Bitcoin intraday time-series momentum

Article

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Abstract

This study examines intraday time-series momentum in Bitcoin. Unlike stock markets, Bitcoin trades 24 hours a day and therefore has not got a clear opening and closing period. Therefore, we use trading volume as a proxy for the market trading time and show that the first half-hour positively predicts the last half-hour return. We find that the first trading sessions with the highest volume or volatility are associated with the greatest predictability for intraday time-series momentum. We also show that intraday momentum-based trading yields substantial economic gains in terms of market timing and asset allocation, especially in periods of a market downturn in Bitcoin. Consistent with foreign exchange markets in Elaut *et al.* (2018), we also show that the intraday momentum is driven by liquidity provision not late-informed trading.

JEL: G12, G13, G15

Keywords: Intraday Predictability; Time-Series Momentum; Bitcoin; Cryptocurrencies; Liquidity Provision

1. Introduction

Momentum is a well-known effect in financial markets and is broadly the idea that assets that have performed well in the past, continue to perform well in the future. The seminal work in this area, by Jegadeesh and Titman (1993), shows that winners (losers) over the past six months to a year tend to continue to be winners (losers) over the next six months to a year. This is known as cross-sectional momentum which has been confirmed by numerous studies in global stock markets (Rouwenhorst, 1998; Griffin *et al.*, 2003; Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016), currency markets (Burnside *et al.*, 2011; Menkhoff *et al.*, 2012; Kroencke *et al.*, 2014; Raza *et al.*, 2014) and commodity futures (Miffre and Rallis, 2007; Shen *et al.*, 2007; Fuertes *et al.*, 2010; Narayan *et al.*, 2015).

Related to cross-sectional momentum is time-series momentum, first proposed by Moskowitz *et al.* (2012), who show that the previous twelve-month return of an asset positively predicts futures returns. This finding has been strongly supported in the literature by Asness *et al.* (2013) Georgopoulou and Wang (2017) and Lim *et al.* (2018). Conversely, Huang *et al.* (2020) question the strength of time-series momentum and that its investment performance is weak, especially for a large cross section of assets. Recently however, intraday time-series momentum has been proposed by Gao *et al.* (2018) who show that the first half-hour return on the S&P 500 ETF predicts the last half-hour return. They show that this effect is also present in other US ETFs, robust to transaction costs and other time frames. Consistent with this finding, Elaut *et al.* (2018) find that the first half-hour return can be used to predict the last half-hour return in the RUB-USD FX market during the financial crisis. Recently, Baltussen *et al.* (2021) provide strong evidence of market intraday momentum everywhere by using intraday returns on over 60 futures on equities, bonds, commodities, and currencies covering more than 40 years. Li *et al.* (2021b) also document that intraday time series momentum is economically sizable and statistically significant in 16 developed markets. Jin *et al.* (2020) and Zhang *et al.* (2020) show significant evidence of time-series intraday momentum in Chinese commodity markets. Therefore there is a modest but growing literature of intraday time-series momentum in financial markets.

Growing stunningly in recent years, the market capitalization (539.05 billion US dollars) of Bitcoin at the end of 2020 is still 57.32 times as large as it was at the beginning of 2014 (9.40 billion US dollars). Given the high media attention and dramatic price swings, there has been an explosion of studies examining cryptocurrencies, with special attention devoted to Bitcoin. [1] Some characteristics make Bitcoin different from traditional assets, e.g., unclear intrinsic value, frequent "pump-and-dump" schemes and low barriers to entry. The above features could lead to intensive trading in the Bitcoin markets. Advanced cryptocurrency exchange's API also accelerates high-frequency trading booming, raising issues on intraday patterns of Bitcoin markets.

The existing literature has reported the existence of bubbles (Cheah and Fry, 2015; Corbet *et al.*, 2018a), the inefficiency of Bitcoin (Urquhart, 2016; Nadarajah and Chu, 2017; Tiwari *et al.*, 2018), the hedging and diversification benefits of Bitcoin (Corbet *et al.*, 2018b; Borri, 2019; Guesmi *et al.*, 2019; Urquhart and Zhang, 2019), the volatility dynamics of Bitcoin (Katsiampa, 2017; Klein *et al.*, 2018; Katsiampa, 2019; Katsiampa *et al.*, 2019), the attention from media outlets (Philippas *et al.*, 2019) and the manipulations and illegal activity of Bitcoin (Gandal *et al.*, 2018; Foley *et al.*, 2019). There is also growing literature on the potential benefits of actively trading Bitcoin. For instance, Brière *et al.* (2015) show that the inclusion of Bitcoin dramatically improves the risk-adjusted returns of portfolios, while Kajtazi and Moro (2019) examine the role of Bitcoin in portfolios of US, European and Chinese assets and support previous findings in showing that Bitcoin improves portfolio performance by increasing returns, and not be reducing risk. Recently, Platanakis and Urquhart (2020) conduct a comprehensive study on the benefits of Bitcoin in a well-diversified

[1] Bitcoin has been adopted widely. For example, CFA adds topics related to Bitcoin and blockchain, which can be used as test materials; Some company accept Bitcoin as a payment method; The top 50 universities offer Bitcoin courses.

portfolio and show that even during periods of turmoil, the inclusion of Bitcoin substantially improves the risk-adjusted returns. Regarding other forms of trading, Hudson and Urquhart (2021) show that employing a wide-range of technical trading rules to a broad range of cryptocurrencies generates significant returns to investors while Corbet *et al.* (2019a) show that simple moving average rules and variable-length moving average rules generate significant returns using high-frequency Bitcoin returns, which is supported by Grobys *et al.* (2020).[2] However, Grobys and Sapkota (2019) show no evidence of significant cross-sectional momentum profits in a set of 143 cryptocurrencies. Li *et al.* (2021a), Liu and Tsyvinski (2021), Liu *et al.* (2021) and Zhang *et al.* (2021) document factors that affect the cross-section returns, including size, momentum, extreme returns and etc. Although the above papers explore potential profitability of Bitcoin trading, none of them examine the time-series momentum using high-frequency data. Given the Bitcoin's importance, characteristics and literature gap there is a need to document the intraday momentum in the Bitcoin markets.

We add to the growing literature on the trading potential of Bitcoin by studying intraday time-series momentum in Bitcoin. The intraday time-series momentum of Gao *et al.* (2018) suggests that the first half-hour of the equity trading day predicts the final half-hour. However, the Bitcoin markets do not have opening and closing times and trade 24 hours a day, 7 days a week, unlike traditional stock markets. Unlike previous studies on intraday time-series momentum, we have no clear opening and closing sessions as futures markets of Baltussen *et al.* (2021) and foreign exchange market of Elaut *et al.* (2018). Therefore we select the opening time of each exchange when volumes spikes and the closing time when the 60-minute break of CME Bitcoin futures trading begins at 5pm EST. Further two important macroeconomic variables, the GDP and the CPI, are both released at 8:30am Eastern time, which may have a significant important on the

[2] For a recent review of the literature regarding cryptocurrencies, see Corbet *et al.* (2019b).

investment decisions of traders. For both these reasons, we choose volume spikes as our opening period and 5pm as our closing period. The overnight return captures any overnight return as well as the first 30-minute impact of news releases of GDP and CPI. We use the trading of Bitfinex, Bitstamp, CEX.IO, Coinbase, and Kraken, and find that the first half-hour significantly predicts the last half-hour of Bitcoin, both in the in-sample and out-of-sample setting, thereby indicating the strong evidence of intraday time-series momentum in Bitcoin. We also show that the intraday time-series momentum is stronger when the first trading sessions have the highest volume or volatility and that intraday momentum-based trading yields substantial economic gains in terms of market timing and asset allocation, especially in periods of a market downturn in Bitcoin. This is very important and documents that this strategy could be a useful hedging strategy when there is a downturn in the Bitcoin markets. Also consistent with Gao *et al.* (2018), we show that the intraday momentum is higher on days when past returns are positive rather than negative.

Therefore our paper offers important insights into the cryptocurrency and intraday time-series momentum literature. First, we provide the first Bitcoin study on intraday momentum based on the work of Gao *et al.* (2018). While Gao *et al.* (2018) analyse US ETFs and provide evidence of intraday time-series momentum that the first half-hour return predicts the last half-hour return, we also find significant evidence of intraday time-series momentum in Bitcoin. Specifically, we find that the first half-hour significantly predicts the last half-hour of Bitcoin, both in the in-sample and out-of-sample setting, thereby indicating the strong evidence of intraday time-series momentum in Bitcoin.

Second , there a significant lack of papers that study the intraday dynamics of Bitcoin. A recent survey paper by Bariviera and Merediz-Solà (2021) show that only 14% of published papers on cryptocurrencies study intraday data. As Malceniece *et al.* (2019) note, the scale of high-frequency trading activity varies depending on the market and how broadly high-frequency trading is defined, but there is no doubt that high-frequency trading accounts for a large share of trading volume in most markets and therefore we contribute to the literature on high-frequency trading in a cryptocurrency perspective. We also show that the intraday time-series momentum is stronger when the first trading sessions have the highest volume or volatility, indicating that investors are able to trade on this effect. This is very important in that our finding on intraday time-series momentum is actually tradeable in the Bitcoin markets. Following on from this, we show that intraday momentum-based trading yields substantial economic gains in terms of market timing and asset allocation, especially in periods of a market downturn in Bitcoin. Therefore this strategy is of great interest to Bitcoin investors as well as hedgers within the Bitcoin markets.

Third, we test two possible explanations for the intraday momentum in the Bitcoin markets. The first hypothesis is the late-informed investors hypothesis, i.e., investors, who get the information later or process the information too slowly, buy or sell stock in the last-half trading hour as it is the most liquid period. The second one refers to the liquidity provision hypothesis, i.e., risk aversion of overnight positions and the disposal effect of liquidity providers drive intraday momentum. After a series of tests, we find intraday momentum is driven by the liquidity provision of the trading session after opening, combined with intraday traders' disposition effect and risk aversion to overnight risks. Aside from adding to the literature on pricing in the Bitcoin markets, our conclusions also help to understand the pricing of other "hard-to-value" assets (Detzel *et al.*, 2021).

The remainder of this paper is organized as follows. Section 2 presents the data and empirical methodology. Section 3 presents the empirical results while section 4 tests some possible explanations. Section 5 reports additional analyses and Section 6 summarizes and provides conclusions.

2. Data

In this study, we broadly follow the methodology of Gao *et al.* (2018) and Baltussen *et al.* (2021) to investigate the presence of intraday time-series momentum in Bitcoin. Unlike ETF and futures used in Gao *et al.* (2018), Bitcoin can be traded denominated in different currencies on different exchanges. The market share of Bitcoin trading volume in different currencies are shown in Figure 1[3] where we find USD is always predominant over the sample period with an average market share of 69.83%. According to NewsBTC, the number of US-based monthly active crypto traders is 22.26 million, dominating Bitcoin markets (more than the sum of the next 5 countries) and covering 6.7% of the US population.[4] The US Bitcoin trading of 1523.6 million USD is also significantly ahead of others.[5] Therefore the US markets and investors play a crucial role in the pricing of cryptocurrencies[6] and we select BTC/USD to examine intraday momentum effects. According the statistics of bitcoinity,[7] the market trading share of Bitfinex, Bitstamp, CEX.IO, Coinbase, and Kraken account for more than 91.66% of total Bitcoin markets at the end of 2020. Hence we select Bitcoin trading data from these the world's largest, reputational and long-existing exchanges. We collect tick level data of these five exchanges Bitcoin price from www.bitcoincharts.com from the earliest date to 31st December 2020 in US dollars.[8] The start of

[3] Since Bitcoin trading was no longer legal after 2017 in China, we deleted the trading volume in CNY when calculating the market shares.
[4] https://www.newsbtc.com/news/united-states-crypto-bitcoin-traders/.
[5] https://www.statista.com/statistics/1195753/bitcoin-trading-selected-countries/.
[6] The daily average trading volume during US market hours is 25041.98 BTC, accounting for 56.12% of the entire trading volume.
[7] For more information, please visit https://data.bitcoinity.org/markets/volume/5y/USD?c=e&t=b. The Bitcoin price of these exchanges are widely used in many studies, for instance, Brandvold *et al.* (2015), Urquhart (2017), Gandal *et al.* (2018), Borri (2019), Shen *et al.* (2019) and Alexander and Heck (2020).
[8] Unfortunately, due to a lack of reliable, liquid and long enough high frequency data, we are unable to examine whether intraday time series momentum is also present in other cryptocurrencies. However this may be an area of future research.

the data period is the earliest date available.[9] We then aggregate the tick level data up to the 1-minutely level.

Gao *et al.* (2018) use S&P 500 ETF that have clear opening and closing time but Bitcoin is traded around the clock and therefore its trading hours should be determined. Elaut *et al.* (2018) argue that foreign exchange trading intensifies greatly when the domestic financial markets open and therefore select the trading hours of the MICEX. Baltussen et al. (2021) determine the trading hours of non-equity assets based on spikes in volume or the opening and closing time of relative instruments. Similar in spirit to Elaut et al. (2018) and Baltussen et al. (2021), we select opening times of each exchange when volumes spikes. The closing time is chosen as 5pm EST as CME Bitcoin futures trading has a 60-minute break each day beginning at 5pm EST.[10] Gao *et al.* (2018) use the first half-hour return as the difference between the closing price at 4pm EST and the price at 10am EST the following day, thereby capturing the morning news which includes the important earnings and economic news released before the US markets open. Bitcoin markets trade 24-hours a day and therefore can capture the information from these news stories a lot faster than the US market. Also, Bitcoin traders can trade earlier than they can on US markets and therefore our opening time also takes this into consideration when studying any intraday momentum. US markets also close as 4pm EST, but as Eross *et al.* (2019) show, there is still considerable trading volume in the Bitcoin markets after 4pm EST and therefore we select 5pm EST as our last period of significantly trading in the Bitcoin markets. Therefore if observed Bitcoin intraday momentum is driven by late-informed trading or liquidity provision, the selected trading hours are suitable for tests on possible explanations (Elaut *et al.*, 2018). Table 1 lists the trading hours and daily trading

[9] Although Bitstamp was founded in August 2011, Bitcoin trading on it was not active enough before 2013. There are many first-half-hour/last-half-hour buckets without trading in 2011 and 2012, which may distort the intraday pattern and the impact of volume and volatility. We therefore discard the trading on Bitstamp in 2011 and 2012.
[10] https://www.cmegroup.com/trading/cryptocurrency-indices/cme-options-bitcoin-futures-frequently-asked-questions.html.

volume for all the Bitcoin trading exchanges we used in the paper where we find Bitfinex, Bitstamp and Kraken has larger trading volume.

Specifically, to study the intraday momentum in cryptocurrencies on any trading day *t*, we calculate the first half-hour return using the previous day's (*t-1*) close price (c) and the price of 30 minutes after opening (o) on day *t*,

$$r_{ONFH,t} = \frac{p_{o+30,t}}{p_{c,t-1}} - 1 \qquad (1)$$

where $p_{o+30,t}$ is the price of first half hour on day t, and $p_{c,t-1}$ is the close price on day *t-1*. Therefore the first half-hour return captures the impact of information released overnight. In order to examine the impact of the second-to-last half-hour return on the last half-hour return, we also include the return between the second-to-last half hour and the last half hour,

$$r_{SLH,t} = \frac{p_{c-30,t}}{p_{c-60,t}} - 1 \qquad (2)$$

$$r_{LH,t} = \frac{p_{c,t}}{p_{c-30,t}} - 1 \qquad (3)$$

where $p_{c-30,t}$ is the price of the last half hour on day *t*, $p_{c-60,t}$ is the price of the second-to-last half hour on day *t* and $p_{c,t}$ is the close price on day *t*.

Initially, we model the existence of intraday time-series momentum using the following pooled regression:

$$r_{LH,t} = \alpha + \beta_{ONFH} r_{ONFH,t} + \epsilon_t, \;\; t = 1, \dots, T \qquad (4)$$

$$r_{LH,t} = \alpha + \beta_{ONFH} r_{ONFH,t} + \beta_{SLH} r_{SLH,t} + \epsilon_t, \;\; t = 1, \dots, T \qquad (5)$$

where $r_{LH,t}$ is the return of the last trading session on day t, $r_{ONFH,t}$ is the return during the close price of previous day and the price of the end of first half hour on day t, $r_{SLH,t}$ is the second-to-last half-hour return, and T is the total number of trading days in our sample. Table 2 reports the descriptive statistics of the half-hour returns and trading volume (in BTC) where we find that r_{ONFN} has the highest mean return, while the trading volume during the *ONFH* period also has the highest mean. We also find the *ONFH* period has the largest standard deviation of returns and trading volume, suggesting that a lot of activity takes place during the *ONFH* period of our sample. The mean of all half hour buckets is 0.00008 and the mean trading volume is 178.6 BTC, indicating the Bitcoin markets are liquid.

3. Empirical Results

3.1. Intraday Predictability

Table 3 reports the predictability of the last half-hour returns using the returns of the first and the second-to-last trading sessions as explained previously. Consistent with Baltussen *et al.* (2021), we conduct pooled regressions and find that the first half hour significantly predicts the last half hour with a slope of 0.968. The Newey West t-statistic is 4.38, indicating that this result is highly significant at the 1% level and strong evidence that the first half hour predicts the last half hour of the same day. The R^2 is 1.44%, which is much higher than found in the previous literature (such as Rapach and Zhou (2013)) and fairly close to that found by Gao *et al.* (2018) and Baltussen *et al.* (2021), again showing the strength of the effect. In the second column of Table 1, we examine the case of strong price persistence where the second last half-hour return strong affects the last half-hour return. We can see that strong evidence of anti-persistence where the second last half-hour return is negatively significantly related with the last half-hour return. Therefore this initial result suggests that the second last half hour does not positively predict the last half hour. In the final column of Table 1, we regress the last half hour on the first half hour and the second last half hour, and we see that the first half hour significantly predicts the last half hour at the 1% level of significance. The R^2 of 2.12% is very high and larger than the individual R^2s suggesting that the first half hour and the second last half hour are complementary in forecasting the last half-hour return.[11] Therefore our in-sample results suggest that the first half hour significantly predicts the last half hour thereby supporting intraday time-series momentum.

3.2. Out-of-Sample Predictability

Our previous analysis is based on the entire sample and while the in-sample estimation is econometrically more efficient if regressions are stable over time, we know that the Bitcoin markets has changed dramatically over time and therefore the in-sample predictability does not necessarily imply out-of-sample predictability (as demonstrated by Welch and Goyal (2008)). Therefore we follow Gao *et al.* (2018); Baltussen *et al.* (2021) and define a pooled out-of-sample R^2 measure calculated by:

$$R_{OOS}^2 = 1 - \frac{\sum_{t=1}^{T} \frac{\sum_{i \in B_t} (r_{LH,i,t} - \hat{r}_{LH,i,t})^2}{n(B_t)}}{\sum_{t=1}^{T} \frac{\sum_{i \in B_t} (r_{LH,i,t} - \bar{r}_{LH,i,t})^2}{n(B_t)}} \tag{6}$$

where B_t is the Bitcoin exchanges available on day *t*, $n(B_t)$ is the number of Bitcoin exchanges available on day *t*, $\hat{r}_{LH,i,t}$ is the forecasted last half-hour return from the predictive regression estimated through period *t*–1 in exchange *i*, and $\bar{r}_{LH,i,t}$ is the historical average forecast estimated from the sample mean through period *t*–1 in exchange *i*,. A positive R_{OOS}^2 indicates that the predictive regression forecast beats the simple historical average. Table 3 also reports the results where when we use just the first half-hour return, where the R_{OOS}^2 is 1.09%. When we use the second last half-hour return alone, the R_{OOS}^2 is 1.40%, and when we use both, we get a R_{OOS}^2 of 1.61%. This is much higher than Bond, Commodity and Currency futures contracts' R_{OOS}^2 found in Baltussen *et al.* (2021), thereby confirming the strong significant effect of intraday time-series momentum in Bitcoin.

[11] Gao *et al.* (2018) document an R^2 of 1.6% and argue that the level is considered impressive and relative large compared to other predictors, especially at this data frequency.

3.3. Impact of Volume and Volatility

So far, we have documented strong significance evidence of intraday time series momentum in Bitcoin, but what impact does trading volume have on this momentum? This is an important question since the first half hour of trading is typically characterised by both high volatility and high volume and this may be skewing our results. Therefore we sort the trading days for each year in our sample separately based on the first half hour trading volume, splitting them into three equal groups: low, medium and high volume days. Table 4 shows that the first half hour significantly predicts the final half hour in high and medium volume days, but the result is insignificant in low volume days. The R^2 is 3.86% for high volume days suggesting strong forecasting power, while the R^2 is 1.09% for low volume days. Therefore intraday time series momentum is most prevalent in high volume days and there is no significant effect in low volume days. This supports our finding and suggests that our result is not due to illiquidity in the market and that investors would be able to trade on this intraday time-series momentum.

A related topic is the impact volatility has on intraday momentum. To address this, we sort all trading days in our sample by the first half hour volatility, splitting them into three groups: low, medium and high volatility days based on 1-minutely data. Table 4 reports the results and we find strong significance evidence of intraday time series momentum on days with high volatility, where the first half hour coefficient is statistical significance at the 1% level and the R^2 is 2.83%. However we find no evidence of the first half hour predicting the final half hour in medium or low volatile days indicating that this effect is only prevalent in days with high volatility.

From the above results, we infer that the opening trading sessions with the highest volume or volatility have the greatest intraday time-series momentum predictability for Bitcoin. As investors' participation increases when trading volume is high, we assume that higher the trading volume or volatility in the first half hour means that there are more investors active which in turn leads to greater predictability. This indicates that intraday momentum in the Bitcoin markets is positively associated with volume and volatility, consistent with Gao *et al.* (2018) and Elaut *et al.* (2018).

3.4. Market Timing

To assess the true value of this predictor we examine how well it performs in market timing where we use the first and second last half hours as timing signals to trade the market in the last half hour. We take a long position in the market at the beginning of the last half hour if the timing signal is positive and a short position otherwise. We close the position (long or short) at the market close on each trading day. Specifically

$$\eta(r_{ONFH}) = \begin{cases} r_{LH}, & if\ r_{ONFH} > 0; \\ -r_{LH}, & if\ r_{ONFH} \leq 0. \end{cases}$$
$$\eta(r_{SLH}) = \begin{cases} r_{LH}, & if\ r_{SLH} < 0; \\ -r_{LH}, & if\ r_{SLH} \geq 0. \end{cases} \tag{7}$$

We also examine the case where we use both the first half hour and the second last half hour as trading signals, where we go long if the first half hour is positive and second last half hour is negative, and go short when the first half is negative and the second last half hour is positive. Otherwise, we stay out of the market. Specifically;

$$\eta(r_{ONFH}, r_{SLH}) = \begin{cases} r_{LH}, & if\ r_{ONFH} > 0\ and\ r_{SLH} < 0; \\ -r_{LH}, & if\ r_{ONFH} \leq 0\ and\ r_{SLH} \geq 0; \\ 0, & otherwise. \end{cases} \tag{8}$$

Table 5 reports the summary statistics on returns generated from the different trading strategies. When we use the first half-hour return as the timing signal to trade on the last half hour, the average return is 7.82% on an annual basis. However using the second last half hour to predict the last half hour, returns 17.32% while combining the two signals provides a return of 16.69%. All three strategies return positive Sharpe ratios, and all three have success rates well over 50%. Therefore all three strategies substantially outperform the always long benchmark which returns 6.54% per annum. Conversely the buy-and-hold benchmark return a substantial 154.62% per annum over our full sample period which represents the large increase in the price of Bitcoin. However this figure can be misleading given the huge surge in the price of Bitcoin in 2013 and 2017 and these years may be skewing the results. Even with these dramatic years, the Sharpe ratios of two of our strategies are higher than that of the buy-and-hold strategy indicating that on a risk-return basis, intraday momentum does outperform the buy-and-hold strategy.

To examine this further, we calculate the timing value of intraday momentum on a yearly basis since Bitcoin has performed quite drastically different every year since 2013. The results, also reported in Table 5, show that for years of extreme appreciation of Bitcoin, namely 2013, 2016 and 2017, the buy-and-hold strategy performs much better in terms of yearly returns and Sharpe ratios. However the value of the intraday momentum is clear in 2014, 2015 and 2018, where the buy-and-hold strategy generates negative returns and the intraday momentum generates positive returns and substantially higher Sharpe ratios. This indicates that the intraday time-series momentum strategy can be very beneficial to investors during periods of downturn in the Bitcoin markets and consequently could be used as a hedging strategy during Bitcoin markets turmoil. This is consistent with Hudson and Urquhart (2019) that show that technical trading in cryptocurrencies is especially beneficial during market turndowns. Therefore we show that the intraday momentum strategy does especially well during periods when the Bitcoin markets are falling and suggests that intraday time-series momentum avoids Bitcoin markets drawdowns.

3.5. Utility Gains

The previous analysis on market timing used just the signs of returns to forecast returns, but we can also use the magnitudes of the predictors to forecast expected returns. With these expected returns, we construct the optimal portfolio for a mean-variance investor who allocates funds between Bitcoin and the risk-free asset (Treasury t-bills). The optimal mean variance portfolio weight on the market is:

$$w_t = \frac{1}{\gamma}\frac{\hat{r}_{LH,t+1}}{\hat{\sigma}^2_{LH,t+1}} \tag{9}$$

where $\hat{r}_{LH,t+1}$ is the forecasted last half-hour return on day *t+1* conditional on information available on or before day *t* and the predictor on *t+1*, and $\hat{\sigma}^2_{LH,t+1}$ is the standard deviation of the last half-hour return, both of which are estimated from recursive regressions. γ is the relative risk aversion coefficient, which is set at 5 and we impose the portfolio constraint that the weight on the market must be between -0.5 and 1.5, meaning that the investor is allowed to borrow or short no more than 50% on margin.

Over the out-of-sample period, the realized utility is:

$$U = \hat{\mu}_p - \frac{\gamma}{2}\hat{\sigma}^2_p \tag{10}$$

where $\hat{\mu}_p$ and $\hat{\sigma}^2_p$ are computed based on the realized portfolio returns. In the out-of-sample forecasting literature, the historical average is usually the benchmark and the certainty equivalent return (CER) of predictability is computed as:

$$CER = U_2 - U_1 \tag{11}$$

where U_2 is the realized utility of using the forecasted return $\hat{r}_{LH,t+1}$ and U_1 is the realized utility of using the historical mean forecast, $\bar{r}_{LH,t+1}$. The results are reported in Table 6 where using the first half hour to forecast the last half-hour returns yields an average return of 10.776%, with a standard deviation of 10.33% and large positive skewness. In contrast, using the historical average to predict the last half-hour return only generates an average return of 2.28%, with a standard deviation of 4.33% and hence a Sharpe ratio of 0.53. The CER using the first half-hour return is 5.95% per annum, indicating the sizable economic gains when investors switch from trading based on a random walk to trading based on intraday momentum. When both the first and the second last half-hour returns are used to forecast the last half-hour returns, the portfolio delivers the best results, with an average return of 13.95% per annum, a Sharpe ratio of 1.15, and a CER of 8.09% per annum. Therefore using both signals offers much higher utility gains than a random walk and therefore offers substantial benefits to investors.

3.6. Conditional Predictability

As documented by Murphy and Thirumalai (2017), the intraday cross-sectional momentum is much stronger conditional on negative past returns than on positive past returns. Therefore, we examine how our results of intraday momentum vary conditional on the sign of the first half-hour return. The results are reported in Table 7 where the R^2 for the three predictive regressions are 1.89%, 2.78% and 3.19% respectively when the first half-hour return is positive. In contrast, the R^2 is only 0.11%, 0.88% and 0.89% when the first half-hour return is negative. The first half hour coefficient is statistically significant in each case but much larger in the magnitude for when the past returns are positive, presumably because of good economic news. Therefore we find, consistent with Gao *et al.* (2018), that the intraday momentum effect is stronger when past returns are positive rather than negative. This can be described by two competing explanations. First, many investors can be reluctant to sell in the last half hour on a bad news day even when they should, due to the disposition effect. Second, arbitrageurs are less inclined to arbitrage in a down market as it will be costlier than arbitraging in an up market. Nevertheless, we find strong evidence of intraday time-series momentum even when previous returns are negative.

3.7. Transaction Costs

Up to this point, our analysis has assumed zero transaction costs but in practice these may be significant. Indeed, any trading strategy may predict future price movements in the sense of generating significantly positive returns but still not be profitable once the returns are adjusted for transaction costs. Transaction costs for Bitcoin are difficult to estimate as it can depend on the time of the day, the exchange in which the investor is trading with and whether the trade is executed by a retail investor or an institutional investor. Lintilhac and Tourin (2017) suggest transaction costs of 50bps for Bitcoin, but as mentioned previously, this may change dramatically depending on many factors.[12] Therefore we calculate breakeven transaction costs, which are the transaction costs required to make the profit from employing this strategy zero. Interestingly, many cryptocurrency exchanges have launched margin trading to satisfy the speculative need of investors.[13] We thus calculate the costs (in bps) and profit (%) per trade by using different leverages and profit (%) per trade is the average return on the trading day using the strategies. Table 8 reports the results and shows that the entire-sample breakeven costs of $\eta(r_{ONFH})$,$\eta(r_{SLH})$ and $\eta(r_{ONFH}, r_{SLH})$ are 3, 7 and 10 bps respectively, indicating that all of these three strategies are not profitable given that the trading fee of Bitstamp is 25bps.[14] But margin trading increases the breakeven costs, where 2:1 means that investors can buy twice the amount of Bitcoin by borrowing the same amount of their principal. If Bitcoin investors trade with 10:1 leverage ratio, the break-even costs of $\eta(r_{ONFH})$,$\eta(r_{SLH})$ and $\eta(r_{ONFH}, r_{SLH})$ in the full sample period are 29, 64 and 96

[12] Which has been employed in studies such as Platanakis *et al.* (2018) as well as Platanakis and Urquhart (2020).
[13] Some sites list several exchanges for margin cryptocurrency trading, for example, https://coinsutra.com/margin-trading-crypto-exchanges/.
[14] https://www.bitstamp.net/fee-schedule/.

bps respectively, generating 0.28%, 0.61% and 0.96% per trade. This result shows that the intraday momentum strategies with margin trading are still profitable.

However as previously discussed, Bitcoin has been through some extreme periods price appreciation and depreciation and just studying the full sample may not give a representative outlook. To further gauge the strategy effectiveness, we calculate the above results yearly to give a detailed observation of the changes of the break-even costs and profit per trade. We also report the results in Table 8 and find that the non-margin intraday momentum strategies have low break-even costs except in the year of 2013. However, if we add leverage into the analysis, the break-even costs and profit per trade grow substantially. This result shows that the intraday time-series momentum strategy benefits to the investors with leverage trading. Overall, the break-even costs indicate that the intraday momentum strategies remain profitable after taking trading costs into consideration, especially for margin trading.

4. Possible Explanations

We now have documented the evidence of intraday momentum in the Bitcoin markets, but the possible drivers of intraday momentum have not been tested. Gao *et al.* (2018) and Elaut *et al.* (2018) provided possible explanations, i.e., late-informed investors hypothesis (investors, who get the information later or process the information too slowly, buy or sell stock in the last-half trading hour as it is the most liquid period) and liquidity provision hypothesis (risk aversion of overnight positions and the disposal effect of liquidity providers drive intraday momentum). We therefore explore the late-informed and liquidity provision explanations of intraday momentum in the Bitcoin markets.

4.1. Late-informed Trading

Informed investors tend to conceal the information advantage and reduce price shock via trading in high volume trading sessions, e.g., first half hour (Kyle, 1985; Admati and Pfleiderer, 1988; Gao et al., 2018). However, others investors may get the information later or process the information too slowly so that they fail to trade in the first half hour session. Based on previous studies on information transmission lasting up to a month (Cohen and Frazzini, 2008), we therefore conjecture that some investors could spend up to an entire day to process information. As the most liquid trading session, the last half hour is a good choice for the late-informed investors. If informed investors trade immediately during the first half hour after the opening and the late-informed investors also trade in the other most liquid session with the same direction, this has a price impact and thereby generates a positive correlation between the returns of the first half hour and the last half hour.

If the intraday momentum derives from the late-informed trading, the news on Bitcoin significantly drives the intraday returns predictability, i.e., the intraday momentum is stronger in days with more Bitcoin news than in days with less news. Therefore, to explore how the news influences the magnitude of predictability of the last-half-hour returns, we collect the news associated with Bitcoin from google.com.[15] We run the following regression, including the log number of Bitcoin news and interaction of the first half-hour return and news:

$$\begin{aligned} r_{LH,t} = \alpha + \beta_{News} News_t + \beta_{News*ONFH}(News_t \times r_{ONFH,t}) + \beta_{ONFH} r_{ONFH,t} \\ + \beta_{SLH} r_{SLH,t} + \epsilon_t, \ \ t = 1, \dots, T \end{aligned} \tag{12}$$

where $News_t$ is the log number of Bitcoin news.

[15] We search keyword "Bitcoin" in Google engine with the link https://www.google.com/search?q=bitcoin&tbm=nws and then restrict the date of web pages in a certain date.

We report the summary statistics of Bitcoin news in Panel A of Table 9. The mean log number of news is 2.592 with the 95th percentile of 3.434 and the 5th percentile of 1.386, indicating that Bitcoin is covered with several pieces of news every day. We first regress the last-half-hour returns on Bitcoin news and find the coefficient β_{News} in Column (1) of Panel B is negative but insignificant. We then add the first half-hour returns and second-to-last half-hour returns and the coefficient β_{News} is still insignificant but β_{ONFH} is significant at 1% level. Turning to the other specifications, columns (4) and (5) of Panel B reports the regression results, including the interaction of Bitcoin news and the first half-hour return. The $\beta_{News*ONFH}$ captures the interaction between $r_{ONFH,t}$ and $News_t$. The coefficients $\beta_{News*ONFH}$ in columns (4) and (5) indicate that the predictive relation is not significant in days with more Bitcoin news. Therefore these results fail to lend support to the late-informed trading hypothesis.

4.2. Liquidity Provision

We turn to test another hypothesis on liquidity provision, i.e., some liquidity providers (e.g., intraday traders) also could cause the intraday momentum. Price information disseminates most rapidly in the trading session after opening (Bloomfield *et al.*, 2005), causing order imbalances as investors respond to overnight news with taking similar positions. Intraday traders tend to trade oppositely to provide liquidity of the Bitcoin markets during the trading session after opening.[16] For profitable trades, intraday traders may close positions rapidly. However they may be unwilling to close unprofitable positions quickly because of the disposition effect (Odean, 1998; Locke and Mann, 2005). Nevertheless, intraday traders will close their positions before the end of the day,

[16] There are more and more investors including institutional investors pay their attention to cryptocurrency intraday trading (https://www.bnnbloomberg.ca/bitcoin-intraday-trading-pattern-emerges-as-institutions-pile-in-1.1576050). There are also some tutorials on how to build an intraday trading system in the cryptocurrency markets (https://quantatrisk.com/2020/04/27/intraday-algo-trading-model-cryptocurrencies-bitcoin-buy-signals-python/).

forced by the risk management practices and high overnight risk. They therefore trade with the same directions of first half-hour return to close their positions.

To test the liquidity provision hypothesis, we first define the liquidity over the opening first half hour interval. Since the unavailability of the high-frequency quote in some cryptocurrency exchanges, it is a challenge for us to measure the first half hour liquidity. Luckily, Brauneis *et al.* (2021) test the efficacy of low-frequency liquidity measures describing high-frequency liquidity in the Bitcoin markets. They find that Corwin and Schultz (2012) measure is the best performing for each of the quote spreads liquidity measures on an hourly basis. We consequently employ the Corwin and Schultz (2012) spread estimator (CS) based on high and low prices to estimate liquidity. We calculate the CS liquidity as follows:

$$Spread = \frac{2(\exp(\alpha) - 1)}{1 + \exp(\alpha)}$$

$$\alpha = \frac{\sqrt{2\beta} - \sqrt{\beta}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma}{3 - 2\sqrt{2}}} \tag{13}$$

$$\beta = \left[\ln(\frac{H_i}{L_i})\right]^2 + \left[\ln(\frac{H_{i+1}}{L_{i+1}})\right]^2, \qquad \gamma = \left[\ln(\frac{H_{i,i+1}}{L_{i,i+1}})\right]^2$$

where $Spread$ is the CS estimator, H_i and L_i are the high and low prices at time i while $H_{i,i+1}$ and $L_{i,i+1}$ denote the high and low prices of two adjacent time periods i and $i + 1$. For each Bitcoin exchange, we measure the first half hour spread following Corwin and Schultz (2012). Specifically, we also set negative values of CS estimator to zero.

We now examine how liquidity affects intraday momentum in the Bitcoin markets. If liquidity provision drives intraday momentum, the CS estimator can predict the last-half-hour return. We therefore run the following regression:

$$r_{LH,t} = \alpha + \beta_{Spread}Spread_t + \beta_{Spread*ONFH}(Spread_t \times r_{ONFH,t}) + \beta_{ONFH}r_{ONFH,t} + \beta_{SLH}r_{SLH,t} + \epsilon_t, \ \ t = 1, \dots, T \tag{14}$$

where $Spread$ is the CS spread estimator in the first half hour trading session.

We report the statistics CS spread estimator (multiplied by 100) for each exchange in Panel C of Table 9. Since the sample period for Bitfinex and Bitstamp is longer than others, their CS spread is larger. The first half hour session of Coinbase and Kraken is the most liquid. The results of the liquidity provision hypothesis are reported in Panel D of Table 9. The regression of r_{LH} on $Spread$ in column (1) has t-statistic of 5.33, indicating CS spread estimator has explanatory power on the last-half-hour returns. We then add r_{ONFH}, r_{SLH} as well as the interaction of $Spread$ and r_{ONFH} into the regression. The interaction is to test whether the explanatory power of r_{ONFH} depends on $Spread$. Interestingly, β_{ONFH} is still positively significant at the 1% level in columns (2) and (3)[17] but insignificant after adding the interaction in columns (4) and (5). On the contrary, $\beta_{Spread*ONFH}$ is positively significant at the 1% level with t-statistics of 8.85 and 8.18 in the last two columns, suggesting the intraday momentum is stronger when the spread is high. Taken together, intraday momentum is driven by the liquidity provision the trading session after opening, combined with intraday traders' disposition effect and risk aversion to overnight risks.

5. Additional Analyses

5.1. Return Decomposition

We compute the first half-hour return used in the above analysis with the previous day's close price day and the price of 30 minutes after opening as Gao *et al.* (2018) and Baltussen *et al.* (2021)

[17] We also find the β_{ONFH} is still positively significant controlling quote spreads of previous day.

do. It is interesting to decompose r_{ONFH} into the r_{ON} (calculated with the previous day's close price day and the opening price) and the opening half-hour return r_{FH} (calculated with the opening price and the price of 30 minutes after opening). Return decomposition also helps comprehend the intraday momentum in Bitcoin markets. We then test which return has stronger predictive power on the last-half-hour return. We report the results in Table 10 of the following regression.

$$r_{LH,t} = \alpha + \beta_{ON} r_{ON,t} + \beta_{FH} r_{FH,t} + \beta_{SLH} r_{SLH,t} + \epsilon_t, \;\; t = 1, \dots, T \qquad (15)$$

Although both β_{ON} and β_{FH} are positively significant when regressing r_{LH} on r_{ON} or r_{FH} individually, the t-statistic of β_{FH} is 2.09, smaller than that of β_{ON} with a value of 5.28. The R^2 in the second column is 0.57%, also smaller than that in the first column, indicating that r_{ON} contributes more to predicting r_{LH}. When including r_{ON}, r_{FH} and r_{SLH} simultaneously, the same conclusion is reached. From the third column, the t-statistic of β_{ON} is 4.93, significant at the 1% level but that of β_{FH} is merely 1.92, significant at the 10% level.

This return decomposition test is a supplement to the late-informed trading hypothesis test. If late-informed trading drives the intraday momentum, the positive correlation between r_{LH} and r_{FH} should be stronger than that of r_{LH} and r_{ON}. But our result is inconsistent with this explanation as we find that the r_{ON} is a better predictor than r_{FH}.

5.2. Alternative Trading Pairs

We use r_{ONFH} and r_{SLH} to predict r_{LH} using BTC/USD in the above analysis and now we turn to test whether intraday momentum works based on open-close times of other major markets, i.e., Japan and South Korea markets.[18] We select BTC/JPY and BTC/KRW as the alternative trading

[18] We thank an anonymous referee for this valuable suggestion.

pairs because they are actively traded (shown in Figure 1) and the representatives of east Asia. According the statistics of bitcoinity, the market trading share of bitFlyer, BtcBox and Zaif accounts for more than 90% of BTC/JPY trading at the end of 2020. Korbit is the longest-existing exchange located in South Korea. We hence collect tick level data of these four exchanges Bitcoin price from www.bitcoincharts.com from the earliest date to 31st December 2020 in Japanese Yen and Korean Won. The start of the data period is the earliest date available. In a similar spirit, we follow Gao *et al.* (2018) and Baltussen *et al.* (2021) to determine the opening and closing times of Bitcoin trading of Japan and South Korea markets. We select the opening times of each exchange when the trading volume spikes and determine the closing times when local stock markets close. We report the basic information of trading data usedand in Panel A of Table 11 where we find bitFlyer is the most active while Korbit has longer trading history.

Panels B and C of Table 11 report the predictability of the last half-hour returns using the returns of the first and the second-to-last trading sessions. Consistent with the findings of BTC/USD, the Newey West t-statistic of 2.38 and 2.50, indicating that the intraday momentum of BTC/JPY and BTC/KRW is weaker but still significant at the 5% level. Therefore our in-sample and out-of-sample results suggest that the first half hour significantly predicts the last half hour thereby supporting intraday time-series momentum of BTC/JPY and BTC/KRW. But what drives the intraday momentum based on open-close times of Japan and South Korea markets. Given that Bitcoin is distributed ledger, it is natural to conjecture it is also driven by liquidity provision because there is no information release source in the Bitcoin markets. We then repeat the analysis of Section 4.2 and find $\beta_{Spread*ONFH}$ is significant at 1% level but β_{ONFH} is not, indicating intraday momentum is driven by the liquidity provision. Overall, the results of alternative trading pairs are intuitive and provide evidence on liquidity provision explanation.

5.3. Alternative Predictability

We have studied the intraday time-series momentum between volume spikes to 5pm EST (the beginning of the 60-minute break of CME Bitcoin futures trading) since most of the volume of Bitcoin trading happens during these hours, and they also before the US markets open, and after its close, enabling investors to trade in the Bitcoin markets after the main US markets have closed. Gao et al. (2018) show intraday momentum in US ETFs over the period 10am EST to 4pm EST, arguing that investors take onboard economic and policy announcements in the morning before 10am. Therefore, we re-examine our intraday momentum but now use the time period 10am EST to 4pm EST consistent with Gao et al. (2018), thereby including the first half hour the US market is also open.

Table 12 reports the results and shows that the first half hour does predict the last half hour, but the magnitude of the prediction is a lot smaller in magnitude and statistical significance to our previous results. This suggests that some predictability of the last half hour is lost between volume spikes and 10am and therefore the market has already incorporated any overnight news by volume spikes and Bitcoin traders should not wait until 10am to use this intraday momentum strategy. Since β of r_{H2} is significantly negative in Table 11, it is not surprising that returns between 4pm EST of previous day and 10am EST has lower predictive power. Therefore these findings support our analysis that the intraday time-series momentum is most successful from volume spikes to 5pm EST.[19]

6. Summary and Conclusions

This paper examines the intraday time-series momentum in the largest cryptocurrency market, Bitcoin. Unlike traditional markets, Bitcoin trades 24 hours a day, 7 days a week and therefore has no definite opening and closing times. Therefore, we choose our open and closes based on the

[19] We have also studied alternative periods and find consistent results.

trading volume of Bitcoin and the findings of Eross *et al.* (2019) and use volume spikes to 5pm EST as our opening and closing times. This also fits in with important economic news which is released at 8:30am in the US and therefore enables Bitcoin traders to trade before the main US stock markets open. Specifically, our first half-hour return is from 5pm the previous day to volume spikes the next day, and the last half-hour return is the return between 4:30pm to 5pm. We find that the first half significantly predicts the final half hour both in- and out-of-sample, and intraday momentum-based trading yields substantial economic gains in terms of market timing and asset allocation. We also show that intraday momentum is stronger on days where the first trading sessions have higher trading volume and higher volatility. Consistent with Gao *et al.* (2018), we also show that the intraday momentum is higher on days when past returns are positive rather than negative. Finally, we show that this strategy may have benefits to investors if margin trading is taken into consideration. We also testes possible explanations and find intraday momentum is driven by the liquidity provision the trading session after opening, combined with intraday traders' disposition effect and risk aversion to overnight risks.

Therefore overall, our results show evidence of significant intraday time-series momentum in Bitcoin, which has substantial benefits to investors, especially during periods of downward trends in the market. Consequently these results will be of interest to investors in Bitcoin and may help diversify portfolios when the Bitcoin markets is in decline.

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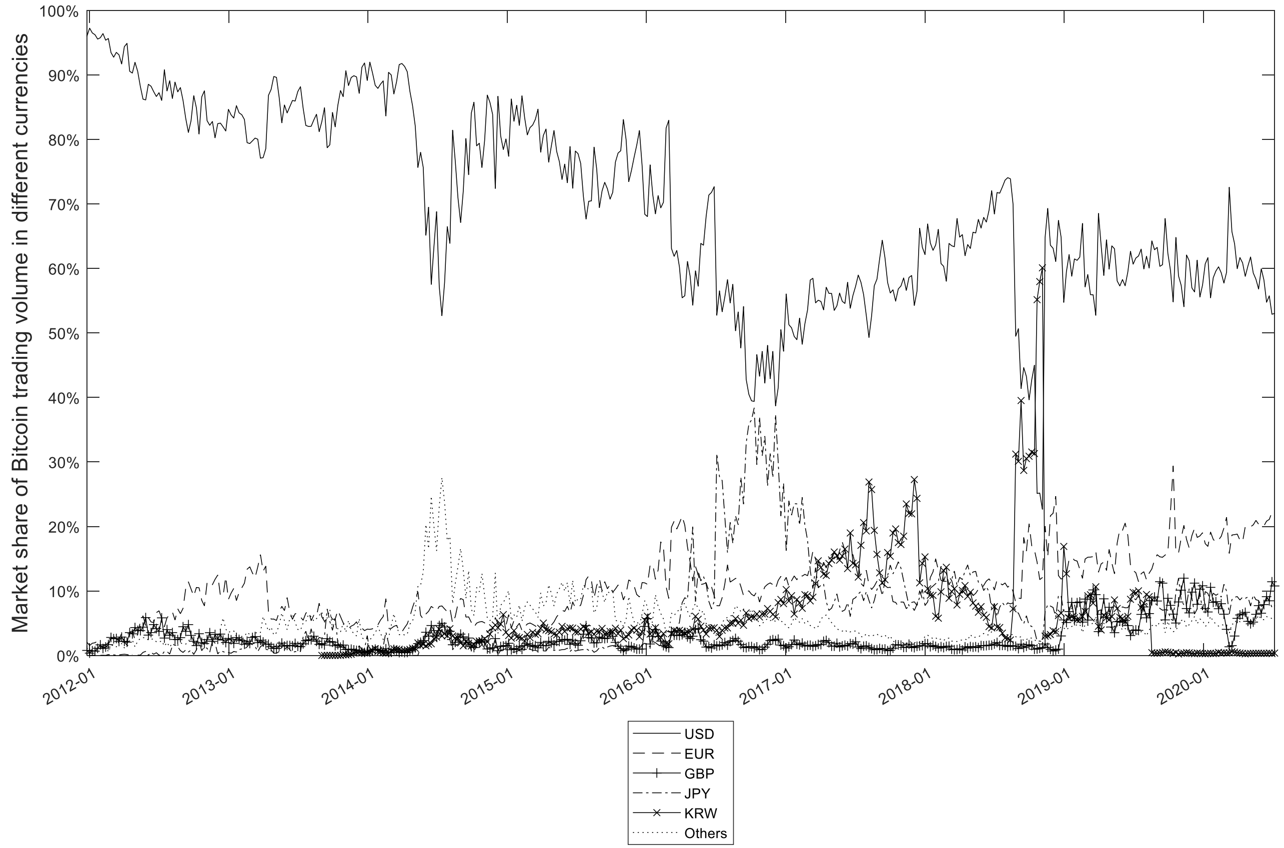

Figure 1. The market share of Bitcoin trading volume in different currencies

Table 1. Overview of Bitcoin trading data used

This table reports the overview of Bitcoin trading data used. Times are trading hours selected based on volume spikes and CME Bitcoin futures break time, expressed in Eastern Standard Time (EST).

Exchanges	Trading pairs	Start	End	Average daily trading volume (BTC)	Obs.	Times (EST)
Bitfinex	BTC/USD	2013-04-02	2020-12-31	18747.49	2827	9:05-17:00
Bitstamp	BTC/USD	2013-01-01	2020-12-31	9732.90	2921	9:00-17:00
CEX.IO	BTC/USD	2014-07-20	2020-12-31	618.02	2356	9:00-17:00
Coinbase	BTC/USD	2014-12-03	2020-12-31	11833.09	2188	9:40-17:00
Kraken	BTC/USD	2014-01-09	2020-12-31	3667.05	2500	9:15-17:00

Table 2. Descriptive statistics

This table reports the descriptive statistics of ONFH, SLH and LH return, volume, as well as all 30-minute return returns and volume together. We report the mean, the standard deviation, the percentile 5, the percentile 95 and the skewness.

		Return					Volume				
		Mean	Std	P5	P95	Skewness	Mean	Std	P5	P95	Skewness
Bitfinex	$ONFH$	0.00201	0.03710	-0.04591	0.05475	0.389	12670.4	16608.2	1400.1	38667.0	4.497
	SLH	-0.00003	0.00740	-0.00844	0.00918	-0.158	428.8	939.8	9.1	1618.7	5.934
	LH	0.00045	0.00771	-0.00841	0.00965	-0.338	451.2	1261.7	7.2	1612.4	9.085
Bitstamp	$ONFH$	0.00294	0.03556	-0.04791	0.05985	0.496	6920.2	7042.6	1293.7	18970.5	4.422
	SLH	0.00009	0.00811	-0.00903	0.00951	-4.041	234.1	407.7	15.7	816.4	10.014
	LH	0.00019	0.00829	-0.00884	0.00937	0.600	212.9	390.9	13.5	801.6	6.971
CEX.IO	$ONFH$	0.00123	0.02977	-0.04199	0.04589	0.148	406.4	504.0	34.5	1395.5	2.934
	SLH	0.00006	0.00676	-0.00825	0.00862	-3.356	12.6	26.4	0.4	42.1	17.897
	LH	0.00024	0.00632	-0.00776	0.00833	-0.718	11.8	22.1	0.3	40.9	7.511
Coinbase	$ONFH$	0.00219	0.03185	-0.04918	0.05059	0.099	6595.8	6512.9	1944.0	17163.3	6.098
	SLH	-0.00008	0.00790	-0.00852	0.00855	-7.566	273.3	339.6	58.6	844.1	5.248
	LH	0.00015	0.00582	-0.00780	0.00842	-0.167	266.2	358.2	57.5	794.1	5.748
Kraken	$ONFH$	0.00190	0.03283	-0.04839	0.05226	-0.170	3143.1	2872.6	299.6	8403.3	2.922
	SLH	0.00026	0.00800	-0.00852	0.00943	-5.143	120.8	182.8	3.3	419.5	5.466
	LH	0.00017	0.00668	-0.00825	0.00866	0.441	109.7	164.6	3.1	361.9	5.204
All exchanges	All buckets	0.00008	0.00743	-0.00857	0.00867	4.572	178.6	439.9	1.0	667.6	14.089

Table 3. In-sample and out-of-sample analysis

This table reports the results of regressing the last half-hour return (r_{LH}) on the first half hour return (r_{ONFH}) and the second to last half hour return (r_{SLH}) of the day. This table shows the in-sample results and the out-of-sample results. We run the pooled regression $r_{LH,t} = \alpha + \beta_{ONFH} r_{ONFH,t} + \beta_{SLH} r_{SLH,t} + \epsilon_t,\ \ t = 1, \dots, T$, where $r_{LH,t}$ is the return of the last trading session on day t, $r_{ONFH,t}$ is the return during the close price of previous day and the price of the end of first half hour on day t, $r_{SLH,t}$ is the second-to-last half-hour return, and T is the total number of trading days in our sample. The returns are annualized where Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5% and 10% level is denoted by ***, ** and * respectively.

Predictor	r_{ONFH}	r_{SLH}	r_{ONFH} and r_{SLH}
Intercept	4.983	5.667	7.237
	(1.02)	(1.27)	(1.39)
β_{ONFH}	0.968***		0.937***
	(4.38)		(4.26)
β_{SLH}		-9.778***	-9.720***
		(-10.22)	(-10.17)
R^2	1.44%	1.98%	2.32%
R^2_{OOS}	1.09%	1.40%	1.81%

Table 4. The impact of volume and volatility

This table reports the predictive regressions under different levels of trading volume and volatility of the first half hour. The first half hour trading volume per year takes into account the increase in trading volume over time, and then combine each volume tercile across all years to form three volume groups. The first half-hour volatility is estimated using one-minute returns, and then all days are split into terciles by their first half hour volatility, low, medium and high. We run the pooled regression $r_{LH,t} = \alpha + \beta_{ONFH} r_{ONFH,t} + \beta_{SLH} r_{SLH,t} + \epsilon_t,\ \ t = 1, \dots, T$ in each group, where $r_{LH,t}$ is the return of the last trading session on day t, $r_{ONFH,t}$ is the return during the close price of previous day and the price of the end of first half hour on day t, $r_{SLH,t}$ is the second-to-last half-hour return, and T is the total number of trading days in our sample. The returns are annualized and Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5% and 10% level is denoted by ***, ** and * respectively.

	Volume			Volatility		
	High	Medium	Low	High	Medium	Low
Intercept	4.167	8.952	2.026	13.383	1.155	-0.228
	(1.32)	(1.32)	(0.97)	(1.26)	(1.30)	(-0.43)
β_{ONFH}	2.013***	1.247*	0.430	2.012***	0.586*	0.786
	(4.74)	(1.78)	(1.30)	(6.25)	(1.69)	(0.96)
β_{SLH}	-15.539***	-10.080***	-5.309***	-15.882***	-5.152***	-11.256***
	(-12.08)	(-8.67)	(-3.54)	(-10.44)	(-3.22)	(-11.41)
R^2	3.86%	2.07%	1.09%	2.83%	2.20%	1.18%

Table 5. Timing strategy

This table reports the economic value of timing the last half-hour market return using the first, second last or both. The benchmark Always Long involves investing in the market during the last half hour of each trading day, while Buy-and-Hold involves buying and holding the market on a daily basis. For each strategy, we report the average return (Avg ret), standard deviation (Std Dev), Sharpe ratio (Sratio), skewness, kurtosis and success rate (Success). The returns are annualized and Newey and West (1987) robust t-statistics are employed and significance at the 1%, 5% and 10% level is denoted by ***, ** and * respectively.

	Timing	Avg ret(%)	Std dev(%)	SRatio	Skewness	Kurtosis	Success(%)
Full sample	$\eta(r_{ONFH})$	7.817**	11.976	0.653	-0.444	62.546	51.598
	$\eta(r_{SLH})$	17.315***	10.096	1.715	0.830	69.809	56.138
	$\eta(r_{ONFH}, r_{SLH})$	16.693***	9.682	1.724	0.108	157.921	58.115
	Always long	6.538**	14.350	0.456	-0.896	68.894	46.959
	Buy-and-Hold	154.623***	101.715	1.520	-1.439	28.437	
2013	$\eta(r_{ONFH})$	49.800*	29.952	1.663	0.597	32.122	52.308
	$\eta(r_{SLH})$	68.776**	28.966	2.374	2.353	34.205	57.895
	$\eta(r_{ONFH}, r_{SLH})$	54.104***	22.129	2.445	3.307	67.031	60.853
	Always long	34.732	29.993	1.158	0.080	32.112	54.437
	Buy-and-Hold	5308.965***	149.835	35.432	-1.877	20.733	
2014	$\eta(r_{ONFH})$	7.480	12.308	0.608	0.640	12.861	50.580
	$\eta(r_{SLH})$	15.445**	10.767	1.435	0.018	12.179	55.758
	$\eta(r_{ONFH}, r_{SLH})$	8.633**	7.420	1.163	-0.050	20.940	56.659
	Always long	1.817(0.23)	14.653	0.124	-4.927	98.777	53.620
	Buy-and-Hold	-56.188	75.641	-0.743	-0.244	8.699	
2015	$\eta(r_{ONFH})$	2.122	14.390	0.147	-4.149	47.288	52.326
	$\eta(r_{SLH})$	1.714	13.081	0.131	-2.805	61.022	54.042
	$\eta(r_{ONFH}, r_{SLH})$	3.941	10.270	0.384	-7.722	117.597	57.364
	Always long	-7.894	14.455	-0.546	-3.620	46.040	48.658
	Buy-and-Hold	34.545	71.418	0.484	-1.183	15.573	
2016	$\eta(r_{ONFH})$	6.206**	6.291	0.986	0.492	15.620	52.136
	$\eta(r_{SLH})$	23.134***	6.122	3.779	1.621	15.629	58.134
	$\eta(r_{ONFH}, r_{SLH})$	14.798***	4.138	3.576	4.266	36.447	61.196
	Always long	2.093	6.301	0.332	0.310	15.611	52.484
	Buy-and-Hold	123.564*	48.340	2.556	-0.975	13.647	
2017	$\eta(r_{ONFH})$	1.788	12.937	0.138	0.020	10.172	52.243
	$\eta(r_{SLH})$	18.930***	12.905	1.467	0.070	10.225	55.986
	$\eta(r_{ONFH}, r_{SLH})$	9.971**	8.304	1.201	0.426	21.204	58.540
	Always long	27.851***	12.874	2.163	0.846	9.978	53.554
	Buy-and-Hold	1322.570***	92.938	14.231	0.112	5.797	
2018	$\eta(r_{ONFH})$	-0.192	12.035	-0.016	-1.445	17.113	51.586
	$\eta(r_{SLH})$	21.496***	11.991	1.793	0.151	17.278	56.215
	$\eta(r_{ONFH}, r_{SLH})$	10.084**	8.864	1.138	-1.478	28.524	57.772
	Always long	-3.108	12.034	-0.258	1.652	17.214	47.517
	Buy-and-Hold	-73.455	84.620	-0.868	-0.450	4.934	
2019	$\eta(r_{ONFH})$	5.395	9.383	0.575	0.009	10.426	51.557
	$\eta(r_{SLH})$	17.323***	9.343	1.854	1.047	10.187	54.720
	$\eta(r_{ONFH}, r_{SLH})$	11.116***	6.280	1.770	2.063	19.001	55.965

	Always long	16.542***	9.354	1.769	-0.489	10.686	55.667
	Buy-and-Hold	93.974	70.103	1.341	0.234	7.093	
2020	$\eta(r_{ONFH})$	3.861	13.579	0.284	-2.510	54.469	50.092
	$\eta(r_{SLH})$	0.475	13.580	0.035	-4.204	54.335	56.077
	$\eta(r_{ONFH}, r_{SLH})$	2.145	10.458	0.205	-7.330	125.741	56.285
	Always long	15.727*	13.559	1.160	3.686	53.796	53.211
	Buy-and-Hold	301.832*	81.072	3.723	-4.176	54.382	

Table 6. Utility gain

This table reports the economic value of recursively predicting the last half-hour market return using the first half-hour return alone, or combining it with the second last half-hour return. We use the predicted returns to form a constrained mean-variance optimal portfolio for a mean-variance investor with a relative risk aversion of five. Portfolio weights are restricted to a range between -0.5 and 1.5. For each strategy, we report the average return (Avg ret), standard deviation (Std dev), Sharpe ratio (SRatio), skewness, kurtosis, and the certainty equivalent gain, CER, calculated as the difference in the certainty equivalent rate of return between the optimal mean-variance strategy and benchmark using the historical average returns instead of the forecasted last half-hour returns. The returns are annualized and in percentage. Newey and West (1987) robust t-statistics are used, and significance at the 1%, 5%, or 10% level is denoted by ***, **, or *, respectively.

Predictor	Avg ret(%)	Std dev(%)	SRatio	Skewness	Kurtosis	CER(%)
$\bar{r}_{LH}$	2.278**	4.328	0.526	29.434	1060.087	
$\beta_{ONFH} r_{ONFH}$	10.776**	10.333	1.043	10.351	553.339	5.945
$\beta_{ONFH} r_{ONFH} + \beta_{SLH} r_{SLH}$	13.951***	12.160	1.147	18.386	611.192	8.093

Table 7. Conditional predictability
This table reports the predictive regression results conditioned on the sign of the first half-hour returns. Panel A reports the regression results when r_{ONFH} is positive, while Panel B reports the regression results when r_{ONFH} is negative. We run the pooled regression $r_{LH,t} = \alpha + \beta_{ONFH} r_{ONFH,t} + \beta_{SLH} r_{SLH,t} + \epsilon_t,\ \ t = 1, \dots, T$ in each group, where $r_{LH,t}$ is the return of the last trading session on day t, $r_{ONFH,t}$ is the return during the close price of previous day and the price of the end of first half hour on day t, $r_{SLH,t}$ is the second-to-last half-hour return, and T is the total number of trading days in our sample. Returns are annualized and in percentage where we use Newey and West (1987) robust t-statistics. Statistical significance at the 1%, 5%, or 10% level is denoted by ***, **, or *, respectively.

	Panel A: When r_{ONFH}>0				Panel B: When r_{ONFH}<0		
Predictor	r_{ONFH}	r_{SLH}	r_{ONFH} and r_{SLH}		r_{ONFH}	r_{SLH}	r_{ONFH} and r_{SLH}
Intercept	-2.205	13.169***	-0.777	Intercept	2.012	1.902	2.670
	(-0.46)	(3.55)	(-0.16)		(0.41)	(0.49)	(0.54)
β_{ONFH}	1.950***		1.777***	β_1	0.050		0.106
	(5.12)		(4.70)		(0.12)		(0.25)
β_{SLH}		-12.471***	-12.186***	β_{16}		-6.109***	-6.120***
		(-9.80)	(-9.59)			(-4.20)	(-4.21)
R^2	1.89%	2.78%	3.19%	R^2	0.11%	0.88%	0.89%

Table 8. Break-even analysis
This table reports the break-even cost (in basis points) and profit per trade. Break-even is the trading costs that reduce performance reported in Table 5 to zero. Profit (%) per trade is the average return on trading day using the strategy. "-" denotes that since the corresponding strategy does not generate positive profit, there does not exist break-even cost. We also report the break-even cost and profit per trade of Bitcoin margin trading with different leverages. 2:1 indicates that Bitcoin investors can use 1,000 USD to buy up 2,000 USD worth of Bitcoin. 5:1 and 10:1 also have the same definition.

Timing		Num of trading days	Break-even	Profit (%) per trade	Break-even	Profit (%) per trade	Break-even	Profit (%) per trade	Break-even	Profit (%) per trade
			Without leverage		2:1		5:1		10:1	
Full sample	$\eta(r_{ONFH})$	3375	3	0.028	6	0.057	15	0.142	29	0.284
	$\eta(r_{SLH})$	3375	7	0.061	13	0.121	32	0.303	64	0.607
	$\eta(r_{ONFH}, r_{SLH})$	1465	10	0.096	20	0.191	48	0.478	96	0.957
	Always long	3375	2	0.020	4	0.040	10	0.099	20	0.198
2013	$\eta(r_{ONFH})$	365	12	0.116	24	0.231	59	0.578	118	1.157
	$\eta(r_{SLH})$	365	17	0.152	33	0.303	82	0.758	163	1.517
	$\eta(r_{ONFH}, r_{SLH})$	160	29	0.284	57	0.568	142	1.419	284	2.838
	Always long	365	9	0.088	18	0.176	44	0.439	88	0.878
2014	$\eta(r_{ONFH})$	365	1	0.003	1	0.007	2	0.017	4	0.035
	$\eta(r_{SLH})$	365	6	0.051	11	0.101	26	0.253	52	0.506
	$\eta(r_{ONFH}, r_{SLH})$	180	6	0.059	12	0.117	30	0.293	59	0.586
	Always long	365	2	0.015	3	0.029	8	0.073	15	0.146
2015	$\eta(r_{ONFH})$	362	4	0.038	8	0.075	19	0.188	38	0.376
	$\eta(r_{SLH})$	362	2	0.012	3	0.025	7	0.062	13	0.125
	$\eta(r_{ONFH}, r_{SLH})$	165	6	0.055	11	0.109	28	0.273	55	0.545
	Always long	362	-	-0.015	-	-0.029	-	-0.074	-	-0.147
2016	$\eta(r_{ONFH})$	366	3	0.020	5	0.040	11	0.100	21	0.201
	$\eta(r_{SLH})$	366	6	0.054	12	0.109	28	0.272	56	0.544
	$\eta(r_{ONFH}, r_{SLH})$	165	9	0.083	17	0.166	42	0.414	83	0.828
	Always long	366	1	0.005	1	0.010	3	0.024	5	0.048

2017	$\eta(r_{ONFH})$	365	1	0.004	1	0.008	2	0.019	4	0.038
	$\eta(r_{SLH})$	365	7	0.063	13	0.127	32	0.317	64	0.634
	$\eta(r_{ONFH}, r_{SLH})$	172	8	0.071	15	0.143	36	0.357	72	0.713
	Always long	365	9	0.083	17	0.165	42	0.413	83	0.826
2018	$\eta(r_{ONFH})$	365	1	0.003	1	0.006	2	0.016	4	0.032
	$\eta(r_{SLH})$	365	7	0.063	13	0.125	32	0.313	63	0.627
	$\eta(r_{ONFH}, r_{SLH})$	188	7	0.064	13	0.128	33	0.320	65	0.641
	Always long	365	-	-0.011	-	-0.022	-	-0.054	-	-0.108
2019	$\eta(r_{ONFH})$	365	2	0.014	3	0.028	7	0.069	14	0.139
	$\eta(r_{SLH})$	365	6	0.058	12	0.116	30	0.290	59	0.580
	$\eta(r_{ONFH}, r_{SLH})$	186	8	0.071	15	0.141	36	0.353	71	0.705
	Always long	365	5	0.048	10	0.096	25	0.240	49	0.480
2020	$\eta(r_{ONFH})$	366	2	0.017	4	0.033	9	0.083	17	0.167
	$\eta(r_{SLH})$	366	1	0.005	2	0.010	3	0.025	6	0.051
	$\eta(r_{ONFH}, r_{SLH})$	182	3	0.022	5	0.044	11	0.109	22	0.218
	Always long	366	5	0.040	9	0.081	21	0.202	41	0.404

Table 9. Potential explanations

This table reports the results of testing potential explanations. We report descriptive statistics for Bitcoin news in panel A and explanation about late-informed trading in Panel B. We run the pooled regression $r_{LH,t} = \alpha + \beta_{News} News_t + \beta_{News*ONFH}(News_t \times r_{ONFH,t}) + \beta_{ONFH} r_{ONFH,t} + \beta_{SLH} r_{SLH,t} + \epsilon_t,\ \ t = 1, \dots, T$, where $r_{LH,t}$ is the return of the last trading session on day t, $News_t$ is the log number of Bitcoin news, $r_{ONFH,t}$ is the return during the close price of previous day and the price of the end of first half hour on day t, $r_{SLH,t}$ is the second-to-last half-hour return, and T is the total number of trading days in our sample. We report descriptive statistics for liquidity measure in panel C and explanation about liquidity provision in Panel D. We run the pooled regression $r_{LH,t} = \alpha + \beta_{Spread} Spread_t + \beta_{Spread*ONFH}(Spread_t \times r_{ONFH,t}) + \beta_{ONFH} r_{ONFH,t} + \beta_{SLH} r_{SLH,t} + \epsilon_t,\ \ t = 1, \dots, T$, where $Spread$ is the Corwin and Schultz (2012) spread estimator in the first half hour trading session. The returns are annualized where Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5% and 10% level is denoted by ***, ** and * respectively.

Panel A: Descriptive statistics for news

Mean	Std	P5	P25	Median	P75	P95	Skewness
2.592	0.671	1.386	2.197	2.708	3.135	3.434	-0.634

Panel B: Explanation about late-informed trading

	(1)	(2)	(3)	(4)	(5)
Intercept	11.612***	11.146	10.527	9.938	9.250
	(2.62)	(1.59)	(1.56)	(1.48)	(1.44)
β_{News}	-0.027	-0.028	-0.027	-0.026	-0.026
	(-1.20)	(-1.25)	(-1.22)	(-1.14)	(-1.11)
$\beta_{News*ONFH}$				-0.405	-0.429
				(-1.17)	(-1.24)
β_{ONFH}		1.129***	1.081***	2.252***	2.268***
		(4.77)	(4.603)	(3.27)	(3.31)
β_{SLH}			-11.919***		-11.926***
			(-11.89)		(-11.90)
R^2	0.06%	1.52%	2.25%	1.54%	2.37%

Panel C: Descriptive statistics for liquidity measure

	Mean	Std	P5	P25	Median	P75	P95	Skewness
Bitfinex	0.992	1.537	0.024	0.184	0.470	1.129	3.614	4.642
Bitstamp	0.995	1.676	0.000	0.233	0.538	1.144	3.364	7.761
CEX.IO	0.914	1.345	0.015	0.243	0.542	1.096	2.888	5.919
Coinbase	0.840	1.959	0.031	0.156	0.411	0.966	2.925	18.579
Kraken	0.817	1.521	0.000	0.001	0.358	0.980	3.280	7.027

Panel D: Explanation about liquidity provision

	(1)	(2)	(3)	(4)	(5)
Intercept	-1.459	-2.699	-2.029	-0.115	0.315
	(-0.46)	(-0.84)	(-0.64)	(-0.04)	(0.10)
β_{Spread}	9.411***	9.874***	9.439***	8.476***	8.174***
	(5.33)	(5.59)	(5.37)	(4.80)	(4.65)
$\beta_{Spread*ONFH}$				0.417***	0.385***
				(8.85)	(8.18)
β_{ONFH}		1.038***	1.003***	-0.401	-0.321
		(4.70)	(4.56)	(-1.47)	(-1.18)
β_{SLH}			-9.593***		-9.025***
			(-10.05)		(-9.46)
R^2	0.68%	1.70%	2.80%	1.88%	3.16%

Table 10. Return decomposition

This table reports the results of regressing the last half-hour return on the overnight return(r_{ON}), the opening half-hour return (r_{FH}), and the second-to-last half-hour return (r_{SLH}). This table shows the in-sample results and the out-of-sample results. We run the pooled regression $r_{LH,t} = \alpha + \beta_{ON} r_{ON,t} + \beta_{FH} r_{FH,t} + \beta_{SLH} r_{SLH,t} + \epsilon_t,\ \ t = 1, \dots, T$, where $r_{LH,t}$ is the return of the last trading session on day t, $r_{ON,t}$ is the return during the close price of previous day and the opening price on day t, $r_{FH,t}$ is the return during the opening price and the price of the end of first half hour on day t, $r_{SLH,t}$ is the second-to-last half-hour return, and T is the total number of trading days in our sample. The returns are annualized where Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5% and 10% level is denoted by ***, ** and * respectively.

Predictor	r_{ON}	r_{FH}	r_{ON}, r_{FH}, and r_{SLH}
Intercept	6.856	7.839	7.248
	(1.24)	(1.50)	(1.40)
β_{ON}	1.181***		1.097***
	(5.28)		(4.93)
β_{FH}		3.936**	3.762*
		(2.09)	(1.92)
β_{SLH}			-9.770***
			(-10.23)
R^2	1.38%	0.57%	2.45%
R^2_{OOS}	0.99%	0.12%	1.78%

Table 11. Alternative trading pairs

This table reports the results of regressing the last half-hour return (r_{LH}) on the first half hour return (r_{ONFH}) and the second to last half hour return (r_{SLH}) of the day in Japan and South Korea markets. This table shows the in-sample and out-of-sample results. We run the pooled regression $r_{LH,t} = \alpha + \beta_{ONFH} r_{ONFH,t} + \beta_{SLH} r_{SLH,t} + \epsilon_t,\ \ t = 1, \dots, T$, where $r_{LH,t}$ is the return of the last trading session on day t, $r_{ONFH,t}$ is the return during the close price of previous day and the price of the end of first half hour on day t, $r_{SLH,t}$ is the second-to-last half-hour return and T is the total number of trading days in our sample. The returns are annualized where Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5% and 10% level is denoted by ***, ** and * respectively.

Panel A: Basic information of trading data used

Exchanges	Trading pairs	Start	End	Average daily trading volume (BTC)	Obs.	Times (Local time)
bitFlyer	BTC/JPY	2015-07-04	2020-12-31	10572.59	2011	9:00-15:00
BtcBox	BTC/JPY	2014-04-11	2020-12-31	4470.82	2456	9:15-15:00
Zaif	BTC/JPY	2017-07-02	2020-12-31	4013.75	1258	9:00-15:00
Korbit	BTC/KRW	2013-09-03	2020-12-31	1355.82	2666	9:15-15:30

Panel B: Intraday momentum in Japan markets

Predictor	r_{ONFH}	r_{SLH}	r_{ONFH} and r_{SLH}
Intercept	2.323	2.904	2.775
	(0.58)	(0.77)	(0.74)
β_{ONFH}	0.631**		0.556**
	(2.20)		(2.38)
β_{SLH}		-27.030***	-26.969***
		(-13.00)	(-14.89)
R^2	0.10%	11.41%	11.60%
R^2_{OOS}	-1.40%	9.93%	8.63%

Panel C: Intraday momentum in South Korea market

Predictor	r_{ONFH}	r_{SLH}	r_{ONFH} and r_{SLH}
Intercept	1.276	3.731	0.183
	(0.20)	(0.61)	(0.03)
β_{ONFH}	2.880***		2.614***
	(3.16)		(2.50)
β_{SLH}		-22.332***	-21.686***
		(-10.80)	(-10.53)
R^2	1.40%	4.19%	5.35%
R^2_{OOS}	0.31%	3.22%	4.33%

Panel D: Explanation on liquidity provision

	(1) BTC/JPY	(2) BTC/KRW
Intercept	3.648	0.269
	(0.94)	(0.04)
β_{Spread}	5.314***	8.054***
	(6.12)	(5.58)
$\beta_{Spread*ONFH}$	0.472***	0.247***
	(6.48)	(7.75)
β_{ONFH}	0.433	1.701
	(1.45)	(0.99)
β_{SLH}	-23.883***	-19.651***
	(-12.60)	(-11.62)
R^2	13.59%	6.59%

Table 12. Alternative predictability

This table reports the alternative time frame results, where we take 9:30am EST as the open and 4pm as the close, consistent with NYSE trading hours. This table shows the in-sample results and the out-of-sample results. We run the pooled regression $r_{LH,t} = \alpha + \beta_{ONFH} r_{ONFH,t} + \beta_{SLH} r_{SLH,t} + \epsilon_t,\ \ t = 1, \dots, T$, where $r_{LH,t}$ is the return of the last trading session on day t, $r_{ONFH,t}$ is the return during the close price of previous day and the price of the end of first half hour on day t, $r_{SLH,t}$ is the second-to-last half-hour return, and T is the total number of trading days in our sample. The returns are annualized where Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5% and 10% level is denoted by ***, ** and * respectively.

Predictor	r_{ONFH}	r_{SLH}	r_{ONFH} and r_{SLH}
Intercept	8.754	10.439	10.031
	(1.35)	(1.07)	(1.40)
β_{ONFH}	0.372**		0.548**
	(2.54)		(2.31)
β_{SLH}		-18.152***	-18.261***
		(-19.10)	(-19.20)
R^2	1.43%	2.53%	2.89%
R^2_{OOS}	0.51%	1.46%	1.92%