Research article

Bitcoin transactions, information asymmetry and trading volume

Lennart Ante[1,2,*]

[1] Blockchain Research Lab, Colonnaden 72, 20354 Hamburg, Germany
[2] University of Hamburg, Faculty of Business, Economics & Social Sciences, Von-Melle-Park 5, 20146 Hamburg, Germany

* Correspondence: Email: ante@blockchainresearchlab.org.

Abstract: The underlying transparency of the Bitcoin blockchain allows transactions in the network to be tracked in near real-time. When someone transfers a large number of Bitcoins, the market receives this information and traders can adjust their expectations based on the new information. This paper investigates trading volume and its relation to asymmetric information around transfers on the Bitcoin blockchain. We collect data on 2132 large transactions on the Bitcoin blockchain between September 2018 and November 2019, where 500 or more Bitcoins were transferred. Using event study methodology, we identify significant positive abnormal trading volume for the 15-minute window before a large Bitcoin transaction as well as during and after the event. Using public information about Bitcoin addresses of cryptocurrency exchanges as proxies for information asymmetry, we find that transactions with high levels of information asymmetry negatively affect abnormal trading volume once the event becomes public knowledge, while some effects are even opposite for transactions with lower information asymmetry. The results show that blockchain transaction activity is a relevant aspect of Bitcoin's microstructure, as informed traders make use of the information in general and adjust their expectations based on the degree of information asymmetry.

Keywords: market efficiency; informational efficiency; asset pricing; asymmetric information; cryptocurrency; event study; transaction activity; informed trading; cryptocurrency exchanges

JEL Codes: C12, C58, G10, G12, G14

1. Introduction

Bitcoin markets are constantly influenced by new information (Karalevicius, 2018; Vidal-Tomás and Ibañez, 2018). They are actively traded 24 hours a day, seven days a week, and traders are heterogenous and need to adapt to ever-changing market conditions. While asset pricing theory states that all market participants act on the basis of the same information (Fama, 1970), in reality information is not equally distributed. Traders receive information at different times or interpret events and information differently. For this reason, information asymmetries and the dissemination of information need to be investigated in order to gain a better understanding of Bitcoin markets. The underlying transparency of the Bitcoin network offers the possibility to track any transfers on the public blockchain infrastructure virtually in real-time. As a result, no network participant is able to move large values without the market recognizing this.

However, the time of disclosure differs across market participants. In principle, there is always at least one party involved in a transaction, the initiator, who possesses private information in advance about a future transfer. Also, the verification of a transactions is not the first time that information about a transfer becomes publicly assessible. Once a transfer is initiated and sent to a node in the Bitcoin network, the node checks the transfer and forwards it to eight other nodes in the network, although the number of forwarding nodes is freely adjustable. The transaction is placed in the Mempool, a sort-of waiting area for pending transactions, and is picked up by miners who insert the transaction in their candidate blocks. Only once a miner successfully mines a transaction, the transfer is verified and becomes part of the blockchain. As on average, every ten minutes a new Bitcoin block is mined, nodes in the network possess private information about an upcoming transfer earlier than non-node market participants, although various risks are tied to unverified transactions, like double-spending attacks or network forks (Decker and Wattenhofer, 2016; Gervais et al., 2015).

While research has extensively analyzed the market economics and efficiency, as well as asset valuation and price formation of cryptocurrencies (Bariviera, 2017; Ciaian et al., 2016; Kristoufek, 2018; Li et al., 2018; Nadarajah and Chu, 2017; Sapuric et al., 2020), the relationship between cryptocurrency markets and blockchain transaction activity remains under-explored. This may be due to the fact that there are hardly any comparable phenomena in other financial markets, and thus existing scientific basis. So-called on-chain transaction activity represents a specific piece of public information that is part of Bitcoin's microstructure. Koutmos (2018) shows for daily data that blockchain transaction activity of Bitcoin (the cumulative number of transactions and the number of unique blockchain addresses) can explain Bitcoin prices and Ante and Fiedler (2020) find abnormal returns associated with a market reaction to large Bitcoin transfers using minute price data. They show that transaction size and presumed motives of the transactions can explain price effects. In Aalborg et al. (2019), it is analyzed how transaction volume and the number of unique Bitcoin addresses relate to return, volatility and trading volume. The authors identify that changes in Bitcoin addresses positively relate to weekly and daily returns. While few studies have analyzed price effects and Bitcoin on-chain activity, the relationship between on-chain information (asymmetry) and trading volume remains unclear.

We are interested in the question if a specific type of unforeseen event on the Bitcoin blockchain, a large transfer, which we define as 500 or more Bitcoins being transacted, leads to a market reaction of

abnormal trading activity and what factors may explain this behavior. For most transfers, the underlying motives remain mostly unclear, i.e. information asymmetry is high, while one or few involved actors possess private information. Therefore, uninformed market participants may not be willing to trade until the information asymmetry is resolved, which would result in a decrease in trading volume until the asymmetry is resolved (Chae, 2005). For some transfers, like intra-cryptocurrency exchange transfers, where Bitcoins are only moved for safekeeping, motives are for the most part clear, why such a large transfer could potentially have no influence on trading volume.

The aim of this study is to assess the statistical properties of actual minutely Bitcoin trading volume and abnormal trading volume for a sample of 2132 large Bitcoin transfers. We apply event study methodology to identify abnormal trading volumes and analyze if publicly known addresses of cryptocurrency exchanges, which can be monitored by market participants, can explain such effects. The results serve to better understand the link between Bitcoin's on-chain activity and secondary market activity and to identify if trading volume of Bitcoin is linked to fundamental economic values and uncertainty. The findings contribute to the research on the market economics and efficiency of cryptocurrencies, which has been identified as a major scientific discourse (Ante, 2020). It also serves to better understand the behavior of participants in the Bitcoin market in response to unforeseen events and information asymmetry and shows how certain transactions, where senders or receivers can be identified, are interpreted by the market.

2. Conceptual background and hypotheses

2.1. Trading volume and its relation to unscheduled events

The opportunity for trade occurs when a potential buyer and seller change their price expectations. Reasons for this can be speculation or liquidity needs but are usually not assessible for external observers. If new information becomes known to the market that is relevant to the price expectations of market participants, it is priced in accordingly. The occurrence of abnormal trading volume reflects a change in the expectations of traders in a market due to an unforeseen or unusual event, which may lead to disagreement in interpretation of the information across investors (Beaver, 1968). However, it is also possible that the same interpretation of an event will lead to abnormal trading volumes, if ex-ante expectations differ across traders (Karpoff, 1986).

Trading volume represents a critical characteristic of financial markets, as it enables price discovery and financial risk-sharing. There are basically two forms of trading volume: informed and uninformed (liquidity trading). According to Kyle (1985), liquidity traders, like market makers, behave exogenously and inelastically to price, which should result in an increase in trading volume with increasing information asymmetry, as informed traders try to exploit private information (Chae, 2005). Another possibility, however, is that liquidity traders have timing discretion (Admati and Pfeiderer, 1988; Foster et al., 1984), which leads to a reduction of their trading volume with increasing information asymmetry. Liquidity traders react to exogenous trade demands by postponing trading until the information asymmetry is resolved (Chae, 2005). A higher probability to trade with informed counterparties leads to a decrease in the willingness of uninformed traders to participate in a market (Black, 1986; Milgrom and Stokey, 1982). So if uninformed traders suspect

informed trading activities, which they oftentimes cannot (Easley et al., 2002), they should decrease their own trading activities. For (mostly) unscheduled events, like large Bitcoin transfers, uninformed investors cannot predict informed trading, i.e. they cannot change their trading activities accordingly. In the Bitcoin market, the executing entity (the sender) has private information at first. Subsequently, operators of Bitcoin nodes (e.g. miners) possess information about unconfirmed transactions until the confirmed transaction is finally broadcasted in a block (on average ten minutes later). Upon confirmation of the transaction, another group of market participants—those who observe the market but do not operate a node—receive information about the transaction, while another group receives information about the transaction with even more delay or not at all. To this extent, market participants can adjust their expectations of the Bitcoin market at different times and react accordingly. If large Bitcoin transfers do represent a relevant aspect of Bitcoin's microstructure, trading volume should increase around transfers, as informed traders update their expectations and carry out purchases and/or sales related to it, while uninformed traders keep their volume at an usual level, resulting in a growth in total trading volume before and with large Bitcoin transactions.

HYPOTHESES 1: *Trading volume increases before and with large Bitcoin transfers.*

2.2. Bitcoin addresses and information asymmetry

While the Bitcoin blockchain is transparent in terms of verified transaction timing, size and (pseudo-anonymous) destination, one can only speculate about reasons for transactions. Basically, it can be said that a very large transaction between unknown addresses will lead to uncertainty, as one motive could be to sell the Bitcoins on a cryptocurrency exchange, which would lead to a negative price effect. Yet, different traders that observe such an event, may not agree on how to interpret it, i.e. how to adjust their price expectations and behavior. In addition, there are always one or two parties who are directly involved in the transfer and therefore have no or limited information asymmetry.

The Bitcoin addresses of cryptocurrency exchanges are often public knowledge, which allows the market to interpret transactions differently based on addresses they are sent to or initiated from. If one or two addresses involved in a transfer are known, information asymmetry is decreased and the interpretation of an unforeseen event with regard to market or price expectation may be less complex for traders. Exchanges usually use so-called hot wallets to handle daily business, such as deposits and withdrawals from customers. Only a relatively small proportion of all Bitcoins deposited on the exchange is stored on hot wallets—a proportion that is sufficient to guarantee daily payouts. The majority of an exchanges' Bitcoins are stored on cold wallet addresses, which have significantly higher security standards and are only used rarely. For example, the cryptocurrency exchange Bitfinex states that about 99.5% of all user funds are in their offline, multi-signature wallet. Four out of seven hardware security modules in the possession of globally-distributed team members are required to initiate a transaction from the address (Bitfinex, 2020). In theory, market participants should know the addresses of major exchanges and may therefore interpret associated transactions differently than ones related to unknown addresses. In total, four overall transaction types based on Bitcoin addresses of cryptocurrency exchanges can be identified:

(1) *Hot wallet deposits.* As Bitcoins are sent to an exchange, the receiving entity is publicly known, i.e. information asymmetry is decreased. Traders are able to interpret possible transfer

motivation, for example that Bitcoins are to be sold, shall be used as collateral for margin trading or are deposited to access services like insurance of funds.

(2) *Hot wallet withdrawals.* The initiating entity is known, as Bitcoins are withdrawn from the exchange to an unknown address.

(3) *Cold wallet deposits.* Excess Bitcoins are sent from the hot wallet of an exchange to the cold wallet, which can be interpreted as a sign that either deposits to the exchange increased or initiated withdrawals decreased. The associated level of information asymmetry is low, as (1) both sender and receiver are known and represent the same entity and (2) the likely transfer motive is known and should not affect the market directly.

(4) *Cold wallet withdrawals.* Excess Bitcoins are sent from the cold wallet of an exchange to the hot wallet, which can be interpreted as a sign that initiated withdrawals increased. Again, information asymmetry is low, as both involved addresses belong to the same entity and the transfer is company-internal.

In summary, transactions on the Bitcoin network can be identified where neither receiver nor initiator is known, where either sender or receiver is known or where both parties are known. The more related parties can be assigned to a transaction, the lower the level of information asymmetry. A lower level of information asymmetry should therefore lead to less disagreement regarding the interpretation of events, and thus lower abnormal trading volume once the information becomes known to the market (Beaver, 1968; Karpoff, 1986).

HYPOTHESES 2: *The degree of information asymmetry tied to large transfers of Bitcoin is negatively correlated with trading volume after information becomes public knowledge.*

3. Data and methods

3.1. Data and sample

Our data set consists of 2132 individual Bitcoin transactions where 500 or more Bitcoins were transferred. Blockchain data was collected from Bitcoin blockchain explorer blockchain.com for transactions that occurred between September 2018 and November 2019. We collected a transaction's timestamp, its size, as well as sender and receiver addresses involved. This way, we are able to identify addresses that are repeatedly involved in transfers. Based on the sender and receiver addresses, we cluster transactions by publicly known Bitcoin addresses of cryptocurrency exchanges and the fact if assets are sent or received, i.e. deposits and withdrawals. For most cryptocurrency exchanges, information on Bitcoin wallets is publicly assessible, for example via bitinfocharts.com. For an overview of the clusters, see Table A.1. in the appendix.

To complement the data set, we collected price and volume data from the cryptocurrency exchange Gemini (gemini.com) for $t = -200$ to 200 minutes around the minute of each Bitcoin transfer. The trading volume of cryptocurrencies is oftentimes inflated or faked, which makes it difficult to analyze. The choice of Gemini as data basis allows to minimize this risk. The US-based exchange is (1) highly regulated, as it (a) has been awarded a BitLicense by the New York State Department of Financial Services, (b) is registered as a Money Services Business with FinCEN and (c) its funds are insured to a certain degree, (2) is a verified entity at the Blockchain Transparency

Institute (bti.live), an industry-lead initiative for the provision of "clean and wash free data" and (3) did not show signs for wash trading in existing studies (Alameda Research, 2019; Fusaro and Hougan, 2019). The market data collected are close prices and trading volume per minute.

3.2. Dependent variables and event study methodology

Based on similar metrics used in the literature on trading volume in stock markets, two volume measures are used: (1) the number of Bitcoins traded per minute (e.g. Harris, 1986; James and Edmister, 1983) and (2) the dollar value of Bitcoins traded per minute (e.g. James and Edmister, 1983; Lakonishok and Vermaelen, 1986). Since both variables are skewed and minutes where no trading takes place appear in the data set, i.e. zero-inflated volume observations, we use the log (x + c) transformation of both variables, where x is the variable's natural expression and c is a constant. The use of log transformed variables is recommended by the literature on abnormal trading volume (Ajinkya and Jain, 1989; Cready and Ramanan, 1991). In line with the literature on stock trading volume, we use a constant value of 1 for trading volume in USD (Ajinkya and Jain, 1989) and a value of 0.000255 for trading volume in the asset itself (Campbell and Wasley, 1996).

We build on volume event study methodology for our analysis. In event studies, the market reaction to specific unexpected or unusual information is assessed by adjusting observed market effects by expected market performance to identify abnormal effects. We choose a simple expectation model, where expected volume is calculated as the average volume over a 121-minutes estimation period (t = −141 to −21). The expected trading volume (EV_{it}) is calculated as the average volume over an estimation period as

$$EV_{it} = \overline{V_{it}} + e_{it} \tag{1}$$

where i is the number of transactions and t is the number of minutes in the estimation period. The term V_{it} is the respective absolute trading volume, either in Bitcoin or in US-dollar, in minute t and transaction i, and e_{it} is the error term. The bar on top of the variable indicates the mean over the estimation window.

Abnormal trading volume (AV_{it}) can then be calculated by subtracting the observed trading volume from the expected trading volume:

$$AV_{it} = V_{it} - EV_{it} \tag{2}$$

Across multiple events of the same type, i.e. transactions, AV_{it} can be aggregated as average abnormal trading volume:

$$AAV_{it} = \frac{1}{N} \sum_{i=1}^{N} AV_{it} \tag{3}$$

When assessing event windows beyond a single minute, the results are summarized in cumulative abnormal trading volume (CAV):

$$CAV(t_1, t_2) = \sum_{t=t_1}^{t_2} AV_{it} \tag{4}$$

Cumulative average abnormal trading volume (CAAV$_{it}$) are calculated as the sum of the CAVs of various transactions:

$$CAAV_{it} = \frac{1}{N} \sum_{i=1}^{N} CAV(t_1, t_2) \tag{5}$$

To test the significance of abnormal trading volumes, we calculate parametric t-tests and the non-parametric Wilcoxon sign rank test (Wilcoxon, 1945), as such financial data is characterized by non-normality in its distribution (Brown and Warner, 1985).

3.3. Independent and control variables

We create five different dummy variables, each of which take a value of one if a transaction can be assigned to one of five clusters, and else zero. The variable *hot wallet withdrawals* indicates that a transaction originates from the hot wallet of a cryptocurrency exchange and is transferred to an address that does not belong to the exchange itself, i.e. the transaction is not sent to the cold wallet of the exchange. Analogously, the variable *hot wallet deposits* takes a value of one if Bitcoins are sent to the hot wallet of an exchange and the transfer is not initiated from the exchanges' cold wallet. *Cold wallet withdrawals* indicates that a transaction is initiated from a cold wallet address of an exchange to any other address (usually the respective hot wallet of the exchange). The variable *cold wallet deposits* is assigned a value of one if Bitcoins are sent to the cold wallet of an exchange (again, usually from the respective hot wallet of the exchange).

As the transfers range from 500 Bitcoins upwards, it is conceivable that as the size of the transactions increases, effects will also increase. The variable *transaction size (BTC)* is calculated as the logarithm of the number of Bitcoins transferred.

Bitcoin is a volatile asset, whose value in dollars fluctuated strongly over the period under consideration from September 2018 to November 2019. A transfer of 500 or more Bitcoins may have very different equivalent value based on market timing. For this reason, we introduce the control variable *Bitcoin price ($1,000)*, which equals the US-dollar value of Bitcoin at the minute of the transaction, divided by 1000.

Trading volume is no stable mechanism but varies across daily hours and week days. Stock market studies show that average trading volume significantly differs for time-of-day and day-of-week (e.g. Jain and Joh, 1988). The assessment of day-of-week effects for Bitcoin has shown that returns are higher on Mondays (Caporale and Plastun, 2019), lower on Sundays (Dorfleitner and Lung, 2018) and trading activity is lower on weekends, as e.g. institutional traders do not trade on weekends (Baur et al., 2019; Kaiser, 2019; Wang et al., 2019). To assess and control for day-of-week effects, we create seven dummy variables, each taking the value of one if the transaction happened on a specific weekday, and else zero. Analogously we create a dummy variable for each hour of the day to control for time-of-day effects.

4. Results

4.1. Descriptive statistics

Table 1 reports summary statistics per month for the sample of large transfers and the Bitcoin market. We identified three-digit numbers of large transfers for the first nine months and lower numbers thereafter. The number of large transfers seems to be negatively correlated to the four metrics total transactions (on the blockchain), price, volume and market capitalization—a plausible fact, as traders seem to orientate themselves at the dollar value of the asset. The price of Bitcoin dropped from $6610 to $3701 over the course of five months before rising to $10,669 over the next six months, "ending" at $8373. This high volatility over the period where data on large transfers has been collected suggests that price should be included as a control variable in empirical models.

Table 2 reports summary statistics for the two volume measures, both the untransformed and the log-transformed expressions for all transactions, i.e. the full data set, the five address clusters and deciles based on the value in USD of a Bitcoin transfer. Mean and standard deviation statistics on trading volume are calculated as the average over the 31-minute-long event window starting 15 minutes before the event. The trading volume per minute for the 31-minute event window and the 401-minute data sample are visualized in Figures A.1 through A.3 for trading volume in USD, both for the full set of transactions and across address clusters and deciles.

For the full set of transactions, the untransformed variables have high skewness (14.12 for Bitcoin; 8.76 for USD) and kurtosis (255.19 for Bitcoin; 108.14 for USD), which clearly shows that there is no normality in distribution. As described above, we use log-transformed variables for correction, which clearly improves skewness (−0.35 for Bitcoin; −0.39 for USD) and kurtosis (0.82 for Bitcoin; 0.86 for USD). The variables' distributions are only close to normality, why, in addition to the t-test, the non-parametric Wilcoxon sign rank test is also used to test for significance.

The average trading volume per minute around large Bitcoin transfers is $17,400 (or 3.081 Bitcoins), which would—in case there are not any abnormal effects identified—result in a daily traded value of little over $25 million (for the cryptocurrency exchange under consideration). The mean traded volume is highest for the sample of non-exchange transfers ($23,800), i.e. the proxy variable with the highest level of associated information asymmetry, and lowest for the two cold wallet variables ($11,700–14,500), i.e. the proxies with lowest associated information asymmetry. Standard deviations are also highest for non-exchange transfers ($101,200) and lowest for cold wallet transactions ($34,500–36,700).

For the size-based deciles, we identify, in comparison to the other lower deciles, a high level of associated trading volume in the lowest decile ($18,200). For three deciles (7th, 8th and 10th), trading volumes higher than $20,000 per minute are identified. This shows that trading volume seems to increase with the size of transactions, but size does not seem to be the only decisive factor.

Table 1. Sample distribution and Bitcoin statistics by month.

Month	Large Bitcoin transfers (sample)	Bitcoin transactions (million)	Bitcoin price ($)	Bitcoin trading volume ($ billion)	Bitcoin market capitalization ($ billion)
Sep 18	135	68.71	6,610.68	4.325	114.171
Oct 18	195	78.63	6,485.12	3.821	112.360
Nov 18	110	80.15	5,404.25	5.279	93.901
Dec 18	403	81.91	3,717.49	5.447	64.787
Jan 19	168	93.25	3,701.56	5.398	64.720
Feb 19	199	92.87	3,711.91	7.111	65.106
Mar 19	128	91.04	3,976.07	9.666	69.882
Apr 19	269	110.03	5,178.47	14.845	91.394
May 19	176	115.05	7,309.70	23.360	129.436
Jun 19	84	104.86	9,415.90	22.529	167.272
Jul 19	63	103.05	10,669.34	21.820	190.132
Aug 19	50	101.7	10,643.25	17.225	190.297
Sep 19	51	97.99	9,814.07	16.018	176.041
Oct 19	73	102.09	8,411.93	19.200	151.386
Nov 19	28	92.02	8,373.57	22.564	151.135

Note: Price, trading volume and market capitalization data has been extracted from crypto data aggregator coinmarketcap.com and are calculated as means over the daily metrics of each month. Bitcoin transaction data has been collected from blockchain.info.

Table 2. Summary statistics of trading volume per minute with and without log transformation around 2132 large Bitcoin transactions between September 2018 and November 2019.

	N	Mean value transacted		Untransformed trading volume measures				Log-transformed trading volume measures			
				Number of Bitcoins traded		USD value traded		Number of Bitcoins traded		USD value traded	
	N	USD (million)	Bitcoin	Mean	(SD)	Mean	(SD)	Mean	(SD)	Mean	(SD)
All transactions	2,132	12.45	2,029	3.081	(11.36)	0.174	(0.744)	−2.605	(3.844)	5.900	(3.939)
Non-exchange transfers	434	21.09	2,745	3.468	(12.74)	0.238	(1.012)	−2.575	(3.759)	6.054	(3.898)
Hot wallet deposits	612	8.25	1,565	3.406	(13.91)	0.173	(0.826)	−2.416	(3.877)	6.008	(3.939)
Hot wallet withdrawals	906	8.53	1,531	2.894	(9.438)	0.153	(0.568)	−2.623	(3.857)	5.857	(3.944)
Cold wallet deposits	51	12.04	1,920	2.267	(5.266)	0.145	(0.345)	−2.661	(3.701)	5.970	(3.850)
Cold wallet withdrawals	129	31.02	5,372	1.869	(5.707)	0.117	(0.367)	−3.451	(3.867)	5.136	(4.045)
Lowest decile	214	1.96	520	4.747	(13.12)	0.182	(0.476)	−1.360	(3.691)	6.866	(3.686)
2	212	3.29	730	2.274	(8.084)	0.113	(0.382)	−3.325	(3.965)	5.114	(4.059)
3	212	4.19	919	2.698	(8.584)	0.127	(0.420)	−2.701	(3.859)	5.753	(3.920)
4	212	5.14	1,182	2.783	(14.33)	0.161	(1.023)	−2.559	(3.743)	5.826	(3.811)
5	216	5.90	1,318	2.233	(5.798)	0.097	(0.262)	−2.511	(3.807)	5.856	(3.824)
6	213	6.46	1,298	2.696	(13.12)	0.120	(0.479)	−2.508	(3.834)	6.014	(3.906)
7	215	7.64	1,497	4.713	(15.94)	0.290	(1.180)	−2.470	(3.884)	6.014	(3.986)
8	211	10.27	1,555	3.413	(12.14)	0.217	(0.845)	−2.469	(3.724)	6.298	(3.883)
9	214	14.07	2,126	1.639	(5.930)	0.154	(0.664)	−3.405	(3.799)	5.265	(4.039)
Largest decile	213	65.62	9,091	3.592	(11.39)	0.280	(1.035)	−2.761	(3.846)	5.977	(4.076)

Note: Untransformed USD value traded is divided by 100,000 for readability. Deciles are calculated based on USD value of the Bitcoin transfers. Mean statistics on trading volume are calculated as minute averages over the 31-minute full event window centered around each Bitcoin transaction (t = −15 to 15).

4.2. Empirical results

4.2.1. Abnormal trading volume around large Bitcoin transactions

Abnormal trading volumes for both trading volume measures described in the previous sections are reported in Table 3 for 21 individual minutes around the Bitcoin transactions (t = −10 to 10) and for four different event windows, two for minutes leading up to the transfer and two for periods starting with the minute of the transfer. We identify significant positive abnormal trading volume for minutes leading up to the transaction, for the minute where the transaction is verified and for minutes thereafter. Both event windows (t = −15 to −1 and −5 to −1) before the Bitcoin transfer is verified show highly significant positive abnormal trading volume. The results obtained therefore allow hypothesis 1 to be confirmed.

Table 3. Abnormal trading volumes around large Bitcoin transactions.

Minute	Volume in USD				Volume in Bitcoin			
	AAV	t-test	z-test	positive	AAV	t-test	z-test	positive
−10	0.1992	2.61***	3.63***	57%	0.1895	2.54**	3.40***	56%
−9	0.0600	0.79	1.76*	56%	0.0529	0.71	1.56	55%
−8	−0.0451	−0.58	0.26	55%	−0.0474	−0.63	0.10	54%
−7	0.0466	0.61	1.43	54%	0.0352	0.47	1.19	54%
−6	0.0373	0.48	1.30	54%	0.0288	0.38	1.07	53%
−5	0.2459	3.28***	4.27***	57%	0.2307	3.16***	4.02***	57%
−4	0.1497	1.99**	2.97***	56%	0.1388	1.89*	2.73***	55%
−3	0.1176	1.54	2.36**	55%	0.1038	1.39	2.09**	54%
−2	0.1298	1.70*	2.84***	57%	0.1176	1.58	2.60***	56%
−1	0.0430	0.56	1.75*	56%	0.0318	0.42	1.54	56%
0	0.1905	2.50**	3.46***	56%	0.1722	2.31**	3.19***	56%
1	0.0453	0.59	1.37	54%	0.0320	0.43	1.11	54%
2	0.1447	1.89*	2.78***	56%	0.1302	1.75*	2.51**	55%
3	0.1022	1.35	2.30**	57%	0.0860	1.16	2.02**	56%
4	0.1505	1.97**	2.65***	55%	0.1352	1.81*	2.39**	55%
5	0.1547	2.02**	3.14***	56%	0.1435	1.92*	2.93***	56%
6	−0.0142	−0.17	0.60	54%	−0.0162	−0.21	0.41	54%
7	0.1214	1.55	2.63***	57%	0.1170	1.54	2.46**	56%
8	0.1442	1.85*	3.01***	57%	0.1336	1.77*	2.80***	56%
9	0.1897	2.37**	3.21***	58%	0.1818	2.33**	3.07***	57%
10	0.1296	1.63	2.40**	55%	0.1244	1.61	2.23**	55%
Window	CAV	t-test	z-test	positive	CAV	t-test	z-test	positive
[−15, −1]	1.6316	2.99***	2.29**	51%	1.4878	2.79***	2.08**	51%
[−5, −1]	0.6860	2.91***	2.60***	52%	0.6227	2.71***	2.37**	52%
[0, 5]	0.7878	2.92***	1.96**	52%	0.6992	2.66***	1.70*	52%
[0, 15]	1.5745	2.58**	0.50	49%	1.4159	2.39**	0.28	49%

Note: *, **, *** indicates significance at the 10%, 5% and 1% level, respectively. The column z-test refers to the non-parametric Wilcoxon sign rank test. The column 'positive' shows the share of observations with positive abnormal trading volume for the respective period.

The results show that the market is interpreting information on large Bitcoin transfers before they are verified. Therefore, informed traders in the form of e.g. involved entities in transactions, node operators or mining ventures try to exploit private information. Uninformed traders are not able to identify that informed counterparties participate in the market (Easley et al., 2002) and therefore do not decrease their own trading.

When comparing the two different volume measures, we identify a high degree of similarity between them, an understandable fact, as both measures show a significant correlation coefficient of 0.94. Due to the high correlation and the identified similarities, we will only examine volumes in USD as a metric in the following analysis, as significance levels are slightly higher and the metric has higher relevance.

4.2.2. Abnormal trading volume and effects of information asymmetry

We analyze the causes of abnormal trading volume around unscheduled large Bitcoin transfers by regressing abnormal returns on information asymmetry proxy variables and control variables. As information asymmetry cannot be measured directly, we use the address cluster dummy variables as proxies. Intuitively, a greater level of information asymmetry should lead to lower levels of trading. Thus, non-exchange transfers, where both sender and receiver are unknown should have the highest, while cold wallet deposits and withdrawals should have the lowest effects. We control for transaction size (BTC), Bitcoin price ($1,000), day-of-week effects and time-of-day effects. The results are shown in Table 4. Descriptive statistics and correlations of the main variables can be assessed in Tables A.2. and A.3. in the appendix. Statistics with further information on day-of-week effects (Table A.4) and time-of-day effects (Figures A.4 and A.5) can also be found in the annex. The daily effects confirm previous findings on the phenomenon in cryptocurrency markets that were described in section 3.3 (Baur et al., 2019; Caporale and Plastun, 2019; Dorfleitner and Lung, 2018; Kaiser, 2019; Wang et al., 2019). In the previous analysis, highly significant positive abnormal trading volumes were identified for the periods $t = -15$ to -1, $t = 0$ and $t = 0$ to 5. Therefore, the abnormal trading volumes of these three periods are chosen as dependent variables for regression analysis. This way, we can assess effects of asymmetric information before, at and after events.

For the period leading up to transfers, we identify that non-exchange transfers positively affect abnormal trading volumes, although the effect does not hold in the model where all information asymmetry proxies are tested. Hot wallet deposits have significant negative coefficients in both tested models, while all other proxy variables lack significance. The results indicate that informed traders interpret initiated large transfers differently. At the minute the transaction is verified and the event become public knowledge, non-exchange transfers show the highest significant negative effect on abnormal volume, while the coefficients for hot wallet deposits are also negative and significant.

The effect of hot wallet withdrawals is significantly negative for the model where all information asymmetry proxies are included. The observed effects turn for transactions where exchange cold wallets are included: Both coefficients for cold wallet deposits and withdrawals show significant and positive effects on abnormal trading volume in the individual models.

Table 4. Regression models predicting average abnormal trading volume in USD across different periods.

Independent variables (information asymmetry proxies) and control variables							
Non-exchange transfers	Hot wallet withdrawals	Hot wallet deposits	Cold wallet withdrawals	Cold wallet deposits	Bitcoin price (in $1,000)	Transaction size (BTC)	R^2
Panel A: Abnormal trading volume in t = −15 to −1							
3.981 (1.442)***					−0.397 (0.225)*	0.689 (0.814)	0.045
	1.122 (1.122)				−0.255 (0.219)	0.546 (0.809)	0.043
		−4.696 (1.243) ***			−0.420 (0.221) *	0.569 (0.807)	0.049
			0.739 (2.287)		−0.273 (0.219)	0.471 (0.811)	0.042
				0.396 (4.076)	−0.268 (0.219)	0.511 (0.810)	0.042
2.428 (2.497)	−0.268 (2.370)	−4.297 (2.475) *		−0.158 (4.633)	−0.488 (0.227) **	0.666 (0.812)	0.050
Panel B: Abnormal trading volume in t = 0							
−0.367 (0.200)*					0.059 (0.035) *	−0.071 (0.108)	0.021
	0.092 (0.158)				0.048 (0.034)	−0.052 (0.108)	0.020
		−0.283 (0.175)*			0.038 (0.034)	−0.051 (0.108)	0.021
			1.199 (0.346) ***		0.036 (0.034)	−0.121 (0.109)	0.025
				0.920 (0.447) **	0.046 (0.034)	−0.058 (0.108)	0.021
−1.391 (0.379) ***	−1.079 (0.357) ***	−1.327 (0.370) ***		−0.232 (0.551)	0.039 (0.035)	−0.129 (0.109)	0.029
Panel C: Abnormal trading volume in t = 0 to 5							
−1.143 (0.694) *					0.266 (0.116) **	0.452 (0.367)	0.045
	0.525 (0.544)				0.233 (0.114) **	0.517 (0.368)	0.044
		−0.794 (0.603)			0.202 (0.115) *	0.513 (0.368)	0.045
			3.246 (1.171) ***		0.202 (0.114) *	0.324 (0.373)	0.048
				0.800 (2.172)	0.227 (0.114) **	0.500 (0.369)	0.044
−3.891 (1.287) ***	−2.746 (1.213) **	−3.586 (1.253) ***		−2.281 (2.438)	0.323 (0.114) ***	0.309 (0.371)	0.049

Note: N = 2132; *, **, *** indicates significance at the 10%, 5% and 1% level, respectively. Standard errors are robust to heteroskedasticity. Cold wallet withdrawals are the reference group in each panels' final model. Constant term, day-of-week and time-of-day control variables are suppressed.

The same type of effect characteristics can be observed for the six-minute period from the public announcement of the confirmed transaction. Non-exchange transfers have highest negative effects, followed by hot wallet transfers, and cold wallet withdrawals positively affect volume, while cold wallet deposits lack significance.

The results indicate that, in line with hypotheses 2, once information about transfers becomes public knowledge, the market assesses the level of information asymmetry tied to the transfers and reacts accordingly. A higher level of information asymmetry results in lower levels of abnormal trading, as uninformed traders' probability to trade with informed traders increases and thus their willingness to participate in the market decreases (Black, 1986; Milgrom and Stokey, 1982).

The Bitcoin price is a significantly positive predictor of abnormal trading volume for the ex-post trading volume (panel c), and a negative—and in some models significant—predictor for ex-ante trading volume. This suggests that market sentiment, i.e. periods with higher Bitcoin prices, result in larger market reactions. This can either be an increase in trading of existing traders or an increase in the number of market participants.

6. Concluding remarks

Using data on large Bitcoin transfers, we find positive abnormal trading volume with large transfers on the Bitcoin blockchain. Trading volume increases even before transactions are confirmed by the network, which can be explained by the fact that informed traders, i.e. traders that operate a Bitcoin node, change their trading behavior based on the information as soon as they learn about an upcoming transaction. Uninformed traders, i.e. market participants who do not operate nodes, cannot identify that informed traders have changed their behavior on the basis of private information and therefore continue to trade at the same level.

Another result is that abnormal trading volume negatively correlates with the degree of information asymmetry associated with transactions, as has been shown for other financial markets (Chae, 2005). We identify this by using the involvement of publicly known Bitcoin addresses of cryptocurrency exchanges in the transactions as a proxy for information asymmetry. Transactions in which neither the initiator nor the receiver are known Bitcoin addresses show the largest positive effect on ex-ante abnormal trading volumes and the largest negative effect ex-post. Transfers of Bitcoin as relocation within a cryptocurrency exchange, i.e. where both initiator and receiver are public knowledge and the market can guess probable motives of a transfer, even positively effect ex-post trading volume.

The main implication of this study is that, as already identified for returns (Ante and Fiedler, 2020; Koutmos, 2018), on-chain activity is a relevant aspect of the microstructure of Bitcoin. The results indicate that specific traders make use of this type of private information, while at least some liquidity traders seem not to do, as they would use timing discretion and reduce their trading volume until the information asymmetry is resolved (Admati and Pfeiderer, 1988; Chae, 2005; Foster et al., 1984). As anyone is able to deploy a node in the Bitcoin network, liquidity traders should operate nodes themselves in order to close the information gap and to be able to assess the probability of trading with informed counterparties (Black, 1986)—yet, the initiator of a transaction will always remain as informed counterparty.

This also results in an open question for future studies. One could classify the moment when a transaction is identified by a node for the first time and the transaction is sent to the Mempool as the announcement date of a transaction. If abnormal trading volumes continue to occur prior to the announcement of a transaction, the only explanation would be that parties directly involved in the transaction are using their private information. Further investigations could of course focus on a more detailed identification of known addresses in the network or investigate other cryptocurrencies. Studies investigating these issues will further serve to understand the relationship between blockchain network transactions and secondary markets of Bitcoin and other cryptocurrencies.

Acknowledgments

Conflicts of interest

The author declares no conflict of interest in this paper.

References

Aalborg HA, Molnár P, de Vries JE (2019) What can explain the price, volatility and trading volume of Bitcoin? *Financ Res Lett* 29: 255–265.

Admati AR, Pfeiderer P (1988) A Theory of Intraday Patterns: Volume and Price Variability. *Rev Financ Stud* 1: 3–40.

Ajinkya BB, Jain PC (1989) The behavior of daily stock market trading volume. *J Account Econ* 11: 331–359.

Alameda Research (2019) Investigation into the Legitimacy of Reported Cryptocurrency Exchange Volume. Available from: https://ftx.com/volume_report_paper.pdf

Ante L (2020) A place next to Satoshi: scientific foundations of blockchain and cryptocurrency in business and economics. *Scientometrics* Available from: https://doi.org/10.1007/s11192-020-03492-8

Ante L, Fiedler I (2020) Market Reaction to Large Transfers on the Bitcoin Blockchain–Do Size and Motive Matter? *Financ Res Lett*. Available from: https://doi.org/10.1016/j.frl.2020.101619.

Bariviera AF (2017) The inefficiency of Bitcoin revisited: A dynamic approach. *Econ Lett* 161: 1–4.

Baur DG, Cahill D, Godfrey K, et al. (2019) Bitcoin time-of-day, day-of-week and month-of-year effects in returns and trading volume. *Financ Res Lett* 31: 78–92.

Beaver WH (1968) The Information Content of Annual Earnings Announcements. *J Account Res* 6: 67–92.

Bitfinex (2020) Bitfinex Security Features. Available from: https://support.bitfinex.com/hc/en-us/articles/213892469-Bitfinex-Security-Features.

Black F (1986) Noise. *J Financ* 41: 528–543.

Brown SJ, Warner JB (1985) Using daily stock returns. The case of event studies. *J Financ Econ* 14: 3–31.

Campbell CJ, Wasley CE (1996) Measuring abnormal daily trading volume for samples of NYSE/ASE and NASDAQ securities using parametric and nonparametric test statistics. *Rev Quant Financ Account* 6: 309–326.

Caporale GM, Plastun A (2019) The day of the week effect in the cryptocurrency market. *Financ Res Lett* 31: 258–269.

Chae J (2005) Trading volume, information asymmetry, and timing information. *J Financ* 60: 413–442.

Ciaian P, Rajcaniova M, Kancs Artis (2016) The economics of BitCoin price formation. *Appl Econ* 48: 1799–1815.

Cready WM, Ramanan R (1991) The power of tests employing log-transformed volume in detecting abnormal trading. *J Account Econ* 14: 203–214.

Decker C, Wattenhofer R (2016) Information propagation in the Bitcoin network, in: 13-Th IEEE International Conference on Peer-to-Peer Computing, 1–10.

Dorfleitner G, Lung C (2018) Cryptocurrencies from the perspective of euro investors: a re-examination of diversification benefits and a new day-of-the-week effect. *J Asset Manage* 19: 472–494.

Easley D, Hvidkjaer S, O'Hara M (2002) Is information risk a determinant of asset returns? *J Financ* 57: 2185–2221.

Fama EF (1970) Efficient Capital Markets: A Review of Theory and Empirical Work. *J Financ* 25: 383–417.

Foster G, Olsen C, Shevlin T (1984) Earnings Releases, Anomalies, and the Behavior of Security Returns. *Account Rev* 59: 574–603.

Fusaro T, Hougan M (2019) Bitwise Asset Management - Presentation to the U.S. Securities and Exchange Commission. Available from: https://www.sec.gov/comments/sr-nysearca-2019-01/srnysearca201901-5164833-183434.pdf.

Gervais A, Ritzdorf H, Karame GO, et al. (2015) Tampering with the delivery of blocks and transactions in Bitcoin, in: Proceedings of the ACM Conference on Computer and Communications Security, 692–705.

Harris L (1986) Cross-Security Tests of the Mixture of Distributions. *J Financ Quant Anal* 21: 39–46.

Jain PC, Joh GH (1988) The Dependence between Hourly Prices and Trading Volume. *J Financ Quant Anal* 23: 269–283.

James C, Edmister RO (1983) The Relation Between Common Stock Returns Trading Activity and Market Value. *J Financ* 38: 1075–1086.

Kaiser L (2019) Seasonality in cryptocurrencies. *Financ Res Lett* 31: 232–238.

Karalevicius V (2018) Using sentiment analysis to predict interday Bitcoin price movements. *J Risk Financ* 19: 56–75.

Karpoff JM (1986) A Theory of Trading Volume. *J Financ* 41: 1069–1087.

Koutmos D (2018) Bitcoin returns and transaction activity. *Econ Lett* 167: 81–85.

Kristoufek L (2018) On Bitcoin markets (in)efficiency and its evolution. *Phys A Stat Mech Appl* 503: 257–262.

Kyle AS (1985) Continuous Auctions and Insider Trading. *Econometrica* 53: 1315–1335.

Lakonishok J, Vermaelen T (1986) Tax-induced trading around ex-dividend days. *J Financ Econ* 16: 287–319.

Li Z, Dong H, Huang Z, et al. (2018) Asymmetric Effects on Risks of Virtual Financial Assets (VFAs) in different regimes: A Case of Bitcoin. *Quant Financ Econ* 2: 860–883.

Milgrom P, Stokey N (1982) Information, Trade and Common Knowledge. *J Econ Theory* 26: 17–27.

Nadarajah S, Chu J (2017) On the inefficiency of Bitcoin. *Econ Lett* 150: 6–9.

Sapuric S, Kokkinaki A, Georgiou I (2020) The relationship between Bitcoin returns, volatility and volume: asymmetric GARCH modeling. *J Enterp Inf Manage.*

Vidal-Tomás D, Ibañez A (2018) Semi-strong efficiency of Bitcoin. *Financ Res Lett* 27: 259–265.

Wang JN, Liu HC, Hsu YT (2019) Time-of-day periodicities of trading volume and volatility in Bitcoin exchange: Does the stock market matter? *Financ Res Lett,* 1–8.

Wilcoxon F (1945) Individual Comparisons by Ranking Methods. *Biometrics Bull* 1: 80–83.