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The impact of transparent money flows: Effects of stablecoin transfers on return and trading volume of Bitcoin

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Abstract: Stablecoins are digital currencies that peg to non-volatile values, such as most commonly fiat currency. Yet unlike fiat currency, stablecoins are fully transparent: every transfer is recorded on a public blockchain. In this regard, they can serve as a valuable case study of the disruptive effect which transparent money flows could have on financial markets. This study analyzes how 1,587 stablecoin transfers of $1 million or more between April 2019 and March 2020 affected Bitcoin returns and trading volume. It finds highly significant positive abnormal trading volume and significant abnormal returns in the hours around stablecoin transfers. The sender and receiver of each transfer are categorized as (1) unknown, (2) cryptocurrency exchange or (3) stablecoin treasury. The effects on trading volume and returns differ across the resulting nine subsamples, which suggests that market participants presume different transfer motives and varying degrees of information asymmetry for each sender-receiver combination. The findings illustrate the feedback effects between cryptocurrency markets and stablecoin usage and suggest that transparent money flows have the potential to increase market efficiency.

Keywords: Market efficiency, Informational efficiency, Price discovery, Asset pricing, Event study, Transaction activity, Tether, Cryptocurrency

1 Introduction

An important aspect of blockchain-based transactions and cryptocurrencies is that they can be monitored by anyone. Every transfer, no matter how important or insignificant, can be tracked in close to real-time, offering unique potential for in-depth analyses that are rarely possible in traditional financial markets. Blockchain technology has given rise to various new markets, such as digital token sales or decentralized finance (DeFi). Meanwhile, central banks are working on central bank digital currency (CBDC) systems, which can also operate transparently if they adopt a public blockchain as their base layer (Mancini-Griffoli et al., 2018; Steinmetz et al., 2020). While transparency is an important aspect of market efficiency, the actual impact of transparent blockchain-based transactions on market efficiency is still unexplored.

Stablecoins are a specific type of cryptocurrency which peg their value to other assets, like fiat currency or gold. Fiat-pegged stablecoins play a vital role in cryptocurrency markets, as they are used as a substitute for fiat currency on cryptocurrency exchanges. While in traditional markets large currency transactions can only be observed by the entities involved, stablecoin transfers (i.e. money transfers via the blockchain) are visible to anyone. The same applies to deposits and withdrawals on cryptocurrency trading platforms, making the movement of both the base and the counter currency transparent. Stablecoin transfers thus offer unique insights into the impact of transparent money flows on market efficiency, which may also shed some more light on traditional financial markets. Stablecoins are particularly suitable as a basis for analysis because they share many similarities with traditional fiat currency. In particular, the most popular stablecoins can be used as a means of payment in virtually any blockchain-based system. Presently, the prime use case of stablecoins is to serve as a substitute for fiat currencies on cryptocurrency exchanges. If, for example, stablecoins worth millions of dollars are sent to a cryptocurrency exchange, market participants may speculate about the motives behind this transfer and adjust their trading behavior accordingly. The suspicion that the deposited money will soon be used to buy cryptocurrency may – depending on market liquidity and the size of the deposit – trigger a positive short-term price effect and an increase in trading volume. Such effects may in turn induce a feedback effect amplifying the original effect through increased activity by traders monitoring on-chain activity. Note that these trading effects may occur independently of whether the deposit is used immediately to buy cryptocurrency, simply because the deposit is interpreted to signal an upcoming purchase.

While academic research has not yet analyzed transfers of stablecoins, studies show that activity on the Bitcoin blockchain affects Bitcoin returns and trading volume, e.g. by considering the number of active addresses (Aalborg et al., 2019), cumulative transaction activity (Koutmos, 2018) and large transactions (Ante, 2020a; Ante and Fiedler, 2020). This finding may also apply to stablecoin transfers, as they represent a major source of liquidity for cryptocurrency in general and Bitcoin in particular. Most stablecoin transfers likely occur shortly before or after cryptocurrency trades, which may in turn lead to abnormal price effects. Even if the price effects from sales and purchases offset each other, we should see an increase in Bitcoin trading volume around large stablecoin transfers.

Research on stablecoins has so far focused primarily on their issuance (Ante et al., 2020; Kristoufek, 2020; Lyons and Viswanath-Natraj, 2020a; Wei, 2018). Issuances tend to take place in negative market phases (Griffin and Shams, 2019). Another stream of research on stablecoins investigates their use as safe haven from volatility (Baur and Hoang, 2020; Wang et al., 2020).

This study analyzes if and how large stablecoin transfers affect Bitcoin returns and trading volume, allowing us to identify the extent to which the monitoring of money transfers via the blockchain allows traders to gain information advantages over non-observing traders. Based on a sample of 1,587 stablecoin transfers of $1 million or more, our event study assesses abnormal returns and abnormal trading volume of Bitcoin around stablecoin transfers. We further analyze if the effects depend on the type of the sender and receiver, distinguishing between cryptocurrency exchanges, stablecoin treasuries and other entities. Lastly, we analyze to what degree event characteristics, specifically the size of stablecoin transfers and different combinations of involved blockchain addresses, can explain abnormal effects. As the prices of other cryptocurrencies are driven by Bitcoin (Kumar and Ajaz, 2019), the results are to a certain degree generalizable for the cryptocurrency market.

The study contributes to an understanding of stablecoins in general, the relevance of large stablecoin transfers for cryptocurrency markets, and the price discovery and efficiency of Bitcoin. The findings add to the emerging literature on the relationship between blockchain activity and cryptocurrency markets. The unique transparency of cryptocurrency markets also allows valuable insights into the market dynamics of more traditional asset classes. Accordingly, the results are not only relevant for cryptocurrency markets but can also indicate whether greater transparency in traditional markets, e.g. via the use of blockchain as a base layer technology, could increase market efficiency.

2 Hypotheses

Transparency promotes market efficiency, and newly available information can change the price expectation of market participants (Fama, 1970). When traders change their expectations in light of an unexpected event, the corresponding effects are abnormal, as they solely relate to this specific event (Beaver, 1968; Karpoff, 1986). It seems logical to conclude that large on-chain transfers of stablecoins may lead to abnormal returns and abnormal trading volume of Bitcoin. Such transfers can have various reasons, which makes it difficult to speculate about the direction of these effects. A transfer may occur because of negative returns that resulted in a sale of cryptocurrency, but it could also occur because of positive returns that resulted in a purchase of cryptocurrency. As research suggests that stablecoin issuances reflect cryptocurrency market demand (Kristoufek, 2020), it can be assumed that large stablecoin transfers are usually related to the purchase or sale of cryptocurrencies, which should result in higher Bitcoin trading volumes around large stablecoin transfers (Hypothesis 1).

Analyzing the blockchain addresses involved in stablecoin transfers, we are able to determine which market participants send and receive the coins. We distinguish between (1) unknown addresses, (2) cryptocurrency exchanges and (3) stablecoin treasuries. Table 1 shows the nine different sender-receiver combinations. Each combination implies a different level of information asymmetry and different presumed transfer motives. Accordingly, we expect that the effect of transfers differs across these combinations. Transfer where both sender and receiver are unknown have the highest degree of information asymmetry, followed by transfers where either sender or receiver or unknown, while the other party is either cryptocurrency exchange or stablecoin treasury. Transfers where both sender and receiver can be identified are associated with the lowest degree of information asymmetry.

If liquidity traders have timing discretion (Admati and Pfeiderer, 1988), they will reduce or postpone their trading activity as information asymmetry increases in order to curb the risk of trading with informed counterparties (Black, 1986; Chae, 2005). Accordingly, if large stablecoin transfers are a relevant aspect for Bitcoin markets, abnormal trading volume should relate to the degree of information asymmetry involved in each of the transaction types.

We thus expect that the degree of information asymmetry associated with stablecoin transfers, as depicted in Table 1, negatively relates to Bitcoin trading volume after information about a transfer becomes public (Hypothesis 2). In other words, while abnormal trading volume may be positive for all stablecoin transfers, it should be lower for transfers with high information asymmetry and higher for transfers with low information asymmetry.

Based on the respective sender or receiver of transfers, different likely reasons for transfers can be identified, as shown in Table 1. For example, stablecoin transfers to cryptocurrency exchanges (i.e. deposits) most likely relate to subsequent purchases of cryptocurrency, while withdrawals most likely relate to prior sales of cryptocurrency. Clearly, there may also be other reasons for such transfers, as stablecoins may have been held for a long time (i.e. no trading of cryptocurrency immediately corresponds to the transfer) or could be used otherwise, e.g. for lending, as a safe haven, or as collateral.

We expect positive subsequent abnormal Bitcoin returns for stablecoin transfers with cryptocurrency exchanges as receivers (Hypothesis 3) and negative prior abnormal Bitcoin returns for stablecoin transfers with cryptocurrency exchanges as senders (Hypothesis 4). This is due to the fact that the most likely motive for a stablecoin transfer to an exchange is to use it to buy cryptocurrency. Similarly, cryptocurrency is sold on the exchange to regain possession of stablecoins, which are then subsequently withdrawn.

Table 1. Information asymmetry and presumed motives associated with large stablecoin transfers. The colors signify the degree of information asymmetry in the transfers: red = high, blue = medium, green = low.

Type		Receiver		
	Entity	Unknown address	Cryptocurrency exchanges	Stablecoin treasuries
Sender	Unknown address	− Unknown	− Ex-post purchase of cryptocurrency	− Burning of stablecoins (decrease in market liquidity)
	Cryptocurrency exchanges	− Ex-ante sale of cryptocurrency	− Ex-ante and/or ex-post purchase or sale of cryptocurrency	− Burning of stablecoins (decrease of market liquidity) − Ex-ante sale of cryptocurrency
	Stablecoin treasuries	− Issuance of stablecoins (increase of market liquidity)	− Issuance of stablecoins (increase of market liquidity) − Ex-post purchase of cryptocurrency	− Unclear / blockchain swap *(very rare transaction type)*

Stablecoin treasuries manage the lifecycle of stablecoins by minting new coins and by removing coins from circulation. Accordingly, transactions that involve treasuries can provide information about potential upstream or downstream market developments. A transfer from a treasury likely means new stablecoins entering the active market (i.e., an increase in market liquidity), while a transfer to a treasury likely entails the subsequent burning of coins, i.e. the withdrawal of liquidity from the market. However, Tether features the special case of so-called chain swaps. Tether is issued on multiple blockchains; occasionally the Tether treasury burns coins on one blockchain but immediately creates the same amount of coins on another blockchain. Keeping this limitation in mind, we nonetheless expect that transfers from stablecoin treasuries – because they lead to subsequent purchases of cryptocurrency or are perceived as a signal of increasing market liquidity – result in positive abnormal returns after the transaction (Hypothesis 5). Because they relate to prior sales of cryptocurrency or are perceived as a signal of decreasing market liquidity, we expect transfers to stablecoin treasuries to result in negative abnormal returns around the transfers (Hypothesis 6).

Larger transfers can generally be assumed to have a stronger effect. A big transaction is likely preceded by a large sale or followed by a large purchase. We therefore expect the size of stablecoin transfers to correlate positively with abnormal effects on returns and trading volume (Hypothesis 7).

3 Data and methods

3.1 Data collection

We collect transaction data on the six stablecoins Tether USD (USDT), USD Coin (USDC), Paxos Standard (PAX), Binance USD (BUSD), Huobi USD (HUSD) and Gemini USD (GUSD) between April 2019 and March 2020 across three different blockchain infrastructures. All stablecoins except USDT operate exclusively on the Ethereum blockchain, for which the block explorer *etherscan.io* is used to collect transaction data. For USDT, additional data is extracted from the TRON blockchain via *tronscan.io* and from Omni, a second-layer protocol operating on the Bitcoin blockchain, via *omniexplorer.info*. Timestamp, transaction size, transaction value in USD and the involved blockchain addresses are collected. All transactions below one million dollars are excluded from the data set. This leaves 1,587 large stablecoin transfers. If a blockchain address is known to belong to a stablecoin treasury or a cryptocurrency exchange, it is assigned to the corresponding category. We identify a total of 19 treasuries and exchanges, which can act both as sender or receiver. All addresses are accordingly clustered in the three groups *unknown*, stablecoin *treasuries*, and cryptocurrency *exchanges* (see Table A.1 for an overview).

Cryptocurrency market data is collected from *cryptodatadownload.com*. Hourly BTC/USD prices and volume data in USD from the cryptocurrency exchange Bitstamp are our main data basis. To test the robustness of the results across different cryptocurrencies, hourly prices for the cryptocurrencies Ethereum (ETH/USD), Ripple (XRP/USD) and Litecoin (LTC/USD) are collected from Bitstamp. To assess if the results also apply to other cryptocurrency exchanges (i.e., are robust), we collect additional data on BTC/USDT from Binance and BTC/USD from both Bitfinex and Coinbase.

3.2 Dependent variables and event study methodology

We use event study methodology to calculate abnormal returns and abnormal trading volumes (Armitage, 1995; Brown and Warner, 1985; Chae, 2005; Fama et al., 1969), which in turn constitute the dependent variables in subsequent analyses. In an event study, a certain period prior to an unexpected or unusual event is chosen as the observation period, based on which expected returns are calculated. This expected return is then compared to the observed return around an event. The abnormal return is the difference between the expected and the observed return, which is directly attributed to the occurrence of the event, in our case the large stablecoin transfer. Abnormal trading volumes are calculated analogously.

In line with the literature, log returns are used to accommodate skewness and kurtosis in the financial data (Brown and Warner, 1985). For trading volume, the transformation $log(x + c)$ is used, where x is the hourly trading volume in USD and $c = 0.000255$ is a constant to account for periods with zero trading volume, as suggested by Campbell and Wasley (1996). A 25-hour event window from -12 to 12 hours around the event is chosen. Expected returns and trading volumes are calculated as the mean over the estimation window from -150 to -15 hours before each stablecoin transfer (constant mean return model). Different windows are used for robustness checks. Using an estimation window of more than 100 periods should produce robust results (Armitage, 1995). Note that our windows can overlap, i.e., the estimated effects of one event may occur in the observation window of another event. Most event studies avoid overlapping windows to ensure that the effects can be fully explained by the event considered. That strategy is not available to us because the data set contains no non-overlapping events. In line with the literature and for the sake of robustness, we test the significance of the results using both *t*-tests and the non-parametric Wilcoxon sign rank test (Wilcoxon, 1945) (referred to as *z*-test in the following). Only results that pass both tests are deemed valid.

3.3 Independent and control variables

A dummy variable is created for each of the nine possible sender-receiver combinations of the three address clusters *unknown, treasuries* and *exchanges*. The variable names are composed of the first two letters of the sender cluster and the first two letters of the receiver cluster. For example, the variable UNTR (UN*known* to TR*easury*) takes a value of one if the transaction was initiated from an unknown address and the recipient is a treasury address. We thus obtain the variables UNUN, UNTR, UNEX, TRUN, TRTR, TREX, EXUN, EXTR and EXEX.

The variable *size (log)* is the logarithm of the stablecoin transfer value in USD. *Bitcoin ($1,000)* is the hourly Bitcoin closing price in dollar directly after the stablecoin transfer, divided by 1,000 for readability, to control for price fluctuations in the time series. Since price effects have been found to differ across stablecoins (Ante et al., 2020), a dummy variable is created for each of the six stablecoins in the sample. Table A.2. in the appendix shows statistics on the number of transfers and transfer values per stablecoin. Finally, we create a dummy variable for each day of the week to control for day-of-the-week effects, which persist in cryptocurrency markets. For example, Caporale and Plastun (2019) find that Bitcoin returns are higher on Mondays, while Dorfleitner and Lung (2018) identify that they are lower on Sundays, and trading volumes are lower on weekends (Baur et al., 2019; Kaiser, 2019; Wang et al., 2019). In line with these results, we find that the fewest stablecoin transfers occurred on Saturdays and Sundays (Figure A.1.), and average trading volumes are lowest on weekends (cf. Figure A.2.).

4 Results

4.1 Descriptive statistics

USDT accounts for the majority (80.1%) of the 1,587 stablecoin transfers, followed by USDC (8.1%), PAX (7.4%), HUSD (0.4%) and GUSD (0.1%). Most transfers are executed on the Ethereum blockchain (62.3%), followed by TRON (19.3%) and Bitcoin/Omni (18.3%). All non-Ethereum blockchain transfers involve USDT, it being the only stablecoin that does not exclusively operate on the Ethereum blockchain. 52.9% of all USDT transfers occurred on Ethereum, 24.2% on TRON and 22.9% on Bitcoin/Omni.

Table 2. Descriptive statistics. Stablecoin transfer size, Bitcoin hourly returns and Bitcoin trading volume for a sample of 1,587 stablecoin transfers of $1 million or more between April 2019 and March 2020, and subgroups based on transaction size and sender/receiver types. Returns and trading volumes are calculated as hourly averages over the time window specified in the top row.

				-150 to -15 hours		-12 to -1 hours		0 to 12 hours	
			Value transferred ($ million)	Return in %	Trading volume ($ million)	Return in %	Trading volume ($ million)	Return in %	Trading volume ($ million)
	Count	Share	Mean (SD)	Mean (SE)	Mean (SE)	Mean (SE)	Mean (SE)	Mean (SE)	Mean (SE)
All transactions	1,587	100%	11.94 (25.11)	0.003 (0.003)	3.802 (0.054)	0.022 (0.008)	3.998 (0.816)	0.024 (0.088)	3.851 (0.086)
Transfer size									
Lowest decile	159	10%	2.89 (0.73)	0.002 (0.005)	3.509 (0.099)	-0.015 (0.017)	2.913 (0.122)	-0.022 (0.014)	2.894 (0.110)
2	159	10%	4.98 (0.02)	0.039 (0.008)	4.013 (0.189)	0.013 (0.023)	4.078 (0.262)	0.021 (0.020)	3.961 (0.299)
3	159	10%	5.01 (0.01)	0.024 (0.008)	4.062 (0.175)	-0.004 (0.026)	4.025 (0.238)	-0.010 (0.022)	3.854 (0.208)
4	158	10%	5.08 (0.11)	-0.005 (0.008)	3.456 (0.175)	0.034 (0.026)	3.475 (0.245)	0.016 (0.019)	3.205 (0.208)
5	159	10%	5.86 (0.21)	-0.019 (0.010)	3.842 (0.158)	0.004 (0.032)	3.987 (0.274)	0.013 (0.040)	4.160 (0.271)
6	159	10%	7.49 (0.67)	-0.013 (0.009)	3.702 (0.168)	-0.001 (0.032)	4.193 (0.277)	0.011 (0.031)	3.920 (0.287)
7	159	10%	9.81 (0.33)	0.012 (0.008)	4.021 (0.192)	0.046 (0.032)	4.799 (0.304)	0.010 (0.027)	4.203 (0.291)
8	159	10%	10.13 (0.22)	0.007 (0.007)	3.805 (0.184)	0.027 (0.025)	3.734 (0.216)	0.044 (0.026)	3.664 (0.262)
9	160	10%	15.50 (0.29)	0.001 (0.009)	3.821 (0.175)	0.041 (0.029)	4.367 (0.251)	0.011 (0.035)	4.267 (0.318)
Largest decile	157	10%	53.10 (66.23)	-0.021 (0.010)	3.589 (0.165)	0.078 (0.031)	4.410 (0.318)	0.153 (0.033)	4.383 (0.362)
Address clusters									
UNUN	69	4.3%	20.03 (20.11)	0.004 (0.010)	3.525 (0.215)	0.010 (0.036)	3.963 (0.303)	0.057 (0.027)	3.605 (0.248)
UNTR	33	2.1%	8.56 (8.06)	-0.043 (0.022)	3.606 (0.327)	-0.091 (0.100)	5.266 (0.940)	-0.097 (0.084)	4.760 (0.760)
UNEX	347	21.9%	9.07 (8.48)	0.001 (0.005)	3.669 (0.111)	0.008 (0.017)	3.573 (0.159)	0.008 (0.018)	3.591 (0.184)
TRUN	327	20.6%	8.89 (5.63)	-0.020 (0.007)	3.694 (0.101)	0.049 (0.024)	4.523 (0.202)	-0.012 (0.022)	3.750 (0.166)
TRTR	2	0.1%	139.83 (190.66)	0.069 (0.078)	6.316 (2.730)	0.019 (0.022)	7.309 (0.601)	0.184 (0.177)	6.147 (0.071)
TREX	216	13.6%	17.27 (39.59)	0.005 (0.006)	3.755 (0.163)	0.058 (0.023)	4.038 (0.228)	0.051 (0.025)	3.756 (0.218)
EXUN	231	14.6%	6.91 (5.43)	0.014 (0.006)	4.089 (0.149)	0.024 (0.018)	3.644 (0.188)	0.020 (0.022)	4.020 (0.232)
EXTR	117	7.4%	28.93 (52.72)	-0.001 (0.011)	4.022 (0.244)	0.060 (0.025)	4.011 (0.293)	0.057 (0.038)	4.069 (0.353)
EXEX	245	15.4%	9.15 (24.06)	0.031 (0.007)	3.959 (0.137)	-0.026 (0.021)	4.005 (0.197)	0.067 (0.020)	4.103 (0.252)

Table 2 shows summary statistics on transfer value, hourly returns and hourly trading volume. On average, a stablecoin transaction is worth $11.9 million. A large standard error of $25.1 million suggests a skewed distribution dominated by a few large transfers. Notably, the average trading volume over the observation period (t = -150 to -15 hours) is lower than over the two periods in the event window. Across size-based deciles, the transferred amount increases disproportionally in the higher classes, especially in the tenth decile – further evidence of the skewed distribution. While stablecoin transactions in general seem to lead to increased trading volume of Bitcoin, there is no consistent pattern across the size-based deciles.

Over the estimation window, the average hourly Bitcoin returns is 0.003%, or 0.4% in sum over the full estimation window. Deciles two (0.039%) and three (0.024%) display the largest average hourly returns. The average returns during the observation period are higher than in the estimation period, which suggests that stablecoin transfers are a relevant metric for Bitcoin returns. In the period before the transfer, the average Bitcoin return is 0.022%, and in the phase including and after the transfer, it is 0.024%. Especially the largest decile shows comparatively high average returns of 0.078% before the event and 0.153% after the event.

In only 4.3% of all transfers, both the sender and the receiver are unknown (UNUN). For detailed statistics and the composition of the address clusters, see Table A.1. in the appendix. The mean transfer amount varies widely among the clusters, from $6.9 million for EXUN to $139.8 million for TRTR. The effect size on return is also largest for TRTR transactions both in the estimation window and in the post transaction period. Note, however, that TRTR comprises only two observations. Most stablecoin transactions are transfers from unknown senders to exchanges (UNEX, 21.9%), followed by treasuries to unknown receivers (TRUN, 20.6%).

The cluster UNTR features negative hourly average returns of -0.1% both before and after the transfers, suggesting that stablecoin transfers to treasuries are associated with sales of Bitcoin. The differences in hourly trading volume between the estimation period ($3.6 million) and the observation period before ($5.3 million) and after ($4.8 million) the transfers from unknown addresses to treasuries may support this conjecture.

The largest effects of stablecoin transactions on Bitcoin returns in the twelve hours leading up to a transfer are found for transfers between treasuries and exchanges, in both directions (TREX: 0.058%; EXTR: 0.06%). Post-transaction returns are largest for transactions between exchanges (0.067%).

4.2 Event study results

Table 3 shows event study results for log returns and log trading volume. A strong positive effect on trading volume is found for all time periods before and after the transactions. Robustness checks using alternative estimation periods and cryptocurrency exchanges as well as other cryptocurrencies (Table A.3) confirm our results. The abnormal effects on trading volume support Hypothesis 1. For returns, by contrast, the period [-12, -1] is the only one in which the abnormal returns on BTC/USD are significant with respect to both test statistics. Ambiguous results regarding the returns across the entire data set are no surprise, since some transfers will be related to purchases and others to sales – effects that offset each other. The significant result for the 12-hour period before the transfer however suggests that purchases predominate in this period.

Table 3. Event study results for Bitcoin log return and log trading volume. Abnormal return (AR) and abnormal trading volume (ATV) per hour and cumulative abnormal return (CAR) and cumulative abnormal trading volume (CATV) of Bitcoin around large stablecoin transfers (N = 1,587). 'z-test' refers to the non-parametric Wilcoxon sign rank test. 'pos' is the share of observations with positive abnormal returns or trading volume.

Hour	Log return				Log trading volume			
	AAR	*t*-test	*z*-test	pos	ATV	*t*-test	*z*-test	pos
−12	-0.000124	-0.83	-1.13	49%	0.2123	9.05***	8.00***	58%
−11	-0.000320	-2.02**	0.21	51%	0.2300	9.55***	8.20***	58%
−10	0.000368	2.58**	1.33	50%	0.1953	8.23***	7.59***	58%
−9	-0.000216	-1.47	-1.24	50%	0.2560	10.68***	9.54***	58%
−8	0.000258	1.33	0.97	51%	0.3076	12.53***	11.36***	61%
−7	0.000269	1.69*	1.48	50%	0.2992	11.94***	10.43***	60%
−6	-0.000093	-0.62	0.19	50%	0.3315	13.44***	13.44***	61%
−5	0.000246	1.62	1.47	52%	0.3273	13.38***	13.38***	61%
−4	0.000342	2.29**	2.91***	51%	0.3350	13.60***	12.32***	63%
−3	0.000273	2.19**	1.66*	51%	0.3411	14.29***	14.29***	63%
−2	-0.000001	-0.01	-0.66	51%	0.3479	14.68***	14.68***	66%
−1	0.000033	0.24	1.02	49%	0.3921	16.37***	16.37***	66%
0	0.000283	1.99**	0.30	51%	0.3343	14.27***	14.27***	65%
1	-0.000051	-0.31	-0.88	50%	0.3380	14.78***	14.78***	65%
2	0.000094	0.55	-1.13	49%	0.2911	12.16***	12.16***	61%
3	-0.000021	-0.15	0.70	52%	0.2415	10.05***	10.05***	58%
4	0.000189	1.19	0.29	50%	0.2690	11.25***	11.25***	60%
5	-0.000096	-0.56	0.64	51%	0.2103	8.92***	8.92***	57%
6	0.000218	1.38	0.01	49%	0.2286	9.64***	9.64***	56%
7	0.000105	0.57	0.57	50%	0.2277	9.53***	7.85***	56%
8	0.000108	0.56	1.03	51%	0.2006	8.10***	6.34***	54%
9	0.000061	0.38	1.32	52%	0.1831	7.39***	5.50***	54%
10	0.000101	0.56	1.55	53%	0.1630	6.37***	4.56***	53%
11	0.000107	0.67	1.16	53%	0.1511	6.09***	4.22***	52%
12	0.000180	1.25	0.81	51%	0.1659	6.70***	5.55***	55%
Window	CAR	*t*-test	*z*-test	pos	CATV	*t*-test	*z*-test	pos
[−12, −1]	0.001034	2.08**	1.77*	51%	3.5752	17.01***	15.10***	65%
[−6, −1]	0.000800	2.24**	1.49	52%	2.0749	17.79***	16.13***	67%
[0, 6]	0.000616	1.48	0.33	51%	1.9128	15.13***	12.34***	65%
[0, 12]	0.001277	2.42**	1.06	50%	3.0043	13.47***	12.34***	62%

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

The next step is the analysis of the individual subsamples based on the address clusters. Figures 1 and 2 show cumulative abnormal returns and cumulative abnormal trading volumes, respectively, for the periods [-12, -1] and [0, 12] for each of the nine sender-receiver combinations. Both figures also show 95% confidence bands. Table A.4. in the appendix reports the coefficients and test statistics for each cluster. As expected, the abnormal returns differ strongly between the clusters, suggesting that the assumed purpose of the transfer matters to the market's reaction to large stablecoin transfers. For the twelve-hour phase prior to transfers, we find significant effects for four address clusters, three positive and one negative. The significant positive effects exhibited by EXTR, TRUN, and TREX are similar in magnitude, between 0.31% and 0.34%. Transfers between exchanges entail significant negative returns (-0.29%; p<.05). The only highly significant result for [0, 12] is for transfers between unknown addresses (0.34%), while the effect for TREX is significant only in the six hours before the transfer event (0.2%; p<.01). Abnormal effects do not agree with the hypothesized effects regarding the degree of underlying information asymmetry, as, e.g., UNUN and UNTR show the largest (significant) positive abnormal trading volume after the occurrence of large stablecoin transfers over the period [0, 12]. Therefore, Hypothesis 2 is rejected.

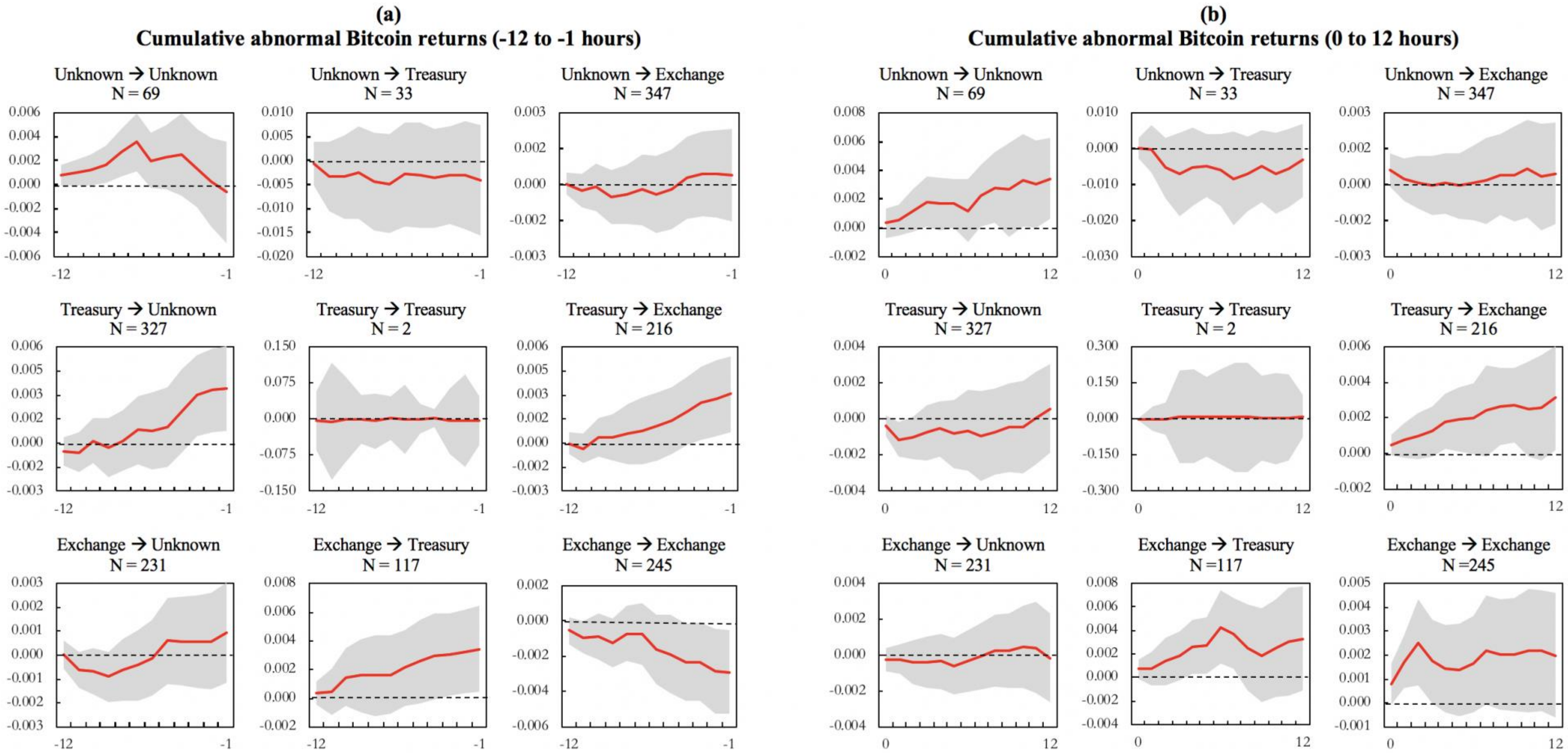

Figure 1. Cumulative abnormal Bitcoin returns around stablecoin transfers based on address clusters. Cumulative abnormal Bitcoin log returns in the twelve hours before (left side) and after (right side) large stablecoins transfers. The grey areas mark 95%-confidence bands.

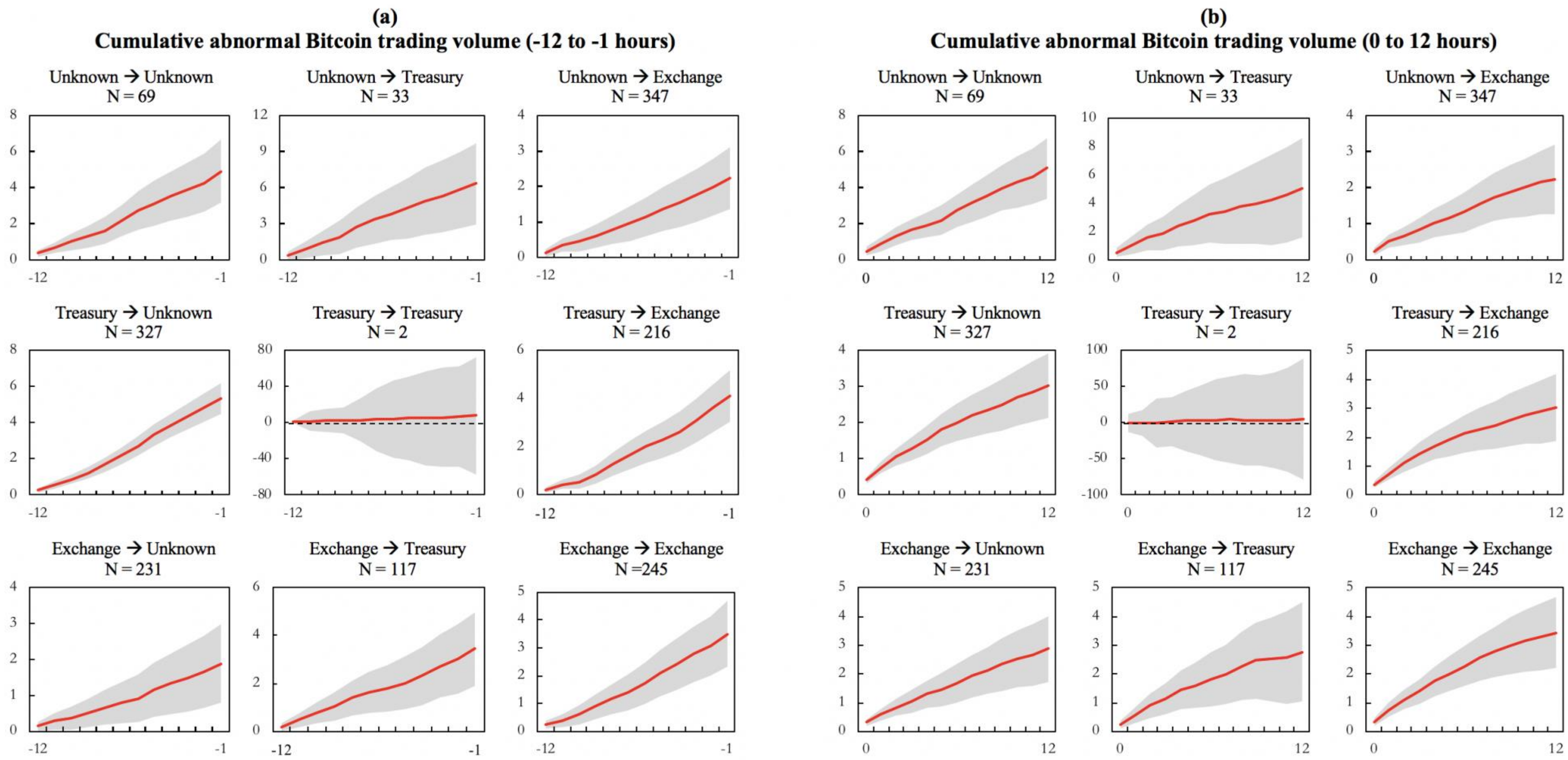

Figure 2. Cumulative abnormal Bitcoin trading volume around stablecoin transfers. Cumulative abnormal Bitcoin trading volume (log) in the twelve hours before (left side) and after (right side) large stablecoin transfers. The grey areas mark 95%-confidence bands.

4.3 Explaining abnormal effects

Next, we test whether transaction size and clustered addresses can explain the abnormal effects. For this purpose, the abnormal returns and volumes are regressed on a set of independent and control variables. For each dependent variable, we run nine models, each one containing a different dummy variable to represent an address cluster. The results are shown in Table 4.

Table 4. Predicting abnormal effects. Regression models predicting cumulative abnormal returns (CAR) and cumulative abnormal trading volume (CATV) of Bitcoin for -12 to -1 hours and 0 to 12 hours around stablecoin transfers (N = 1,587). The row Cluster variable shows the regression coefficient and standard error pertaining to the dummy variable indicated in the second column. Standard errors are robust to heteroskedasticity. All models control for different stablecoins and day-of-the-week effects. Constant term included but not shown.

Dep. var.	Cluster variable	Regression results				
		Bitcoin ($1,000)	Size (log)	Address cluster variable		
		Coef. (SE)	Coef. (SE)	Coef. (SE)	R^2	Adj.R^2
CAR [-12, -1]	UNUN	-0.0004 (0.0003)	0.0022 (0.0006)***	-0.0023 (0.0023)	0.072	0.064
CAR [-12, -1]	UNTR	-0.0005 (0.0003)*	0.0020 (0.0006)***	-0.0089 (0.0054)*	0.075	0.067
CAR [-12, -1]	UNEX	-0.0004 (0.0003)	0.0020 (0.0006)***	-0.0002 (0.0011)	0.072	0.063
CAR [-12, -1]	TRUN	-0.0003 (0.0003)	0.0021 (0.0006)***	0.0023 (0.0014)*	0.074	0.065
CAR [-12, -1]	TRTR	-0.0004 (0.0003)	0.0021 (0.0006)***	-0.0043 (0.0016)***	0.072	0.063
CAR [-12, -1]	TREX	-0.0004 (0.0003)	0.0019 (0.0006)***	0.0024 (0.0013)*	0.073	0.065
CAR [-12, -1]	EXUN	-0.0004 (0.0003)	0.0022 (0.0006)***	0.0012 (0.0012)	0.072	0.064
CAR [-12, -1]	EXTR	-0.0004 (0.0003)	0.0019 (0.0006)***	0.0017 (0.0016)	0.072	0.064
CAR [-12, -1]	EXEX	-0.0004 (0.0003)	0.0017 (0.0006)***	-0.0047 (0.0013)***	0.079	0.070
CAR [0, 12]	UNUN	-0.0019 (0.0003)***	0.0024 (0.0006)***	0.0014 (0.0019)	0.122	0.114
CAR [0, 12]	UNTR	-0.0019 (0.0003)***	0.0025 (0.0006)***	-0.0069 (0.0047)	0.124	0.116
CAR [0, 12]	UNEX	-0.0018 (0.0003)***	0.0025 (0.0006)***	-0.0001 (0.0012)	0.122	0.114
CAR [0, 12]	TRUN	-0.0019 (0.0003)***	0.0025 (0.0007)***	-0.0028 (0.0015)*	0.125	0.117
CAR [0, 12]	TRTR	-0.0019 (0.0003)***	0.0024 (0.0007)***	0.0133 (0.0114)	0.123	0.115
CAR [0, 12]	TREX	-0.0018 (0.0003)***	0.0024 (0.0006)***	0.0005 (0.0013)	0.124	0.116
CAR [0, 12]	EXUN	-0.0019 (0.0003)***	0.0025 (0.0006)***	0.0005 (0.0013)	0.122	0.114
CAR [0, 12]	EXTR	-0.0018 (0.0003)***	0.0025 (0.0007)***	-0.0001 (0.0022)	0.122	0.114
CAR [0, 12]	EXEX	-0.0019 (0.0003)***	0.0024 (0.0007)***	0.0013 (0.0013)	0.123	0.115
CATV [-12, -1]	UNUN	-0.3317 (0.0910)***	0.9197 (0.2914)***	-0.5721 (0.9035)	0.151	0.143
CATV [-12, -1]	UNTR	-0.3202 (0.0906)***	0.8945 (0.2853)***	0.6242 (1.6039)	0.150	0.143
CATV [-12, -1]	UNEX	-0.3231 (0.0911)***	0.8618 (0.2843)***	-0.7111 (0.4797)	0.152	0.144
CATV [-12, -1]	TRUN	-0.2964 (0.0907)***	0.8920 (0.2839)***	1.1230 (0.4742)**	0.153	0.145
CATV [-12, -1]	TRTR	-0.3378 (0.0913)***	0.8788 (0.2858)***	3.1989 (2.3063)	0.151	0.143
CATV [-12, -1]	TREX	-0.3329 (0.0911)***	0.8689 (0.2853)***	0.4113 (0.5751)	0.151	0.143
CATV [-12, -1]	EXUN	-0.3124 (0.0913)***	0.7951 (0.2922)***	-1.1286 (0.5858)**	0.152	0.145
CATV [-12, -1]	EXTR	-0.3340 (0.0907)***	0.9799 (0.2935)***	-0.9465 (0.7781)	0.151	0.144
CATV [-12, -1]	EXEX	-0.3376 (0.0910)***	0.9531 (0.2873)***	0.8763 (0.5968)	0.152	0.144
CATV [0, 12]	UNUN	0.0846 (0.0949)	0.9313 (0.2931)***	0.9259 (0.8951)	0.121	0.114
CATV [0, 12]	UNTR	0.0993 (0.0943)	0.9805 (0.2868)***	1.4158 (1.6965)	0.121	0.114
CATV [0, 12]	UNEX	0.0934 (0.0945)	0.9616 (0.2873)***	-0.3278 (0.5222)	0.121	0.113
CATV [0, 12]	TRUN	0.0606 (0.0950)	0.9759 (0.2872)***	-0.8304 (0.5100)*	0.122	0.114
CATV [0, 12]	TRTR	0.0891 (0.0950)	0.9780 (0.2884)***	-0.5595 (3.8970)	0.121	0.113
CATV [0, 12]	TREX	0.0878 (0.0948)	0.9890 (0.2861)***	-0.2348 (0.6422)	0.121	0.113
CATV [0, 12]	EXUN	0.0809 (0.0954)	1.0092 (0.2943)***	0.3905 (0.6149)	0.121	0.113
CATV [0, 12]	EXTR	0.0884 (0.0944)	1.0587 (0.2947)***	-0.8983 (0.8486)	0.122	0.114
CATV [0, 12]	EXEX	0.0835 (0.0950)	1.0605 (0.2903)***	1.2230 (0.6225)**	0.123	0.115

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

While the Bitcoin price has a significant negative impact on subsequent abnormal returns and prior abnormal trading volumes, the effects are insignificant for the other two combinations of dependent variable and period. Transaction size has a highly significant positive effect on both abnormal returns and trading volume. The models explain about 15% of the variance – the highest value in this set of regressions. The models predicting prior abnormal returns have the lowest R^2. These models yield a single significant positive effect for TREX (0.24%, p<.1) and multiple negative ones, of which TRTR (-0.43%) and EXEX (-0.47%) are significant at the 1%-level. Since we do not obtain any generalizable result for all transfers initiated by or sent to exchanges , Hypotheses 3 and 4 are rejected.

When predicting subsequent returns, we find a significant (and negative) effect only for TRUN (-0.28%). Since the expected positive subsequent effect on returns cannot be confirmed, Hypothesis 5 is rejected. This suggests that (some of) the differences in identified effect strength between the address clusters are attributable not to the presumed transfer motives or the associated information asymmetry but rather to market sentiment and the average transaction size associated with these clusters. As all significant effects of transfers to treasuries in the [-12, -1] window are negative, Hypothesis 6 is accepted.

Looking at the models that explain abnormal trading volume, we find significant effects of TRUN (positive) and EXUN (negative) before the transfer event. Similarly, significant positive (EXEX) and negative (TRUN) downstream effects are found. Given the highly significant results for the size of the stablecoin transfers, Hypothesis 7 can be confirmed: Larger transactions yield greater effects. However, this result could conceivably be attributable to a few very large observations. To address this possibility, we run a set of regression models that test effects of stablecoin transfer size (using dummy variables for size-based deciles) for abnormal effects. The results are shown in Table 5. Using the same dependent variables as in the previous table, models without and with control variables for the address clusters are estimated. For abnormal returns, the tenth (i.e. largest) decile shows highly significant effects before and after stablecoin transfers. This may partly be due to the skewed distribution, but it also shows the strong impact of extremely large stablecoin transfers on Bitcoin returns. At the same time, significant effects occur in the third and fourth deciles. In models five through eight, most deciles predict significant positive abnormal trading volume. The results are similar across the two different models per dependent variable.

While there is no clear trend with increasing deciles, the greatest effects are found in the tenth decile, and the second greatest in the ninth. Thus, the largest stablecoin transfers have the greatest effect on trading volumes – a plausible result. Yet the lack of a monotonous trend across the deciles shows that transfer size cannot fully explain effect size.

Table 5. Regression models predicting the effects of stablecoin transaction size on abnormal Bitcoin returns. Regression models predicting the effects of size-based deciles of stablecoin transfer value on cumulative abnormal returns (CAR) and cumulative abnormal trading volume (CATV) of Bitcoin for -12 to -1 hours and 0 to 12 hours around stablecoin transfers (N = 1,587). For each dependent variable, two models are estimated: with and without controlling for address cluster variables. Standard errors are robust to heteroskedasticity. All models control for different stablecoins, Bitcoin price and day-of-the-week effects. Constant term included but not shown. The first decile is excluded, serving as the reference group.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Coeff. (SE)	Coeff. (SE)	Coeff. (SE)	Coeff. (SE)	Coeff. (SE)	Coeff. (SE)	Coeff. (SE)	Coeff. (SE)
2th decile	0.0015 (0.0017)	0.0015 (0.0017)	-0.0008 (0.0016)	-0.0010 (0.0016)	1.791** (0.829)	0.617** (0.822)	1.686** (0.818)	1.656** (0.828)
3rd decile	0.0017 (0.0019)	0.0020 (0.0019)	-0.0033* (0.0018)	-0.0038** (0.0018)	2.162** (0.853)	2.094** (0.850)	2.641*** (0.806)	2.560*** (0.809)
4th decile	0.0042** (0.0018)	0.0036** (0.0018)	0.0005 (0.0016)	0.0006 (0.0017)	2.225*** (0.787)	2.082*** (0.799)	1.535* (0.824)	1.744** (0.836)
5th decile	0.0020 (0.0020)	0.0016 (0.0020)	-0.0003 (0.0020)	-0.0002 (0.0021)	1.634** (0.798)	1.499* (0.811)	2.921*** (0.892)	3.127*** (0.904)
6th decile	0.0039 (0.0021)	0.0029 (0.0022)	0.0001 (0.0022)	0.0008 (0.0023)	2.979*** (0.814)	2.738*** (0.836)	2.061** (0.922)	2.464** (0.950)
7th decile	0.0034* (0.0020)	0.0031 (0.0020)	-0.0009 (0.0017)	-0.0004 (0.0018)	3.083*** (0.935)	2.929*** (0.943)	1.981** (0.942)	2.080** (0.951)
8th decile	0.0028 (0.0019)	0.0025 (0.0018)	-0.0001 (0.0018)	-0.0004 (0.0018)	1.930** (0.879)	1.817** (0.904)	1.307 (0.959)	1.359 (0.980)
9th decile	0.0040** (0.0019)	0.0030 (0.0021)	-0.0013 (0.0022)	-0.0006 (0.0024)	2.936*** (0.785)	2.730*** (0.846)	2.403** (0.931)	2.840*** (0.996)
10th decile	0.0071*** (0.0020)	0.0062*** (0.0021)	0.0079*** (0.0020)	0.0077*** (0.0022)	3.243*** (0.910)	3.297*** (0.962)	3.731*** (1.002)	4.095*** (1.070)
Address cluster controls	No	Yes	No	Yes	No	Yes	No	Yes
Dep. variable	CAR [-12, -1]	CAR [-12, -1]	CAR [0, 12]	CAR [0, 12]	CATV [-12, -1]	CATV [-12, -1]	CATV [-12, -1]	CATV [-12, -1]
R^2 (Adj. R^2)	0.07 (0.06)	0.09 (0.07)	0.13 (0.12)	0.14 (0.12)	0.16 (0.14)	0.16 (0.15)	0.13 (0.11)	0.13 (0.11)

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

5 Discussion

Our results show that large stablecoin transfers affect Bitcoin prices and trading volume. While the effect on trading volume exists for all types of transactions, the price effect differs depending on the sender and receiver. It cannot be said whether these reactions are directly related to the entities involved (i.e. senders and receivers), non-involved traders' monitoring of blockchains or to what extent they are affected or reinforced by subsequent market movements (e.g. price or volume reactions). Nevertheless, the insights provide important insights into the functioning of cryptocurrency markets and explicitly the relationship between stablecoins and Bitcoin. On a more general level, the results provide evidence on the relevance and implications of (blockchain-based) market transparency for secondary markets. This can help in understanding other blockchain-based markets and their monitoring, planning and development.

Testing our first hypothesis, we analyze whether stablecoin transfers coincide with unusually high Bitcoin trading volume. Indeed finding evidence of increased trading volume, we are able to confirm both our hypothesis, which is in line with similar findings from other studies on stablecoin issuance (Ante et al., 2020; Griffin and Shams, 2019). This finding holds various implications. The increased Bitcoin trading volume before stablecoin transfers can be caused by the involved entities but could also be the reason for a subsequent initiation of a transfer. That is, independently of stablecoin transfers, increased trading volume in the cryptocurrency market may trigger stablecoin transfers but need not be caused by them. A future analysis could examine the extent to which extraordinary market movements such as explosive price jumps or extreme increases in trading volume (e.g. of Bitcoin) have an impact on the number and size of stablecoin transfers.

Lacking information on future money flows on the blockchain, uninformed market participants cannot adjust their price expectations. Abnormal cryptocurrency trading volume initiated by the sender or receiver of stablecoin transfers (i.e. informed trading) is interpreted as market demand, which encourages liquidity traders to also increase their own volume and may trigger a cascade effect. As soon as the stablecoin transaction is confirmed on the public blockchain infrastructure, the information becomes public knowledge and previously uninformed market participants can adjust their expectations accordingly.

The second hypothesis states that the degree of public information asymmetry in stablecoin transfers, which is operationalized by the number of "unknown" addresses involved in a transfer, negatively relates to Bitcoin trading volume after the information becomes public. Information asymmetry represents a proxy for market uncertainty, which is why market participants should trade less when information asymmetry is high. Our results fail to confirm this hypothesis. A reason might be that selling cryptocurrency usually takes place before the actual stablecoin transfer, i.e., the actually relevant information has already lost its value by the time the stablecoin transfer is publicly confirmed on the blockchain. Any impact on the Bitcoin price or volume has already occurred. There is limited risk for traders that transferred stablecoins are sold and, for example, negatively affect the liquidity of an order book – unlike for native cryptocurrencies like Bitcoin, where large transfers are associated with an subsequent sell-off risk (Ante, 2020a). These stablecoins can only increase market liquidity, unless they are sent to a treasury or used for short-selling.

In Section 2, we listed the presumed motives for transfers between different groups of market participants and the corresponding presumed market reactions. Regarding any positive subsequent effect of transfers to cryptocurrency exchanges (Hypothesis 3), we obtain significant results in only one of the three subsamples, namely transfers from stablecoin treasuries to exchanges, which signal new capital flowing into the market.

While we find significant negative effects prior to stablecoin transfers between exchanges, the effects for transfers from exchanges to treasuries are significant and positive, which may come as a surprise. One explanation could be that these transfers are related to arbitrage (Lyons and Viswanath-Natraj, 2020b). Clarifying this question can be an important starting point for future research. Note also that this effect appears to be distorted by the size of the transfers: when transfer size is controlled for, only the significant negative effect of transactions between exchanges remains.

For transfers initiated by stablecoin treasuries, i.e. the expected issuance of new capital into the cryptocurrency market, the expected positive subsequent effect on returns could not be confirmed. The regression models even yield a negative effect for transactions from treasuries to unknown addresses. Accordingly, Hypothesis 5 is rejected. However, we find significant positive prior abnormal returns for transfers to exchanges and unknown addresses. This could be related to a price increase on BTC/USD markets creating an arbitrage opportunity for traders buying Bitcoin with stablecoins (e.g., BTC/USDT or BTC/USDC), thus creating an incentive to sell cryptocurrency against USD and send this USD to the stablecoin treasury. Another explanation could be informed trading by insiders. The presumed positive effect therefore exists – but earlier than expected. This yields promising research questions for future research: Are the effects related to individual cryptocurrency exchanges or to spreads (of Bitcoin or stablecoin markets) closed by arbitrageurs, e.g. trading algorithms that observe the mempool of unconfirmed transactions (Daian et al., 2020)?

Hypothesis 6 states that transfers to stablecoin treasuries result in negative abnormal returns around the transfers. Stablecoin transfers relate to prior sales of cryptocurrency or are perceived as a signal of declining market liquidity, which should result in negative abnormal returns around transfers. Indeed, we find significant negative abnormal returns for transactions initiated from both unknown addresses and treasuries, while the effects of transfers initiated by exchanges remain insignificant. Accordingly, Hypothesis 6 is confirmed.

The size of stablecoin transfers is of significant relevance and has a positive impact on abnormal returns and trading volumes. Accordingly, Hypothesis 7 is accepted. Through further analysis, we find that this relationship is by no means linear; most of the effect on returns is attributable to the largest transfers. Regarding trading volume, we find significant effects for virtually all size-based deciles, but the effect does not increase linearly. Here, too, the strongest effects occur in the largest decile. The significant results around the actual size of stablecoin transfers suggest that future investigations could focus on more precise investigations. In addition to individual transfers with a cutoff value of, e.g., $1 million, the cumulative transaction size of individual wallets could also be considered. It seems conceivable that specific wallets' many comparatively smaller transactions, which however potentially become large in total, run systematically and are, for example, arbitrage bots, which in turn could provide significant insight into the functioning of the cryptocurrency market. Additionally, the overall significance of individual wallets could be better assessed by considering cumulative transactions.

Another challenge for future research is to cluster blockchain addresses better or more granular, which can increase the significance of the results. Addresses can be divided into more categories or more effort can be put into identifying unknown addresses. While we were trying to assign blockchain addresses as best as possible to market participants, a possible source of error in our analysis is that we may have classified addresses as “unknown” (amounting to 28% of senders and 40% of receivers) that actually belong to an unidentified cryptocurrency exchange or stablecoin treasury. Among the “unknown” senders, six blockchain addresses initiated ten or more large stablecoin transfers, the maximum being 43 transactions. One address received 67 transfers and initiated 20. Eleven unknown receiving addresses had ten or more send or receive events. Some of these addresses may belong to (smaller) cryptocurrency exchanges.

While this study mainly refers to Bitcoin, the results can to some extent be generalized to the overall market. Some of our findings already concern the cryptocurrencies Ether, Ripple and Litecoin (cf. Table A.3). Indeed, the results are more pronounced for these currencies, which may suggest that the effects are larger for less liquid or efficient cryptocurrency markets. An analysis of the relationships, cointegration and differences between various cryptocurrency markets could provide more clarity in this regard. Appropriate starting points can be found in the existing literature (e.g. Bouri et al., 2019; Moratis, 2020; Zięba et al., 2019). Since the prices of all cryptocurrencies strongly correlate with Bitcoin (Kumar and Ajaz, 2019), it is unclear whether the identified abnormal price and volume effects are directly attributable to the stablecoin transfer or rather indirectly to the reaction to changes in the Bitcoin price.

Our robustness checks show that the abnormal price effects are similar but not identical across the different cryptocurrency exchanges. These exchanges are very much the driving forces of or closely related to individual stablecoins (Binance and BUSD, Bitfinex and USDT, Coinbase and USDC). This raises the question of whether individual transfers are increasingly coming to or from these exchanges and whether particular market reactions can be identified. For example, it seems possible that most USDC transfers to and from exchanges relate to the Coinbase exchange. Correspondingly, it is conceivable that such large stablecoin transfers are first priced in on the Coinbase BTC/USD pair and effects only later spread to other exchanges. In order to assess this, a study would have to use shorter or different time intervals (e.g. seconds or minutes). One reason for sourcing the data from Bitstamp was that this exchange is not affiliated with any of the observed stablecoins. A more detailed analysis of exchange-specific effects could be conducted in future studies, particularly against the background of the connection between exchanges and stablecoins. The study by Griffin and Shams (2019) on the influence of Tether on cryptocurrency markets may be a starting point for such an endeavor.

As the hourly trading volume differs by cryptocurrency exchange, the identified volume effects also differ. While all effects are significantly positive across all exchanges, for some exchanges, the effects are greater before the transfer (Bitstamp and Bitfinex), while others exhibit mostly subsequent effects (Binance and Coinbase). Thus, it could be investigated whether the information transmission across cryptocurrency markets or the market reactions depend on transfers being made to specific exchanges. Where exactly does the trading volume increase and when, and what triggers the effects on other exchanges? Such an analysis could expand on the existing research on information transmission across cryptocurrency markets and price discovery on cryptocurrency exchanges (e.g. Brandvold et al., 2015; Dimpfl and Baur, 2020; Giudici and Abu-Hashish, 2018; Pagnottoni and Dimpfl, 2019).

With the rapid growth of decentralized finance (DeFi) markets from mid-2020 onwards (cf. e.g. defiprime.com/dex-volume), other market actors have gained systemic relevance, and they could be considered as separate address clusters in future studies. One example are decentralized exchanges (DEXes), i.e. smart contract-based exchanges which allow direct trading without the need to register or perform know-your-customer (KYC) procedures (Ante, 2020b; Daian et al., 2020; Warren and

Bandeali, 2017). Since all trades on DEXes can also be tracked transparently via the respective blockchain infrastructures, this study could be replicated and expanded accordingly. Unlike with centralized treasuries and exchanges, follow-up activity can be observed on DEXes (or decentralized treasuries like DAI). An analysis of decentralized markets and their fully transparent life cycles could provide deeper insights into the actual benefits of stablecoins, which, besides trading, include their use as a non-volatile safe haven, a means for unwinding arbitrage and their use in DeFi to access loans or other financial products.

6 Conclusion

This study has analyzed the relationship between stablecoin transactions of at least $1 million and cryptocurrency returns and trading volume. We use data on 1,587 stablecoin transfers between April 2019 and March 2020 to test their impact on Bitcoin returns and trading volume using event study methodology. Identifying significant increases in trading volume before and after the transfers, we conclude that these stablecoins are likely directly used to trade cryptocurrency, and they may trigger a cascade effect of increased trading volume. The price effects are less pronounced: When looking at all transactions we find significant abnormal returns "only" over the twelve hours before a transfer.

Further analysis broken down by transaction type has revealed abnormal returns before transactions that originate from stablecoin treasuries, but – with the exception of transfers between unknown addresses – not after the transaction occurs. As expected, negative price effects occur prior to transfers to treasuries, i.e. the withdrawal of capital from the cryptocurrency market. Similarly, transfers between two cryptocurrency exchanges are associated with negative returns, which may be related to arbitrage opportunities, although the logic is less straightforward.

In summary, this study shows that the disclosure and real-time traceability of cash flows – a unique phenomenon of cryptocurrency markets – provides transparency that allows deeper insights into historical and future market events compared to traditional markets. We thus conclude that on-chain data analysis can provide cryptocurrency market participants with additional information and thus make markets more efficient. Against the background of the rapid growth of stablecoins and developments such as Facebook's Libra (Libra Association, 2020), blockchain-based securities (e.g. BMJV and BMF, 2020) or central bank digital currency initiatives (e.g. Forbes 2020), the topic of transaction monitoring on blockchains is likely to increase in relevance.

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Appendix

Table A.1. Summary statistics on clusters based on publicly known blockchain addresses associated with stablecoin transfers. For each cluster, the corresponding addresses or entities and their statistics are listed. The table is divided into transactions in which a cluster acts as sender (left side) or receiver (right side). The cluster 'exchanges' include exchange-like financial service providers Bitbank, RenrenBit and Nexo.

	Sender				Receiver			
	Count	Share	USD (million)		Count	Share	USD (million)	
			Mean	SD			Mean	SD
Cluster 1: Unknown								
Unknown	449	28.3%	10.72	11.72	627	39.5%	9.39	9.29
Cluster 2: Treasuries								
Tether	354	22.3%	14.95	34.23	20	1.3%	6.36	4.36
Paxos	131	8.3%	6.01	2.44	126	7.9%	29.87	55.58
USD Coin	60	3.8%	13.99	7.32	6	0.4%	9.28	3.22
Cluster 3: Exchanges								
Bitfinex	261	16.4%	12.14	12.52	261	16.4%	11.29	10.14
Huobi	158	10.0%	7.63	4.38	247	15.6%	6.95	5.18
Binance	85	5.4%	23.15	68.97	198	12.5%	16.71	45.68
OKEx	26	1.6%	12.26	43.88	33	2.1%	14.90	40.13
Poloniex	26	1.6%	10.39	9.56	18	1.1%	13.03	10.55
Bitbank	9	0.6%	6.33	2.13	13	0.8%	5.59	1.58
Bittrex	7	0.4%	16.22	23.27	3	0.2%	28.03	35.74
Kraken	6	0.4%	7.51	1.81	14	0.9%	9.93	4.97
RenrenBit	6	0.4%	5.83	0.76	9	0.6%	6.38	1.73
FTX	4	0.3%	5.48	0.55	2	0.1%	7.85	3.05
CoinBene	3	0.2%	4.34	1.17	1	0.1%	5.02	-
HitBTC	1	0.1%	1.02	-	1	0.1%	1.02	-
KuCoin	1	0.1%	4.97	-	0	0.0%	-	-
Nexo	0	0.0%	-	-	5	0.3%	5.50	1.58
Gate.io	0	0.0%	-	-	2	0.1%	6.06	0.03
UPbit	0	0.0%	-	-	1	0.1%	5.69	-
All	1,587	100.0%	11.94	25.11	1,587	100.0%	11.94	25.11

Table A.2. Number of transfers and value transferred in dollar by stablecoin solution.

Stablecoin (ticker)		Value transferred (USD million)				
	Transfers	Mean	SD	Median	Min	Max
Tether (USDT)	1,271	12.79	27.81	6.94	1.47	301.02
USD Coin (USDC)	129	11.96	8.21	10.00	1.01	39.90
Paxos Standard (PAX)	117	6.19	3.53	5.16	1.00	22.82
Binance USD (BUSD)	63	6.11	2.05	5.28	4.93	15.43
Huobi USD (HUSD)	6	6.44	3.43	5.01	5.00	13.45
Gemini USD (GUSD)	1	1.02	-	1.02	1.02	1.02

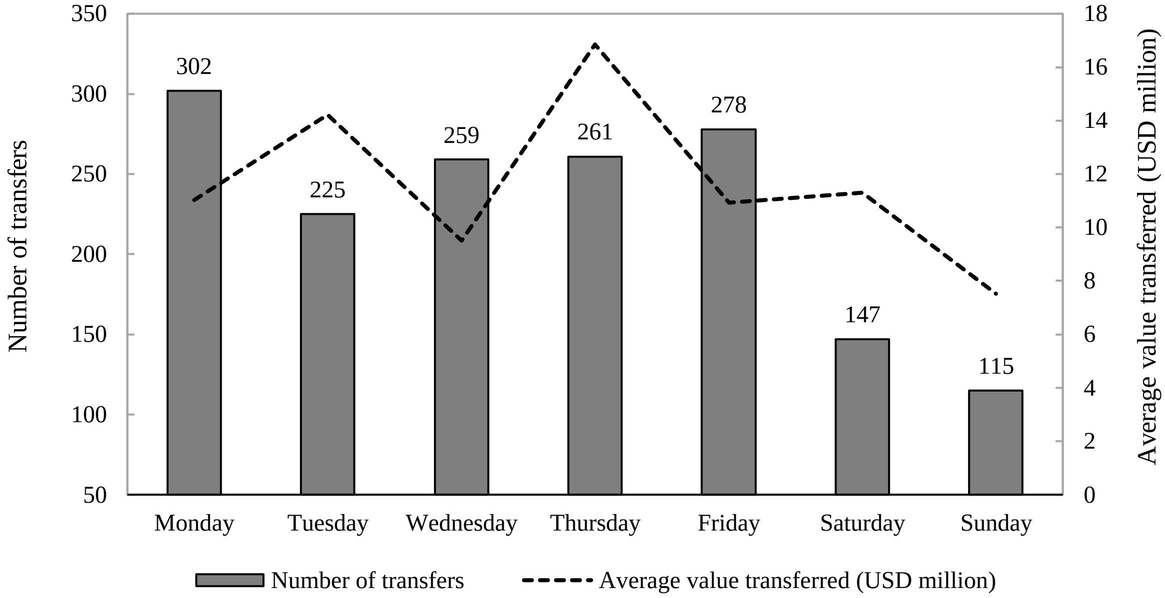
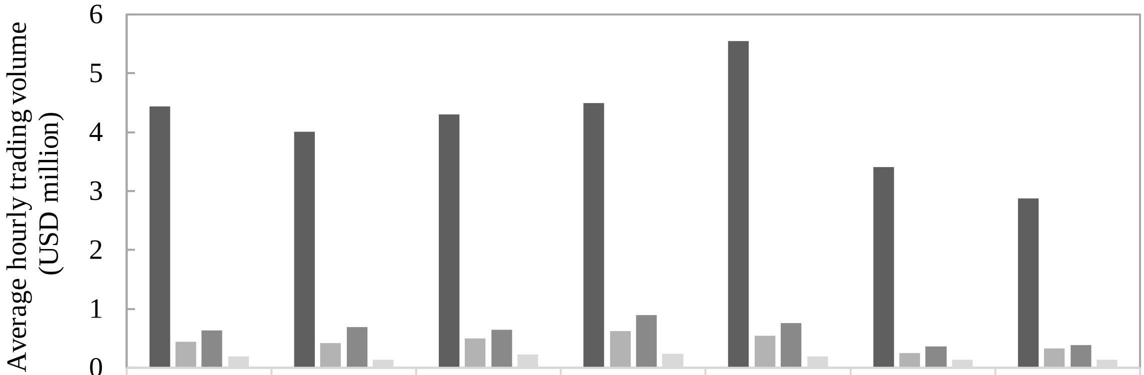


Figure A.1. Number of large stablecoin transfers and average value transferred per day of the week.



	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
BTC/USD	4.43	4.01	4.30	4.49	5.55	3.41	2.87
ETH/USD	0.45	0.42	0.50	0.62	0.54	0.25	0.33
XRP/USD	0.64	0.69	0.64	0.89	0.76	0.37	0.39
LTC/USD	0.20	0.14	0.23	0.24	0.19	0.13	0.14

Figure A.2. Mean hourly trading volume of four major trading pairs per day of the week. The figure presents the average trading volume in million dollars on Bitstamp for four trading pairs.

Table A.3. Robustness checks. Event study results for Bitcoin returns and trading volume around large stablecoin transfers. The panels test alternative estimation windows (A and B), market data from other cryptocurrency exchanges (C, D and E), and effects on alternative cryptocurrencies (F, G and H). All panels test 1,587 observations. 'z-test' refers to the non-parametric Wilcoxon sign rank test. 'pos' is the share of observations with positive abnormal trading volume.

	Returns				Trading volume			
Window	CAR	t-test	z-test	pos	CATV	t-test	z-test	pos
Panel A: Shorter estimation window (-120 to -15)								
[−12, −1]	0.001004	2.00**	1.94*	52%	3.7012	17.96***	15.91***	66%
[−6, −1]	0.000785	2.19**	1.33	52%	2.1379	18.48***	16.69***	68%
[0, 0]	0.000280	1.97**	0.18	50%	0.3448	14.71***	13.64***	64%
[0, 6]	0.000598	1.42	-0.29	48%	1.9863	15.85***	14.71***	64%
[0, 12]	0.001244	2.32**	0.68	50%	3.1407	14.11***	12.70***	61%
Panel B: Shorter estimation window (-150 to -30)								
[−12, −1]	0.000990	2.00**	1.36	51%	3.8941	17.66***	15.66***	65%
[−6, −1]	0.000777	2.16**	1.40	51%	2.2343	18.45***	16.67***	68%
[0, 0]	0.000279	1.97**	0.18	50%	0.3609	14.99***	13.81***	65%
[0, 6]	0.000590	1.42	0.40	51%	2.0989	16.06***	14.96***	66%
[0, 12]	0.001229	2.34**	1.07	50%	3.3498	14.63***	13.56***	64%
Panel C: Alternative market data (Binance exchange: BTC/USDT pair)								
[−12, −1]	0.001019	2.07**	1.72*	52%	2.1878	5.06***	19.80***	71%
[−6, −1]	0.000905	2.61***	1.86*	52%	1.5337	6.65***	21.26***	73%
[0, 0]	0.000302	2.20**	0.66	52%	0.2283	4.77***	17.15***	67%
[0, 6]	0.000633	1.54	0.56	52%	1.4682	6.20***	18.35***	68%
[0, 12]	0.001331	2.53**	1.17	50%	2.6432	8.02***	18.26***	69%
Panel D: Alternative market data (Bitfinex exchange: BTC/USD pair)								
[−12, −1]	0.000961	1.97**	1.61	51%	3.3362	15.06***	13.17***	62%
[−6, −1]	0.000814	2.33**	1.80*	52%	1.8249	14.46***	13.61***	63%
[0, 0]	0.000275	1.98**	0.19	51%	0.2536	6.03***	10.84***	62%
[0, 6]	0.000656	1.62	0.20	50%	1.5884	8.22***	11.25***	61%
[0, 12]	0.001345	2.59**	1.03	49%	2.6261	8.94***	9.75***	57%
Panel E: Alternative market data (Coinbase exchange: BTC/USD pair)								
[−12, −1]	0.001047	2.11**	1.80*	51%	2.8881	15.14***	13.81***	64%
[−6, −1]	0.000820	2.29**	1.53	51%	1.6365	14.09***	13.71***	63%
[0, 0]	0.000292	2.03**	0.41	52%	0.3106	14.06***	12.71***	63%
[0, 6]	0.000612	1.47	0.16	51%	2.0916	16.55***	16.25***	67%
[0, 12]	0.001297	2.47**	1.06	50%	3.3991	15.53***	15.33***	66%
Panel F: Alternative cryptocurrency data (Bitstamp exchange: ETH/USD)								
[−12, −1]	0.001106	2.13**	3.37***	54%	2.4999	11.41***	11.41***	62%
[−6, −1]	0.000872	2.42**	2.89***	52%	1.4698	11.93***	12.30***	64%
[0, 0]	0.000279	2.01**	1.23	51%	0.1982	4.87***	10.03***	61%
[0, 6]	0.000487	1.17	2.04**	51%	1.1556	8.33***	8.29***	59%
[0, 12]	0.001616	3.04***	4.18***	55%	1.6427	6.82***	6.35***	56%
Panel G: Alternative cryptocurrency data (Bitstamp exchange: XRP/USD)								
[−12, −1]	0.001212	2.84***	4.14***	55%	2.3004	13.04***	13.23***	66%
[−6, −1]	0.000843	2.57***	3.17***	52%	1.3292	13.09***	13.30***	66%
[0, 0]	0.000211	1.61	1.16	52%	0.1919	7.83***	10.82***	64%
[0, 6]	0.000242	0.69	1.54	52%	1.2500	10.96***	11.41***	63%
[0, 12]	0.001030	2.28**	4.05***	53%	1.8745	9.46***	9.62***	60%
Panel H: Alternative cryptocurrency data (Bitstamp exchange: LTC/USD)								
[−12, −1]	0.001605	2.79***	2.47**	50%	2.4391	9.52***	8.78***	58%
[−6, −1]	0.001199	3.12***	2.67***	53%	1.4160	9.66***	9.52***	60%
[0, 0]	0.000162	1.02	0.04	50%	0.2139	5.02***	9.94***	59%
[0, 6]	0.000149	0.37	0.20	50%	1.3115	8.35***	7.05***	56%
[0, 12]	0.001493	2.83***	3.20***	53%	1.8297	6.77***	5.50***	55%

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

Table A.4. Event study results for Bitcoin returns and trading volume around large stablecoin transfers across the nine different address cluster samples. 'z-test' refers to the non-parametric Wilcoxon sign rank test. 'pos' is the share of observations with positive abnormal trading volume.

	Returns				Trading volume			
Window	CAR	t-test	z-test	pos	CATV	t-test	z-test	pos
				UNUN (n = 69)				
[−12, −1]	-0.000616	-0.29	-0.16	55%	4.9291	5.63 ***	4.67 ***	72%
[−6, −1]	-0.004190	-2.29**	-1.53	43%	2.7460	4.95 ***	4.27 ***	68%
[0, 0]	0.000363	0.71	1.01	58%	0.5054	4.13 ***	3.61 ***	65%
[0, 6]	0.001220	1.10	0.91	48%	2.7238	5.93 ***	4.85 ***	75%
[0, 12]	0.003445	2.42**	2.64 ***	70%	5.0840	6.09 ***	5.09 ***	81%
				UNTR (n = 33)				
[−12, −1]	-0.004014	-0.71	0.51	48%	6.3401	3.78 ***	3.28 ***	67%
[−6, −1]	0.000699	0.31	1.01	64%	2.9822	3.75 ***	2.89 ***	64%
[0, 0]	0.002058	0.14	0.30	55%	0.5396	3.19 ***	2.80 ***	73%
[0, 6]	-0.005909	-1.20	-1.51	39%	3.2625	3.25 ***	2.76 ***	64%
[0, 12]	-0.003105	-0.62	-0.58	48%	5.0817	2.94 ***	2.67 ***	67%
				UNEX (n = 347)				
[−12, −1]	0.000395	0.40	0.46	49%	2.2352	5.05 ***	4.17 ***	58%
[−6, −1]	0.005880	0.79	0.79	50%	1.2782	5.11 ***	4.49 ***	56%
[0, 0]	0.000630	1.82*	0.24	50%	0.2458	4.74 ***	4.39 ***	59%
[0, 6]	0.000063	0.08	0.05	51%	1.3261	4.82 ***	4.51 ***	61%
[0, 12]	0.000477	0.45	0.22	49%	2.2391	4.63 ***	4.19 ***	59%
				TRUN (n = 327)				
[−12, −1]	0.003404	2.52**	4.11 ***	56%	5.3556	12.46 ***	10.55 ***	74%
[−6, −1]	0.002597	2.65***	3.65 ***	59%	3.1812	13.18 ***	11.27 ***	80%
[0, 0]	-0.000368	-1.30	1.44	50%	0.4123	8.54 ***	7.62 ***	68%
[0, 6]	-0.000630	-0.55	-0.22	47%	2.0112	7.68 ***	7.01 ***	65%
[0, 12]	0.000570	0.46	0.29	49%	3.0147	6.63 ***	6.05 ***	60%
				TRTR (n = 2)				
[−12, −1]	-0.002859	-0.73	-0.45	50%	7.6238	1.49	1.34	100%
[−6, −1]	-0.004879	-19.05***	-1.34	0%	3.8794	1.63	1.34	100%
[0, 0]	0.000582	1.30	1.34	100%	0.1092	0.11	0.45	50%
[0, 6]	0.009367	0.60	0.45	50%	4.1021	0.93	0.45	50%
[0, 12]	0.011533	1.65	1.34	100%	4.8848	0.74	0.45	50%
				TREX (n = 216)				
[−12, −1]	0.003050	2.54**	2.92 ***	57%	4.1140	7.75 ***	7.01 ***	71%
[−6, −1]	0.002274	2.54**	2.75 ***	58%	2.4621	8.43 ***	7.70 ***	75%
[0, 0]	0.000473	1.52	1.20	53%	0.3736	6.37 ***	6.32 ***	71%
[0, 6]	0.001962	1.93*	1.93 *	54%	2.1333	6.51 ***	6.28 ***	72%
[0, 12]	0.003126	2.09**	1.30	49%	3.0236	5.14 ***	4.96 ***	64%
				EXUN (n = 231)				
[−12, −1]	0.000935	0.87	-0.12	50%	1.8928	3.45 ***	3.09 ***	59%
[−6, −1]	0.001360	1.77*	0.68	51%	1.1046	3.54 ***	3.26 ***	60%
[0, 0]	-0.000278	-0.85	-1.13	47%	0.3112	5.03 ***	4.77 ***	64%
[0, 6]	-0.000309	-0.35	-0.75	54%	1.6678	4.99 ***	4.54 ***	63%
[0, 12]	-0.000143	-0.12	-0.57	50%	2.8677	4.90 ***	4.34 ***	61%
				EXTR (n = 117)				
[−12, −1]	0.003447	2.28**	1.97 **	60%	3.4320	4.40 ***	3.93 ***	67%
[−6, −1]	0.001804	1.66*	1.94 *	62%	1.8207	4.37 ***	4.03 ***	69%
[0, 0]	0.000704	1.66*	1.29	53%	0.2343	3.14 ***	2.99 ***	65%
[0, 6]	0.004262	2.71***	1.46	55%	1.7998	3.85 ***	3.59 ***	67%
[0, 12]	0.003282	1.47	1.10	51%	2.7588	3.17 ***	2.62 ***	59%
				EXEX (n = 245)				
[−12, −1]	-0.002885	-2.37**	-4.56 ***	38%	3.4894	5.86 ***	5.10 ***	62%
[−6, −1]	-0.002143	-2.64***	-4.65 ***	35%	2.0954	6.65 ***	5.88 ***	63%
[0, 0]	0.000804	1.82*	0.64	53%	0.3166	4.81 ***	4.35 ***	62%
[0, 6]	0.001642	1.60	-0.70	51%	2.2751	6.39 ***	5.89 ***	64%
[0, 12]	0.001999	1.51	-0.44	45%	3.4220	5.48 ***	4.81 ***	62%

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

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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