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Trading patterns in the bitcoin market

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ABSTRACT

Despite the growing literature on Bitcoin and other cryptocurrencies, we know relatively little about who are involved in trading, transacting and using these assets and how they behave. Examining millions of Bitcoin transaction records, we show that less than 1% of Bitcoin users contribute to more than 95% of the market volumes. These 'whales' are often associated with strategic trading/transaction volumes, market reactions and timing patterns. Using K-means clustering on a comprehensive transaction dataset, we establish a typology of traders by learning their trading exchange patterns, strategies and impact risk and market microstructure. Our approach 'learns' and identifies five distinct groups or types of Bitcoin users, which are somewhat, though not entirely, comparable to popular categorisations used in conventional market such as fundamental, technical, retail and institutional traders as well as market makers. Four of these groups present distinguishable trading patterns with a strong impact on liquidity provision and trading signals.

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1. Introduction

As a cryptocurrency by design, the core function of Bitcoin was meant to be a medium of exchange similar to any conventional currency. However, this functionality has not materialized in full to date. Hence, Bitcoin has instead assumed the role of an investment and, particularly, speculative asset (Duan et al. 2021). The speculative behaviour of Bitcoin has been documented in both regulatory reports (e.g. Wolla 2018) and academic literature (see, inter alia, Bouoiyour and Selmi 2015; Cheah and Fry 2015; Li, Sakkas, and Urquhart 2022).

The dramatic rise in the price of Bitcoin through most of its life so far has attracted many unsophisticated investors. The addresses[1] recorded in our data sample show the number of Bitcoin traders jumped from 353 million since the beginning of 2018 – which marks the end of the 2017 bubble – to around 776 million by the end of January 2021. Moreover, Bitcoin price became far more volatile after 2017 following a temporary collapse at around \$3000, the price surged again and exceeded its previous historical record of \$20, 000 and reaching close to \$70, 000 in November 2021. This considerable initial rise, dramatic fall and subsequent sharp rebound in prices, within a span of only a few years, has attracted much academic attention (Shen, Urquhart, and Wang 2020; Urquhart 2017) to spark debates on whether Bitcoin is the safe haven it was once assumed to be.

The Bitcoin trading platforms are not typically well regulated. The direct implication of this is that while investors enjoy the flexibility, convenience, low cost and easy access to trading and transactions, they are exposed to high risks such as hacking and other cyber risks. This leads to price, spreads and volume irregularities across different exchanges. For instance, the 'bid-ask spreads' of Bitcoin at CoinBene have been often much higher than Coinbase at the same time.[2] Thus, the price formation of Bitcoin may not coincide with the the classic asset pricing theories and model forecasts. In contrast, the transactions are the true records of the address activities, trade sizes and market volumes etc., reflecting orders (buy and sell) and trades that imply the demand and

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supply of the crypto currency. In other words, the transaction records could demonstrate how Bitcoin users go about using this cryptocurrency (e.g. exchanging goods, investing). Therefore, any distinctive behaviour patterns revealed from the transaction records would be highly informative and telling on how the real 'prices' are formed and evolving.

We conduct some preliminary check and identify that, among all Bitcoin addresses, the top active ones that are associated with high level of transactions only account for a small proportion, effectively less than 1%. Most of these addresses were registered after 2017. For example, the most active address (id: *1HckjUpRGcrrRAtFaaCAUaGjsPx9oYmLaZ*) appeared on 2017/10/28 (block #492078) and maintains an average of 87, 123.88 transactions per month with the total transactions of 3, 484, 955. In contrast, over 91.22% (70, 790, 2731 out of 776, 059, 989) addresses have no more than 2 transactions in total and the majority of them have been inactive for years. We notice that the majority of Bitcoin traders (addresses) appear to be casual traders while a fraction of large addresses appear to be exceptionally active and dominant.

Many artifacts show that the decentralized infrastructure and high risk profile of the Bitcoin market can yield speculative opportunities and market inefficiencies. In this context, our paper aims to examine the behavioural fingerprint of each transaction and to learn trader types active in the market, thus filling a gap in our understanding of clear identity of Bitcoin users and market participants and the structure and decomposition of this important yet cryptic market. In other words, we aim to study the heterogeneity among Bitcoin traders[3] and explore how many distinct types of Bitcoin market participants exist, thus impacting the microstructure of the Bitcoin market. To accomplish this, we apply the K-means algorithm, an unsupervised machine learning algorithm that allows us to cluster traders according to distances of their (trading/transaction) feature vectors. This analysis provides more in-depth understanding of Bitcoin investors following the recent work (Dubey 2022; Karaa et al. 2021; Wang et al. 2022; Wüstenfeld and Geldner 2022) that verified the use of similar strategies in both Bitcoin and equity markets, such as technical analysis, positive feedback trading and fundamental factor analysis. Similar time-series and market microstructure properties mentioned in Panagiotidis, Stengos, and Vravosinos (2019), Wang, Liu, and Hsu (2020) and Detzel et al. (2021) also indicate potential linkage or similarity of investor compositions across Bitcoin and the classic financial markets.

Through mining millions of the transaction records and testing their features, we robustly distinguish five trade behaviour types (#1 to #5) of investors with each demonstrating strong and unique trade features. We further study their trade behaviour features and find that, more interestingly, they echo, to some extent, the classifications of equity traders.[4] For instance, we identify a huge proportion of casual, low volume trading activities among the transaction records that match well with what retail traders would normally do – buying and selling randomly (type #1). In the market microstructure literature, these traders are often considered to be uninformed and price takers. In contrast, the small percentage of extremely active addresses have highly concentrated transaction volumes and short intervals (type #5). To an extent, they behave similarly to high-frequency equity traders who arbitrage on cross-market price differences and adopt sophisticated trading strategies. Thus, these traders tend to dominate the price discovery over the non-sophisticated traders because of their information and speed approaches (Dao, McGroarty, and Urquhart 2018). Another study (Manahove and Urquhart 2021) also concluded the dominance of HFTs in the Bitcoin market. Yet, another group of traders remain active but trade less often and deal, usually, with large volumes per transaction (type #3). This reminds us of institutional traders given they appear to be better informed traders and liquidity takers.

Our findings contribute to finance and fintech literature in a three ways. *Firstly*, we directly study the user behaviour of all individuals (addresses) involved in the Bitcoin network, and in doing so, extend the work of Urquhart (2017) and Shen, Urquhart, and Wang (2020) among others. In fact, we find that the unique characteristics of Bitcoin market participants are highly indicative of their involvement in the market (e.g. type #5). *Secondly*, we draw parallels between Bitcoin behaviour patterns and typical and popular equity trading characteristics, an area which has not been explored in depth in the emerging literature on cryptocurrencies. *Thirdly*, we show how one can identify risk exposures in this market so that effective regulatory regimes could be put in place.

The rest of the paper is organized as follows. Section 2 reviews existing work on the Bitcoin or wider cryptocurrency market. We then explain the use of K-means algorithm in Section 3. Section 4 discusses the output of the model and presents five preliminary trade classes. Section 5 provides some case studies associated with these findings, and Section 6 concludes.

2. Theoretical framework

It has been more than a decade since the emergence of Bitcoin as the first major cryptocurrency and this market has accumulated a considerable volume of research on both the technological aspects of Bitcoin blockchain and its economic functions as a financial asset. The clear growth in Bitcoin trading and mining and its distributed finance features have provided a novel setting for researchers to better understand the drivers of trading behaviour.

Bitcoin trading possesses many features that market microstructure theories can interpret. For instance, Manahove and Urquhart (2021) found evidence that the Bitcoin market is populated by HFTs alike and substantial trading volumes seem to come more from those who trade at higher frequency (e.g. 1-min) than those who are slower (e.g. 5-min). In contrast, infrequent traders are noticed to absorb liquidity shocks by delaying their transactions (see Li, Sakkas, and Urquhart 2022; Shen, Urquhart, and Wang 2022). Shen, Urquhart, and Wang (2022) examined the Bitcoin trading activity during general 'business hours' and found some seasonality, with the first half-hour predicting the last half-hour return and the volume during the first trading session appear to be the highest (also see Li, Sakkas, and Urquhart 2022). These present strong evidence of the intraday momentum driving trading in the Bitcoin markets. Li et al. (2021) further validated the 'MAX momentum' effect and concluded that the magnitude of Bitcoin price momentum is associated with investor sentiment.

Cryptocurrencies have also received much attention from a market efficiency and asset pricing perspective. Shen, Urquhart, and Wang (2020) conducted a simple three-factor model, considering more than 1700 cryptocurrencies' returns against their capital-weighted market portfolio, size and reversal factors. They find a size effect that smaller cryptocurrencies tend to obtain higher returns and a stronger reversal effect for smaller cryptocurrencies. Urquhart (2016) also pointed out inefficiency in this market in early years between 2010 and 2016. Although the market efficiency improves as this new investment continues, this market still did not conform to weak-form efficiency. In fact, Cheung, Roca, and Su (2015) and Cheah and Fry (2015) found evidence of both short-lived and persistent bubbles in the Bitcoin market; and Fry and Chea (2016) argued the Bitcoin and other cryptocurrencies are characterized by negative bubbles.

Apart from the evidence of momentum trading mentioned above, it has been shown that many traders opt for classic trading strategies established on inefficient and imperfect markets. For example, Hudson and Urquhart (2021) stated that there are more than 15,000 technical trading rules adopted in cryptocurrency trading, which resulted in fierce competition, data-snooping and higher break-even transaction costs for the crypto traders who subsequently would demand higher risk-adjusted returns. The intraday price dynamics documented in Eross et al. (2019) have been used to develop hedging tools (see Urquhart and Zhang 2019) or portfolio formation (see Platanakis and Urquhart 2019, 2020). On the other hand, the long-term information efficiency is related to a wider scope of market segmentation. For instance, Duan et al. (2021) analysed various currency-against-Bitcoin price pairs and confirmed their features present fractional cointegration that could provide cross-market statistical arbitrage opportunities, suggesting that the Bitcoin market efficiency is also populated by the non-HFTs.

Often the cryptocurrency prices show clustering effects, jumps and even structural breaks (Shen, Urquhart, and Wang 2020; Urquhart 2017), which makes the risk profile of such financial instrument more complex. Both economic uncertainty and trading behaviours contribute to Bitcoin market risks, intensify the contagion effect and possibly cause price crashes (Bouri et al. 2017; Corbet et al. 2019). Sentiment-driven trading is a common behaviour factor in crypto markets (Corbet et al. 2020; Kalyvas et al. 2021), which is also verified by Shen, Urquhart, and Wang (2019) as a factor to realize volatility and trading volume fluctuation. While another study by Urquhart (2018) also pointed out that social media trends, albeit sometimes attract investors to trade Bitcoin, do not always have predictive power for the realized volatility or returns.

3. Classification of trade behaviour

As mentioned above, the Bitcoin market is liquid with increasing popularity in recent years. While comparing with traditional capital markets, we notice some apparently uncommon 'trade habits'. There are many 'taster traders', who, maybe out of curiosity, try very few Bitcoin transactions before disappearing from this market.

Some other users seem to enter the Bitcoin transactions with specific purposes but only engage with a handful of trades. Regardless of these disengaged traders, we are interested in behaviour patterns for those who are actively engaged with the Bitcoin market, especially those behave as if they are likely involved in active Bitcoin investment. Our findings enable us to believe there are stereotypes of Bitcoin users who exhibit trading characteristics and patterns alike the value investors, technical traders, HFTs, etc. in stock markets; and it is such a behaviour pattern making them distinguishable. To find these 'stereotypes', in this paper, we use the K-means algorithm to do a preliminary classification. We then further analyse the classification results to solve two problems: (1) to identify and screen out the disengaged traders; (2) to present descriptive features of trade/transaction activities for each active trader types.

3.1. K-means clustering algorithm

K-means is an unsupervised classification algorithm. The rational is to group observations with shorter distances into the same class so that they can be distinguished from those far away. In this algorithm, each observation $\{X_i : i = 1, 2, \dots, n\}$ is described by a feature vector

$$X_i = \left(x_{i,1}, x_{i,2}, \dots, x_{i,m}\right),$$

where m counts the total features. We use the Euclidean distance measure (Equation 1) for our classification.

$$\mathcal{D}(X, Y) = \sqrt{\sum_{k=1}^{m} \left(x_k - y_k\right)^2} \tag{1}$$

where $(x_1, x_2, \dots, x_m)$ and $(y_1, y_2, \dots, y_m)$ are the feature vectors of X and Y, respectively. Assume we group observations into K classes and denote the classes as $\{\mathcal{C}_k : k = 1, 2, \dots, K\}$. Each class is a set of observations, i.e. $X_i \in C_k$ means the ith observation is in the kth class. Each class $\mathcal{C}_k$ has a centroid O_k defined as the average feature vector of all observations in the class (see below).

$$O_k = \frac{1}{\sum_i \mathbf{1}_{\mathcal{C}_k}(X_i)} \sum_i \mathbf{1}_{\mathcal{C}_k}(X_i) X_i, \quad k = 1, 2, \dots, K \tag{2}$$

where $\mathbf{1}_A(x)$ is a binary function defined as

$$\mathbf{1}_A(x) = \begin{cases} 1, & \text{if } x \in A \\ 0, & \text{otherwise} \end{cases}.$$

The K-means algorithm starts with K randomly sampled classes. Then each observation is assigned to the class with the closest centroid so that new classes are grouped. This process will iterate until there is no update to the classification. We write this process in Algorithm 1.[5]

3.2. Data

While Bitcoin blockchain data are publicly available and can be obtained by running a Bitcoin node, we obtain the data from Cardiff University Bitcoin Database (CUBiD) that process and structure the raw Bitcoin blockchain data into two data layers: the original blockchain data and the post processed address-level data.[6] This study uses the fist layer that includes information of all blocks and transactions. It is worth noting that there is no transaction time in Bitcoin data because transactions are only recognized until being verified in a block. The only timestamp of the transaction is the time that the block is mined (also called block time).

We know that, theoretically, the blockchain system ensures that mining one block takes on average 10 minutes – approximately 144 blocks per day. We examine the block arrival time using data from January 2018 to January 2021, during which the Bitcoin network has high liquidity and stable hash rate[7]. We fit the block time intervals

Algorithm 1: K-means clustering algorithm

Data: $X = \{X_i : i = 1, 2, \ldots, n\}$
Result: $\mathcal{C} = \{\mathcal{C}_k : k = 1, 2, \ldots, K\}$
Input : The number of classes K, the termination condition $\epsilon = 1e - 8$
Output: $\{\mathbf{1}_{\mathcal{C}_k}(i) : i = 1, 2, \ldots, n$ and $k = 1, 2, \ldots, K\}$

$e \leftarrow 1e8$ `// initialize a large distance between centroids`

for $i \leftarrow 1$ **to** n **by** 1 **do**
  $l \leftarrow \mathrm{RandInt}(1, K)$ `// randomly select a class`
  $$\mathbf{1}_{\mathcal{C}_j}(i) = \begin{cases} 0, \&\text{if } j = l \\ 1, \&\text{otherwise} \end{cases}, \; j = 1, 2, \ldots, K$$
end

`/* iterate over all classes */`
for $k \leftarrow 1$ **to** K **by** 1 **do**
  $O_k = \frac{1}{\sum_i \mathbf{1}_{\mathcal{C}_k}(i)} \sum_{X_i \in \mathcal{C}_k} X_i$
end

`/* loop until the centroids of newly developed clusters stay the same */`
while $e \geq \epsilon$ **do**
  for $i \leftarrow 1$ **to** n **by** 1 **do**
    `/* iterate over all observations */`
    $\tilde{l} = \arg\min_k \mathcal{D}(X_i, O_k)$
    `// update to the closest class`
    $$\mathbf{1}_{\mathcal{C}_j}(i) = \begin{cases} 0, \&\text{if } j = \tilde{l} \\ 1, \&\text{otherwise} \end{cases}, \; j = 1, 2, \ldots, K$$
  end
  `/* update all class centroids */`
  for $k \leftarrow 1$ **to** K **by** 1 **do**
    $\tilde{O}_k = \frac{1}{\sum_i \mathbf{1}_{\mathcal{C}_k}(i)} \sum_i \mathbf{1}_{\mathcal{C}_k}(i) X_i$
  end
  $e = \mathcal{D}(O_k, \tilde{O}_k)$ `// update the distance between centroids`
  $\boldsymbol{O} = \tilde{\boldsymbol{O}}$ `// update centroids`
end

to an exponential distribution and Figure 1 shows a good fitness of the model with an intensity parameter of 9.33 minutes, close to on average 10-minute per block. We also confirm that the block arrivals follow a Poisson process, which is consistent with the design of the Bitcoin blockchain system.

As the unverified Bitcoins are restricted to be further traded and likely to be cancelled, we believe that only verified transactions are meaningful in understanding clearing and price formation in the market. In this sense, we regard the block time as the transaction time in this study.

We collect the transactions associated with all addresses that joined the Bitcoin market before 2021-01-31 and/or traded from 2018-01-01 to 2021-01-31. We show the new address arrival rate in the Bitcoin market in Figure 2. Generally, the trend is trivial.

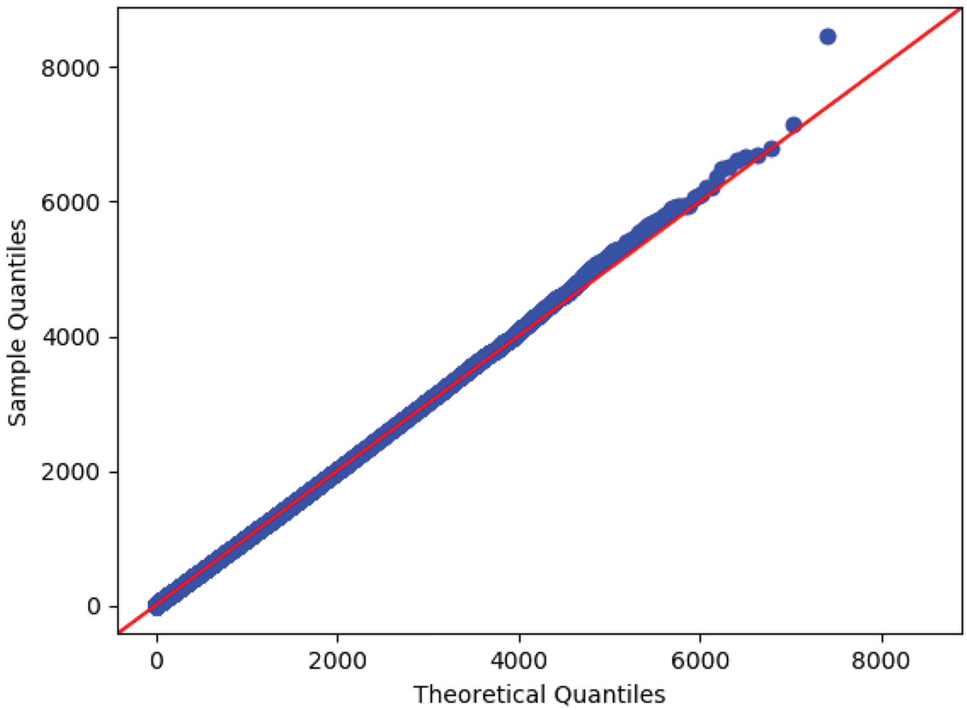


Figure 1. QQ plot: Block time intervals fitting to a exponential distribution (intensity = 9.33 minutes).

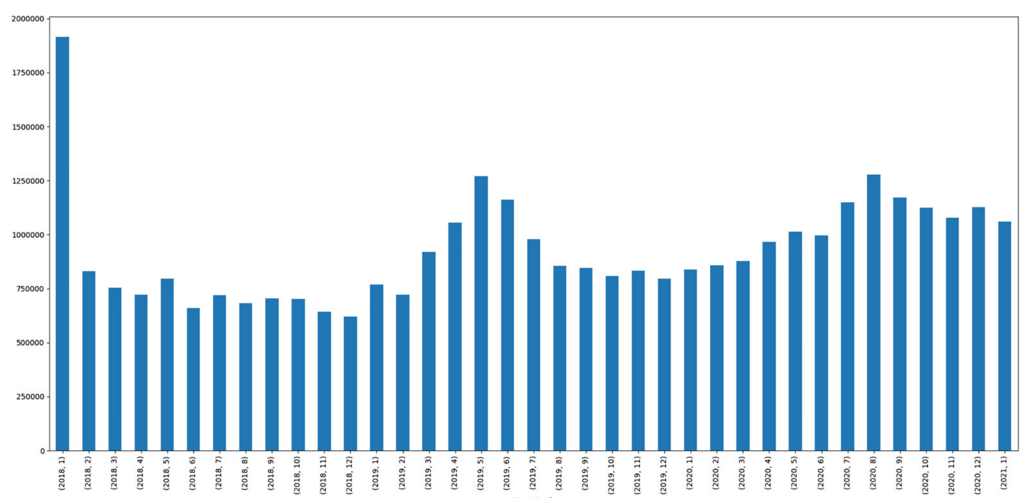


Figure 2. Number of new traders in the Bitcoin market.

3.3. Bitcoin user/trader features

To achieve the objective of Bitcoin user/trader classification, we need to compute address-level features for inputs of the K-means algorithm. Although one trader may have multiple addresses with similar or completely different trade profiles, we do not consider mapping addresses to individuals in this study.[8] In other words, we equivalent the concept of 'trader' and 'Bitcoin address' in this paper. This assumption will not affect the trader type classification or analysis of the linkages to equity markets.

We create an address-level dataset using Bitcoin transaction data for this experiment. In this dataset, we denote the start and end date as D_s and D_e, respectively, including M blocks, N transactions and n addresses in total. In addition, we aggregate the following information.

- $N^{(i)}$ the number of transactions for address i.
- $M^{(i)}$ the number of blocks that address i had transactions.
- $D_j^{(i)}$ the block date of jth transaction for address i.
- $T_j^{(i)}$ the block time of jth transaction for address i.
- $\Lambda_{D,k}^{(i)}$ number of transactions of address i in day k.
- $\Lambda_{W,k}^{(i)}$ number of transactions of address i in week k.
- $\Lambda_{M,k}^{(i)}$ number of transactions of address i in month k.
- $H^{(i)}$ the number of days from address i's first transaction block date to the end date of the dataset defined as the number of days. In short, we call it 'lift time' of address i.

$$H^{(i)} = D_e - D_1^{(i)}, \quad i = 1, 2, \ldots, n.$$

- $\Delta T_j^{(i)}$ the time interval from the $(j-1)$th to the jth transaction of address i.

$$\Delta T_j^{(i)} = T_{j+1}^{(i)} - T_{j-1}^{(i)}, \quad j = 1, 2, \ldots, N^{(i)} - 1 \quad \text{and} \quad i = 1, 2, \ldots, n.$$

We define 12 features for K-means classification inputs in Table 1. Note that all features are statistics in address level. We do not count the value involved in transactions in any of these features. This is because we think the value is mainly decided by the wealth of a trader, not his/her 'trade strategy'. But we do examine transaction values in the case study of selected addresses in Section 5 to understand better about specific investment applications. In the features we defined, the first four are related to trade frequency. This is the simplest way to distinguish traders. In general, Bitcoins are not traded in a high frequency. Apart from trade frequency, we also want to see whether a trader is trading with a good level of consistency (e.g. to trade every week) or strategically entering/exiting the market (e.g. to conduct several speculative trading in a week then wait for months for another opportunity). This is described by *MedIntv*, *RangeIntv* and *StdIntv* from different perspectives using statistics of transaction intervals. The rest of features are related to life time of an address.

4. Five trader stereotypes

To get valid features to process the K-means classification and sufficient observations for trade pattern identification, we only include addresses that had more than 10 transactions and were traded in the market in more than 3 different weeks. After screening, 6,108,128 addresses are involved in the classification experiment.

4.1. Selection of K

We examine the selection of K for the K-means classification using the 'the elbow method'. In this method, we calculate the within-cluster-sum of squared error (WSS) defined below.

$$WSS(K) = \sum_{k=1}^{k=K} \sum_{i=1}^{n} \mathbf{1}_{\mathcal{C}_k}(X_i) \mathcal{D}(X_i, O_k)^2$$

In Figure 3, it is clear that from $K = 5$ WSS starts to diminish.

Table 1. Definition of address-level trading features.

	Feature	Equation
1:	Number of transactions per block (in logarithm scale).	$CntTransB_i = \frac{N^{(i)}}{M^{(i)}}$
2:	Average number of transactions per day (excluding zero transaction days).	$CntTransD_i = \frac{N^{(i)}}{\sum_k \mathbf{1}_{>0}(\Lambda^{(i)}_{D,k})}$
3:	Average number of transactions per week (excluding zero transaction weeks).	$CntTransW_i = \frac{N^{(i)}}{\sum_k \mathbf{1}_{>0}(\Lambda^{(i)}_{W,k})}$
4:	Relative standard deviation of the number of transactions per week (excluding transaction weeks).	$StdCntTransW_i = \frac{\sqrt{\frac{\sum_k (\Lambda^{(i)}_{W,k} - CntTransW_i)^2}{\sum_k \mathbf{1}_{>0}(\Lambda^{(i)}_{W,k})}}}{CntTransW_i}$
5:	Median of transaction time intervals (in weeks).	$MedIntv_i = \frac{\mathrm{Med}_j(\Delta T^{(i)}_j)}{60 \cdot 24 \cdot 7}$
6:	Average transaction time intervals (in weeks).	$MeanIntv_i = \frac{1}{N^{(i)} - 1} \sum_{j=1}^{N^{(i)}-1} \frac{\Delta T^{(i)}_j}{60 \cdot 24 \cdot 7}$
7:	Relative range of transaction intervals.	$RngIntv_i = \frac{\max_j \Delta T^{(i)}_j - \min_j \Delta T^{(i)}_j}{MeanIntv_i}$
8:	Relative standard deviation of transaction intervals.	$StdIntv_i = \frac{\sqrt{\frac{\sum_j (\Delta T^{(i)}_j - MeanIntv_i)^2}{N^{(i)} - 1}}}{MeanIntv_i}$
9:	Active time ratio.	$ActTime2L_i = 100 \times \frac{D^{(i)}_{N^{(i)}} - D^{(i)}_1}{H^{(i)}}$
10:	Transaction days to life time ratio.	$TransD2L_i = 100 \times \frac{\sum_k \mathbf{1}_{>0}(\Lambda^{(i)}_{D,k})}{H^{(i)}}$
11:	Transaction weeks to life time ratio.	$TransW2L_i = 100 \times \frac{\sum_k \mathbf{1}_{>0}(\Lambda^{(i)}_{W,k})}{H^{(i)}/7}$
12:	Transaction months to life time ratio.	$TransM2L_i = 100 \times \frac{\sum_k \mathbf{1}_{>0}(\Lambda^{(i)}_{M,k})}{H^{(i)}/30}$

Table 2. Summary of Bitcoin trader types.

Class	Num. of addr.	Trader category	Matches to 'stereotypes'
1	2, 089, 694	Bitcoin tasters	NA
2	2, 101, 244	Liquidity takers	Fundamental traders
3	1, 023, 726		Technical traders
4	566	Liquidity providers	Market makers
5	269		High-frequency traders

4.2. Trader classes and their conventional parallels

As the K-means algorithm starts with a randomized classification, the results may vary when using different random seeds. To observe robust components of each trader class, we run the algorithm 10 times and collect consistent classifications. Finally, we find that 5,215,499 (out of 6,108,128) addresses have the same classification throughout all runs.

According to the centroid vectors of K-means clustering (see Table 3), we find some clear characteristics of traders in each class and are able to associate some of them with typical types of traders in the traditional financial market (summarized in Table 2). Note that we 'name' the trader classes based on the centroid.

The Class #1 centroid indicates that this class is, in general, not active. Traders in this class only contribute a few transactions – 1 transaction per block and 2 transactions per active day (see Table 3(a)); only having exchanges/transactions in the first 20.07% of time after joining in the market (see Table 3(c)). The deviation of

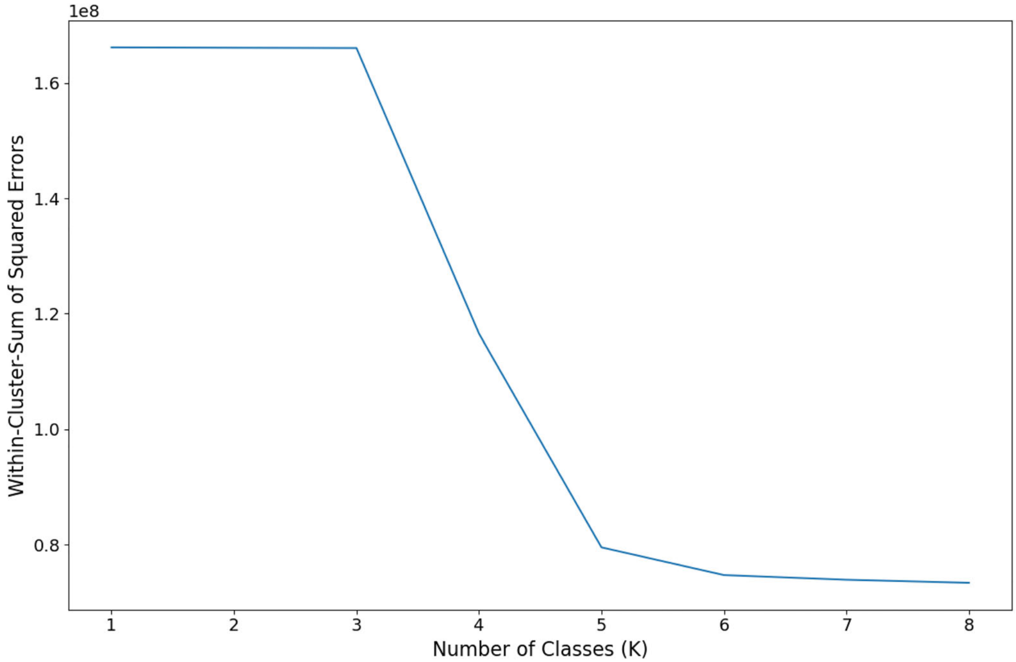
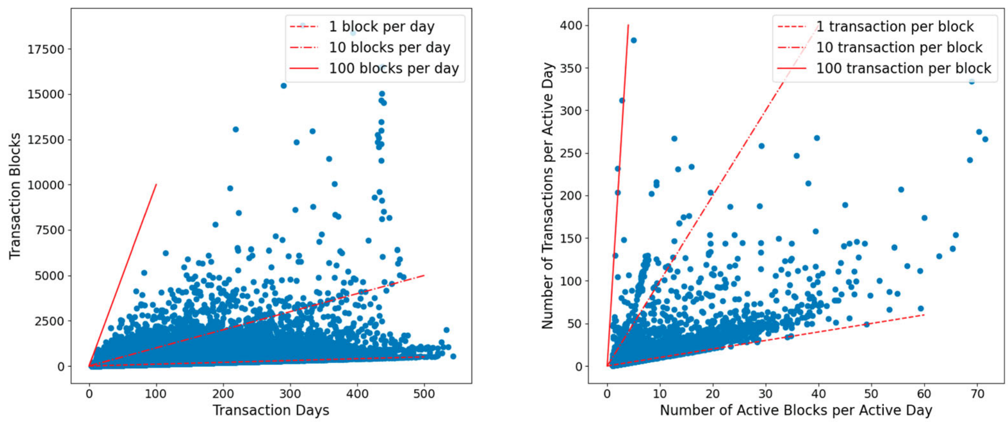


Figure 3. WSSE for *K* selection.

Table 3. K-means clustering results.

(a) Trading frequency features				
Class	*CntTransB*	*CntTransD*	*CntTransW*	*StdCntTransW*
1	1.07	2.00	4.28	0.53
2	1.04	1.71	3.01	0.49
3	1.05	1.85	4.66	0.57
4	2.08	70.38	389.43	0.82
5	13.95	560.35	2569.68	0.85
(b) Waiting time features				
Class	*MedIntv* (Days)	*MeanIntv* (Days)	*RngIntv*	*StdIntv*
1	1.57	7.27	8.92	1.87
2	3.21	22.36	13.72	2.33
3	2.24	4.86	13.04	1.74
4	0.02	0.14	1893.16	27.01
5	0.01	0.11	366.16	8.89
(c) Active trading features				
Class	*ActTime2L* (%)	*TransD2L* (%)	*TransW2L* (%)	*TransM2L* (%)
1	20.07	3.07	10.24	19.38
2	72.65	4.63	17.84	39.56
3	88.37	21.24	61.90	88.53
4	72.35	34.13	40.68	48.11
5	31.24	24.61	28.04	33.05

waiting time is small, e.g. *RngIntv* is 8.92, which also tells us that transactions occur with a consistent 'rhythm', e.g. one trade per day, without an indication of information-based trade decisions. Traders in this class are not really engaging in Bitcoin trading and transactions and behave like 'tasters'. We call this a casual trader class.



(a) (b)

Figure 4. Class #2 behavioural specifics. (a) Active blocks vs. Active days and (b) Number of transactions vs. Active blocks.

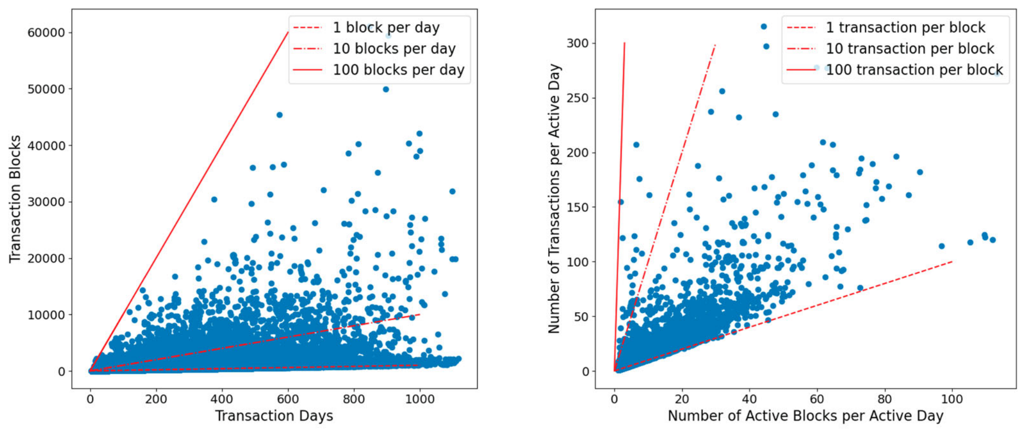
Class #2 and #3 achieve much longer engaging time *ActTime*2*L* than the casual traders (see Table 3(c)). As these traders persistently trade, they take and consume liquidity in the Bitcoin market. These two classes do not show clear differences in terms of number of transactions in the long run (see Table 3(a)), while the average waiting time *MeanIntv* and active days *TransD*2*L* may indicate two different trading strategies. Class #2 traders hold positions for longer time, on average 22 days (see Table 3(b)) so that a trader in this class only trade 4.63% of their 'life time' (see Table 3(c)). It is very likely that these traders attempt to make profits by chasing long-term Bitcoin price movements and trade in relatively low frequency, like fundamental traders in the stock market. On the other hand, traders in Class #3 keep faster turnover with an average position holding no longer than 5 days (see Table 3(b)) and actively engage and transact in 21.24% of days in their 'life time'. We think traders in this class may rely on trading signals of some short-term momentum and reversal strategies, similar to technical traders.

Class #4 and #5 have high level of daily transactions *CntTransD* and extremely high trade frequency *MeanIntv*, especially Class #5 (see Table 3(a,b)). It is not unreasonable to assume most users in these categories are direct Bitcoin traders and investors. Note that due to mining time constraints, trading frequencies in the Bitcoin market cannot be as high as that in the stock market. There is an obvious gap in volumes of these two classes. Class #5 trades consistently everyday with low *ActTime*2*L*, which may be an indication of professional intraday trading strategy and techniques of switching address to hide their trading intention – similar to HFTs. Class #4 traders are more like a classic market maker (e.g. specialists in stock exchanges) who only function when the market liquidity is low.

We further observe how traders behave in each class in active days (see Figures 4–7). We find that traders in Classes #4 and #5 are generally more active. Most of them trade in $10 \sim 100$ blocks in a day, compared with fewer than 10 blocks for traders in the other two classes. There are even some traders in Class #5 achieved trading in more than 100 blocks in a day (see Figure 7(a)). Meanwhile, we also observe that number of transactions in a block is consistent across all classes. Hence, the much higher trading frequency of Classes #4 and #5 is mainly due to engagement in more blocks per day rather than achieving high number of transactions per block. In other words, traders are less likely to achieve high-frequency trading in the Bitcoin market as if in equity markets. This should be a Bitcoin market microstructure characteristic associated with the design of its mining mechanism.

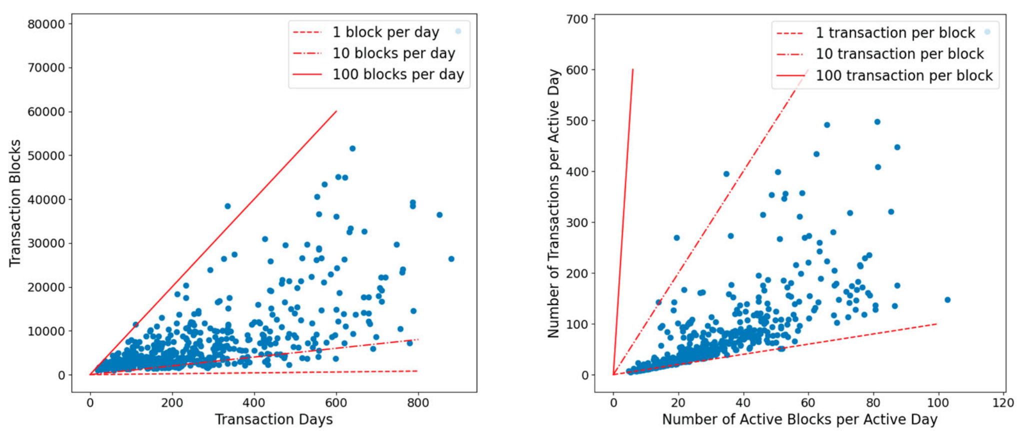
5. Some case studies

We look into a few cases in each stereotype traders to observe trading strategies more precisely. We plot the number of transactions, Bitcoin sent and received and Bitcoin positions of each trader in the life time. We pick the representative trader from each class whose feature vector is the closest to the centroid.



(a) (b)

Figure 5. Class #3 behavioural specifics. (a) Active blocks vs. Active days and (b) Number of transactions vs. Active blocks.



(a) (b)

Figure 6. Class #4 behavioural specifics. (a) Active blocks vs. Active days and (b) Number of transactions vs. Active blocks.

We show a Class #2 trader in Figure 8. The trader only enters the market a few times a year and the trading volume is low. The trader tends to hold the Bitcoins for a few months for capital increase.

In Figure 9, we observe that the Class #3 trader trades a few times every week. The trader watches the market closely. According to the transaction records in 2019, the trader increased holding of Bitcoin gradually in bull market and successfully cleared the positions at the peak.

Class #4 trader had extremely large transactions during 2019 when the Bitcoin market was rather popular and its price rocketed up (see Figure 10). We think this trader contributed large transaction volumes mainly to assist wider trader groups in the market because he kept rather low Bitcoin balance. In other words, the trader performed intraday trading which targets on closing all positions every day.

In Figure 11, we observe that the trader in Class #5 traded in a regular pace, at least once every month. Some balances are held for a few days to weeks. More transactions were attempted when the Bitcoin price is low during

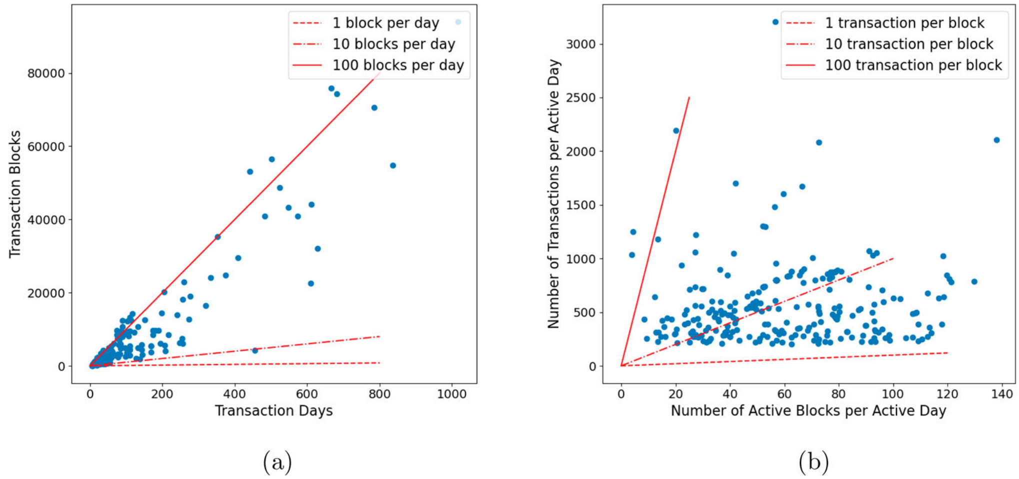


Figure 7. Class #5 behavioural specifics. (a) Active blocks vs. Active days and (b) Number of transactions vs. Active blocks.

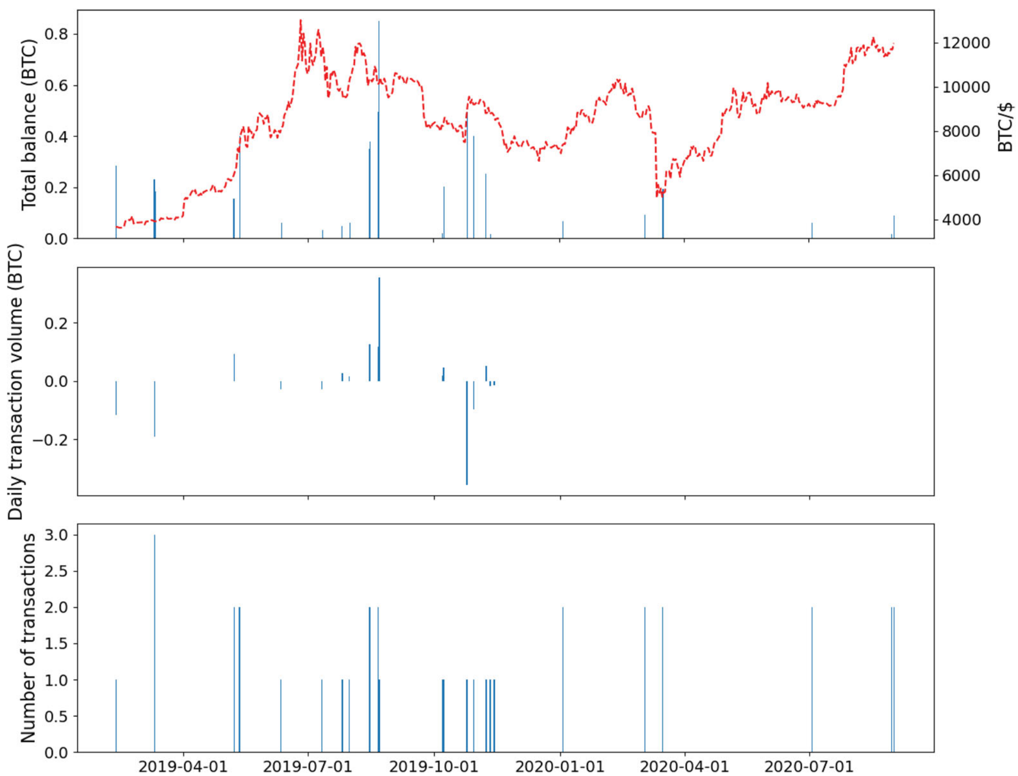


Figure 8. A Class #2 trader case.

early 2020. Although the Bitcoin balance is low regarding the large daily transactions, we can see that this trader strategically and actively invest in Bitcoin for capital increase. This is different from the trader in Class #4 that almost maintained zero balance every day.

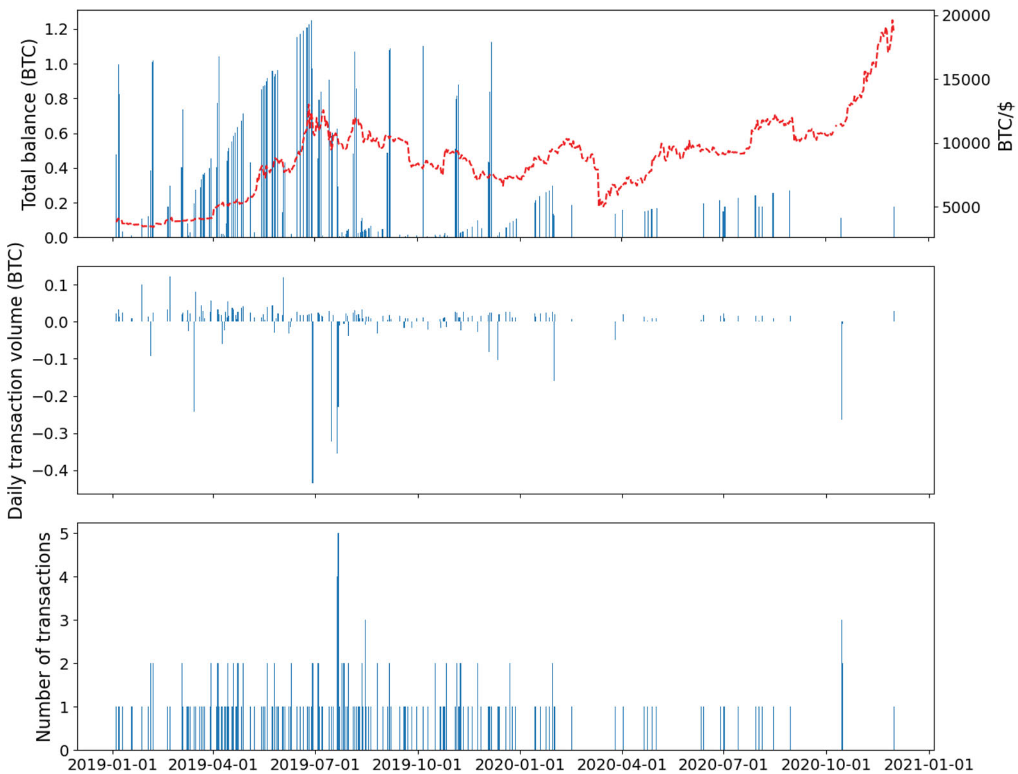


Figure 9. A Class #3 trader case.

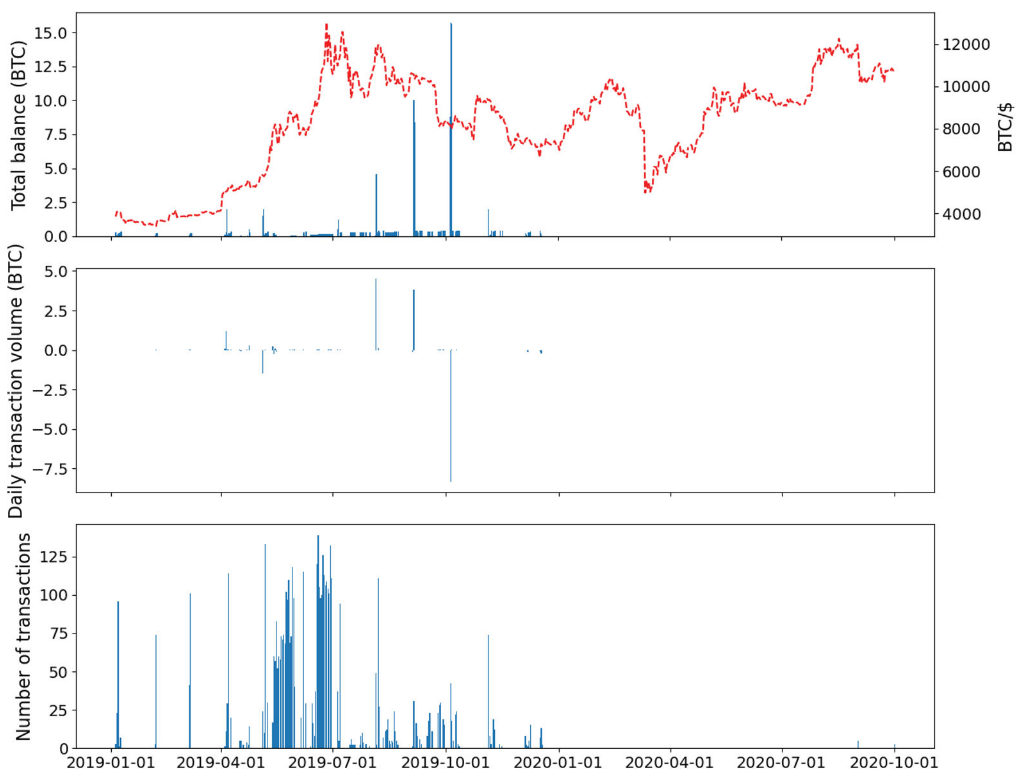


Figure 10. A Class #4 trader case.

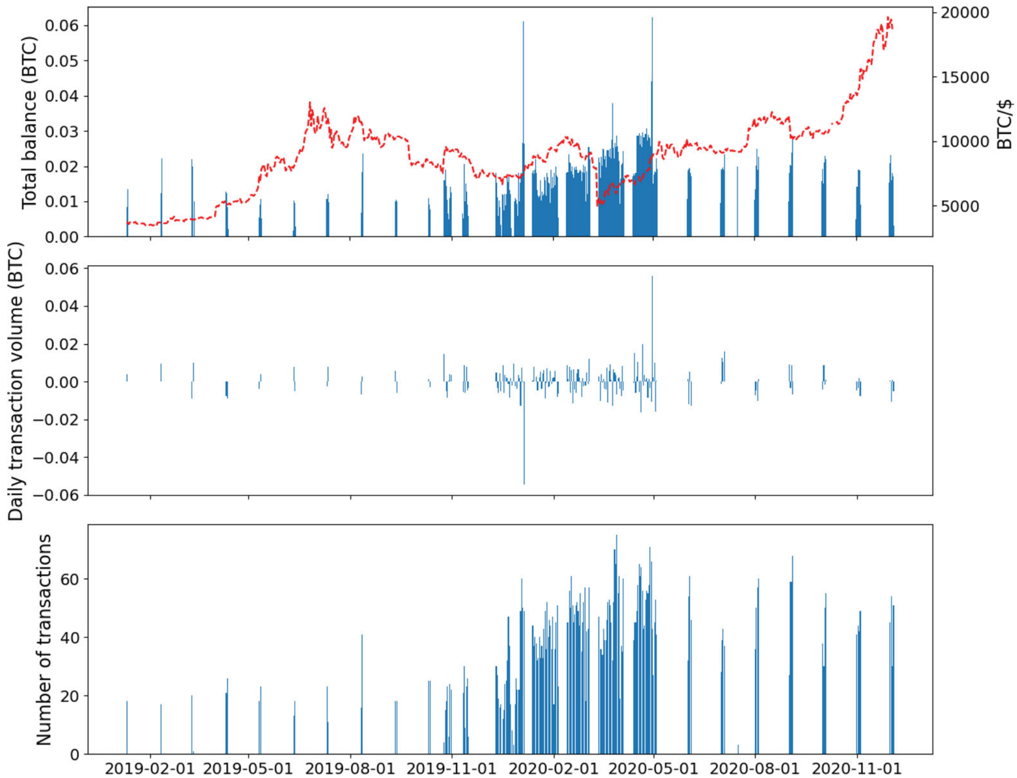


Figure 11. A Class #5 trader case.

6. Conclusion

Our aim is to find an approach to establish robust trader types in the Bitcoin market through recognizing their potentially unique behaviour patterns through transaction and trade features. Consequently, we could shed light on the traders' strategies and their impact on the market such as risk, hedging and the market structure. In particular, we would assume, when a market is full of trading activities, indicators that can approximate market provisions such as liquidity revealed by traders' behaviour would provide significantly insightful information about the market microstructure. For instance, we discuss above that certain types of equity traders exhibit prominent features and, subsequently, introduce the segmentation into the equity trading. Even until this day, debates on whether the high-frequency traders (HFTs) are super liquidity providers that help keep orderly and fair market, or actually predators, are still on-going. Informed and uninformed traders function differently regarding contributing to market liquidity, which would be critical to locate the demand, supply and the trading imbalance in the market. Meanwhile, the informed traders are also known to be categorized by their trading strategies (e.g. information arbitrage, speed arbitrage); uninformed traders tend to trade randomly. In fact, it is the regulatory requirement that the HFTs disclose their trading strategies to the Commodity Futures Trading Commission (CFTC). Bitcoin as the new financial innovation driven heavily by the advanced technology inevitably has resulted in intense trading that could have all these potential impacts from various traders' characteristics. But so far, how their trading behaviour and distinctive typology affecting the market microstructure remain very much a under-explored yet a crucial area.

Understanding the trading behaviour of cryptocurrency network users is important for academic literature and also for the cryptocurrency industry sector and the financial regulators. Knowing the different types of Bitcoin traders active on the network – not only in terms of technical but also behavioural profile such as short-term, long-term, active, passive, high-frequency, etc. – can equip the regulators with important toolkits to prevent speculative or fraudulent behaviour in the market and provide more stability in these networks. This is important for various reasons including protecting vulnerable users who engage with cryptoassets without sufficient background, knowledge and financial cushion to absorb the inherent volatility of such markets.

Notes

1. Note that all Bitcoin traders must get a 'Bitcoin address' for sending and receiving payments.
2. Bitwise Asset Management Presentation to the U.S. Securities and Exchange Commission, Memorandum (File No. SR-NYSE Arca-2019-01).
3. The term of 'Bitcoin traders', 'Bitcoin trading' or 'trades' is loosely used in this paper. It is not designated to Bitcoin investments. Instead, it broadly refers to Bitcoin transactions, trades or exchanges of some kind that associates with both the investment and currency function of a Bitcoin, such as investment (e.g. buying or selling Bitcoin directly), purchasing goods, depositing, etc. Our purpose is to understand how the transactions might indicate visible and distinguishable behaviour patterns of broader Bitcoin users. Our results show distinctive behaviour patterns that demonstrate some strong comparative similarity to popular terminologies such as technical traders in general trading, say stocks. Therefore, we adopt these terms of 'traders', 'trading' and 'trades' so that readers can feel ease to connect to these concepts and findings.
4. To echo how we refer to terms such as 'Bitcoin traders', we emphasize that the five types of Bitcoin groups exhibit similar features to the well-known equity traders'. But we are not suggesting the addresses falling into each Bitcoin type are all directly trading Bitcoin.
5. This algorithm is implemented by the KMeans function in the sklearn Python package. See https://scikit-learn.org/stable/modules/generated/sklearn.cluster.KMeans.html for more details.
6. See Jahanshahloo, Irresberger, and Urquhart (2023) and https://www.cardiff.ac.uk/business-school/resources/cubid for further information on CUBiD data layers and structure and more in-depth analysis of Bitcoin blockchain.
7. Hash rate is a measure of miners' computing power in the Bitcoin network.
8. Bitcoin wallet records may help us identify which addresses belong to the same trader, thus understanding how the individual Bitcoin user/trader receive and spend the Bitcoin and other capital flow related questions etc. In this paper, we aim to identify patterns through transaction patterns that will inform us of the habits of different type of users, thus not using wallet data will not affect our purposes or results, hence we have not included them in our data source.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Appendix. K-means classification centroids: 10 runs

Table A1. Class #1.

	Num	CntTransB	CntTransD	CntTransW	StdTransW	MedIntv	MeanIntv	RngIntv	StdIntv
1	2982323	1.0686	1.9978	4.2762	0.5268	0.2241	1.0379	8.9240	1.8709
2	2982327	1.0686	1.9978	4.2762	0.5268	0.2241	1.0379	8.9240	1.8709
3	2982327	1.0686	1.9978	4.2762	0.5268	0.2241	1.0379	8.9240	1.8709
4	2982313	1.0686	1.9978	4.2760	0.5268	0.2241	1.0379	8.9238	1.8709
5	2982327	1.0686	1.9978	4.2762	0.5268	0.2241	1.0379	8.9240	1.8709
6	2982327	1.0686	1.9978	4.2762	0.5268	0.2241	1.0379	8.9241	1.8709
7	2982327	1.0686	1.9978	4.2762	0.5268	0.2241	1.0379	8.9240	1.8709
8	2982325	1.0686	1.9978	4.2762	0.5268	0.2241	1.0379	8.9240	1.8709
9	2982327	1.0686	1.9978	4.2762	0.5268	0.2241	1.0379	8.9240	1.8709

Table A2. Class #2.

	Num	CntTransB	CntTransD	CntTransW	StdTransW	MedIntv	MeanIntv	RngIntv	StdIntv
1	2101244	1.0447	1.7126	3.0098	0.4910	0.4586	3.1943	13.7232	2.3331
2	2101242	1.0447	1.7126	3.0098	0.4910	0.4586	3.1943	13.7232	2.3331
3	2101242	1.0447	1.7126	3.0098	0.4910	0.4586	3.1943	13.7232	2.3331
4	2101239	1.0447	1.7126	3.0100	0.4910	0.4586	3.1943	13.7234	2.3331
5	2101242	1.0447	1.7126	3.0098	0.4910	0.4586	3.1943	13.7232	2.3331
6	2101242	1.0447	1.7126	3.0098	0.4910	0.4586	3.1943	13.7232	2.3331
7	2101242	1.0447	1.7126	3.0098	0.4910	0.4586	3.1943	13.7232	2.3331
8	2101243	1.0447	1.7126	3.0098	0.4910	0.4586	3.1943	13.7232	2.3331
9	2101242	1.0447	1.7126	3.0098	0.4910	0.4586	3.1943	13.7232	2.3331

Table A3. Class #3.

	Num	CntTransB	CntTransD	CntTransW	StdTransW	MedIntv	MeanIntv	RngIntv	StdIntv
1	1023726	1.0541	1.8482	4.6644	0.5673	0.3195	0.6936	13.0358	1.7397
2	1023724	1.0541	1.8482	4.6644	0.5673	0.3195	0.6936	13.0359	1.7397
3	1023724	1.0541	1.8482	4.6644	0.5673	0.3195	0.6936	13.0359	1.7397
4	1023741	1.0541	1.8482	4.6644	0.5673	0.3195	0.6936	13.0359	1.7397
5	1023724	1.0541	1.8482	4.6644	0.5673	0.3195	0.6936	13.0359	1.7397
6	1023724	1.0541	1.8482	4.6644	0.5673	0.3195	0.6936	13.0359	1.7397
7	1023724	1.0541	1.8482	4.6644	0.5673	0.3195	0.6936	13.0359	1.7397
8	1023725	1.0541	1.8482	4.6644	0.5673	0.3195	0.6936	13.0359	1.7397
9	1023724	1.0541	1.8482	4.6644	0.5673	0.3195	0.6936	13.0359	1.7397

Table A4. Class #4.

	Num	CntTransB	CntTransD	CntTransW	StdTransW	MedIntv	MeanIntv	RngIntv	StdIntv
1	566	2.0798	70.3805	389.4250	0.8151	0.0031	0.0205	1893.1588	27.0081
2	566	2.0798	70.3805	389.4250	0.8151	0.0031	0.0205	1893.1588	27.0081
3	566	2.0798	70.3805	389.4250	0.8151	0.0031	0.0205	1893.1588	27.0081
4	566	2.0798	70.3805	389.4250	0.8151	0.0031	0.0205	1893.1588	27.0081
5	566	2.0798	70.3805	389.4250	0.8151	0.0031	0.0205	1893.1588	27.0081
6	566	2.0798	70.3805	389.4250	0.8151	0.0031	0.0205	1893.1588	27.0081
7	566	2.0798	70.3805	389.4250	0.8151	0.0031	0.0205	1893.1588	27.0081
8	566	2.0798	70.3805	389.4250	0.8151	0.0031	0.0205	1893.1588	27.0081
9	566	2.0798	70.3805	389.4250	0.8151	0.0031	0.0205	1893.1588	27.0081

Table A5. Class #5.

	Num	CntTransB	CntTransD	CntTransW	StdTransW	MedIntv	MeanIntv	RngIntv	StdIntv
1	269	13.9539	560.3478	2569.6837	0.8536	0.0011	0.0161	366.1559	8.8901
2	269	13.9539	560.3478	2569.6837	0.8536	0.0011	0.0161	366.1559	8.8901
3	269	13.9539	560.3478	2569.6837	0.8536	0.0011	0.0161	366.1559	8.8901
4	269	13.9539	560.3478	2569.6837	0.8536	0.0011	0.0161	366.1559	8.8901
5	269	13.9539	560.3478	2569.6837	0.8536	0.0011	0.0161	366.1559	8.8901
6	269	13.9539	560.3478	2569.6837	0.8536	0.0011	0.0161	366.1559	8.8901
7	269	13.9539	560.3478	2569.6837	0.8536	0.0011	0.0161	366.1559	8.8901
8	269	13.9539	560.3478	2569.6837	0.8536	0.0011	0.0161	366.1559	8.8901
9	269	13.9539	560.3478	2569.6837	0.8536	0.0011	0.0161	366.1559	8.8901