Bitcoin Investors' Style, Skill, Sentiment, Seasonal Trading, and Anchoring Bias

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ABSTRACT

I examine the style of Bitcoin traders in a U.S. based exchange and show that Bitcoin traders are contrarians, and their order flow indicates seasonality by the hour-of-the-day and the day-of-the-week. Additionally, evidence of anchoring bias (momentum strategy) is found for the largest (mid-size) investors after Bitcoin hits its 30-, 90- and 120-day highs (lows), although anchoring bias in high days is more likely to generate negative returns. Analysis of investors' sentiment and attention reveals that both sentiment and attention intensify buying (selling) among smaller (the largest) investors while attention and sentiment induced trading do not lead to significant returns. In addition, the order flow of the largest investors has a negative correlation with equity market returns, consistent with the substitution effect. Unlike sellers, all but the tiniest buyers show market timing skills for two hours. Moreover, the tiniest (largest) traders are better at timing a decrease (increase) in Bitcoin's price. Furthermore, the contrarian trading strategy of investors can positively predict Bitcoin returns, consistent with liquidity provision. Lastly, analyses of trades from an alternative exchange shows that the order flow of eastern traders positively correlates with concurrent Bitcoin returns; also eastern traders do not have market timing skills , and they exercise more caution when Bitcoin hits highs (lows).

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The market for investing in Bitcoin has grown considerably over the last several years, from just over 1.54 billion dollars in April 2013 to 717.6 billion dollars in April 2022. While some investors have earned spectacular returns in a short amount of time[2], the risk associated with investing in Bitcoin is dramatically higher as well. For example, on March 12, 2020, the price of Bitcoin dropped by over 38% in one day, whereas the Dow declined 9.99%, the Dow's largest one-day drop since the Black Monday of 1987. Over the 2016-2021 period, the daily volatility of Bitcoin prices has been approximately 4.16%, more than three times the daily volatility of the equity market of 1.14%.

I investigate how Bitcoin traders in a U.S. based exchange respond to such price fluctuations. Aiming to understand how efficient security markets are, many scholars study how investors revise their priors after observing price changes (see Jegadeesh, and Titman (1993), and Boehmer, Jones, Zhang, and Zhang (2021) [3]). George, and Hwang (2005) find that investors use the 52-week high as a reference point against which they evaluate the impact of news. I examine how Bitcoin traders revise their priori when Bitcoin hits highs (lows) at different frequencies. Similar to papers that evaluate anomalies, such as seasonal and sentiment trading in the equity market, I explore whether investors follow specific strategies in the Bitcoin market, and what that says about their beliefs regarding the Bitcoin value. Identifying the extent to which such anomalies impact investors trading decisions can shed light on how efficient the Bitcoin market is, a building block in comprehending this market.

Bitcoin's "fundamental value" is hard to pin down because unlike most financial assets, Bitcoin has undefined future cash flows. Biais, Bisiere, Bouvard, Casamatta and Menkveld (2022) define the fundamental value of cryptocurrencies as a stream of transactional benefits, and propose that Bitcoin's future cash flows are the transactional benefits to cryptocurren-

[2]For instance, an individual who invested in Bitcoin on June 1, 2016, enjoyed Bitcoin value appreciation of 8100% by September 30, 2021.

[3]Documenting the existence of momentum in stock returns, Jegadeesh, and Titman (1993) propose that buying winner stocks and selling losers generate significant positive returns. Boehmer, Jones, Zhang, and Zhang (2021) find that retail investors are in average contrarians and their order flow can predict the cross-section of future stock returns.

cies. However, unlike equity cash flows (e.g. dividends) transactional benefits depend on investor beliefs about future prices of cryptocurrencies. Hence, for price discovery, understanding investors' trading style–how they revise their priors–is even more crucial for Bitcoin than for traditional financial assets. Thus, using lagged prices of Bitcoin, a growing number of scholars aim to interpret investors' style (e.g. Lee, Li and Zheng (2020), Koutmos, and Payne (2021), and Tang, and Liu (2022)). Since investor trades may not be the only driver of Bitcoin prices, as studies in equity markets suggest[4], using investor transaction data provides a more reliable basis for interpreting investors' style.

I study the trading strategy of Bitcoin investors based on market orders data gathered from the most popular US-based cryptocurrency exchange, Coinbase. Since Coinbase mostly provides service to western countries[5], the results generated from the trades on this exchange mostly characterize western traders' strategies. My analysis is focused on Bitcoin's order imbalance, defined as net buy volume scaled by total transaction volume, at various frequencies. This measure is relevant because Bitcoin pricing is still largely speculative, hence supply and demand forces play an essential role in price discovery. My style measure is motivated by Grinblatt, Titman and Wermers (1995); it is the inner product of Bitcoin's order imbalance (scaled by volume) with its preceding period return. While Grinblatt, Jostova, Petrasek, and Philipov (2020) and Grinblatt, Titman and Wermers (1995) use the style measure in a cross-sectional setting, I modify the style measure to fit a time series analysis. The null hypothesis is that the mean value of the style measure is not statistically different from zero. If the null hypothesis is rejected, a significantly positive (negative) style measure implies a momentum (contrarian) strategy of Bitcoin investors.

My results suggest that all but the tiniest Bitcoin traders consistently implement a con-

[4]Previous studies examining investor style include Grinblatt, Titman and Wermers (1995) studying mutual funds style, using portfolio weight changes, Grinblatt, Jostova, Petrasek, and Philipov (2020) exploring hedge funds style, using portfolio weight changes, Boehmer, Jones, Zhang, and Zhang (2021) studying retail investors' style, using order imbalance, etc.)

[5]Coinbase provides service to the traders in the U.S., Canada, Australia, United Kingdom, Singapore and some of the European countries.

trarian trading strategy for different hourly durations. When the Bitcoin price falls (rises), Bitcoin investors' buying (selling) intensifies over the subsequent 24 hours. Throughout the paper, I examine Bitcoin traders' style by trade size, dividing the trades into size quartiles based on dollar value. I show that the style measure gets more contrarian with increase in trade size. As the trades studied in this paper are market orders, it can be implied that placing market orders which are instantly filled, all but the tiniest traders who seek and provide immediacy are mostly contrarians and trade against those who place orders in the order book whose trades are filled only if their specified price margin is reached. My results remain robust to controlling for alternative potential leading factors such as the overall tendency of market traders, outliers, and autocorrelation of standard errors. Additionally, traders on this exchange may, in essence, trade against traders on other exchanges, because in such an integrated market, the aggregate trading activities of all traders around the world determine Bitcoin tick prices.

Bitcoin traders' style may not be the same on the buy and sell side, and the style of one side may overshadow the style of the other side. I capture this difference by decomposing traders to buyers and sellers[6], and show that the concurrent trading strategy of both buyers and sellers is contrarian. The study of traders' style in the subsequent hours suggests that most buyers follow a contrarian trading strategy, while the tiniest buyers follow a momentum strategy. However, sellers of all sizes adopt a contrarian trading strategy.

Additionally, I explore other factors impacting order imbalance such as seasonality, investor sentiment and attention. Seasonality of Bitcoin returns, trading volume and volatility has been studied in the literature to assess the predictability of the Bitcoin market (see Padysak, and Vojtko (2022), Catania, and Sandholdt (2019), Kaiser (2019), Long, Zaremba, Demir, Szczygielski and Vasenin (2020), etc). I go beyond inspecting the seasonality of trading volume and examine the seasonality of order imbalance (direction of trading by volume),

[6]Following Grinblatt, Jostova, Petrasek, and Philipov (2020), I divide the dataset into two subsets: 1. Periods in which buy volume exceeds sell volume. 2. Periods in which sell volume exceeds buy volume.

which is representative of traders' expectation of Bitcoin future prices. I show that for all but the tiniest investors the order imbalance is the highest on Mondays and the lowest on Saturdays. Investigating intraday seasonality of order imbalance, I show that the order imbalance of investors of all quartiles is minimum at times 24:00 (UTC) and 23:00 (UTC) and maximum at 11:00 (UTC). Furthermore, Bitcoin average returns are the highest at times 22:00 (UTC) and 23:00 (UTC), the hour following New York and Toronto stock exchanges closure[7] (operation time: 14:30-21:00 UTC), and the lowest at 4:00 (UTC).

Moreover, I examine how sentiment and attention impact order flows in the Bitcoin market, using Reddit data. While previous research has explored the correlation between Twitter sentiment (see Gao, Huang, and Wang (2021), Liu, and Tsyvinski (2018), Shen, Urquhart and Wang (2019), etc.) or Bitcointalk.org sentiment and Bitcoin prices (see Kantorovitch and Heineken (2021)), to the best of knowledge, no research has yet explored the correlation between Reddit sentiment and Bitcoin order imbalance. Reddit is a social news aggregator with various topic-specific divisions. While a large portion of Twitter audience are from countries that do not have access to the Coinbase platform,[8]approximately 70% of Reddit users are from countries to which Coinbase provides service. Thus, the population exposed to Reddit sentiment is well targeted in terms of relevance to Coinbase traders. I classify the sentiment expressed in Reddit's Bitcoin posts as positive, negative and neutral, using VADER, Valence Aware Dictionary and sEntiment Reasoner, which is a sentiment analysis tool that is specifically attuned to sentiments expressed in social media (see Elbagir, and Yang (2019) and Huang, and Shelar (2018)). Creating a sentiment index, I inspect the relationship between investor sentiment and Bitcoin order imbalance. Furthermore, utilizing the number of posts in each hour, I define an *Attention* index and explore the impact of

[7]This is consistent with the findings of Padysak, and Vojtko (2022), who argue that the highest Bitcoin returns are during the times when major stock exchanges around the world are closed.

[8]Countries such as Japan, India, Indonesia, Brazil, Turkey, Mexico, Saudi Arabia and Thailand are among the top 10 countries as far as share of Twitter audience. However, Coinbase does not provide service to the mentioned countries. Website: The Latest Twitter Statistics: Everything You Need to Know — DataReportal – Global Digital Insights

attention on Bitcoin's order flow.

My results suggest that mid-size investors' order imbalance is positively correlated with the aggregate sentiment during its preceding 2-hour and 24-hour periods among, while that of the largest investors has no correlation with the sentiment. Thus, it appears that while mid-size investors' trading decision is impacted by social media sentiment, investors of the largest size do not consider social media sentiment as an informative tool for taking a position. Moreover, the order imbalance of majority of (the largest) Bitcoin investors has a significantly positive (negative) correlation with the attention index, implying that higher attention stimulates more buying than selling among all but the largest investors, which may appear to create a good selling opportunity for the largest traders, moving against the crowd. However, further analysis reveals that attention- and sentiment-driven trading do not lead to significant returns for traders of either side.

I examine investors' propensity to sell (buy) on and after a 30-, 90- and 120- highs (lows), through performing a regression analysis controlling for Newey and West (1987) standard errors. My results indicate that the largest Bitcoin traders anchor when Bitcoin hits its highs and lows; their daily sell (buy) volume significantly exceeds their daily buy (sell) volume after the studied highs (lows), consistent with the contrarian trading strategy of Bitcoin traders. George, and Hwang (2005) explain anchoring bias of traders by investors' reluctance to revise their valuation of a stock based on the new information that a stock's price nearness to its 52-weeks highs (lows) implies. Similarly, when Bitcoin's price hits 52-weeks highs (lows), the largest traders, reluctant to bid the price higher (lower), place market sells (buys). Substituting order imbalance with its mean deviation preceding 180-day average after high and low days, my results remain robust. Moreover, mid-size investors' buy (sell) volume exceeds its average after Bitcoin hits its highs (lows), suggesting a momentum trading strategy. Further analysis, reveals positive Bitcoin returns with a 95% confidence interval after highs which propose a challenge to the efficiency of the Bitcoin market, suggesting that following a momentum strategy on high days is more likely to yield positive returns during the next days. My results are in line with the findings of George, and Hwang (2005) in the equity market, suggesting that when a stock price hits 52-week high, a continuation of the upward price movement is likely.

Moreover, I explore whether the changes in the stock market impact the Bitcoin order flow for investors of different sizes. I show that the order imbalance of investors of the largest size has a negative correlation with the stock market return (S&P 500 and NASDAQ), consistent with the substitution effect, suggesting that the largest investors consider Bitcoin as an alternative investment; when the stock market is down, large investors are incentivized to move to the Bitcoin market, and when the stock market is up, large investors shift to the stock market which is less risky.

In addition to Bitcoin investors' style, I study Bitcoin traders' market timing skills. Coinbase data does not contain any identifier for individual traders, and hence, it is not possible to observe when individual traders close their positions. Therefore, I examine how effective traders are at placing their market orders before prices move against them. I perform a regression analysis examining returns in hours subsequent to periods in which OIB>0, and OIB<0 separately, controlling for standard errors following Newey and West (1987). I show that unlike sellers, all but the tiniest buyers have significant market timing skills for up to two hours.

Furthermore, I examine the conditional market timing skills of traders of different sizes, forecasting up and down prices, inspired by Henriksson, and Merton (1981). Conditioning on Bitcoin price being up (down), I calculate the probability of observing positive (negative) order imbalance in the preceding hour. My results suggest that the largest (tiniest) investors outperform others in calling up (down) prices, and the probability of an hour with a positive (negative) order imbalance immediately before an increase (decrease) in Bitcoin price decreases consistently as the size of traders decreases (increases). Controlling for the overall trading direction of traders, I generate consistent and stronger results.

Additionally, I examine the predictability of different components of order imbalance for Bitcoin returns during the next hour. I decompose hourly order imbalance of investors of different sizes to five components, using a 2-stage decomposition method, inspired by Boehmer, Jones, Zhang, and Zhang (2021). For a component of order imbalance, I define $Persistence$ representing investors' persistence in directional trading, $Contrarian$ representing the contrarian style of investors, *Sentiment* and *Attention* representing sentiment- and attention-induced trades, and *Other* representing other relevant information contained in the order flow regarding Bitcoin returns in the next hour.

My results show that, the contrarian trading strategy of investors has a significantly positive correlation with Bitcoin's return during the next hour. This is consistent with the liquidity provision proposed by Kaniel, Saar and Titman (2008) arguing that risk-averse investors adopting a contrarian trading strategy, selling at high and buying at low, provide liquidity to meet less risk-averse investors' demand for immediacy and generate excess returns. Moreover, sentiment- and attention-induced trades do not yield significant returns.

Finally, I study the impact of investors' cultural differences on their trading activities using market orders data from an alternative exchange, Binance. Since Bitcoin is a non-commodity financial asset to which investors' exposure and interest go beyond countries' boarders, different strategies of investors of different cultures can be identified independent from fundamentally different investment opportunities that exchanges of each country provide.

During the time period of this analysis, traders of eastern nations such as China, India, Russia, etc., were able to trade on Binance, while U.S. traders were banned from trading on this platform[9]. Coinbase on the other hand, provides service to the traders in the U.S., Canada, Australia, United Kingdom, Singapore and some of the European countries. The two exchanges' difference in the countries to which they provide service creates a unique opportunity to compare trading strategies and market timing skills of traders of different cultures. The presence of traders from countries to which both exchanges provide service does not impose any concerns to my analysis, because their exclusion will only make my results stronger.

My results show that unlike traders placing market orders on the Coinbase exchange (e.g. U.S. traders), those who place market orders on the Binance exchange (eastern traders) do not follow a contrarian trading strategy. The concurrent mean value for the style measure ($L0M$) is positive for traders of all quartiles in the Binance exchange. The interpretation of a positive mean value for $L0M$ is not as conclusive as a negative mean, because it is hard to distinguish if traders' increase in order imbalance led to the same-hour increase in the Bitcoin, or vice versa. Regardless of the causality, although not outwardly apparent, it can be implied that traders of the Coinbase whose net sell volume increase and traders of Binance whose net buy volume increases, in a very same hour, trade against each other, determining Bitcoin's tick price.

In addition, I show that while the largest traders from a U.S.-based exchange anchor on highs, the largest traders of eastern countries do not demonstrate any significant trading strategy on/following highs. My results suggest that compared to U.S. traders, eastern traders appear more cautious, anchoring by smaller transaction sizes, when Bitcoin hits its lows (highs). Lastly, I compare the market timing skills of Binance traders with that of Coinbase traders, and suggest that when placing market orders, U.S. traders are more likely to correctly time the market compared to eastern traders.

[9] While Binance stopped accepting U.S. traders, its U.S.-based version, Binance.US, starting a partnership with Financial Crimes Enforcement Network (FinCEN), started providing services into the U.S. market. The dataset used for the analysis in this research is from Binance which does not contain the transactions from the U.S. traders in the other platform, Binance.US.

In sum, using market order data from a U.S.-based exchange, this research extends the Bitcoin literature in several ways: 1.It sheds light on the style of Bitcoin investors of different sizes and at different frequencies. 2. It identifies hourly and daily seasonality in Bitcoin's order flow. 3. It shows the impact of investors' sentiment and attention on hourly order imbalance 4. It documents anchoring bias (momentum trading strategy) of Bitcoin's largest (mid-size) investors 5. It investigates the market timing skills of traders and illustrates that the largest (tiniest) traders are more skillful in correctly forecasting up (down) prices. 6. It shows that most buyers are better than sellers in timing the market. 7. It provides evidence for the existence of liquidity provision in the Bitcoin market. 8. It suggests the existence of substitution effect for investors of the largest size. 9. It implements trades data from an alternative exchange, and examines the impact of Bitcoin traders' cultural differences on their trading strategies and market timing skills.

I. Literature Review

The Bitcoin literature started with Nakamoto (2009) who proposes a peer-to-peer version of electronic cash as a secure solution for double spending problem caused by existence of third-parties in monetary transactions. As decentralized monetary systems gained attention, the literature started to develop around Bitcoin as an alternative investment. As described by Kayal and Rohilla (2021), Bitcoin research evolved in five strands: price dynamics, volatility and bubbles, economics and efficiency of Bitcoin, Bitcoin as a currency vs an asset, and social media and investor sentiment's impact on the Bitcoin market.

Research on Bitcoin's price dynamics aims to determine the source of Bitcoin value. The most common principle in determining Bitcoin's price is the theory of supply and demand. Blundell-Wignall (2014) attributes the rising prices of Bitcoin to its inelastic demand and tight supply. Brandvold, Molnar, Vagstad and Valstad (2015) note that exchanges can enhance Bitcoin's price discovery and sharing information. McIntyre and Harjes (2016) show that order flow, which they define as the difference between buyer- and seller-initiated trading volumes, has positive and significant explanatory power in determining Bitcoin prices. Biais, Bisiere, Bouvard, Casamatta and Menkveld (2022) propose that the fundamental value of cryptocurrencies is determined by their transactional benefits which depend on investor beliefs about future prices. They emphasize the importance of transactional benefits in cryptocurrency valuation by analogizing transactional benefits to cryptocurrencies as dividends (future cash flows) to stocks. Building on findings of Biais, Bisiere, Bouvard, Casamatta and Menkveld (2022), I propose that if investors' belief about Bitcoin's future prices can be considered a fundamental parameter in its price discovery, investors order flow, which can be reasonably assumed to reflect investor beliefs regarding future prices, can be illuminating in Bitcoin valuation, and hence I inspect what parameters impact Bitcoin traders' order flow.

The Bitcoin literature in economics and efficiency aims to explain Bitcoin design aspects and investigates the efficiency of Bitcoin. Most of the literature establishes that being in an embryonic stage, the Bitcoin market is volatile but in the long run it is expected to move towards stabilized prices, less volatility and fewer bubbles. Urquhart (2016) studies the efficiency of the Bitcoin market and shows that the Bitcoin market is inefficient. Li and Wang (2017) argue that in the long run the mining process will become more efficient thanks to better mining technology. Houy (2014) proposes that introducing a transaction fee and imposing a cap for block size can correct the inefficiency of an externality's free market but lead to loss of efficiency due to introducing a fee. In addition, seasonality of Bitcoin returns, trading volume and volatility has been studied in the literature to assess the predictability of the Bitcoin market. Padysak, and Vojtko (2022) study the intraday seasonality of returns in Bitcoin using Gemini exchange data. Dividing days into trading hours, overnight hours and closed market days, holidays and weekends, they suggest that returns for times 22:00 (UTC) and 23:00 (UTC) are likely to be the highest. Using Coinbase Pro exchange, I generate consistent results implying maximum returns at times 22:00 (UTC) and 23:00 (UTC) and minimum returns at 4:00 (UTC). Catania, and Sandholdt (2019) find increasing trading volume during Monday to Friday and a decreasing volume over Saturday and Sunday, consistent with the results I generate using Coinbase Pro transaction data. Kaiser (2019) considers the cross-section of 10 cryptocurrencies and finds less trading volume in January, during summer months and weekends. Long, Zaremba, Demir, Szczygielski and Vasenin (2020) show that average past same-weekday returns are positively correlated with the cross-sectional future performance.

Studies of volatility and bubbles in the Bitcoin market focus on Bitcoin's price fluctuations and the potential of extreme returns. Studying extreme volatilities in Bitcoin prices, Bouoiyour and Selmi (2015) show that negative news has a larger impact on Bitcoin's price volatility than positive news. Chevapatrakul and Mascia (2019) document that investors overreact during days of sharp declines and weeks of sharp rises in the Bitcoin price. Studying why markets crash, and using Bitcoin market's order book, Doniar and Bouchaud (2015) show that the main reason for market crashes is not selling pressure but rather the scarcity of buyers. Their dollar-based amount analysis shows a large sell-off before a crash, which occurs when price is at peak; this is in line with my results showing that the largest traders selling intensifies when Bitcoin hits its high 30-, 90-, and 120-day prices. Silantyev (2019) shows that Bitcoin's trade flow imbalance exhibits strong explanatory power for contemporaneous Bitcoin price changes. Exploring traders' order flow from two different exchanges, I find consistent results showing significant correlation between Bitcoin's concurrent returns and order flow. Scaillet, Treccani, and Trevisan (2020) look at Bitcoin's price jumps, and show that the order imbalance, significance of aggressive traders, and widening of the bid ask-spread can predict jumps. Feng, Wang, and Zhang (2018) examine informed trading based on order imbalance around major events. They pick 42 events, around which they conduct their analysis. Their results suggest informed trading of buyers, two days prior to large positive events, and of sellers, one day before large negative events.

Another strand in the Bitcoin literature investigates whether Bitcoin is more like an asset or a currency. On the one hand, Bitcoin's lower transaction cost makes it an inexpensive fund transfer system that facilitates access to financial services (see Kayal and Rohilla (2021), Folkinshteyn, Lennon and Reilly (2015) and Chowdhury and Mendelson (2013)). On the other hand, Baur, Hong and Lee (2018) and Kajtazi and Moro (2019) argue that Bitcoin is widely used for speculative and investment purposes rather than for buying goods and services. Inspired by the findings of the asset pricing literature, Liu, Tsyvinski, and Wu (2022) investigate common risk factors in the cryptocurrency market and show that returns on the cryptocurrency market, size, and momentum have an explanatory power for the cross-sectional expected cryptocurrency returns.

A large body of literature has been focused on the impact of social media and investors' sentiment on Bitcoin's price as Bitcoin's price is driven by future expectations of the Bitcoin holders (see Kayal and Rohilla (2021)). Ibikunle, McGroarty and Rzayev (2020) investigate the relationship between investors' attention and price discovery. They show that high levels of investor attention is related to noise rather than to underlying value. Using Reddit sentiment data, I show that trading on attention does not lead to significant returns, and hence I find no underlying value in investor attention, consistent with the findings of Ibikunle, McGroarty and Rzayev (2020). Kantorovitch and Heineken (2021) explore comments in Bitcointalk.org and suggest that high levels of disagreement in comments lead to negative future returns. Gao, Huang, and Wang (2021) perform a high frequency analysis using Twitter sentiment and indicate that bullish sentiment is followed by a higher Bitcoin return and volatility over the next 24 hours, while bearish sentiment does not have any predictive power. Using Reddit sentiment data, I show that while negative sentiment leads to a decrease in the net buy volume of investors over the following hours, it does not have any predictive power for Bitcoin returns.

Exploring the style and skill of Bitcoin traders in U.S. based exchange, this research fits into the price efficiency strand of the Bitcoin literature. In a highly speculative market, where Bitcoin's price, to a large extent, is driven by traders' buying and selling activities, discovering the traders' style and behavioral biases can shed light on the pricing mechanism of the Bitcoin market. I go beyond inspecting the seasonality of trading volume and examine the seasonality of the order imbalance (direction of trading by volume), which represents traders' expectation of future prices. Utilizing Bitcoin order imbalance, I investigate the style of Bitcoin traders both in buyer- and seller-dominant periods. Additionally, I inspect market timing skills of traders forecasting both an increase and a decrease in Bitcoin's price and show that while small traders are better at forecasting down markets, the largest traders are better at forecasting up markets. Furthermore, I show that while the largest Bitcoin traders have anchoring bias: they anchor on Bitcoin 30-, 90- and 120-day high and low prices, mid-size traders follow a momentum strategy. In addition, I explore correlations of investors' sentiment and attention with hourly order imbalance and Bitcoin returns, and I detect significant correlations. Moreover, I provide evidence of liquidity provision in the Bitcoin market by showing that the part of hourly order imbalance that is explained by contrarian trading strategy of investors has a positive predictive correlation with Bitcoin's return in the next hour. Finally, using an alternative cryptocurrency exchange data, I explore the impact of Bitcoin traders' cultural differences on their style and market timing skills.

II. Data

The data for Bitcoin market trades was gathered from Coinbase Pro exchange from June1, 2016 to September 30, 2021. I pick June 1, 2016 as a start date to minimize the number of hours missing transactions while maintaining an ample time period of study. I choose Coinbase Pro exchange because it is one of the most widely used exchanges, and because its trade books distinguishes buyers from sellers. The latter eliminates the need for using the tick rule to identify buyers and sellers (e.g. Feng, Wang, and Zhang (2018)), reducing measurement error. The data consists of market orders, which Coinbase refers as Taker Orders. Coinbase matches Taker Orders with the earliest in time Maker Orders at the best price on the Order Book. Thus, a transaction labeled as a "Buy" refers to a market buy order matched with the earliest sell order at the best price from the Order Book.

Coinbase is the largest cryptocurrency exchange in the U.S. (according to Forbes), and provides service to United States, United Kingdom, Canada, Australia, Singapore and mostly European countries. Comprising one fifth of Bitcoin 24-hour trading volume, Coinbase has the second largest 24-hour trading volume for Bitcoin. Coinbase Pro is a platform of Coinbase which offers lower fees, and advanced charting and trading options. While beginners may find Coinbase more user friendly for its simple interface, lower fees and various types of transactions offered by Coinbase Pro incentivize investors to pick Coinbase Pro over Coinbase platform. Since Bitcoin is an innovative product of Blockchain technology– a breakthrough technological advance– for which the market is very young and unknown to many investors, it is plausible that investors who enter the cryptocurrency market are mostly on the more adventurous side of the spectrum and are more open to learning about unconventional investments. Therefore, if investors choose the Coinbase exchange and start trading with the Coinbase platform, they are highly likely to switch to the Coinbase Pro after a short amount of time. Not surprisingly, more than 80% of Coinbase's Bitcoin trading volume takes place in the Coinbase Pro exchange[10]. Thus, the transaction data gathered from Coinbase Pro is a proper representation of transactions of overall Bitcoin investors in the U.S.

Each month, I sort market orders based on their dollar value into four quartiles. I investigate the style and skill of investors whose trades fall into each quartile separately. This methodology helps to distinguish whether a specific style or skill is demonstrated by

[10] 24-hour Bitcoin trading volume for Bitcoin is generated from www.bitcointradevolume.com and for Coinbase Pro is generated from www.coinranking.com/exchanges?search=coinbase

a more likely retail or institutional investor. It could be argued that some institutional investors may break their transactions into smaller lots, making it hard to identify them. However, as argued by Feng, Wang, and Zhang (2018), unlike the stock market, there is no incentive to break transactions to smaller ones in the cryptocurrency market for three main reasons. First, one of the main incentives of institutional investors for breaking their transactions is to avoid regulatory consequences of informed trading. In the cryptocurrency market, since there exists anonymity along with no regulatory supervising body protecting retail investors from informed trading, such incentive does not exist. Second, it is often possible to benefit from a discount for larger orders. Third, if institutional investors are informed, they aim to act fast to benefit from their information, and breaking transactions reduces their trading speed. As a result, breaking transactions in the cryptocurrency market is not as common as it is in the securities markets. Moreover, potential misclassification due to breaking transaction, would only weaken my results.

The results presented in this research are generated by exploiting all the market order data points for my analyses. Controlling for outliers, in each quartile, I censored the data points whose transaction dollar value is less (greater) than 0. 1 (99.9) or whose transaction volume is less (greater) than 0.0001 (99.999) percentile of the transactions in their corresponding quartile group, and I generate consistent results (see Appendix B). I obtain hourly prices of Bitcoin through Coinbase Pro exchange and use each hour's closing price for the hourly returns calculation. Merging the hourly returns and trades data, I end up with 46,752 hours, 1948 days, 278 weeks and 64 months of observation.

As I work with time series data, it is important to learn the autocorrelation of the main variables, namely Bitcoin's order imbalance and returns. Figure A.1 and Figure A.3, show the hourly autocorrelation and partial autocorrelation of Bitcoin order imbalance for each quartile respectively. As indicated by Figure A.1 and Figure A.3, order imbalance autocorrelation is significant for numerous lags. Therefore, when performing regression analyses, and controlling for autocorrelation using Newey and West (1987), I control for the autocorrelation of order imbalance for several lags, as there exists significant autocorrelation.

Figure A.2 shows autocorrelation of Bitcoin returns. Unlike order imbalance, returns autocorrelation only persists for a few lags for which my regressions are controlled following Newey and West (1987) methodology. The autocorrelation of returns in an hourly frequency is consistent with the findings of Urquhart (2016), suggesting that the Bitcoin market is inefficient because in an efficient market, prices should be uncorrelated and unpredictable.

Figure A.4 shows a heatmap of correlation among different variables of study. The order imbalance for traders of each quartile is positively correlated with its value in the previous hour. Furthermore, negative correlations of order imbalance and concurrent Bitcoin returns are suggestive of concurrent contrarian trading strategy of Bitcoin traders: An increase in Bitcoin price incentivizes selling more than buying. Representing the daily returns of the market, S&P 500 ($Sprtrn1$) has a negative correlation with Bitcoin order imbalance—suggestive of substitution effect—and a positive correlation with concurrent Bitcoin returns. In addition, the correlations among sentiment, attention and Bitcoin returns are not high, implying that social media attention and sentiment variables capture different information that is not reflected in the concurrent Bitcoin price.

III. Methodology

Grinblatt, Jostova, Petrasek, and Philipov (2020) conduct a cross-sectional analysis on the style and skill of hedge fund and mutual fund managers using the style and skill measures, initially proposed by Grinblatt, Titman and Wermers (1995). They calculate the style measure, called $LOM_{\mathrm{i,q}}$, by multiplying the weight change of stock j in the portfolio of fund manager i to the stock j's return at concurrent and previous quarters. Then, they take an average of $LOM_{\mathrm{i,q}}$ measures among fund managers of each type in each quarter. To determine the style for the fund manager of each type they calculate t-statistics and test whether it is significantly different from zero or not. For the calculation of t-statistics, they calculate the average and the standard error of LOM_{q} among the number of quarters in the sample period.

$$LOM = \frac{1}{Q} \sum_{q=1}^{Q} LOM_q \tag{1}$$

$$t - stat(LOM) = \frac{LOM}{\frac{\sigma(LOM_q)}{\sqrt{Q}}} \tag{2}$$

For determining Bitcoin investors' style, I follow Grinblatt, Jostova, Petrasek, and Philipov (2020) and use their methodology with an adjustment to make it suitable for time series analysis. Since I only look into one asset, for which investors are not identifiable, my analysis is centered on only one dimension, which is the Bitcoin's order imbalance. My measure of order imbalance is close to that of Easley, Engle, O'Hara and Wu (2008) and Feng, Wang, and Zhang (2018) in each window of study, and defined as:

$$OIB_{t,k} = \frac{\sum_{t}^{t-k+1} Buy_t - Sell_t}{\sum_{t}^{t-k+1} Buy_t + Sell_t} \tag{3}$$

Where t represents observations' time period and k represents the length of time period that investors trading behavior is studied. $\mathrm{Buy_t}$ and $\mathrm{Sell_t}$ both are based on Bitcoin volume of trades in each hour.

Table I Panel A and B show the summary statistics of hourly market order imbalance, in terms of volume and dollar values respectively, for different quartiles. As can be seen, market order imbalance during the hours of study is mostly negative, implying that, in general, more Bitcoin volume is liquidated than purchased via market orders in the period of study. The only positive order imbalance values indicated in Table I belong to 4th quartile investors, order imbalances above 75 percentile. Coinbase describes traders who place market orders as Takers who, in exchange for immediacy, forgo potential price advantages and lower fees. Therefore, while a zero-mean order imbalance is expected in the stock market, a negative average for order imbalance is reasonable in the Bitcoin market because Bitcoins are mined every 10 minutes as a reward for those verifying one block of Bitcoin transactions (see Balan (2021)). Consequently, it is plausible that there are more sellers who merely seek liquidity rather than price advantage, and not surprisingly the volume of market sells exceed market buys in the exchanges.

As this study involves time series analysis, the stationarity of hourly order imbalance for each quartile is tested. Table I Panel C shows the results for Augmented Dickey-Fuller test, implying that hourly order imbalance in all quartiles of study is stationary. Table II Panel A shows summary statistics for hourly order imbalance in different quartiles conditional on buy volume exceeding sell volume, i.e. dominant buyers. Buyers of the 1st quartile have the largest mean of order imbalance followed by 4th quartile investors. Table II Panel B indicates summary statistics for hourly order imbalance conditional on negative net buys volume, i.e. dominant sellers. As Table II Panel B shows, moving from the 1st quartile to the 4th, the absolute value of order imbalance decreases which implies that institutional investors are less likely than retail investors to liquidate their positions when buying volume is less than selling volume. Comparing the two panels of Table II, we see that, overall, there are fewer hours in which order imbalance is positive than negative. As we move from the 1st quartile to the 4th quartile, the number of periods with positive (negative) order imbalance increases (decreases).

The intuition behind the Grinblatt, Jostova, Petrasek, and Philipov (2020) style measure is to explore the behavior of different fund managers after each period's returns. Similarly, I explore how traders' order imbalance changes after each hour's return. Buy and sell volumes during each hour, represent the transaction volumes taking place from the previous hour to the current hour. For instance, Buy_t (Sell_t) represents the volume of buy (sell) trades filled from time t-1 to t. Likewise, $\text{Buy}_{t\text{-}1}$ ($\text{Sell}_{t\text{-}1}$) represents the volume of buy (sell) trades filled from time t-2 to t-1. Thus, to examine traders' style after observing Bitcoin's return in a certain point of time, for example $R_{t\text{-}2}$, I use buy and sell values reported for periods staring from one period after the return's time period, in this case t-1, so that there is no overlap between returns and the consequent trading activity. Hence, LkM_t in my model is defined as:

$$LkM_t = (OIB_{t,k}) \times R_{t-k} \tag{4}$$

Where t represents time and k represents the length of the time period that investors trading period is studied. Hence, LkM_t is the investors' style measure at time t which is calculated by transactions of its previous k hours.

Null hypothesis: Bitcoin investors do not follow any specific trading strategy; the mean value LkM is not significantly different from zero. Alternative hypothesis: Bitcoin investors follow a trading strategy which could be momentum if LkM is significantly positive or contrarian if LkM is significantly negative. To test the null hypothesis, I calculate LkM's t-statistics by:

$$t - stat(LkM) = \frac{L\bar{k}M}{\frac{\sigma(LkM_t)}{\sqrt{T}}} \tag{5}$$

$$L\bar{k}M = \frac{1}{T}\sum_{t}^{T} LkM \tag{6}$$

, where $\sigma(LkM_t)$ is the standard deviation of LkM measure, and T is the number of the periods of study. As a robustness check, I regress $\mathrm{OIB}_{\mathrm{t,k}}$ values on $R_{\text{t-k}}$, controlling for Newey and West (1987) standard errors of several lags, and compare the coefficients in terms of sign and significance with t-statistics calculated for the LkM measure.

$$OIB_{t,k} = \beta \times R_{t-k} + \epsilon \tag{7}$$

IV. Results

V.1. Style

The results from Bitcoin investors' style measure, LkM, are displayed in Table III Panel A. The numbers in Panel A of Table III represent t-statistics testing whether the mean value of LkM is significantly different from zero or not. As negative t-statistics shown in Table III Panel A suggest, investors in all quartiles in the Coinbase exchange follow a contrarian trading strategy for durations of up to twenty four hours. The results generated from performing regression analysis, controlling for autocorrelation of several lags following Newey and West (1987) methodology, is consistent with findings of Panel A suggesting contrarian trading strategy of investors in all quartiles. Controlling for the overall trading direction of market traders, steering clear of look ahead bias, I use the deviation of order flows from its average during the preceding 720 hours (30 days) and my results remain robust (see appendix Table A.1).

Order imbalance is impacted by the style of both buyers and sellers. The style of Bitcoin buyers and sellers may be different and one side may sway the style measure more than the other. To capture this difference, following Grinblatt, Jostova, Petrasek, and Philipov (2020), I divide the dataset to two subsets: 1. Periods with positive OIB, in which buy volume exceeds sell volume, i.e. dominant buyers 2. Periods with negative OIB, in which sell volume exceeds buy volume, i.e. dominant sellers.

As can be seen from Table IV, the concurrent trading strategy of both buyers and sellers is contrarian ($L0M$), and in the subsequent hours, while the tiniest buyers mostly follow a momentum trading strategy, others follow a contrarian trading strategy; that is an increase in Bitcoin price is followed by a decrease in the net buy volume of sellers (i.e. increase in net sells) and all but the tiniest buyers in the subsequent hours. Note that in buyer- and seller- specific style analysis, I do not perform regression analysis because regressing sorted dependent variable is not econometrically correct due to look ahead bias.

Next, I inspect the skill of buyers and sellers in timing the market for placing their trades. I perform a regression analysis per equation:

$$Return_t = \beta_0 + \beta_1 \times OIB_{t-1}$$

For buyers the analysis is performed on a subset of data with positive order imbalance (OIB>0), and for sellers the analysis is performed on a subset of data with negative order imbalance (OIB<0). The autocorrelation of standard errors are controlled, following Newey and West (1987).

Table V shows the results regarding buyers' and sellers' skill, suggesting that buyers whose trades fall in all but the 1$^{\text{st}}$ quartile have significant market timing skills for a duration of two hours. In other words, 2-hour periods in which buyers' trading volume exceeds sellers' trading volume, are followed by significant increases in Bitcoin price. In contrast, sellers do not demonstrate any market timing skills, as no positive correlation is seen between sellers' order imbalance and Bitcoin returns in the subsequent hours. For robustness, instead of order imbalance, I use mean deviation of order imbalance from its preceding 720 hours (30 days) and show consistent results (see appendix Table A.2 and Table A.3). For further robustness, I determine buyers and sellers based on transaction labels (buy vs sell) reported by Coinbase Pro and calculate a skill measure (FkM) in the spirit of Grinblatt, Titman and Wermers

(1995) but modified to fit a time series setting. I calculate FkM as the vector product of buyers' (sellers') trade volume to the Bitcoin return in the next period per equation:

$$FkM_t = (OIB_{t-1,k}) \times R_t \tag{8}$$

I use buy and sell values reported for periods staring from one period prior to the return's time period and go back. $\mathrm{OIB}_{\mathrm{t\text{-}1,k}}$, to avoid overlap between current returns and the preceding trading activity. Both buy and sell volumes are scaled by Bitcoin's preceding 24-hour trading volume. Next, I perform a regression analysis as:

$$FkM_t = \beta_0 + \beta_1 \times Seller_t$$

$Seller_{\mathrm{t}}$ is a dummy variable equal to 1 if the FkM_{t} is calculated based on seller-originated OIB and 0 if the FkM_{t} is calculated based on buyer-originated OIB. I show that the skill measure of buyers is significantly higher than sellers for investors of all sizes (see Appendix Table A.4), supporting the hypothesis that buyers are better than sellers in timing the Bitcoin market.

As a further robustness check, I include both sellers and buyers in a same regression. I define a dummy variables $d_{1,t,k}$ and $d_{2,t,k}$ equal to 1 if OIB>0 and OIB<0 respectively and zero otherwise. Then, I perform the following regression with no intercept term:

$$Return_t = \beta_1 \times d_{1,t,k} + \beta_2 \times d_{2,t,k} \tag{9}$$

Table VI shows the results including buyers and sellers in a same regression. Consistent with the results found in Table V, Table VI Panel A shows that buyers in the 2^{nd}, 3^{rd} and 4^{th} quartiles have some market timing skills. Table VI Panel B suggests that moving from periods when $d_{2,t,k}$=0 to $d_{2,t,k}$=1, when sellers become dominant and net sell volume becomes positive, an increase in the following period's Bitcoin price is observed, suggesting that sellers place their trades too early.

Furthermore, I examine the style and skill of investors for time durations of daily, and weekly. Tables VII, and VIII suggest that although evidence for the contrarian behavior of investors decays with longer time periods, it persists until monthly durations. The order imbalance of monthly durations are not stationary. Therefore, in appendix Table A.5, calculating the first difference of order imbalance, I explore the changes in the order imbalance for monthly durations and show that an increase in returns intensifies larger increase in order imbalance.

V.1. Seasonality

Figure A.5 displays mean values of order imbalance during different hours of the day and different days of the week. As illustrated in Figure A.5, the order imbalance of different traders tend to be maximum at time 11:00 (UTC) and minimum at times 23:00 (UTC) and 24:00 (UTC). Thus, Bitcoin order imbalance appears to show seasonality based on the hour-of-the-day. Furthermore, the order imbalance of different traders tend to be maximum on Mondays and minimum on Saturdays. Thus, it can implied that Bitcoin order imbalance show seasonality based on the day-of-the-week.

Moreover, I explore the seasonality of Bitcoin returns based on the hour-of-the-day and the day-of-the-week. Figure A.7 indicates that Bitcoin returns tend to be maximum at times 22:00 (UTC) and 23:00 (UTC), the hours following the closure of New York Stock Exchange and Toronto Stock Exchange (21:00 UTC), while they do not show significant seasonality based on the-day-of-the-week.

Furthermore, I explore Bitcoin trading volume and price volatility in Figure A.6 and Figure A.8 to understand the mechanisms incentivizing certain trading positions (buy vs sell) in traders. Bitcoin price volatility is the highest at midnight, and lowest at 6:00 (UTC). Thus, it appears that Bitcoin order imbalance is the lowest, concurrent with highest levels of Bitcoin price, in hours following times when Bitcoin return is the highest, suggesting that the contrarian trading strategy of traders positively correlates Bitcoin's concurrent price volatility following an increase in Bitcoin returns. Additionally, Bitcoin price volatility and trading volume is higher during weekdays and lower on weekends. Also, trading volume for investors of all sizes is maximum at 17:00 (UTC) and minimum at 10:00 (UTC).

V.2. Anchoring Bias

So far, my results show that in the largest U.S.-based exchange, investors follow a contrarian trading strategy implying that after an increase in Bitcoin's price, net sell exceeds net buys for investors in all quartiles. In this section, I examine whether investors have anchoring bias by inspecting order imbalance after Bitcoin's price hits its 30-, 90- and 120-day high and low prices. I perform a regression analysis per equation:

$$OIB_t = \beta_0 + \ beta_1 d_{t-1}$$

d is a dummy variable equal to 1 if Bitcoin's price hits its 30- , 90- and 120-day highs. Following Newey and West (1987), I control for autocorrelation of standard errors.

Table B.3 Panel A shows negative and significant coefficients for d_{t-1} among 4^{th} quartile investors, suggesting that the largest investors adopt a contrarian strategy, selling when Bitcoin hits its high 30-, 90, and 120-day prices. For robustness, I conduct the following regression analysis:

$$MDOIB_t = \beta_0 + \ beta_1 d_{t-1}$$

where $MDOIB_{\text{t}}$ is the mean deviation of order imbalance from its preceding 180-day (6-month) average. Table B.4 Panel A shows consistent results: Negative and significant values of β_1 for investors of the 4^{th} quartile suggest that after Bitcoin price hits its highs, the largest investors' order imbalance drops to below its average. Moreover, Table B.4 Panel A shows positive and significant β_1 among investors with trade size of mid 50-percentile, referred as mid-size investors, which is suggestive of momentum trading strategy.

Furthermore, following the same methodology, I study the trading strategy of investors after Bitcoin's price hits its 30-, 90- and 120-day low prices. Table B.3 Panel B shows positive and significant t-statistics for the 4^{th} quartile investors in all durations, implying that when Bitcoin price hits its lows, the largest investors' net trade direction is buy, which consistent with their contrarian trading strategy. Table B.4 Panel B demonstrate consistent results when using mean deviation of order imbalance in the analysis of low days. On low days, the buy volume among 4^{th} quartile investors exceeds its preceding 180-day average, i.e. concurrent contrarian trading strategy. Table B.4 Panel B indicates significantly negative values for β_1 among mid-size investors, implying that when Bitcoin price hits its lows, mid-size investors order imbalance drops to below its preceding 180-day average, i.e. momentum trading strategy.

Additionally, I explore Bitcoin realized returns after Bitcoin price hits its 30-, 90-, and 120-day highs and lows to assess the trading strategy of which group is more likely to be profitable. I perform a regression analysis as:

$$Return_t = \beta_0 + \ beta_1 d_{t-1}$$

d is a dummy variable equal to 1 if Bitcoin's price hits its 30- , 90- and 120-day highs (lows). Table XI shows significantly positive values for β_1 following highs and no significant values for β_1 following low days. Hence, while a positive return is likely after Bitcoin hits its highs, no significant return is likely after Bitcoin hits its lows (except for 120-day low). Thus, it appears that following a momentum trading strategy when Bitcoin hits its highs tends to be profitable.

Furthermore, I investigate the likelihood of profitable trades on high days for buyers and sellers separately. I define a dummy variable Buy_{t} ($Sell_{\mathrm{t}}$) equal to 1 (-1) if, at time t, Bitcoin price is at highs and order imbalance is positive (negative). I calculate buyers' (sellers') return by the vector product of variable Buy_{t} ($Sell_{\mathrm{t}}$) and the cumulative Bitcoin return in the following days:

$$BuyerReturn_t = Buy_{t-k} \times cReturn_{t,k}$$

$$SellerReturn_t = Sell_{t-k} \times cReturn_{t,k}$$

, where $cReturn_{t,k}$ is the cumulative return from day $t-k$ to t. k is the number of days during which the trader holds his/her position after highs. Then, the t-statistic for mean values of $SellerReturn_t$ ($BuyerReturn_t$) is calculated per equation:

$$t - stat(SellerReturn) = \frac{Seller\bar{R}eturn}{\frac{\sigma(SellerReturn)}{\sqrt{T}}}$$

$$t - stat(BuyerReturn) = \frac{Buyer\bar{R}eturn}{\frac{\sigma(BuyerReturn)}{\sqrt{T}}}$$

$$Seller\bar{R}eturn = \frac{1}{T}\sum_{t}^{T} SellerReturn$$

$$Buyer\bar{R}eturn = \frac{1}{T}\sum_{t}^{T} BuyerReturn$$

,where $\sigma(SellerReturn)$ is the standard deviation of $SellerReturn$ ($BuyerReturn$) and T is the number of days of study. The null hypothesis is that t-statistics are not significantly different from zero, implying that trading on highs will not generate significant returns. The alternative hypothesis is that investors sells or buys on highs will generate significant returns: A significantly negative (positive) t-statistics implies that investors' trades on highs leads to negative (positive) returns. Table XII Panel A shows the t-statistics for seller returns. Since dummy $Sell_{\mathrm{t}}$ is equal to -1, negative t-statistic values presented in Table XII Panel A suggest positive returns after sells are placed: sellers placing trades too soon. Table XII Panel B presents t-statistics for buyers. t-statistic values are mostly insignificant which could be due to limited number of periods in which traders place buys on highs (see (Table A.6 Panel C Appendix). For robustness, I perform regression analysis controlling for Newey and West (1987) standard errors autocorrelation and generate consistent results (Table A.6 Appendix).

Moreover, a sound judgment determining a strategy with the highest potential return can be made only if skewness of returns on days following highs are considered. Thus, I compute 95% confidence intervals for Bitcoin returns following highs. Figure A.9 illustrates Bitcoin' cumulative returns around 30-, 90- and 120-day highs. In all scenarios, Bitcoin cumulative returns 1- and 5- days following highs are positive with a 95% confidence interval. Therefore, traders are more likely to generate higher returns if they wait at least one day when Bitcoin hits highs.

In sum, the study of anchoring biases of investors in different quartiles shows that the largest investors adopt a contrarian trading strategy when Bitcoin price hits its highs and lows. However, mid-size investors order imbalance exceeds its average following highs and goes below its average following low days. Furthermore, when Bitcoin hits its high, a momentum trading strategy seems to be profitable since positive returns are observed during the subsequent 5 days. My results are consistent with the findings of George, and Hwang (2005) in the equity market, suggesting that when a stock price hit 52-week high, a continuation of the upward price movement is likely.

V.3. Market Timing Skills of Investors in Forecasting Up and Down Markets

So far, my results suggest that unlike sellers, all but the tiniest buyers in the Coinbase exchange show market timing skills for up to 2 hours. In this section, I examine market timing skills of traders by calculating the probability of a correct forecast, conditional on the Bitcoin's actual return, inspired by Henriksson, and Merton (1981). Conditioning on an up (down) market, when Bitcoin return is positive (negative), I calculate the probability that the immediately preceding hour has positive (negative) net buy volume (OIB). Therefore, the probability of a correct forecast in an up is defined as:

$$P(OIB_{t-1} > 0 | Return_t > 0) = \frac{\sum_{t>1}^{H_1} d_{1,t-1}}{H_1} \tag{10}$$

Where H_1 is the number of hours in which Bitcoin return is positive. $d_{1,\text{t-1}}$ is a dummy variable which equals to 1 if the order imbalance in time t-1, one hour prior to any hour with a positive return, is positive and 0 otherwise. Similarly, the probability of a correct forecast in a down market is defined as:

$$P(OIB_{t-1} < 0 | Return_t < 0) = \frac{\sum_{t>1}^{H_2} d_{2,t-1}}{H_2} \tag{11}$$

Where H_2 is the number of hours in which Bitcoin return is negative. $d_{2,\text{t-1}}$ is a dummy variable which equals to 1 if the order imbalance in time t-1, one hour prior to an hour with a negative return, is negative and 0 otherwise.

Table XIII Panel A shows the results for the probability of correct forecast by traders of different quartiles in up and down markets, and suggests that the largest traders outperform others in up markets; that is: the probability of traders correctly placing net buys before an increase in Bitcoin's price is the highest for the largest traders. However, in down markets, the smallest traders outperform others by demonstrating the highest probability of correctly placing net sells before a decrease in Bitcoin price.

Since the number of hours with negative order imbalance is more than those with positive order imbalance, and since in general average hourly order imbalance is negative due to mining, the results may be impacted the dominant negative order imbalance in the Bitcoin market. Therefore, for robustness, I control for noise traders by calculating the mean deviation of order imbalance from its preceding 350-hour (15-day) average with which I assess the conditional probability of correct forecasts in up and down markets.

Panel B of Table XIII shows the probability of correct forecast by traders of different quartiles in up and down markets, using demeaned order imbalance. Consistent with Panel A, the largest traders outperform others in up markets and the probability of a correct forecast before an increase in Bitcoin price consistently declines as the size of traders decreases. An opposite pattern can be identified in down markets, that is: the smallest traders outperform others in down markets and the probability of a correct forecast before a decrease in Bitcoin price consistently declines as the size of traders increases. Thus, it appears that in general, larger traders are more optimistic about Bitcoin returns comparing with small traders. The *Overallskill* shows the probability of traders correctly timing the market per equation:

$$OverallSkill_t = P_1 \times \frac{TruePositive}{ActualPositive} + P_2 \times \frac{TrueNegative}{ActualNegative} \tag{12}$$

,where P_1 is the probability of Bitcoin price being up, and P_2 is the probability of Bitcoin price being down at time t. Table XIII suggests that the overall market timing skills of traders increases with their size.

Figure A.10 presents a confusion matrix, which is a machine learning tool generally used for evaluating the performance of a classification model illustrating what types of errors a classification model makes (Type I vs Type II). I use confusion matrix for visualizing and summarizing investors' performance in market timing in each scenario (up vs down prices). Traders' predictions are presented in x-axes and realized returns are presented in the y-axes. In each subplot, each sub-box represents the probability of a scenario as:

$$Upper-leftsub-box : TrueNegative = P(R_t < 0) \times P(OIB_{t-1} < 0|R_t < 0) \quad (13)$$

$$Lower-leftsub-box : FalseNegative = P(R_t t > 0) \times P(OIB_{t-1} < 0|R_t > 0) \quad (14)$$

$$Upper-rightsub-box : FalsePositive = P(R_t < 0) \times P(OIB_{t-1} > 0|R_t < 0) \quad (15)$$

$$Lower-rightsub-box : TruePositive = P(R_t > 0) \times P(OIB_{t-1} > 0|R_t > 0) \quad (16)$$

$TrueNegative$ is when traders' OIB at time t-1 is negative, meaning that traders predict a decrease in Bitcoin's price for time t and Bitcoin price actually declines at time t. $FalseNegative$ is when traders' OIB at time t-1 is negative, meaning that traders predict a decrease in Bitcoin's price for time t while Bitcoin price increases at time t. Similarly, $TruePositive$ ($FalsePositive$) is when traders, at time t-1, correctly (incorrectly) predict an increase in Bitcoin price at time t.

The summation of probabilities presented in sub-boxes on the right (left) side equals to the probability of investors' predicting an up (down) price ($OIB_{t-1}>0$). Likewise, the summation of probabilities presented in sub-boxes on the upper (lower) side equals to the probability of the Bitcoin price actually being up (down) at time t ($R_t>0$). Finally, the summation of the probabilities in all boxes equals to 1 as:

$$\begin{aligned} &P(R_t < 0) \times [P(OIB_{t-1} < 0|R_t < 0) + P(OIB_{t-1} > 0|R_t < 0)] \\ &\quad + P(R_t > 0) \times [P(OIB_{t-1} < 0|R_t > 0) + P(OIB_{t-1} > 0|R_t > 0)] = 1 \end{aligned} \quad (17)$$

Figure A.10 shows that while the probability of a price increase (upper side sub-boxes) is roughly equal to the probability of a decrease (lower-side sub-boxes), investors of all quartiles mostly predict a down market as the summation of probabilities on the left side is significantly higher than the right side. This is consistent with order imbalance summary statistics, showing more hours with negative order imbalance. Investing fiat money into Bitcoin, when placing buys investors, in general, are more likely to seek price advantage over immediacy, while when placing sells, pulling their fiat money out of the Bitcoin market, investors tend to seek immediacy over price advantage, due to the highly risky nature of Bitcoin and presence of miners. The heavy inclination of traders to sell is less sever for investors of the 4^{th} quartile. This could be due to the largest traders' higher risk tolerance level, as they are more of institutional investors rather than retail investors. Furthermore, if traders obtain some private material information, when investing fiat money in the Bitcoin market, allocating larger dollar amounts, the largest traders tend to place market orders, choosing immediacy to take advantage of their time sensitive information.

To control for trades placed by noise traders and Bitcoin miners, Figure A.11 summarizes investors' market timing performance using demeaned order imbalance, the deviation of order imbalance from its preceding 350-hour (15-day) moving average. The predictions of an increase and decrease in Bitcoin price (the left and right sides) in all subplots looks close to balanced.

Consistently, Figure A.11 shows that largest investors are better in predicting an increase in Bitcoin price comparing with both other investors and their own performance in predicting a decrease in Bitcoin price. The probability that investors in the 4^{th} quartile correctly predict an up market is 27.06% and a down market is 25.56%. The probability of correctly predicting an increase in Bitcoin price decreases with the size of investors and is the lowest for 1^{st} quartile investors with the probability of 24.21%. Furthermore, the probability that investors in the 1^{st} quartile correctly predict a down market is 27.21% , which is the highest comparing with those of investors of other quartiles. The probability of correctly predicting a decrease in Bitcoin price decreases as the size of investors increases and is the lowest for investors of the 4^{th} quartile.

Moreover, consistent with my findings that buyers outperform sellers in market timing, Figure A.11 shows that in all quartiles when investors buy (right-side sub-boxes), they are more likely to correctly time the market comparing with when they sell. For instance, investors of the 2^{nd} quartile, buy 46.52% (21.55% + 24.97%) of times, 53.68% ((24.97%/46.52%) of which they correctly time the market, and Bitcoin price increases in the subsequent hour; while from the 53.48% (26.76% + 26.71%) of times that they sell, they correctly time the market 50% (26.76%/53.48%) of times. Comparing the probability of a false positive with that of a false negative in all subplots, the same conclusion can be drawn as the probability of a false positive is less than a false negative for investors of all quartiles.

V.4. Sentiment Analysis

My earlier results indicate that Bitcoin returns, and the time of trade contains information on Bitcoin's next hour order flow. To better understand the changes in Bitcoin's order flow, I explore the impact of social media sentiment and attention on Bitcoin order imbalance, and I examine whether the contrarian trading strategy of the largest U.S.-based exchange traders remains significant when controlling for seasonality, sentiment, and traders' persistence in directional trading.

I obtain sentiment data from Reddit, which unlike Twitter has not been exploited for sentiment analysis of Bitcoin investors yet. Reddit, is a social news aggregator and is divided to different topic specific subsections, called subreddit. More than 68% of Reddit users are between 20-50 years old, the age range that would be more interested in innovative investments. Approximately 70% of Reddit users are from United States, United Kingdom, Canada, Australia, and Germany. Since Coinbase where I generate investors' trade data provides service to United States, United Kingdom, Canada, Australia, Singapore and mostly

European countries, the population exposed to Reddit sentiment is well targeted in terms of relevance. I specifically look at Bitcoin subreddit which has more than 4,000,000 subscribers, people who specifically look for Reddit information.

I classify Reddit posts as positive, neutral and negative, using Valence Aware Dictionary and sEntiment Reasoner (VADER), which is a lexicon and rule-based tool specifically adjusted for social media sentiment analysis. VADER provides advantages beyond most of other language processing models (see Hutto, and Gilbert (2014)). First, it recognizes punctuations which impact the intensity of a semantic orientation (e.g."!"). Second, it captures the capitalization used by a writer for emphasis. Third, it takes into account the degree adverbs which clarify the intensity of an expression (e.g. 'extremely'). Fourth, it identifies the polarity shift using conjunctions (e.g. but). Fifth, it captures polarity negation by examining the three words preceding a sentiment-laden lexical feature (e.g. "The Bitcoin price isn't that high"). After classifying Reddit posts as positive, negative and neutral, I calculate average positive and negative sentiment scores in each hour.

$$Pos_t = \frac{PositivePosts_t}{TotalPosts_t} \tag{18}$$

$$Neg_t = \frac{NegativePosts_t}{TotalPosts_t} \tag{19}$$

Pos_t (Neg_t) represents the percentage of positive (negative) posts in each hour. Since the sentiment in the Bitcoin market rapidly changes, I standardize these values based on Reddits positive and negative sentiment during the preceding 336 hours (2 weeks) to obtain more relevant results.

$$Z_Positive_t = \frac{Pos_t - \mu_{pos}}{\sigma_{pos}} \tag{20}$$

$$Z_Negative_t = \frac{Neg_t - \mu_{neg}}{\sigma_{neg}} \tag{21}$$

, where μ_{pos} (μ_{neg}) and σ_{pos} (σ_{neg}) are the average and standard deviation of positive (negative) scores in the preceding 336 hours. Finally I calculate Hourly sentiment per equation:

$$Sentiment_t = Z_P ositive_t - Z_N egative_t \tag{22}$$

As my measure of sentiment is scaled by the total number of posts in each hour, it does not take into account the changes in attention towards Bitcoin. For instance, there may be hours when the number of posts substantially increases while the sentiment does not necessarily change. Including an *Attention* index based on the number of hourly posts can properly proxy for investors' attention towards Bitcoin. I define my attention proxy as:

$$Attention_t = Posts_t – \mu_p / \sigma_p \tag{23}$$

Where $\mathrm{Posts_t}$ is the number of posts during hour t. μ_p and σ_p are the rolling mean and standard deviation of the number of posts during the preceding 336 hours (2 weeks). Since one hour is likely to be a tight window for an average investor to interpret sentiment from Reddit posts and take action accordingly, I consider 2-hour windows for attention and sentiment and estimate OIB_t as:

$$\begin{aligned} OIB_t = \beta_1 \times Ret_{t-1} + \beta_2 \times 2Sentiment_{t-1} + \beta_3 \times 2Attention_{t-1} \\ + \beta_4 \times SP_t + \beta_6 \times 24OIB_{t-1} + W + H \end{aligned} \tag{24}$$

$Return_\mathrm{t\text{-}1}$ is Bitcoin' return at time t-1. $2Sentiment_\mathrm{t\text{-}1}$ is a proxy for aggregate 2-hour sentiment ($Sentiment_\mathrm{t\text{-}1}$ + $Sentiment_\mathrm{t\text{-}2}$). $2Attention_\mathrm{t\text{-}1}$ is a proxy for aggregate 2-hour attention calculated as the summation attention scores during the past 2 hours. $\mathrm{SPRet_{t\text{-}1}}$ is the daily return on the stock market. Since the Bitcoin market is open every day but the stock market is closed on weekends, for the days that the market is close, I use the daily return on the stock market from the most recent day that the market was open. For instance, when I examine Bitcoin's order imbalance on a Sunday, the stock market return for Friday is the most recent information that investors have from the stock market daily performance. W and H represent control variables used to capture the seasonality of order imbalance. As illustrated in Figure A.3, the partial autocorrelation between order imbalance and its previous lags is significant until lag 24. To further control for such high autocorrelation, I calculate the aggregate OIB during the past 24-hours (OIB24), for which I control my model. $24OIB_{\text{t-1}}$ is the summation of order imbalance values from time t-25 to t-1.

The results, presented in Table XIV Panel A, show significantly positive coefficients for $24OIB_{\text{t-1}}$, implying that the directional trading of investors of all sizes is persistent. In addition, the significantly negative coefficient for $R_{\text{t-1}}$ for all but the tiniest investors is consistent with my earlier finding of investors' contrarian trading strategy. The coefficient for $R_{\text{t-1}}$ for the tiniest traders while negative loses significance, when controlling for investors' sentiment, directional trading, attention, and seasonality. Furthermore, the coefficient of $2Sentiment_{\text{t-1}}$ for mid-size investors is positive and significant, suggesting that mid-size investors use social media sentiment as an informative resource for taking a position. The coefficients of $2Attention_{\text{t-1}}$ suggest that while the order imbalance of all but the largest traders are positively impacted by investor attention during the previous hour, the order imbalance of the largest traders are negatively impacted by attention during the previous hour. It can be implied that when smaller investors increase net buy due to an increase in attention, the largest investors find it as a good opportunity to sell their Bitcoin positions, moving against smaller investors.

Moreover, a negative and significant coefficient is detected for the daily market return for investors of the 4^{th} quartile, consistent with the largest investors perceiving Bitcoin as an alternative investment, i.e. substitution effect. When the performance of the stock market is not satisfactory, large investors are incentivized to switch to the Bitcoin market, and when the performance of stock market is attractive, investors shift towards the stock market. The significant coefficients of time-of-the-day and day-of-the-week is consistent with the seasonality of Bitcoin order imbalance established earlier in this research. For robustness, I also show that the order imbalance of investors of the largest size has a significantly negative correlation with NASDAQ returns (see Appendix Table A.7 Panel A). Furthermore, I examine whether the order flow of investors of different sizes is impacted by the returns on the S&P Financial Select Sector Index (XLF), which aims to track the financial sector. If investors consider Bitcoin as a currency, I expect to see significant correlation between Bitcoin's order flow and XLF; however, I did not find any significant correlations supporting such hypothesis (see Appendix Table A.7 Panel B).

In addition, I decompose 2-hour sentiment to 2-hour positive and negative scores. 2-hour positive (negative) is calculated as summation of standardized positive scores from time t-3 to t-1. Table XIV Panel B shows negative coefficients for negative sentiment among all but the largest investors, but no significant coefficient for investors of any size, implying that negative news has a larger impact on investors trading decisions comparing to positive ones, consistent with findings of Chevapatrakul and Mascia (2019) arguing that Bitcoin investors overreact during days following days of sharp declines in Bitcoin price. As a further robustness check, I estimate the mean deviation of order imbalance from its previous 24 lags, using the same explanatory variables, and I generate consistent results for contrarian trading strategy of all but the tiniest investors, and for sentiment- and attention-induced trading of mid-size investors. (see Appendix. Table A.8).

Since investors may consider information of several hours before making a buy or sell decision, I expand the time window to 24 hours for receiving sentiment and estimate order imbalance at time t by:

$$OIB_t = \beta_1 \times Ret_{t-1} + \beta_2 \times 24Sentiment_{t-1}$$
$$+ \beta_3 \times 24Attention_{t-1} + \beta_6 \times 24OIB_{t-1} + W + H$$

Table XV Panel A shows significantly positive coefficients for aggregate 24-hour $OIB_{\text{t-1}}$ ($24OIB$) which suggests persistence in directional trading of investors. Also, the $Return_{\text{t-1}}$ shows a significantly negative coefficient for investors of all but the tiniest quartile, consistent with earlier findings of contrarian trading strategy of Bitcoin investors. The previous 24-hour sentiment has a significantly positive coefficient for all but the largest investors, consistent with the findings of Table XIV. Although the 2-hour sentiment coefficient was not significant for the tiniest traders in Table XIV, it turns significant as I expand the time window from 2-hour to 24-hour in Table XV. It can be implied that it takes longer for smaller traders to receive, interpret and act on the sentiment. Also, the significance of attention-induced trading vanishes for the most part as I expand the time window from 2-hours to 24-hours. Considering a significant coefficients of attention among all investors in the 2-hour window, and insignificant coefficients in the 24-hour window, it appears that investors react more quickly to attention, and hence controlling for the preceding aggregate 24-hour order imbalance, which most likely reflects the impact of attention, dissipates the significant of 24-hour attention.

V.5. Can Different Components of Bitcoin's Order Flow Provide Useful information for future Bitcoin Returns?

The literature suggests that order imbalance has a positive predictive power in Bitcoin returns (see McIntyre and Harjes (2016), Silantyev (2019), Scaillet, Treccani, and Trevisan (2020), Doniar and Bouchaud (2015), etc.). I perform a regression analysis on the predictive power of Bitcoin order imbalance for future returns and provide consistent results with the literature (see Appendix Table A.9). In this section, I go beyond the predictive ability of

Bitcoin order imbalance and inspect whether different components of order imbalance have any explanatory power for the next hour return. To discover predictive ability of different components of order imbalance at time t-1 for Bitcoin's return at time t, I utilize a two-step decomposition, following Boehmer, Jones, Zhang, and Zhang (2021). In the first stage I estimate order imbalance at time t-1 as:

$$\begin{aligned} OIB_{t-1} = d_0 + \beta_1 \times OIB24_{t-2} + \beta_2 \times Return_{t-2} \\ + \beta_3 \times 2Hour - Sentiment_{t-2}\beta_4 \times 2Hour - Attention_{t-2} + u_4 \end{aligned} \tag{25}$$

I further define:

$$\begin{aligned} \widehat{OIB_{Persistence}} &= \beta_1 \times OIB24_{t-2} \\ \widehat{OIB_{Contrarian}} &= \beta_2 \times Return_{t-2} \\ \widehat{OIB_{Sentiment}} &= \beta_2 \times 2Hour - Sentiment_{t-2} \\ \widehat{OIB_{Attention}} &= \beta_3 \times 2Hour - Attention_{t-2} \\ \widehat{OIB_{Other}} &= d_0 + u_4 \end{aligned} \tag{26}$$

Therefore, I can write:

$$OIB_{t-1} = \widehat{OIB_{Persistence_{t-1}}} + \widehat{OIB_{Contrarian_{t-1}}} + \widehat{OIB_{Sentiment_{t-1}}} + \widehat{OIB_{Attention_{t-1}}} + \widehat{OIB_{Other_{t-1}}} \tag{27}$$

I denote the part of OIB estimated from attention and sentiment as *Attention* and *Sentiment* respectively, the part from past order imbalance as *Persistence* and the part related to past returns as *Contrarian* which relates to liquidity provision (see Boehmer, Jones, Zhang, and Zhang (2021)). *Other* accounts for some other information that has not been taken into account in the model but may be related to the future Bitcoin return.

In the second stage, I estimate the following regression using the components of order imbalance at time t-1:

$$\begin{aligned} Return_t = \omega_0 + \omega_1 \times Persistence_{t-1} + \omega_2 \times Contrarian_{t-1} \\ + \omega_3 \times Sentiment_{t-1}\omega_4 \times Attention_{t-1} + \omega_5 \times Other_{t-1} + Controls \end{aligned} \tag{28}$$

Table XVI shows the results for the first stage. The results are similar to those of Table XIV , showing positive and significant coefficient for $OIB24_{\text{t-2}}$, which is indicative of persistence of directional trading of investors, negative significant coefficient for $Return_{\text{t-2}}$, which is indicative of investors' contrarian trading strategy. *Attention* shows significantly negative coefficients for the largest investors and significantly positive coefficients for other, and *Sentiment* has a significantly positive coefficient for the mid-size investors.

The lower section of Table XVI shows the results for the second stage. Contrarian has a positive and significant coefficient of 6.30, 4.10 and 2.40 for quartiles 2, 3 and 4 respectively. This is in line with liquidity provision arguing that following a contrarian trading strategy, risk averse investors provide liquidity to meet less risk-averse investors' demand for immediacy and generate excess returns over the following period (see Kaniel, Saar and Titman (2008) and Boehmer, Jones, Zhang, and Zhang (2021)).

Furthermore, for the 4$^{\text{th}}$ quartile investors, the coefficient estimate of *Persistence* in directional trading is -0.19 with the *p*-value of 0.002 implying that the persistence in the directional trading of the largest investors significantly and negatively contributes to the predictability of order imbalance for Bitcoin return. No significant coefficients are found for the *Attention* and *Sentiment* of Bitcoin traders which suggests that social media attention and sentiment do not provide profitable opportunities.

Table XVII shows the results for performing this analysis with 24-hour sentiment and the previous hour attention. All but the largest investors trade with sentiment and attention, while the largest investors trade against attention. Consistent with the results of Table XVI, no significant predictive power is detected for attention- and sentiment-induced trading, suggesting that attention- and sentiment-induced trading do not provide useful information in predicting Bitcoin returns.

V.6. An Alternative Exchange: Binance

In this section, I use trades data from an alternative exchange, Binance, the largest cryptocurrency exchange in the world, and I study the impact of investors' cultural differences on their trading activities. Emergence of cryptocurrencies, specifically Bitcoin due to its prevalence, provides a solid basis for conducting such analysis because it is a non-commodity financial asset to which investors' exposure and interest go beyond countries' boarders. Conducting such an analysis before the appearance of cryptocurrencies, lacks the essential common ground as investors of different cultures around the world tend to invest in different markets. For instance, investors in London, UK, most likely invest in the London Stock Exchange whereas investors in Tokyo invest in the Tokyo Stock Exchange. Therefore, different strategies of investors with different cultures could be attributed to fundamentally different investment opportunities that exchanges of each country provide.

The time period of this analysis is from October,1, 2019 to October,1, 2021, during which traders of supreme eastern nations such as China, India, Russia, Singapore, etc., although some of whom were restricted later, were able to trade on the Binance exchange, while U.S. traders were banned from trading on this platform[11]. Coinbase on the other hand, provides service to the traders in the U.S., Canada, Australia, United Kingdom, Singapore and some of the European countries. The presence of traders from countries to which both exchanges provide service will only make my results weaker, and hence does not impose any concerns. Thus, although there are some countries to which both exchanges provide

[11] While Binance stopped accepting U.S. traders, its U.S.-based version, Binance.US, starting a partnership with Financial Crimes Enforcement Network (FinCEN), started providing services into the U.S. market. The dataset used for the analysis in this research is from Binance which does not contain the transactions from the U.S. traders in the other platform, Binance.US.

service, the differences in strategies pursued by traders of the two platforms can be reasonably attributed to the cultural differences among traders of the countries where the two exchanges don't have in common, i.e. the U.S and the eastern countries. Accordingly, I perform each analysis on the trades from the Binance exchange and the Coinbase Pro exchange separately during October 1, 2019 to October 1, 2021. Since Most of the results generated from the Coinbase Pro exchange are consistent with those presented earlier in this paper (from June 1, 2016-October 1, 2021), for brevity I present Coinbase Pro results in the appendix section.

Table XVIII shows the summary statistics of Bitcoin market orders in the Binance exchange for investors in different quartiles. In the Binance exchange, the mean values of order imbalance across different quartiles are within -2% and 2%, a tighter range around zero compared to those of the Coinbase Pro exchange which are within -54% and -6% for the same time period (see appendix Table A.10). Therefore, while among U.S. traders those who demand immediacy, placing market orders, are mostly sellers by volume, among eastern traders the immediacy demand among buyers and sellers is close. Furthermore, the average dollar value of a transaction in the Binance exchange is less than Coinbase Pro exchange in each quartile.

Figure A.12 shows the intraday seasonality of Bitcoin order imbalance in the Binance and Coinbase Pro exchanges during the same time period (from October 1, 2019 to October 1, 2021). In the Binance exchange, the largest traders don't move in the same direction as other traders; the Bitcoin order imbalance of all but the largest investors are minimum from 00:00 to 01:00 UTC, the first hour of Tokyo Stock Exchange operation. In the Coinbase exchange, the order imbalance graph of the largest traders, compared to that of smaller traders looks inverted; that is: the net buy volume of the largest traders is minimum when the net buy volume of other traders is closer to maximum (e.g. 10:00 to 11:00 UTC). Thus, it can be implied that the largest traders in the Coinbase exchange move against the crowd. In the Binance exchange, the largest traders' net buy volume of Bitcoin is minimum (maximum) during 7:00 to 8:00 UTC (1:00 to 2:00 UTC), and in the Coinbase Pro exchange is minimum (maximum) during 10:00-11:00 UTC (3:00 to 4:00 UTC), a few hours later.

Furthermore, I determine the style of Bitcoin traders in Binance by calculating t-statistics for the LkM measure as explained earlier in this research. Results in Table XIX suggest that unlike traders in the Coinbase Pro exchange, the traders in the Binance exchange do not follow a contrarian trading strategy. The t-statistics for the contemporaneous movements of Bitcoin's order flow and return ($L0M$) are positive for traders of all quartiles. A negative t-statistic for the mean values of the $L0M$ measure (the vector product of concurrent/same-hour returns and order imbalance) can be reasonably interpreted as a concurrent contrarian trading strategy of investors; that is: an increase in Bitcoin returns leads to an increase in its net sell volume during the same hour. However, the interpretation of a positive t-statistic regarding traders' strategy is not as conclusive as a negative t-statistic, because a positive t-statistic for the mean values of the $L0M$ measure can be also observed when Bitcoin returns increase as a result of an increase in Bitcoin's net buy volume during the same hour. Therefore, no specific trading style can be attributed to Binance traders while TableA.11 shows a concurrent contrarian trading strategy for traders of all sizes in Coinbase during the same time frame. Therefore, in a specific hour when Bitcoin price is increasing the net selling volume of U.S. based traders increases while the net buying volume of eastern traders increases. Thus, although it may not be apparent at the first glance, trading on different exchanges, U.S. and eastern traders trade against each other because the trades they place on a common asset with a limited supply are influential in setting tick prices. For robustness, I perform a regression analysis controlling for Newey and West (1987) standard errors, and I generate consistent results presented in Panel B of Tables XIX and A.11. Next, I investigate how changes in the Bitcoin price impact Bitcoin order imbalance deviation from its average in the previous 720 hours (30 days). Panel C of Tables XIX shows that in the Binance exchange, an increase in Bitcoin price is positively correlated with concurrent positive mean deviation of Bitcoin order imbalance across all quartile, consistent with results presented in Panel A and Panel B. Also, the tiniest investors' net buy volume increases from its average following an increase in Bitcoin Return, suggesting a momentum trading strategy. The results of the same analysis on the Coinbase trades shows that while an increase in Bitcoin returns intensifies the largest and smallest investors' net selling volume more than its average in the previous 720 hours, contrarian trading strategy, it intensifies mid-size investors' net buying volume in the following hours, momentum trading strategy (see appendix Table A.11).

Moreover, I examine whether eastern traders show anchoring bias following the same methodology I used earlier for Coinbase traders.

$$OIB_{t,k} = \beta_0 + \beta_1 d_{t-k}$$

Estimating order imbalance of Binance traders at time t for duration of k days ($\mathrm{OIB_{t,k}}$), Table reftable21 Panel A shows the coefficients for dummy variable $\mathrm{d_{t\text{-}k}}$, which is equal to 1 if Bitcoin price hits its highs at time t-k. Table reftable21 Panel A shows positive coefficients for traders in the 2^{nd} quartile, suggesting that the 2^{nd} quartile traders follow a momentum trading strategy; that is: the order imbalance (net buy volume) of the traders in the 2^{nd} quartile increases after Bitcoin price hits its 30-, 90- and 120-day highs. Table reftable21 Panel B presents the coefficients of $\mathrm{d_{t\text{-}k}}$, if Bitcoin price hits its lows at time t-k. Positive coefficients suggest that when Bitcoin hits its lows an increase in net buy volume is observed during the same or following days. Table reftable21 Panel B shows that 1^{st} and 3^{rd} quartile traders anchor on the days following Bitcoin hits its lows, and the 2^{nd} quartile traders anchor on the same day as Bitcoin hits lows. Analysis of Coinbase traders' anchoring bias during October 1, 2019, October 1, 2021 generates results consistent with those shown earlier (see appendix Table A.12). The largest investors anchor on and following days that Bitcoin hits its highs, while mid-size investors follow a momentum trading strategy. After Bitcoin hits its 90- and 120-day lows, on the other hand, both the smallest and the largest traders show anchoring bias. The anchoring bias following low days by the smallest traders in the

Coinbase is consistent with Binance smallest traders.

Controlling for the general order imbalance of each exchange, I also investigate the mean deviation of order imbalance from its preceding 90 days after high and low days. Panel A of Table XXI shows that the net buy volume of Binance traders after Bitcoin hits highs is not significantly different from the average net buy volume of traders during the prior 90 days. However, Panel B of Table XXI shows that the net buy volume of traders in the 1st and 3rd quartiles exceeds its average during the prior 90 days, after Bitcoin hits its lows. Mirroring the same analysis on the Coinbase traders during the same time period shows that the net buy volume of smaller traders (1st and 2nd quartiles) on and following the days Bitcoin hits its highs exceeds their average net buy volume during the preceding 90 days (see appendix Table A.13 Panel A). For a speculative financial asset whose price is highly impacted by supply and demand forces, an increase in the net buy volume, pushing the price up, during the days preceding highs (when Bitcoin hits high 30-, 90-, 120-day highs) is plausible. Thus, the positive coefficients for order imbalance mean deviation of traders of 1st and 2nd quartiles imply that such traders' buy volume increases even more than the preceding days after Bitcoin hits its highs, consistent with momentum trading strategy. In addition, when Bitcoin price hits lows the order imbalance of traders of all sizes increases beyond its average during the preceding 90 days, suggesting anchoring bias following low days (see appendix Table A.13 Panel B).

In sum, while the largest traders from a U.S.-based exchange anchor on highs, the largest traders of eastern countries do not demonstrate any significant trading strategy on/following highs. On the other hand, the 2nd quartile traders of both exchanges follow a momentum trading strategy on/following highs. In the case of low days (90- and 120-day lows), 1st and 3rd quartile traders from the eastern countries, and the largest and smallest U.S.-based traders are more likely to anchor. The smallest traders of both eastern countries and the U.S. anchor on and following low days. It appears that when Bitcoin hits lows, those who want to take advantage of low prices place market buys, but they allocate a smaller budget for placing market buys due to the risky nature of Bitcoin and the fear of losing money. As their ability to tolerate losses is more than an average person, the largest U.S. traders (with an average trade size of approximately \$6,500) appear to be less risk averse, allocating high budgets for placing market buys to take advantage of Bitcoin lows. Whereas, it appears that those eastern traders with more financial flexibility when anchoring on lows and placing market buys in the Binance exchange, exercise more caution (compared to U.S. traders) and allocate smaller trade sizes which place them among the 3$^{\text{rd}}$ quartile traders with an average transaction value of \$280.

Finally, I study the market timing skill of Binance traders and compare it to that of Coinbase traders during the same time frame. I calculate the conditional probabilities of traders placing market buys (sells) 1-hour prior to an increase (decrease) in Bitcoin price. As Table XXII Panel A shows the conditional probability of Bitcoin traders buying (selling) before Bitcoin price goes up (down) is highest among the 3$^{\text{rd}}$ (4$^{\text{th}}$) quartile traders, suggesting that the 3$^{\text{rd}}$ quartile traders (the largest) traders are best at buying (selling) before the market goes up (down). However, in the Coinbase exchange the largest traders are the best in buying before Bitcoin price goes up and the smallest traders are the best at selling before Bitcoin price goes down (Table A.14 Panel A). Controlling for traders' overall tendency to place market buys and sells, I investigate whether traders' net buy volume increases (decreases) from its average during the previous 15 days. Table XXII Panel B suggests that in the Binance exchange, 3$^{\text{rd}}$ quartile investors have better market timing skills comparing to other traders. Nevertheless, the overall market timing skill of Binance traders in all quartiles is less than 50%, inferior to that of Coinbase traders, which is above 51%. Thus, it appears that when placing market orders, U.S. traders are more likely to correctly time the market compared to eastern traders.

V. Conclusion

This research studies the style and skill of Bitcoin traders of different sizes in a U.S.-based exchange. The study of traders' style consistently suggests that Bitcoin traders follow a contrarian trading strategy; an increase (decrease) in Bitcoin's price nudges traders to sell (buy). Moreover, I separate hours in which buyers are dominant from hours in which sellers are dominant and compare their style and skill. My results suggest that all but the smallest buyers have market timing skills for up to two hours. However, sellers' market timing skills seem to be inferior regardless of their trade size and duration of trading activity.

In addition, I discover seasonality in Bitcoin's order imbalance in certain hours of a day and days of a week. Bitcoin Order imbalance is the lowest during the last hours of a day and the highest at 11:00 (UTC). For all but the tiniest investors, order imbalance is the highest on Mondays and lowest on Saturdays. Besides, I show that the order flow of the largest investors has a significantly negative correlation with the market daily return, consistent with the substitution effect.

Furthermore, I examine the market timing skills of Bitcoin traders forecasting up prices and down prices for the next hour and show that the largest traders are more skilled at forecasting an increase in Bitcoin's price during the next hour while the smallest traders are the most skilled in forecasting a decrease in Bitcoin's price in the next hour; this can indicate that large traders take a more optimistic standpoint towards Bitcoin returns compared to smaller traders.

Also, I inspect the impact of investor attention and sentiment on Bitcoin's hourly order flow. My results show that, in general, mid-size investors trade with sentiment. Furthermore, an increase in attention leads to a decrease in the net buy of the largest investors, yet an increase in the net buy of other investors.

Additionally, I examine whether Bitcoin investors show anchoring bias. The results of studying the days on which Bitcoin hits its 30-, 90- and 120-day highs and lows indicate that the largest investors anchor on high and low prices. On the other hand, mid-size investors are more likely to adopt a momentum strategy after Bitcoin hits its 30-, 90- and 120-day lows. Bitcoin positive returns on days following highs suggest that when Bitcoin price hits its highs, following a momentum strategy is profitable.

Moreover, I inspect the predictive ability of different components of order imbalance for the Bitcoin return in the next hour. My results provide evidence of the liquidity provision in the Bitcoin market in that the contrarian component of order imbalance has a significantly positive predictive power for Bitcoin returns during the next hour. Furthermore, sentiment- and attention-induced trading do not have any predictive power for Bitcoin return in the next hour.

Finally, I examine the impact of cultural differences of Bitcoin traders on their trading activities by using data from an alternative exchange which while providing service to eastern countries does not provide service to the U.S. during the time period of analysis. My findings suggest that although in different exchanges, U.S. traders are likely to trade against eastern traders because an increase in Bitcoin price in any hour is correlated with an increase in U.S. traders' market net sell volume and an increase in eastern traders' market net buy volume. Also, when Bitcoin hits its lows, eastern traders exercise more caution allocating a tighter budget for anchoring comparing to their U.S. peers. Lastly, in average U.S. traders have better market timing skills compared with eastern traders.

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Table I
Hourly Summary Statistics

Table I Panel A and B show the summary statistics for 1-hour order imbalance in terms of volume, and the average dollar value for trades in all quartiles, respectively. Order imbalance is defined as the difference between the buy volume and sell volume, divided by the total trading volume during any given hour, and the hourly average dollar value of trades is calculated by dividing the aggregate hourly dollar value of transactions by the number of transactions per hour. Panel C shows the *p*-value and ADF statistic obtained from Augmented Dickey-Fuller test on the order imbalance of each quartile of study to investigate stationarity.

			Order Imbalance			
	(1)	(2)	(3)	(4)	(5)	(6)
Quartiles	Count	Mean	25%	50%	75%	SD
1	45903.0	-0.3725	-0.6032	-0.4496	-0.1634	0.3268
2	45913.0	-0.3157	-0.4910	-0.3484	-0.1730	0.2490
3	45913.0	-0.1944	-0.3408	-0.1929	-0.0560	0.2162
4	45912.0	-0.0600	-0.2374	-0.0577	0.1201	0.2710
			Average Transaction USD Volume			
	(1)	(2)	(3)	(4)	(5)	(6)
Quartiles	Count	Mean	25%	50%	75%	SD
1	45,903.0	18.01	8.37	16.85	25.20	12.39
2	45,913.0	88.13	41.61	83.82	116.87	57.77
3	45,913.0	413.87	179.07	405.53	547.01	259.73
4	45,912.0	4,818.97	2,440.36	4,517.03	6,844.88	2,945.89

	Panel C: Stationarity Statistics	
	(1)	(2)
Quartiles	ADF Statistic	p-value
1	-7.7216	0.0000
2	-9.9255	0.0000
3	-11.7051	0.0000
4	-15.5625	0.0000

Table II
Buyer-Seller Summary Statistics

Based on the hourly order imbalance in each quartile, the dataset is divided into two subsets: 1. Periods with positive OIB (OIB>0), in which buy volume exceeds sell volume 2. Periods with negative OIB (OIB<0), in which sell volume exceeds buy volume. Panel A shows the order imbalance summary statistics of the buyer-dominated hours (OIB>0), and Panel B shows the order imbalance summary statistics of the seller-dominated hours (OIB<0), where order imbalance is defined as the difference between the buy volume and sell volume, divided by the total trading volume during any given hour.

Buyers vs Sellers Order Imbalance Summary Statistic

			Panel A: Buyers			
	(1)	(2)	(3)	(4)	(5)	(6)
Quartiles	Count	Mean	25%	50%	75%	SD
1	6,795.0	0.2091	0.0711	0.1626	0.3023	0.1781
2	5,086.0	0.1729	0.0573	0.1331	0.2502	0.1493
3	7,978.0	0.1270	0.0396	0.0936	0.1788	0.1174
4	19,028.0	0.1928	0.0720	0.1573	0.2771	0.1529

			Panel B: Sellers			
	(1)	(2)	(3)	(4)	(5)	(6)
Quartiles	Count	Mean	25%	50%	75%	SD
1	39,108.0	-0.4735	-0.6251	-0.5010	-0.3171	0.2255
2	40,827.0	-0.3766	-0.5084	-0.3795	-0.2424	0.1831
3	37,935.0	-0.2620	-0.3725	-0.2395	-0.1312	0.1654
4	26,884.0	-0.2390	-0.3422	-0.2032	-0.0977	0.1778

Table III
Style

Panel A presents t-statistics calculated based on LkM measure for investors of each quartile in each hourly frequency(1-hour, 2-hour, 4-hour, 8-hour, 12-hour, 24-hour) per equations:

$$LkM = OIB_t \times Return_{t-1}$$

$$t - stat(LkM) = \frac{L\bar{k}M}{\frac{\sigma(LkM_t)}{\sqrt{T}}}$$

$$L\bar{k}M = \frac{1}{T}\sum_{t}^{T} LkM$$

$\sigma(LkM_t)$ is the standard deviation of LkM measure and T is the number of hours. In Panel B results of a regression analysis is presented per equation:

$$OIB_t = \beta_1 \times Return_{t-1} + \epsilon$$

OIB_{t} is order imbalance at time t, calculated as the difference between the buy volume and sell volume divided by the total trading volume at time t.

	Panel A: LkM Measure			
	(1) Q1	(2) Q2	(3) Q3	(4) Q4
L0Mvol	-45.24	-50.99	-59.49	-82.21
L1Mvol	-5.27	-8.36	-12.86	-20.06
L2Mvol	-3.29	-5.49	-8.87	-17.20
L4Mvol	-2.82	-4.05	-6.21	-14.57
L8Mvol	-2.59	-2.61	-3.46	-10.43
L12Mvol	-2.56	-2.38	-2.46	-9.26
L24Mvol	-2.60	-2.61	-2.96	-9.04

	Panel B: Regression Analysis			
	(1) Q1	(2) Q2	(3) Q3	(4) Q4
$Return_{t}$	-0.10***	-0.09***	-0.08***	-0.12***
$Return_{t-1}$	-0.01***	-0.01***	-0.02***	-0.02***
$Return_{t-2}$	-0.01**	-0.01***	-0.01***	-0.02***
$Return_{t-4}$	-0.01**	-0.01***	-0.01***	-0.01***
$Return_{t-8}$	-0.01**	-0.00**	-0.00**	-0.01***
$Return_{t-12}$	-0.01**	-0.00**	-0.00*	-0.01***
$Return_{t-24}$	-0.01**	0.00**	-0.00**	-0.01***

Table IV
Buyers' vs Sellers' Style

Table IV presents t-statistics calculated based on LkM measure for buyers and sellers of each quartile in each hourly frequency(1-hour, 2-hour, 4-hour, 8-hour, 12-hour, 24-hour), per equation:

$$LkM = OIB_{t,k} \times Return_{t-k}$$

$$t - stat(LkM) = \frac{L\bar{k}M}{\frac{\sigma(LkM_t)}{\sqrt{T}}}$$

$$L\bar{k}M = \frac{1}{T}\sum_{t}^{T} LkM$$

$OIB_{\mathrm{t,k}}$ is order imbalance at time t, calculated as the difference between the buy volume and sell volume divided by the total trading volume for the duration of k hours. In Panel A, for buyers, the analysis is perfomed on a subset of data with positive OIB_{t}, and in Panel B, for sellers, the analysis is performed on a subset of data with negative OIB_{t}.

	Buyers' Style			
	(1) Q1	(2) Q2	(3) Q3	(4) Q4
LOM_T_Stat	-36.34	-31.70	-33.12	-52.39
L1M_T_Stat	0.17	-7.06	-10.20	-12.91
L2M_T_Stat	2.11	-4.91	-7.39	-10.74
L4M_T_Stat	2.76	-4.27	-4.88	-9.16
L8M_T_Stat	2.36	-2.72	-3.01	-6.64
L12M_T_Stat	2.67	-2.64	-1.85	-5.87
L24M_T_Stat	1.42	-2.56	-1.95	-5.83

	Sellers' Style			
	(1) Q1	(2) Q2	(3) Q3	(4) Q4
LOM_T_Stat	-35.95	-42.40	-49.76	-63.36
L1M_T_Stat	-5.41	-6.82	-9.85	-15.45
L2M_T_Stat	-3.67	-4.62	-6.98	-13.57
L4M_T_Stat	-3.19	-3.43	-5.11	-11.54
L8M_T_Stat	-2.84	-2.29	-2.85	-8.33
L12M_T_Stat	-2.80	-2.10	-2.13	-7.50
L24M_T_Stat	-2.71	-2.41	-2.67	-7.48

Table V
Buyers' vs Sellers' Skill

Table V explores the skills of Buyers and sellers per equation:

$$Return_t = \beta_0 + \beta_1 \times OIB_{t-1,k}$$

$OIB_{\text{t-1,k}}$ is order imbalance at time $t-1$, calculated as the difference between the buy volume and sell volume divided by the total trading volume in a duaration of k hours ending at time $t-1$. For buyers, Panel A, the analysis is perfomed on a subset of data with positive $OIB_{\text{t-1}}$, and for sellers, Panel B, the analysis is performed on a subset of data with negative $OIB_{\text{t-1}}$. Following Newey and West (1987), the autocorrelation of standard errors are controlled for 2 lags.

		Buyers' Skill		
	(1) Q1	(2) Q2	(3) Q3	(4) Q4
OIB_{t-1}	-0.02	0.03	0.10	0.05
OIB_{t-2}	-0.05	0.29**	0.32**	0.09*
OIB_{t-4}	-0.03	0.04	0.40*	-0.03
OIB_{t-8}	0.02	0.02	0.35	-0.05
OIB_{t-12}	-0.20	-0.07	0.36	-0.06
OIB_{t-24}	-0.29	-0.22	-0.05	-0.04

		Sellers' Skill		
	(1) Q1	(2) Q2	(3) Q3	(4) Q4
OIB_{t-1}	0.02	0.03	0.00	-0.00
OIB_{t-2}	-0.01	0.02	-0.01	-0.01
OIB_{t-4}	-0.01	0.01	0.02	-0.07*
OIB_{t-8}	0.00	0.00	0.04	-0.03
OIB_{t-12}	-0.01	0.01	0.02	-0.06
OIB_{t-24}	0.00	0.02	0.01	-0.08

Table VI
Buyers and Sellers Skill in a Same Regression

Table VI presents beta coefficients of $d_{1,t,k}$ and $d_{2,t,k}$ per regression analysis of equation:

$$Return_t = \beta_1 \times d_{1,t,k} + \beta_2 \times d_{2,t,k} \tag{29}$$

Panel A represents the coefficient of buyers, dummy variable $d_{1,t,k}$, which is equal to 1 if OIB>0 and 0 otherwise. Panel B represents the coefficient of sellers, dummy variable $d_{2,t,k}$, which is equal to 1 if OIB<0 and 0 otherwise.

	Panel A: Buyers' Coefficients (d_1)			
	(1) Q1	(2) Q2	(3) Q3	(4) Q4
$d_{1,t,1}$	-0.51***	-0.64***	-0.55***	-0.37***
$d_{1,t-1,1}$	0.01	0.04***	0.05***	0.03***
$d_{1,t-2,2}$	0.02*	0.05***	0.06***	0.03***
$d_{1,t-4,4}$	0.02	0.05**	0.04**	0.02***
$d_{1,t-8,8}$	0.00	0.06***	0.03*	0.01**
$d_{1,t-12,12}$	0.01	0.04*	0.02	0.01
$d_{1,t-24,24}$	-0.01	0.02	0.01	0.00

	Panel B: Sellers' Coefficients (d_2)			
	(1) Q1	(2) Q2	(3) Q3	(4) Q4
$d_{2,t,1}$	0.10***	0.09***	0.13***	0.29***
$d_{2,t-1,1}$	0.01***	0.01**	0.00	0.00
$d_{2,t-2,2}$	0.01***	0.01**	0.00	0.00
$d_{2,t-4,4}$	0.01***	0.01**	0.01**	0.01
$d_{2,t-8,8}$	0.01***	0.01**	0.01***	0.01**
$d_{2,t-12,12}$	0.01***	0.01***	0.01***	0.02***
$d_{2,t-24,24}$	0.02***	0.01***	0.01***	0.02***

Table VII
Daily Style

Panel A presents t-statistics calculated based on LkM measure for investors of each quartile in each daily frequency (1-day, 2-day, 3-day, 4-day,5-day, 6-day) per equations:

$$LkM = OIB_t \times Return_{t-1}$$

$$t - stat(LkM) = \frac{\bar{LkM}}{\frac{\sigma(LkM_t)}{\sqrt{T}}}$$

$$\bar{LkM} = \frac{1}{T}\sum_{t}^{T} LkM$$

, where $\sigma(LkM_t)$ is the standard deviation of LkM measure and T is the number of days. Panel B presents β_1 coefficients for the regression analysis of equation:

$$OIB_{t,k} = \beta_1 \times Return_{t-k} + \epsilon$$

, where $OIB_{\mathrm{t,k}}$ is order imbalance, calculated as the difference between the buy volume and sell volume divided by the total trading volume during the k days ending at day t.

	Panel A: LkM Measure			
	(1) Q1	(2) Q2	(3) Q3	(4) Q4
L0M	-5.53	-5.95	-7.84	-20.51
L1M	-2.65	-1.64	-1.18	-1.48
L2M	-2.64	-2.11	-1.65	-2.46
L3M	-2.62	-2.26	-1.90	-2.87
L4M	-2.76	-2.39	-2.07	-2.99
L5M	-2.93	-2.53	-2.34	-3.72
L6M	-2.88	-2.54	-2.50	-3.88

	Panel B: Regression Analysis			
	(1) Q1	(2) Q2	(3) Q3	(4) Q4
Return	-1.22***	-0.95***	-0.78***	-1.35***
$Return_{t-1}$	-0.58**	-0.26	-0.12	-0.09
$Return_{t-2}$	-0.58**	-0.33**	-0.16	-0.13
$Return_{t-3}$	-0.58**	-0.36*	-0.18	-0.14*
$Return_{t-4}$	-0.61**	-0.38**	-0.19	-0.14**
$Return_{t-5}$	-0.64**	-0.40**	-0.21*	-0.17**
$Return_{t-6}$	-0.63**	-0.40**	-0.23*	-0.17**

Table VIII
Weekly Style

Panel A presents t-statistics calculated based on LkM measure for investors of each quartile in each weekly frequency (1-week, 2-week, 3-week, 4-week,5-week, 6-week) per equations:

$$LkM = OIB_t \times Return_{t-1}$$

$$t - stat(LkM) = \frac{L\bar{k}M}{\frac{\sigma(LkM_t)}{\sqrt{T}}}$$

$$L\bar{k}M = \frac{1}{T}\sum_{t}^{T} LkM$$

,where $\sigma(LkM_t)$ is the standard deviation of LkM measure and T is the number of weeks. Panel B presents β_1 coefficients for the regression analysis of equation:

$$OIB_{t,k} = \beta_1 \times Return_{t-1} + \epsilon$$

, where $OIB_{\mathrm{t,k}}$ is order imbalance, calculated as the difference between the buy volume and sell volume divided by the total trading volume during k weeks ending at week t.

Panel A: LkM Measure

	(1) Q1	(2) Q2	(3) Q3	(4) Q4
L0M	-3.32	-3.29	-3.49	-7.43
L1M	-3.21	-2.85	-2.80	-4.51
L2M	-3.03	-2.83	-2.70	-4.30
L3M	-2.84	-2.76	-2.51	-4.11
L4M	-2.90	-2.81	-2.26	-3.95
L5M	-2.73	-2.75	-2.14	-3.93
L6M	-2.77	-2.73	-2.13	-3.82

Panel B: Regression Analysis

	(1) Q1	(2) Q2	(3) Q3	(4) Q4
$Return_{t}$	-0.64****	-0.47***	-0.30***	-0.35***
$Return_{t-1}$	-0.65***	-0.41**	-0.25**	-0.21***
$Return_{t-2}$	-0.61**	-0.40**	-0.23**	-0.18***
$Return_{t-3}$	-0.54**	-0.39**	-0.22**	-0.18***
$Return_{t-4}$	-0.54**	-0.40**	-0.20**	-0.18***
$Return_{t-5}$	-0.49**	-0.39**	-0.19*	-0.17***
$Return_{t-6}$	-0.50**	-0.39**	-0.19**	-0.17***

Table IX Panel A
Investors' Style Following High Days
Table IX presents the values of coefficient β_1, estimating Bitcoin's order flow after high days, per equation:

$$OIB_{t,k} = \beta_0 + \beta_1 d_{t-k}$$

$OIB_{t,k}$ is the order imbalance during k days from day t-k+1 to t, and d_{t-k} is a dummy variable equal to 1 if Bitcoin's price hits its 30-, 90- and 120-day highs on day t-k. Following Newey and West (1987), I control for autocorelation of standard errors using 90 lags.

Panel A: OIB Following High Days				
	Q1	**Q2**	**Q3**	**Q4**
30-Day High				
d_t	-0.03	0.02	-0.00	-0.08***
d_{t-1}	-0.01	0.03	0.01	-0.04***
d_{t-2}	-0.01	0.03	0.01	-0.04***
d_{t-3}	-0.01	0.03	0.01	-0.04***
d_{t-4}	-0.00	0.03	0.01	-0.04***
d_{t-5}	-0.00	0.03	0.02	-0.04***
d_{t-6}	0.00	0.03	0.02	-0.04***
90-Day High				
d_t	-0.05	0.02	-0.01	-0.10***
d_{t-1}	-0.03	0.03	0.01	-0.06***
d_{t-2}	-0.02	0.04	0.01	-0.06***
d_{t-3}	-0.02	0.04	0.02	-0.06***
d_{t-4}	-0.02	0.04	0.02	-0.05***
d_{t-5}	-0.01	0.04	0.02	-0.05***
d_{t-6}	-0.01	0.05	0.02	-0.05***
120-Day High				
d_t	-0.03	0.03	-0.01	-0.11***
d_{t-1}	-0.01	0.04	0.01	-0.07***
d_{t-2}	-0.01	0.04	0.01	-0.07***
d_{t-3}	-0.01	0.04	0.02	-0.07***
d_{t-4}	-0.00	0.04	0.02	-0.06***
d_{t-5}	-0.00	0.05	0.02	-0.06***
d_{t-6}	0.00	0.05	0.02	-0.06***

Table IX Panel B
Investors' Style Following Low Days

Table IX Panel B presents the values of coefficient β_1, estimating Bitcoin's order flow after low days, per equation:

$$OIB_{t,k} = \beta_0 + \beta_1 d_{t-k}$$

$OIB_{t,k}$ is the order imbalance during k days from day t-k+1 to t, and d_{t-k} is a dummy variable equal to 1 if Bitcoin's price hits its 30-, 90- and 120-day lows on day t-k. Following Newey and West (1987), I control for autocorelation of standard errors using 90 lags.

	Panel B: OIB Following Low Days			
	Q1	**Q2**	**Q3**	**Q4**
	30-Day Low			
d_t	0.03	0.02	0.03	0.07***
d_{t-1}	0.01	-0.01	-0.00	0.02**
d_{t-2}	0.00	-0.01	0.01	0.02**
d_{t-3}	0.01	-0.01	0.01	0.02**
d_{t-4}	0.01	-0.00	0.02	0.03**
d_{t-5}	0.01	-0.00	0.02	0.03**
d_{t-6}	0.01	-0.00	0.02	0.03**
	90-Day Low			
d_t	0.00	-0.07	-0.03	0.08***
d_{t-1}	-0.02	-0.10**	-0.05*	0.04**
d_{t-2}	-0.02	-0.10**	-0.04	0.05***
d_{t-3}	-0.02	-0.10**	-0.03	0.04***
d_{t-4}	-0.02	-0.10**	-0.02	0.04***
d_{t-5}	-0.02	-0.10***	-0.02	0.04***
d_{t-6}	-0.02	-0.09**	-0.02	0.04**
	120-Day Low			
d_t	-0.01	-0.07	-0.03	0.08***
d_{t-1}	-0.04	-0.11**	-0.06*	0.05**
d_{t-2}	-0.05	-0.10**	-0.05	0.05**
d_{t-3}	-0.05	-0.11**	-0.04	0.05***
d_{t-4}	-0.05	-0.11**	-0.03	0.05***
d_{t-5}	-0.05	-0.11***	-0.03	0.05**
d_{t-6}	-0.05	-0.10***	-0.02	0.05**

Table X
Investors' Style Following High and Low Days- Demeaned OIB

Table X presents the values of coefficient β_1, estimating 180-day mean deviation of Bitcoin's order flow after highs, per equation:

$$DMOIB_{t,k} = \beta_0 + \beta_1 d_{t-k}$$

$DMOIB_{\mathrm{t,k}}$ is the k-days order flow, on day t, deviation from its mean value calculated from day t-k-1 to day t-k-181, and d_{t-k} is a dummy variable equal to 1 if Bitcoin's price hits its 30-, 90- and 120-day highs on day t-k. Following Newey and West (1987), I control for autocorelation of standard errors using 70 lags.

Panel A: DM-OIB Following High Days				
	Q1	**Q2**	**Q3**	**Q4**
30-Day High				
d_t	-0.00	0.04**	0.02	-0.06***
d_{t-1}	0.01	0.05**	0.03	-0.03**
d_{t-2}	0.01	0.05**	0.03	-0.03**
d_{t-3}	0.01	0.05**	0.03	-0.03**
d_{t-4}	0.01	0.05***	0.04*	-0.02**
d_{t-5}	0.02	0.05***	0.04*	-0.02**
d_{t-6}	0.02	0.06***	0.04**	-0.02**
90-Day High				
d_t	-0.01	0.05**	0.02	-0.06***
d_{t-1}	0.01	0.07**	0.04	-0.03*
d_{t-2}	0.01	0.06**	0.04	-0.03
d_{t-3}	0.01	0.07**	0.04	-0.02*
d_{t-4}	0.01	0.07**	0.05*	-0.02
d_{t-5}	0.02	0.07***	0.05*	-0.02
d_{t-6}	0.02	0.08***	0.05*	-0.02
120-Day High				
d_t	0.00	0.06**	0.02	-0.06***
d_{t-1}	0.02	0.06**	0.04	-0.02
d_{t-2}	0.02	0.06**	0.04	-0.02
d_{t-3}	0.02	0.06**	0.04	-0.02
d_{t-4}	0.02	0.07**	0.04	-0.02
d_{t-5}	0.02	0.07**	0.04*	-0.02
d_{t-6}	0.03	0.07***	0.04*	-0.02

Table X Panel B
Investors' Style Following Low Days- Demeaned OIB

Table X presents the values of coefficient β_1, estimating 180-day mean deviation of Bitcoin's order flow after low days, per equation:

$$DMOIB_{t,k} = \beta_0 + \beta_1 d_{t-k}$$

$DMOIB_{\mathrm{t,k}}$ is the k-days order flow, on day t, deviation from its mean value calculated from day t-k-1 to day t-k-181. d_{t-k} is a dummy variable equal to 1 if Bitcoin's price hits its 30-, 90- and 120-day lows on day t-k. Following Newey and West (1987), I control for autocorelation of standard errors using 70 lags.

Panel B: DM-OIB Following Low Days				
	Q1	**Q2**	**Q3**	**Q4**
30-Day Low				
d_{t}	0.02	0.00	0.01	0.05***
d_{t-1}	-0.01	-0.03	-0.02	0.01
d_{t-2}	-0.01	-0.02	-0.01	0.01
d_{t-3}	-0.01	-0.03	-0.00	0.01
d_{t-4}	-0.00	-0.03	0.00	0.01
d_{t-5}	0.00	-0.02	0.01	0.02
d_{t-6}	0.00	-0.02	0.01	0.02
90-Day Low				
d_{t}	0.02	-0.04	-0.02	0.04***
d_{t-1}	0.00	-0.07***	-0.04	0.01
d_{t-2}	0.01	-0.06**	-0.03	0.01
d_{t-3}	0.01	-0.07**	-0.02	0.01
d_{t-4}	0.01	-0.07**	-0.01	0.01
d_{t-5}	0.01	-0.06**	-0.01	0.01
d_{t-6}	0.01	-0.06**	-0.01	0.01
120-Day Low				
d_{t}	-0.04	-0.04	-0.07	0.04***
d_{t-1}	-0.06	-0.09***	-0.04	0.00
d_{t-2}	-0.07	-0.07***	-0.02	0.01
d_{t-3}	-0.07	-0.08***	-0.01	0.00
d_{t-4}	-0.07	-0.08***	-0.01	0.01
d_{t-5}	-0.07	-0.08***	-0.00	0.01
d_{t-6}	-0.07	-0.07***	0.00	0.01

Table XI
Bitcoin Returns after High and Low Days

Table XI Panel A presents coefficient β_1 for estimating Bitcoin's return on the days following Bitcoin hitting 30-, 90-, and 120-day highs, and Panel B presents coefficient β_1 for estimating Bitcoin's return on the days following Bitcoin hitting 30-, 90-, and 120-day lows, per equation:

$$Return_t = \beta_0 + \beta_1 d_{t-k}$$

In Panel A, d_{t-k} is a dummy variable equal to 1 if Bitcoin's price hits its 30-, 90- and 120-day highs and 0 otherwise, and in Panel B, d_{t-k} is a dummy variable equal to 1 if Bitcoin's price hits its 30-, 90- and 120-day lows and 0 otherwise. Following Newey and West (1987), I control for autocorelation of standard errors using 1 lag.

	30-Day	**90-Day**	**120-Day**
	Panel A: Bitcoin Return after High Days		
d_t	0.03***	0.03***	0.03***
d_{t-1}	0.01**	0.01**	0.01**
d_{t-2}	0.00	0.01*	0.01
d_{t-3}	0.00	0.01	0.01*
d_{t-4}	0.01**	0.01**	0.01*
d_{t-5}	0.00	0.01*	0.01*
d_{t-6}	0.01**	0.01*	0.00
	Panel B: Bitcoin Return after Low Days		
d_t	-0.03***	-0.03***	-0.03***
d_{t-1}	0.00	0.01	0.01
d_{t-2}	0.01	0.00	0.01
d_{t-3}	-0.00	0.00	0.00
d_{t-4}	-0.00	-0.00	-0.00
d_{t-5}	-0.00	-0.00	-0.00
d_{t-6}	0.00	0.00	0.01

Table XII Panel A
Seller's Return After High Days

Table XII shows the t-statistics for mean values of the vector product:

$$SellerReturn_t = Sell_{t-k} \times cReturn_{t,k}$$

$$t - stat(SellerReturn) = \frac{Seller\bar{R}eturn}{\frac{\sigma_{SellerReturn}}{\sqrt{T}}}$$

$$Seller\bar{R}eturn = \frac{1}{T}\sum_{t}^{T} SellerReturn$$

$Sell_{\text{t-k}}$ ($Buy_{\text{t-k}}$) is a dummy variable equal to -1 (1) if Bitcoin price is at highs (30-, 90-, and 120-day) and order imbalance is negative (positive) at time t-k, representing traders who sell (buy) at highs. $\sigma_{SellerReturn}$ ($\sigma_{BuyerReturn}$) is the standard deviation of $SellerReturn$ ($BuyerReturn$), and T is the number of days in the study. Panel A shows the t-statistics for seller returns and Panel B shows t-statistics for buyer returns.

	Q1	**Q2**	**Q3**	**Q4**
		Seller Returns After 30-Day High		
$Sell_{t-1}$	-2.83	-2.75	-2.82	-2.40
$Sell_{t-2}$	-3.76	-3.68	-3.87	-3.65
$Sell_{t-3}$	-4.48	-4.44	-4.72	-4.83
$Sell_{t-4}$	-5.32	-5.22	-5.46	-5.47
$Sell_{t-5}$	-5.79	-5.65	-5.96	-5.93
$Sell_{t-6}$	-6.49	-6.45	-6.73	-6.45
		Seller Returns After 90-Day High		
$Sell_{t-1}$	-2.55	-2.60	-2.52	-2.30
$Sell_{t-2}$	-3.39	-3.47	-3.42	-3.13
$Sell_{t-3}$	-4.06	-4.16	-4.06	-4.20
$Sell_{t-4}$	-4.65	-4.73	-4.64	-4.64
$Sell_{t-5}$	-5.10	-5.16	-5.18	-5.13
$Sell_{t-6}$	-5.56	-5.63	-5.66	-5.42
		Seller Returns After 120-Day High		
$Sell_{t-1}$	-2.48	-2.54	-2.46	-2.23
$Sell_{t-2}$	-3.29	-3.41	-3.32	-3.06
$Sell_{t-3}$	-4.03	-4.15	-4.04	-4.10
$Sell_{t-4}$	-4.53	-4.63	-4.53	-4.52
$Sell_{t-5}$	-4.97	-5.07	-5.06	-5.00
$Sell_{t-6}$	-5.34	-5.46	-5.45	-5.24

Table XII Panel B
Buyer's Return After High Days

	Q1	**Q2**	**Q3**	**Q4**
		Buyer Returns After 30-Day High		
Buy_{t-1}	0.39	1.17	0.53	1.75
Buy_{t-2}	0.39	0.69	-0.12	0.87
Buy_{t-3}	0.29	0.19	-0.70	-0.16
Buy_{t-4}	-0.01	-0.02	-0.65	0.30
Buy_{t-5}	0.10	0.33	-0.43	0.19
Buy_{t-6}	0.60	0.62	-0.08	1.34
		Buyer Returns After 90-Day High		
Buy_{t-1}	1.08	0.61	0.79	1.46
Buy_{t-2}	0.99	0.42	0.72	1.75
Buy_{t-3}	0.57	-0.02	0.58	0.48
Buy_{t-4}	0.63	0.14	0.71	1.04
Buy_{t-5}	0.74	0.47	0.56	0.82
Buy_{t-6}	1.02	0.61	0.73	1.64
		Buyer Returns After 120-Day High		
Buy_{t-1}	1.08	0.65	0.79	1.48
Buy_{t-2}	0.99	0.15	0.72	1.63
Buy_{t-3}	0.57	-0.07	0.58	0.57
Buy_{t-4}	0.63	0.10	0.71	1.00
Buy_{t-5}	0.74	0.31	0.56	0.76
Buy_{t-6}	1.02	0.38	0.73	1.51

Table XIII
Investors' Market Timing Skills for Calling Bitcoin Prices UP and Down

Table XIII shows investors market timing skills at correctly forecasting an increase in Bitcoin's price (*sensitivity*) and correctly forecasting a decrease in Bitcoin' price (*specificity*). Panel A shows the results corresponding to analysis based on raw oder imbalance values, and Panel B presents the results using order imbalance mean deviation from its average during the preceding 350 hours (15 days). The first column in each panel represents *sensitivity* which is the probability of a *positive* call for an actually-positive (*True-Positive*) price movement, and the second column in each panel represents *specificity* which is the probability of a negative call for an actually-negative price movement (*True-negative*). The third column, *OverallSkill* is the the total probability of trader's correct market timing per equation:

$$Overall_t = P_1 \times TruePositive + P_2 \times TrueNegative$$

,where P_1 is the probability of Bitcoin price being up, and P_2 is the probability of Bitcoin price being down at time t.

Sensitivity and Specificity

Panel A: By Order Imbalance

	(1)	(2)	(3)
	TruePositive	*TrueNegative*	*OverallSkill*
Q1	0.154021	0.858982	0.493547
Q2	0.116961	0.896228	0.492260
Q3	0.186034	0.839061	0.500535
Q4	0.438108	0.610935	0.521342

Panel B: By Demeaned Order Imbalance

	(1)	(2)	(3)
	TruePositive	*TrueNegative*	*OverallSkill*
Q1	0.469158	0.562296	0.514144
Q2	0.483101	0.553424	0.517005
Q3	0.502936	0.532913	0.517389
Q4	0.523610	0.529044	0.526230

Table XIV Panel A
Order Imbalance and Investors' Style, Sentiment and Seasonality
Table XIV shows results for exploring the impact of investors' style and sentiment on the Order imbalance per equation:

$$OIB_t = \beta_1 \times Ret_{t-1} + \beta_2 \times 2Hr\_Sent_{t-1} + \beta_3 \times 2Hr\_Att_{t-1} + \beta_4 \times SP_t + \beta_6 \times 24OIB_{t-1} + W + H$$

$Ret_{\text{t-1}}$ is Bitcoin' return at time t-1. $2Hr\_Sent_{\text{t-1}}$ is a proxy for aggregate 2-hour sentiment ($Sentiment_{\text{t-1}}$ + $Sentiment_{\text{t-2}}$), where $Sentiment_{\text{t}}$ is defined as the difference between the standardized (based on 336 hours/2 weeks) hourly average posititve and negative sentiment in Reddit from t-1 to t. $2Hr\_Att_{\text{t-1}}$ is a proxy for aggregate 2-hour attention calculated as the summation of standardized (based on 336 hours/2 weeks) values of number of Bitcoin-related Reddit posts during the past 2 hours. Both $2Hr\_Sent_{\text{t-1}}$ and $2Hr\_Att_{\text{t-1}}$ are scaled by 100. $24OIB_{\text{t-1}}$ is the summation of order imbalance values from time t-24 to t-1. SP_{t} is the daily return on the Standard & Poor's Composite Index. W and H are dummy variables representing dummy variables of the day of a week and the hour of the day respectively.

	Panel A: 2-Hour Sentiment			
	Q1	Q2	Q3	Q4
$OIB24_{t-1}$	0.04***	0.04***	0.04***	0.03***
Ret_{t-1}	-0.00	-0.01**	-0.01***	-0.02***
$2Hr\_Sent_{t-1}$	0.00	0.11***	0.08*	0.01
$2Hr\_Att_{t-1}$	0.42***	0.56***	0.46***	-0.21**
SP_t	-0.06	0.04	0.03	-0.21*
Tuesday	-0.01**	-0.03***	-0.03***	-0.01
Wednesday	-0.01***	-0.03***	-0.03***	-0.01**
Thursday	-0.02***	-0.03***	-0.03***	-0.01
Friday	-0.02***	-0.03***	-0.04***	-0.02**
Saturday	-0.01***	-0.03***	-0.04***	-0.02**
Sunday	-0.01*	-0.02***	-0.03***	-0.01
1-2	-0.02***	-0.00	-0.01***	-0.01
2-3	-0.02**	-0.00	-0.00	-0.00
3-4	-0.00	0.01	-0.00	0.02**
4-5	-0.00	0.00	0.00	0.01
5-6	0.00	0.01	0.01	0.01
6-7	0.00	0.01	0.00	0.01
7-8	-0.00	-0.00	0.00	-0.01
8-9	0.03*	0.01	0.02	-0.00
9-10	0.03*	0.03	0.04***	0.02
10-11	0.04**	0.03	0.04***	0.03
11-12	0.02	0.02	0.02	0.01
12-13	0.02	0.02	0.02	0.00
13-14	0.02**	0.01	0.01	-0.00
14-15	0.02**	0.01	0.01	0.01
15-16	0.01	0.01	0.01	0.01
16-17	-0.01	-0.00	0.00	0.00
17-18	-0.01	-0.02	-0.01	0.00
18-19	-0.01	-0.01	-0.01	0.01
19-20	-0.02**	-0.02*	-0.01	0.01
20-21	-0.00	-0.02	-0.01	0.00
21-22	-0.01	-0.02**	-0.01	0.00
22-23	-0.02***	-0.03***	-0.02***	-0.01
23-24	-0.03***	-0.02***	-0.02***	-0.01*
Adj-R^2	0.51	0.34	0.29	0.08
F-statistic	803.2	7.557	250.7	61.35

Table XIV Panel B
Order Imbalance and Investors' Style, Sentiment and Seasonality

Panel B represensts results for the same regression analysis as Panel A with $2Hr\_Sent_{\text{t-1}}$ decomposed to $2Hr\_Pos_{\text{t-1}}$ and $2Hr\_Neg_{\text{t-1}}$ which are the aggregarte standardized average posititve and negative Reddit sentiment from $t-3$ to $t-1$ respectively. Both $2Hr\_Pos_{\text{t-1}}$ and $2Hr\_Neg_{\text{t-1}}$ are scaled by 100.

	Panel B: 2-Hour Positive and Negative			
	Q1	Q2	Q3	Q4
$OIB24_{t-1}$	0.04***	0.04***	0.04***	0.03***
Ret_{t-1}	-0.00	-0.01**	-0.01***	-0.02***
$2Hr\_Pos_{t-1}$	-0.13	0.05	-0.05	0.03
$2Hr\_Neg_{t-1}$	-0.13*	-0.17**	-0.20***	-0.00
$2Hr\_Att_{t-1}$	0.44***	0.57***	0.47***	-0.22*
SP_t	-0.06	0.04	0.03	-0.21*
Tuesday	-0.01**	-0.03***	-0.03***	-0.01
Wednesday	-0.01***	-0.03***	-0.03***	-0.01**
Thursday	-0.02***	-0.03***	-0.03***	-0.01
Friday	-0.02***	-0.03***	-0.04***	-0.02**
Saturday	-0.01***	-0.03***	-0.04***	-0.02**
Sunday	-0.01*	-0.02***	-0.03***	-0.01
1-2	-0.02***	-0.00	-0.01***	-0.01
2-3	-0.02**	-0.00	-0.00	-0.00
3-4	-0.00	0.01	-0.00	0.02**
4-5	-0.00	0.00	0.00	0.01
5-6	0.00	0.01	0.01	0.01
6-7	0.00	0.01	0.00	0.01
7-8	-0.00	-0.00	0.00	-0.01
8-9	0.03*	0.01	0.02	-0.00
9-10	0.03*	0.03	0.04***	0.02
10-11	0.04**	0.03	0.04***	0.03
11-12	0.02	0.02	0.02	0.01
12-13	0.02	0.02	0.02	0.00
13-14	0.02*	0.01	0.01	-0.00
14-15	0.02**	0.01	0.01	0.01
15-16	0.01	0.01	0.01	0.01
16-17	-0.01	-0.00	0.00	0.00
17-18	-0.01	-0.02	-0.01	0.00
18-19	-0.01	-0.01	-0.01	0.01
19-20	-0.02**	-0.02*	-0.01	0.01
20-21	-0.00	-0.02	-0.01	0.00
21-22	-0.01	-0.02**	-0.01	0.00
22-23	-0.02***	-0.03***	-0.02***	-0.01
23-24	-0.03***	-0.02***	-0.02***	-0.01*
Adj-R^2	0.51	0.34	0.29	0.08
F-statistic	830.9	736.0	242.9	60.65

Table XV Panel A
Order Imbalance and Investors' Style, Seasonality, and 24-Hour Sentiment

Table XV Panel A shows results for exploring the impact of investors' style and sentiment on the Order imbalance per equation:

$$OIB_t = \beta_1 \times Ret_{t-1} + \beta_2 \times 24Hr\_Sent_{t-1} + \beta_3 \times 24Hr\_Att_{t-1} + \beta_6 \times 24OIB_{t-1} + W + H$$

$Ret_{t\text{-}1}$ is Bitcoin' return at time t-1. $24Hr\_Sent_{t\text{-}1}$ is a proxy for aggregate 24-hour sentiment ($Sentiment_{t\text{-}24}$ + $Sentiment_{t\text{-}23}$+ ...+$Sentiment_{t\text{-}1}$), where $Sentiment_{t}$ is defined as the difference between the standardized (based on 336 hours/2 weeks) average posititve and the negative Reddit sentiment from t-1 to t. $24Hr\_Att_{t\text{-}1}$ is a proxy for aggregate 24-hour attention calculated as the summation standardized (based on 336 hours/2 weeks) values of number of Bitcoin-related Reddit posts during the past 24 hours. Both $24Hr\_Sent_{t\text{-}1}$ and $24Hr\_Att_{t\text{-}1}$ are scaled by 100. $24OIB_{t\text{-}1}$ is the summation of order imbalance values from time t-24 to t-1. W and H are dummy variables representing dummy variables of the day of a week and the hour of the day respectively.

	Panel A: Past 24-Hour Sentiment			
	Q1	Q2	Q3	Q4
$OIB24_{t\text{-}1}$	0.04***	0.04***	0.04***	0.03***
$Return_{t\text{-}1}$	-0.00	-0.01**	-0.01***	-0.02***
$L24\_Sentiment_{t\text{-}1}$	0.03**	0.04***	0.03***	0.02
$L24\_Attention_{t\text{-}1}$	0.02	0.02	0.02*	-0.00
Tuesday	-0.01**	-0.03***	-0.03***	-0.01*
Wednesday	-0.02***	-0.03***	-0.03***	-0.01**
Thursday	-0.02***	-0.03***	-0.03***	-0.01*
Friday	-0.02***	-0.03***	-0.04***	-0.02***
Saturday	-0.02***	-0.03***	-0.04***	-0.02**
Sunday	-0.01**	-0.02***	-0.03***	-0.01
1-2	-0.02***	-0.00	-0.02***	-0.01
2-3	-0.02**	-0.00	-0.01	0.00
3-4	-0.00	0.01	-0.00	0.02**
4-5	-0.00	0.00	0.00	0.01*
5-6	0.00	0.01	0.01	0.01
6-7	0.00	0.01	0.00	0.01
7-8	-0.00	-0.00	0.00	-0.01
8-9	0.03*	0.01	0.02	-0.00
9-10	0.03*	0.03	0.04***	0.02
10-11	0.04**	0.03	0.04***	0.03
11-12	0.02*	0.02	0.02*	0.01
12-13	0.02*	0.02	0.02*	0.00
13-14	0.02**	0.01	0.01	-0.00
14-15	0.02***	0.02	0.02**	0.01
15-16	0.01	0.02	0.01*	0.00
16-17	-0.00	0.01	0.01	-0.00
17-18	-0.00	-0.01	-0.00	0.00
18-19	-0.00	-0.01	0.00	0.00
19-20	-0.01	-0.01	-0.00	0.01
20-21	0.00	-0.01	-0.00	0.00
21-22	-0.01	-0.02*	-0.01	0.00
22-23	-0.02***	-0.03***	-0.02***	-0.01
23-24	-0.02***	-0.02***	-0.02***	-0.01*
Adj-R^2	0.51	0.34	0.29	0.08
F-statistic	915.2	1094	238.6	58.15

Table XVI
The Predictibility of Bitcoin's Next-Hour Returns through Order Imbalance Components (2-Hr Sentiment)

Table XVI shows the results for conducting a two stage decomposition of order imbalance. In the first stage, order imbalance is estimated at time t-1, per equation:

$$OIB_{t-1} = \beta_0 + \beta_1 \times OIB24_{t-2} + \beta_2 \times Return_{t-2} + \beta_3 \times 2Hr\_Att_{t-2} + \beta_4 \times 2Hr\_Sent_{t-2} + T + W + U_4$$

$OIB24_{t\text{-}2}$ is the aggregate 24 hour order imbalance from t-2 to t-25. $Return_{t\text{-}2}$ is the Bitcoin return at time t-2, and $2Hr\_Att_{t\text{-}2}$ is the number of Reddit posts at during t-4 to t-2 standardized by the number of posts during the preceding 336 hours (2 weeks). $2Hr\_Sent_{t\text{-}1}$ is a proxy for aggregate 2-hour sentiment ($Sentiment_{t\text{-}2}$ + $Sentiment_{t\text{-}3}$), where $Sentiment_t$ is defined as the difference between the standardized average posititve Reddit and negative Reddit sentiment from t-1 to t. Both $2Hr\_Sent_{t\text{-}1}$ and $2Hr\_Att_{t\text{-}1}$ are scaled by 100. In the above regression, the second component, $\beta_1 \times OIB24_{t\text{-}1}$ is defined as $Persistence$, the third component, $\beta_2 \times Return_{t\text{-}2}$ is defined as $Contrarian$, the fourth component, $\beta_3 \times 2Hr\_Att_{t\text{-}2}$, is called $Attention$, the fifth component, $\beta_4 \times 2Hr\_Sent_{t-2}$, is called $Sentiment$, and the summation of intercept, seasonality and error terms is called $Other$. Then, in the second stage, Return_t is estimated using the identified components as:

$$Return_t = \beta_0 + \beta_1 \times Persistence_{t-1} + \beta_2 \times Contrarian_{t-1} + \beta_3 \times Attention_{t-1} + \beta_4 \times Sentiment_{t-1} + \beta_5 \times other_{t-1} + Controls$$

, where $Controls$ represents control variables such as different lags of Bitcoin returns and return volatility. The results of the first and second stages are presented at the top and bottom sections of Panel A respectively.

	2-Hour Sentiment			
	(1) Q1	(2) Q2	(3) Q3	(4) Q4
Stage I: Decomposition of $\mathbf{OIB_{t\text{-}1}}$				
$OIB24_{t\text{-}2}$	0.04***	0.04***	0.04***	0.03***
$Return_{t\text{-}2}$	-0.00	-0.01**	-0.01***	-0.02***
$2\_Hr\_Sentiment_{t\text{-}2}$	0.01	0.12***	0.09**	0.02
$2\_Hr\_Attention_{t\text{-}2}$	0.39***	0.44***	0.40***	-0.21**
Stage II: Estimation of Return $_t$				
$Persistence_{t\text{-}1}$	-0.02	0.01	-0.03	-0.19***
$Contrarian_{t\text{-}1}$		6.30***	4.10***	2.40***
$Sentiment_{t\text{-}1}$		0.37	0.46	
$Attention_{t\text{-}1}$	1.30	1.14	1.29	-2.34
$Other_{t\text{-}1}$	-0.02	-0.02	-0.00	-0.02
$Return_{t\text{-}1}$	-0.04***	-0.04***	-0.04***	-0.05***
$Return_{t\text{-}24}$	-0.03***	-0.03***	-0.03***	-0.03***
$Return\_Volatility_{t\text{-}1}$	0.02	0.02	0.02	0.02
Adj-R^2	0.003	0.004	0.004	0.005
F-statistic	6.16	5.17	5.57	7.67

Table XVII
The Predictibility of Bitcoin's Next-Hour Returns through Order Imbalance Components (24-Hr Sentiment)

Table XVII shows the results for conducting a two stage decomposition of order imbalance. In the first stage, order imbalance is estimated at time t-1, per equation:

$$\begin{aligned} OIB_{t-1} &= \beta_0 + \beta_1 \times OIB24_{t-2} + \beta_2 \times Return_{t-2} \\ &+ \beta_3 \times Attention_{t-2} + \beta_4 \times 24Hr\_Sent_{t-2} + T + W + U_4 \end{aligned}$$

$OIB24_{\text{t-2}}$ is the aggregate 24 hour order imbalance from t-2 to t-25. $Return_{\text{t-2}}$ is the Bitcoin return at time t-2, and $Attention_{\text{t-2}}$ is the number of Reddit posts at during t-2 to t-1 standardized by the number of posts during the preceding 336 hours (2 weeks). $24Hr\_Sent_{\text{t-2}}$ is a proxy for the aggregate 24-hour sentiment ($Sentiment_{\text{t-2}}$ +....+ $Sentiment_{\text{t-26}}$), where $Sentiment_{\text{t}}$ is defined as the difference between the standardized average posititve and negative Reddit sentiment from t-1 to t. $24Hr\_Sent_{\text{t-1}}$ is scaled by 100 and $Attention_{\text{t-2}}$ is scaled by 10. In the above regression, the second component, $\beta_1 \times OIB24_{\text{t-1}}$ is defined as *Persistence*, the third component, $\beta_2 \times Return_{\text{t-2}}$ is defined as *Contrarian*, the fourth component, $\beta_3 \times Attention_{\text{t-2}}$, is called *Attention*, the fifth component, $\beta_4 \times 24Hr\_Sent_{t-2}$, is called *Sentiment*, and the summation of intercept, seasonality and error terms is called *Other*. Then, in second stage, Return_{t} is estimated using the identified components as:

$$\begin{aligned} Return_t = \beta_0 + \beta_1 \times Persistence_{t-1} + \beta_2 \times Contrarian_{t-1} + \beta_3 \times Attention_{t-1} \\ + \beta_4 \times Sentiment_{t-1} + \beta_5 \times other_{t-1} + Controls \end{aligned}$$

, where *Controls* represents control variables such as different lags of Bitcoin returns and return volatility. The results of the first and second stages are presented at the top and bottom sections of Panel A respectively.

	24-Hour Sentiment			
	(1) Q1	(2) Q2	(3) Q3	(4) Q4
Stage I: Decomposition of $\text{OIB}_{\text{t-1}}$				
$\text{OIB24}_{\text{t-2}}$	0.04***	0.04***	0.04***	0.03***
$\text{Return}_{\text{t-2}}$	-0.00	-0.01**	-0.01***	-0.02***
$\text{24Hr\_Sent}_{\text{t-2}}$	0.03**	0.04***	0.04***	0.02
$\text{Attention}_{\text{t-2}}$	0.01***	0.01***	0.01***	-0.00***
Stage II: Estimation of Return_{t}				
$\text{Persistence}_{\text{t-1}}$	-0.02	0.01	-0.03	-0.19***
$\text{Contrarian}_{\text{t-1}}$		6.30***	4.14***	2.39***
$\text{Sentiment}_{\text{t-1}}$	1.41	1.20	1.24	
$\text{Attention}_{\text{t-1}}$	1.31	0.92	1.06	-1.96
$\text{Other}_{\text{t-1}}$	-0.02	-0.02	-0.01	-0.02
$\text{Return}_{\text{t-1}}$	-0.04***	-0.04***	-0.04***	-0.05***
$\text{Return}_{\text{t-24}}$	-0.03***	-0.03***	-0.03***	-0.03***
$\text{Return\_Volatility}_{\text{t-1}}$	0.02	0.02	0.02	0.02
Adj-R^2	0.003	0.004	0.004	0.005
F-statistic	5.62	5.44	5.77	6.91

Table XVIII
Hourly Summary Statistics Binance

Table XVIII Panel A and B show the summary statistics for 1-hour order imbalance in terms of volume, and the average dollar value for Binance exchange's trades in all quartiles, respectively. Order imbalance is defined as the difference between the buy volume and sell volume, divided by the total trading volume during any given hour, and the hourly average dollar value of trades is calculated by dividing the aggregate hourly dollar value of transactions by the number of transactions per hour.

			Panel A: Order Imbalance			
	(1)	(2)	(3)	(4)	(5)	(6)
Quartiles	Count	Mean	25%	50%	75%	SD
Q1	16,766.0	0.0170	-0.0615	0.0242	0.1100	0.1918
Q2	16,767.0	-0.0288	-0.1063	0.0007	0.0784	0.2367
Q	16,806.0	0.0192	-0.0513	0.0205	0.0956	0.1997
Q4	16,774.0	-0.0284	-0.1267	-0.027	0.0689	0.2252
			Panel B: Average Transaction USD Value			
	(1)	(2)	(3)	(4)	(5)	(6)
Quartiles	Count	Mean	25%	50%	75%	SD
Q1	16,766.0	18.15	12.83	17.94	23.24	6.21
Q2	16,767.0	82.87	44.62	64.56	121.09	48.26
Q3	16,806.0	280.18	94.01	133.27	513.53	248.28
Q4	16,774.0	2,375.36	1,077.80	1,533.53	4,024.19	1,619.49

Table XIX
Style (Binance)

Panel A presents t-statistics calculated based on LkM measure for investors of each quartile in Binance for each hourly frequency (1-hour, 2-hour, 4-hour, 8-hour, 12-hour, 24-hour), from October 1, 2019 to October 1, 2021, per equations:

$$LkM = OIB_t \times Return_{t-1}$$

$$t - stat(LkM) = \frac{L\bar{k}M}{\frac{\sigma(LkM_t)}{\sqrt{T}}}$$

$$L\bar{k}M = \frac{1}{T}\sum_{t}^{T} LkM$$

In Panel B results of a regression analysis, controlling for Newey and West (1987) autocorrelation of standard erros for up to 500 lags, is presented per equation:

$$OIB_t = \beta_1 \times Return_{t-1} + \epsilon$$

OIB_t is order imbalance at time t, calculated as the difference between the buy volume and sell volume divided by the total trading volume at time t. $\sigma(LkM_t)$ is the standard deviation of LkM measure and T is the number of hours. Panel C shows the results of estimating mean deviation of order imbalance from its preceeding 720 hours (15 days), controlling for Newey and West (1987) autocorrelation of standard errors for up to 900 lags.

$$DMOIB_{t,k} = \beta_0 + \beta_1 Return_{t-k}$$

		Panel A: LkM Measure		
	Q1	Q2	Q3	Q4
L0Mvol	46.41	23.12	26.41	33.17
L1Mvol	2.75	0.27	0.28	-2.26
L2Mvol	1.35	-0.51	-0.21	-2.07
L4Mvol	1.04	-0.83	-0.66	-1.07
L8Mvol	0.20	-0.94	-0.16	-1.69
L12Mvol	0.73	-0.54	0.18	-1.81
L24Mvol	0.83	-0.48	-0.37	-2.68
		Panel B: Regression Analysis		
	Q1	Q2	Q3	Q4
$Return_t$	7.24***	4.05***	3.09***	4.78***
$Return_{t-1}$	0.37*	0.05	0.03	-0.29
$Return_{t-2}$	0.15	0.09	-0.02	-0.21*
$Return_{t-4}$	0.10	-0.14	-0.07	-0.09
$Return_{t-8}$	-0.01	-0.09	-0.04	-0.06
$Return_{t-12}$	0.05	-0.08	0.02	-0.11
$Return_{t-24}$	0.05	-0.06	-0.03	-0.13**
		Panel C: Mean Deviation of Order Imbalance Regression Analysis		
	Q1	Q2	Q3	Q4
$Return_t$	9.68***	5.45***	4.16***	5.69***
$Return_{t-1}$	0.71***	0.09	-0.00	-0.40
$Return_{t-2}$	0.41***	0.00	-0.15	-0.31
$Return_{t-4}$	0.30***	-0.07	-0.07	-0.09
$Return_{t-8}$	0.26***	-0.08	-0.00	-0.10
$Return_{t-12}$	0.21***	0.00	0.00	-0.09
$Return_{t-24}$	0.12**	0.04	-0.09	-0.09

Table XX Panel A
Binance Investors' Style Following High Days

Table XX presents the values of coefficient β_1, estimating Bitcoin's order flow after high days, per equation:

$$OIB_{t,k} = \beta_0 + \beta_1 d_{t-k}$$

$OIB_{t,k}$ is the order imbalance during k days from day t-k+1 to day t, and d_{t-k} is a dummy variable equal to 1 if Bitcoin's price hits its 30-, 90- and 120-day highs on day t-k. Following Newey and West (1987), I control for autocorelation of standard errors using 20 lags.

	Panel A: OIB Following High Days			
	Q1	**Q2**	**Q3**	**Q4**
	30-Day High			
d_t	0.01	0.07 **	-0.04	-0.01
d_{t-1}	-0.00	0.06*	-0.04**	-0.01
d_{t-2}	-0.00	0.06*	-0.04*	-0.00
d_{t-3}	-0.00	0.06*	-0.03*	-0.00
d_{t-4}	-0.00	0.06*	-0.03 *	-0.00
d_{t-5}	-0.01	0.06*	-0.03*	-0.00
d_{t-6}	-0.01	0.06*	-0.03*	-0.00
	90-Day High			
d_t	0.01	0.08**	-0.03	0.00
d_{t-1}	-0.00	0.06**	-0.03*	-0.00
d_{t-2}	-0.00	0.07**	-0.02	0.00
d_{t-3}	0.00	0.07**	-0.02	-0.00
d_{t-4}	0.00	0.07**	-0.02	-0.00
d_{t-5}	-0.00	0.07**	-0.02	0.00
d_{t-6}	0.00	0.07**	-0.02	0.00
	120-Day High			
d_t	0.01	0.06**	-0.03	0.01
d_{t-1}	-0.00	0.06*	-0.03*	0.00
d_{t-2}	-0.00	0.06**	-0.03	0.00
d_{t-3}	0.00	0.06**	-0.02	0.01
d_{t-4}	0.00	0.06**	-0.02	0.01
d_{t-5}	0.00	0.06**	-0.02	0.01
d_{t-6}	0.00	0.06**	-0.01	0.01

Table XX Panel B
Binance Investors' Style Following Low Days
Table XX Panel B presents the values of coefficient β_1, estimating Bitcoin's order flow after low days, per equation:

$$OIB_{t,k} = \beta_0 + \beta_1 d_{t-k}$$

$OIB_{t,k}$ is the order imbalance during k days from day t-k+1 to day t. d_{t-k} is a dummy variable equal to 1 if Bitcoin's price hits its 30-, 90- and 120-day lows on day t-k. Following Newey and West (1987), I control for autocorelation of standard errors using 20 lags.

	Panel B: OIB Following Low Days			
	Q1	**Q2**	**Q3**	**Q4**
		30-Day Low		
d_t	-0.01	-0.03	0.01	-0.00
d_{t-1}	0.02	-0.02	0.03	-0.00
d_{t-2}	0.02*	-0.02	0.02	-0.01
d_{t-3}	0.02*	-0.02	0.02	-0.01
d_{t-4}	0.01	-0.02	0.02	-0.01
d_{t-5}	0.01	-0.02	0.02	-0.02*
d_{t-6}	0.01	-0.03	0.02	-0.02*
		90-Day Low		
d_t	0.01	0.07**	0.01	-0.00
d_{t-1}	0.04***	0.04	0.05**	0.02
d_{t-2}	0.04***	0.05	0.04**	0.02*
d_{t-3}	0.03***	0.05	0.04**	0.02
d_{t-4}	0.03***	0.04	0.03**	0.01
d_{t-5}	0.03***	0.04	0.04**	0.01
d_{t-6}	0.03***	0.04	0.04**	0.01
		120-Day Low		
d_t	0.00	0.10***	0.01	-0.02
d_{t-1}	0.04**	0.03	0.06***	0.03
d_{t-2}	0.04***	0.05	0.05***	0.03*
d_{t-3}	0.03***	0.04	0.05***	0.02
d_{t-4}	0.03**	0.03	0.04***	0.01
d_{t-5}	0.03**	0.03	0.05***	0.01
d_{t-6}	0.03**	0.03	0.05***	0.01

Table XXI
Binance Traders' Style Following High and Low Days- Demeaned OIB
Table XXI presents the values of coefficient β_1, estimating Bitcoin's order flow 90-day mean deviation after high days, per equation:

$$DMOIB_{t,k} = \beta_0 + \beta_1 d_{t-k}$$

$DMOIB_{\mathrm{t,k}}$ is the k-days order flow deviation, on day t, from its mean value calculated from day t-k-1 to day t-k-181. d_{t-k} is a dummy variable equal to 1 if Bitcoin's price hits its 30-, 90- and 120-day highs at time t-k and 0 otherwise. Following Newey and West (1987), I control for autocorelation of standard errors using 25 lags.

Panel A: DM-OIB Following High Days				
	Q1	**Q2**	**Q3**	**Q4**
30-Day High				
d_t	0.01	0.05	-0.03	-0.01
d_{t-1}	-0.00	0.03	-0.03	-0.01
d_{t-2}	-0.00	0.03	-0.02	-0.00
d_{t-3}	-0.00	0.03	-0.02	-0.00
d_{t-4}	-0.00	0.03	-0.02	-0.00
d_{t-5}	-0.01	0.03	-0.02	-0.00
d_{t-6}	-0.00	0.03	-0.02	-0.00
90-Day High				
d_t	0.01	0.04	-0.01	0.00
d_{t-1}	-0.00	0.02	-0.01	-0.00
d_{t-2}	-0.00	0.02	-0.01	-0.00
d_{t-3}	-0.00	0.02	-0.01	-0.00
d_{t-4}	-0.00	0.02	-0.01	-0.00
d_{t-5}	-0.00	0.02	-0.00	-0.00
d_{t-6}	-0.00	0.02	-0.00	-0.00
120-Day High				
d_t	0.01	0.02	-0.00	0.01
d_{t-1}	-0.00	0.01	-0.01	0.00
d_{t-2}	-0.00	0.01	-0.00	0.00
d_{t-3}	0.00	0.01	-0.00	0.01
d_{t-4}	0.00	0.01	0.00	0.01
d_{t-5}	0.00	0.01	0.00	0.01
d_{t-6}	0.00	0.01	0.00	0.01

Table XXI Panel B
Binance Traders' Style Following Low Days- Demeaned OIB

Table XXI presents the values of coefficient β_1, estimating Bitcoin's order flow 90-day mean deviation after low days, per equation:

$$DMOIB_{t,k} = \beta_0 + \beta_1 d_{t-k}$$

$DMOIB_{\mathrm{t,k}}$ is the k-days order flow deviation, on day t, from its mean value calculated from day t-k-1 to day t-k-181. d_{t-k} is a dummy variable equal to 1 if Bitcoin's price hits its 30-, 90- and 120-day lows on day t-k and 0 otherwise. Following Newey and West (1987), I control for autocorelation of standard errors using 25 lags.

Panel B: DM-OIB Following Low Days				
	Q1	**Q2**	**Q3**	**Q4**
30-Day Low				
d_{t}	-0.01	-0.01	0.02	0.00
d_{t-1}	0.03*	-0.00	0.03	0.01
d_{t-2}	0.03**	-0.00	0.03	0.01
d_{t-3}	0.03*	0.01	0.02	0.00
d_{t-4}	0.02*	0.01	0.02	-0.00
d_{t-5}	0.02*	-0.00	0.02	-0.00
d_{t-6}	0.02*	-0.00	0.02	-0.00
90-Day Low				
d_{t}	-0.01**	-0.01	0.03	-0.01
d_{t-1}	0.02***	-0.07	0.07*	0.03
d_{t-2}	0.02**	-0.06	0.07*	0.03
d_{t-3}	0.02	-0.06*	0.06*	0.02
d_{t-4}	0.01	-0.07*	0.05	0.01
d_{t-5}	0.01	-0.07*	0.05	0.01
d_{t-6}	0.01	-0.07*	0.05	0.01
120-Day Low				
d_{t}	-0.01**	-0.01	0.03	-0.01
d_{t-1}	0.02***	-0.07	0.07*	0.03
d_{t-2}	0.02**	-0.06	0.07*	0.03
d_{t-3}	0.02	-0.06*	0.06*	0.02
d_{t-4}	0.01	-0.07*	0.05	0.01
d_{t-5}	0.01	-0.07*	0.05	0.01
d_{t-6}	0.01	-0.07*	0.05	0.01

Table XXII
Binance Traders' Market Timing Skills for Calling Bitcoin Prices UP and Down

Table XXII shows Binance traders' market timing skills at correctly forecasting an increase in Bitcoin's price (*sensitivity*) and correctly forecasting a decrease in Bitcoin' price ($specificity$). Panel A shows the results corresponding to analysis based on raw oder imbalance values, and Panel B presents the results using order imbalance mean deviation from its average during the preceding 350 hours (15 days). The first column in each panel represents *sensitivity* which is the probability of a *positive* call for an actually-positive ($True$-$Positive$) price movement, and the second column in each panel represents $specificity$ which is the probability of a negative call for an actually-negative price movement ($True$-$negative$). The third column, $OverallSkill$ is the the total probability of trader's correct market timing per equation:

$$Overall_t = P_1 \times \frac{Positive}{ActualPositive} + P_2 \times \frac{Negative}{ActualNegative}$$

,where P_1 is the probability of Bitcoin price being up, and P_2 is the probability of Bitcoin price being down at time t.

Sensitivity and Specificity

Panel A: By Order Imbalance

	(1)	(2)	(3)
	$\frac{Positive}{ActualPositive}$	$\frac{Negative}{ActualNegative}$	$OverallSkill$
Q1	0.561660	0.403102	0.484114
Q2	0.489307	0.484612	0.487011
Q3	0.573711	0.410088	0.493684
Q4	0.408273	0.563301	0.484089

Panel B: By Demeaned Order Imbalance

	(1)	(2)	(3)
	$\frac{Positive}{ActualPositive}$	$\frac{Negative}{ActualNegative}$	$OverallSkill$
Q1	0.475736	0.485215	0.480398
Q2	0.481612	0.489546	0.485513
Q3	0.482113	0.499914	0.490866
Q4	0.474844	0.494079	0.484296

Table A.1
Style

Table A.1 presents the values for the coeffcient, β_1, for estimating demeaned order imbalance per equation:

$$DMOIB_{t,K} = \beta_0 + \beta_1 \times Return_{t-k} + \epsilon$$

$DMOIB_{\mathrm{t,k}}$ is mean deviation of order imbalance at time t, using its preceding 720 hours (30 days), where order imbalance is calculated as the difference between the buy volume and sell volume divided by the total trading volume during k hours ending at time t. Following Newey and West (1987), the autocorrelation of standard errors are controlled for up to 3500 lags.

	Mean Deviation of Order Imbalance Regression Analysis			
	(1)	(2)	(3)	(4)
	Q1	Q2	Q3	Q4
$\mathrm{Return_{t}}$	-0.08***	-0.08***	-0.07***	-0.11***
$\mathrm{Return_{t\text{-}1}}$	-0.01***	-0.01*	-0.01***	-0.02***
$\mathrm{Return_{t\text{-}2}}$	-0.00	-0.00	-0.01**	-0.01***
$\mathrm{Return_{t\text{-}4}}$	0.00	-0.00	-0.00	-0.01***
$\mathrm{Return_{t\text{-}8}}$	0.00	0.00	0.00	-0.01***
$\mathrm{Return_{t\text{-}12}}$	0.00	0.00	0.00	-0.00***
$\mathrm{Return_{t\text{-}24}}$	0.00	0.00	0.00	-0.00***

Table A.2
Buyer's vs Seller's Style by Order Imbalance Mean Deviation
Table A.2 shows t-statistics for the mean values of buyer and seller style measure calculated as:

$$LkM = DMOIB_t \times Return_{t-1}$$

$$t - stat(LkM) = \frac{L\bar{k}M}{\frac{\sigma(LkM_t)}{\sqrt{T}}} \tag{1}$$

$$L\bar{k}M = \frac{1}{T}\sum_{t}^{T} LkM \tag{2}$$

$DMOIB_{\mathrm{t}}$ is order imbalance mean deviation from its preceding 720 hours (30 days), where order imbalance is calculated as the difference between the buy volume and sell volume divided by the total trading volume during k hours ending at time t. For buyers, the analysis is perfomed on a subset of data with positive $DMOIB_{\mathrm{t}}$, and for sellers, the analysis is performed on a subset of data with negative $DMOIB_{\mathrm{t}}$.

	Q1	**Q2**	**Q3**	**Q4**
		Buyers' Style		
LOM_T_Stat	-27.33	-31.06	-31.58	-42.35
L1M_T_Stat	-1.76	-2.81	-5.64	-9.94
L2M_T_Stat	0.24	-0.36	-2.91	-8.64
L4M_T_Stat	1.05	0.63	-1.03	-6.43
L8M_T_Stat	1.34	2.17	1.06	-3.96
L12M_T_Stat	1.40	2.52	2.18	-3.06
L24M_T_Stat	1.34	1.99	2.13	-3.04
		Sellers' Style		
LOM_T_Stat	-34.79	-38.38	-38.72	-52.74
L1M_T_Stat	-3.46	-6.44	-7.80	-12.26
L2M_T_Stat	-2.33	-3.88	-5.07	-10.33
L4M_T_Stat	-1.71	-1.94	-3.10	-8.65
L8M_T_Stat	-0.72	-0.27	-0.67	-5.95
L12M_T_Stat	-0.44	-0.12	0.18	-4.93
L24M_T_Stat	-0.30	-0.55	-0.72	-4.94

Table A.3
Buyer's vs Seller's Skill by Order Imbalance Mean Deviation
Table A.3 presents the values for the coeffcient, β_1, for exploring the skillset of buyers and sellers per equation:

$$Return_t = \beta_0 + \beta_1 \times DMOIB_{t-1} \tag{3}$$

$DMOIB_{\text{t-1}}$ is order imbalance mean deviation from its preceding 720 dours (30 days), where order imbalance is calculated as the difference between the buy volume and sell volume divided by the total trading volume during k hours ending at time t. For buyers, the analysis is perfomed on a subset of data with positive $DMOIB_{\text{t-1}}$, and for sellers, the analysis is performed on a subset of data with negative $DMOIB_{\text{t-1}}$. Following Newey and West (1987), the autocorrelation of standard errors are controlled for 2 lags.

	Q1	**Q2**	**Q3**	**Q4**
		Buyers' Skill		
$DMOIB_{t-1}$	0.07*	0.06	0.13***	0.14***
$DMOIB_{t-2}$	0.07	0.13***	0.14**	0.18***
$DMOIB_{t-4}$	0.09**	0.03	0.09	0.03
$DMOIB_{t-8}$	0.06	0.05	0.17*	0.01
$DMOIB_{t-12}$	0.07	0.05	0.14	0.08
$DMOIB_{t-24}$	0.06	-0.04	0.06	-0.07
		Sellers' Skill		
$DMOIB_{t-1}$	-0.01	-0.11***	-0.06*	-0.03
$DMOIB_{t-2}$	0.02	-0.05	-0.09*	-0.00
$DMOIB_{t-4}$	-0.00	-0.05	-0.08	-0.09**
$DMOIB_{t-8}$	0.00	-0.01	0.13**	-0.05
$DMOIB_{t-12}$	0.04	-0.04	0.09	0.01
$DMOIB_{t-24}$	0.07	-0.06	-0.12	-0.05

Table A.4
Buyer and Seller Comparison of Skill
Table A.4 shows results for exploring the relative market timing skills of buyers and sellers per equations:

$$FkM_t = \beta_0 + \beta_1 \times Seller_{k,t} \tag{4}$$

$$FkM_t = TradeVolume_{i,k,t-1} \times Return_t, i = Buyer, Seller \tag{5}$$

$$TradeVolume_{i,k,t-1} = \frac{\sum_{t-k}^{t-1} TradeVolume_{i,t}}{AvgKHrTradingVol_{t-1}}, i = Buyer, Seller \tag{6}$$

, where FkM_{t} is the skill measure at time t, calculated as the vector product of $Return_{\mathrm{t}}$ and the scaled buy or sell volume at time t-1; and $Seller_{\mathrm{t}}$ is a dummy variable equal to 1 (0) if the FkM_{t} is calculated based on sellers' (buyers') trading volume.

	(1) Q1	(2) Q2	(3) Q3	(4) Q4
$\mathrm{Seller}_{1,t}$	-0.04***	-0.02***	-0.02***	-0.02***
$\mathrm{Seller}_{2,t}$	-0.05***	-0.02***	-0.02***	-0.02***
$\mathrm{Seller}_{4,t}$	-0.01	-0.02***	-0.02***	-0.02***
$\mathrm{Seller}_{8,t}$	-0.07**	-0.02***	-0.02***	-0.02***
$\mathrm{Seller}_{12,t}$	-0.01	-0.01***	-0.01***	-0.01***
$\mathrm{Seller}_{24,t}$	-0.30***	-0.01***	-0.02***	-0.01***

Table A.5
Monthly Style

Panel A presents t-statistics for LkM calculated based on differenced $OIB_{t,k}$ measure for investors of each quartile in each monthly frequency (1-month, 2-month, 3-month, 4-month,5-month, 6-month) per equations:

$$dOIB_{t,k} = OIB_{t,k} - OIB_{t-1,k} \tag{7}$$

$$LkM = dOIB_{t,k} \times Return_{t-1} \tag{8}$$

$$t - stat(LkM) = \frac{\bar{LkM}}{\frac{\sigma(LkM_t)}{\sqrt{T}}} \tag{9}$$

$$\bar{LkM} = \frac{1}{T}\sum_{t}^{T} LkM \tag{10}$$

,where $\sigma(LkM_t)$ is the standard deviation of LkM measure and T is the number of months. Panel B presents β_1 coefficients for the regression analysis of equation:

$$dOIB_t = \beta_0 + \beta_1 \times Return_{t-1} \tag{11}$$

, where $dOIB_{\mathrm{t,k}}$ is the difference between the order imbalance at time t and the order imbalance at time t-1, and $OIB_{\mathrm{t,k}}$ is calculated as the difference between the buy volume and sell volume divided by the total trading volume during the k periods leading to time t. Following Newey and West (1987), I control for autocorelation of standard errors using up to 2 lags.

Panel A: LkM Measure

	(1) Q1	(2) Q2	(3) Q3	(4) Q4
L0M	1.13	0.02	0.43	-2.02
L1M	-0.01	2.11	2.10	2.24
L2M	-0.81	2.50	2.71	2.83
L3M	2.11	1.54	1.73	2.22
L4M	1.56	1.53	1.37	2.32
L5M	0.64	0.89	0.85	3.06
L6M	1.34	0.75	0.48	3.00

Panel B: Regression Analysis

	(1) Q1	(2) Q2	(3) Q3	(4) Q4
$Return_{t}$	0.15	0.00	0.02	-0.06***
$Return_{t-1}$	-0.00	0.09**	0.08***	0.06***
$Return_{t-2}$	-0.10	0.07***	0.06***	0.05***
$Return_{t-3}$	0.03***	0.03	0.03***	0.03***
$Return_{t-4}$	0.02*	0.03*	0.03*	0.02***
$Return_{t-5}$	0.01	0.02	0.01	0.03***
$Return_{t-6}$	0.01	0.01	0.01	0.02***

Table A.6 Panel A
Seller's Return After High Days

Table A.6 shows the β_1 and β_2 from performing a regression analysis, investigating buyers' vs sellers' returns after highs, per equation:

$$cReturn_{t+k} = \beta_0 + \beta_1 \times Sell_{t-k} + \beta_2 \times Buy_{t-k} \tag{12}$$

$Sell_{\text{t-k}}$ is a dummy variable equal to 1 if at time t-k, Bitcoin price is at highs and order imbalance is negative, representing sellers at highs. Similarly, $Buy_{\text{t-k}}$ is a dummy variable equal to 1 if at time t-k, Bitcoin price is at highs and order imbalance is positive, representing buyers at highs. The corfficients of $Sell_{\text{t-k}}$ (β_1) are presented in Panel A and $Buy_{\text{t-k}}$ (β_2) are presented in Panel B. Following Newey and West (1987), I control for autocorelation of standard errors using 1 lag.

	Q1	**Q2**	**Q3**	**Q4**
			Seller Returns After 30-Day High	
$Sell_{t-1}$	-0.00**	-0.00**	-0.00**	-0.00
$Sell_{t-2}$	-0.01**	-0.01**	-0.01**	-0.01**
$Sell_{t-3}$	-0.01***	-0.01***	-0.01***	-0.01***
$Sell_{t-4}$	-0.02***	-0.02***	-0.02***	-0.02***
$Sell_{t-5}$	-0.02***	-0.02***	-0.02***	-0.02***
$Sell_{t-6}$	-0.03***	-0.03***	-0.03***	-0.03***
			Seller Returns After 90-Day High	
$Sell_{t-1}$	-0.00**	-0.01**	-0.00*	-0.00*
$Sell_{t-2}$	-0.01**	-0.01**	-0.01**	-0.01**
$Sell_{t-3}$	-0.01***	-0.01***	-0.01***	-0.01***
$Sell_{t-4}$	-0.02***	-0.02***	-0.02***	-0.02***
$Sell_{t-5}$	-0.02***	-0.02***	-0.02***	-0.03***
$Sell_{t-6}$	-0.03***	-0.03***	-0.03***	-0.03***
			Seller Returns After 120-Day High	
$Sell_{t-1}$	-0.00*	-0.01**	-0.00*	-0.00
$Sell_{t-2}$	-0.00	-0.00	-0.00	-0.00
$Sell_{t-3}$	-0.00	-0.00*	-0.00*	-0.01***
$Sell_{t-4}$	-0.01*	-0.00*	-0.00	-0.00
$Sell_{t-5}$	-0.00	-0.00	-0.00	-0.01**
$Sell_{t-6}$	-0.01*	-0.01**	-0.01*	-0.00

Table A.6 Panel B
Buyer's Return After High Days

	Q1	Q2	Q3	Q4
			Buyer Returns After 30-Day High	
Buy_{t-1}	0.00	0.01	0.01	0.01
Buy_{t-2}	0.00	0.01	-0.01	0.00
Buy_{t-3}	-0.00	-0.00	-0.02	-0.01
Buy_{t-4}	-0.01	-0.01	-0.03	-0.01
Buy_{t-5}	0.01	0.01	-0.03	-0.01
Buy_{t-6}	0.00	0.02	-0.02	0.01
			Buyer Returns After 90-Day High	
Buy_{t-1}	0.01	0.00	0.01	0.01
Buy_{t-2}	0.01	0.01	0.01	0.01
Buy_{t-3}	0.01	-0.01	0.01	0.00
Buy_{t-4}	0.01	-0.00	-0.01	0.01
Buy_{t-5}	0.03	0.02	0.02	0.00
Buy_{t-6}	0.04	0.02	0.03	0.03
			Buyer Returns After 120-Day High	
Buy_{t-1}	0.01	0.01	0.01	0.01
Buy_{t-2}	0.00	-0.01	-0.00	0.00
Buy_{t-3}	-0.01	-0.01	-0.00	-0.01
Buy_{t-4}	0.00	0.00	0.01	0.01
Buy_{t-5}	0.01	0.01	-0.00	-0.01
Buy_{t-6}	0.01	0.00	0.01	0.03***

Table A.6 Panel C
Buyer vs Seller Counts On Highs

Table A.6 Panel C shows the number of high days on which Bitcoin traders of different quartiles place a net buy ($OIB>0$) in the top section, and the number of high days on which Bitcoin traders of different quartiles place a net sell ($OIB<0$) in the bottom section.

	Q1	Q2	Q3	Q4
Buyers' Count On Highs				
High-30	16	6	13	49
High-90	7	5	8	24
High-120	7	4	8	19
Sellers' Count On Highs				
High-30	304	314	307	271
High-90	218	220	217	201
High-120	199	202	198	187

Table A.7 Panel A
Order Imbalance and Investors' Style, Sentiment and Seasonality, NASDAQ
Table A.7 shows results for exploring the impact of investors' style and sentiment on the Order imbalance per equation:

$$OIB_t = \beta_0 + \beta_1 \times Ret_{t-1} + \beta_2 \times 2Hr\_Sent_{t-1} + \beta_3 \times 2Hr\_Att_{t-1} + \beta_4 \times NASDAQ_t + \beta_6 \times 24OIB_{t-1} + W + H \tag{13}$$

$Return_{\text{t-1}}$ is Bitcoin' return at time t-1. $2Hr\_Sent_{\text{t-1}}$ is a proxy for aggregate 2-hour sentiment ($Sentiment_{\text{t-1}}$ + $Sentiment_{\text{t-2}}$), where $Sentiment_{\text{t}}$ is defined as the difference between the standardized average number of posititve Reddit posts and the negative Reddit posts from t-1 to t. $2Hr\_Att_{\text{t-1}}$ is a proxy for aggregate 2-hour attention calculated as the summation standardized (based on 336 hours/2 weeks) values of number of Bitcoin-related Reddit posts during the past 2 hours. Both $2Hr\_Sent_{\text{t-1}}$ and $2Hr\_Att_{\text{t-1}}$ are scaled by 100. $24OIB_{\text{t-1}}$ is the summation of order imbalance values from time t-25 to t-1. $NASDAQ_{\text{t}}$ is the daily return on the NASDAQ. W and H are dummy variables representing the day of a week and the hour of a day respectively. Following Newey and West (1987), I control for autocorelation of standard errors using 1600 lags.

	Q1	Q2	Q3	Q4
$OIB24_{t-1}$	0.04***	0.04***	0.04***	0.03***
Ret_{t-1}	-0.00	-0.01**	-0.01***	-0.02***
$2Hr\text{-}Sent_{t-1}$	0.00	0.11***	0.08*	0.02
$2Hr\text{-}Att_{t-1}$	0.42***	0.56***	0.46***	-0.21*
$NASDAQ_t$	-0.08	0.02	-0.01	-0.25**
Tuesday	-0.01**	-0.03***	-0.03***	-0.01
Wednesday	-0.01***	-0.03***	-0.03***	-0.01**
Thursday	-0.02***	-0.03***	-0.03***	-0.01
Friday	-0.02***	-0.03***	-0.04***	-0.02***
Saturday	-0.01***	-0.03***	-0.04***	-0.02**
Sunday	-0.01*	-0.02***	-0.03***	-0.01
1-2	-0.02***	-0.00	-0.01***	-0.01
2-3	-0.02**	-0.00	-0.00	-0.00
3-4	-0.00	0.01	-0.00	0.02**
4-5	-0.00	0.00	0.00	0.01
5-6	0.00	0.01	0.01	0.01
6-7	0.00	0.01	0.00	0.01
7-8	-0.00	-0.00	0.00	-0.01
8-9	0.03*	0.01	0.02	-0.00
9-10	0.03*	0.03	0.04***	0.02
10-11	0.04**	0.03	0.04***	0.03
11-12	0.02	0.02	0.02	0.01
12-13	0.02	0.02	0.02	0.00
13-14	0.02**	0.01	0.01	-0.00
14-15	0.02**	0.01	0.01	0.01
15-16	0.01	0.01	0.01	0.01
16-17	-0.01	-0.00	0.00	0.00
17-18	-0.01	-0.02	-0.01	0.00
18-19	-0.01	-0.01	-0.01	0.01
19-20	-0.02**	-0.02*	-0.01	0.01
20-21	-0.00	-0.02	-0.01	0.00
21-22	-0.01	-0.02**	-0.01	0.00
22-23	-0.02***	-0.03***	-0.02***	-0.01
23-24	-0.03***	-0.02***	-0.02***	-0.01*
Adj-R^2	0.51	0.34	0.29	0.08
F-statistic	793.0	767.1	247.6	62.95

Table A.7 Panel B
Order Imbalance and Investors' Style, Sentiment and Seasonality, XLF
Table A.7 shows results for exploring the impact of investors' style and sentiment on the Order imbalance per equation:

$$OIB_t = \beta_0 + \beta_1 \times Ret_{t-1} + \beta_2 \times 2Hr\_Sent_{t-1} + \beta_3 \times 2Hr\_Att_{t-1} + \beta_4 \times XLF_t + \beta_6 \times 24OIB_{t-1} + W + H \quad (14)$$

$Return_{\text{t-1}}$ is Bitcoin' return at time t-1. $2Hr\_Sent_{\text{t-1}}$ is a proxy for aggregate 2-hour sentiment ($Sentiment_{\text{t-1}}$ + $Sentiment_{\text{t-2}}$) , where $Sentiment_{\text{t}}$ is defined as the difference between the standardized average number of posititve Reddit posts and the negative Reddit posts from t-1 to t. $2Hr\_Att_{\text{t-1}}$ is a proxy for aggregate 2-hour attention calculated as the summation standardized (based on 336 hours/2 weeks) values of number of Bitcoin-related Reddit posts during the past 2 hours. Both $2Hr\_Sent_{\text{t-1}}$ and $2Hr\_Att_{\text{t-1}}$ are scaled by 100. $24OIB_{\text{t-1}}$ is the summation of order imbalance values from time t-25 to t-1. XLF_{t} is the daily return on the XLF, S&P Financial Select Sector Index . W and H are dummy variables representing the day of a week and the hour of a day respectively. Following Newey and West (1987), I control for autocorelation of standard errors using 1600 lags.

	Q1	Q2	Q3	Q4
$OIB24_{t-1}$	0.04***	0.04***	0.04***	0.03***
Ret_{t-1}	-0.00	-0.01**	-0.01***	-0.02***
$2Hr\text{-}Sent_{t-1}$	0.00	0.11***	0.08*	0.01
$2Hr\text{-}Att_{t-1}$	0.42***	0.56***	0.46***	-0.21*
XLF_t	-0.00	0.03	0.06	-0.07
Tuesday	-0.01**	-0.03***	-0.03***	-0.01
Wednesday	-0.01***	-0.03***	-0.03***	-0.01**
Thursday	-0.02***	-0.03***	-0.03***	-0.01
Friday	-0.02***	-0.03***	-0.04***	-0.02***
Saturday	-0.01***	-0.03***	-0.04***	-0.02**
Sunday	-0.01*	-0.02***	-0.03***	-0.01
1-2	-0.02***	-0.00	-0.01***	-0.01
1-2	-0.02***	-0.00	-0.01***	-0.01
2-3	-0.02**	-0.00	-0.00	-0.00
3-4	-0.00	0.01	-0.00	0.02**
4-5	-0.00	0.00	0.00	0.01
5-6	0.00	0.01	0.01	0.01
6-7	0.00	0.01	0.00	0.01
7-8	-0.00	-0.00	0.00	-0.01
8-9	0.03*	0.01	0.02	-0.00
9-10	0.03*	0.03	0.04***	0.02
10-11	0.04**	0.03	0.04***	0.03
11-12	0.02	0.02	0.02	0.01
12-13	0.02	0.02	0.02	0.00
13-14	0.02**	0.01	0.01	-0.00
14-15	0.02**	0.01	0.01	0.01
15-16	0.01	0.01	0.01	0.01
16-17	-0.01	-0.00	0.00	0.00
17-18	-0.01	-0.02	-0.01	0.00
18-19	-0.01	-0.01	-0.01	0.01
19-20	-0.02**	-0.02*	-0.01	0.01
20-21	-0.00	-0.02	-0.01	0.00
21-22	-0.01	-0.02**	-0.01	0.00
22-23	-0.02***	-0.03***	-0.02***	-0.01
23-24	-0.03***	-0.02***	-0.02***	-0.01*
Adj-R^2	0.51	0.34	0.29	0.08
F-statistic	863.3	780.6	258.3	58.31

Table A.8
Order Imbalance Mean Deviation and Investor Style, Sentiment (Past 2 Hours)

Table A.8 shows results for exploring the impact of investors' style and sentiment on the demeaned Order imbalance ($DMOIB$), looking at its preceeding 24 hours, using equation:

$$DMOIB_t = \beta_0 + \beta_1 \times Return_{t-1} + \beta_2 \times 2Hr\_Sent_{t-1} + \beta_3 \times 2Hr\_Att_{t-1} + W + H \quad (15)$$

$Return_{\text{t-1}}$ is Bitcoin' return at time t-1. $2Hr\_Att_{\text{t-1}}$ is a proxy for attantion at time t-1 calculated as the summation of standardized number of Reddit posts (based on rolling 336 hours, 2 weeks) in t-1 and t-2. Samely, $2Hr\_Sent_{\text{t-1}}$ is a proxy for sentiment at time t-1 calculated as the summation of the differnce between the standardized average number of positive and negative Reddit posts (based on rolling 336 hours, 2 weeks) in t-1 and t-2. Both $2Hr\_Sent_{\text{t-1}}$ and $2Hr\_Att_{\text{t-1}}$ are scaled by 100. W and H are dummy variables representing the day-of-the week and the hour-of-the-day. Following Newey and West (1987), I control for autocorelation of standard errors using 1600 lags.

	(1) Q1	(2) Q2	(3) Q3	(4) Q4
$\text{Return}_{\text{t-1}}$	-0.00	-0.01**	-0.01***	-0.01***
$\text{2Hr\_Sentiment}_{\text{t-1}}$	0.00	0.12***	0.09**	0.05
$\text{2Hr\_Attention}_{\text{t-1}}$	0.00	0.55***	0.47***	-0.12
Adjusted R^2	0.01	0.01	0.02	0.00
F-statistic	11.84	14.42	19.82	7.77

Table A.9
Bitcon Return, Order flow and Seasonality

Table A.9 shows results for exploring Bitcoin return predictability based on investors order flow and seasonality per equation:

$$Return_t = \beta_0 + \beta_1 \times OIB_{t-1} + \beta_2 \times Return_{t-24} + \beta_3 \times ReturnVol_{t-1} + H \quad (16)$$

$Return_{\text{t-24}}$ is Bitcoin' return at time t-24. $ReturnVol_{\text{t-1}}$ is the standard deviation of Bitcoin returns during the past 168 hours (7 days) from t-1 to t-168. H is a dummy variable representing the hour of the day. $OIB_{\text{t-1}}$ is the order imbalance at time t-1, calculated by the net buy volume divided by the total trade volume during t-2 to t-1.

		(1)	(2)	(3)	(4)
		Q1	Q2	Q3	Q4
OIB_{t-1}		0.01	0.05***	0.06***	0.04***
$Return_{t-24}$	-0.03***	-0.03***	-0.03***	-0.03***	-0.03***
$ReturnVol_{t-1}$	0.01	0.01	0.01	0.01	0.01
1-2	0.01	0.01	0.01	0.01	0.01
2-3	-0.03	-0.03	-0.03	-0.03	-0.03
3-4	-0.05*	-0.05*	-0.05*	-0.05*	-0.04*
4-5	-0.04	-0.04	-0.04	-0.04	-0.04
5-6	-0.02	-0.02	-0.02	-0.02	-0.02
6-7	0.00	0.00	0.00	0.00	0.00
7-8	0.02	0.02	0.02	0.02	0.02
8-9	-0.02	-0.02	-0.02	-0.02	-0.02
9-10	-0.03	-0.03	-0.03	-0.03	-0.03
10-11	-0.04	-0.04	-0.04	-0.04	-0.04
11-12	0.02	0.02	0.02	0.02	0.02
12-13	0.00	0.00	0.00	0.00	0.00
13-14	-0.02	-0.02	-0.02	-0.02	-0.02
14-15	-0.04	-0.04	-0.04	-0.04	-0.04
15-16	0.02	0.02	0.02	0.02	0.02
16-17	0.00	0.00	0.00	0.00	0.00
17-18	-0.02	-0.02	-0.02	-0.02	-0.02
18-19	-0.03	-0.03	-0.03	-0.03	-0.03
19-20	0.01	0.01	0.01	0.01	0.01
20-21	-0.02	-0.02	-0.02	-0.02	-0.02
21-22	0.05	0.06*	0.06*	0.06*	0.06**
22-23	0.04	0.04	0.04	0.04	0.04
23-24	-0.01	-0.01	-0.01	-0.01	-0.01
Adj-R^2	0.001	0.001	0.001	0.002	0.001
F-statistic	2.27	2.19	2.31	2.47	2.38

Table A.10
Hourly Summary Statistics Coinbase (Sub-Period)

Table A.10 shows the summary statistics for Bitcoin trades placed on Coinbase exchange from October 1, 2019 to October 1, 2021. Panel A and B show the summary statistics for 1-hour order imbalance in terms of volume, and the average dollar value for trades in all quartiles, respectively. Order imbalance is defined as the difference between the buy volume and sell volume, divided by the total trading volume during any given hour, and the hourly average dollar value of trades is calculated by dividing the aggregate hourly dollar value of transactions by the number of transactions per hour.

Panel A: Order Imbalance

	(1)	(2)	(3)	(4)	(5)	(6)
Quartiles	Count	Mean	25%	50%	75%	SD
Q1	16,930.0	-0.5399	-0.6500	-0.5651	-0.4546	0.1604
Q2	16,930.0	-0.3701	-0.4897	-0.3795	-0.2627	0.1674
Q3	16,930.0	-0.1540	-0.2562	-0.1544	-0.0541	0.1533
Q4	16,930.0	-0.0624	-0.2038	-0.0646	0.0790	0.2171

Panel B: Average Transaction USD Value

	(1)	(2)	(3)	(4)	(5)	(6)
Quartiles	Count	Mean	25%	50%	75%	SD
Q1	16,930.0	28.42	20.85	26.12	29.65	12.18
Q2	16,930.0	131.48	100.92	113.85	148.66	53.67
Q3	16,930.0	555.19	407.84	493.10	646.79	232.97
Q4	16,930.0	6,499.90	4,616.81	6,048.15	7,862.29	2,494.71

Table A.11
Coinbase Investors' Style (Sub-period)
Panel A presents t-statistics calculated based on LkM measure for investors of each quartile in each hourly frequency (1-hour, 2-hour, 4-hour, 8-hour, 12-hour, 24-hour), from October 1, 2019 to October 1, 2021, per equations:

$$LkM = OIB_t \times Return_{t-1}$$

$$t - stat(LkM) = \frac{L\bar{k}M}{\frac{\sigma(LkM_t)}{\sqrt{T}}}$$

$$L\bar{k}M = \frac{1}{T}\sum_{t}^{T} LkM$$

$\sigma(LkM_t)$ is the standard deviation of LkM measure and T is the number of hours. In Panel B and Panel C display values of β_1 coefficient from regression analyses estimating order imbalance and mean deviation of order imablance respectively, per equations:

$$OIB_t = \beta_1 \times Return_{t-1}$$

$$DMOIB_{t,k} = \beta_0 + \beta_1 Return_{t-k}$$

OIB_{t} is order imbalance at time t, calculated as the difference between the buy volume and sell volume divided by the total trading volume at time t. $DMOIB_{\text{t,k}}$ is the deviation of order imbalnce in a duation of k hours from its average in the preceeding 720 hours (30 days), starting from t-k-1 to t-k-721. The regression analyses control for the Newey and West (1987) autocorrelation of standard errors for up to 2250 lags.

		Panel A: LkM Measure		
	(1)	(2)	(3)	(4)
	Q1	Q2	Q3	Q4
L0Mvol	-14.07	-15.82	-24.57	-47.76
L1Mvol	-3.77	-2.12	-2.04	-13.40
L2Mvol	-2.71	-1.03	-0.57	-12.01
L4Mvol	-2.24	-0.50	0.83	-9.60
L8Mvol	-2.07	-0.21	1.76	-5.88
L12Mvol	-2.07	-0.31	1.74	-5.91
L24Mvol	-2.04	-0.70	0.53	-6.78
		Panel B: Regression Analysis		
	Q1	Q2	Q3	Q4
$Return_{t}$	-0.05***	-0.04***	-0.04***	-0.08***
$Return_{t-1}$	-0.02***	-0.01*	-0.00	-0.02***
$Return_{t-2}$	-0.01**	-0.00	-0.00	-0.01***
$Return_{t-4}$	-0.01**	-0.00	0.00	-0.01***
$Return_{t-8}$	-0.01**	-0.00	0.00	-0.01***
$Return_{t-12}$	-0.01**	-0.00	0.00	-0.00***
$Return_{t-24}$	-0.01**	-0.00	0.00	-0.00***
		Panel C: Mean Deviation Regression Analysis		
	Q1	Q2	Q3	Q4
$Return_{t}$	-0.04***	-0.04***	-0.04***	-0.08***
$Return_{t-1}$	-0.01***	0.00	-0.00	-0.02***
$Return_{t-2}$	-0.00	0.00***	0.00	-0.01***
$Return_{t-4}$	0.00	0.01***	0.00***	-0.01***
$Return_{t-8}$	0.00	0.01***	0.01***	-0.00***
$Return_{t-12}$	0.00	0.01***	0.01***	-0.00***
$Return_{t-24}$	0.00	0.00***	0.00***	-0.00***

Table A.12 Panel A
Coinbase Traders' Style Following High Days (Sub-Period)
Table A.12 shows values of coefficient β_1 estimating Bitcoin's order flow after high days, for the period October 1, 2019 to October 1, 2021, per equation:

$$OIB_{t,k} = \beta_0 + \beta_1 d_{t-k}$$

$OIB_{t,k}$ is the order imbalance during k periods from t-k+1 to t. d_{t-k} is a dummy variable equal to 1 if Bitcoin's price hits its 30-, 90- and 120-day highs at time t-k. Following Newey-West (1987), I control for autocorelation of standard errors using 20 lags.

Panel A: OIB Following High Days				
	Q1	**Q2**	**Q3**	**Q4**
30-Day High				
$Return_t$	0.01	0.06***	0.02*	-0.05***
$Return_{t-1}$	0.02	0.05***	0.02*	-0.02
$Return_{t-2}$	0.02	0.05***	0.02*	-0.02
$Return_{t-3}$	0.02	0.05**	0.02*	-0.02*
$Return_{t-4}$	0.02	0.05**	0.02**	-0.02*
$Return_{t-5}$	0.02	0.05**	0.02**	-0.02*
$Return_{t-6}$	0.02	0.05**	0.02**	-0.02*
90-Day High				
$Return_t$	0.01	0.07***	0.02	-0.05***
$Return_{t-1}$	0.02	0.07***	0.02	-0.02*
$Return_{t-2}$	0.02	0.07***	0.02*	-0.02*
$Return_{t-3}$	0.02	0.07***	0.02*	-0.02**
$Return_{t-4}$	0.02	0.07***	0.02**	-0.02**
$Return_{t-5}$	0.02	0.07***	0.02**	-0.02**
$Return_{t-6}$	0.02	0.08***	0.02**	-0.02**
120-Day High				
$Return_t$	0.01	0.07***	0.01	-0.07***
$Return_{t-1}$	0.02	0.07***	0.01	-0.03***
$Return_{t-2}$	0.02	0.07***	0.01	-0.03***
$Return_{t-3}$	0.02	0.07**	0.01	-0.04***
$Return_{t-4}$	0.02	0.07**	0.02	-0.04***
$Return_{t-5}$	0.02	0.07***	0.02	-0.04***
$Return_{t-6}$	0.02	0.07***	0.02	-0.03***

Table A.12 Panel B
Coinbase Traders' Style Following Low Days (Sub-Period)

Table A.12 Panel B shows values of coefficient β_1 estimating Bitcoin's order flow after low days, from October 1, 2019 to October 1, 2021, per equation:

$$OIB_{t,k} = \beta_0 + \beta_1 d_{t-k}$$

$OIB_{t,k}$ is the order imbalance during k periods from t-k+1 to t. d_{t-k} is a dummy variable equal to 1 if Bitcoin's price hits its 30-, 90- and 120-day lows at time t-k. Following Newey-West (1987), I control for autocorelation of standard errors using 20 lags.

	Panel B: OIB Following Low Days			
	Q1	**Q2**	**Q3**	**Q4**
	30-Day Low			
Return_{t}	0.02	-0.01	-0.02	0.05***
Return_{t-1}	0.01	-0.01	-0.01	0.01
Return_{t-2}	0.01	-0.01	0.00	0.00
Return_{t-3}	0.01	-0.01	0.01	0.00
Return_{t-4}	0.02	-0.00	0.01	0.00
Return_{t-5}	0.01	-0.01	0.01	0.01
Return_{t-6}	0.01	-0.00	0.01	0.00
	90-Day Low			
Return_{t}	0.15***	0.07**	-0.01	0.05***
Return_{t-1}	0.15***	0.06	-0.00	0.03**
Return_{t-2}	0.14***	0.06	-0.00	0.03***
Return_{t-3}	0.14***	0.06	0.01	0.02***
Return_{t-4}	0.13***	0.06*	0.01	0.02*
Return_{t-5}	0.11**	0.04	0.01	0.02
Return_{t-6}	0.11**	0.06*	0.01	0.01
	120-Day Low			
Return_{t}	0.12**	0.03	-0.03	0.06***
Return_{t-1}	0.10**	0.01	-0.03	0.04*
Return_{t-2}	0.08*	-0.00	-0.02	0.03***
Return_{t-3}	0.07	0.00	-0.01	0.02**
Return_{t-4}	0.06	0.01	-0.00	0.01
Return_{t-5}	0.02	-0.02	-0.01	0.01
Return_{t-6}	0.03	0.01	0.00	0.01

Table A.13
Coinbase Traders' Style Following High and Low Days- Demeaned OIB (Sub-Period)
Table A.13 shows values of coefficient β_1 estimating Bitcoin's order flow 90-day mean deviation after high days, from October 1, 2019 to October 1, 2021, per equation:

$$DMOIB_{t,k} = \beta_0 + \beta_1 d_{t-k}$$

, where $DMOIB_{\mathrm{t,k}}$ is the deviation of order flow for the preceeding k periods at time t from its mean value calculated from t-k-1 to t-k-181, and d_{t-k} is a dummy variable equal to 1 if Bitcoin's price hits its 30-, 90- and 120-day highs at time t-k. Following Newey-West (1987), I control for autocorelation of standard errors using 25 lags.

	Q1	**Q2**	**Q3**	**Q4**
Panel A: DM-OIB Following High Days				
30-Day High				
$Return_{t}$	0.03*	0.05***	-0.00	-0.04***
$Return_{t-1}$	0.03*	0.05***	-0.00	-0.01
$Return_{t-2}$	0.03*	0.05***	-0.01	-0.01
$Return_{t-3}$	0.03	0.05**	-0.01	-0.01
$Return_{t-4}$	0.03	0.05**	-0.00	-0.01
$Return_{t-5}$	0.03	0.05**	-0.00	-0.01
$Return_{t-6}$	0.03	0.05**	-0.00	-0.01
90-Day High				
$Return_{t}$	0.04**	0.06***	-0.02	-0.03***
$Return_{t-1}$	0.05**	0.07***	-0.01	0.01
$Return_{t-2}$	0.05**	0.07***	-0.01	0.01
$Return_{t-3}$	0.05**	0.06***	-0.01	0.00
$Return_{t-4}$	0.05**	0.07***	-0.01	0.00
$Return_{t-5}$	0.05**	0.07***	-0.01	0.00
$Return_{t-6}$	0.05***	0.07***	-0.01	0.01
120-Day High				
$Return_{t}$	0.05**	0.06***	-0.02	-0.03***
$Return_{t-1}$	0.05**	0.06***	-0.02	0.01
$Return_{t-2}$	0.05**	0.06***	-0.02*	0.01
$Return_{t-3}$	0.05**	0.06***	-0.02*	0.00
$Return_{t-4}$	0.05**	0.06***	-0.02	0.00
$Return_{t-5}$	0.06***	0.06***	-0.02	0.01
$Return_{t-6}$	0.06***	0.07***	-0.01	0.01

Table A.13 Panel B
Coinbase Traders' Style Following Low Days- Demeaned OIB (Sub-Period)

Table A.13 shows values of coefficient β_1 estimating Bitcoin's order flow 90-day mean deviation after low days, from October 1, 2019 to October 1, 2021, per equation:

$$DMOIB_{t,k} = \beta_0 + \beta_1 d_{t-k}$$

, where $DMOIB_{\mathrm{t,k}}$ is the deviation of order flow for the preceeding k periods at time t from its mean value calculated from t-k-1 to t-k-181, and d_{t-k} is a dummy variable equal to 1 if Bitcoin's price hits its 30-, 90- and 120-day lows at time t-k. Following Newey-West (1987), I control for autocorelation of standard errors using 25 lags.

Panel B: DM-OIB Following Low Days				
	Q1	**Q2**	**Q3**	**Q4**
30-Day Low				
$\mathrm{Return_t}$	0.04	-0.00	0.01	0.05***
$\mathrm{Return_{t-1}}$	0.04	-0.02	0.01	-0.00
$\mathrm{Return_{t-2}}$	0.04	-0.01	0.02	0.00
$\mathrm{Return_{t-3}}$	0.05	-0.01	0.02	0.00
$\mathrm{Return_{t-4}}$	0.06	-0.00	0.03**	0.00
$\mathrm{Return_{t-5}}$	0.05	-0.00	0.03**	0.00
$\mathrm{Return_{t-6}}$	0.05	-0.00	0.03**	0.00
90-Day Low				
$\mathrm{Return_t}$	0.19***	0.05***	0.02**	0.03***
$\mathrm{Return_{t-1}}$	0.19***	0.05**	0.03***	0.01
$\mathrm{Return_{t-2}}$	0.19***	0.05*	0.03***	0.01
$\mathrm{Return_{t-3}}$	0.18***	0.05*	0.03***	0.00
$\mathrm{Return_{t-4}}$	0.18***	0.05**	0.03***	0.00
$\mathrm{Return_{t-5}}$	0.17***	0.05**	0.04***	0.00
$\mathrm{Return_{t-6}}$	0.17***	0.05**	0.04**	0.00
120-Day Low				
$\mathrm{Return_t}$	0.24***	0.05***	0.03***	0.03***
$\mathrm{Return_{t-1}}$	0.22***	0.02	0.02**	-0.01
$\mathrm{Return_{t-2}}$	0.20***	0.01	0.03***	-0.00
$\mathrm{Return_{t-3}}$	0.19***	0.1	0.04***	-0.01
$\mathrm{Return_{t-4}}$	0.17***	0.02	0.04***	-0.01**
$\mathrm{Return_{t-5}}$	0.16***	0.02	0.05***	-0.01**
$\mathrm{Return_{t-6}}$	0.15***	0.02	0.05***	-0.02**

Table A.14
Coinbase Traders' Market Timing Skills for Calling Bitcoin Prices UP and Down (Sub-Period)

Table A.14 shows investors market timing skills at correctly forecasting an increase in Bitcoin's price (*sensitivity*) and correctly forecasting a decrease in Bitcoin' price (*specificity*), from October 1, 2019 to October 1, 2021. Panel A shows the results corresponding to analysis based on raw oder imbalance values, and Panel B presents the results using order imbalance mean deviation from its average during the preceding 350 hours (15 days). The first column in each panel represents *sensitivity* which is the probability of a *positive* call for an actually-positive (*True-Positive*) price movement, and the second column in each panel represents *specificity* which is the probability of a negative call for an actually-negative price movement (*True-negative*). The third column, *OverallSkill* is the the total probability of trader's correct market timing per equation:

$$Overall_t = P_1 \times \frac{Positive}{ActualPositive} + P_2 \times \frac{Negative}{ActualNegative}$$

,where P_1 is the probability of Bitcoin price being up, and P_2 is the probability of Bitcoin price being down at time t.

Sensitivity and Specificity

Panel A: By Order Imbalance

	(1) $\frac{Positive}{ActualPositive}$	(2) $\frac{Negative}{ActualNegative}$	(3) $OverallSkill$
Q1	0.008864	0.991620	0.487087
Q2	0.021872	0.980447	0.488328
Q3	0.160239	0.854991	0.498316
Q4	0.403246	0.637722	0.517345

Panel B: By Demeaned Order Imbalance

	(1) $\frac{Positive}{ActualPositive}$	(2) $\frac{Negative}{ActualNegative}$	(3) $OverallSkill$
Q1	0.458647	0.577577	0.516496
Q2	0.483709	0.547214	0.514599
Q3	0.515104	0.522563	0.518732
Q4	0.517214	0.520752	0.518935

Table A.14 Panel B
Binance Traders' Seasonality of Order Imbalance
Table A.14 shows intraday and intraweek seasonality of Binance traders' order imbalance, controlling for Newey and West (1987) autocorrelation of standard errors for 500 lags, per equation:

$$OIB_{t,k} = \beta_0 + \beta_1 W + \beta_2 T$$

, where $OIB_{t,k}$ is the order imbalance during k periods from t-k+1 to t. W is a dummy variable representing the day of a week and T is a dummy variable representing the hour of a day.

	Q1	**Q2**	**Q3**	**Q4**
		Intraweek		
Tuesday	-0.01	-0.02	0.01	0.01
Wednesday	-0.00	-0.01	0.01	-0.00
Thursday	-0.00	-0.02	0.01	0.00
Friday	0.00	-0.01	0.01	-0.01
Saturday	0.00	-0.01	-0.00	-0.00
Sunday	0.01	-0.01	0.00	0.01
		Intraday		
1-2	0.04**	0.03***	0.02*	0.03***
2-3	0.02*	0.01	0.02	0.01
3-4	0.02*	-0.00	0.02**	-0.00
4-5	0.01	-0.00	0.02**	0.00
5-6	0.03***	0.00	0.03***	0.01
6-7	0.03***	0.01	0.03***	0.01
7-8	0.02***	0.02**	0.02***	-0.02*
8-9	0.03***	0.02	0.03**	-0.00
9-10	0.04***	0.04**	0.03***	-0.01
10-11	0.05***	0.03***	0.03***	-0.00
11-12	0.04***	0.03**	0.03***	0.00
12-13	0.05***	0.01**	0.03***	-0.00
13-14	0.03***	0.02**	0.02**	-0.00
14-15	0.03***	0.01*	0.01*	0.00
15-16	0.04***	0.03*	0.03*	-0.00
16-17	0.04***	0.01	0.02*	0.01
17-18	0.03***	0.02**	0.01*	-0.01
18-19	0.03***	0.01***	0.02***	0.01
19-20	0.05***	0.01***	0.02***	0.01
20-21	0.04***	0.02**	0.01*	0.00
21-22	0.06***	0.03***	0.00	0.00
22-23	0.04***	0.02*	0.02**	0.01
23-24	0.03**	0.01	0.01**	0.01**

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Table B.1
Hourly Summary Statistics Coinbase Pro; Censorized Data

Table B.1 Panel A and B show the summary statistics for 1-hour order imbalance in terms of volume, and the average dollar value for trades in all quartiles, respectively, using a subset of Coinbase trades whose transaction dollar value is greater (less) than 0.1 (99.9) or whose transaction volume is greater (less) than 0.0001 (99.999) percentile of the transactions in their corresponding quartile. Order imbalance is defined as the difference between the buy volume and sell volume, divided by the total trading volume during any given hour, and the hourly average dollar value of trades is calculated by dividing the aggregate hourly dollar value of transactions by the number of transactions per hour.

			Panel A: Order Imbalance			
	(1)	(2)	(3)	(4)	(5)	(6)
Quartiles	Count	Mean	25%	50%	75%	SD
Q1	45,902.0	-0.37	-0.60	-0.45	-0.16	0.33
Q2	45,913.0	-0.32	-0.49	-0.35	-0.17	0.25
Q3	45,913.0	-0.19	-0.34	-0.19	-0.06	0.22
Q4	45,912.0	-0.06	-0.23	-0.06	0.12	0.27
			Panel B: Average Transaction USD Value			
	(1)	(2)	(3)	(4)	(5)	(6)
Quartiles	Count	Mean	25%	50%	75%	SD
Q1	45,902.0	18.00	8.38	16.88	25.24	12.31
Q2	45,913.0	88.19	41.62	83.90	116.88	57.40
Q3	45,913.0	413.68	178.99	405.53	547.05	257.97
Q4	45,912.0	4,695.89	2,417.40	4,447.30	6,678.74	2,800.72

Table B.2
Investors' Style (Coinbase Pro); Censorized Data
Panel A presents t-statistics calculated based on LkM measure for investors of each quartile in each hourly frequency (1-hour, 2-hour, 4-hour, 8-hour, 12-hour, 24-hour), using a subset of Coinbase trades whose transaction dollar value is greater (less) than 0.1 (99.9) or whose transaction volume is greater (less) than 0.0001 (99.999) percentile of the transactions in their corresponding quartile, per equations:

$$LkM = OIB_t \times Return_{t-1}$$

$$t - stat(LkM) = \frac{L\bar{k}M}{\frac{\sigma(LkM_t)}{\sqrt{T}}}$$

$$L\bar{k}M = \frac{1}{T}\sum_{t}^{T} LkM$$

,where $\sigma(LkM_t)$ is the standard deviation of LkM measure and T is the number of hours. Panel B and Panel C display values of β_1 coefficient for estimating order imbalance and mean deviation of order imablance respectively, per equations:

$$OIB_t = \beta_1 \times Return_{t-1}$$

$$DMOIB_{t,k} = \beta_0 + \beta_1 Return_{t-k}$$

OIB_t is order imbalance at time t, calculated as the difference between the buy volume and sell volume divided by the total trading volume at time t. $DMOIB_{t,k}$ is the deviation of order imbalnce in a duation of k hours from its average in the preceeding 720 hours (30 days), starting from t-k-1 to t-k-721. The regression analyses control for the Newey and West (1987) autocorrelation of standard errors for up to 3500 lags.

		Panel A: LkM Measure		
	(1)	(2)	(3)	(4)
	Q1	Q2	Q3	Q4
L0Mvol	-45.28	-50.97	-59.38	-82.33
L1Mvol	-5.27	-8.36	-12.91	-20.19
L2Mvol	-3.29	-5.49	-8.90	-17.12
L4Mvol	-2.82	-4.05	-6.23	-14.25
L8Mvol	-2.59	-2.62	-3.48	-10.13
L12Mvol	-2.54	-2.39	-2.47	-9.02
L24Mvol	-2.59	-2.62	-2.95	-8.71
		Panel B: Regression Analysis		
	Q1	Q2	Q3	Q4
$Return_t$	-0.10***	-0.09***	-0.08***	-0.12***
$Return_{t-1}$	-0.01***	-0.01***	-0.02***	-0.02***
$Return_{t-2}$	-0.01**	-0.01***	-0.01***	-0.02***
$Return_{t-4}$	-0.01**	-0.01***	-0.00**	-0.01***
$Return_{t-8}$	-0.01**	-0.00**	-0.00	-0.01***
$Return_{t-12}$	-0.01**	-0.00**	0.00	-0.01***
$Return_{t-24}$	-0.01**	-0.00**	0.00	-0.01***
		Panel C: Mean Deviation Regression Analysis		
$Return_t$	-0.08***	-0.08***	-0.07***	-0.11***
$Return_{t-1}$	-0.01***	-0.01*	-0.01***	-0.02***
$Return_{t-2}$	-0.00	-0.00	-0.01**	-0.01***
$Return_{t-4}$	0.00	-0.00	-0.00	-0.01***
$Return_{t-8}$	0.00	0.00	0.00	-0.00***
$Return_{t-12}$	0.00	0.00	0.00	-0.00***
$Return_{t-24}$	0.00	0.00	0.00	-0.00***

Table B.3 Panel A
Investors' Style Following High Days; Coinbase Censorized Data

Table B.3 shows values of coefficient β_1 estimating Bitcoin's order flow after high days, using a subset of Coinbase trades whose transaction dollar value is greater (less) than 0.1 (99.9) or whose transaction volume is greater (less) than 0.0001 (99.999) percentile of the transactions in their corresponding quartile, per equation:

$$OIB_{t,k} = \beta_0 + \beta_1 d_{t-k}$$

, where $OIB_{t,k}$ is the order imbalance during k periods from t-k+1 to t, and d_{t-k} is a dummy variable equal to 1 if Bitcoin's price hits its 30-, 90- and 120-day highs at time t-k and 0 otherwise. Following Newey-West (1987), I control for autocorelation of standard errors using 90 lags.

	Panel A: OIB Following High Days			
	Q1	**Q2**	**Q3**	**Q4**
		30-Day High		
Return_{t}	-0.03	0.02	-0.00	-0.08***
Return_{t-1}	-0.01	0.03	0.01	-0.04***
Return_{t-2}	-0.01	0.03	0.01	-0.04***
Return_{t-3}	-0.01	0.03	0.01	-0.04***
Return_{t-4}	-0.00	0.03	0.01	-0.04***
Return_{t-5}	-0.00	0.03	0.02	-0.04***
Return_{t-6}	0.00	0.03	0.02	-0.04***
		90-Day High		
Return_{t}	-0.05	0.02	-0.01	-0.10***
Return_{t-1}	-0.03	0.04	0.01	-0.06***
Return_{t-2}	-0.02	0.04	0.01	-0.06***
Return_{t-3}	-0.02	0.04	0.02	-0.06***
Return_{t-4}	-0.01	0.04	0.02	-0.06***
Return_{t-5}	-0.01	0.04	0.02	-0.05***
Return_{t-6}	-0.01	0.05	0.02	-0.05***
		120-Day High		
Return_{t}	-0.03	0.03	-0.01	-0.11***
Return_{t-1}	-0.01	0.04	0.01	-0.07***
Return_{t-2}	-0.01	0.04	0.01	-0.07***
Return_{t-3}	-0.01	0.04	0.02	-0.07***
Return_{t-4}	-0.00	0.04	0.02	-0.06***
Return_{t-5}	-0.00	0.05	0.02	-0.06***
Return_{t-6}	0.00	0.05	0.02	-0.06***

Table B.3 Panel B
Investors' Style Following Low Days; Coinbase Censorized Data

Table B.3 Panel B shows values of coefficient β_1 estimating Bitcoin's order flow after low days, using a subset of Coinbase trades whose transaction dollar value is greater (less) than 0.1 (99.9) or whose transaction volume is greater (less) than 0.0001 (99.999) percentile of the transactions in their corresponding quartile, per equation:

$$OIB_{t,k} = \beta_0 + \beta_1 d_{t-k}$$

, where $OIB_{t,k}$ is the order imbalance during k periods from t-k+1 to t, and d_{t-k} is a dummy variable equal to 1 if Bitcoin's price hits its 30-, 90- and 120-day lows at time t-k. Following Newey-West (1987), I control for autocorelation of standard errors using 90 lags.

	Panel B: OIB Following Low Days			
	Q1	**Q2**	**Q3**	**Q4**
			30-Day Low	
Return_{t}	0.03	0.02	0.03	0.07***
Return_{t-1}	0.01	-0.01	-0.00	0.02**
Return_{t-2}	0.00	-0.01	0.01	0.02**
Return_{t-3}	0.01	-0.01	0.01	0.02**
Return_{t-4}	0.01	-0.00	0.02	0.03**
Return_{t-5}	0.01	-0.00	0.02	0.03**
Return_{t-6}	0.01	-0.00	0.02	0.03**
			90-Day Low	
Return_{t}	0.00	-0.07	-0.03	0.08***
Return_{t-1}	-0.02	-0.10**	-0.05*	0.04***
Return_{t-2}	-0.02	-0.10**	-0.04	0.05***
Return_{t-3}	-0.02	-0.10**	-0.03	0.04***
Return_{t-4}	-0.02	-0.10**	-0.02	0.05***
Return_{t-5}	-0.02	-0.10**	-0.02	0.04***
Return_{t-6}	-0.02	-0.09**	-0.02	0.04***
			120-Day Low	
Return_{t}	-0.01	-0.07	-0.03	0.09***
Return_{t-1}	-0.04	-0.11**	-0.06*	0.05***
Return_{t-2}	-0.05	-0.10**	-0.05	0.05***
Return_{t-3}	-0.05	-0.11**	-0.04	0.05***
Return_{t-4}	-0.05	-0.11**	-0.03	0.05***
Return_{t-5}	-0.05	-0.11***	-0.03	0.05***
Return_{t-6}	-0.05	-0.10**	-0.02	0.05***

Table B.4 Panel A
Investors' Style Following High and Low Days - Demeaned OIB; Coinbase Censorized Data

Table B.4 shows values of coefficient β_1 estimating Bitcoin's order flow 180-day mean deviation after high days, using a subset of Coinbase trades whose transaction dollar value is greater (less) than 0.1 (99.9) or whose transaction volume is greater (less) than 0.0001 (99.999) percentile of the transactions in their corresponding quartile, per equation:

$$DMOIB_{t,k} = \beta_0 + \beta_1 d_{t-k}$$

,where $DMOIB_{\mathrm{t,k}}$ is the deviation of order flow for the preceeding k periods at time t from its mean value calculated from t-k-1 to t-k-181, and d_{t-k} is a dummy variable equal to 1 if Bitcoin's price hits its 30-, 90- and 120-day highs at time t-k. Following Newey-West (1987), I control for autocorelation of standard errors using 70 lags.

	Panel A: DM-OIB Following High Days			
	Q1	**Q2**	**Q3**	**Q4**
		30-Day High		
$\mathrm{Return_{t}}$	-0.00	0.04**	0.02	-0.06***
$\mathrm{Return_{t\text{-}1}}$	0.01	0.05**	0.03	-0.03**
$\mathrm{Return_{t\text{-}2}}$	0.01	0.05**	0.03	-0.03**
$\mathrm{Return_{t\text{-}3}}$	0.01	0.05***	0.03	-0.03**
$\mathrm{Return_{t\text{-}4}}$	0.01	0.05***	0.04*	-0.03**
$\mathrm{Return_{t\text{-}5}}$	0.02	0.05***	0.04*	-0.02**
$\mathrm{Return_{t\text{-}6}}$	0.02	0.06***	0.04**	-0.02**
		90-Day High		
$\mathrm{Return_{t}}$	-0.01	0.05**	0.02	-0.06***
$\mathrm{Return_{t\text{-}1}}$	0.01	0.07**	0.04	-0.03
$\mathrm{Return_{t\text{-}2}}$	0.01	0.06**	0.04	-0.02
$\mathrm{Return_{t\text{-}3}}$	0.01	0.07**	0.04	-0.02
$\mathrm{Return_{t\text{-}4}}$	0.01	0.07**	0.05*	-0.02
$\mathrm{Return_{t\text{-}5}}$	0.02	0.07***	0.05*	-0.02
$\mathrm{Return_{t\text{-}6}}$	0.02	0.08***	0.05*	-0.02
		120-Day High		
$\mathrm{Return_{t}}$	0.00	0.06**	0.02	-0.06***
$\mathrm{Return_{t\text{-}1}}$	0.02	0.06**	0.04	-0.02
$\mathrm{Return_{t\text{-}2}}$	0.02	0.06**	0.04	-0.02
$\mathrm{Return_{t\text{-}3}}$	0.02	0.06**	0.04	-0.02*
$\mathrm{Return_{t\text{-}4}}$	0.02	0.07**	0.04	-0.02
$\mathrm{Return_{t\text{-}5}}$	0.02	0.07**	0.04*	-0.02
$\mathrm{Return_{t\text{-}6}}$	0.03	0.07***	0.04*	-0.02

Table B.4 Panel B
Investors' Style Following Low Days- Demeaned OIB; Coinbase Censorized Data

Table B.4 shows values of coefficient β_1 estimating Bitcoin's order flow 180-day mean deviation after low days, using a subset of Coinbase trades whose transaction dollar value is greater (less) than 0.1 (99.9) or whose transaction volume is greater (less) than 0.0001 (99.999) percentile of the transactions in their corresponding quartile, per equation:

$$DMOIB_{t,k} = \beta_0 + \beta_1 d_{t-k}$$

, where $DMOIB_{\mathrm{t,k}}$ is the deviation of order flow for the preceeding k periods at time t from its mean value calculated from t-k-1 to t-k-181, and d_{t-k} is a dummy variable equal to 1 if Bitcoin's price hits its 30-, 90- and 120-day lows at time t-k. Following Newey-West (1987), I control for autocorelation of standard errors using 70 lags.

Panel B: DM-OIB Following Low Days				
	Q1	**Q2**	**Q3**	**Q4**
30-Day Low				
$\mathrm{Return}_{\mathrm{t}}$	0.02	0.00	0.01	0.05***
$\mathrm{Return}_{\mathrm{t-1}}$	-0.01	-0.03	-0.02	0.01
$\mathrm{Return}_{\mathrm{t-2}}$	-0.01	-0.02	-0.01	0.01
$\mathrm{Return}_{\mathrm{t-3}}$	-0.01	-0.03	-0.00	0.01
$\mathrm{Return}_{\mathrm{t-4}}$	-0.00	-0.03	0.00	0.01
$\mathrm{Return}_{\mathrm{t-5}}$	0.00	-0.02	0.01	0.02
$\mathrm{Return}_{\mathrm{t-6}}$	0.00	-0.02	0.01	0.02
90-Day Low				
$\mathrm{Return}_{\mathrm{t}}$	0.02	-0.04	-0.02	0.05***
$\mathrm{Return}_{\mathrm{t-1}}$	0.00	-0.07***	-0.04	0.01
$\mathrm{Return}_{\mathrm{t-2}}$	0.01	-0.06**	-0.03	0.02
$\mathrm{Return}_{\mathrm{t-3}}$	0.01	-0.07**	-0.02	0.01
$\mathrm{Return}_{\mathrm{t-4}}$	0.01	-0.07**	-0.01	0.01
$\mathrm{Return}_{\mathrm{t-5}}$	0.01	-0.06**	-0.01	0.01
$\mathrm{Return}_{\mathrm{t-6}}$	0.01	-0.06**	-0.01	0.01
120-Day Low				
$\mathrm{Return}_{\mathrm{t}}$	-0.04	-0.04	-0.01	0.04***
$\mathrm{Return}_{\mathrm{t-1}}$	-0.06	-0.09***	-0.04	0.00
$\mathrm{Return}_{\mathrm{t-2}}$	-0.07	-0.07***	-0.02	0.01
$\mathrm{Return}_{\mathrm{t-3}}$	-0.07	-0.08***	-0.01	0.00
$\mathrm{Return}_{\mathrm{t-4}}$	-0.07	-0.08***	-0.01	0.01
$\mathrm{Return}_{\mathrm{t-5}}$	-0.07	-0.08***	-0.00	0.01
$\mathrm{Return}_{\mathrm{t-6}}$	-0.07	-0.07***	0.00	0.01

Table B.5 Panel A

Order Imbalance and Investors' Style, Seasonality, and 2-Hour Sentiment; Coinbase Censorized Data

Table B.5 shows the coefficients for estimating order imbalance, using a subset of Coinbase trades whose transaction dollar value is greater (less) than 0.1 (99.9) or whose transaction volume is greater (less) than 0.0001 (99.999) percentile of the transactions in their corresponding quartile, per equation:

$$OIB_t = \beta_1 \times Ret_{t-1} + \beta_2 \times 2Sent_{t-1} + \beta_3 \times 2Att_{t-1} + \beta_6 \times 24OIB_{t-1} + W + H$$

	Panel A: Past 2-Hour Sentiment			
	Q1	Q2	Q3	Q4
OIB24	0.04***	0.04***	0.04***	0.03***
lag1_Return	-0.00	-0.01**	-0.01***	-0.02***
L2_Sentiment	0.00	0.10***	0.07*	0.03
L2_Attention	0.42***	0.56***	0.46***	-0.24*
SP	-0.06	0.04	0.03	-0.22*
Tuesday	-0.01**	-0.03***	-0.03***	-0.01
Wednesday	-0.01***	-0.03***	-0.03***	-0.01**
Thursday	-0.02***	-0.03***	-0.03***	-0.01
Friday	-0.02***	-0.03***	-0.04***	-0.02***
Saturday	-0.01***	-0.03***	-0.04***	-0.02**
Sunday	-0.01*	-0.02***	-0.03***	-0.01
1-2	-0.02***	-0.00	-0.01***	-0.01
2-3	-0.02**	-0.00	-0.00	-0.00
3-4	-0.00	0.01	-0.00	0.02**
4-5	-0.00	0.00	0.00	0.01
5-6	0.00	0.01	0.01	0.01
6-7	0.00	0.01	0.00	0.01
7-8	-0.00	-0.00	0.00	-0.01
8-9	0.03*	0.01	0.02	-0.00
9-10	0.03**	0.03	0.04***	0.02
10-11	0.04***	0.03	0.04***	0.03
11-12	0.02	0.02	0.02	0.01
12-13	0.02	0.02	0.02	0.00
13-14	0.02**	0.01	0.01	-0.00
14-15	0.02**	0.01	0.01	0.01
15-16	0.01	0.01	0.01	0.01
16-17	-0.01	-0.00	0.00	0.00
17-18	-0.01	-0.02	-0.01	0.00
18-19	-0.01	-0.01	-0.01	0.01
19-20	-0.02**	-0.02*	-0.01	0.01
20-21	-0.00	-0.02	-0.01	0.00
21-22	-0.01	-0.02**	-0.01	0.00
22-23	-0.02***	-0.03***	-0.02***	-0.01
23-24	-0.02***	-0.02***	-0.02***	-0.01
Adj-R^2	0.51	0.34	0.29	0.08
F-statistic	809.7	749.3	252.3	66.34

Table B.5 Panel B

Order Imbalance and Investors' Style, Seasonality, and 2-Hour Positive/Negative; Coinbase Censorized Data

Panel B represensts results for the same regression analysis as Panel A but it decomposes $2Sent_{\text{t-1}}$ to $2Positive_{\text{t-1}}$ and $2Negative_{\text{t-1}}$ which are the aggregarte standardized average number of posititve and negative Reddit posts from t-3 to t-1 respectively.

$$OIB_t = \beta_1 \times Ret_{t-1} + \beta_2 \times 2Pos_{t-1} + \beta_3 \times 2Neg_{t-1} + \beta_4 \times 2Att_{t-1} + \beta_5 \times 24OIB_{t-1} + W + H$$

	Panel B: Past 2-Hour Positive/Negative			
	Q1	Q2	Q3	Q4
OIB24	0.04***	0.04***	0.04***	0.03***
lag1_Return	-0.00	-0.01***	-0.01***	-0.02***
L2_Positive	-0.13	0.05	-0.05	0.04
L2_Negative	-0.13*	-0.16**	-0.20***	-0.02
L2_Attention	0.44***	0.57***	0.47***	-0.24**
SP	-0.06	0.04	0.03	-0.22**
Tuesday	-0.01**	-0.03***	-0.03***	-0.01
Wednesday	-0.01***	-0.03***	-0.03***	-0.01**
Thursday	-0.02***	-0.03***	-0.03***	-0.01
Friday	-0.02***	-0.03***	-0.04***	-0.02***
Saturday	-0.01***	-0.03***	-0.04***	-0.02**
Sunday	-0.01*	-0.02***	-0.03***	-0.01
1-2	-0.02***	-0.00	-0.01***	-0.01
2-3	-0.02**	-0.00	-0.00	-0.00
3-4	-0.00	0.01	-0.00	0.02**
4-5	-0.00	0.00	0.00	0.01
5-6	0.00	0.01	0.01	0.01
6-7	0.00	0.01	0.00	0.01
7-8	-0.00	-0.00	0.00	-0.01
8-9	0.03*	0.01	0.02	-0.00
9-10	0.03**	0.03	0.04***	0.02
10-11	0.04***	0.03	0.04***	0.03
11-12	0.02	0.02	0.02	0.01
12-13	0.02	0.02	0.02	0.00
13-14	0.02**	0.01	0.01	-0.00
14-15	0.02**	0.01	0.01	0.01
15-16	0.01	0.01	0.01	0.01
16-17	-0.01	-0.00	0.00	0.00
17-18	-0.01	-0.02	-0.01	0.00
18-19	-0.01	-0.01	-0.01	0.01
19-20	-0.02**	-0.02*	-0.01	0.01
20-21	-0.00	-0.02	-0.01	0.00
21-22	-0.01	-0.02**	-0.01	0.00
22-23	-0.02***	-0.03***	-0.02***	-0.01
23-24	-0.02***	-0.02***	-0.02***	-0.01
Adj-R^2	0.51	0.33	0.29	0.08
F-statistic	835.15	730.1	244.5	65.34

Table B.6 Panel A

Order Imbalance and Investors' Style, Seasonality, and 24-Hour Sentiment; Coinbase Censorized Data

Table B.6 shows the coefficients for estimating order imbalance, using a subset of Coinbase trades whose transaction dollar value is greater (less) than 0.1 (99.9) or whose transaction volume is greater (less) than 0.0001 (99.999) percentile of the transactions in their corresponding quartile, per equation:

$$OIB_t = \beta_1 \times Ret_{t-1} + \beta_2 \times 24Sent_{t-1} + \beta_3 \times 24Att_{t-1} + \beta_4 \times 24OIB_{t-1} + W + H$$

	Panel A: Past 24-Hour Sentiment			
	Q1	Q2	Q3	Q4
OIB24	0.04***	0.04***	0.04***	0.03***
lag1_Return	-0.00	-0.01**	-0.01***	-0.02***
L24_Sentiment	0.03**	0.04***	0.03***	0.02
L24_Attention	0.02	0.02	0.02*	-0.00
Tuesday	-0.01***	-0.03***	-0.03***	-0.01*
Wednesday	-0.02***	-0.03***	-0.03***	-0.01**
Thursday	-0.02***	-0.03***	-0.03***	-0.01
Friday	-0.02***	-0.03***	-0.04***	-0.02***
Saturday	-0.02***	-0.03***	-0.04***	-0.02**
Sunday	-0.01***	-0.02***	-0.03***	-0.00
1-2	-0.02***	-0.00	-0.02***	-0.00
2-3	-0.02***	-0.00	-0.01	0.00
3-4	-0.00	0.00	-0.00	0.02**
4-5	-0.00	0.00	0.00	0.01*
5-6	0.00	0.01	0.01	0.02
6-7	0.00	0.01	0.00	0.01
7-8	-0.00	-0.00	0.00	-0.01
8-9	0.03*	0.01	0.02	-0.00
9-10	0.03*	0.03	0.04***	0.02
10-11	0.02*	0.03	0.04***	0.03
11-12	0.02*	0.02	0.02*	0.01
12-13	0.02*	0.02	0.02*	0.00
13-14	0.02**	0.01	0.01	-0.00
14-15	0.02***	0.02	0.02**	0.01
15-16	0.01	0.02	0.01*	0.00
16-17	-0.00	0.00	0.01	-0.00
17-18	-0.00	-0.01	-0.00	0.00
18-19	0.00	-0.01	0.00	0.00
19-20	-0.01	-0.01	-0.00	0.01
20-21	0.00	-0.01	-0.00	0.00
21-22	-0.01	-0.02*	-0.01	0.00
22-23	-0.02***	-0.03***	-0.02***	-0.01
23-24	-0.02***	-0.02***	-0.02***	-0.01
Adj-R^2	0.51	0.34	0.29	0.08
F-statistic	915.7	1108	243.4	60.23

Table B.6 Panel B

Order Imbalance and Investors' Style, Seasonality, and 24-Hour Positive/Negative; Coinbase Censorized Data

Panel B represensts results for the same regression analysis as Panel A but it decomposes $24Sent_{\text{t-1}}$ to $24Positive_{\text{t-1}}$ and $24Negative_{\text{t-1}}$ which are the aggregarte standardized average number of posititve and negative Reddit posts from $t-25$ to $t-1$ respectively.

$$OIB_t = \beta_1 \times Ret_{t-1} + \beta_2 \times 24Pos_{t-1} + \beta_3 \times 24Neg_{t-1} + \beta_4 \times 24Att_{t-1} + \beta_5 \times 24OIB_{t-1} + W + H$$

	Panel B: Past 24-Hour Positive/Negative			
	Q1	Q2	Q3	Q4
OIB24	0.04***	0.04***	0.04***	0.03***
lag1_Return	-0.00	-0.01**	-0.01***	-0.02***
L24_Positive	0.00	0.01	0.01	0.01
L24_Negative	-0.06***	-0.06***	-0.05***	-0.03*
L24_Attention	0.03**	0.02**	0.03**	0.00
Tuesday	-0.01**	-0.03***	-0.03***	-0.01*
Wednesday	-0.02***	-0.03***	-0.03***	-0.01**
Thursday	-0.02***	-0.03***	-0.03***	-0.01
Friday	-0.02***	-0.03***	-0.04***	-0.02***
Saturday	-0.02***	-0.03***	-0.04***	-0.02**
Sunday	-0.01**	-0.02***	-0.03***	-0.00
1-2	-0.02***	-0.00	-0.02***	-0.00
2-3	-0.02**	-0.00	-0.01	0.00
3-4	-0.00	0.00	-0.00	0.02**
4-5	-0.00	0.00	0.00	0.01*
5-6	0.00	0.01	0.01	0.02
6-7	0.00	0.01	0.00	0.01
7-8	-0.00	-0.00	0.00	-0.01
8-9	0.03*	0.01	0.02	-0.00
9-10	0.03*	0.03	0.04***	0.02
10-11	0.04**	0.03	0.04***	0.03
11-12	0.02*	0.02	0.02*	0.01
12-13	0.02*	0.02	0.02*	0.00
13-14	0.02**	0.01	0.01	-0.00
14-15	0.02***	0.02	0.02**	0.01
15-16	0.01	0.02	0.01*	0.00
16-17	-0.00	0.00	0.01	-0.00
17-18	-0.00	-0.01	-0.00	0.00
18-19	0.00	-0.01	0.00	0.00
19-20	-0.01	-0.01	-0.00	0.01
20-21	0.00	-0.01	-0.00	0.00
21-22	-0.01	-0.02**	-0.01	0.00
22-23	-0.02***	-0.03***	-0.02***	-0.01
23-24	-0.02***	-0.02***	-0.02***	-0.01
Adj-R^2	0.51	0.34	0.29	0.08
F-statistic	984.4	1076	241.8	57.37

Table B.7
The Predictibility of Bitcoin's Next-Hour Returns through Order Imbalance Components (2-Hr Sentiment); Coinbase Censorized Data

Table B.7 shows the results for conducting a two-stage decomposition of order imbalance, using a subset of Coinbase trades whose transaction dollar value is greater (less) than 0.1 (99.9) or whose transaction volume is greater (less) than 0.0001 (99.999) percentile of the transactions in their corresponding quartile. In the first stage, order imbalance is estimated at time t-1, per equation:

$$OIB_{t-1} = \beta_0 + \beta_1 \times OIB24_{t-2} + \beta_2 \times Return_{t-2} + \beta_3 \times 2Hr\_Att_{t-2} + \beta_4 \times 2Hr\_Sent_{t-2} + T + W + U_4$$

$OIB24_{\text{t-2}}$ is the aggregate 24 hour order imbalance from t-2 to t-25. $Return_{\text{t-2}}$ is the Bitcoin return at time t-2, and $2Hr\_Att_{\text{t-2}}$ is the number of Reddit posts at during t-4 to t-2 standardized by the number of posts during the preceding 336 hours (2 weeks). $2Hr\_Sent_{\text{t-1}}$ is a proxy for aggregate 2-hour sentiment ($Sentiment_{\text{t-2}}$ + $Sentiment_{\text{t-3}}$), where $Sentiment_{\text{t}}$ is defined as the difference between the standardized average posititve Reddit and negative Reddit sentiment from t-1 to t. Both $2Hr\_Sent_{\text{t-1}}$ and $2Hr\_Att_{\text{t-1}}$ are scaled by 100. In the above regression, the second component, $\beta_1 \times OIB24_{\text{t-1}}$ is defined as $Persistence$, the third component, $\beta_2 \times Return_{\text{t-2}}$ is defined as $Contrarian$, the fourth component, $\beta_3 \times 2Hr\_Att_{\text{t-2}}$, is called *Attention*, the fifth component, $\beta_4 \times 2Hr\_Sent_{t-2}$, is called *Sentiment*, and the summation of intercept, seasonality and error terms is called *Other*. Then, in the second stage, Return_{t} is estimated using the identified components as:

$$Return_t = \beta_0 + \beta_1 \times Persistence_{t-1} + \beta_2 \times Contrarian_{t-1} + \beta_3 \times Attention_{t-1} + \beta_4 \times Sentiment_{t-1} + \beta_5 \times other_{t-1} + Controls$$

,where *Controls* represents control variables such as different lags of Bitcoin returns and return volatility. The results of the first and second stages are presented at the top and bottom sections of Panel A respectively.

	2-Hour Sentiment			
	(1) Q1	(2) Q2	(3) Q3	(4) Q4
1^{st} Stage				
lag1_OIB24	0.04***	0.04***	0.04***	0.03***
lag2_Return	-0.00	-0.01**	-0.01***	-0.02***
lag1_L2_Sentiment	0.01	0.12***	0.09**	0.03
lag1_L2_Attention	0.39***	0.44***	0.40***	-0.23**
2^{nd} Stage				
EPersistence	-0.02	0.00	-0.03	-0.19***
EContrarian		6.30***	4.05***	2.44***
ESentiment		0.38	0.46	
EAttention	1.30	1.14	1.29	-2.05
Other	-0.02	-0.02	-0.00	-0.02
lag1_Return	-0.04***	-0.04***	-0.04***	-0.05***
lag24_Return	-0.03***	-0.03***	-0.03***	-0.03***
lag1_Return_Votality	0.02	0.02	0.02	0.02
Adj_R^2	0.003	0.004	0.004	0.005
F-statistic	6.15	5.17	5.57	7.73

Table B.8
The Predictibility of Bitcoin's Next-Hour Returns through Order Imbalance Components (24-Hr Sentiment); Coinbase Censorized Data

Table B.8 shows the results for conducting a two stage decomposition of order imbalance, using a subset of Coinbase trades whose transaction dollar value is greater (less) than 0.1 (99.9) or whose transaction volume is greater (less) than 0.0001 (99.999) percentile of the transactions in their corresponding quartile. In the first stage, order imbalance is estimated at time *t*-1, per equation:

$$OIB_{t-1} = \beta_0 + \beta_1 \times OIB24_{t-2} + \beta_2 \times Return_{t-2} + \beta_3 \times Attention_{t-2} + \beta_4 \times 24Hr\_Sent_{t-2} + T + W + U_4$$

$OIB24_{\text{t-2}}$ is the aggregate 24 hour order imbalance from *t*-2 to *t*-25. $Return_{\text{t-2}}$ is the Bitcoin return at time *t*-2, and $Attention_{\text{t-2}}$ is the number of Reddit posts at during *t*-2 to *t*-1 standardized by the number of posts during the preceding 336 hours (2 weeks). $24Hr\_Sent_{\text{t-2}}$ is a proxy for the aggregate 24-hour sentiment ($Sentiment_{\text{t-2}}$ +....+ $Sentiment_{\text{t-26}}$), where $Sentiment_{\text{t}}$ is defined as the difference between the standardized average posititve and negative Reddit sentiment from *t*-1 to *t*. $24Hr\_Sent_{\text{t-1}}$ is scaled by 100 and $Attention_{\text{t-2}}$ is scaled by 10. In the above regression, the second component, $\beta_1 \times OIB24_{\text{t-1}}$ is defined as *Persistence*, the third component, $\beta_2 \times Return_{\text{t-2}}$ is defined as *Contrarian*, the fourth component, $\beta_3 \times Attention_{\text{t-2}}$, is called *Attention*, the fifth component, $\beta_4 \times 24Hr\_Sent_{t-2}$, is called *Sentiment*, and the summation of intercept, seasonality and error terms is called *Other*. Then, in second stage, Return_{t} is estimated using the identified components as:

$$Return_t = \beta_0 + \beta_1 \times Persistence_{t-1} + \beta_2 \times Contrarian_{t-1} + \beta_3 \times Attention_{t-1} + \beta_4 \times Sentiment_{t-1} + \beta_5 \times other_{t-1} + Controls$$

, where *Controls* represents control variables such as different lags of Bitcoin returns and return volatility. The results of the first and second stages are presented at the top and bottom sections of Panel A respectively.

	24-Hour Sentiment			
	(1)	(2)	(3)	(4)
	Q1	Q2	Q3	Q4
1st Stage				
lag1_OIB24	0.04***	0.04***	0.04***	0.03***
lag2_Return	-0.00	-0.01**	-0.01***	-0.02***
lag1_L24_Sentiment	0.03**	0.04***	0.04***	0.02
lag2_Attention	0.01***	0.01***	0.01***	-0.00**
2nd Stage				
EPersistence	-0.02	0.01	-0.03	-0.19***
EContrarian		6.30***	4.10***	2.44***
ESentiment	1.40	1.23	1.23	
EAttention	1.31	0.92	1.04	-1.75
Other	-0.02	-0.02	-0.00	-0.02
lag1_Return	-0.04***	-0.04***	-0.04***	-0.05***
lag24_Return	-0.03***	-0.03***	-0.03***	-0.03***
lag1_Return_Votality	0.02	0.02	0.02	0.02
Adj_R^2	0.003	0.004	0.004	0.005
F-statistic	5.63	5.45	5.77	7.73

Table B.9
Hourly Summary Statistics (Binance); Censorized

Table B.9 Panel A shows the 1-hour order imbalance in terms of volume. Panel B, C and Panel D show the average dollar value of a transaction, the average hourly trade count, and aggregate hourly dollar volume for traders of all quartiles, respectively.

			Panel A: Order Imbalance			
	(1)	(2)	(3)	(4)	(5)	(6)
Quartiles	Count	Mean	25%	50%	75%	SD
Q1	16,766.0	0.02	-0.06	0.02	0.11	0.19
Q2	16,767.0	-0.03	-0.11	0.00	0.08	0.24
Q3	16,806.0	0.02	-0.05	0.02	0.10	0.20
Q4	16,774.0	-0.03	-0.13	-0.03	0.07	0.22
			Panel B: Average Transaction USD Value			
	(1)	(2)	(3)	(4)	(5)	(6)
Quartiles	Count	Mean	25%	50%	75%	SD
Q1	16,766.0	18.37	12.99	18.24	23.49	6.18
Q2	16,767.0	82.80	44.62	64.56	121.09	47.99
Q3	16,806.0	279.94	94.96	133.30	513.53	247.37
Q4	16,774.0	2,320.37	1,078.81	1,525.25	3,934.10	1,541.26

Table B.10

Investors' Style (Binance); Censorized

Panel A presents t-statistics calculated based on LkM measure for investors of each quartile in each hourly frequency (1-hour, 2-hour, 4-hour, 8-hour, 12-hour, 24-hour), using a subset of Binance trades whose transaction dollar value is greater (less) than 0.1 (99.9) or whose transaction volume is greater (less) than 0.0001 (99.999) percentile of the transactions in their corresponding quartile, per equations:

$$LkM = OIB_t \times Return_{t-1}$$

$$t - stat(LkM) = \frac{L\bar{k}M}{\frac{\sigma(LkM_t)}{\sqrt{T}}}$$

$$L\bar{k}M = \frac{1}{T}\sum_{t}^{T} LkM$$

,where $\sigma(LkM_t)$ is the standard deviation of LkM measure and T is the number of hours. Panel B and Panel C display values of β_1 coefficient for estimating order imbalance and mean deviation of order imablance respectively, per equations:

$$OIB_t = \beta_1 \times Return_{t-1}$$

$$DMOIB_{t,k} = \beta_0 + \beta_1 Return_{t-k}$$

OIB_{t} is order imbalance at time t, calculated as the difference between the buy volume and sell volume divided by the total trading volume at time t. $DMOIB_{\mathrm{t,k}}$ is the deviation of order imbalnce in a duation of k hours from its average in the preceeding 720 hours (30 days), starting from t-k-1 to t-k-721. The regression analyses control for the Newey and West (1987) autocorrelation of standard errors for up to 1500 lags.

	(1)	(2)	(3)	(4)
Panel A: LkM Measure				
	Q1	Q2	Q3	Q4
L0Mvol	46.18	23.08	26.40	33.31
L1Mvol	2.78	0.27	0.27	-2.40
L2Mvol	1.40	-0.50	-0.23	-2.33
L4Mvol	1.10	-0.81	-0.69	-1.22
L8Mvol	0.26	-0.93	-0.19	-1.70
L12Mvol	0.79	-0.52	0.15	-1.91
L24Mvol	0.88	-0.46	-0.39	-2.66
Panel B: Regression Analysis				
	Q1	Q2	Q3	Q4
$Return_t$	7.24***	4.06***	3.10***	4.70***
$Return_{t-1}$	0.37	0.05	0.03	-0.30
$Return_{t-2}$	0.16	-0.10	-0.03	-0.24
$Return_{t-4}$	0.11	-0.10	-0.07	-0.10
$Return_{t-8}$	0.02	-0.14	-0.02	-0.11
$Return_{t-12}$	0.06	-0.07	0.01	-0.11
$Return_{t-24}$	0.05	-0.06	-0.03	-0.13**
Panel C: Mean Deviation Regression Analysis				
	Q1	Q2	Q3	Q4
$Return_t$	7.21***	4.11***	3.07***	4.74***
$Return_{t-1}$	0.34	0.10	-0.00	-0.26
$Return_{t-2}$	0.13	-0.04	-0.05	-0.19
$Return_{t-4}$	0.08	-0.08	-0.10	-0.06
$Return_{t-8}$	-0.00	-0.09	-0.04	-0.06
$Return_{t-12}$	0.03	-0.02	-0.00	-0.06
$Return_{t-24}$	0.03	-0.01	-0.04	-0.07

Table B.11

Order Imbalance and Investors' Style, Seasonality (Binance); Censorized

Table B.11 shows coefficients for investors' style intraday and intraweek seasonality of Binance traders' order imbalance,β_1 and β_2 , using a subset of Binance trades whose transaction dollar value is greater (less) than 0.1 (99.9) or whose transaction volume is greater (less) than 0.0001 (99.999) percentile of the transactions in their corresponding quartile , controlling for Newey and West (1987) autocorrelation of standard errors, per equation:

$$OIB_t = \beta_0 + \beta_1 \times Ret_{t-1} + \beta_2 \times 24OIB_{t-1} + W + H$$

	Q1	Q2	Q3	Q4
$OIB24_{t-1}$	0.03***	0.04***	0.04***	0.02***
$Return_{t-1}$	0.20	-0.23	-0.07	-0.37
Tuesday	0.00	-0.01	0.00	0.01
Wednesday	0.00	0.01	-0.00	0.00
Thursday	0.00	-0.00	0.00	0.00
Friday	0.01	0.00	-0.00	0.00
Saturday	0.00	0.00	-0.01	0.01
Sunday	0.01	-0.00	0.00	0.01
1-2	0.03***	0.02***	0.01*	0.04***
2-3	0.02**	0.00	0.01	0.02
3-4	0.01	-0.01	0.02**	-0.01
4-5	0.00	-0.01	0.02**	0.01
5-6	0.03***	0.00	0.03***	0.02*
6-7	0.03***	0.00	0.03***	0.01
7-8	0.02***	0.01	0.02***	-0.01
8-9	0.03***	0.01	0.03**	-0.01
9-10	0.04***	0.02***	0.03***	-0.01
10-11	0.05***	0.02***	0.03***	-0.00
11-12	0.04***	0.02***	0.03***	-0.00
12-13	0.04***	0.01**	0.03***	-0.00
13-14	0.03***	0.01**	0.02***	-0.00
14-15	0.02***	0.01*	0.01*	0.00
15-16	0.04***	0.01**	0.02**	-0.00
16-17	0.03***	0.00	0.01*	0.01
17-18	0.03***	0.02***	0.02**	-0.00
18-19	0.03***	0.01**	0.03***	0.01
19-20	0.04***	0.01**	0.02***	0.02
20-21	0.03***	0.01**	0.01**	0.01
21-22	0.06***	0.03***	0.00	-0.00
22-23	0.04***	0.01	0.02**	0.01
23-24	0.02***	0.00	0.01*	0.02**
Adj-R^2	0.08	0.51	0.32	0.02
F-statistic	68.4	871.8	429.6	36.40

Table B.12 Panel A
Investors' Style Following High Days (Binance); Censorized

Table B.12 shows values of coefficient β_1 estimating Bitcoin's order flow after high days, using a subset of Binance trades whose transaction dollar value is greater (less) than 0.1 (99.9) or whose transaction volume is greater (less) than 0.0001 (99.999) percentile of the transactions in their corresponding quartile, per equation:

$$OIB_{t,k} = \beta_0 + \beta_1 d_{t-k}$$

, where $OIB_{t,k}$ is the order imbalance during k periods from t-k+1 to t, and d_{t-k} is a dummy variable equal to 1 if Bitcoin's price hits its 30-, 90- and 120-day highs at time t-k and 0 otherwise. Following Newey and West (1987), I control for autocorelation of standard errors using 20 lags.

	Panel A: OIB Following High Days			
	Q1	**Q2**	**Q3**	**Q4**
		30-Day High		
Return_{t}	0.01	0.07**	-0.04**	-0.01
Return_{t-1}	-0.00	0.06*	-0.04*	-0.01
Return_{t-2}	-0.00	0.06*	-0.04*	-0.00
Return_{t-3}	-0.00	0.06*	-0.03*	-0.00
Return_{t-4}	-0.00	0.06*	-0.03*	-0.00
Return_{t-5}	-0.01	0.06*	-0.03*	-0.00
Return_{t-6}	-0.01	0.06*	-0.03*	-0.00
		90-Day High		
Return_{t}	0.01	0.08***	-0.03	0.00
Return_{t-1}	-0.00	0.06**	-0.03*	-0.00
Return_{t-2}	-0.00	0.07**	-0.02	0.00
Return_{t-3}	0.00	0.07**	-0.02	-0.00
Return_{t-4}	0.00	0.07**	-0.02	-0.00
Return_{t-5}	-0.00	0.07**	-0.02	0.00
Return_{t-6}	0.00	0.07**	-0.02	0.00
		120-Day High		
Return_{t}	0.01	0.06**	-0.03	0.01
Return_{t-1}	-0.00	0.06*	-0.03**	0.00
Return_{t-2}	-0.00	0.06**	-0.03	0.00
Return_{t-3}	0.00	0.06**	-0.02	0.01
Return_{t-4}	0.00	0.06**	-0.02	0.01
Return_{t-5}	0.00	0.06**	-0.02	0.01
Return_{t-6}	0.00	0.06**	-0.01	0.01

Table B.12 Panel B
Investors' Style Following Low Days (Binance); Censorized

Table B.12 Panel B shows values of coefficient β_1 estimating Bitcoin's order flow after low days, using a subset of Binance trades whose transaction dollar value is greater (less) than 0.1 (99.9) or whose transaction volume is greater (less) than 0.0001 (99.999) percentile of the transactions in their corresponding quartile, per equation:

$$OIB_{t,k} = \beta_0 + \beta_1 d_{t-k}$$

, where $OIB_{t,k}$ is the order imbalance during k periods from t-k+1 to t, and d_{t-k} is a dummy variable equal to 1 if Bitcoin's price hits its 30-, 90- and 120-day lows at time t-k. Following Newey and West (1987), I control for autocorelation of standard errors using 20 lags.

	Panel B: OIB Following Low Days			
	Q1	**Q2**	**Q3**	**Q4**
		30-Day Low		
Return_{t}	-0.01	-0.03	0.01	-0.00
Return_{t-1}	0.02	-0.02	0.03	-0.00
Return_{t-2}	0.02*	-0.02	0.02	-0.01
Return_{t-3}	0.02*	-0.02	0.02	-0.01
Return_{t-4}	0.01	-0.02	0.02	-0.02*
Return_{t-5}	0.01	-0.02	0.02	-0.02*
Return_{t-6}	0.01	-0.03	0.02	-0.02*
		90-Day Low		
Return_{t}	0.01	0.07**	0.01	-0.01
Return_{t-1}	0.04***	0.04	0.05**	0.02
Return_{t-2}	0.04***	0.05	0.04**	0.02
Return_{t-3}	0.03***	0.05	0.04**	0.02
Return_{t-4}	0.03***	0.04	0.03**	0.01
Return_{t-5}	0.03***	0.04	0.04**	0.01
Return_{t-6}	0.03***	0.04	0.04**	0.01
		120-Day Low		
Return_{t}	0.00	0.10***	0.01	-0.02
Return_{t-1}	0.03*	0.03	0.06***	0.02
Return_{t-2}	0.04***	0.05	0.05***	0.03
Return_{t-3}	0.03***	0.04	0.05***	0.02
Return_{t-4}	0.03**	0.03	0.04***	0.01
Return_{t-5}	0.03**	0.03	0.05***	0.01
Return_{t-6}	0.03**	0.03	0.05***	0.01

Table B.13 Panel A
Investors' Style Following High and Low Days- Demeaned OIB (Binance); Censorized
Table B.13 shows values of coefficient β_1 estimating Bitcoin's order flow 180-day mean deviation after high

days, using a subset of Binance trades whose transaction dollar value is greater (less) than 0.1 (99.9) or whose transaction volume is greater (less) than 0.0001 (99.999) percentile of the transactions in their corresponding quartile, per equation:

$$DMOIB_{t,k} = \beta_0 + \beta_1 d_{t-k}$$

,where $DMOIB_{\mathrm{t,k}}$ is the deviation of order flow for the preceeding k periods at time t from its mean value calculated from t-k-1 to t-k-181, and d_{t-k} is a dummy variable equal to 1 if Bitcoin's price hits its 30-, 90- and 120-day highs at time t-k. Following Newey and West (1987), I control for autocorelation of standard errors using 25 lags.

Panel A: DM-OIB Following High Days				
	Q1	**Q2**	**Q3**	**Q4**
			30-Day High	
$\mathrm{Return_t}$	0.01	0.04	-0.03	-0.00
$\mathrm{Return_{t-1}}$	-0.00	0.03	-0.03	-0.01
$\mathrm{Return_{t-2}}$	-0.00	0.03	-0.02	-0.00
$\mathrm{Return_{t-3}}$	-0.00	0.03	-0.02	-0.00
$\mathrm{Return_{t-4}}$	-0.00	0.03	-0.02	-0.00
$\mathrm{Return_{t-5}}$	-0.01	0.03	-0.02	-0.00
$\mathrm{Return_{t-6}}$	-0.00	0.03	-0.02	-0.00
			90-Day High	
$\mathrm{Return_t}$	0.01	0.04	-0.01	0.00
$\mathrm{Return_{t-1}}$	-0.00	0.02	-0.01	-0.00
$\mathrm{Return_{t-2}}$	-0.00	0.02	-0.01	-0.00
$\mathrm{Return_{t-3}}$	-0.00	0.02	-0.01	-0.00
$\mathrm{Return_{t-4}}$	-0.00	0.02	-0.01	-0.00
$\mathrm{Return_{t-5}}$	-0.00	0.02	-0.00	-0.00
$\mathrm{Return_{t-6}}$	-0.00	0.02	-0.00	-0.00
			120-Day High	
$\mathrm{Return_t}$	0.01	0.02	-0.00	0.01
$\mathrm{Return_{t-1}}$	-0.00	0.01	-0.01	0.00
$\mathrm{Return_{t-2}}$	-0.00	0.01	-0.00	0.00
$\mathrm{Return_{t-3}}$	0.00	0.01	-0.00	0.01
$\mathrm{Return_{t-4}}$	0.00	0.01	0.00	0.01
$\mathrm{Return_{t-5}}$	0.00	0.01	0.00	0.01
$\mathrm{Return_{t-6}}$	0.00	0.01	0.00	0.01

Table B.13 Panel B
Investors' Style Following Low Days- Demeaned OIB (Binance); Censorized

Table B.13 shows values of coefficient β_1 estimating Bitcoin's order flow 180-day mean deviation after low days, using a subset of Binance trades whose transaction dollar value is greater (less) than 0.1 (99.9) or whose transaction volume is greater (less) than 0.0001 (99.999) percentile of the transactions in their corresponding quartile, per equation:

$$DMOIB_{t,k} = \beta_0 + \beta_1 d_{t-k}$$

, where $DMOIB_{\mathrm{t,k}}$ is the deviation of order flow for the preceeding k periods at time t from its mean value calculated from t-k-1 to t-k-181, and d_{t-k} is a dummy variable equal to 1 if Bitcoin's price hits its 30-, 90- and 120-day lows at time t-k. Following Newey-West (1987), I control for autocorelation of standard errors using 25 lags.

Panel B: DM-OIB Following Low Days				
	Q1	**Q2**	**Q3**	**Q4**
			30-Day Low	
Return_{t}	-0.01	-0.01	0.02	0.00
Return_{t-1}	0.03*	-0.00	0.03	0.01
Return_{t-2}	0.03**	-0.00	0.03	0.01
Return_{t-3}	0.03*	0.01	0.02	0.00
Return_{t-4}	0.02*	0.01	0.02	-0.00
Return_{t-5}	0.02*	-0.00	0.02	-0.00
Return_{t-6}	0.02*	-0.00	0.02	-0.00
			90-Day Low	
Return_{t}	-0.01**	-0.01	0.03	-0.02
Return_{t-1}	0.02**	-0.07	0.08*	0.02
Return_{t-2}	0.02**	-0.06	0.07*	0.03
Return_{t-3}	0.02	-0.06*	0.06*	0.02
Return_{t-4}	0.01	-0.07*	0.05	0.01
Return_{t-5}	0.01	-0.07*	0.05	0.01
Return_{t-6}	0.01	-0.07*	0.05	0.01
			120-Day Low	
Return_{t}	-0.01**	-0.01	0.03	-0.02
Return_{t-1}	0.02**	-0.07	0.08*	0.02
Return_{t-2}	0.02**	-0.06	0.07*	0.03
Return_{t-3}	0.02	-0.06*	0.06*	0.02
Return_{t-4}	0.01	-0.07*	0.05	0.01
Return_{t-5}	0.01	-0.07*	0.05	0.01
Return_{t-6}	0.01	-0.07*	0.05	0.01

Figure A.1: Autocorrelation of Order Imbalance in Different Quartiles

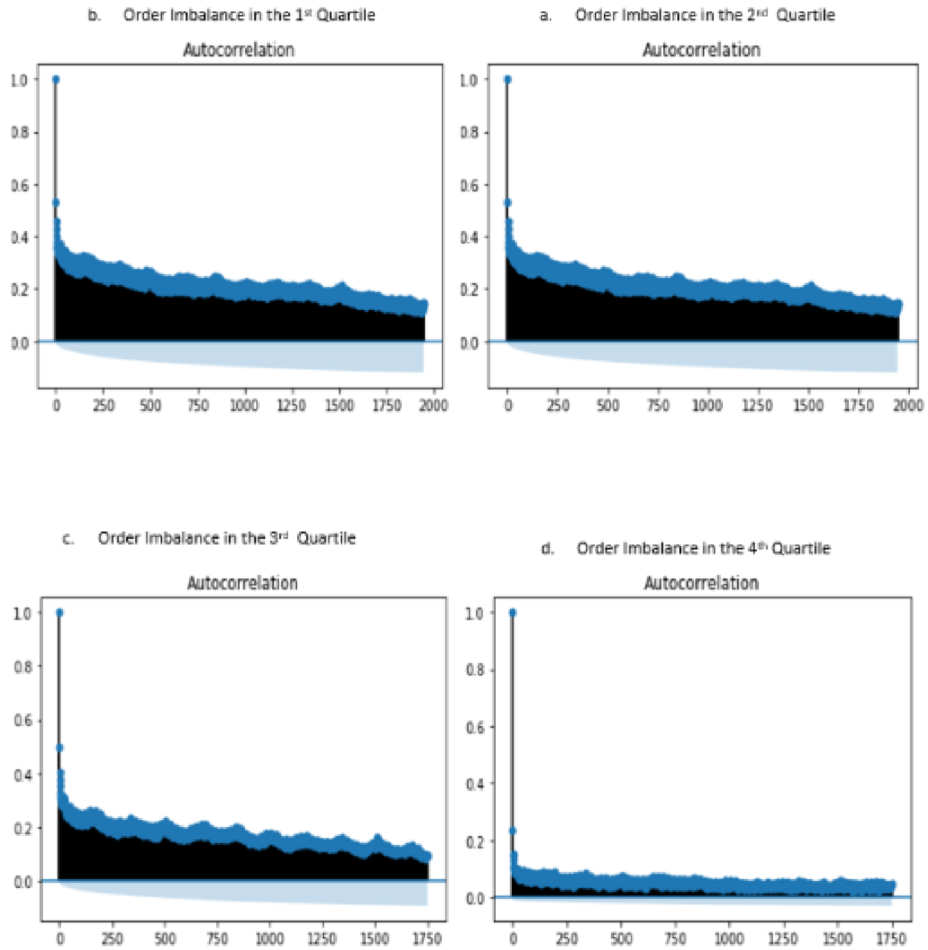


Figure A.2: Autocorrelation of Bitcoin Returns

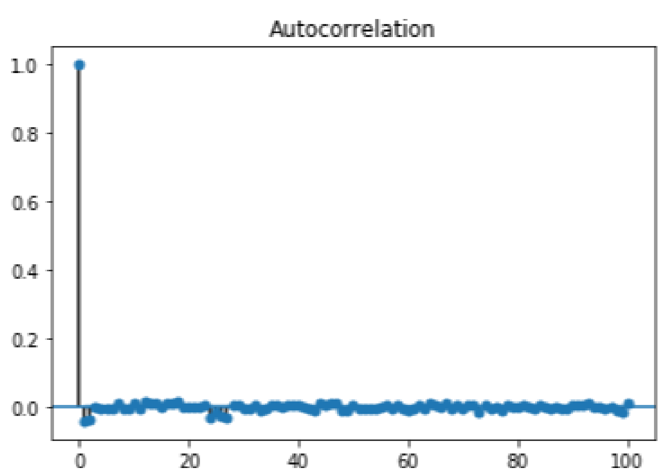


Figure A.3: Partial Autocorrelation Function of Order Imbalance in Different Quartiles (PACF)

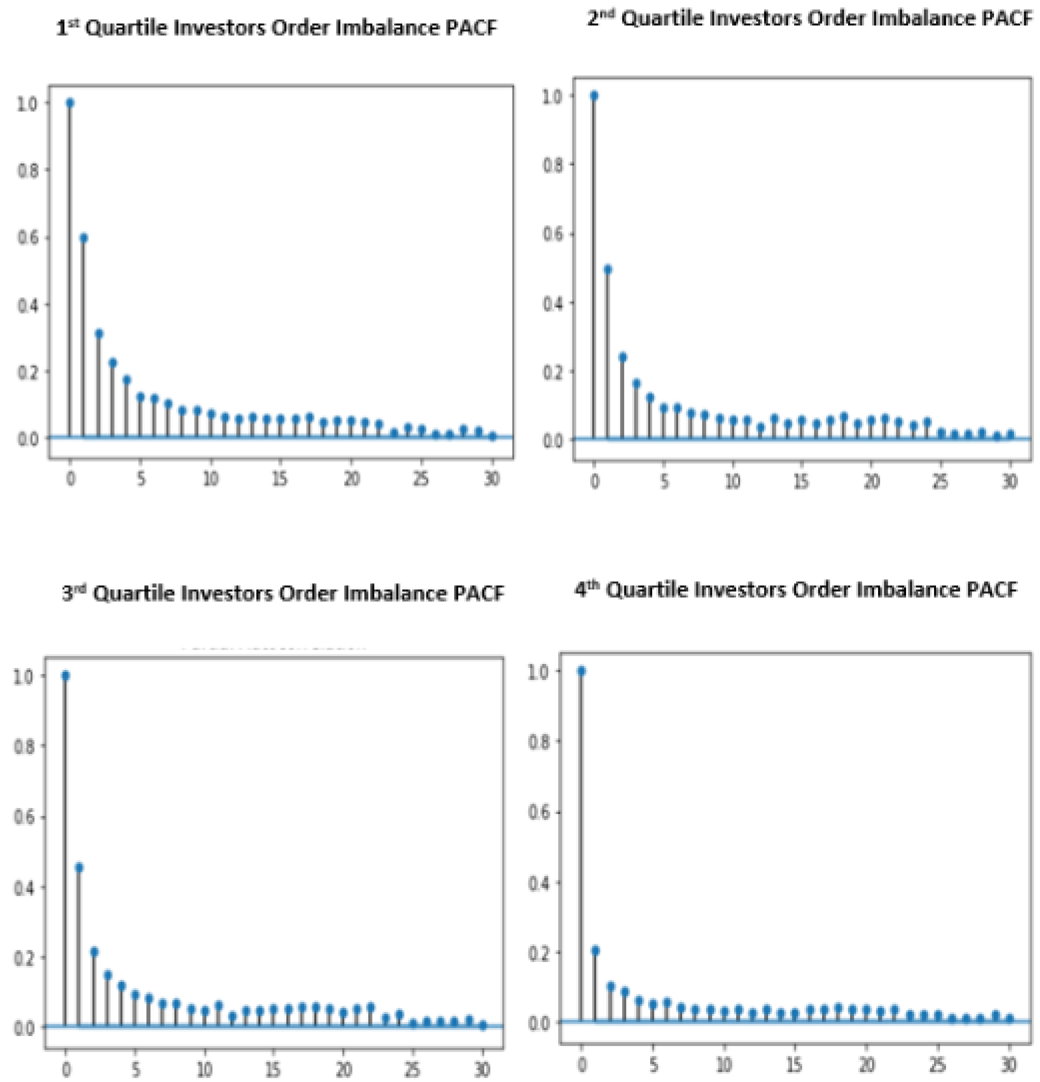


Figure 3 shows the partial autocorrelation function for order imbalance of investors of different quartiles; that is: the autocorrelation of OIB_t with each of its previous lags removing the impact of the in-between lags.

Figure A.4: Correlation Heatmap

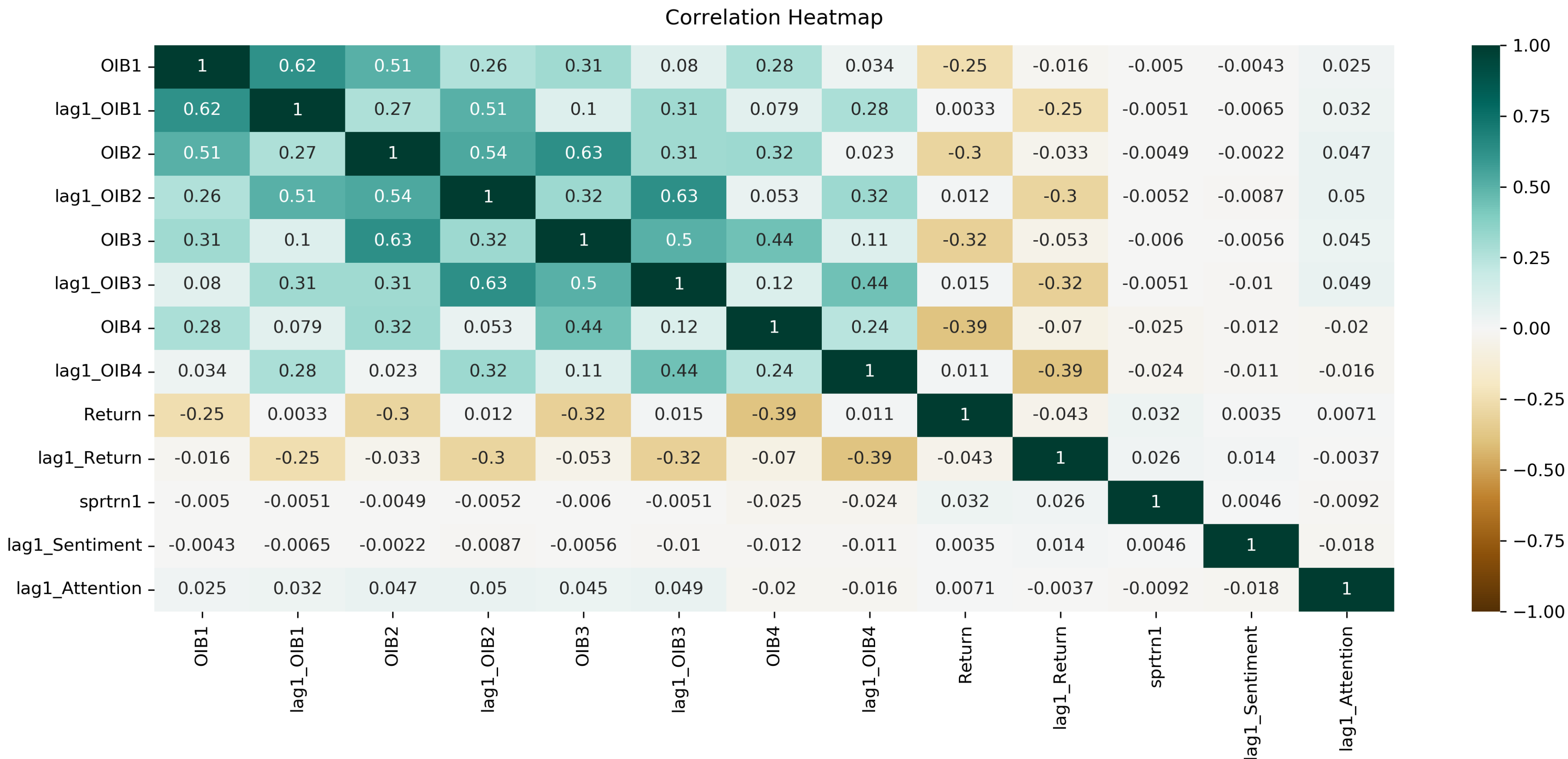
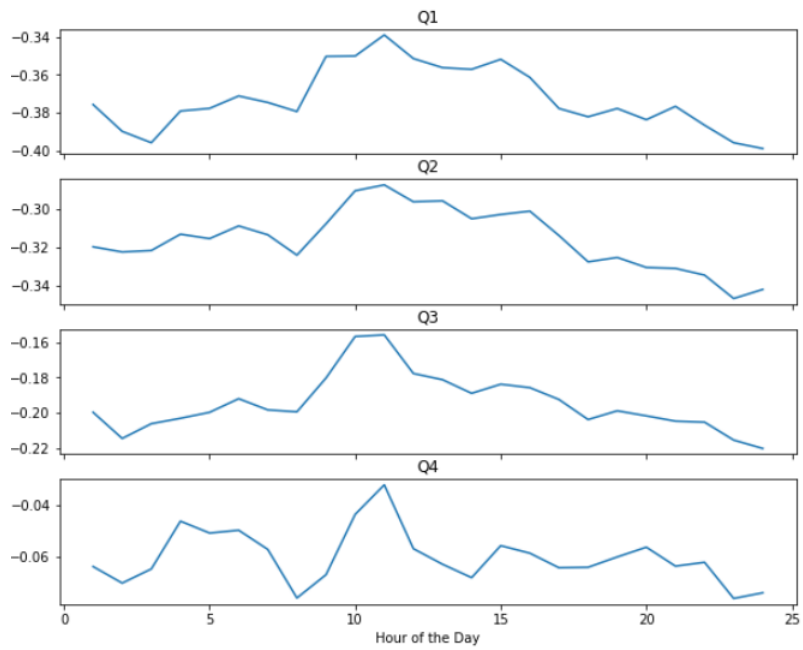
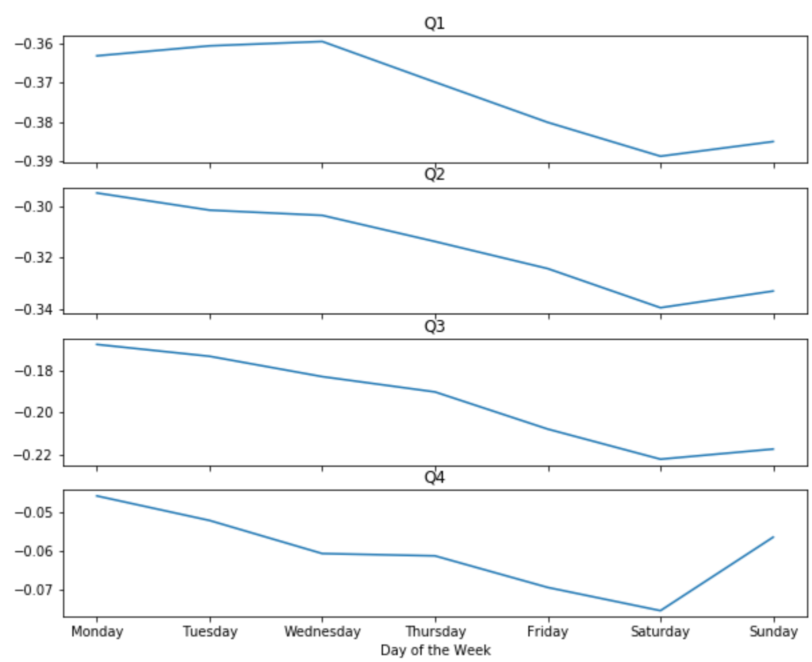


Figure A.5: Seasonality of Order Imbalance

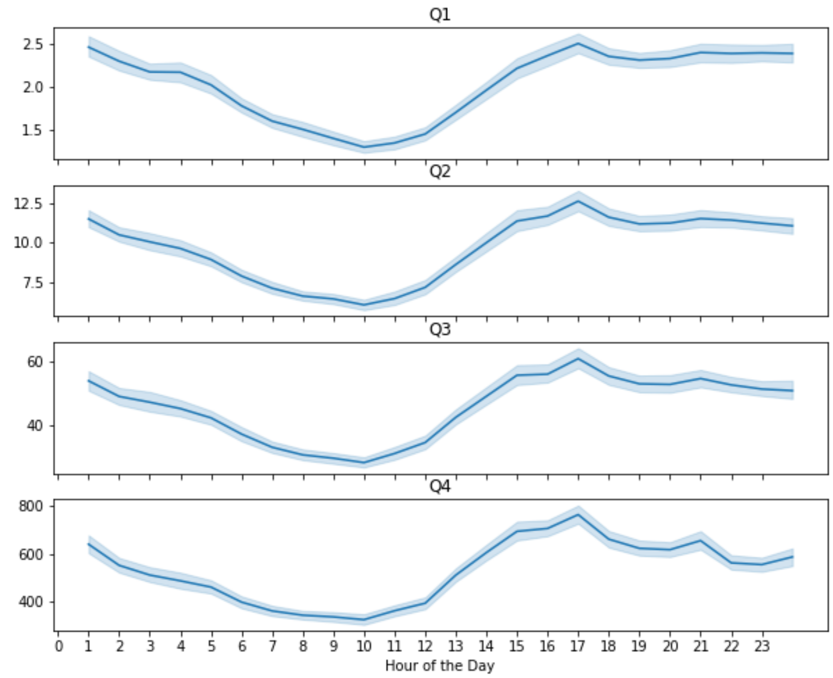


a) Intraday Seasonality

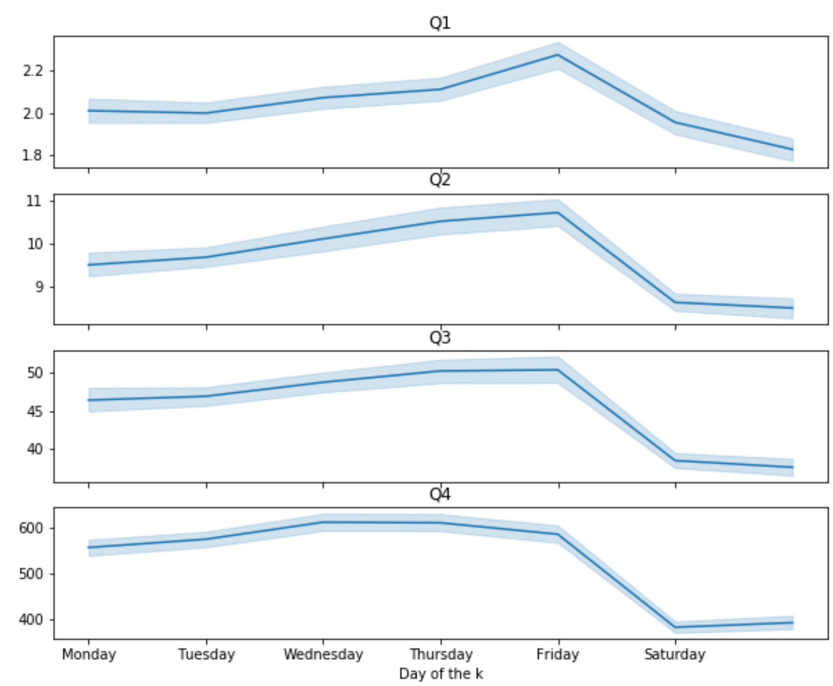


a) Intraweek Seasonality

Figure A.6: Seasonality of Bitcoin Trading Volume



a) Intraday Seasonality



a) Intraweek Seasonality

Figure A.7: Seasonality of Average Bitcoin Returns

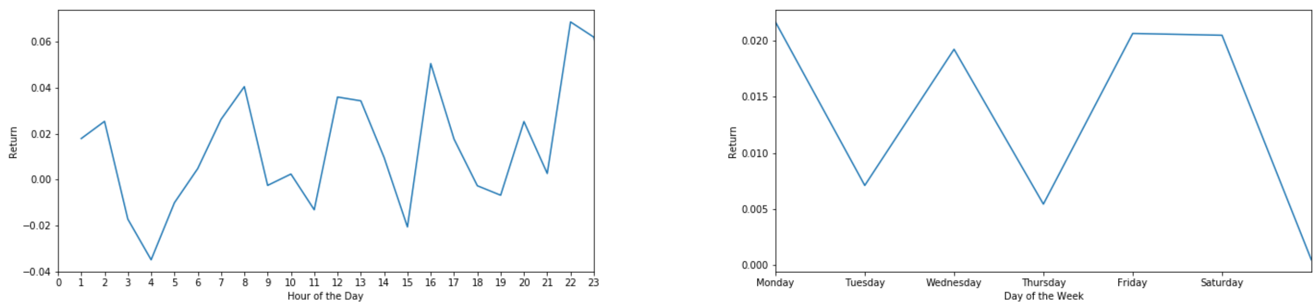


Figure A.8: Seasonality of Bitcoin Price volatility

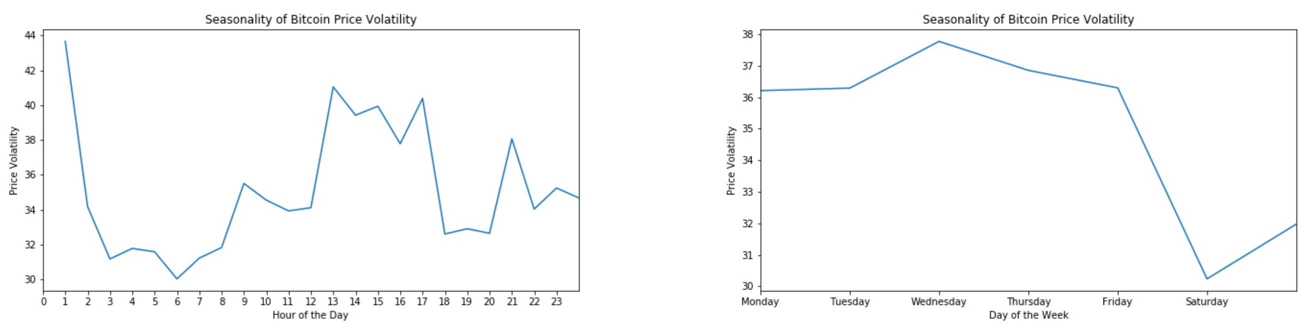
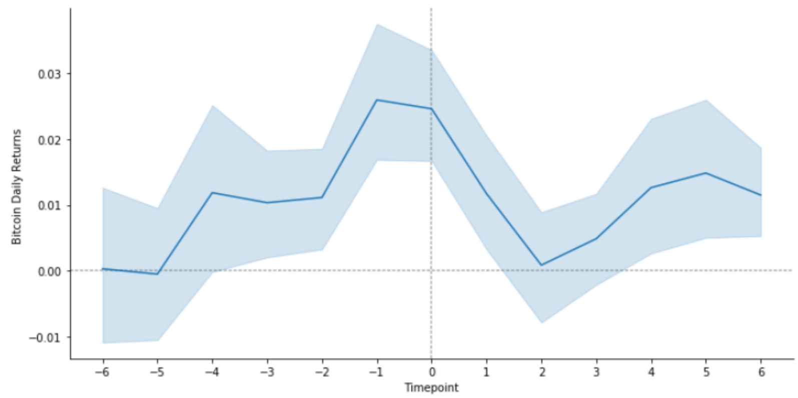
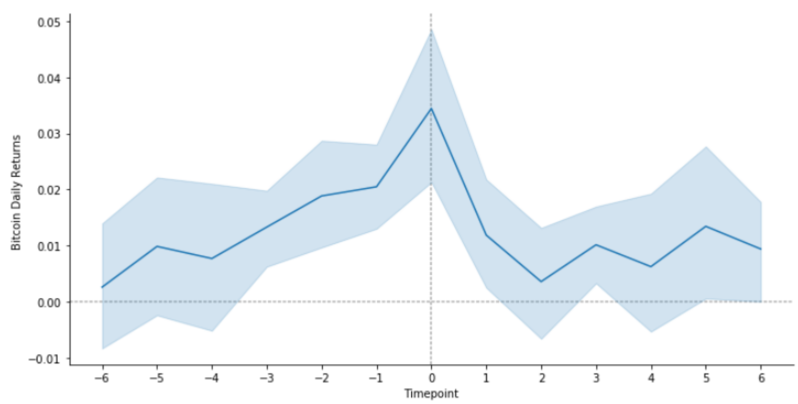


Figure A.9: Bitcoin Returns Around High Days (95% Confidence Interval)

30-Day High



90-Day High



120-Day High

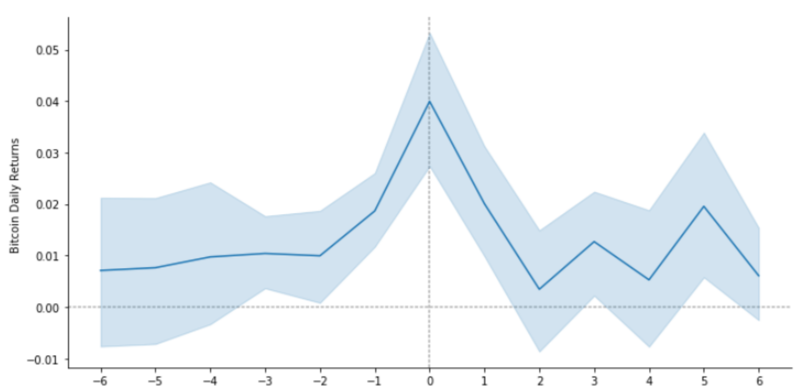


Figure A.10: Market Timing Skills of Investors in Forecasting Bitcoin's Up and Down Prices

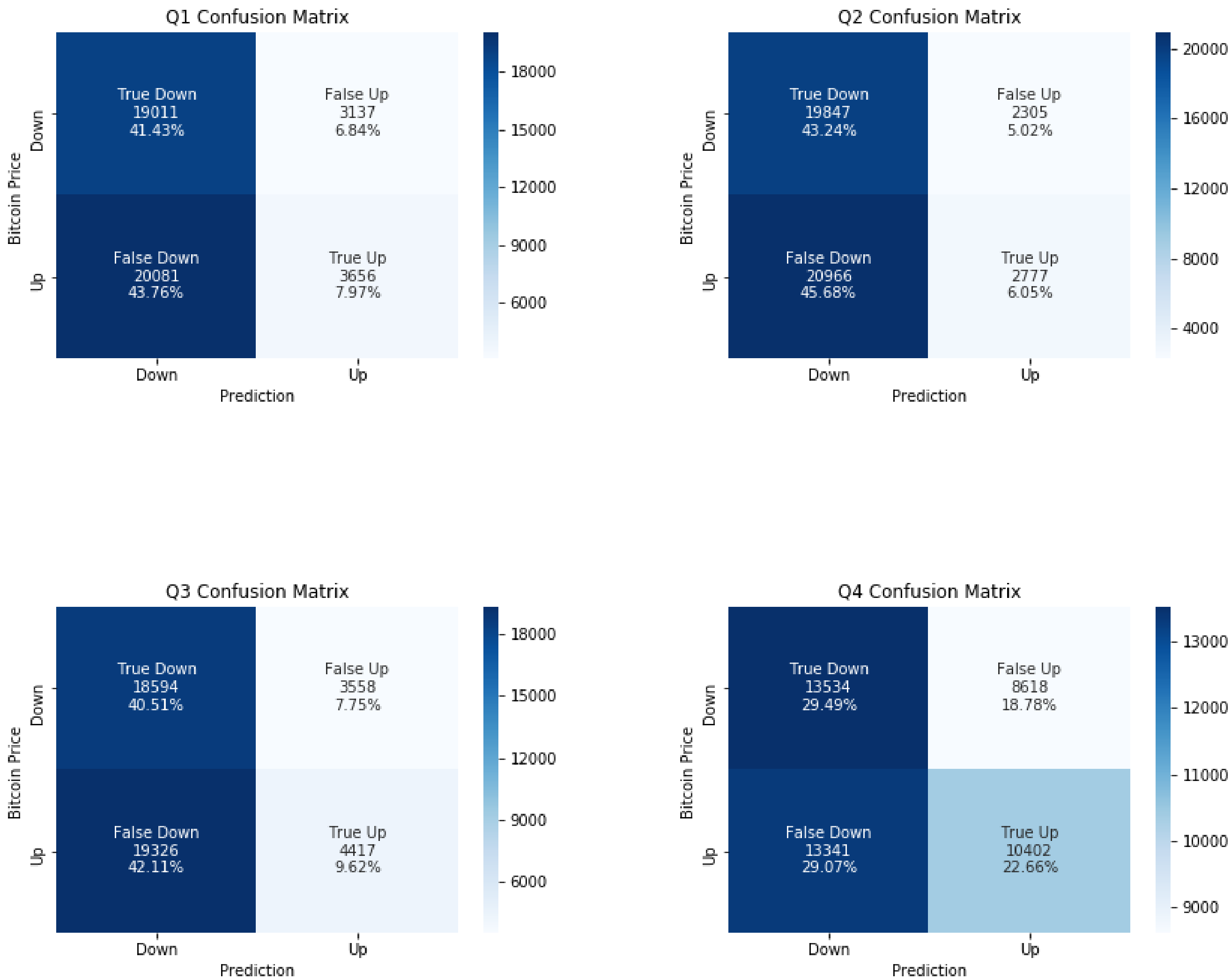


Figure A.11: Market Timing Skills of Investors in Forecasting Bitcoin's Up and Down Prices (Demeaned)

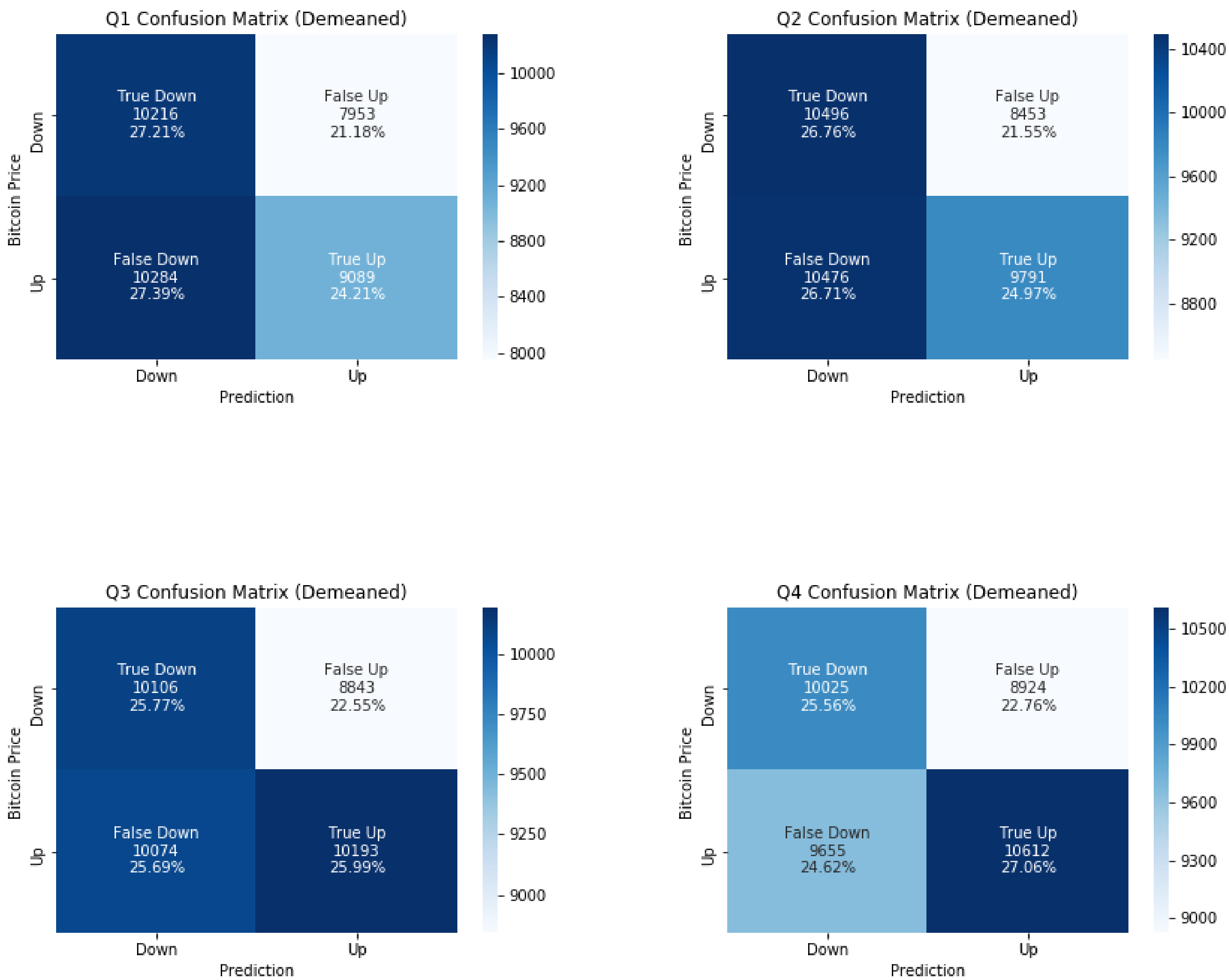
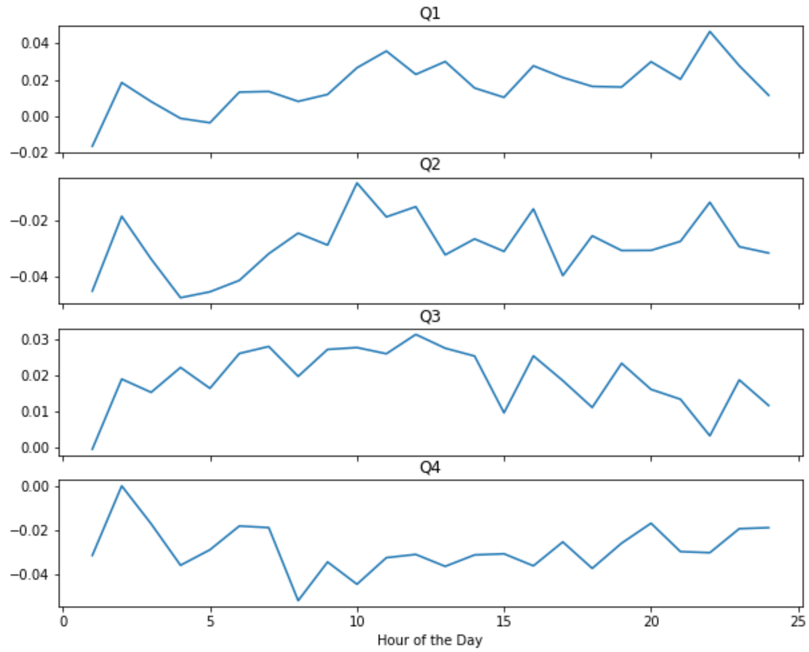
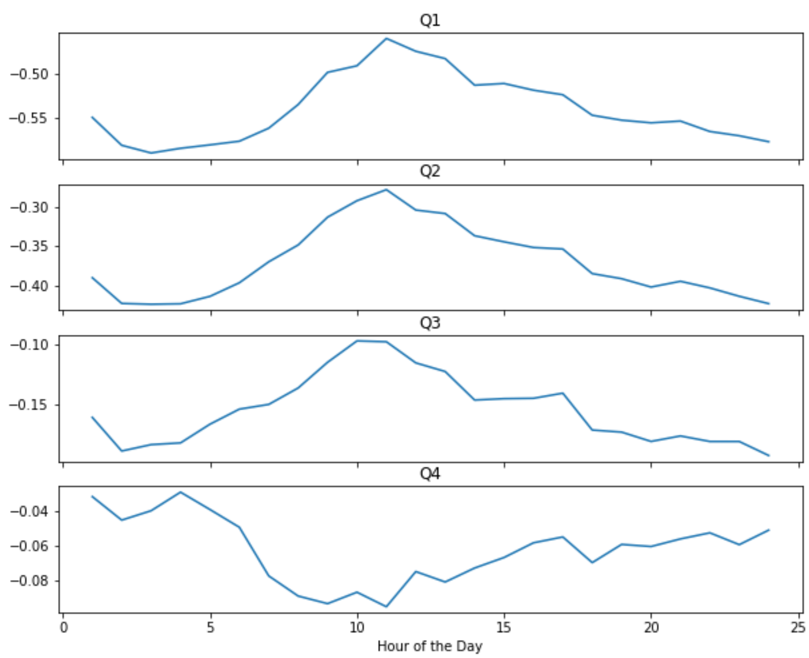


Figure A.12: Intraday Seasonality of Order Imbalance (Binance vs Coinbase Pro)

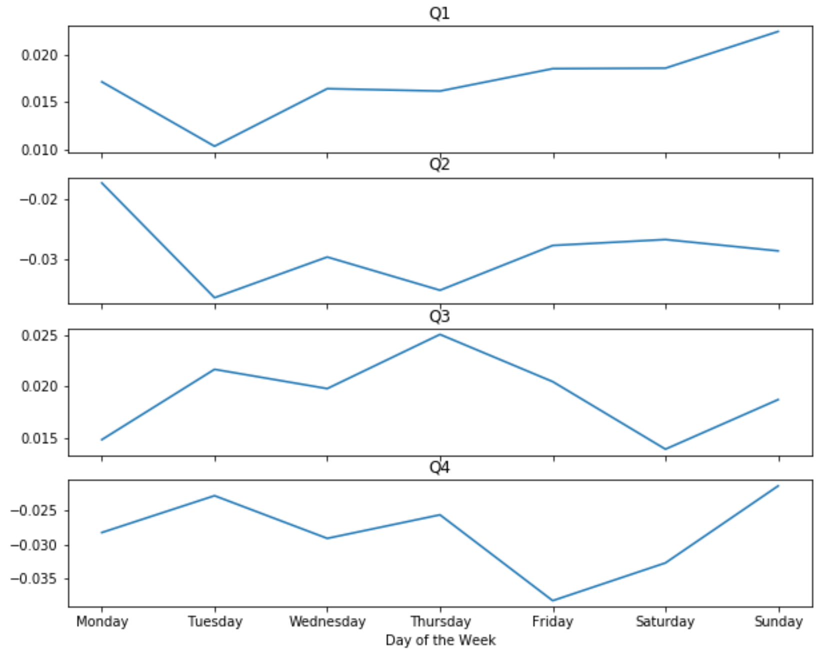


a) Binance

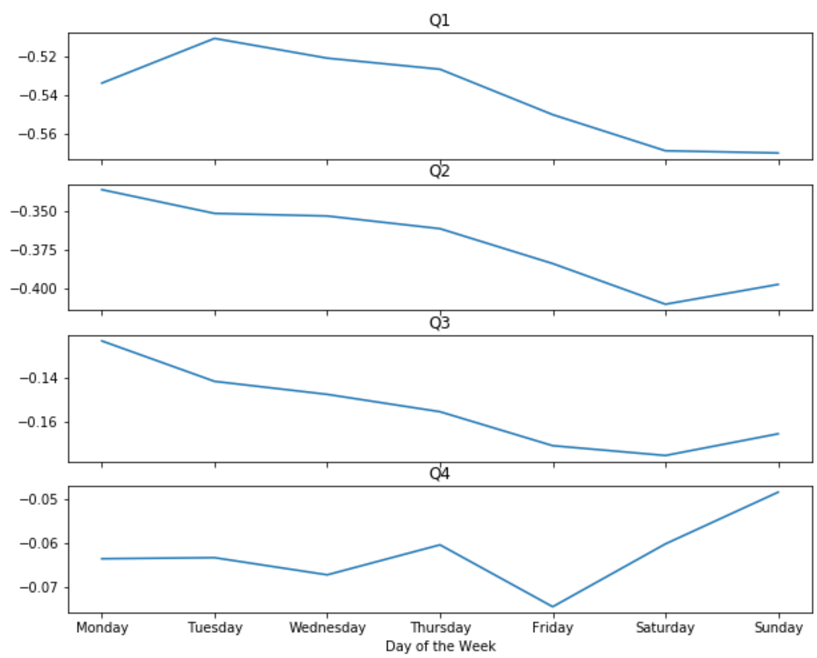


b) Coinbase

Figure A.13: Intrweek Seasonality of Order Imbalance (Binance vs Coinbase Pro)



a) Binance



b) Coinbase

Figure A.14: Seasonality of Average Bitcoin Returns (Coinbase Pro vs Binance)