Monetary flows and feedback trading in cryptocurrency markets: Effects of stablecoin transfers on return and trading volume of Bitcoin

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Abstract: Stablecoins are non-volatile digital currencies pegged to other assets like fiat currencies. They are a digital substitute for fiat currency and have become an important aspect of cryptocurrency markets. We analyze 1,587 stablecoin transfers of one million dollars or more between April 2019 and March 2020 to find out how they affect Bitcoin returns and trading volume. We find highly significant positive abnormal trading volume and significant abnormal returns in the hours around transfers. We further categorize the sender and receiver of each transfer as one of the following: cryptocurrency exchange, stablecoin treasury, unknown. Effects on trading volume and returns differ across the resulting nine subsamples, which suggests that information asymmetry and transfer motives vary among these groups or the market at least interprets it that way. Our findings illustrate the feedback effects between cryptocurrency markets and stablecoin usage.

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

1 Introduction

A special feature of cryptocurrencies is that anyone can monitor them on their public blockchain infrastructure. Every transfer, no matter how important or insignificant, can be tracked in close to real-time via blockchains, which offers the potential for in-depth analyses that are rarely possible for traditional currencies and markets.

Stablecoins are a specific type of cryptocurrency which peg their value to other assets, like fiat currency or gold. They play a vital role in cryptocurrency markets, as they are used a substitute for fiat currency on cryptocurrency exchanges.

While in traditional markets large currency transactions can only be observed by a small circle of involved entities, stablecoin transfers, i.e. money transfers via the blockchain, can be observed by anyone. The same applies to deposits and withdrawals on cryptocurrency trading platforms. Stablecoins therefore offer unique insight that can potentially also help to better understand traditional markets. If, for example, stablecoins worth millions of dollars are sent to an exchange, market participants could speculate on the motives behind this transfer and adjust their behavior accordingly. If one suspects that the deposited money will soon be used to buy cryptocurrency, it could happen that – depending on market liquidity and size of the deposit – a positive short-term price effect and an increase in trading volume will follow the deposit. Correspondingly, as soon as such a transaction becomes publicly observable, it could result in a feedback effect amplifying the first order effect through increased activity by observing traders. The deposit might not even be used immediately for the purchase of cryptocurrency, but might still trigger trading activity because it is interpreted as a signal for an upcoming purchase.

While academic researchers have 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). We hypothesize that this is also the case for stablecoin transfers, as they represent a major source of liquidity for cryptocurrency in general and Bitcoin in particular. We expect that most stablecoin transfers occur shortly before or after cryptocurrency trades, which in turn potentially leads to abnormal price effects. Even if price effects from sales and purchases cancel each other out, we should result increased trading volume.

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

We analyze if and how large stablecoin transfers affect Bitcoin returns and trading volume. Through this, we identify to what extent the monitoring of money transfers via the blockchain allows traders to gain information advantages.

Based on a sample of 1,587 stablecoin transfers of one million dollars or more, we conduct an event study to assess 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, where we distinguish 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.

We contribute to an understanding of stablecoins in general, the relevance of large stablecoin transfers in particular for cryptocurrency markets, and the price discovery and efficiency of Bitcoin. Our findings contribute to the emerging literature on the relationship between blockchain activity (i.e. on-chain events) and cryptocurrency markets. The unique transparency of cryptocurrency markets also allows valuable insights into the dynamics of financial markets that are difficult to obtain for more traditional asset classes.

2 Hypotheses

Newly available information can change the price expectation of market participants. When traders in a market change their expectations due to an unexpected or unforeseen event, the corresponding effects are abnormal, as they solely relate to this specific event (Beaver 1968; Karpoff 1986). It is thus reasonable to assume that large on-chain transfers of stablecoins may lead to abnormal returns and trading volume. Such transfers can have various reasons, which makes it difficult to reason about the direction of these effects. For example, 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 the stablecoin issuances reflect cryptocurrency market demand (Kristoufek 2020), it can be assumed that in most cases large stablecoin transfers will be related to the purchase or sale of cryptocurrencies, which should result in higher Bitcoin trading volumes around large stablecoin transfers (Hypothesis 1).

By analyzing blockchain addresses involved in stablecoin transfers, we are able to determine which market participants send and receive coins. We distinguish (1) unknown addresses, (2) cryptocurrency exchanges and (3) stablecoin treasuries. Table 1 shows an overview of the nine different transfer combinations between these three different entities on the blockchain. These combinations imply different levels of information asymmetry and different presumed transfer motives. We therefore assume that the effect of transfers differs among these combinations.

If liquidity traders have timing discretion (Admati and Pfeiderer 1988), they will decrease or postpone their trading activity with increased information asymmetry in order to decrease 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 their respective degree of information asymmetry.

Table 1. Levels of information asymmetry and presumed transfer motives associated with large stablecoin transfers between different market participants. Color represent the respective degree of information asymmetry associated with 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)*

We thus expect that the degree of information asymmetry tied to stablecoin transfers, as depicted in Table 1, negatively relates to Bitcoin trading volume after information becomes public (Hypothesis 2). In other words, abnormal trading volume can be positive for all stablecoin transfers but 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 (or even fairly certain, depending on the type) 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 ex-post purchases of cryptocurrency, while withdrawals most likely relate to ex-ante sales of cryptocurrency. Obviously, there may also be other reasons for such transfers, as stablecoins may have been held by someone for a long time (i.e. no short-term trading of cryptocurrency) or could be used otherwise, e.g. for lending, or as a safe haven or collateral.

With regard to the most probable motive for these transfers, we expect positive ex-post abnormal Bitcoin returns for stablecoin transfers with cryptocurrency exchanges as receivers (Hypothesis 3) and negative ex-ante abnormal Bitcoin returns for stablecoin transfers with cryptocurrency exchanges as senders (Hypothesis 4).

Stablecoin treasuries manage the life cycle of stablecoins by minting new coins and by removing coins from circulation. Accordingly, transactions in which treasuries are involved can provide conclusions about potential upstream or downstream market developments. A transfer from a treasury likely refers to new stablecoins entering the active market, while a transfer to a treasury likely leads to the subsequent burning of the coins, i.e. the withdrawal of liquidity from the market. However, there is the special case of so-called chain swaps, in which stablecoins are transferred from one blockchain to another. This can only be the case with Tether, which uses different blockchain infrastructures. Keeping that limitation in mind, we expected that transfers from stablecoin treasuries lead to ex-post purchases of cryptocurrency or are perceived as signal of increasing market liquidity, which results in positive abnormal returns after the transaction (Hypothesis 5). Transfers sent to stablecoin treasuries can be expected to lead to ex-ante sales of cryptocurrency or are perceived as signal of decreasing market liquidity, which results in negative abnormal returns around transfers (Hypothesis 6).

It can generally be assumed that the monetary value of a transfer correlates with the strength of the effect. A higher value should be preceded by a comparatively larger sale or may be followed by a comparatively larger purchase. We thus hypothesize that the size of stablecoin transfers correlates positively with abnormal effects on returns and trading volume (Hypothesis 7).

3 Data and methods

3.1 Data collection

We collect stablecoin transaction data between April 2019 and March 2020. Data on the six different stablecoins Tether USD (USDT), USD Coin (USDC), Paxos Standard (PAX), Binance USD (BUSD), Huobi USD (HUSD) and Gemini USD (GUSD) are collected across three different blockchain infrastructures. All stablecoins but USDT operate exclusively on the Ethereum blockchain, for which we use the block explorer *etherscan.io* to collect transaction data. For USDT, we additionally extract data from the TRON blockchain via *tronscan.io* and from Omni, a second-layer protocol operating on the Bitcoin blockchain, via *omniexplorer.info*. We collect timestamp, transaction size, transaction value in USD and involved blockchain addresses. As we are interested in large transfers, we choose the arbitrary cut-off value of one million dollars of value transferred in a single transaction and exclude all transactions below that threshold. We end up with 1,587 large stablecoin transfers as data basis. If a blockchain address is known to belong to a stablecoin treasury or a cryptocurrency exchange, we assign it to the respective entity. We identify 19 treasuries and exchanges, which can act both as sender or receiver. We cluster addresses accordingly 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 price and volume data in USD from the cryptocurrency exchange Bitstamp are used as main data basis. To test the robustness of our results across different cryptocurrencies, we also collect hourly data for the cryptocurrencies Ethereum (ETH/USD), Ripple (XRP/USD) and Litecoin (LTC/USD) from Bitstamp. To assess if results are robust for other cryptocurrency exchanges, we additionally collect BTC/USDT from Binance and BTC/USD from both Bitfinex and Coinbase.

3.2 Dependent variables and event study methodology

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

In line with the literature, we use log returns to account for skewness and kurtosis in the financial data (Brown and Warner 1985). For trading volume, we use a $log(x + c)$ transformation, 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). We choose a 25-hour event window from -12 to 12 hours around the event. Expected returns and trading volumes are calculated as the mean over the estimation window from -150 to -15 hours before each stablecoin transfer. We also use different windows for robustness checks. By using an estimation window of more than 100 time intervals the results should be robust (Armitage 1995). As we analyze 1,587 events over a window of about one year, observed windows overlap, i.e. the estimated abnormal effects of one event may be in the observation window of another event. Therefore, overall results must be interpreted with caution. In line with the literature, we assess the significance of results not only via t-tests but also use the non-parametric Wilcoxon sign rank test (Wilcoxon 1945) for robustness (called z-test in the following). We only deem results valid that are significant in both tests.

3.3 Independent and control variables

We create nine dummy variables based on all possible combinations of the three address clusters *unknown*, *treasuries* and *exchanges*. Variable names are accordingly 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 sent to a treasury address and the variable EXUN (EX*change* to UN*known*) takes a value of one if the initiator in a cryptocurrency exchange and the receiver is unknown. Thus, we end up with 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. We create the variable *Bitcoin ($1,000)*, which is the hourly Bitcoin closing price in dollar directly after the stablecoin transfer, divided by 1,000 to control for market conditions.

Since price effects have previously been observed to differ across stablecoins (Ante et al. 2020), we create a dummy variable for each of the six stablecoins in our sample. Table A.2. in the appendix shows statistics on the number of transfers and transfer values per stablecoin. Finally, we create seven dummy variables, one for each day of the week. This way, we can control for day-of-week effects, which have been found relevant for cryptocurrency markets. For example, Caporale and Plastun (2019) find that Bitcoin returns are higher on Monday, 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 findings, we identify that the lowest number of 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%). The majority of transfers are executed on the Ethereum blockchain (62.3%), followed by TRON (19.3%) and Bitcoin/Omni (18.3%). All non-Ethereum blockchain transfers can be attributed to USDT, as it is the only stablecoin that does not exclusively operate on the Ethereum blockchain. A share of 52.9% of all USDT transfers occurred on Ethereum, 24.2% on TRON and 22.9% on Bitcoin/Omni.

Table 2 shows summary statistics of transfer value, hourly returns and hourly trading volume per hour.

Table 2. Descriptive statistics. Value transferred, hourly returns and 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 in dollar (deciles calculated with Stata's *xtile* command) and sender/receiver types. Statistics on return and trading volume 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)

On average, a stablecoin transaction has a value of \$11.9 million. A comparatively 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 compared to the two periods in the event window. Across size-based deciles, we find that the transferred amount is increasing disproportionally in the higher, especially the 10th decile, giving further evidence of the distribution being affected by a few large transfers. While stablecoin transactions in general seem to increase trading volume, we do not identify consistent patterns for size-based deciles.

With regard to sender and receiver types, the largest share are transfers of unknown senders to exchanges (UNEX, 21.9%), followed by stablecoin treasuries to unknown addresses (TRUN, 20.6%).

Over the estimation window, the average hourly Bitcoin returns is 0.003%, or 0.4% over the full one-year period. 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 with 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 sender and receiver are unknown (UNUN). For detailed statistics and 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. Among the remaining clusters, transactions sent from an exchange to a treasury (\$28.9 million) and between unknown wallets (\$20 million) are largest. The effect size on return is also largest for the TRTR transactions both in the estimation window and in the post transaction period, although one must consider that the group consists of only two observations.

The cluster UNTR shows negative hourly average returns of -0.1%, each before and after the transfers, suggesting that stablecoin transfers to treasuries may relate to sales of Bitcoin. The large differences in hourly trading volume between estimation period (\$3.6 million), observation period before (\$5.3 million) and after (\$4.8 million) the transfers from unknown addresses to treasuries support this assumption.

The largest effects of stablecoin transactions on Bitcoin return in the twelve hours leading up to a transfer can be found for transfers between treasuries and exchanges, in both directions (TREX = 0.058%; EXTR = 0.06%). Returns after the transaction are largest for transactions sent between exchanges (0.067%).

4.2 Event study results

Table 3 shows event study results for log returns and log trading volume. We find strong positive effects on trading volume for all time windows and hours before and after the transactions. To confirm this result, we perform robustness checks for alternative estimation periods and cryptocurrency exchanges as well as for other cryptocurrencies (Table A.3) and find that the results are largely robust. With respect to trading volume, we clearly identify abnormal effects around large stablecoin transfers and accordingly confirm Hypothesis 1. For returns, by contrast, we find periods -12 to -1 as the only ones in which abnormal returns for BTC/USD are significant for both test statistics. The robustness checks reveal significant positive abnormal returns also for other cryptocurrencies for the periods -6 to -1 and 0 to 12 hours. Ambiguous results regarding the returns over the complete data set are no surprise, since we assume that some transfers are related to purchases and others to sales – effects that can cancel each other out. The significant result for the 12-hour ex-ante period suggests that purchases predominate in this phase. All coefficients for windows lasting several hours are positive and thus also point in this direction.

The next step is the analysis of individual subsamples based on the address clusters. Figure 3 shows cumulative abnormal returns and Figure 4 cumulative abnormal trading volumes for the periods -12 to -1 hours and 0 to 12 hours around large stablecoin transfers for each of the nine sender-receiver combinations. Both figures also show 95% confidence bands. Table A.4. in the appendix reports coefficients and test statistics for each cluster.

Abnormal returns differ strongly depending on the cluster. We conclude that the assumed purpose of the transfer plays a role in how the market reacts to large stablecoin transfers.

For the twelve-hour phase prior to transfers, we identify significant effects for four different address clusters, three times positive and once negative. The magnitude of the significant positive effects is similar for EXTR, TRUN, and TREX, lying between 0.31% and 0.34%. Transfers between exchanges lead to statistically significant negative returns (-0.29%; p<.05).

The only highly significant result for the 12-hour window starting with the transfer event is for transfers between unknown addresses (0.34%), while the effect for TREX is significant only in the six hours before the transfer event at the 1% level (0.2%). Over the whole period under consideration, the *z*-statistic is no longer significant. While we identify significantly abnormal effects, they do not fit our hypothesized effects regarding the underlying information asymmetry. Therefore, we reject Hypothesis 2.

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). The column *z*-test refers to the non-parametric Wilcoxon sign rank test. The column pos shows the share of observations with positive abnormal trading volume for the respective period.

	Log return				Log trading volume			
Hour	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.

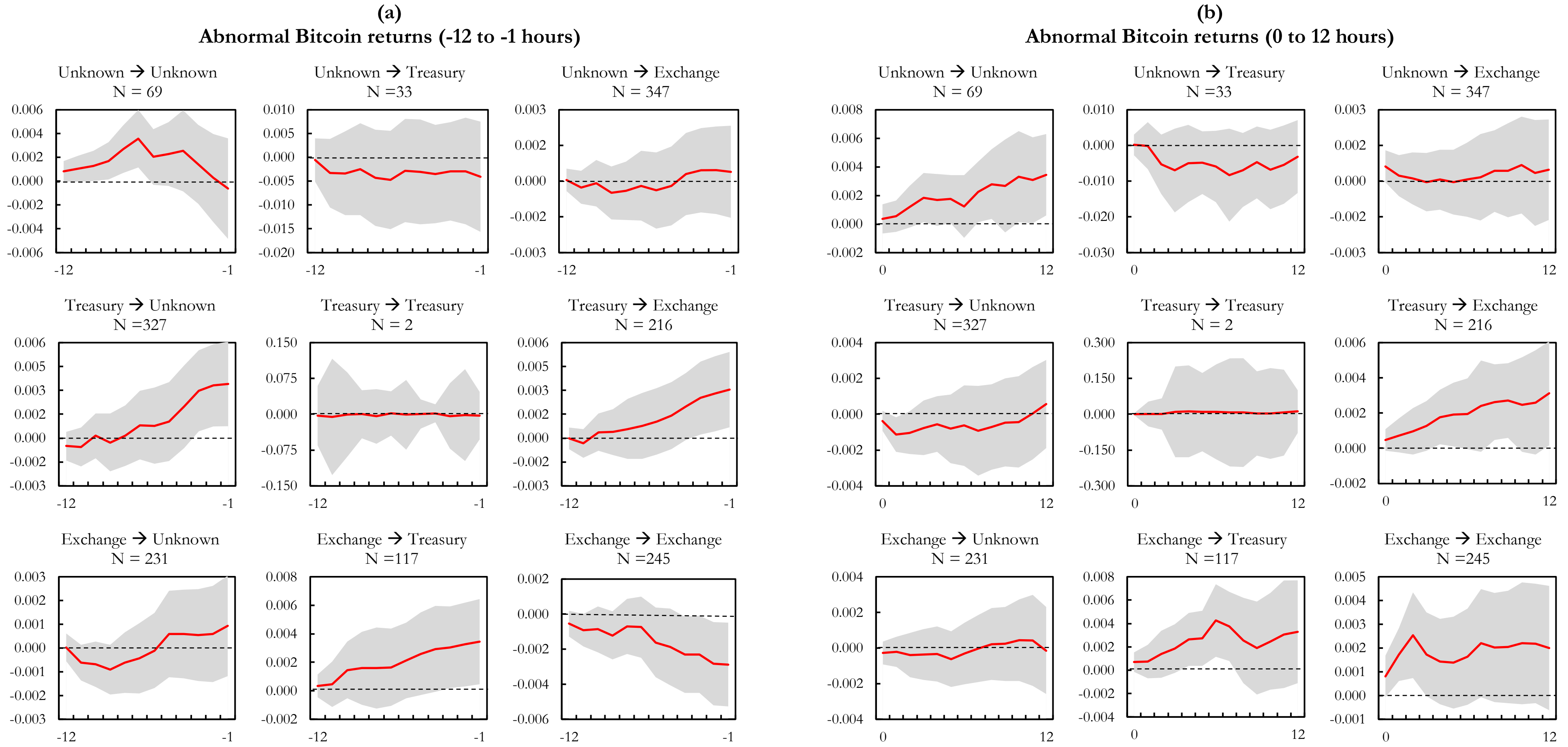


Figure 1. Cumulative abnormal Bitcoin returns around stablecoin transfers based on address clusters. Cumulative abnormal Bitcoin log returns in the twelve hours before (left side) and after (right side) large stablecoins transfers. Abnormal log returns are on the *y*-axes, hours are on the *x*-axes.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

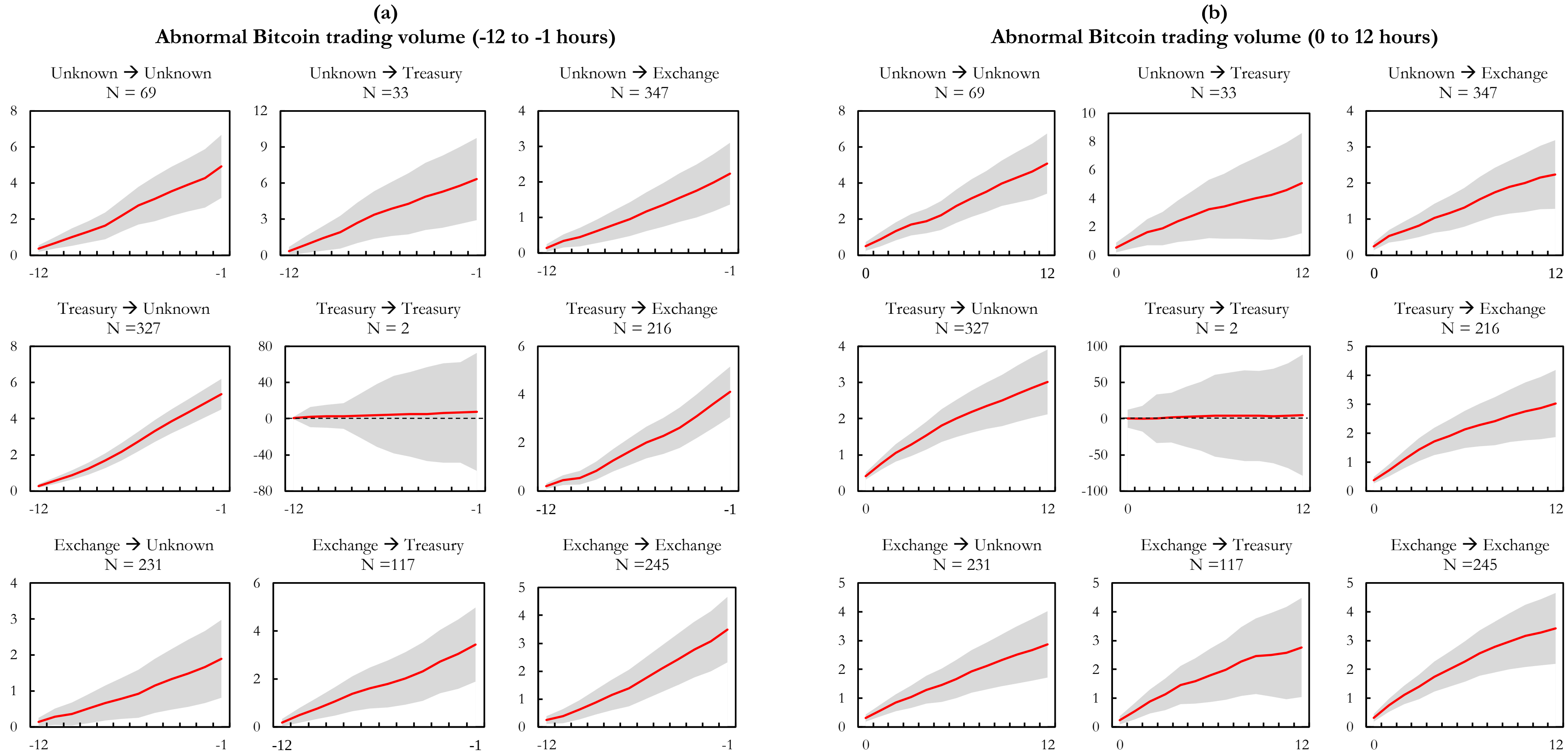


Figure 2. Cumulative abnormal Bitcoin trading volume around stablecoin transfers. Cumulative abnormal Bitcoin trading volume (log) in the twelve hours before (left side) and after (right side) large stablecoin transfers. Abnormal log trading volume is on the *y*-axes, hours on the *x*-axes. The grey areas are 95%-confidence bands.

4.3 Explaining abnormal effects

In the next step of the analysis, we identify whether transaction size and clustered addresses can explain abnormal effects. For this purpose, we regress abnormal returns and volumes on independent and control variables. In each model a different dummy variable is used for the respective address cluster. The results are shown in Table 4.

While the Bitcoin price has a significant negative impact on ex-post abnormal returns and ex-ante abnormal trading volumes, effects are insignificant for the other two dependent variables or periods considered. Transaction size has a highly significant positive effect on both abnormal returns and trading volume.

Table 4. Predicting abnormal effects. Regression models predicting cumulative abnormal return (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 *address cluster variable* shows the regression coefficient and standard error of the respective dummy variable shown in the column *cluster variable*. Standard errors are robust to heteroskedasticity. All models control for different stablecoins and day-of-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
	UNTR	-0.0005 (0.0003)*	0.0020 (0.0006)***	-0.0089 (0.0054)*	0.075	0.067
	UNEX	-0.0004 (0.0003)	0.0020 (0.0006)***	-0.0002 (0.0011)	0.072	0.063
	TRUN	-0.0003 (0.0003)	0.0021 (0.0006)***	0.0023 (0.0014)*	0.074	0.065
	TRTR	-0.0004 (0.0003)	0.0021 (0.0006)***	-0.0043 (0.0016)***	0.072	0.063
	TREX	-0.0004 (0.0003)	0.0019 (0.0006)***	0.0024 (0.0013)*	0.073	0.065
	EXUN	-0.0004 (0.0003)	0.0022 (0.0006)***	0.0012 (0.0012)	0.072	0.064
	EXTR	-0.0004 (0.0003)	0.0019 (0.0006)***	0.0017 (0.0016)	0.072	0.064
	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
	UNTR	-0.0019 (0.0003)***	0.0025 (0.0006)***	-0.0069 (0.0047)	0.124	0.116
	UNEX	-0.0018 (0.0003)***	0.0025 (0.0006)***	-0.0001 (0.0012)	0.122	0.114
	TRUN	-0.0019 (0.0003)***	0.0025 (0.0007)***	-0.0028 (0.0015)*	0.125	0.117
	TRTR	-0.0019 (0.0003)***	0.0024 (0.0007)***	0.0133 (0.0114)	0.123	0.115
	TREX	-0.0018 (0.0003)***	0.0024 (0.0006)***	0.0005 (0.0013)	0.124	0.116
	EXUN	-0.0019 (0.0003)***	0.0025 (0.0006)***	0.0005 (0.0013)	0.122	0.114
	EXTR	-0.0018 (0.0003)***	0.0025 (0.0007)***	-0.0001 (0.0022)	0.122	0.114
	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
	UNTR	-0.3202 (0.0906)***	0.8945 (0.2853)***	0.6242 (1.6039)	0.150	0.143
	UNEX	-0.3231 (0.0911)***	0.8618 (0.2843)***	-0.7111 (0.4797)	0.152	0.144
	TRUN	-0.2964 (0.0907)***	0.8920 (0.2839)***	1.1230 (0.4742)**	0.153	0.145
	TRTR	-0.3378 (0.0913)***	0.8788 (0.2858)***	3.1989 (2.3063)	0.151	0.143
	TREX	-0.3329 (0.0911)***	0.8689 (0.2853)***	0.4113 (0.5751)	0.151	0.143
	EXUN	-0.3124 (0.0913)***	0.7951 (0.2922)***	-1.1286 (0.5858)**	0.152	0.145
	EXTR	-0.3340 (0.0907)***	0.9799 (0.2935)***	-0.9465 (0.7781)	0.151	0.144
	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
	UNTR	0.0993 (0.0943)	0.9805 (0.2868)***	1.4158 (1.6965)	0.121	0.114
	UNEX	0.0934 (0.0945)	0.9616 (0.2873)***	-0.3278 (0.5222)	0.121	0.113
	TRUN	0.0606 (0.0950)	0.9759 (0.2872)***	-0.8304 (0.5100)*	0.122	0.114
	TRTR	0.0891 (0.0950)	0.9780 (0.2884)***	-0.5595 (3.8970)	0.121	0.113
	TREX	0.0878 (0.0948)	0.9890 (0.2861)***	-0.2348 (0.6422)	0.121	0.113
	EXUN	0.0809 (0.0954)	1.0092 (0.2943)***	0.3905 (0.6149)	0.121	0.113
	EXTR	0.0884 (0.0944)	1.0587 (0.2947)***	-0.8983 (0.8486)	0.122	0.114
	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.

The models explain between 15% and 15.3% of variance (the best fit in comparison to the other models), while the adjusted terms, i.e. adjusted R^2's, are roughly 1% lower on average. Regression models predicting ex-ante abnormal returns have the lowest explanatory value, explaining between 7.2% and 7.9% of variance. For these models, we find 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 identify generalizable result for all transfers of exchanges, we reject Hypotheses 3 and 4.

When predicting ex-post returns, we only find a significant effect for TRUN (-0.28%). As we do not find the expected positive ex-post effect on returns, we reject hypothesis 5. This suggests that (a certain degree of) the differences between address clusters may not refer to presumed transfer motives or associated information asymmetry but are rather due to market sentiment (Bitcoin price) and average transaction size associated with these clusters. As all significant effects of transfers to treasuries in the window from -12 to -1 hours before the event are negative, we accept hypothesis 6.

Looking at the models that explain abnormal trading volume, we identify significant effects of TRUN (positive) and EXUN (negative) before the transfer event. Similarly, we find significant positive (EXEX) and negative (TRUN) downstream effects.

Given the highly significant results for the size of stablecoin transfers, we can confirm Hypothesis 7: larger transaction volumes lead to greater effects. However, we also want to identify whether this is always the case or the result is due to a few very large observations. To answer this question, we use regression models that test effects of size-based deciles for abnormal effects. The results are shown in Table 5.

Table 5. Regression models predicting effects of stablecoin transaction size on abnormal Bitcoin returns. Regression models predicting effects of size-based deciles of stablecoin transfer value in dollar on cumulative abnormal return (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: one without and one with controlling for effects of address cluster variables. Standard errors are robust to heteroskedasticity. All models control for different stablecoins, Bitcoin price and day-of-week effects. Constant term included but not shown. The first decile is excluded as reference group in all models.

	(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.

We use the same dependent variables as in the previous table and determine for each a model without and with control for address cluster dummy variables. For abnormal returns the tenth (i.e. largest) decile shows highly significant effects before and after stablecoin transfers. This may be in part due to the skewed distributions of the deciles (see Table 2), but also shows the strong impact of extremely large stablecoin transfers on Bitcoin returns. At the same time, we find significant effects in the third and fourth deciles. When assessing models five through eight, the majority of deciles predict significant positive abnormal trading volume. Results are similar across the two different models per dependent variable.

There is no clear linear trend with increasing deciles, but the greatest effects are found in the tenth decile and the second greatest in the ninth. Accordingly, the largest stablecoin transfers also have the greatest effect on trading volumes – a plausible result. The fact that there is no clear increase per decile shows that not only the size of transfers is a decisive factor for the explanation of market effects.

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. The observed effects can occur directly through entities involved in transfers or through downstream reactions. We cannot say whether these reactions are directly related to the monitoring of blockchains (or rather monetary flow via stablecoins) or whether they are caused by observed market movements (e.g. price or volume reactions).

In our first hypothesis, we analyze whether stablecoin transfers are preceded or followed by positive abnormal trading volume. This is indeed the case. We conclude that, similar to findings of other studies for stablecoin issuances (Griffin and Shams 2019; Ante et al. 2020), stablecoin transfer activity on the blockchain is an important metric for Bitcoin and other cryptocurrencies. This seems plausible stablecoins are often used to trade cryptocurrencies. The occurrence of abnormal volumes without significant abnormal returns also shows that such transfers are related to both purchases and sales, leading to opposing effects which cancel each other out.

Various implications can be derived from this. The increased volume before stablecoin transfers can be caused by the involved entities but could also be the explicit reason for the subsequent initiation of a transfer. An increased trading volume (independent of stablecoin transfers) in the cryptocurrency market could lead to stablecoins being transferred in the first place. For example, a future analysis could examine the extent to which extraordinary market movements such as explosive price jumps or extreme increases in trading volume (of e.g. Bitcoin) have an impact on the number and size of stablecoin transfers.

In the absence of public information, other market participants have no possibility to adjust their expectations. The trading volume by the sender or receiver is interpreted as market demand, which encourages liquidity traders to increase their own volume as well and this could result in a cascade effect. As soon as the stablecoin transfer on the blockchain is initiated or confirmed, market participants are generally able to observe the transfer and adjust their expectations accordingly.

In our second hypothesis, we assume that the degree of information asymmetry of stablecoin transfers could be seen as a proxy for market uncertainty and that market participants could reduce their volume in line with higher information asymmetry. We cannot confirm this. 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 besides explaining historic volatility. Any impact and effects on the Bitcoin price or volume have already taken place. There is no real risk for traders that these stablecoins will be sold and, for example, negatively affect the liquidity of an order book – other than for native cryptocurrencies like Bitcoin, where large transfers are associated with an ex-post sell-off risk (Ante 2020a). These stablecoin can only increase market liquidity unless they are sent to the address of a treasury or are used for short-selling.

A possible source of error in our analysis is that we might have classified addresses as "unknown" which belong to a cryptocurrency exchange or a stablecoin treasury. Potentially, a larger share of the unknown transactions (28% of senders and 40% of receivers) can be attributed to individual relevant market participants that we simply could not identify. Among "unknown" senders, six blockchain addresses initiated more ten or more large stablecoin transfers, with the largest one initiating 43 transactions. One address received 67 transfers and initiated 20. Of the eleven receiving addresses with ten or more observations, 40% initiated more than ten transfers, i.e. are part of the six large unknown initiator addresses. In the course of our research we were not able to identify which owner could be behind these addresses. Accordingly, we cannot exclude the possibility that some of these addresses are (smaller) cryptocurrency exchanges.

We have listed presumed motives for transfers between different market participants and named corresponding presumed market reactions. With regard to the positive ex-post effect of transfers to cryptocurrency exchanges (Hypothesis 3), we find significant ex-post effects in only one of the three subsamples and therefore reject the hypothesis. These are transfers from stablecoin treasuries to exchanges, which signal that new capital is flowing into the market.

Regarding presumed negative ex-ante abnormal Bitcoin returns around stablecoin transfers initiated by exchanges, we find a significantly negative effect prior to stablecoin transfers between exchanges. The effects, however, are significant and positive for transfers from exchanges to treasuries, which seems implausible at first. 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. We also note that this effect is apparently distorted by the size of transfers and that when the size of transfers is controlled, only the significant negative effect of transactions between exchanges remains.

If we look at transfers of stablecoin treasuries, i.e. expected new issuances of capital in the cryptocurrency market, we do not find the expected positive ex-post effect on returns. The regression models even display a negative effect for transactions from treasuries to unknown addresses. Accordingly, we reject Hypothesis 5. However, an interesting result is that we find significant positive ex-ante abnormal returns for both unknown and exchanges as target addresses. This suggests that informed trading occurs before the actual transfer. This can come from respective recipients, who for example already carry out (leveraged) trading in advance, or from other informed traders. The positive effect we suspected is therefore present –but earlier than expected. We see this as an exciting research question for future studies. Does information about upcoming stablecoin transfers leak to third parties? Are the effects related to individual cryptocurrency exchanges or to spreads (of Bitcoin or stablecoin markets) closed by arbitrageurs?

In Hypothesis 6, we have assumed that transfers relate to ex-ante sales of cryptocurrency or are perceived as a signal of decreasing market liquidity, which results in negative abnormal returns around transfers. In fact, we identify significantly negative abnormal returns for transactions initiated from both unknown and treasury counterparties, while effects of transfers initiated by exchanges remain insignificant. Accordingly, we confirm Hypothesis 6: cryptocurrency sales take place before transfers to treasuries.

The size of stablecoin transfers is of significant relevance and has a positive impact on abnormal returns and trading volumes. However, it should be noted that we only consider transfers with an equivalent value of $1 million and more. Accordingly, we confirm Hypothesis 7. In the course of further analysis, we find that this is by no means a linear relationship; returns are mostly impacted by extremely large transfers. In the case of trading volume, we identify significant effects for virtually all size-based deciles, but the effect does not increase linearly. Here, too, the strongest effects are in the largest decile.

While this study mainly refers to Bitcoin, it serves as a proxy for the overall market. Interesting implications can already be identified based on the few other results for the cryptocurrencies Ether, Ripple and Litecoin (cf. Table A.3). For these currencies, we identify more significant and stronger results, which might suggest that corresponding market reactions are negatively related to the liquidity or efficiency of individual cryptocurrencies. An analysis focusing on relationships, cointegration and differences between various cryptocurrency markets could provide more clarity in this regard. Appropriate starting points can already be found in the literature (e.g. Bouri et al., 2019; Moratis, 2020; Zięba et al., 2019). Since the prices of all cryptocurrencies are highly correlated with the price of Bitcoin, it is unclear whether these effects can be directly attributed to the stablecoin transfer or indirectly to the reaction to changes in the Bitcoin price. In any case, the results suggest that the results obtained here are not only valid for Bitcoin, but also for other cryptocurrencies.

As part of the robustness checks, we find that abnormal price effects are similar but not identical across different cryptocurrency exchanges. A more detailed analysis of exchange-specific effects could be investigated in future analyses, particularly against the background of the connection between exchanges and stablecoins. The study of Griffin and Shams (2019) that deals with the influence of Tether on cryptocurrency markets may be a starting point for such an endeavor. The exchanges included in the robustness checks are very much driving forces 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 or whether particular market reactions can be identified. Does the Coinbase BTC/USD pair show the largest market reaction to USDC transfers (in general or to and from Coinbase itself)? Among other reasons, we have chosen the Bitstamp exchange as data source as it is not affiliated with any of the observed stablecoins.

Since hourly trading volume differs per cryptocurrency exchange, identified volume effects also differs. While all effects are significantly positive across all exchanges, some exchanges show higher effects ex-ante (Bitstamp and Bitfinex) and others ex-post (Binance and Coinbase). Correspondingly, it could be investigated whether information transmission across cryptocurrency markets or market reactions differ when transfers to specific exchanges occur. Where exactly does the trading volume increase and when, and what triggers effects on other exchanges? This way, 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) could be expanded.

With the rapid growth of decentralized finance (DeFi) markets from mid 2020 on (e.g. *https://defiprime.com/dex-volume*), other entities have gained systemic relevance that should or 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 (Warren and Bandeali 2017; Ante 2020b; Daian et al. 2020). While these are still comparatively unimportant in the period under review in this study, they have become relevant markets by mid-2020. Since all trades on DEXes can also be tracked transparently via the respective blockchain infrastructures, this study could be replicated and expanded accordingly. In contrast to centralized treasuries and exchanges, which represent black boxes once funds are deposited, follow-up activity can be observed on DEXes (or decentralized treasuries like DAI). An analysis of decentralized markets, i.e. fully transparent life cycles, could provide more precise insights into the actual benefits of stablecoins. Besides trading, such benefits could be the use as non-volatile safe haven, means for unwinding arbitrage or the use in DeFi for accessing loans or other financial products.

6 Conclusion

This study analyzed the relationship between stablecoin transactions of one million dollars and more and cryptocurrency returns and trading volumes. For this purpose, 1,587 stablecoin transfer events were identified between April 2019 and March 2020 and their impact on Bitcoin returns and trading volume was tested using event study methodology. We identified significant increases in trading volumes before and after transfers, which shows that the same stablecoins are likely directly used for trading of cryptocurrency and possibly trigger a cascade effect of increased trading volume. Regarding price effects, we find less strong effects: Only over the twelve hours before a transfer, we find significantly abnormal returns.

In further analysis, we identify abnormal returns before transactions that originate from stablecoin treasuries, suggesting that informed traders, which include initiators, are aware of upcoming stablecoin transfers and react accordingly.

As expected, we find negative price effects prior to transfers to treasuries, i.e. the withdrawal of capital from the cryptocurrency market. Similarly, transfers between two cryptocurrency exchanges lead to negative returns, which may be related to arbitrage opportunities.

Against the background of the rapid growth of stablecoins in the cryptocurrency market and further developments such as Facebook's Libra (Libra Association 2020) or central bank digital currency (CBDC) initiatives (e.g. Forbes 2020), we believe that the topic is likely to increase in relevance and consequently the scientific literature on the topic will grow rapidly.

In summary, this study shows that disclosure and real-time traceability of cash flows – a unique phenomenon of cryptocurrency markets – can provide insights into historical and future market events. In this respect, we conclude that on-chain data analysis can provide market participants in the cryptocurrency market with information advantages.

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. https://doi.org/10.1016/j.frl.2018.08.010

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

Ante L (2020a) Bitcoin transactions, information asymmetry and trading volume. Quant Financ Econ 4:365–381. https://doi.org/10.3934/QFE.2020017

Ante L (2020b) Smart Contracts on the Blockchain – A Bibliometric Analysis and Review. https://doi.org/10.13140/RG.2.2.23964.03207

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

Ante L, Fiedler I, Strehle E (2020) The Influence of Stablecoin Issuances on Cryptocurrency Markets. https://doi.org/10.13140/RG.2.2.18405.83683

Armitage S (1995) Event study methods and evidence on their performance. J Econ Surv 9:25–52. https://doi.org/10.1111/j.1467-6419.1995.tb00109.x

Baur DG, Cahill D, Godfrey K, (Frank) Liu Z (2019) Bitcoin time-of-day, day-of-week and month-of-year effects in returns and trading volume. Financ Res Lett 31:78–92. https://doi.org/10.1016/j.frl.2019.04.023

Baur DG, Hoang LT (2020) A crypto safe haven against Bitcoin. Financ Res Lett. https://doi.org/10.1016/j.frl.2020.101431

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

Black F (1986) Noise. J Finance 41:528–543. https://doi.org/10.1111/j.1540-6261.1986.tb04513.x

Bouri E, Jawad S, Shahzad H, Roubaud D (2019) Co-Explosivity in the Cryptocurrency Market. Financ Res Lett 29:178–183. https://doi.org/10.1016/j.frl.2018.07.005

Brandvold M, Molnár P, Vagstad K, et al (2015) Price discovery on Bitcoin exchanges. J Int Financ Mark Institutions Money 36:18–35. https://doi.org/10.1016/j.intfin.2015.02.010

Brown SJ, Warner JB (1985) Using daily stock returns. The case of event studies. J financ econ 14:3–31. https://doi.org/10.1016/0304-405X(85)90042-X

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. https://doi.org/10.1007/BF00245187

Caporale GM, Plastun A (2019) The day of the week effect in the cryptocurrency market. Financ Res Lett 31:258–269. https://doi.org/10.1016/j.frl.2018.11.012

Chae J (2005) Trading volume, information asymmetry, and timing information. J Finance 60:413–442. https://doi.org/10.1111/j.1540-6261.2005.00734.x

Daian P, Goldfeder S, Kell T, et al (2020) Flash Boys 2.0: Frontrunning in Decentralized Exchanges, Miner Extractable Value, and Consensus Instability. In: 2020 IEEE Symposium on Security and Privacy (SP). pp 910–927

Dimpfl T, Baur DG (2020) Information Transmission across Cryptocurrency Markets and the Role of the Blockchain. https://doi.org/10.2139/ssrn.3573367

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 Manag 19:472–494. https://doi.org/10.1057/s41260-018-0093-8

Fama EF, Fisher L, Jensen MC, Roll R (1969) The Adjustment of Stock Prices to New Information. Int Econ Rev (Philadelphia) 10:1. https://doi.org/10.2307/2525569

Forbes (2020) These Chinese Blockchain Platforms Are Launching Soon, Here Is Why. https://www.forbes.com/sites/biserdimitrov/2020/04/16/these-chinese-blockchain-platforms-are-launching-soon-here-is-why. Accessed 11 May 2020

Giudici P, Abu-Hashish I (2018) What determines bitcoin exchange prices? A network VAR approach. Financ Res Lett 28:309–318. https://doi.org/10.1016/j.frl.2018.05.013

Griffin JM, Shams A (2019) Is Bitcoin Really Un-Tethered?

Kaiser L (2019) Seasonality in cryptocurrencies. Financ Res Lett 31:232–238. https://doi.org/10.1016/j.frl.2018.11.007

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

Koutmos D (2018) Bitcoin returns and transaction activity. Econ Lett 167:81–85. https://doi.org/10.1016/j.econlet.2018.03.021

Kristoufek L (2020) On the role of stablecoins in cryptoasset pricing dynamics https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3672909

Libra Association (2020) Libra White Paper v2.0. https://libra.org/en-US/white-paper. Accessed 15 Mar 2020

Lyons RK, Viswanath-Natraj G (2020a) Stable coins don't inflate crypto markets. In: VOX CEPR Policy Portal. https://voxeu.org/article/stable-coins-dont-inflate-crypto-markets. Accessed 12 May 2020

Lyons RK, Viswanath-Natraj G (2020b) What Keeps Stablecoins Stable? https://doi.org/10.2139/ssrn.3508006

Moratis G (2020) Quantifying the spillover effect in the cryptocurrency market. Financ Res Lett 101534. https://doi.org/10.1016/j.frl.2020.101534

Pagnottoni P, Dimpfl T (2019) Price discovery on Bitcoin markets. Digit Financ 1:139–161.

https://doi.org/10.1007/s42521-019-00006-x
Wang GJ, Ma XY, Wu HY (2020) Are stablecoins truly diversifiers, hedges, or safe havens against traditional cryptocurrencies as their name suggests? Res Int Bus Financ 54:101225. https://doi.org/10.1016/j.ribaf.2020.101225
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. https://doi.org/10.1016/j.frl.2019.07.016
Warren W, Bandeali A (2017) 0x : An open protocol for decentralized exchange on the Ethereum blockchain. https://0x.org/pdfs/0x_white_paper.pdf. Accessed 26 Jun 2019
Wei WC (2018) The impact of Tether grants on Bitcoin. Econ Lett 171:19–22. https://doi.org/10.1016/j.econlet.2018.07.001
Wilcoxon F (1945) Individual Comparisons by Ranking Methods. Biometrics Bull 1:80–83
Zięba D, Kokoszczyński R, Śledziewska K (2019) Shock transmission in the cryptocurrency market. Is Bitcoin the most influential? Int Rev Financ Anal 64:102–125. https://doi.org/10.1016/j.irfa.2019.04.009

Appendix

Table A.1. Summary statistics of 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) of a transaction. The cluster 'exchanges' include non-exchange 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

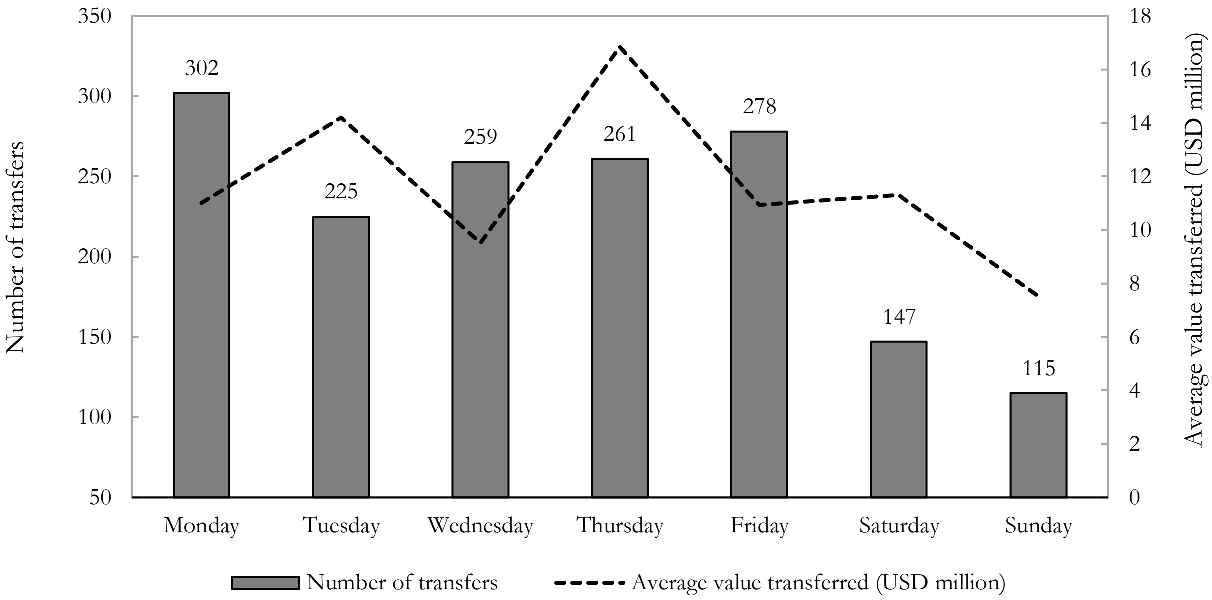
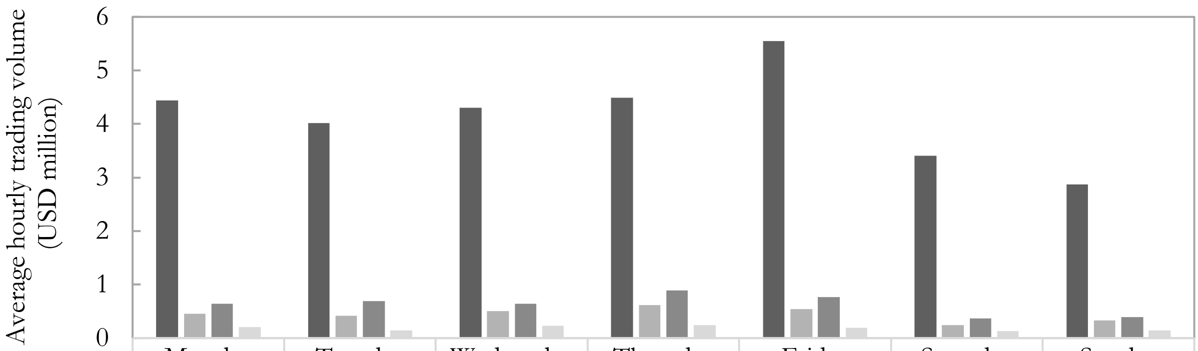


Figure A.1. Number of large stablecoin transfers and average value transferred per day-of-week. Gray bars represent the absolute number of stablecoin transfers over $1 million in our sample per day-of-week. The dotted line represents the average amount transferred per stablecoin transfer in million dollars.



	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-week. The figure represents the average absolute trading volume in million dollars on Bitstamp over the period considered in this study (Apr 2019 to March 2020) for four trading pairs. Bars represent the average hourly trading volume per day-of-week. The data table below the graph shows the corresponding trading pairs and associated numbers.

Table A.3. Robustness checks. Event study results for Bitcoin return and trading volume around large stablecoin transfers across different panels. Panels differ in that they test an alternative estimation window (panels A and B), test market data from other cryptocurrency exchanges (panels C, D and E) or test effects on alternative cryptocurrencies (panels F, G and H). All panels test 1,587 observations. The column z-test refers to the non-parametric Wilcoxon sign rank test. The column 'pos' shows the share of observations with positive abnormal trading volume for the respective period.

	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 return and trading volume around large stablecoin transfers across the nine different address cluster samples. The column z-test refers to the non-parametric Wilcoxon sign rank test. The column 'pos' shows the share of observations with positive abnormal trading volume for the respective period.

	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.