1 \sim r_{12}$	$r_1 \sim r_{47}$	$r_2 \sim r_{18}$	$r_3 \sim r_{10}$	$r_3 \sim r_{28}$	$r_3 \sim r_{30}$	$r_4 \sim r_{35}$	$r_4 \sim r_{40}$
Coeff.	0.08**	-0.07**	0.07**	-0.18**	0.09**	-0.2**	0.07**	-0.09**	-0.12***
T-value	[2.47]	[-2.57]	[2.34]	[-2.24]	[2.31]	[-2.05]	[2.02]	[-2.57]	[-2.58]
$Adj.R^2$(%)	0.68	0.52	0.40	2.36	1.09	3.80	0.48	0.80	1.42

	$r_4 \sim r_{43}$	$r_5 \sim r_{12}$	$r_5 \sim r_{30}$	$r_6 \sim r_9$	$r_6 \sim r_{17}$	$r_6 \sim r_{23}$	$r_6 \sim r_{27}$	$r_6 \sim r_{30}$	$r_6 \sim r_{33}$
Coeff.	-0.05**	-0.09**	-0.18***	-0.07**	-0.08***	0.09***	0.12***	-0.13***	0.1**
T-value	[-2.12]	[-2.30]	[-2.79]	[-2.42]	[-2.69]	[3.31]	[3.19]	[-2.91]	[2.14]
$Adj.R^2$(%)	0.32	0.75	2.82	0.91	0.87	1.47	1.54	2.63	1.27

	$r_6 \sim r_{40}$	$r_7 \sim r_8$	$r_7 \sim r_{42}$	$r_8 \sim r_{11}$	$r_8 \sim r_{27}$	$r_9 \sim r_{18}$	$r_9 \sim r_{45}$	$r_{10} \sim r_{16}$	$r_{11} \sim r_{18}$
Coeff.	0.09**	-0.2***	-0.1***	-0.07**	-0.12***	-0.15***	-0.09***	0.12**	-0.18***
T-value	[2.04]	[-5.32]	[-3.23]	[-2.15]	[-3.30]	[-2.59]	[-2.62]	[2.40]	[-2.64]
$Adj.R^2$(%)	1.09	5.05	0.78	0.48	0.88	1.64	0.70	1.14	2.30

	$r_{11} \sim r_{19}$	$r_{12} \sim r_{13}$	$r_{13} \sim r_{33}$	$r_{15} \sim r_{39}$	$r_{16} \sim r_{24}$	$r_{17} \sim r_{34}$	$r_{19} \sim r_{21}$	$r_{19} \sim r_{30}$	$r_{20} \sim r_{43}$
Coeff.	0.08**	-0.17***	0.09**	0.07***	-0.16***	0.11***	-0.09**	0.1***	0.07**
T-value	[2.03]	[-3.01]	[2.01]	[2.58]	[-3.17]	[2.60]	[-2.19]	[2.73]	[2.23]
$Adj.R^2$(%)	0.51	3.38	0.62	0.36	2.15	1.18	0.62	0.94	0.56

	$r_{22} \sim r_{35}$	$r_{24} \sim r_{33}$	$r_{25} \sim r_{29}$	$r_{25} \sim r_{34}$	$r_{25} \sim r_{35}$	$r_{25} \sim r_{36}$	$r_{25} \sim r_{40}$	$r_{25} \sim r_{42}$	$r_{25} \sim r_{43}$
Coeff.	-0.07**	-0.13**	-0.03***	0.04***	-0.01***	0.01***	0.02***	-0.02***	0.01***
T-value	[-2.29]	[-2.48]	[-12.39]	[15.72]	[-5.19]	[8.64]	[10.39]	[-10.42]	[6.37]
$Adj.R^2$(%)	0.57	1.56	2.31	4.91	0.10	0.24	0.90	0.78	0.15

	$r_{25} \sim r_{46}$	$r_{25} \sim r_{47}$	$r_{26} \sim r_{28}$	$r_{26} \sim r_{32}$	$r_{26} \sim r_{34}$	$r_{26} \sim r_{35}$	$r_{26} \sim r_{36}$	$r_{26} \sim r_{37}$	$r_{26} \sim r_{38}$
Coeff.	-0.01**	-0.01***	0.04***	0.03***	-0.04***	0.01***	-0.01***	-0.01***	0***
T-value	[-2.25]	[-11.67]	[11.27]	[18.58]	[-40.10]	[5.38]	[-7.81]	[-11.35]	[3.03]
$Adj.R^2$(%)	0.10	0.60	3.95	3.26	5.53	0.09	0.22	0.44	0.04

	$r_{26} \sim r_{40}$	$r_{26} \sim r_{41}$	$r_{26} \sim r_{43}$	$r_{26} \sim r_{47}$	$r_{26} \sim r_{48}$	$r_{27} \sim r_{38}$	$r_{27} \sim r_{42}$	$r_{29} \sim r_{48}$	$r_{32} \sim r_{33}$
Coeff.	-0.02***	0.08***	-0.01***	0.02***	0.03***	0.06**	-0.11**	0.06**	-0.12***
T-value	[-11.51]	[52.49]	[-4.05]	[7.14]	[15.09]	[1.98]	[-2.18]	[2.15]	[-2.80]
$Adj.R^2$(%)	1.18	15.83	0.31	0.78	2.64	0.42	1.14	0.33	1.26

	$r_{33} \sim r_{42}$	$r_{39} \sim r_{42}$
Coeff.	-0.08**	-0.09**
T-value	[-2.05]	[-2.15]
$Adj.R^2$(%)	0.50	0.67

Notes: This table presents the analysis results for the efficient intraday predictability using half-hour returns. The pair $r_i \sim r_j$ denotes the predictability of the *i*th half-hour return to the *j*th, i.e., r_i and r_j denote the independent and the dependent variables, respectively. The numbers in the brackets are the Newey and West (1987) robust t-statistics. *, ** and *** denote the significance at the level of 10%, 5% and 1%, respectively.

Table 9. Description of other cryptocurrencies

Symbol	Name	Sample period
XRP	Ripple	05/19/2017—05/01/2021
ETH	Ethereum	03/09/2016--05/01/2021
LTC	Litecoin	05/19/2013--05/01/2021

Note: This table describes other indices in the Bitcoin market used for the robustness analysis. These are the leading cryptocurrency measured by the market capitalization as of June, 2019.

Table 10. Robustness check using *XRP* for the intraday predictability analysis

	$r_1 \sim r_{11}$	$r_7 \sim r_{11}$	$r_7 \sim r_{20}$	$r_8 \sim r_{22}$	$r_{11} \sim r_{13}$	$r_{11} \sim r_{20}$	$r_{12} \sim r_{21}$
Coeff.	0.07**	0.14**	0.09**	0.13**	-0.13**	0.08**	-0.11**
T-value	[2.49]	[2.40]	[2.03]	[1.97]	[-2.49]	[2.48]	[-2.09]
$Adj.R^2$(%)	0.60	1.57	0.89	1.86	2.00	0.85	1.24
	$r_{12} \sim r_{24}$	$r_{14} \sim r_{21}$	$r_{14} \sim r_{22}$	$r_{15} \sim r_{20}$	$r_{16} \sim r_{18}$	$r_{17} \sim r_{18}$	
Coeff.	0.12**	-0.07**	0.09**	-0.07**	-0.17**	-0.15***	
T-value	[2.25]	[-2.03]	[2.16]	[-2.00]	[-2.34]	[-2.89]	
$Adj.R^2$(%)	1.56	0.58	1.05	0.73	4.16	3.07	

Note: this table presents the results of the intraday predictability analysis using *XRP*. The numbers in the brackets are the Newey and West (1987) robust t-statistics. *, ** and *** denote the significance at the level of 10%, 5% and 1%, respectively.

Table 11. Robustness check using *ETH* for the intraday predictability analysis

	$r_1{\sim}r_5$	$r_3{\sim}r_{13}$	$r_7{\sim}r_{17}$	$r_8{\sim}r_{22}$	$r_9{\sim}r_{22}$	$r_{11}{\sim}r_{19}$
Coeff.	-0.05**	0.08**	0.09**	0.13***	0.07**	0.08***
T-value	[-2.41]	[2.13]	[2.16]	[2.83]	[2.24]	[2.74]
$Adj.R^2$(%)	0.45	0.48	0.38	1.56	0.44	0.58
	$r_{12}{\sim}r_{13}$	$r_{12}{\sim}r_{24}$	$r_{16}{\sim}r_{17}$	$r_{17}{\sim}r_{18}$	$r_{20}{\sim}r_{21}$	
Coeff.	-0.12***	0.12***	-0.11***	-0.07**	-0.11**	
T-value	[-2.82]	[3.18]	[-3.52]	[-2.31]	[-2.20]	
$Adj.R^2$(%)	1.53	1.36	1.18	0.77	1.19	

Note: this table presents the results of the intraday predictability analysis using *ETH.* The pair $r_i{\sim}r_j$ denotes the predictability of the ith hourly return to the jth hourly return, i.e., r_i and r_j denote the independent and the dependent variables, respectively. The numbers in the brackets are the Newey and West (1987) robust t-statistics. *, ** and *** denote the significance at the level of 10%, 5% and 1%, respectively.

Table 12. Robustness check using *LTC* for the intraday predictability analysis

	$r_3{\sim}r_5$	$r_4{\sim}r_5$	$r_5{\sim}r_6$	$r_5{\sim}r_{24}$	$r_6{\sim}r_7$	$r_7{\sim}r_{17}$	$r_7{\sim}r_{21}$	$r_7{\sim}r_{24}$
Coeff.	-0.08***	-0.1**	-0.12**	0.06**	-0.19***	0.07**	-0.1**	0.14***
T-value	[-2.75]	[-2.01]	[-2.06]	[2.34]	[-3.44]	[2.10]	[-2.06]	[2.85]
$Adj.R^2$(%)	0.74	0.96	1.23	0.30	3.41	0.19	0.33	1.92
	$r_8{\sim}r_{10}$	$r_8{\sim}r_{22}$	$r_9{\sim}r_{18}$	$r_{12}{\sim}r_{22}$	$r_{13}{\sim}r_{20}$	$r_{13}{\sim}r_{24}$	$r_{16}{\sim}r_{23}$	$r_{22}{\sim}r_{23}$
Coeff.	0.08**	0.07**	0.1***	-0.07**	0.07**	0.08**	-0.05**	-0.15***
T-value	[2.40]	[2.20]	[3.95]	[-2.17]	[2.18]	[2.38]	[-2.13]	[-2.63]
$Adj.R^2$(%)	0.52	0.57	1.33	1.06	0.35	0.82	0.63	1.73

Note: this table presents the results of the intraday predictability analysis using *LTC.* The pair $r_i{\sim}r_j$ denotes the predictability of the ith hourly return to the jth hourly return, i.e., r_i and r_j denote the independent and the dependent variables, respectively. The numbers in the brackets are the Newey and West (1987) robust t-statistics. *, ** and *** denote the significance at the level of 10%, 5% and 1%, respectively.

Appendix

A.1. Rapid burgeoning of bitcoin trading

As shown in Figure A.1 extracted from bitcoinity, Bitstamp ranks the third place among the exchanges of Bitcoin trading, with a trading share of 13.96% till May 2021.

[Insert Figure A.1 about here]

Besides, bitcoinity also provides the market shares of Bitcoin trading in various fiat currencies, as shown by Figure A.2. We can see that Bitcoin trades in CNY is ranked in the first place with trading volume of 1.40G BTC and a market share of 80.26%, whereas Bitcoin trades in USD is ranked in the second place with a trading volume of 239M BTC and a market share of 13.74%. Bitcoin trading was firstly being prosperous in developed markets such as US and Europe, even though trading in China started a bit late but then has risen sharply to be one of the largest markets. Therefore, we focus on the pair of BTC/USD in the main analysis, and in the robustness check we use data of several cryptocurrency trading on the other digital platform.

[Insert Figure A.2 about here]

The sample period spans from March 3, 2013 to May 31, 2020, as shown by Figure A.3. At the beginning stage, the total trading volume of exchanges all over the world has been very low and it has increased sharply after 2013. Besides, our data sample also includes the COVID-19 epidemic period from Jan 1, 2020 to May 31, 2020, which enables us to uncover the possible impacts of the epidemic on the intraday return predictability.

[Insert Figure A.3 about here]

A.2. Construction of realized jump measures

To examine the potential influence of jumps on the intraday predictability, the measure of jump risks is constructed using high-frequency intraday data. First, the realized variance is defined as in Eq. A.1 referring to the work of Barndorff-Nielsen and Shephard (2004),

$$RV_t = \sum_{i=1}^{n} r_{t,i}^2, \tag{A.1}$$

where n denotes the total number of observations. $r_{t,i}$ is the ith 5-min return during each hourly interval. Then, again referring to Barndorff-Nielsen and Shephard (2004), as well as Huang and Tauchen (2005), the bipower variation is computed as

$$BV_t = \frac{\pi}{2}\frac{n}{n-1}\sum_{i=2}^{n}|r_{t,i}|\,|r_{t,i-1}|, \tag{A.2}$$

We detect the presence of a jump during the hourly interval using the statistic as following,

$$\hat{J} = \sqrt{(RV_t - BV_t) \times I\left(ZJ_t \geq \Phi_{\tilde{\alpha}}^{-1}\right)}, \tag{A.3}$$

where ZJ_t is specifically defined as

$$\mu_k = 2^{k/2}\frac{\Gamma[(k+1)/2]}{\Gamma[1/2]}, k > 0, \tag{A.4}$$

$$TP_t = m\mu_{4/3}^{-3}\frac{n}{n-2}\sum_{i=3}^{n}|r_{t,i-2}|^{4/3}\,|r_{t,i-1}|^{4/3}|r_{t,i}|^{4/3}, \tag{A.5}$$

$$RJ_t = \frac{RV_t - BV_t}{RV_t}, \tag{A.6}$$

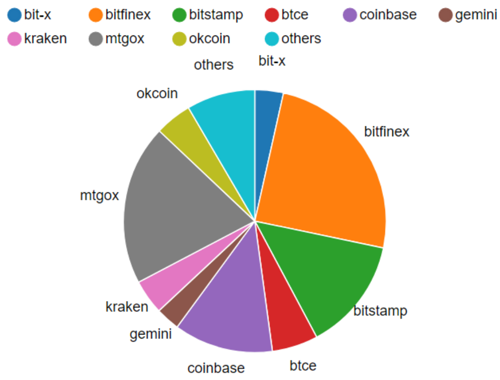
$$ZJ_t = \frac{RJ_t}{\sqrt{\frac{\left\{\left(\frac{\pi}{2}\right)^2 + \pi - 5\right\}}{m} \times max\left(1, \frac{TP_t}{BV_t^2}\right)}}, \tag{A.7}$$

and $\Phi_{\tilde{\alpha}}^{-1}$ is the inverse cumulative distribution function of the standard normal distribution, I denotes an indicative function (i.e., it takes 1 if the criterion is satisfied, and otherwise 0), and Γ denotes the gamma function. Then a jump is assumed to exist, if the probability exceeds 99.9%, as defined in Equation (A.3).

Figure A.1. Trading volume of BTC in different exchanges (USD)

Total in this period

Exchange	Volume [BTC]	Market share
bitfinex	60.2M	24.77%
mtgox	48.0M	19.74%
bitstamp	33.9M	13.92%
coinbase	29.7M	12.22%
others	20.5M	8.43%
btce	13.8M	5.66%
okcoin	11.0M	4.52%
kraken	10.4M	4.26%
bit-x	8.53M	3.51%
gemini	7.22M	2.97%

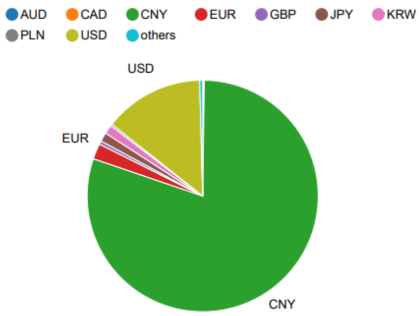


Notes: The above figure shows the trading volume in USD and market shares of BTC in various exchanges, the sample data ranges from July 1, 2010 to May 1, 2021, by referring to the link *https://data.bitcoinity.org/markets/volume/all/USD?c=e&r=month&t=b*.

Figure A.2. Trading volume of BTC in different exchanges (USD)

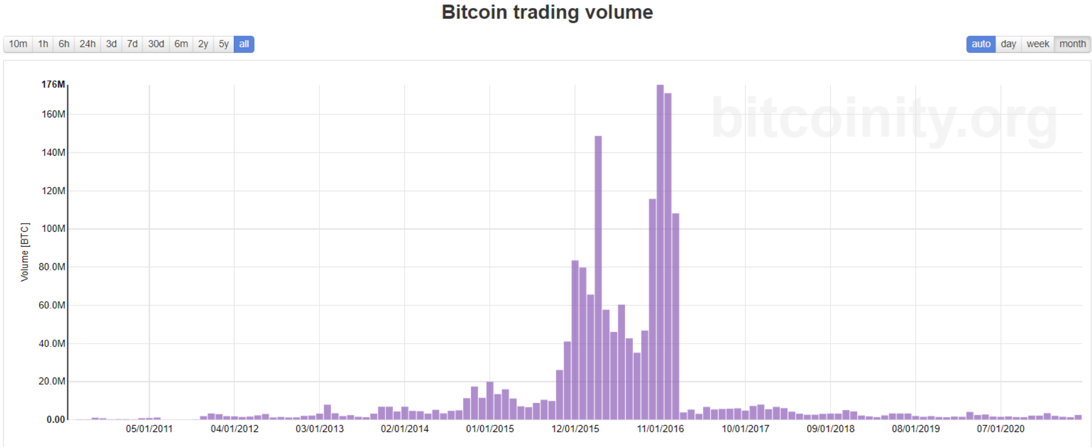
Total in this period

Exchange	Volume [BTC]	Market share
CNY	1.40G	80.00%
USD	243M	13.94%
EUR	38.1M	2.18%
JPY	21.9M	1.25%
KRW	21.7M	1.24%
GBP	8.39M	0.48%
others	7.39M	0.42%
PLN	4.55M	0.26%
AUD	1.90M	0.11%
CAD	1.83M	0.11%



Notes: The above figure shows the trading volume and market shares of BTC in various currencies, the sample data ranges from July 1, 2010 to May 1, 2021, by referring to the link *https://data.bitcoinity.org/markets/volume/all/USD?c=e&r=month&t=b*.

Figure A.3. Total Trading volume of BTC in all exchanges



Notes: The above figure shows the total trading volume of BTC in all exchanges and currencies, the sample data ranges from July 1, 2010 to May 1, 2021, by referring to the link *https://data.bitcoinity.org/markets/volume/all?t=b*.

Table A.1. Intraday return predictability using quantile regression

	r_3~r_5	r_3~r_{15}	r_3~r_{17}	r_8~r_{22}	r_{10}~r_{11}	r_{12}~r_{13}	r_{22}~r_{23}
Panel A: OLS							
Coeff.	-0.1***	-0.16***	0.09***	0.13***	-0.14**	-0.10***	-0.11**
T-value	[-4.46]	[-3.50]	[2.77]	[3.60]	[-1.98]	[-2.70]	[-2.09]
$Adj.R^2$(%)	1.67	3.61	1.01	1.26	1.33	1.17	1.47
Panel B: Quantile (0.25)							
Coeff.	-0.07***	-0.08***	0.05***	0.06***	-0.10***	-0.11***	-0.14***
T-value	[-7.39]	[-5.89]	[4.00]	[4.85]	[-7.15]	[-7.56]	[-11.55]
$Pseudo\ R^2$(%)	0.53	0.41	0.26	0.27	0.57	0.69	1.42
Panel C: Quantile (0.5)							
Coeff.	-0.07***	-0.04***	0.07***	0.05***	-0.12***	-0.15***	-0.14***
T-value	[-11.79]	[-5.45]	[9.07]	[6.84]	[-16.58]	[-18.15]	[-21.16]
$Pseudo\ R^2$(%)	0.33	0.11	0.24	0.24	0.95	1.28	1.14
Panel D: Quantile (0.75)							
Coeff.	-0.04***	-0.03**	0.09***	0.09***	-0.13***	-0.15***	-0.12***
T-value	[-3.88]	[-2.44]	[7.30]	[5.44]	[-10.15]	[-9.83]	[-9.10]
$Pseudo\ R^2$(%)	0.93	1.36	0.35	0.16	0.35	0.19	1.11

Notes: This table presents the quantile analysis results for the efficient intraday predictability in the Bitcoin market. The pair r_i~r_j denotes the predictability of the ith hourly return to the jth hourly return, i.e., r_i and r_j denote the independent and the dependent variables, respectively. The numbers in the brackets are the Newey and West (1987) robust t-statistics. *, ** and *** denote the significance at the level of 10%, 5% and 1%, respectively.