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Market Reaction to Large Transfers on the Bitcoin Blockchain - Do Size and Motive Matter?

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Abstract: Cryptocurrency markets are often deemed inefficient. This paper explores how the market reacts to a specific form of public information: large Bitcoin transactions. The event study examines the price effects of 2,132 transactions involving at least 500 Bitcoins over the period September 2018 to November 2019. Across all transactions, we find significant negative price effects for the minutes closely around the events. Yet the effects are positive over the period from the event to 15 minutes thereafter. We analyze further effects of the size and the probable motive of the transfers by dividing the sample into quartiles and by clustering specific Bitcoin addresses of cryptocurrency exchanges involved in the transfers. We find that the price effects can differ significantly depending on the size and type of a transaction. The results indicate that the market recognizes the nature of the transfer and prices in new information. While this constitutes evidence of efficiency, yet more efficient reactions remain conceivable.

Keywords: Market efficiency, Cryptocurrency, Event study, Transaction activity

1 Introduction

The empirical literature has attempted to explain Bitcoin's pricing behavior and concluded that its prices may be decoupled from fundamental economic values (e.g. Katsiampa 2017; Nadarajah and Chu 2017). Yet the Efficient Market Hypothesis (EMH) posits that asset prices, i.e. also Bitcoin, reflect all available information (Fama 1970, 1991). This paper examines whether Bitcoin transactions of a certain size trigger a market reaction.

A fundamental feature of the Bitcoin network is that the underlying blockchain technology allows all transactions to be tracked publicly. Anyone is able to set up a Bitcoin node to directly access the network or to look up blockchain information online via data aggregators, so-called block explorers (e.g. *blockchain.com*). Research has already examined Bitcoin transactions with regard to their economics (Ron and Shamir 2014), (transaction) costs (Kim 2017), and user intentions and underlying anonymity (Glaser et al. 2014). However, the connection between blockchain transaction activity and prices (or returns) has so far received only very limited attention. Koutmos (2018) analyzes how the cumulated blockchain transaction volume of Bitcoin can explain Bitcoin prices. For a 31-day observation window, he finds that transaction activity is an important part of Bitcoin's microstructure. So if on-chain transaction activity affects secondary market prices in a matter of days, are there also short-term (minutes) effects of transaction activity?

The market can observe transactions in real time and additionally guess the motives behind a transaction. Initiated Bitcoin transactions are first kept in the so called Mempool, a kind of waiting area operated by every node in the network. When a transaction is initiated and propagated across the network, miners see the transaction before the actual confirmation. While on average new Bitcoin blocks are mined every ten minutes, the actual time between two blocks is random. A transaction propagated in the network can be confirmed within few seconds or after many minutes. Hence, while it is useful to consider the time before the transaction is confirmed, it is difficult to determine the most relevant period. For this reason, the time of the actual confirmation of a transaction is the most significant event for a market reaction. For example, the Bitcoin addresses of cryptocurrency exchanges are public knowledge and a large transaction that is sent to an exchange could be interpreted as a sign of future selling pressure. While selling pressure may be the likeliest reason for the transfer, Bitcoins could also be used as leverage for margin trading und thus signal future buying pressure. Alternatively, a transfer from an exchange to a private address could be interpreted as a sign that these Bitcoins will not be sold for a while, which could have a positive price effect. In an efficient market, relevant events should be priced in as soon as the transactions become known. It remains unclear to what degree the Bitcoin market efficiently observes these events, whether larger transactions lead to larger corresponding effects, and whether the market reaction, if any, differs according to the motives for the transfers.

To investigate these questions, we conduct an event study of large Bitcoin transactions and short-term price reactions. We collect data on 2,132 large transfers, which we define as 500 or more Bitcoins sent or received in a single transaction. The transfers are additionally divided into quartiles by size. While any transaction can be interpreted as a signal, it is reasonable to assume that the strength of the signal is proportional to the size of a transaction. We thus expect stronger market reaction for larger transactions, i.e. the effects should be greater with each quartile.

Exchanges use hot and cold wallets as security mechanisms. While hot wallets serve the users' everyday deposits and withdrawals, cold wallets are used less frequently, typically for the safe long-term storage of larger sums of Bitcoin. It is possible to distinguish deposits and withdrawals from these wallets, which we use as indication for the potential motive of a transfer and to construct the following clusters:

- *Cold wallet deposits*: A transaction is sent to the cold wallet of an exchange. Bitcoins are effectively removed from circulation which can be interpreted as a positive price signal.

- *Cold wallet withdrawals*: A transaction is sent from the cold wallet of an exchange. Bitcoins are effectively brought into circulation which can be interpreted as a negative price signal.
- *Hot wallet deposits*: A transaction is sent to the hot wallet of an exchange from a non-exchange-related address (transactions initiated from cold wallets are excluded). Bitcoins are deposited with the exchange, which can be interpreted as selling pressure and thus a negative price signal.
- *Hot wallet withdrawals*: A transaction is sent from the hot wallet of an exchange to a non-exchange-related address (transactions sent to cold wallets are excluded). These Bitcoins will no longer be sold on the exchange, at least in the short term, which can be interpreted as a positive price signal.

It should be noted that the listed presumed causes and effects are only the most likely ones. Though a large Bitcoin hot wallet deposit should generally signal selling pressure, deposited Bitcoins could also be used as collateral for margin trading, and therefore lead to buying pressure.

Absent any other information, we expect that large transfers are perceived as signal of uncertainty and thus yield negative price effects. For example, a large transaction with unknown purpose could mean that Bitcoins that have not been moved for a long time once again enter the market as active supply. Previously there was a possibility that the cryptographic key to the Bitcoins was no longer available (i.e. that they were lost) or that the Bitcoins were a long-term investment. Another potential reason for resulting uncertainty is that a large transaction could be attributed to a hack or theft (Ante 2018). Such transactions form our fifth cluster:

- *Non-exchange transfers*: Neither transmitter nor receiver are exchange-related addresses. The market cannot suspect the presumed motive for the transfer, which can be interpreted as a sign of uncertainty and thus a negative price signal.

2 Data, methodology and sample description

We data on collect 2,132 transactions comprising 500 or more Bitcoins from *blockchain.com*, recording their timestamp, transaction size and the sender and receiver addresses. The transactions are clustered by the five types explained above and, where a publicly known addresses of a cryptocurrency exchange is concerned, by the exchanges. Summary statistics on the clusters are shown in Table 1. Minute close prices for the currency pair Bitcoin/US-Dollar as listed on the US-based exchange Gemini are obtained from *cryptodatadownload.com* and are recorded for the period from 141 minutes before to 20 minutes after each transaction. We calculate the value of each transaction in million USD based on the closing price in t = 0, the minute the transfer is processed. To assess any size effects, the sample is divided into quartiles based on the transaction size in Bitcoin: 500-976; 979-1,205; 1,206-1,839; 1,841-130,004.

Table 1 shows the distribution of transactions across the five clusters and across the identified exchanges within each cluster. The 2,132 transfers amount to a total of 4.3 million Bitcoins, or \$26.4 billion, for an average of 2,020 Bitcoins (\$12.4 million) per transaction. While the smallest recorded transaction exactly equals the cutoff limit, the largest comprises 130,004 Bitcoins. The largest group of transactions (42.5%) involves withdrawals from the hot wallets of exchanges and the second largest group is exchange deposits (28.7%), comprising the exchanges Bitfinex (20.9%) and Binance (7.8%). Non-exchange transfers account for 20.4% of all observations. The two proportionally smallest clusters refer to cold wallet withdrawals (6.1%) and cold wallet deposits (2.4%).

For the event study proper, we calculate Bitcoin's average return over a two-hour period (t = -141 to -21) to obtain our expected return. Abnormal returns (ARs), or average abnormal returns (AAR) for multiple observations, are then calculated as the difference between the expected return and the actual return over the event window (t = -15 to 15) (Mean Return Model). Cumulative abnormal returns (CARs) or cumulative average abnormal returns (CAARs) are calculated as the sum of the ARs of various transactions. To assess the significance of the results, we calculate t-statistics and z-statistics (Wilcoxon sign rank test).

Table 1. Summary statistics for address clusters.

			Bitcoin				USD (million)	
	#	%	Sum	Min	Max	Mean	Sum	Mean
Non-exchange transfers	434	20.4%	1,191,422	500	107,848	2,745	9,154	21.0
Cold wallet deposits	51	2.4%	97,935	505	8,047	1,920	614	12.0
Bitfinex	29	1.4%	47,669	505	8,047	1,644	311	10.7
Coincheck	9	0.4%	111,175	713	815	1,241	57	6.3
Binance	8	0.4%	16,000	2,000	2,000	2,000	103	12.8
Huobi	3	0.1%	10,091	1,000	6,031	3,363	65	21.6
Bitstamp	2	0.1%	13,000	5,000	8,000	6,500	79	39.6
Cold wallet withdrawals	129	6.1%	693,056	500	130,004	5,373	4,001	31.0
Bitfinex	98	4.6%	260,611	1000	30,000	2659	1,595	16.3
Coincheck	20	0.9%	17,400	500	2,600	870	110	5.5
Huobi	6	0.3%	108,032	1,900	36,349	18,005	842	140.3
Binance	3	0.1%	157,010	8,888	109,234	52,337	912	303.9
Bittrex	2	0.1%	150,003	19,999	130,004	75,002	535	271.8
Hot wallet deposits	612	28.7%	957,655	500	11.941	1,565	5,050	8.3
Bitfinex	445	20.9%	807,873	1,000	11,941	1,815	4,025	9.0
Binance	167	7.8%	149,782	500	10,000	897	1,026	6.1
Hot wallet withdrawals	906	42.5%	1,387,346	500	43,652	1,531	7,726	8.5
Bitfinex	521	24.4%	935,938	598	12,054	1,796	4,634	8.9
Binance	378	17.7%	377,884	500	9,999	1,000	2,489	6.6
Bittrex	7	0.3%	53,707	599	43,652	7,672	495	70.8
All transfers	2,132	100.0%	4,307,597	500	130,004	2,020	26,437	12.4

The compositions / sub-clusters of the groups are shown indented under the main category.

3 Results and discussion

3.1 Effect of transaction sizes

Figure 1 shows cumulated Bitcoin returns from 140 minutes before an event until 20 minutes afterwards for all transfers and the four size quartiles. In the 140 minutes before the confirmation of a transaction, the average price increases by 0.055%. This change includes a drop by 0.015% in the final 15 minutes before the event (Figure 1a). In the first 15 minutes after the event, the price rises again by 0.037%. Regarding the individual quartiles, we find the largest price movement in the first quartile. Over the full period, the price rises by 0.41%, more than in Q3 (0.09%) and Q4 (0.1%). By contrast, Q2 features a cumulative return of -0.13%. This may be due to the large proportion of non-exchange transfers in this quartile (36.77%, see Table A1 in the appendix). In sum, the average returns suggest that large transactions do entail price effects. At the same time, however, there is no linear relationship between transaction size and market reaction.

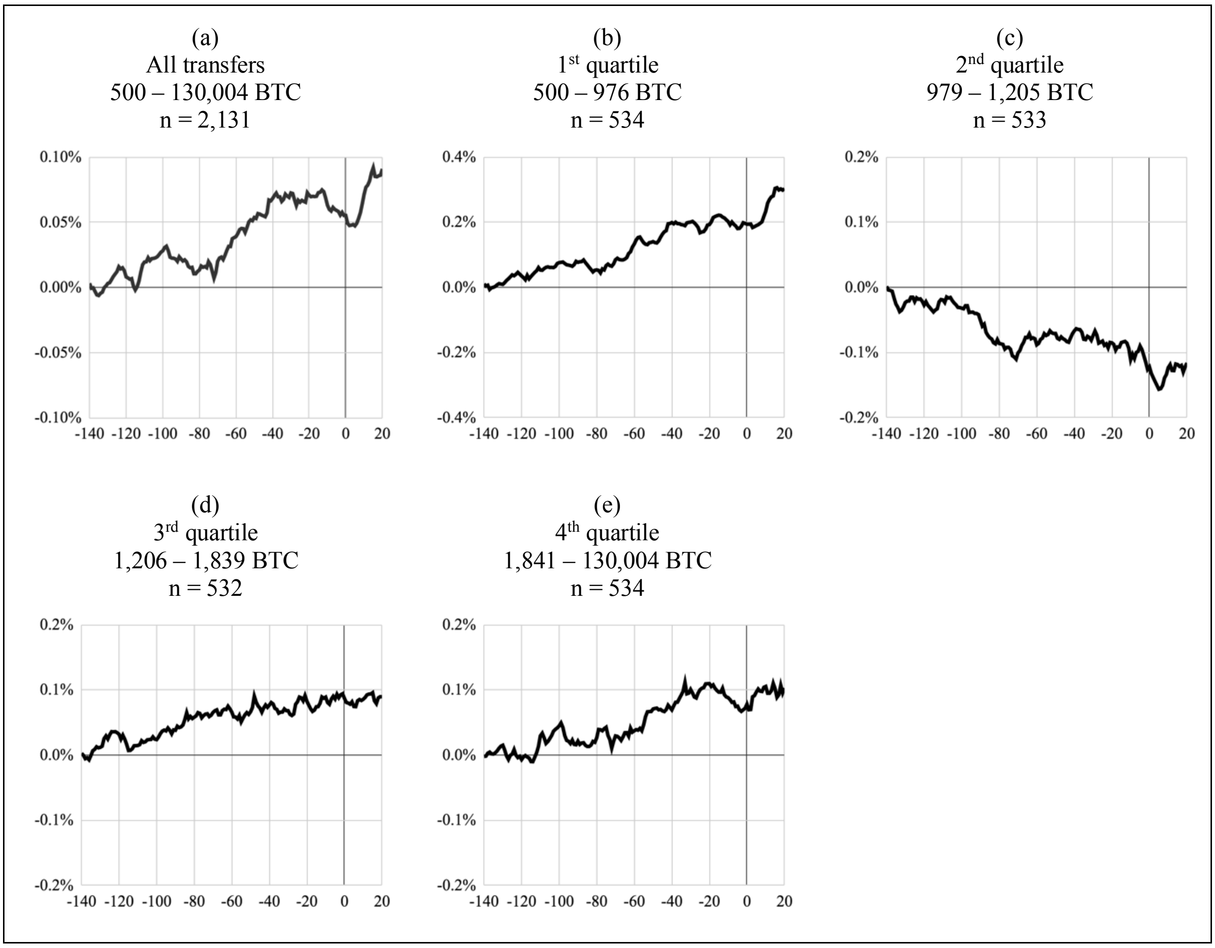

Figure 1. Bitcoin returns around large on-chain transactions by transfer size.

Table 2 shows event study results for the five groups across various time windows. In addition, AARs for each individual minute are shown in Figure A1 for the five samples. The most important result is a significant negative AAR of -0.0067% in the minute after the transaction. Looking at the quartiles, each effect in t = 1 is negative, but only the values for Q2 (-0.0091%) and Q4 (-0.0094%) are significant. The results indicate that large Bitcoin transactions are a signal of uncertainty, which is negatively priced in. However, comparing the effects across the quartiles, we find no evidence of a size effect.

Table 2. Event study results for all transfers and size quartiles.

		I.	II.	III.	IV.	V.
Window	Metrics	All transfers: 500 – 130,004	1st quartile: 500 – 976	2nd quartile: 979 – 1,205	3rd quartile: 1,206 – 1,839	4th quartile: 1,841 – 130,004
-15 to 15	CAAR %	0.0014	0.0356	-0.0035	-0.0006	-0.0262
	t-stat.	0.06	0.61	-0.08	-0.02	-0.75
	z-stat.	-0.83	-1.81*	-0.85	-0.27	0.58
-5 to 5	CAAR %	-0.0200	-0.0161	-0.0499	0.0260	0.0120
	t-stat.	-1.70*	-0.66	-1.67*	-1.49	0.59
	z-stat.	-1.00	0.75	-1.64*	-2.37**	1.28
-2 to 2	CAAR %	-0.0110	-0.0008	-0.0299	-0.0116	-0.0018
	t-stat.	-1.65*	-0.06	-2.16**	-0.90	-0.14
	z-stat.	-0.11	2.24**	-1.51	-1.00	-0.09
0 to 15	CAAR %	0.0264	0.0823	0.0196	-0.0115	0.0150
	t-stat.	1.68*	1.76*	0.78	-0.50	0.61
	z-stat.	0.36	-0.92	0.77	-0.33	1.24
0 to 5	CAAR %	-0.0123	-0.0162	-0.0259	-0.0267	0.0195
	t-stat.	-1.67*	-1.05	-1.66*	-2.01**	1.33
	z-stat.	-0.13	0.47	-1.07	-1.55	1.85*
2	AAR %	-0.0022	-0.0010	-0.0056	-0.0016	-0.0006
	t-stat.	-0.76	-0.16	-0.93	-0.28	-0.11
	z-stat.	-0.65	0.41	-1.36	0.78	-1.36
1	AAR %	-0.0067	-0.0014	-0.0091	-0.0068	-0.0094
	t-stat.	-2.52**	-0.23	-2.12**	-1.47	-2.00**
	z-stat.	-1.50	0.84	-1.66*	-1.45	-1.85*
0	AAR %	-0.0006	-0.0043	0.0044	-0.0078	0.0053
	t-stat.	-0.21	-0.67	0.91	-1.47	0.94
	z-stat.	-0.97	-0.49	-0.47	-1.26	0.65
-1	AAR %	-0.0029	-0.0035	-0.0105	0.0009	0.0014
	t-stat.	-0.97	-0.52	-1.95*	0.15	0.26
	z-stat.	-1.16	0.77	-2.81***	-0.14	-0.50
-2	AAR %	0.0014	0.0093	-0.0091	0.0038	0.0015
	t-stat.	0.48	1.89*	-1.27	0.62	0.31
	z-stat.	-0.23	2.32**	-1.81*	-0.49	-0.86
-5 to 0	CAAR %	-0.0083	-0.0042	-0.0196	-0.0072	-0.0021
	t-stat.	-1.00	-0.21	-1.04	-0.61	-0.16
	z-stat.	-0.98	1.13	-1.19	-2.02**	0.16
-15 to 0	CAAR %	-0.0257	-0.0510	-0.0187	0.0030	-0.0359
	t-stat.	-2.02**	-1.73*	-0.62	0.16	-1.67*
	z-stat.	-1.21	-0.39	-0.73	-0.73	-0.57
	N	2,132	534	533	532	533

*, **, *** indicates significance at the 10%, 5% and 1% level, respectively.

3.2 Effects of transfer motives

In addition to size, the (likely) motive for a transfer may also be associated with price effects. The cumulative returns from t = -140 to t = 20 for the five different clusters are shown in Figure 2. There are considerable differences both among the individual clusters and in comparison to the full sample (cf. Figure 1a). Non-exchange transfers and cold wallet deposits appear to result in negative price developments after the transaction, while cold wallet withdrawals and especially hot wallet deposits seem to entail price increases. This comparison of average return metrics suggests that the motive for a transfer plays an important role and the market incorporates this information in the form of positive and negative price reactions.

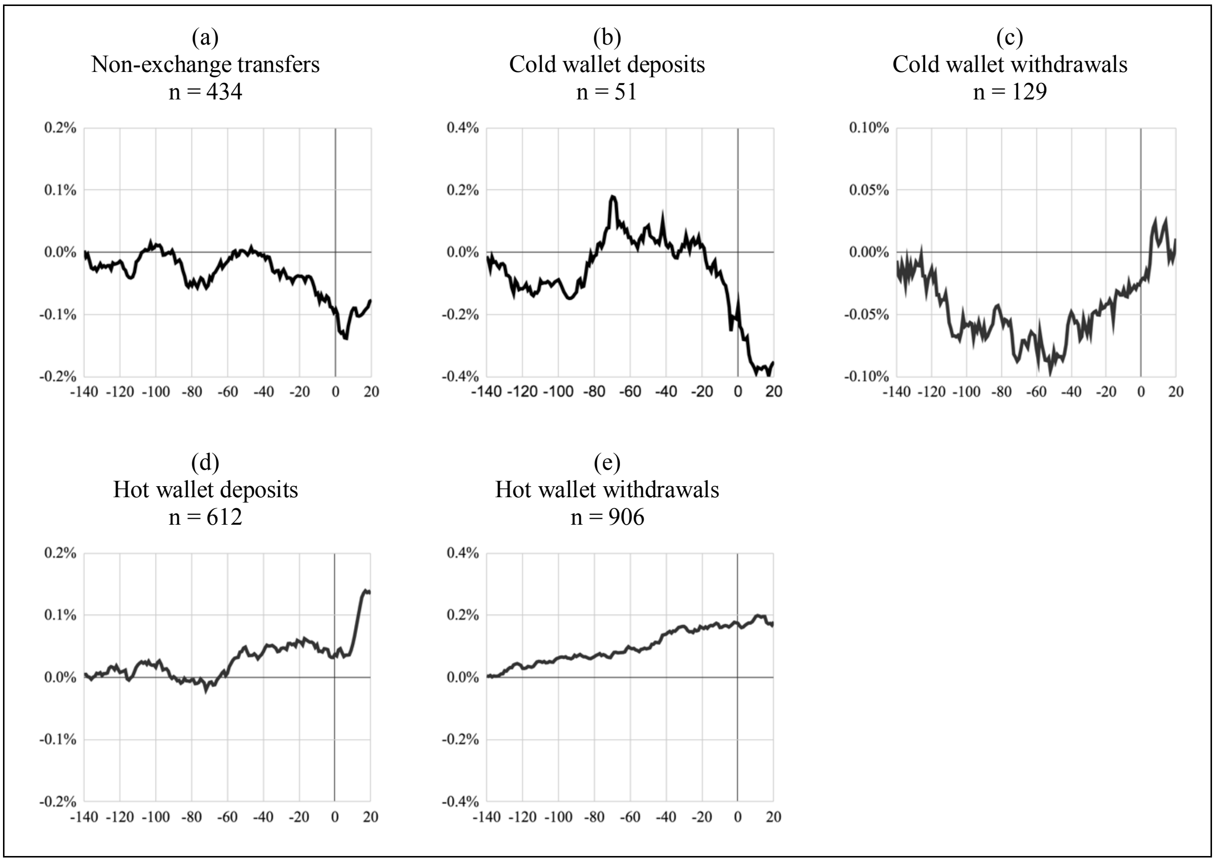

Figure 2. Bitcoin returns around large on-chain transactions by address clusters.

Table 3 shows the results of the event study for the total sample and the five address clusters. In addition, individual AARs for each minute from t = -15 to 15 are visualized for all transactions and each cluster in Figure A2. For non-exchange transfers, we find a highly significant AAR of -0.0267% for t = 2, which may also explain the significant periods (-2, 2) and (0, 5). The findings show that the market classifies large ‘unknown’ transactions as a sign of uncertainty, which leads to a negative price effect.

For cold wallet deposits, we find a highly significant positive AAR of 0.0404% in the minute the transactions take place. However, for the full 31-minute event window, the CAAR is negative (-0.3444%, $p_t < .05$). Potentially, traders interpret cold wallet deposits as additional selling pressure resulting from either one large deposit that is deposited directly into the cold wallet or from a constant excess of hot wallet deposits over hot wallet withdrawals that triggers a rebalancing transaction from the hot to the cold wallet of an exchange. For cold wallet withdrawals, we do not find any significant effects for the minutes surrounding the event, yet the CAAR for the full event window is significant (0.0746%, $p_{t,z} < .05$). The explanation for this positive price effect could be the opposite of the one for cold wallet deposits: Traders interpret it as the demand for Bitcoin exceeding what the exchange can serve from the hot wallet, which means buying pressure.

Table 3. Event study results for clustered addresses

		I.	II.	III.	IV.	V.
Window	Metrics	Regular transfers	Cold wallet deposits	Cold wallet withdrawals	Hot wallet deposits	Hot wallet withdrawals
-15 to 15	CAAR %	-0.0357	-0.3444	0.0746	-0.0572	-0.0096
	t-stat.	-0.88	-2.06**	2.06**	1.39	-0.26
	z-stat.	-1.53	-0.61	2.11**	0.57	-0.33
-5 to 5	CAAR %	-0.0535	-0.1472	0.0255	-0.0165	-0.0056
	t-stat.	-1.55	-1.87*	1.13	-0.99	-0.31
	z-stat.	-1.97**	-0.38	1.47	-1.07	0.31
-2 to 2	CAAR %	-0.0355	-0.0455	0.0091	0.0083	-0.0132
	t-stat.	-2.82***	-0.60	0.81	0.75	-1.14
	z-stat.	-2.60***	1.84*	1.67*	0.53	0.24
0 to 15	CAAR %	0.0042	-0.1665	0.0422	0.0091	0.0021
	t-stat.	0.16	-1.82*	1.41	2.45**	0.09
	z-stat.	-0.55	-1.06	2.20**	0.99	-0.47
0 to 5	CAAR %	-0.0386	-0.0640	0.0187	0.0006	-0.0092
	t-stat.	-2.00**	-0.9	0.92	-0.04	-0.87
	z-stat.	-2.33**	1.77*	0.735	0.76	0.04
2	AAR %	-0.0267	-0.0116	-0.0006	0.0092	0.0021
	t-stat.	-3.02***	-0.36	-0.12	1.94*	0.55
	z-stat.	-4.24***	0.47	-1.52	1.94*	0.37
1	AAR %	-0.0072	-0.0042	0.0018	-0.0028	-0.0069
	t-stat.	-1.59	-0.17	0.34	-0.64	-1.52
	z-stat.	-1.06	0.79	0.30	-0.48	-1.19
0	AAR %	0.0054	0.0405	0.0042	0.0047	-0.0101
	t-stat.	1.04	3.12***	0.7	0.94	-2.06**
	z-stat.	-1.65*	3.29***	0.643	1.29	-2.27**
-1	AAR %	-0.0073	-0.0042	-0.0002	-0.0004	-0.0029
	t-stat.	-1.34	-0.17	-0.04	-0.09	-0.53
	z-stat.	-3.31*	0.79	-0.28	-0.15	0.37
-2	AAR %	0.0003	-0.0044	0.0040	-0.0025	0.0045
	t-stat.	0.05	-0.32	0.92	-0.68	0.81
	z-stat.	-0.98	-0.19	1.18	-0.35	0.27
-5 to 0	CAAR %	-0.0095	-0.0426	0.0110	-0.0112	-0.0065
	t-stat.	-0.51	-1.44	0.87	-1.07	-0.42
	z-stat.	-0.167	-0.48	0.46	-1.36	0.30
-15 to 0	CAAR %	-0.0346	-0.1374	0.0366	-0.0290	-0.0217
	t-stat.	-1.32	-1.23	1.79*	-1.89*	-0.90
	z-stat.	-0.89	0.81	0.89	-1.73*	-0.29
	N	434	51	129	612	

*, **, *** indicates significance at the 10%, 5% and 1% level, respectively.

Contrary to the expectations formulated above, for hot wallet deposits we identify a positive effect in t = 2 (0.0091%, $p_{t,z} < .1$) and a negative effect for the 16-minute interval leading up to the transfer (-0.029%; $p_{t,z} < .1$). Speculating on a possible explanation, large deposits may be used to fund purchases of leverage long positions. Another explanation could be informed traders (e.g. Bitcoin node operators) reacting to the information of a transaction as soon as it is propagated in the network. The positive effect in t = 2 could then be a contrary recovery effect that occurs after the transaction has been processed.

For hot wallet withdrawals, we find negative AARs of -0.0101% ($p_{t,z} < .05$) in the minute the transaction is confirmed. Further analysis of liquidity and trading volume around such events could help to shed more light on the effect.

4 Concluding remarks

The transparency of the Bitcoin network and the automatic distribution of information about (large) transfers across the network allows market participants to immediately identify such events, to classify them according to their likely motive and to incorporate this information into their trading strategies. Our results show that the market reacts to large Bitcoin transfers, which makes them a relevant aspect of Bitcoin's market structure. Yet the identified effects are only weak, so that a trading strategy based solely on transaction monitoring might not be able to overcome transaction costs such as trading fees. Such a strategy may however be viable for high frequency traders and market makers, who buy or sell anyway and may use this information to optimize their market timing.

This study provides a starting point for further research, for instance regarding the existence of similar effects with respect to other cryptocurrencies. A number of open questions also remain regarding the Bitcoin network itself. Besides minute intervals, similar effects may also exist for shorter or longer intervals. Also, the transactions could be clustered according to other market participants, such as miners, Bitcoin wallet providers or various other exchanges. In general, the market reactions to large Bitcoin transfers that we have found can be interpreted as a sign of market efficiency. Yet it remains unclear, of course, whether these reactions are optimal or whether there is still room for more efficiency.

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Appendix

Table A1. Distribution of transaction types across size-based quartiles

Quartile	Q1	Q2	Q3	Q4
Range (BTC)	500 – 976	979 – 1,205	1,206 – 1,839	1,841 – 130,004
Observations	534	533	532	534
Non-exchange transfers	26.97%	36.77%	3.01%	14.63%
Cold wallet deposits	3.37%	1.31%	1.50%	3.38%
Bitfinex	2.25%	0.94%	1.50%	0.75%
Coincheck	1.12%	0.19%	0%	0.38%
Binance	0%	0%	0%	1.50%
Huobi	0%	0.19%	0%	0.38%
Bitstamp	0%	0%	0%	0.38%
Cold wallet withdrawals	2.81%	7.88%	0.56%	12.95%
Bitfinex	0%	7.69%	0%	10.69%
Coincheck	2.81%	0.19%	0.56%	0.19%
Huobi	0%	0%	0%	1.13%
Binance	0%	0%	0%	0.56%
Bittrex	0%	0%	0%	0.38%
Hot wallet deposits	23.60%	21.95%	42.48%	26.83%
Bitfinex	0%	28.14%	39.47%	33.40%
Binance	23.60%	1.50%	3.01%	3.19%
Hot wallet withdrawals	43.26%	32.08%	52.44%	42.21%
Bitfinex	41.95%	6.75%	7.33%	16.32%
Binance	2.62%	25.89%	46.43%	27.77%
Bittrex	0.37%	0.38%	0.19%	0.38%

The compositions / sub-clusters of the groups are shown indented under the main category.

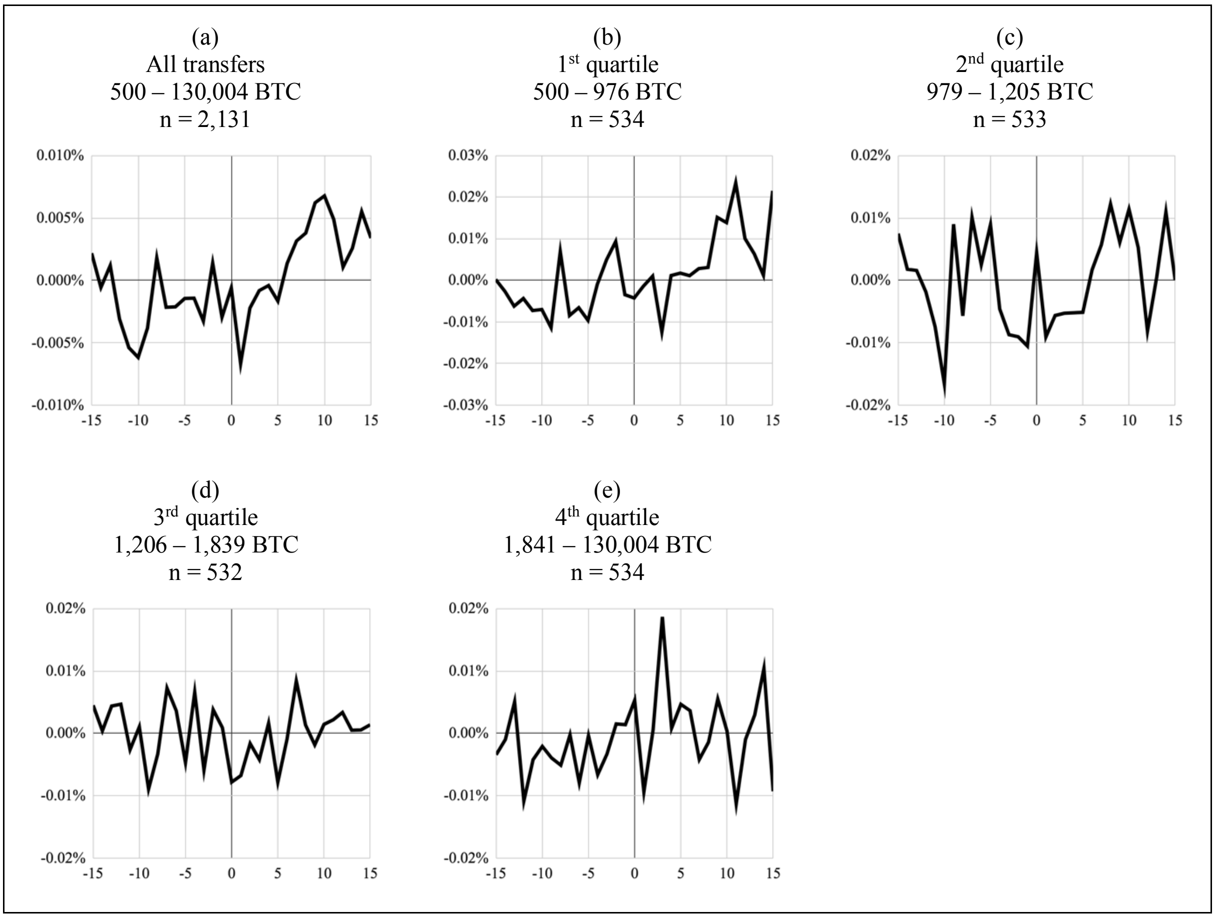

Figure A1. AARs per minute around large Bitcoin on-chain transactions based on transacted value.

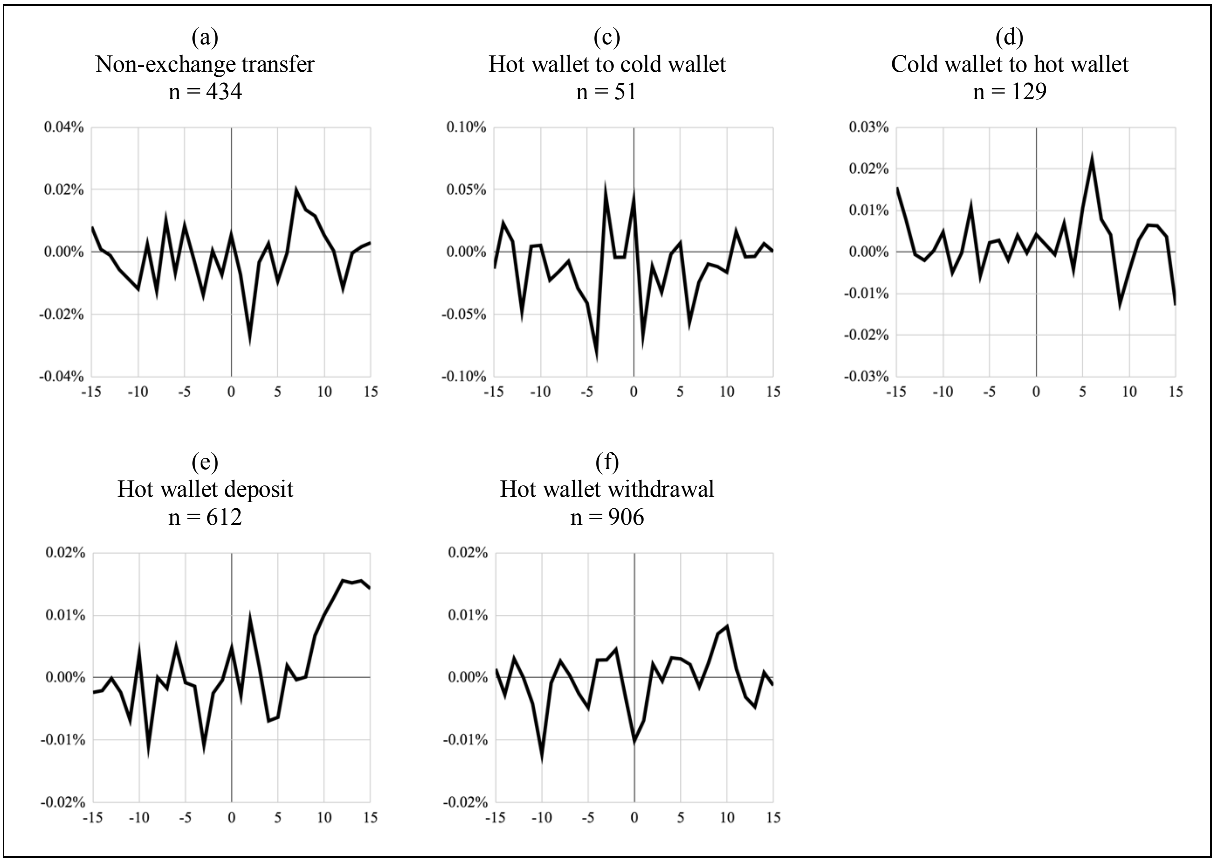

Figure A2. AARs per minute around large Bitcoin on-chain transactions for clustered address samples.

Declarations

Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on request.

Conflicts of interest

Not applicable.

Funding

Not applicable.

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About the Blockchain Research Lab

The Blockchain Research Lab promotes independent science and research on blockchain technologies and the publication of the results in the form of scientific papers and contributions to conferences and other media. The BRL is a non-profit organization aiming, on the one hand, to further the general understanding of the blockchain technology and, on the other hand, to analyze the resulting challenges and opportunities as well as their socio-economic consequences.

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