Analysis of the Relationship Between Bitcoin and Tether

Pre-interview task for the Financial Economist role in a London based economic consulting firm

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Contents

Disclaimer: *The company that sent me the data had no involvement in the design, analysis, interpretation, or conclusions of this research. The company's sole contribution was the provision of the data used in this study.*

1. Introduction

On the 11th of November 2025 I was given by a London-based economic consulting company a pre-interview task that I had to complete in 90 minutes, and if my work was up to standard, I would have been invited for an interview for the Financial Economist role. Although I did not manage to be selected for interview, I took my time after the submission of the task to examine the data in more detail. The objective of the task was to evaluate the relationship between Tether transactions and Bitcoin, and identify potential market manipultion during the first quarter of 2018. The content of the task was the following:

- **Tether_Q1_2018.csv:** CSV file with the Tether (USDT) transactions by address, with the amount of transactions, transaction type and fees, from the 1st of January 2018 to the 31st of March 2018
- **EOD_BTC_data.csv:** CSV file with the daily Bitcoin open, close, high and low price, return and volume, from the 1st of January 2018 to the 31st of March 2018

Hence, this is my attempt, without particular time constraints, of testing the relationship between USDT transactions and the price of Bitcoin, with the data that was provided. The data is limited to just one quarter of 2018, thus coefficient estimates, statistical significance and results must be interpreted with the caution of the fact that estimating the relationship between variables would benefit from further data. However, by concentrating on this quarter, I can work on event studies on what happened when particular addresses participated in transactions or when there have been particular days of interesting/high USDT transactions.

This report will start with my answers on questions 3-1 and 3-2 (the first questions of the task which will be written below). After that I will demonstrate my attempt on answering the rest of the questions, for which I have used an approach that questions the general relationship between USDT transactions and the price of Bitcoin, followed by a focus on USDT transaction types, and finally looking specifically at addresses and dates of interest. The tools I used for this project are SQL for data cleaning, R for specifying and running statistical models, Tableau and Excel for data visualisation.

2. Literature and topic background

Tether (USDT) is a blockchain-enabled platform designed to facilitate the use of fiat currencies in a digital manner. It is designed to be pegged to the US dollar (it is aimed to value 1-1 with the US dollar, in contrast with the volatility of cryptocurrencies). Its main purpose is to provide a stable digital asset within the volatile cryptocurrency market, allowing for easier trading and transactions without the risk of large price fluctuations. According to Onesafe, USDT responds to Bitcoin price spikes when investors pull out USDT by buying BTC. However, throughout this report my main focus will be on whether USDT movement affects the price of Bitcoin. The CaseBitcoin website, the site that "*makes the case for Bitcoin everyday*", refutes the claim that when new Tether units are issued (minted) out of thin air they are used to buy Bitcoin, thus dramatically inflating the price of Bitcoin artificially, citing various sources including academic papers that show that Tether issuances do not cause BTC price movements. With this report, I will add to this literature by not only analysing the general relationship between BTC and USDT transactions, but also by focusing on Tether issuances, which are categorised by the "Grant Property Tokens" transactions.

3. Question 3-1

Question 3-1 is:

"*Make a single table containing the daily Bitcoin price and the daily USDT transaction volume*".

The daily USDT transaction volume, which will be defied here as $USDT_t$, is:

$$\text{Tether Transaction Volume on day } t = USDT_t = \sum_i amount_{i,t}\,, \qquad i = \text{one transaction}$$

Table 3.1: Daily Bitcoin price and USDT transaction volume

Date	Bitcoin close price ($)	Tether transaction volume
01/01/2018	13,657	128,506,593
02/01/2018	14,982	260,353,283
03/01/2018	15,201	342,706,223
04/01/2018	15,599	594,174,889
05/01/2018	17,430	257,593,824
06/01/2018	17,527	165,673,928
07/01/2018	16,478	151,097,947
08/01/2018	15,170	345,947,160
09/01/2018	14,595	268,778,294
10/01/2018	14,973	310,553,750
11/01/2018	13,406	372,379,827
12/01/2018	13,981	334,580,647
13/01/2018	14,360	185,327,852
14/01/2018	13,772	339,477,360
15/01/2018	13,820	614,125,224
16/01/2018	11,491	660,299,376
17/01/2018	11,189	714,712,647
18/01/2018	11,475	903,950,277

19/01/2018	11,607	548,746,201
20/01/2018	12,899	387,887,181
21/01/2018	11,600	514,449,558
22/01/2018	10,931	237,761,765
23/01/2018	10,868	576,538,114
24/01/2018	11,359	313,409,486
25/01/2018	11,259	297,916,557
26/01/2018	11,171	376,183,441
27/01/2018	11,441	217,954,443
28/01/2018	11,786	440,894,904
29/01/2018	11,296	323,711,091
30/01/2018	10,106	719,461,624
31/01/2018	10,221	541,747,833
01/02/2018	9,171	385,792,869
02/02/2018	8,831	425,737,851
03/02/2018	9,175	263,695,844
04/02/2018	8,277	222,739,209
05/02/2018	6,955	431,979,432
06/02/2018	7,754	386,527,473
07/02/2018	7,621	286,346,232
08/02/2018	8,266	344,734,696
09/02/2018	8,737	165,284,857
10/02/2018	8,622	246,003,606
11/02/2018	8,130	254,341,857
12/02/2018	8,927	213,405,166
13/02/2018	8,598	163,092,800
14/02/2018	9,495	173,762,419
15/02/2018	10,166	216,511,071
16/02/2018	10,234	137,951,281
17/02/2018	11,113	171,256,176
18/02/2018	10,552	141,189,954
19/02/2018	11,225	131,178,437
20/02/2018	11,404	203,261,293
21/02/2018	10,690	268,123,709
22/02/2018	10,005	810,077,786
23/02/2018	10,301	241,755,162
24/02/2018	9,813	245,000,840
25/02/2018	9,665	102,671,057
26/02/2018	10,367	195,027,704
27/02/2018	10,726	172,537,871
28/02/2018	10,398	145,786,822
01/03/2018	10,951	171,445,424
02/03/2018	11,086	159,552,166
03/03/2018	11,490	128,964,344
04/03/2018	11,513	118,624,250
05/03/2018	11,573	248,790,159
06/03/2018	10,780	277,662,637
07/03/2018	9,966	296,601,539
08/03/2018	9,395	276,740,377
09/03/2018	9,338	342,566,004

10/03/2018	8,866	163,693,722
11/03/2018	9,579	199,320,965
12/03/2018	9,205	197,284,309
13/03/2018	9,195	278,255,344
14/03/2018	8,270	260,000,821
15/03/2018	8,301	465,482,903
16/03/2018	8,338	329,967,625
17/03/2018	7,917	281,466,201
18/03/2018	8,224	446,291,288
19/03/2018	8,631	522,795,949
20/03/2018	8,913	632,117,133
21/03/2018	8,929	418,747,342
22/03/2018	8,728	639,070,096
23/03/2018	8,880	327,595,930
24/03/2018	8,668	125,969,620
25/03/2018	8,496	112,385,682
26/03/2018	8,209	264,658,297
27/03/2018	7,833	346,512,950
28/03/2018	7,954	316,524,771
29/03/2018	7,166	274,714,930
30/03/2018	6,891	461,758,286
31/03/2018	6,974	136,727,374

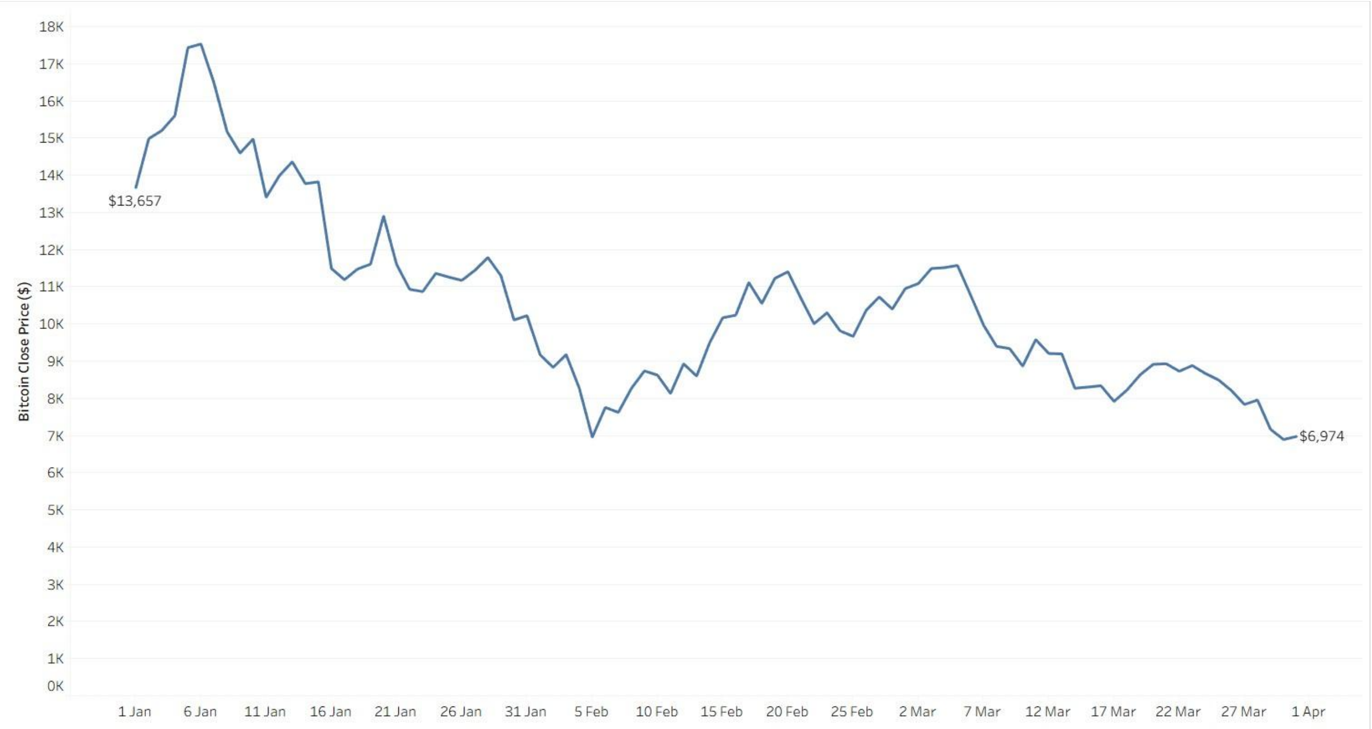
The variables I will focus on for my analysis will be primarily the two tabulated above, i.e. the Bitcoin (BTC) close price and the total amount of transactions. I will concentrate my analysis on total daily Tether transactions first rather than average daily Tether transaction size because total transaction size can be interpreted as a proxy for daily USDT activity, thus one of the questions I will try to answer on the initial analysis will be: *on days when there is higher activity and movement in the Tether market, what happens to Bitcoin?* Furthermore, average Tether transaction size will be considered later with the deepened analysis on issuance days (when there is usually a higher average daily transaction size as the issuance transactions are much higher than the Simple Send transactions), on the addresses and on the days of interest analysis.

4. Question 3-2

Question 3-2 is:

"*Make a plot of BTC/USD daily rate*".

Figure 4.1: BTC/USD, Bitcoin daily close price ($)



The Bitcoin close price fell by 48%, from $13,657.20 on the 1st of January 2018 to $6,973.53 on the 31st of March.

5. How to answer questions 3-3 and 4

Questions 3-3 and 4 recite:

Question 3-3: "*Bonus question: can you find what are the wallets of the crypto exchanges, and what are the wallets of the tether treasury? (i.e., the entity issuing tether coins)*".

Question 4: "*Our client would like to understand whether some Tether transactions could be affecting the price of Bitcoin. Provide a brief description of what further analysis you would like to propose, have a think about:*

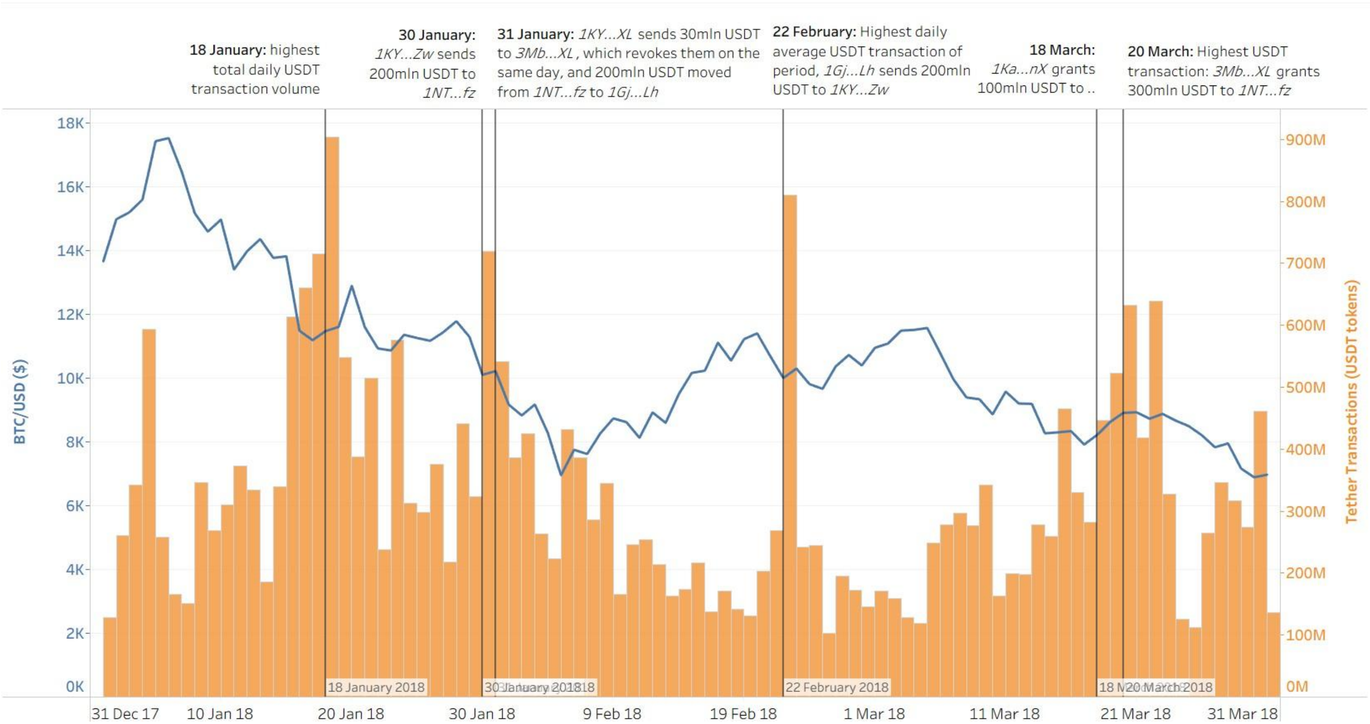
- *How you would like to test any relationship between given USDT transactions and the price of Bitcoin*

➢ *What type of transactions could affect the price of Bitcoin? How would you find out?*

Please write your brief description clearly and concisely, and in such a way that it could be understood by a non-specialist."

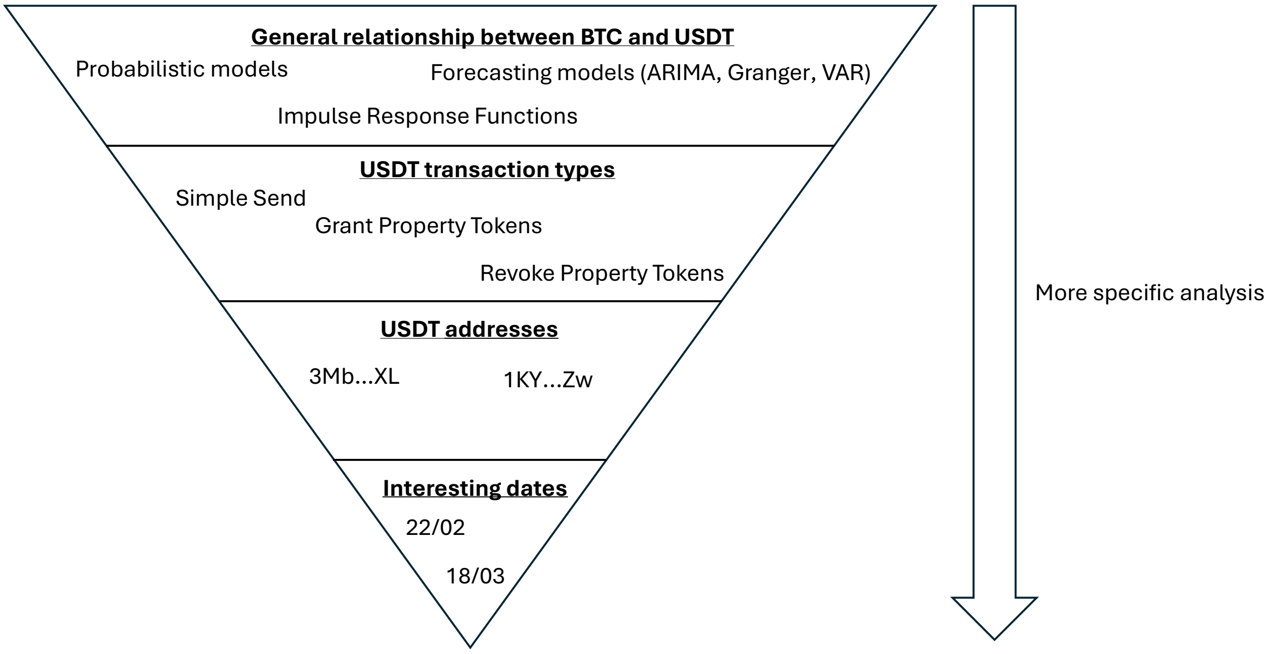
We can visualise BTC/USD (Close) and Tether transactions together in Figure 5.1 below.

Figure 5.1: Daily Bitcoin Close price and total Tether transactions



To test the relationship between Tether transactions and the price of Bitcoin during this period, I imagined an approach where I first looked into the general data and relationship between the two variables, and then went into specific transactions and addresses, as roughly illustrated in the diagram below. The answer to question 3-3. will come with the analysis focusing on the transaction types and sending and reference addresses.

Figure 5.2: Analysis plan



6. The big picture: Analysing the general relationship between Bitcoin and Tether

Before going into specific transactions, I looked at the generic relationship between the price of Bitcoin and Tether transactions using diverse statistical models. A model's reliability can be tested by its *p* values, giving us a measure of whether the relationships we find are coincidental, the *R* values, giving us a measure of how much the model explains the variations in data, the *F* statistic, giving us a measure of whether the model explains the relationships better than random chance, and their *AIC*, *AICc* and *BIC* values, which balance the goodness of fit of the models with their complexity: the smaller these numbers, the better.

6.1. Probabilistic models: do higher Tether transactions increase the possibilities of a Bitcoin price increase on the same day?

Firstly, I looked into simple probability models to evaluate if the increase in the price of Bitcoin (the difference between the close and open price) is correlated with an increase in Tether transactions on the same day, thus without taking into account past values. I added the following calculations in R:

$$\Delta BTC_t = Close_t - Open_t$$

$$BTC\_Increase_t = \begin{cases} 1, & \Delta BTC_t > 0 \\ 0, & \Delta BTC_t < 0 \end{cases}$$

ΔBTC_t is the difference in the price of Bitcoin at the end of day t. Hence, I ran the following logistic model:

$$BTC\_Increase_t = \beta_0 + \beta_1 USDT_t$$

Where:

$BTC\_Increase =$ binary variable which is equal to 1 if the Bitcoin price increased on day t

$USDT_t =$ Tether transactions volume on day t

The value of β_1 gives the effect of a one-unit change in Tether transactions on the log-odds of BTC increasing. A positive β_1 indicates that higher Tether transactions increase the probability of the Bitcoin price going up, whilst a negative β_1 indicates that higher Tether transactions decrease this probability. The logistic model tested does not provide statistically significant values, and I found the same with the probit model.

To better assess the relationship between the Bitcoin price and Tether transactions, I took into account the autoregressive component of BTC, given that its price heavily depends on past values. I tried to repeat the logistic model with lagged variables:

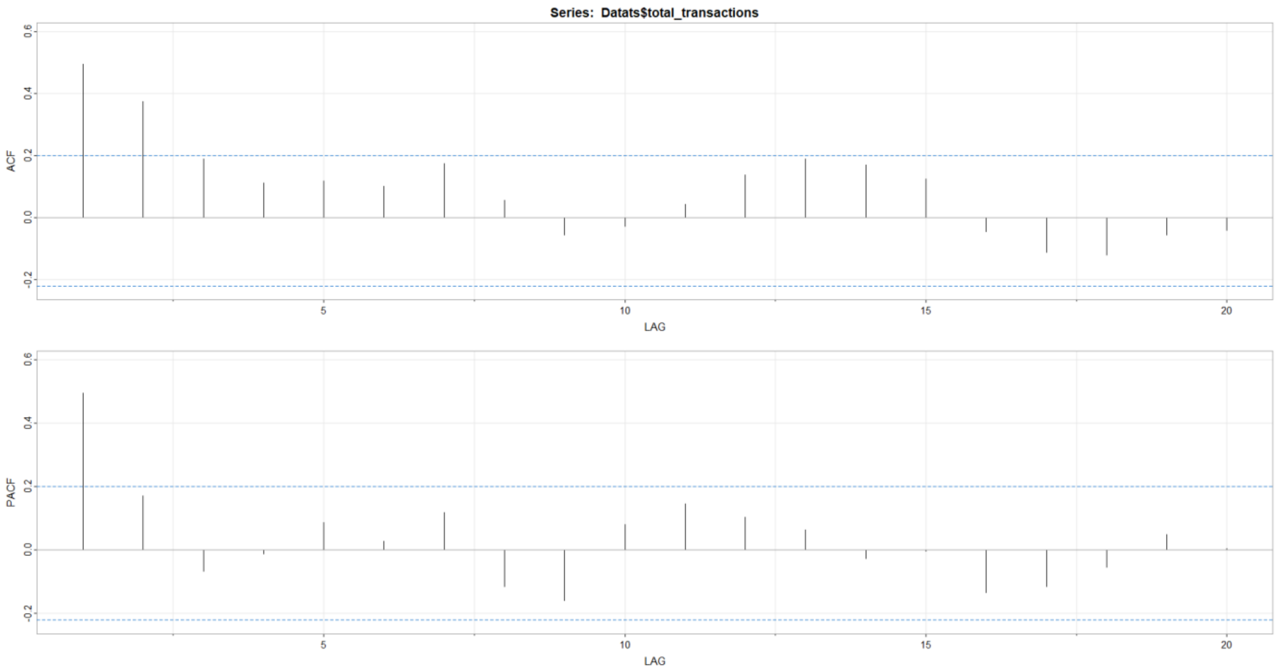
$$BTC\_Increase_t = \beta_0 + \beta_1 USDT_t + \beta_2 USDT_{t-1} + \beta_3 BTC\_Increase_{t-1}$$

This however still gave an unreliable model, with not statistically significant coefficient estimates, and similar results are found with the Tether average transaction size. This shows that it is superficial to hypothesise that higher Tether transactions in one day increase chances of higher Bitcoin prices on that same day.

6.2. Differencing: is it better to work with differenced data, and is there a seasonal pattern?

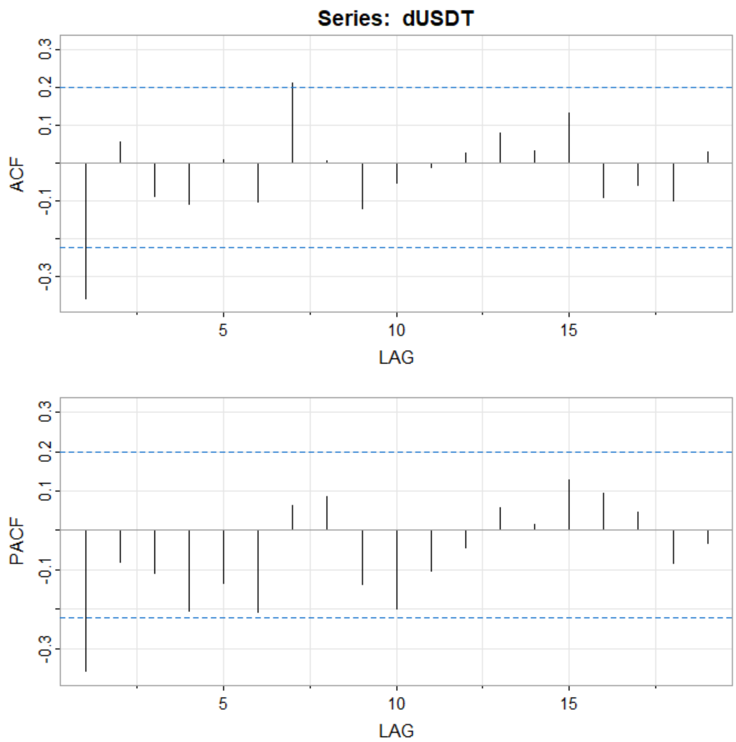
Before trying other models, I inspected the data to check whether differencing of the variables of interest is needed, given that Bitcoin's price is downward trending and Tether's transaction volume is highly volatile (with a standard deviation of >1,000,000). Figure 6.2.1 shows the autocorrelations of Tether transactions (the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF)). Given that there is some autocorrelation (ACF, PACF>0.2 for the first lags), it is recommended to de-trend Tether transactions by differencing.

Figure 6.2.1: Tether transactions, ACF and PACF



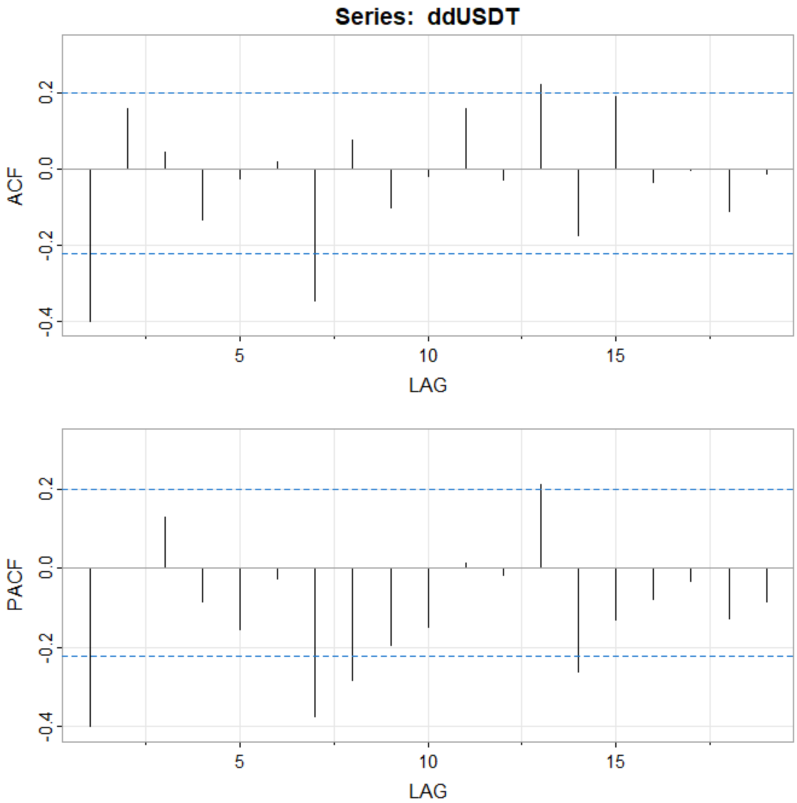
Hence, I differenced the Tether data, and Figure 6.2.2 below is the ACF and PACF representations of this. Whilst most of the lags are under 0.2, the first lags are over the blue line both for the ACF and PACF, which would suggest that, when working with forecasting models such as ARIMA models, taking into account the first Moving Average (MA) error will help us give a reliable model.

Figure 6.2.2: Differenced Tether transactions, ACF and PACF



Given how the graphed Tether transactions data looks in Figure 5.1, I experimented with differencing the data again to check for seasonal trends, like weekly trends of transactions. Below is the ACF and PACF of the USDT data differenced twice, the second time being with a lag of 7 days. The autocorrelations now are larger and more volatile, suggesting that there is no need to take into account seasonal components for the USDT data, and that there is no seasonal trend that needs to be considered for the analysis.

Figure 6.2.3: Differenced Tether transactions, differenced with a lag of 7 days, ACF and PACF



Hence, when running models, I did so by differencing the data once, and on a daily basis, and I worked with the following calculated measurement:

$$\Delta \log(USDT_t) = \log(USDT_t) - \log(USDT_t) \cong \Delta\% USDT_t$$

I did the same differencing testing for the Bitcoin data and found similar results, i.e. it's best to difference the data once and there is no important seasonal trend, thus I used the following measurement in my models:

$$\Delta \log(BTC\_Close_t) = \log(BTC\_Close_t) - \log\left(BTC_{Close_{t-1}}\right) \cong \Delta\% BTC_{Close_t} \equiv r_t$$

The log-differenced BTC value at time t, $\Delta \log(BTC\_Close_t)$, will be interpreted as Bitcoin returns at time t: r_t.

6.3. Distributed lag models: relationship between Bitcoin and past USDT values

Given that Bitcoin depends heavily on past values, I tried to test distributed lag models which take this into account: models with lagged explanatory variables. Distributed lag models are models that can be used for time series analysis that show how an event's effect is distributed over multiple time periods. I tested different models and the best model I evaluated to estimate the data, in terms of having a balance of a high *R* squared, low error terms, low *AIC* and *BIC* values, and statistically significant coefficient estimates, was a model with 5 lags of USDT transactions:

$$r_t = \beta_0 + \beta_1 r_{t-1} + \sum_{i=0}^{5} \beta_{2+i} \Delta \log(USDT_{t-i}) + \varepsilon_t$$

However, these types of models gave low, not statistically significant estimations of the β_i's, with high *AIC* and *BIC* values and with high general error terms, thus, these do not provide any evidence that USDT transactions generally affect the price of Bitcoin.

Another type of model I tried is ARIMA models, to assess whether Tether transactions can help in forecasting the price of Bitcoin.

6.4. ARIMA models: do Tether transactions help to forecast Bitcoin?

Autoregressive, Integrated Moving Average (ARIMA) models with exogenous variables could help us understand how Tether transactions affect and predict Bitcoin prices in the future. ARIMA models are constructed with 3 components: the Autoregressive (AR) part is the number of regressors used to regress the variable on past values of itself, the Integrated (I) part defines whether to difference the data or not in order to de-trend the data, and the Moving Average (MA) part is about the number of error terms of the variable to use to take into account past errors. As discussed in the differencing section, and as can be seen below, I visualised the ACF and PACF of the Bitcoin close price, and found that ACF tapers off and the PACF cuts off after lag 1. Then, when I differenced the data, I found that there was no more autocorrelation. Hence, this suggests using $ARIMA(1,1,0)$. However, I am going to use the daily change in Bitcoin returns and daily change in Tether transactions, thus I do not need to include differencing in the ARIMA model (hence, in ARIMA, $I = 0$), which is why I will use an $ARIMA(1,0,0)$ model.

Figure 6.4.1: ACF and PACF of the Bitcoin close price. PACF is high at lag 1, suggesting AR(1) is useful

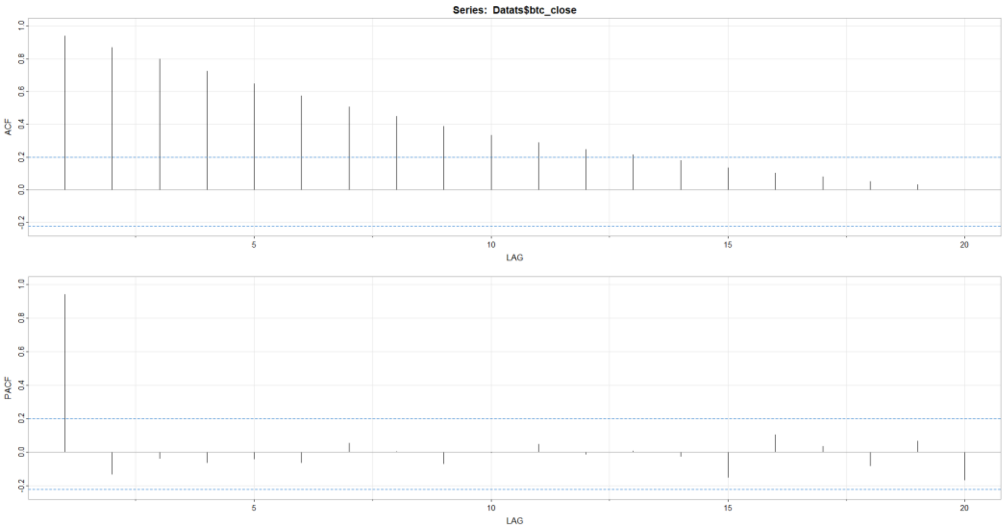
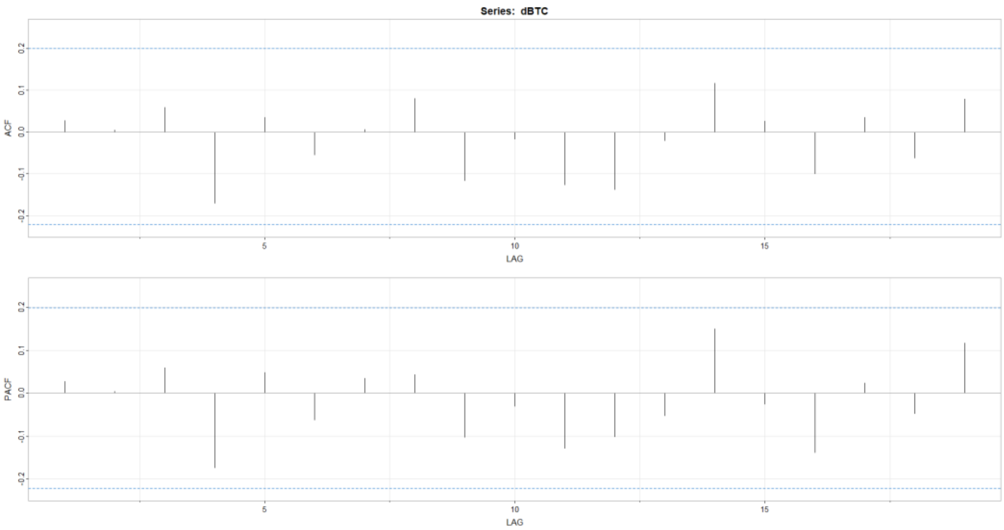


Figure 6.4.2: ACF and PACF of differenced data. As predicted, differencing is needed



Hence, I compared two ARIMA models, the $ARIMA(1,0,0)$ of Bitcoin returns:

$$r_t = \alpha_0 + \alpha_1 r_{t-1} + \varepsilon_t$$

…with the $ARIMA(1,0,0)$ of Bitcoin returns including USDT transactions as an exogenous regressor:

$$r_t = \beta_0 + \beta_1 r_{t-1} + \beta_2 \Delta \log(USDT_t) + \varepsilon_t$$

…to try and answer the question: *does including Tether transactions help us better forecast Bitcoin returns?* The results of the comparison of the models are as follows:

Table 6.4.3: Comparison between ARIMA model with USDT and without

Criterion	**With USDT**	**Without USDT**	**Better?**
RMSE	0.06014	0.06084	USDT model slightly better
MAE	0.0479	0.0483	USDT model better
MAPE	133.38	124.49	simple model better — but MAPE is unreliable for returns
MASE	0.6880	0.6945	USDT model better
AIC	-239.79	-239.75	USDT model better (very small improvement)
BIC	-229.84	-232.28	simple model better (penalises parameters more)
Significance of β_2	β_2 = -0.0197 (standard error = 0.0138)		not significant

The BIC value penalises complexity, and the estimate of β_2 is not statistically significant because the t value is:

$$t = \frac{\beta_2}{se(\beta_2)} = -1.43 > -1.645$$

For β_2 to be statistically significant at the 95% level, we need to find that t is smaller than -1.645, which is not the case, thus we cannot reject the null hypothesis that $\beta_2 = 0$. Hence, I did not find evidence that USDT transactions help to forecast Bitcoin returns. Error terms might be smaller when including USDT, however the change is too small to properly consider. If one wants to forecast BTC, it would be better to use a model that does not use USDT transactions volume data. For clearance, I ran the same model with the Bitcoin close price, and adding a differencing - i.e. using an $ARIMA(1,1,0)$ - in the model. The results are similar and I get to the same conclusion.

We can look at another family of models to better fit Tether transactions into Bitcoin forecasts and assess in which direction do variables work with each other.

6.5. Granger causality: do USDT transactions help forecast BTC or vice versa?

The Granger causality test is a statistical hypothesis test to determine whether a variable is useful in forecasting another variable, hence it is a very similar test that I did with the ARIMA models. Using the

Granger causality test, I will test whether 5 lagged values of USDT – like one of the best measured distributed lag models - can help us Granger-forecast BTC price increases, thus I will compare:

$$r_t = \gamma + \sum_{i=1}^{5} \alpha_i r_{t-i} + \sum_{i=1}^{5} \beta_i \Delta \log(USDT_{t-i}) + \varepsilon_t$$

…with:

$$r_t = \beta_0 + \sum_{i=1}^{5} \beta_i r_{t-i} + \varepsilon_t$$

The null hypothesis of this test, H_0, is that USDT transactions do not Granger-cause BTC returns increases, whilst the alternative hypothesis, H_a, is that USDT transactions do Granger-cause BTC returns increases. We can reject the null hypothesis if $p < 0.05$. The results are as follows, as printed in R:

Model 1: BTC_log_returns ~ Lags(BTC_log_returns, 1:5) + Lags(USDT_diff_log_transactions, 1:5)

Model 2: BTC_log_returns ~ Lags(BTC_log_returns, 1:5)

Model	Res.Df	Df	F	Pr(>F)
1	73			
2	78	-5	0.1398	0.9824

The *p* value is 0.98, which is much higher than the 5% level, thus we cannot reject the null hypothesis, which confirms the result we found on the ARIMA models. If we work on the opposite relationship, i.e. making USDT transactions the dependent variable and BTC returns the explanatory variable, we get the following result in R:

Model 1: USDT_diff_log_transactions ~ Lags(USDT_diff_log_transactions, 1:5) + Lags(BTC_log_returns, 1:5)

Model 2: USDT_diff_log_transactions ~ Lags(USDT_diff_log_transactions, 1:5)

Res.Df	Df	F	Pr(>F)
73			
78	-5	1.2068	0.3146

Although, the *p* value is smaller, we fail to reject the null hypothesis here as well. This means that there is no evidence to demonstrate that either USDT transactions helps forecasting BTC returns, nor that BTC returns helps forecast USDT transactions. If I were to do the Granger test with 1 lag instead of 5, just like in the ARIMA models, I get similar results, but with a weak statistical significance on the

Granger-causality of Bitcoin returns on USDT transactions increases ($p = 0.095 < 10\%$). This might be because there is a stronger short run effect of one day rather than a medium-term effect after 5 days. With these results, one might wonder if there is a measurable effect of a shock of USDT transactions on Bitcoin, and vice versa, which is what I dive into in the next chapter.

6.6. VAR models and IRFs: what is the effect of a USDT shock on Bitcoin, and vice versa?

I used Vector Autoregression (VAR) models to assess how a shock in the variable affects the other variable, visualising the results with the Impulse Response Functions (IRF). The VAR is a statistical model used to capture the relationship between variables as they change over time. In R I can use the *VARselect* function to help me determine the number of lags that minimise the error terms and *AIC* values. The IRF gives the reaction of a dynamic system in response to an external change.

I tested parsimonious lag-1 VAR models, as suggested by the *VARselect*:

$$r_t = \alpha_0 + \alpha_1 r_{t-1} + \alpha_2 \Delta \log(USDT_{t-1}) + \varepsilon_t$$

$$\Delta \log(USDT_t) = \beta_0 + \beta_1 \Delta \log(USDT_t) + \beta_2 r_{t-1} + \epsilon_t$$

The first model, with the Bitcoin change rate as the dependent variable, is below summarised from R:

Estimation results for equation BTC_log_returns:

===

BTC_log_returns = BTC_log_returns.l1 + USDT_diff_log_transactions.l1 + const

Variable	Estimate	Std. Error	t value	Pr(>|t|)
BTC_log_returns.l1	-0.0122086	0.1079373	-0.113	0.910
USDT_diff_log_transactions.l1	0.0005048	0.0142677	0.035	0.972
const	-0.0087924	0.0065864	-1.335	0.185
Residual standard error		0.06129 on 85 degrees of freedom		
Multiple R-Squared	0.0001823	**Adjusted R-squared**	-0.02334	
F-statistic	0.007751 on 2 and 85 DF	**p-value**	0.9923	

The *R* squared is extremely low, highlighting that the model does not explain the majority of the data's volatility. The *p* value is extremely high (close to 1), meaning that the model is not statistically significant, and the same is with the coefficient estimates.

The model with the change in USDT transactions is summarised below:

Estimation results for equation USDT_diff_log_transactions:

===

USDT_diff_log_transactions = BTC_log_returns.l1 + USDT_diff_log_transactions.l1 + const

Variable	Estimate	Std. Error	t value	Pr(>|t|)	Signif. Code
BTC_log_returns.l1	-1.34795	0.79955	-1.686	0.09549	.
USDT_diff_log_transactions.l1	-0.32812	0.10569	-3.105	0.00259	**
const	-0.01303	0.04879	-0.267	0.79008	
Model Summary					
Residual standard error	0.454 on 85 degrees of freedom				
Multiple R-Squared:	0.1166	**Adjusted R-squared:**			0.09579
F-statistic:	5.608 on 2 and 85 DF,	**p-value:**			0.005154

The model with USDT change in transactions is a better fit due to the more significant coefficient estimates: the *p* value for the coefficient estimate on BTC returns is significant at the 10% level ($p < 0.1$), and it is negative (-1.35), meaning that there is an estimated negative correlation between BTC returns and USDT change in transactions the day after. The *R* squared is slightly higher and the *p* value is much lower than the model with BTC as the dependent variable. This signifies that the VAR models suggest that it is not USDT that affects the price of Bitcoin, but rather, that BTC price changes affect how much USDT is exchanged in the economy: if the price of Bitcoin rises, then traders will tend to withdraw their USDT tokens to buy Bitcoin, and when Bitcoin price falls, they will tend to trade more USDT, given that it is supposed to be a safer, less volatile asset than cryptocurrency.

Figures 6.6.1 and 6.6.2 below display the visualisations of the IRFs. Figure 6.6.1 is the IRF of Bitcoin returns on a shock of one standard deviation of USDT transactions. Clearly, the 95% Confidence Interval (CI, the area between the two dotted red lines) fluctuates around 0 and is quite large, meaning that if we were to test the data on 100 samples, 95 times the effect should be between the two red lines, thus there is a lot of ambiguity on whether the USDT shock makes BTC returns increase or decrease, and there is essentially no effect on BTC returns. Figure 6.6.2 is the IRF of USDT transactions on a shock of one standard deviation of Bitcoin returns. Figures 6.6.1 and 6.6.2 are essentially displaying the following IRFs respectively:

$$IRF_{BTC}(h) = \frac{dr_{t+h}}{d\epsilon_t}$$

$$IRF_{USDT}(h) = \frac{d\Delta \log(USDT_{t+h})}{d\varepsilon_t}$$

These IRFs are the clear demonstrations of the results of the VAR models: USDT transactions have in general no effect on Bitcoin returns, whilst there is some small negative effect of USDT transactions on Bitcoin returns. This might be due to the fact that when there are high USDT transactions, traders tend to sell their BTC holdings expecting the price to drop.

Figure 6.6.1: Impulse Response Function of Bitcoin returns after USDT shock

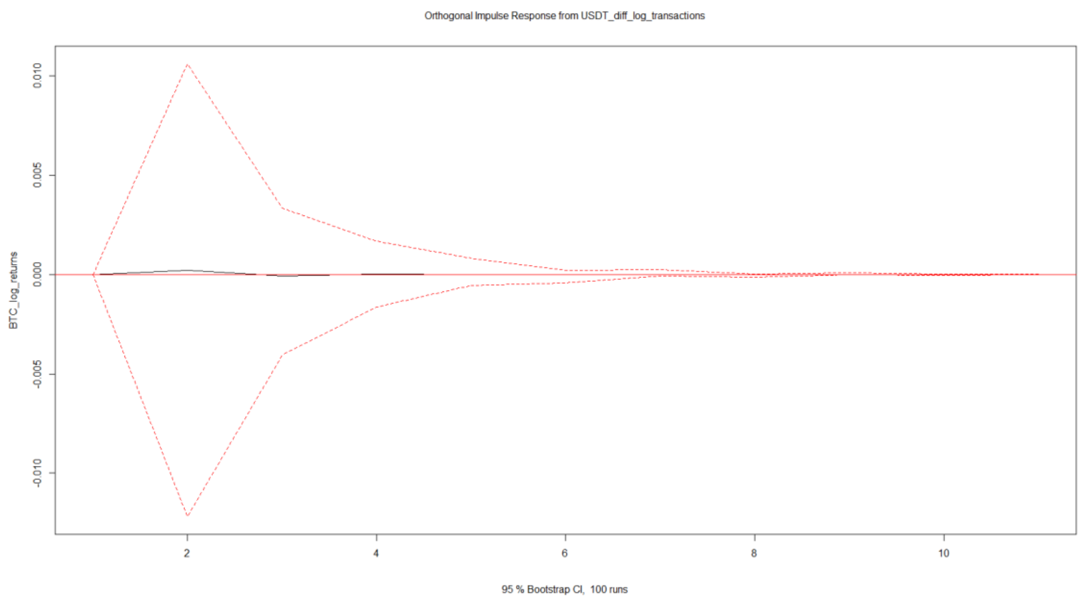
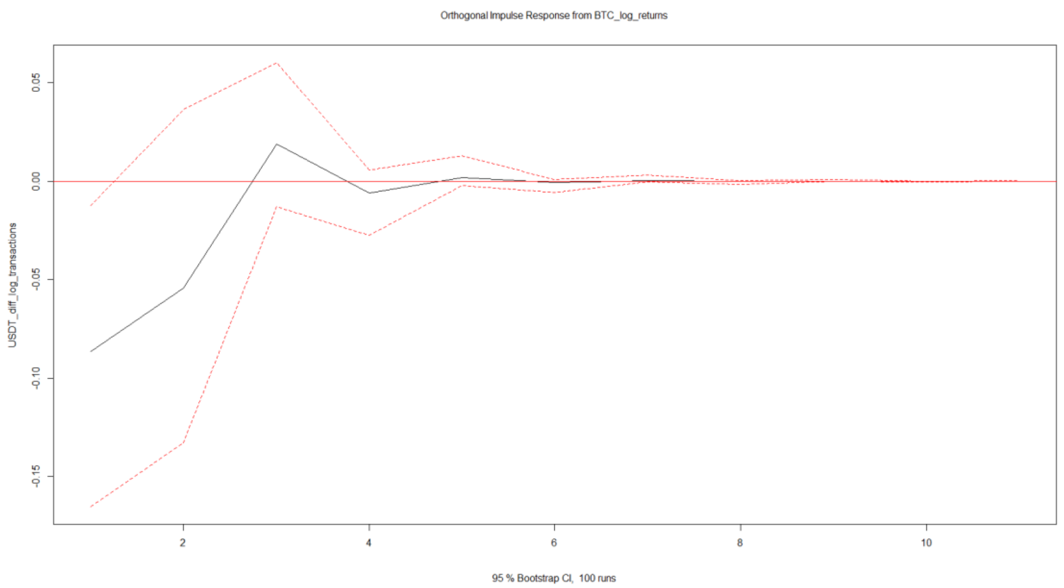


Figure 6.6.2: Impulse Response Function of USDT after Bitcoin shock



The models examined all demonstrate that there is no general effect of USDT transactions on Bitcoin returns: the probabilistic models I used gave no evidence that BTC was affected on the day of increased USDT transactions. Distributed lag, ARIMA and Granger causality models congruently came to the conclusion that there is no evidence that USDT transactions had forecasting power on Bitcoin, and VAR and IRFs demonstrated that USDT shocks had a low to no effect on BTC, rather, there is a small effect of BTC on USDT. With this knowledge, the next step is to assess whether it's specific types of Tether transactions that stimulate BTC price increases, hence, in the next chapter, I dive into specific transaction types of Tether.

7. Transaction type

The 3 types of Tether transactions in the data are Simple Send, Grant Property Tokens and Revoke Property Tokens. Those who are concerned with the topic suggest that Grant Property Tokens have the function of pumping up the price of Bitcoin. Hence, I am going to firstly investigate the effect that Grant Property Tokens transactions have had on the price of Bitcoin.

7.1. Grant Property Tokens

These types of transactions are those that the literature on the topic discuss the most when it comes to this topic. Grant Property Tokens happen when new USDT tokens are issued, or minted. For example, if the Tether treasury mints 100 million in USDT, these appear as a Grant transaction. Throughout the first quarter of 2018 there have been 11 minting events, as listed in the table below. There have been a total of 1.25 billion USDT issued during the first quarter of 2018.

Table 7.1.1: Grant Property Tokens transactions. Each day is a minting event

Date (minting event)	**Sending address**	**Reference address**	**Amount**
04/01/2018	3MbYQMMmSkC3AgWkj9FMo5LsPTW1zBTwXL	1NTMakcgVwQpMdGxRQnFKyb3G1FAJysSfz	100,000,000
14/01/2018	3MbYQMMmSkC3AgWkj9FMo5LsPTW1zBTwXL	1NTMakcgVwQpMdGxRQnFKyb3G1FAJysSfz	50,000,000
15/01/2018	3MbYQMMmSkC3AgWkj9FMo5LsPTW1zBTwXL	1NTMakcgVwQpMdGxRQnFKyb3G1FAJysSfz	100,000,000
16/01/2018	3MbYQMMmSkC3AgWkj9FMo5LsPTW1zBTwXL	1NTMakcgVwQpMdGxRQnFKyb3G1FAJysSfz	100,000,000
17/01/2018	3MbYQMMmSkC3AgWkj9FMo5LsPTW1zBTwXL	1NTMakcgVwQpMdGxRQnFKyb3G1FAJysSfz	100,000,000
18/01/2018	3MbYQMMmSkC3AgWkj9FMo5LsPTW1zBTwXL	1NTMakcgVwQpMdGxRQnFKyb3G1FAJysSfz	100,000,000
19/01/2018	3MbYQMMmSkC3AgWkj9FMo5LsPTW1zBTwXL	1NTMakcgVwQpMdGxRQnFKyb3G1FAJysSfz	100,000,000
20/01/2018	3MbYQMMmSkC3AgWkj9FMo5LsPTW1zBTwXL	1NTMakcgVwQpMdGxRQnFKyb3G1FAJysSfz	100,000,000
23/01/2018	3MbYQMMmSkC3AgWkj9FMo5LsPTW1zBTwXL	1NTMakcgVwQpMdGxRQnFKyb3G1FAJysSfz	100,000,000
18/03/2018	1Kaecr9gsYjRDJ8AWqZTBjQ6fd7RUwHynX	1MmiapMcvzovzF2dFcfRJN34jyRwJxUYLU	100,000,000
20/03/2018	3MbYQMMmSkC3AgWkj9FMo5LsPTW1zBTwXL	1NTMakcgVwQpMdGxRQnFKyb3G1FAJysSfz	300,000,000

From the table above we notice that there are essentially 2 sending addresses that grant tokens: *3Mb…XL* and *1Ka…nX*. Hence, these two addresses are the addresses that issue Tether coins, and they answer question 3-3 of the assignment. Meanwhile, there are 2 reference addresses that are in this list: *1NT…fz* and *1Mm…LU*. Later in this report (Section 8) we will see how these other two addresses might be of interest.

As similarly done in Section 6.6 of this report, I ran a VAR model to visualise an Impulse Response Function of minting events on BTC returns, as seen in Figure 7.1.2 below. This is a similar analysis to the one done in Lyons's and Viswanath-Natraj's paper on the topic, on page 31 (Figure 11). In R I ran a parsimonious model with one lag, as suggested by the SC(n) property of the *VARselect* function. Thus, I examined the following models:

$$r_t = \alpha_0 + \alpha_1 r_{t-1} + \alpha_2 USDT\_Issuance_{t-1} + \varepsilon_{1t}$$

$$USDT\_Issuance_t = \beta_0 + \beta_1 r_{t-1} + \beta_2 USDT\_Issuance_{t-1} + \varepsilon_{2t}$$

Where:

$$USDT\_Issuance_t = \begin{cases} 1, & t = \text{day when new USDT issued} \\ 0, & t = \text{day when no new USDT issued} \end{cases}$$

The model specified is not statistically strong as it gives statistically insignificant coefficient estimators ($p = 0.79$ and high p values for the coefficients on the first regression), implying that the binary variable of USDT issuance days does not help forecast the value of BTC returns.

Estimation results for equation BTC:

===================================

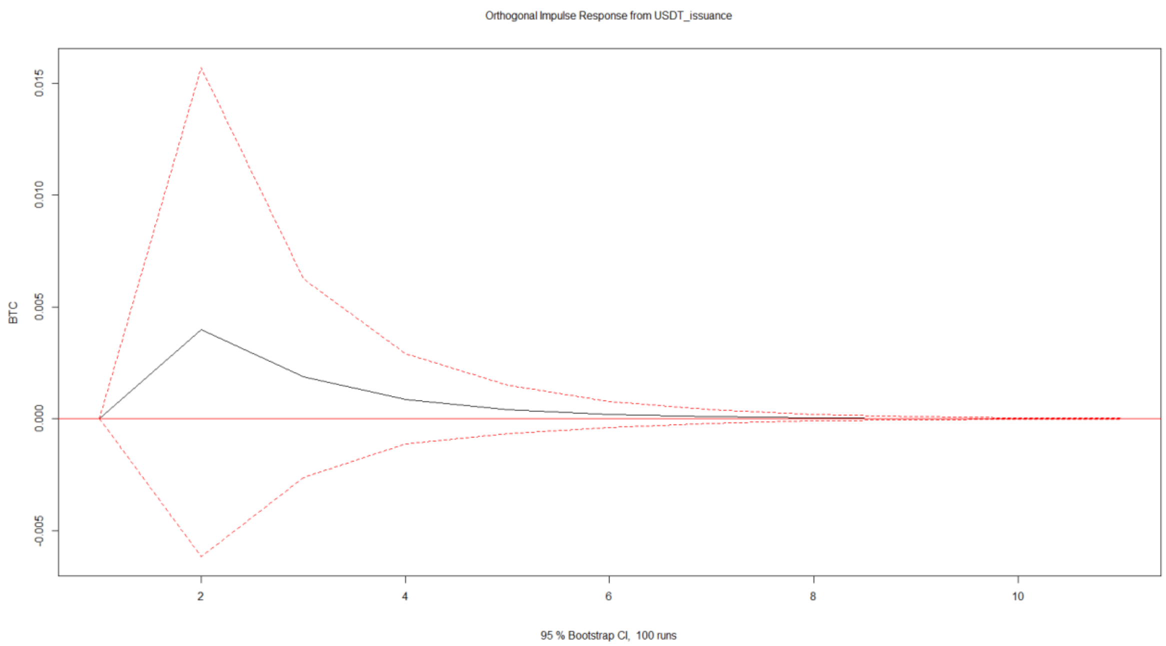
BTC = BTC.l1 + USDT_issuance.l1 + const

Variable	**Estimate**	**Std. Error**	**t value**	**Pr(>|t|)**
BTC.l1	-0.015572	0.106621	-0.146	0.884
USDT_issuance.l1	0.013531	0.019715	0.686	0.494
const	-0.010503	0.007026	-1.495	0.139
Residual standard error		0.06112 on 85 degrees of freedom		
Multiple R-Squared	0.005678	Adjusted R-squared	-0.01772	
F-statistic	0.2427 on 2 and 85 DF	p-value	0.785	

Nonetheless, I plotted the following IRF at horizon h:

$$IRF(h) = \frac{dr_{t+h}}{d\varepsilon_{2t}}$$

Figure 7.1.2: Impulse Response Function of BTC returns given a USDT issuance day shock



There seems to be a slightly larger increase in BTC returns compared to the IRF with all of the USDT data (see Figure 6.6.1). However, also in this case there is no statistically significant effect: the 95% confidence interval revolves around 0 and the small effect fades after a few days. This is a similar result to Lyons's and Viswanath-Natraj's result on their study, as highlighted on pages 30 and 31, where they conclude that "there is no systematic effect" when looking at issuance data.

To look at what the IRF does not capture, we can analyse issuance data with an event study. Let an event window be defined as 5 days before and after an event occurs, with such event being defined as t. Let an abnormal return be defined as:

$$AR_{i,t} = r_{i,t} - E\left(r_{i,t} \mid \text{no issuance event window}\right)$$

$r_{i,t}$ = BTC returns around issuance event i, with $t \in [t-5, t+5]$

$E(r_{i,t} \mid \text{no issuance event window}) = \text{average BTC returns excluding days in event windows}$

Then, the Average abnormal returns at period t are:

$$AAR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{i,t}$$

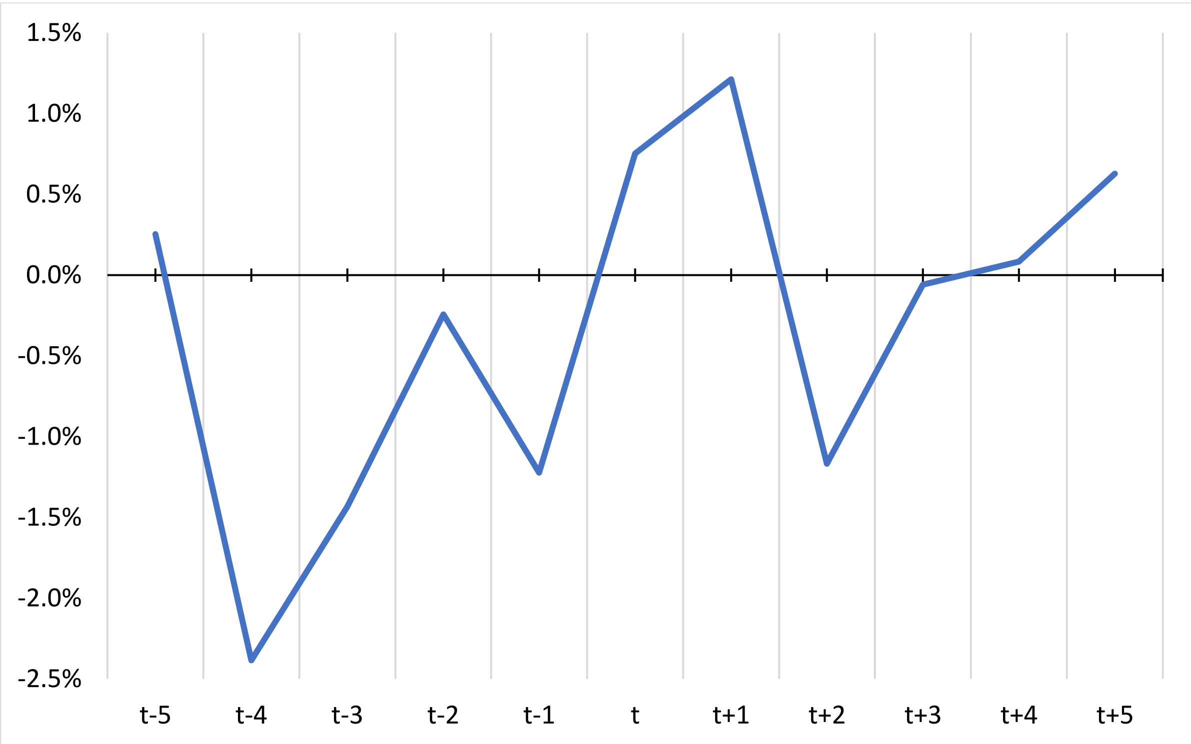
Moreover, I calculated the Cumulative Average Abnormal Returns (CAAR):

$$CAAR_{t+i,t+j} = \sum_{i}^{j} AAR_{t+i}$$

For example, I can use it to calculate the cumulative average returns from the day before the minting event ($t-1$) to the day after ($t+1$).

The graph below shows the average abnormal returns event study of an average day when a Grant Property Token transaction took place.

Figure 7.1.3: Average Abnormal Bitcoin price change before ($-$) and after ($+$) minting event (t)



It seems that there is a drop in Bitcoin returns 4 to 5 days before the minting event, with returns increasing from the day before ($t-1$) to the day after ($t+1$), which is what the IRF did not capture. However, to test statistical significance of these values, I evaluated t tests for each day. The t test has null hypothesis H_0: $AAR_t = 0$ and alternative hypothesis H_a: $AAR_t \neq 0$. We reject the null hypothesis if:

$$t = \left|\frac{AAR_t}{se(AAR_t)}\right| > 1.96$$

With 1.96 being the critical value at the 95% level, i.e., if we reject the null hypothesis, then the value will be statistically significant at the 95% level. The standard error is calculated as:

$$se(AAR_t) = \frac{\sigma_t}{\sqrt{n}}$$

With σ_t being the standard deviation of the Bitcoin returns at time t and n the number of minting events examined. The same is done with CAARs, with null hypothesis H_0: $CAAR_{t+i,t+j} = 0$ and alternative hypothesis H_a: $CAAR_{t+i,t+j} \neq 0$. The results are listed in Table 7.1.4.

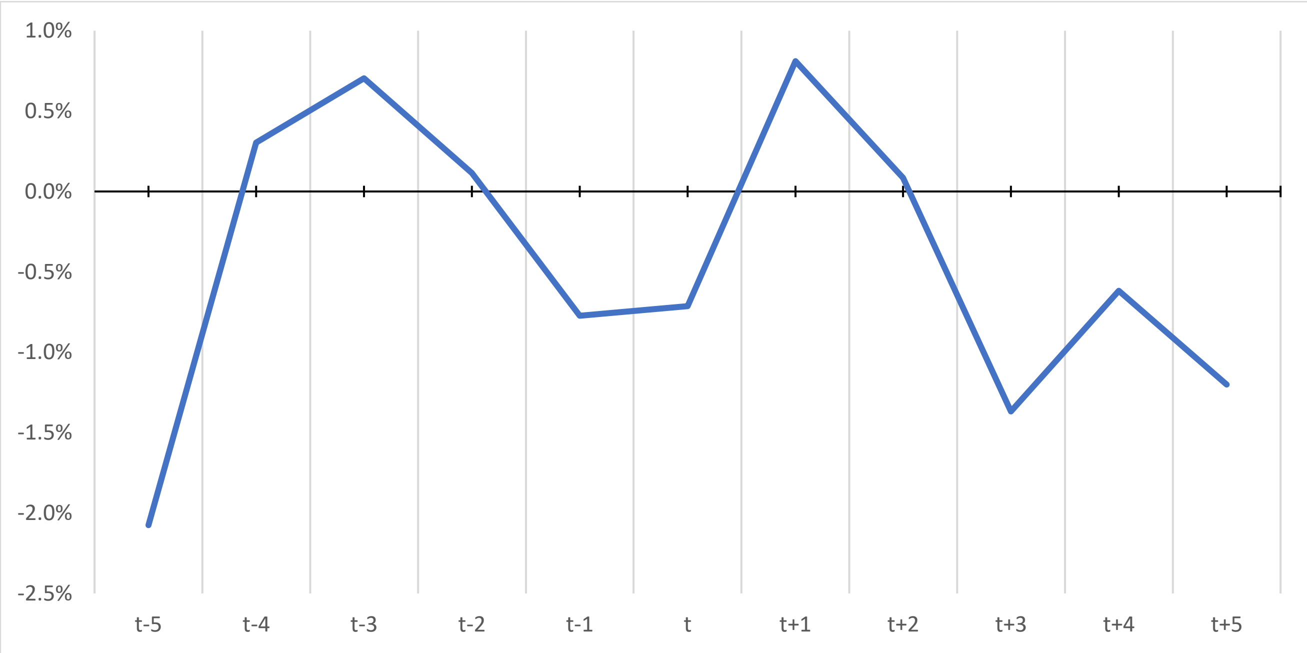
Table 7.1.4: t test results for the issuance event study on Bitcoin price change

Measurement	Period	Value	Standard errors	t tests	t tests results
AAR	***t-5***	0.3%	0.014468938	0.175644427	Fail to reject null
AAR	***t-4***	-2.4%	0.023978949	-0.994584055	Fail to reject null
AAR	***t-3***	-1.4%	0.025736711	-0.556525344	Fail to reject null
AAR	***t-2***	-0.2%	0.023259373	-0.10453984	Fail to reject null
AAR	***t-1***	-1.2%	0.019491244	-0.628017425	Fail to reject null
AAR	***t***	0.8%	0.021659945	0.34777951	Fail to reject null
AAR	***t+1***	1.2%	0.026017389	0.466104308	Fail to reject null
AAR	***t+2***	-1.2%	0.023043244	-0.50661555	Fail to reject null
AAR	***t+3***	-0.1%	0.016674688	-0.035401269	Fail to reject null
AAR	***t+4***	0.1%	0.018200929	0.04623352	Fail to reject null
AAR	***t+5***	0.6%	0.016818193	0.373417558	Fail to reject null
CAAR	***t-5, t+5***	-3.6%	0.069151507	-0.517503725	Fail to reject null
CAAR	***t-5, t-1***	-5.0%	0.047822882	-1.051864577	Fail to reject null
CAAR	***t+1, t+5***	0.7%	0.045058756	0.155000903	Fail to reject null
CAAR	***t-1, t+1***	0.7%	0.038779796	0.191307382	Fail to reject null

Since we fail to reject the null hypothesis for all days, we can say that every AAR from $t-5$ to $t+5$ is statistically insignificant, thus there is no evidence to show that when new tokens are created, Bitcoin returns get affected in any day 5 days prior or after. The volatility of the variables may have had an effect on these results: high standard deviations may have made Bitcoin returns noisy. Insignificant AARs indicate that daily abnormal returns are noisy and dominated by volatility.

With the same event study analysis, I investigated what happened 5 days before and after to the change in BTC volatility and volume. Let BTC volatility be defined as $|r_t|$, i.e. the absolute value of BTC returns is a proxy for BTC daily volatility. Then, below is the graphical representation of Average Abnormal Volatility (volatility at time t less the average volatility on days not included in event windows) around an average issuance event, conveying a large drop in volatility 5 days before the event.

Figure 7.1.5: Average Abnormal Volatility change before ($-$) and after ($+$) minting event (t)



However, the $t-5$ value seems to be the only statistically significant value out of all those calculated, as can be seen by the t test results below.

Table 7.1.6: t test results for Average Abnormal Volatility (AAV) and Cumulative AAV (CAAV) around issuance events

Measurement	**Period**	**Value**	**Standard errors**	**t tests**	**t tests results**
Average Abnormal Volatility	***t-5***	-2.1%	0.010052671	-2.064437768	Reject null
Average Abnormal Volatility	***t-4***	0.3%	0.018733576	0.161843767	Fail to reject null
Average Abnormal Volatility	***t-3***	0.7%	0.01808896	0.389747792	Fail to reject null

Average Abnormal Volatility	***t-2***	0.1%	0.016272373	0.070770845	Fail to reject null
Average Abnormal Volatility	***t-1***	-0.8%	0.01495298	-0.517092701	Fail to reject null
Average Abnormal Volatility	***t***	-0.7%	0.016193434	-0.44051015	Fail to reject null
Average Abnormal Volatility	***t+1***	0.8%	0.017570634	0.461325739	Fail to reject null
Average Abnormal Volatility	***t+2***	0.1%	0.016967589	0.04971224	Fail to reject null
Average Abnormal Volatility	***t+3***	-1.4%	0.011639474	-1.174729842	Fail to reject null
Average Abnormal Volatility	***t+4***	-0.6%	0.011052413	-0.559518808	Fail to reject null
Average Abnormal Volatility	***t+5***	-1.2%	0.010886854	-1.103627145	Fail to reject null
Cumulative Average Abnormal Volatility	***t-5, t+5***	-4.7%	0.048968746	-0.966084012	Fail to reject null
Cumulative Average Abnormal Volatility	***t-5, t-1***	-1.7%	0.034927632	-0.493922277	Fail to reject null
Cumulative Average Abnormal Volatility	***t+1, t+5***	-2.3%	0.030462832	-0.752491262	Fail to reject null
Cumulative Average Abnormal Volatility	***t-1, t+1***	-0.7%	0.028126801	-0.240328185	Fail to reject null

Let the daily volume change be calculated as $\Delta \log(BTC\_Volume)$. Then, in terms of the Average Abnormal Volume values (volume change values less average change in volume on days not included in event windows), results are quite similar in that although there can be seen a visual pattern (as seen in Figure 7.1.7 below), most values calculated do not pass the t test, thus not being statistically significant. The Cumulative Average Abnormal Volume (CAAVm) for the day after to 5 days after $(t + 1, t + 5)$ is a total decrease in volume of 24.5% and is statistically significant as we reject the null hypothesis that $CAAVm_{t+1,t+5} = 0$. Hence, when new USDT is issued, the BTC market tends to have a decline in activity, dispersed through several days, rather than as an immediate daily reaction.

Figure 7.1.7: Average Abnormal Volume change before (−) and after (+) minting event (t)

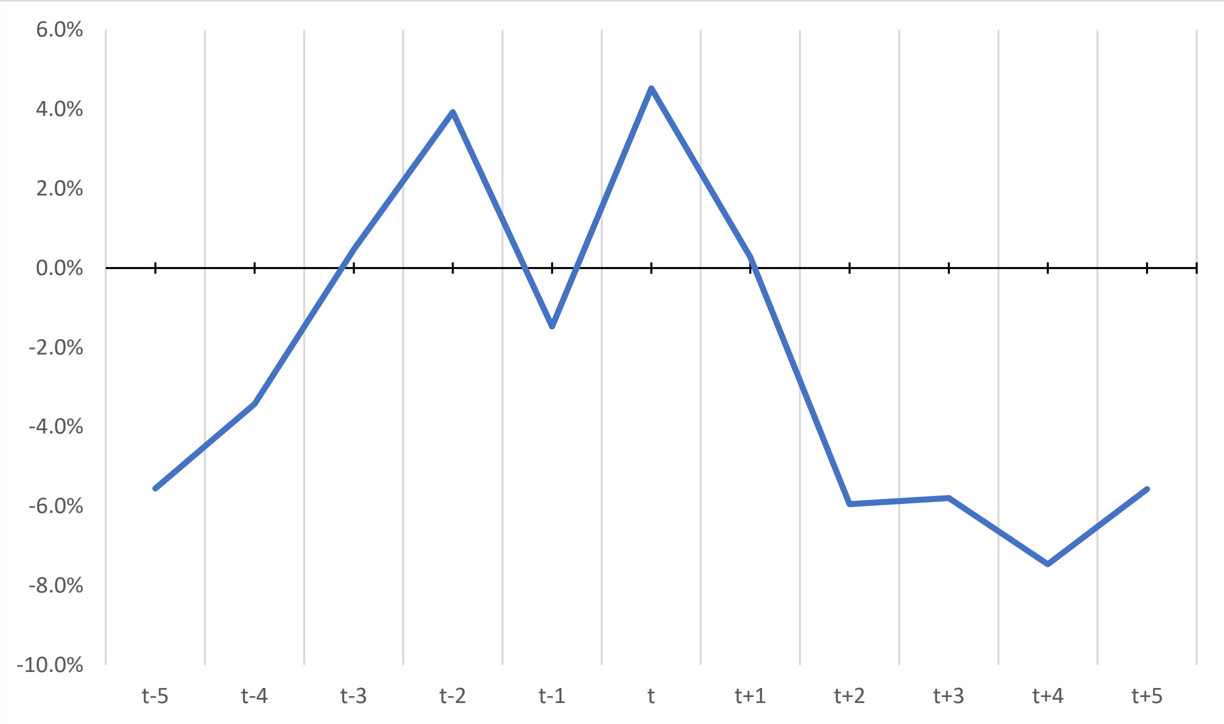


Table 7.1.8: t test results for Average Abnormal Volume (AAVm) and Cumulative AAVm (CAAVm) around issuance events

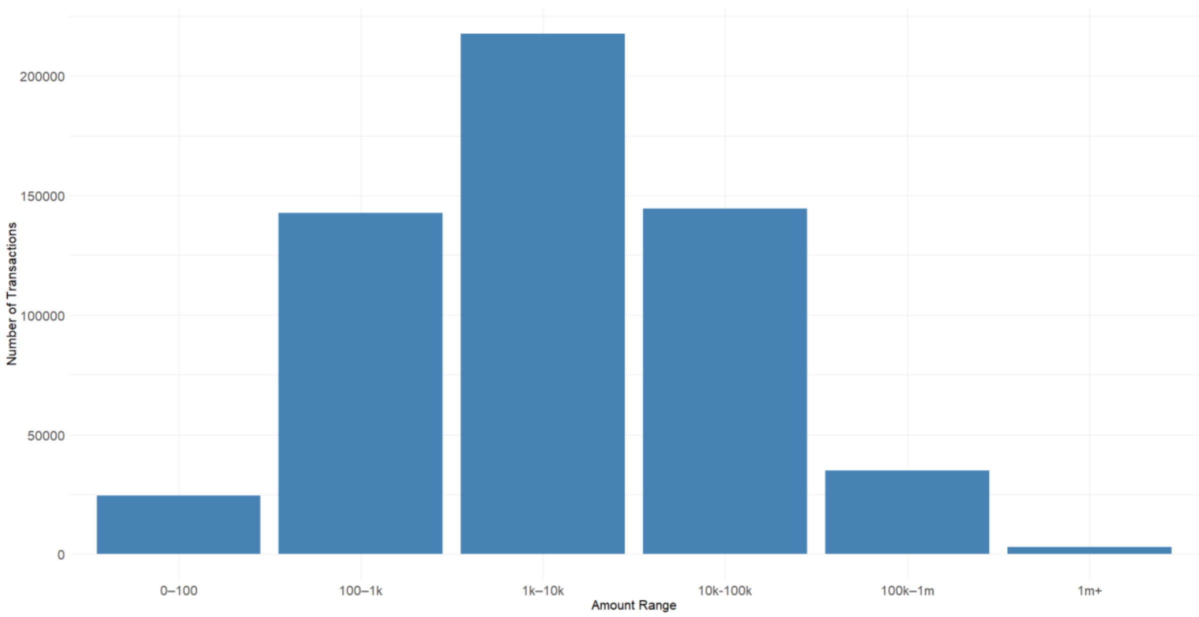
Measurement	Period	Value	Standard errors	t tests	t tests results
Average Abnormal Volume	***t-5***	-5.6%	0.047000402	-1.182124745	Fail to reject null
Average Abnormal Volume	***t-4***	-3.4%	0.073500376	-0.466371914	Fail to reject null
Average Abnormal Volume	***t-3***	0.5%	0.062516344	0.074631706	Fail to reject null
Average Abnormal Volume	***t-2***	3.9%	0.087175592	0.450917524	Fail to reject null
Average Abnormal Volume	***t-1***	-1.5%	0.059561256	-0.247558677	Fail to reject null
Average Abnormal Volume	***t***	4.5%	0.073099472	0.61947619	Fail to reject null
Average Abnormal Volume	***t+1***	0.3%	0.059270829	0.04607171	Fail to reject null
Average Abnormal Volume	***t+2***	-5.9%	0.060740518	-0.979231987	Fail to reject null
Average Abnormal Volume	***t+3***	-5.8%	0.043338285	-1.336979326	Fail to reject null
Average Abnormal Volume	***t+4***	-7.5%	0.046626939	-1.600331731	Fail to reject null
Average Abnormal Volume	***t+5***	-5.6%	0.043242255	-1.28768735	Fail to reject null
Cumulative Average Abnormal Volume	***t-5, t+5***	-26.0%	0.197813232	-1.315976103	Fail to reject null
Cumulative Average Abnormal Volume	***t-5, t-1***	-6.1%	0.147470459	-0.410991136	Fail to reject null
Cumulative Average Abnormal Volume	***t+1, t+5***	-24.5%	0.113242902	-2.163418747	Reject null

Cumulative Average Abnormal Volume	***t-1, t+1***	3.3%	0.110811736	0.300231601	Fail to reject null

7.2. Simple Send

A simple Send transaction is a standard USDT transfer from one address to another. As the distribution of Simple Send transactions in Figure 7.2.1 highlights, most of these transactions are in the range of 1,000 to 10,000 tokens.

Figure 7.2.1: Distribution of Simple Send transactions by amount



I used ARIMA and Granger models to test whether the highest Simple Send transactions (over 100k USDT or over 1 million USDT transactions) have a significant relationship with Bitcoin. The results are similar to the analysis in Section 6, in that there is weak, statistically insignificant correlation and no forecasting power. In the upcoming sections, there will be a focus on a particular selection of Simple Send transactions that are associated with addresses of interest.

7.3. Revoke Property Tokens

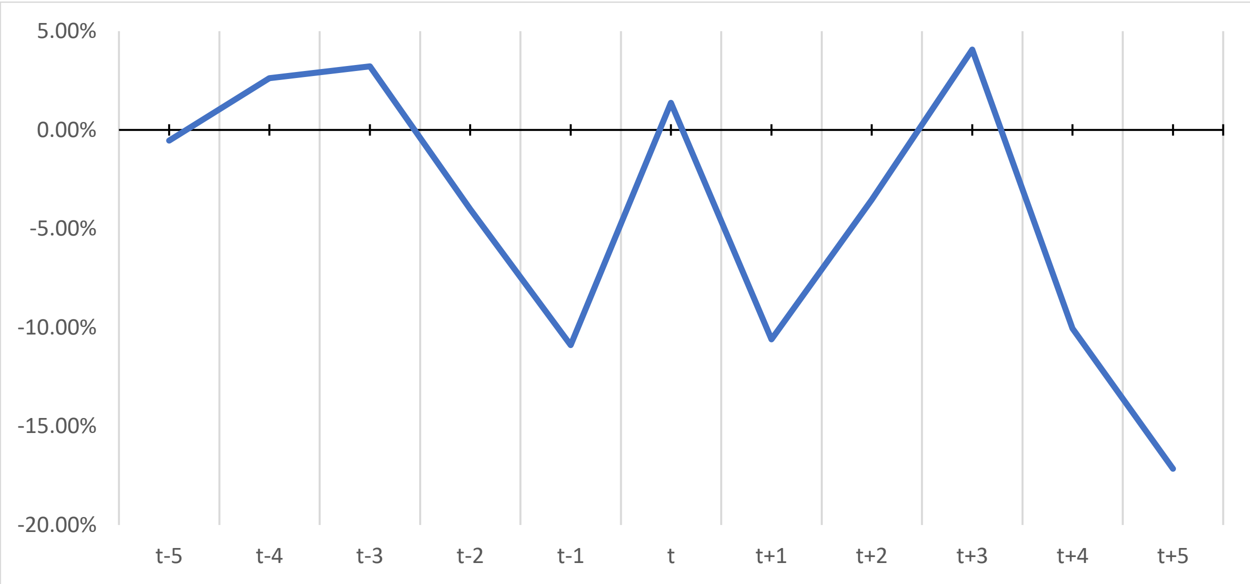
Revoke tokens are essentially the opposite of Grant Property Tokens, i.e. these happen when USDT tokens are destroyed, reducing the USDT supply, which could happen, if, for example, USDT is redeemed in US dollars. On the 31st of January 2018, address *3Mb…XL* revoked 30 million Tether coins. This is also the address that issued most of the tokens during the first quarter of 2018.

Table 7.3.1: Revoke Property Tokens event in the first quarter of 2018

Date	Sending address	Reference address	Amount
31/01/2018	3MbYQMMmSkC3AgWkj9FMo5LsPTW1zBTwXL		30,000,000

The graph below demonstrates the change in Bitcoin returns before and after this event, with t being the 31st of January 2018, $t-5$ being 5 days before and $t+5$ being 5 days after. There is a small increase in Bitcoin returns on the day when 30 million Tether coins have been burned, with them falling right after ($t+1$) and then rising again. There is no sufficient evidence to suppose that burning Tether coins was made with the objective of manipulating the Bitcoin market, given by the noisy movement in the range examined.

Figure 7.3.2: Abnormal Bitcoin price change before (-) and after (+) revoke event



BTC returns are much more volatile in the revoke event study than in the average issuance event study. However, it is crucial to consider that the revoke event study looks at only one event (the 31st of January), hence it is a single-day event study. From $t+3$ onwards, BTC returns get abnormally lower than usual, and there is no significant change in returns prior to the revoke event. This change in the BTC market post event can be seen by its abnormal volatility and volume too, with a significant drop in volume at $t+3$, and an increase in volatility and volume after. Hence, 3 to 5 days after the revoke event, traders were selling BTC more than usual.

Figure 7.3.3: Abnormal Bitcoin volatility before (-) and after (+) revoke event

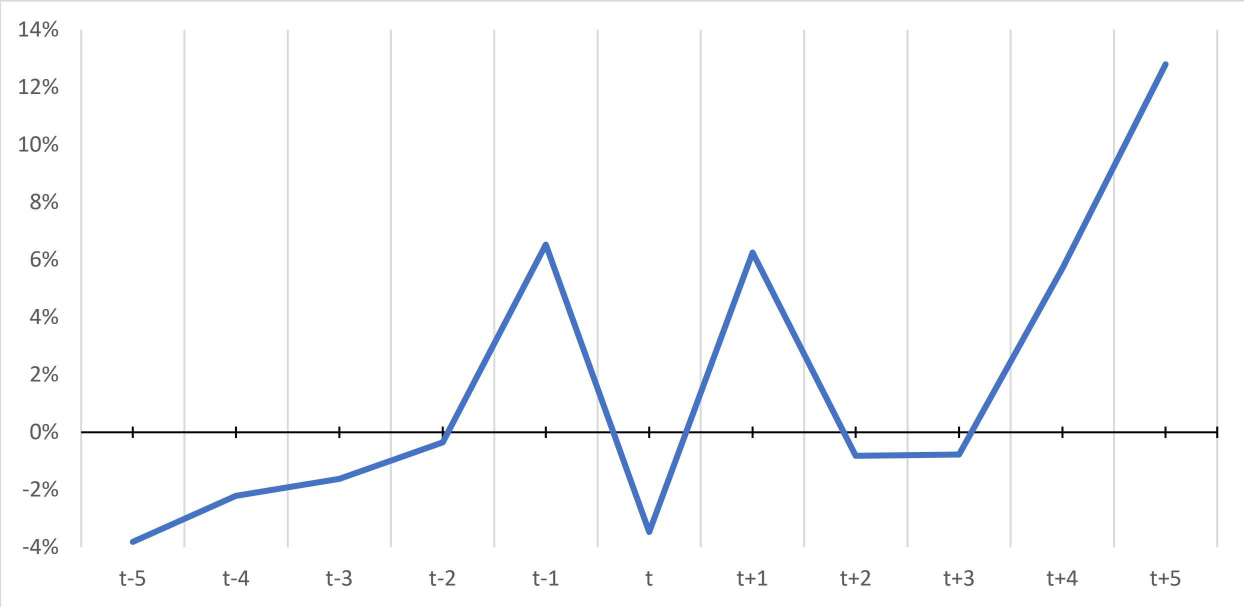
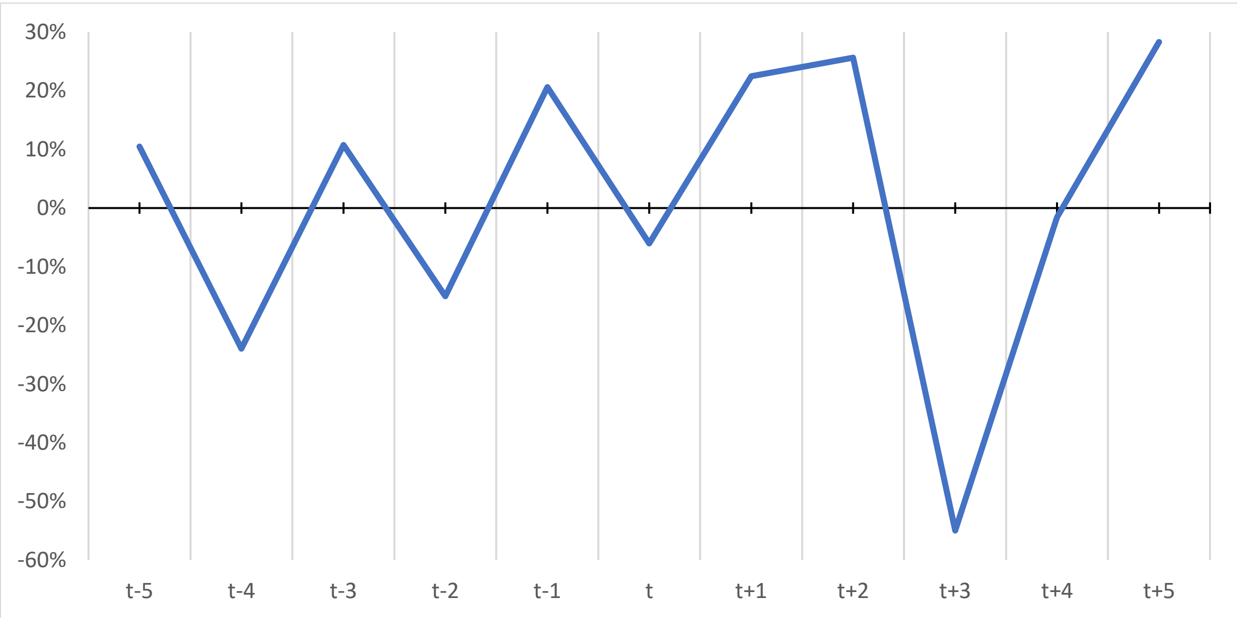


Figure 7.3.4: Abnormal Bitcoin volume before (-) and after (+) revoke event

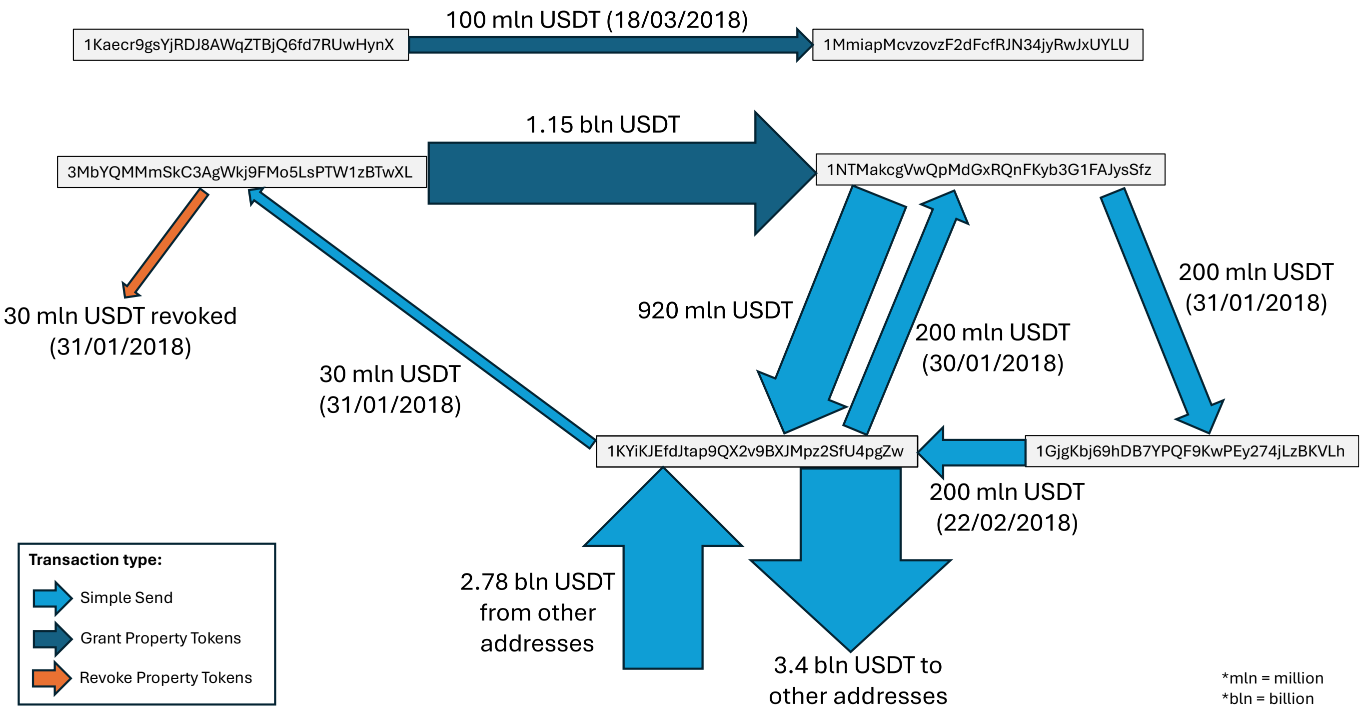


Unlike issuance events, the revoke event is characterised by sharp and irregular abnormal movements in both volatility and trading volume. This likely reflects the fact that the analysis is centred on a single, discrete event, making the estimated abnormal effects more sensitive to short-term market noise. Despite the fact that we did not find any particular suspicious types of transactions or general effects of Tether on Bitcoin, we now know what addresses are creating tokens (those of the Grant Property type) and the one that burns them (the Revoke type): the addresses that issue Tether coins are *3Mb...XL* and *1Ka...nX*, with the former being also the address that revoked, or burned, some tokens. We can now focus on the transactions of these specific addresses.

8. Tether addresses

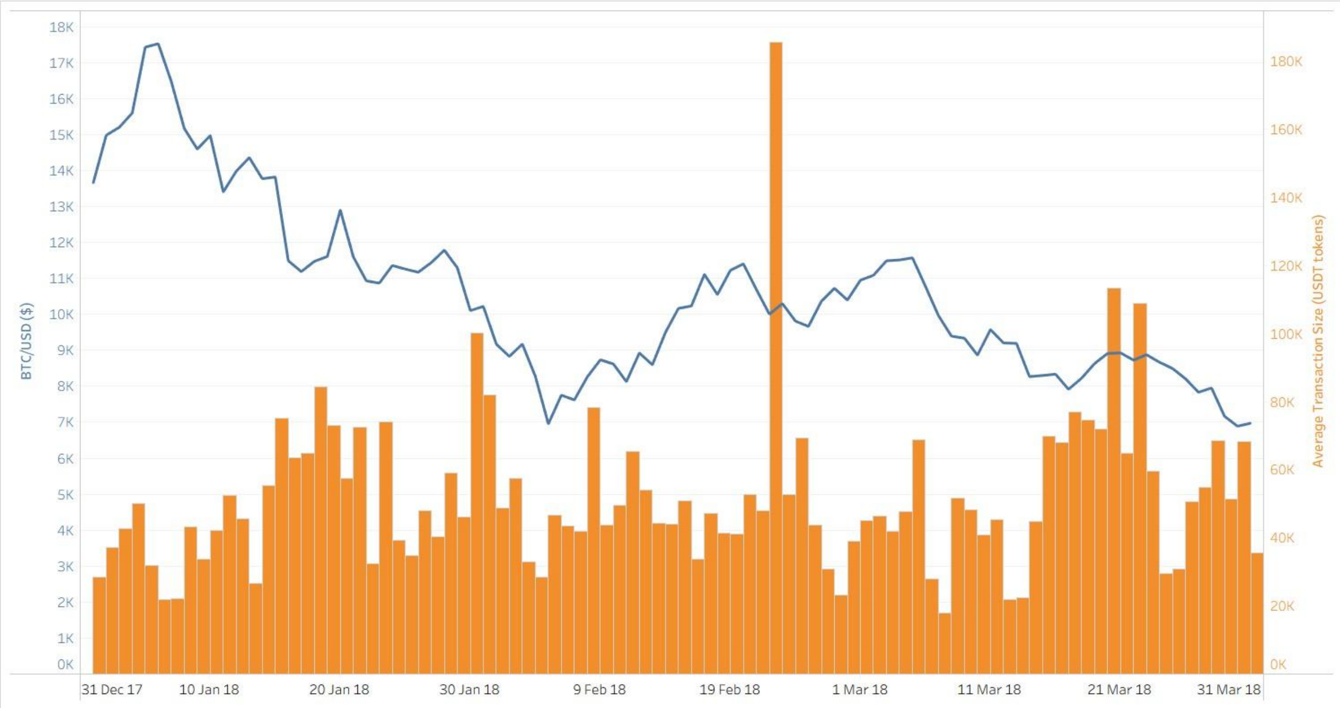
From the Grant Property Tokens transactions, we find that there are 2 addresses that issue, or mint, new USDT tokens: *1Ka…nX*, which issued 100 million UST to the address *1Mm…LU* on the 18th of March 2018, and *3Mb…XL*, which issued a total of 1.15 billion USDT to *1NT…fz* during the first quarter of 2018. By looking at the other transactions where these 4 addresses were involved, I found that *1NT…fz* sent tokens only to *1KY…Zw* and *1Gj…Lh*, for a total of roughly the amount that it received in issued coins from *3Mb…XL*. Hence, *3Mb…XL* and *1Ka…nX* are issuers and *1NT…fz* is an intermediary distribution node, which behaves like a treasury or liquidity-routing address: it receives newly issued USDT from the issuing address and reallocates the liquidity downstream to other addresses. The Tether transactions of and between these addresses can be summarised in the diagram below (Figure 8.1).

Figure 8.1: Transactions related to the issuing addresses diagram, 01/01/2018 – 31/03/2018



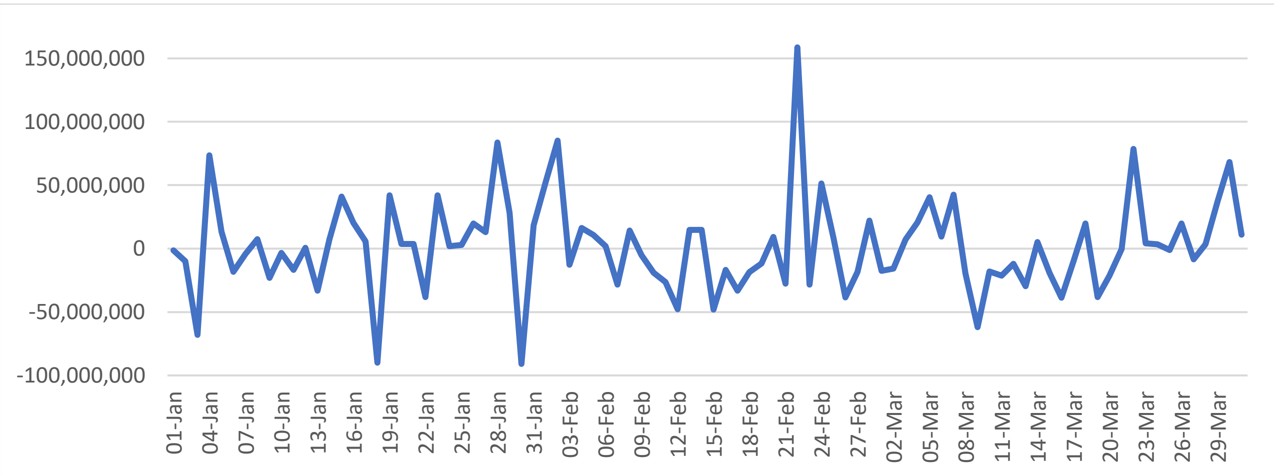
Where the date is shown, it illustrates that the transactions occurred during a singular day throughout the period examined. For instance, *1KY…Zw* sent 30 million USDT to *3Mb…XL* with one transaction on the 31st of January, which in turn revoked, or burned, the same amount on the same day. There is also an interesting movement of 200 million USDT that starts from *1KY…Zw* going to *1NT…fz* on the 30th of January, then moved to *1Gj…Lh* the day after, and then went back to *1KY…Zw* on the 22nd of February 2018, and it is noteworthy that the average transaction size ranges from 18k USDT to 185k USDT, as can be seen in Figure 8.2 below. This 200 million USDT movement can be seen as a supply management event, not a demand shock.

Figure 8.2: Daily BTC close price and average USDT transaction size



Hence, given the illustration of transactions that happened around the issuing addresses in Figure 8.1, which addresses are worth considering? The address that issues most of the tokens – *3MB…XL* – has already been examined in the Grant Property section, given that most issuance transactions come from this address. Address *1KY…Zw* is another interesting address: on aggregate, it sends 3.4 billion USDT to other addresses and receives 2.78 billion USDT from other addresses. It can be referred as a liquidity injector, as it deliberately adds liquid assets into the Tether economy. The average transaction size of *1KY…Zw* is 239,196 USDT, which is more than the highest daily average of all transactions (185k on 22/02/2018 as can be seen in Figure 8.2). I calculated the daily net flows of this address (graphed below in Figure 8.3) and I questioned whether net flows of this address relate in some way to the price of Bitcoin.

Figure 8.3: Net transactions (Reference - Sending) of *1KY…Zw*



8.1. *1KY…Zw* net flows and BTC returns

To focus on this address, I filtered the USDT data twice: in the Simple Send analysis in Section 7 I concluded that there is no statistically interesting relationship between Simple Send USDT transactions and Bitcoin returns. Hence, rather than looking at days with large transactions, in R I filtered the filtered *1KY…Zw* data to have the bottom 5% and top 95% of net flow transaction data of this address, and the result is a list of transactions that are tabulated below.

Table 8.1.1: Extreme inflows and outflows days of the *1KY…Zw* address

Date	BTC Close	BTC Volume	1KY Net Transactions	BTC log returns	BTC volatility	BTC differenced log volume	Event type
03/01/2018	15,201.00	16,871,900,160	-67,939,224	1.45%	1.45%	0.15%	Extreme Outflow
04/01/2018	15,599.20	21,783,199,744	73,608,666	2.59%	2.59%	25.55%	Extreme Inflow
18/01/2018	11,474.90	15,020,399,616	-89,905,834	2.53%	2.53%	-22.61%	Extreme Outflow
28/01/2018	11,786.30	8,350,360,064	83,602,030	2.98%	2.98%	9.64%	Extreme Inflow
30/01/2018	10,106.30	8,637,859,840	-90,903,655	-11.13%	11.13%	19.50%	Extreme Outflow
02/02/2018	8,830.75	12,726,899,712	85,146,461	-3.78%	3.78%	24.52%	Extreme Inflow
15/02/2018	10,166.40	9,062,540,288	-48,015,958	6.84%	6.84%	13.60%	Extreme Outflow
22/02/2018	10,005.00	8,040,079,872	158,702,654	-6.63%	6.63%	-15.68%	Extreme Inflow
09/03/2018	9,337.55	8,704,190,464	-61,971,652	-0.61%	0.61%	19.17%	Extreme Outflow
22/03/2018	8,728.47	5,530,390,016	78,733,995	-2.27%	2.27%	-8.87%	Extreme Inflow

I ran a VAR model and visualised an Impulse Response Function (IRF) on how the shocks of these events affect BTC returns, just like I have done for issuance events (see Section 7.1), but with the dummy variable being equal to 1 on days when there are extreme *1KY…Zw* net flows. I used a parsimonious lag 1 model, which is not statistically strong given that the *p* value is high (=0.4) and the *R* squared is low (=0.02), thus the IRF will not give statistically strong results.

Estimation results for equation BTC_E:

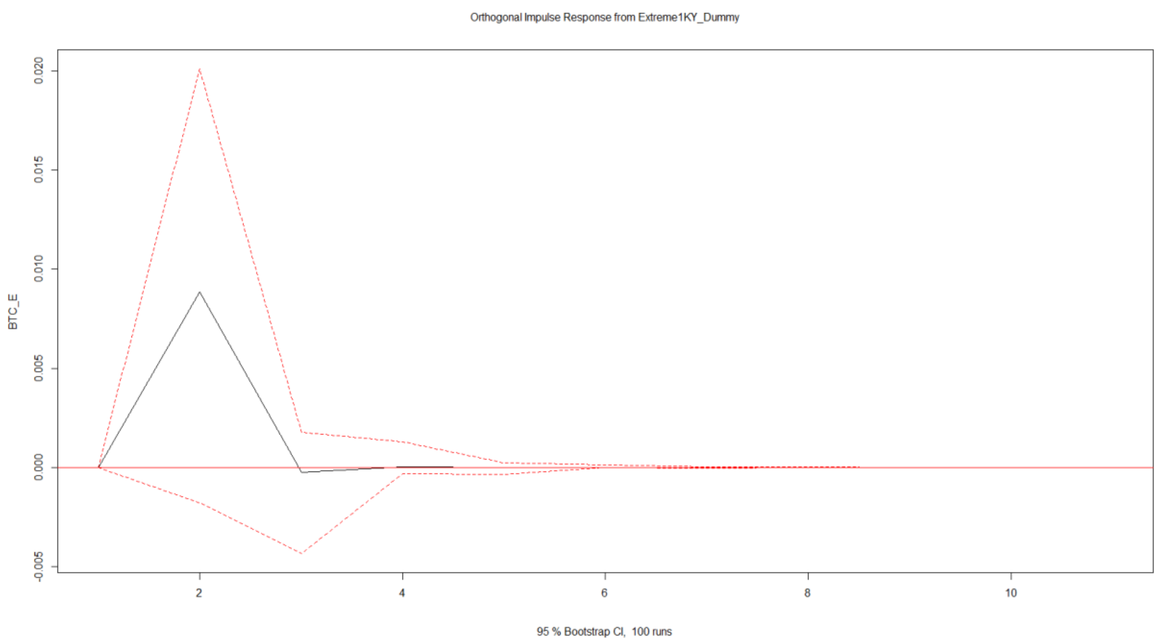
=====================================

BTC_E = BTC_E.l1 + Extreme1KY_Dummy.l1 + const

Variable	**Estimate**	**Std. Error**	**t value**	**Pr(>|t|)**
BTC_E.l1	-0.012525	0.105713	-0.118	0.9060
Extreme1KY_Dummy.l1	0.027456	0.020369	1.348	0.1813
const	-0.011908	0.006915	-1.722	0.0887
Residual standard error	Degrees of freedom	Multiple R-Squared	Adjusted R-squared	F-statistic
0.06064	85	0.02109	-0.001942	0.9157 on 2 and 85 DF, p-value: 0.4041

Nonetheless, if we compare the IRF of the effect of these events on BTC seen in Figure 8.1.2 below with the effect from issuance events of Figure 7.1.2, the effect is slightly larger for extreme *1KY…Zw* net flow days than issuance days, however the effect of issuance days takes slightly longer to dissipate completely (given a shock of an issuance day, the effect on BTC returns takes 6 to 8 days to dissipate completely, whilst given an extreme *1KY…Zw* net flow day it takes 4 to 5 days).

Figure 8.1.2: Impulse Response Function of extreme 1KY…Zw net flow day dummy on BTC returns



I analysed the data also by doing an event study around an average day when there are extreme net flow transactions of address *1KY…Zw*. Let the average BTC daily returns excluding the extreme *1KY…Zw* net flow windows be:

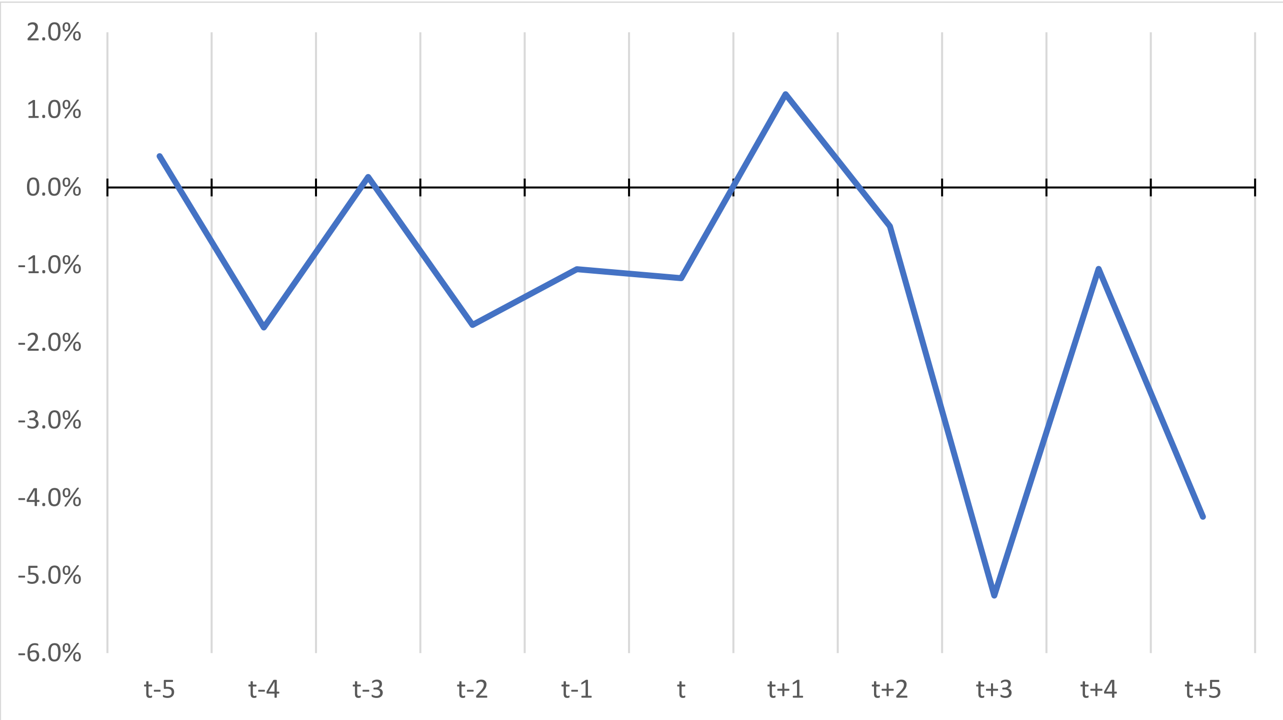
$$E(r_{i,t} \mid \text{no extreme } 1KY \dots Zw \text{ net flow event})$$

Then the Abnormal Returns of event i on period t are:

$$AR_{i,t} = r_{i,t} - E(r_{i,t} \mid \text{no extreme } 1KY \dots Zw \text{ net flow event})$$

And hence the average Abnormal Returns are the averages across period t, and the results can be seen below

Figure 8.1.3: Average Abnormal Bitcoin price change before $(-)$ and after $(+)$ extreme *1KY...Zw* net flow event (t)



It seems that there is no anticipatory effect on BTC returns, and a significant drop 3 days after an average event of extreme *1KY...Zw* net flows. I checked the results by looking into differences between extreme net inflow and outflow and did not find any noteworthy differences. I then tested these results by using the t test statistic. Just like for the issuance events, the t test statistic is done against these null and alternative hypotheses:

$$H_0: AAR_t = 0, \qquad H_a: AAR_t \neq 0$$

And for the Cumulative Average Abnormal Returns, I tested the following hypotheses:

$$H_0: CAAR_{t+i,t+j} = 0, \qquad H_a: CAAR_{t+i,t+j} \neq 0$$

We can reject the null hypotheses if $t > 1.96$. The results of the t tests can be seen in Table 8.1.4 below. Out of the days examined, I found that 3 days after the average extreme net flow event, there is a statistically significant drop in Bitcoin returns (-4.9%), and 5 days after the event there is also a statistically significant drop (-3.9%), i.e. the BTC market does not react significantly to extreme trading flows of this address immediately, but rather 3 to 5 days later. With regards to the cumulative AARs (CAAR), there is no statistically significant change in BTC returns when looking at the 5 days before the event ($CAAR_{t-5,t-1}$), the 5 days after ($CAAR_{t+1,t+5}$) and the day before together with the day after and the event day itself ($CAAR_{t-1,t+1}$). What is statistically significant is the cumulative change in BTC returns around the average event 5 days prior and after ($CAAR_{t-5,t+5}$). While individual daily abnormal returns are largely insignificant due to high volatility, abnormal returns following extreme *1KY…Zw* net flow events are consistently negative across several days. This persistence causes cumulative abnormal returns to become statistically significant even when most single-day effects are not.

Table 8.1.4: t test results for the *1KY…Zw* extreme net flow event study on Bitcoin price change

Measurement	**Period**	**Value**	**Standard errors**	**t tests**	**t tests results**
AAR	**t-5**	0.8%	0.013052896	0.585837847	Fail to reject null
AAR	**t-4**	-1.4%	0.013412699	-1.073591963	Fail to reject null
AAR	**t-3**	0.5%	0.022637028	0.219501826	Fail to reject null
AAR	**t-2**	-1.4%	0.025041612	-0.562553135	Fail to reject null
AAR	**t-1**	-0.7%	0.020156787	-0.343500807	Fail to reject null
AAR	**t**	-0.8%	0.015872396	-0.506983234	Fail to reject null
AAR	**t+1**	1.6%	0.013388958	1.168796277	Fail to reject null
AAR	**t+2**	-0.1%	0.027188299	-0.050305451	Fail to reject null
AAR	**t+3**	-4.9%	0.016691104	-2.933528079	Reject null
AAR	**t+4**	-0.7%	0.02205999	-0.311529964	Fail to reject null
AAR	**t+5**	-3.9%	0.014307201	-2.713619876	Reject null
CAAR	**t-5,t+5**	-11.1%	0.060628968	-1.834459675	Reject null
CAAR	**t-5,t-1**	-2.3%	0.020808277	-1.095483584	Fail to reject null
CAAR	**t+1,t+5**	-8.0%	0.05391297	-1.490907142	Fail to reject null
CAAR	**t-1,t+1**	0.1%	0.018905863	0.035864677	Fail to reject null

8.2. *1KY…Zw* net flows and BTC volatility

By testing the effect on volatility, we ask if extreme *1KY…Zw* net flow days coincide with higher BTC uncertainty or trading stress. Given that there are some statistically significant abnormal returns after an average event, I used 2 methods to test this: running a regression model with a binary variable and run an event study. BTC volatility is again defined as the absolute value of BTC returns:

$$Vol(BTC)_t = |r_t|$$

I tried to run a simple model with binary variables and I found that the best model is a parsimonious model with the 4th lag:

$$Vol(BTC)_t = \alpha + \beta_1 Extreme_{t-4} + \varepsilon_t$$

$$Extreme_{t-i} = \begin{cases} 1, & \text{Extreme } 1KY \dots Zw \text{ net flow } t - i \text{ days ago} \\ 0, & \text{Otherwise} \end{cases}$$

What I found is that the parsimonious model with an estimated coefficient on the 4th lag is significant, and the model is summarised below:

Call:

dynlm(formula = BTC_volatility ~ L(Extreme_Dummy, 4), data = BTC_Net1KY_Data_zoo)

Term	**Estimate**	**Std. Error**	**t value**	**Pr(>|t|)**	**Signif. code**
(Intercept)	0.043703	0.004248	10.288	<2e-16	***
L(Extreme_Dummy, 4)	0.029125	0.013132	2.218	0.0293	*
Residual standard error	Degrees of freedom	Multiple R-squared	Adjusted R-squared	F-statistic	p-value
0.03728	84	0.05532	0.04408	4.919 on 1 and 84 DF	0.02926

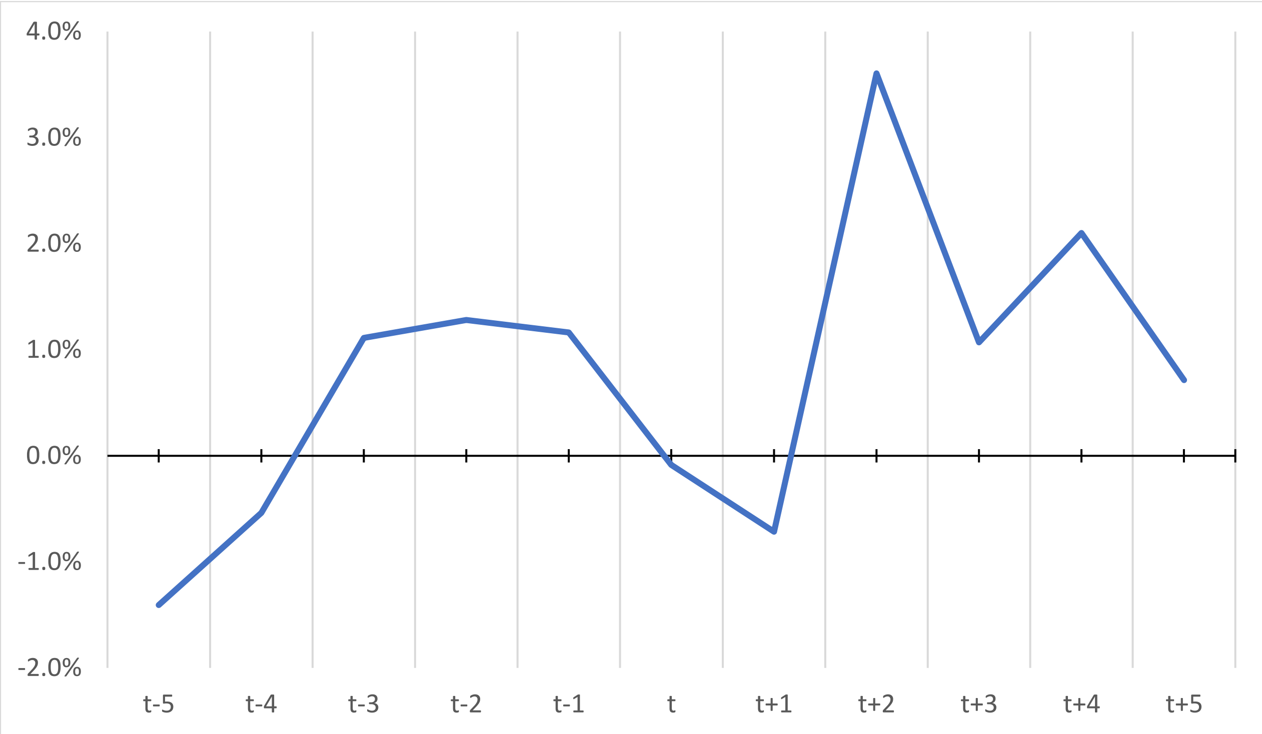
Hence it is estimated that on extreme net flow days of *1KY…Zw*, the average BTC volatility increases 4 days later by:

$$Vol(BTC)_t \cong 0.043703 + 0.029125(1) = 0.073$$

Regressions of Bitcoin volatility on lagged indicators of extreme net USDT flows show no contemporaneous or short-run effects. However, a statistically significant increase in volatility emerges four days after extreme flow events. This suggests that the market impact of large stablecoin flows materialises with delay rather than immediately.

By doing an event study on volatility I found that the results are similar. Below is the graphical representation of Average Abnormal Volatility values, calculated just like for BTC returns.

Figure 8.2.1: Average Abnormal change in volatility before (−) and after (+) extreme *1KY…Zw* net flow event (t)



I ran t tests for the values and tabulated them below. Extreme *1KY…Zw* net flow events coincide with higher BTC volatility and trading stress 2 to 4 days after an average event, not before, with statistical confidence, which is also demonstrated by the statistical significance of the Cumulative Average Abnormal Volatility from the day after to 5 days after an average event ($CAAR_{t+1,t+5} = 6.8\%$). This result is compatible with the BTC returns event study and the volatility regression model examined above. On the day of an average extreme *1KY…Zw* net flow event, stablecoins move but with no immediate price turbulence, 2 to 3 days after the market adjusts with arbitrage and it absorbs liquidity, and 4 days after there is a rise in volatility as positions unwind and information diffuses. This time frame is consistent with *3MB…XL* issuing USDT to *1NT…fz*, which then liquidates these to *1KY…Zw*. Moreover, rather than market manipulation, this lagged response can suggest portfolio rebalancing under uncertainty.

Table 8.2.2: t test results for Average Abnormal Volatility (AAV) and Cumulative AAV (CAAV) for extreme net flow *1KY…Zw* events

Measurement	Period	Value	Standard errors	t tests	t tests results
Average Abnormal Volatility	**t-5**	-1.4%	0.008127788	-1.731176182	Fail to reject null
Average Abnormal Volatility	**t-4**	-0.5%	0.005756103	-0.936183528	Fail to reject null
Average Abnormal Volatility	**t-3**	1.1%	0.011575914	0.959768436	Fail to reject null

Average Abnormal Volatility	**t-2**	1.3%	0.01617181	0.791532922	Fail to reject null
Average Abnormal Volatility	**t-1**	1.2%	0.010748015	1.082850289	Fail to reject null
Average Abnormal Volatility	**t**	-0.1%	0.009143522	-0.093762249	Fail to reject null
Average Abnormal Volatility	**t+1**	-0.7%	0.008775085	-0.814934836	Fail to reject null
Average Abnormal Volatility	**t+2**	3.6%	0.011095461	3.250037588	Reject null
Average Abnormal Volatility	**t+3**	1.1%	0.014905955	0.716738494	Fail to reject null
Average Abnormal Volatility	**t+4**	2.1%	0.009475158	2.216712126	Reject null
Average Abnormal Volatility	**t+5**	0.7%	0.01033235	0.690056792	Fail to reject null
Cumulative Average Abnormal Volatility	**t-5,t+5**	8.3%	0.035007627	2.369749645	Reject null
Cumulative Average Abnormal Volatility	**t-5,t-1**	1.6%	0.023424882	0.686868165	Fail to reject null
Cumulative Average Abnormal Volatility	**t+1,t+5**	6.8%	0.024410711	2.77447144	Reject null
Cumulative Average Abnormal Volatility	**t-1,t+1**	0.4%	0.016550682	0.219329411	Fail to reject null

8.3. *1KY…Zw* net flows and BTC volume

We can also look at what happened to BTC volume. Using a similar regression model as the one ran for volatility, I found that one lag is statistically significant, and it associates a 15% decline in BTC volume the day after an extreme *1KY…Zw* net flow event. This seems to be a strong statistical model, with $p = 0.02$, which is parsimonious and has one lag:

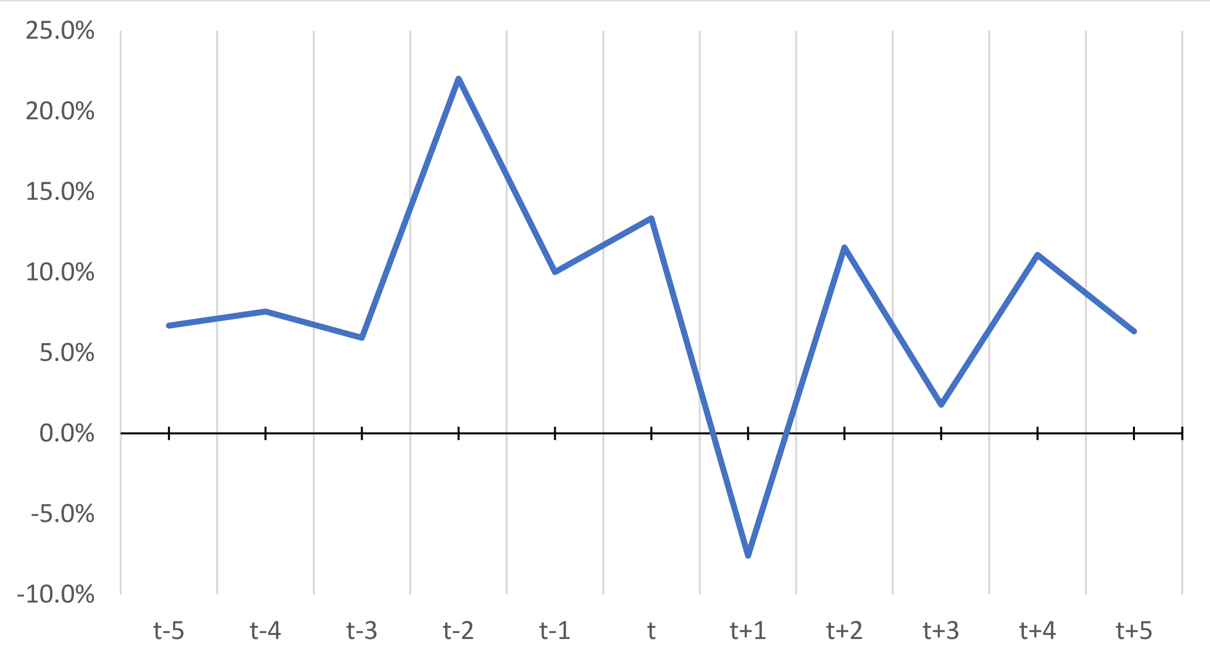
$$\%\Delta BTC\_Volume_t = \alpha + \beta_1 Extreme_{t-1} + \varepsilon_t$$

Call: dynlm(formula = BTC_diff_log_volume ~ L(Extreme_Dummy, 1), data = BTC_Net1KY_Data_zoo)

Term	**Estimate**	**Std. Error**	**t value**	**Pr(>|t|)**
(Intercept)	0.007959	0.022279	0.357	0.7218
L(Extreme_Dummy, 1)	-0.152383	0.066466	-2.293	0.0243
Residual standard error		0.198 on 87 degrees of freedom		
Multiple R-squared	0.05697	Adjusted R-squared	0.04614	
F-statistic	5.256 on 1 and 87 DF	p-value	0.02428	

Below is also the graphical representation of the event study of average change in volume around the event of extreme net flow days of *1KY...Zw*.

Figure 8.3.1: Average Abnormal change in volume before $(-)$ and after $(+)$ extreme *1KY...Zw* net flow day (t)



If we run *t* tests for these results, we find, as seen in Table 8.3.2, that the value at $t-2$ and $t+1$ are statistically significant, while the rest of the daily values are not. There is a significant rise in volume 2 days before an average extreme *1KY...Zw* net flow day, and a similar drop in volume the day after, and then dissipating from $t+2$ onwards. Extreme net flows of *1KY...Zw* are associated with lower participation, and the lagged drop in volume may be due to liquidity consolidation, post market inactivity or rebalancing across addresses and brokers.

Table 8.3.2: *t* test results for Average Abnormal Volume (AAV) and Cumulative AAV (CAAV) for extreme net flow *1KY...Zw* events

Measurement	**Period**	**Value**	**Standard errors**	**t tests**	**t tests results**
Average Abnormal Volume	**t-5**	6.7%	0.03902362	1.714434818	Reject null
Average Abnormal Volume	**t-4**	7.6%	0.059248693	1.27551274	Fail to reject null
Average Abnormal Volume	**t-3**	5.9%	0.043918504	1.351518749	Fail to reject null
Average Abnormal Volume	**t-2**	22.0%	0.059917242	3.67582409	Reject null

Average Abnormal Volume	**t-1**	10.0%	0.068880918	1.452254852	Fail to reject null
Average Abnormal Volume	**t**	13.3%	0.049480836	2.697076871	Reject null
Average Abnormal Volume	**t+1**	-7.6%	0.074296498	-1.022121271	Fail to reject null
Average Abnormal Volume	**t+2**	11.5%	0.044513192	2.591514587	Reject null
Average Abnormal Volume	**t+3**	1.8%	0.053709	0.332832479	Fail to reject null
Average Abnormal Volume	**t+4**	11.1%	0.080198949	1.381594365	Fail to reject null
Average Abnormal Volume	**t+5**	6.3%	0.057490985	1.101402634	Fail to reject null
Cumulative Average Abnormal Volume	**t-5,t+5**	88.7%	0.190156703	4.664468204	Reject null
Cumulative Average Abnormal Volume	**t-5,t-1**	52.2%	0.121189955	4.308199359	Reject null
Cumulative Average Abnormal Volume	**t+1,t+5**	23.1%	0.138729514	1.668107866	Reject null
Cumulative Average Abnormal Volume	**t-1,t+1**	15.8%	0.111231293	1.416384091	Fail to reject null

8.4. Comparison with issuance activity

Whilst minting events are associated with broad pre-event price declines, BTC price effects associated with extreme net flows from address *1KY…Zw* materialise gradually in the days following the event, consistent with delayed liquidity effects rather than information shocks. The analysis on address *1KY…Zw* gave us a more confident result than the analysis on issuance events. A large proportion of abnormal values I calculated were not statistically significant (due to high volatility or limited data), yet, 2 to 5 days after extreme *1KY…Zw* net flow events we can measure statistically significant abnormal decline in BTC returns (4-5%) and an abnormal increase in volatility (2-4%), with elevated trading volumes around the event window. These results suggest that there has been increased trading activity, heightened market uncertainty and lagged BTC price adjustments after extreme *1KY…Zw* net flow trading. Nonetheless, these findings do not provide sufficient evidence to conclude market manipulation by this address. We can compare the event study of BTC returns given issuance days and given extreme *1KY…Zw* net flow days like in the summary table below.

Table 8.4.1: Summary comparison of effects on BTC between USDT issuance and extreme *1KY…Zw* net flow events

	Issuing tokens events	**Extreme 1KY...Zw net flow days**
Returns (AARs)	Small drops in returns pre-event, not statistically significant	Statistically significant 4-5% drop in returns 3 to 5 days after event

Returns (CAARs)	Small 5% cumulative drop distributed 5 days before event, not statistically significant	10% cumulative drop accumulated 5 days after event, statistically significant
Volatility (AAVs)	General drop in volatility but not statistically significant	Post event statistically significant effect 2 to 4 days after (2-4%)
Volatility (CAAVs)	Small cumulative drop but not statistically significant	Statistically significant increase in cumulative abnormal volatility 1 to 5 days after event
Volume (AAVms)	Slight increase on event day, general drop in volume after but not statistically significant	Statistically significant abnormal change in volume 2 days before (22%) and 2 days after (12%)
Volume (CAAVms)	24% less cumulative volume spread 5 days after event which is statistically significant	50%+ more change in volume before event, 20%+ more change in volume after event
Summary	Pre-event negative effect but not statistically significant, thus cannot conclude that issuers used insider information. Only statistically significant effect is a decline in cumulative BTC trading volume in the post-event window (*t-5, t+5*), consistent with a temporary reallocation of trading activity away from BTC. Window (*t-1, t+1*) is not statistically significant, meaning no immediate price reaction.	Whilst there is a small, non-statistically significant negative effect before issuance events, there is a statistically significant negative effect 3 to 5 days after extreme *1KY...Zw* net flow event, which could be due to periods of more trading on USDT and less on BTC with related addresses. BTC became more volatile - thus there has been more uncertainty - after event. Statistically significant larger BTC volumes traded before and after event, but cannot confidently conclude that this is due to market manipulation by this address. Window (*t-1, t+1*) is not statistically significant, meaning no immediate price reaction.

If we put these types of events together, and considering Figure 8.1, essentially the process that might have happened was:

1) The issuing address *3MB…XL* issued new tokens to *1NT…fz*
2) *1NT…fz* redistributed newly issued tokens to active addresses, especially to *1KY…Zw*
3) *1KY…Zw* traded USDT with other addresses
4) High trading activity
5) BTC price dropped 3 to 5 days after as traders perceived USDT as a lower-volatility store of value

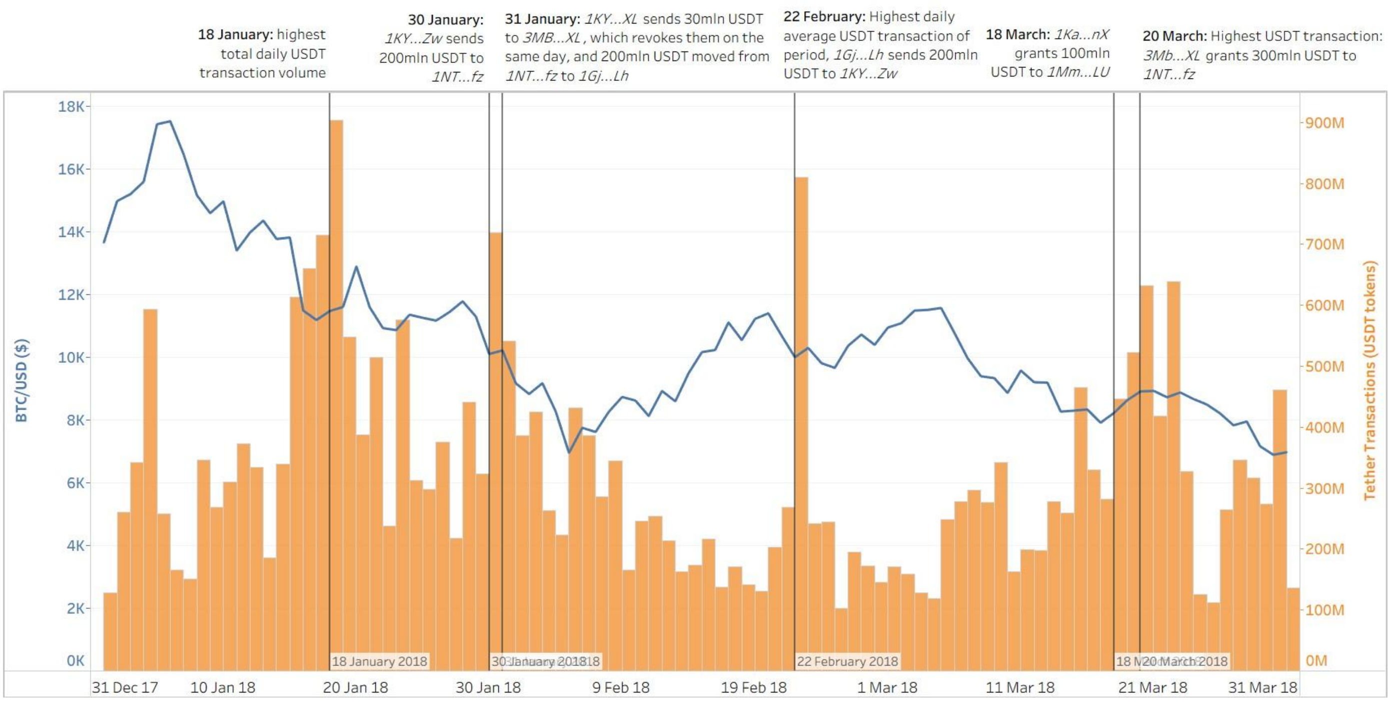
Although one could theoretically argue that a predictable lag between issuance and market activity might enable strategic timing, the empirical evidence in this study does not support such a mechanism. This is primarily because there is no statistically significant pre-event effect on Bitcoin returns around issuance days, nor is there a significant impulse response of Bitcoin to issuance shocks. The delayed effects observed following extreme *1KY…Zw* net flows are more consistent with operational liquidity redistribution and portfolio rebalancing under uncertainty rather than with deliberate price manipulation.

To consider other addresses and interesting events, we can also focus on particular days of interest, and run event studies on them, as I have done in the following section.

9. Interesting days

Recall the interesting transactions in the diagram in Figure 8.1. From there we can pinpoint a few interesting transactions that occurred on particular dates, which are indicated in the graph below (Figure 9.1).

Figure 9.1: BTC and USDT labelled with interesting dates



As highlighted in Figure 9.1, in the first quarter of 2018, the dates that I found worth giving attention to are:

- **18th January:** this is the date with the highest USDT transaction volume. Right before this date, BTC dropped, and the day after it slightly increased
- **30th and 31st January:** the start of when 200 million USDT move around different addresses, and the revoking of 30 million USDT
- **22nd February:** Highest daily average USDT transaction size of period, with *1KY…Zw* receiving back the 200 million USDT that it sent on the 30th of January
- **18th March:** the only time that *1Ka…nX* issues tokens and makes a transaction (100 million USDT)

- **20th March:** highest USDT transaction recorded in period, with 300 million USDT issued by *3Mb…XL*

I have already looked through the event study of the Revoke Property Token transaction of the 30th of January. Moreover, since I will continue to work with event studies and the 20th of March is close to the 18th, I will proceed to analyse event studies for the 18th of January, the 22nd of February and the 18th of March, as I believe that these have been particularly interesting days.

9.1. 18 January 2018

Tabulated below are the top 20 USDT transactions on the 18th of January 2018 by volume. The top transaction is an issuance transaction.

Table 9.1.1: top 20 USDT transactions on 18th January 2018

Sending Address	Reference Address	Amount
3MbYQMMmSkC3AgWkj9FMo5LsPTW1zBTwXL	1NTMakcgVwQpMdGxRQnFKyb3G1FAJysSfz	100,000,000
1NTMakcgVwQpMdGxRQnFKyb3G1FAJysSfz	1KYiKJEfdJtap9QX2v9BXJMpz2SfU4pgZw	100,000,000
1J1dCYzS5EerUuJCJ6iJYVPytCMVLXrgM9	1Po1oWkD2LmodfkBYiAktwh76vkF93LKnh	35,747,000
1HckjUpRGcrrRAtFaaCAUaGjsPx9oYmLaZ	1LAnF8h3qMGx3TSwNUHVneBZUEpwE4gu3D	20,868,300
1AA6iP6hrZfYiacfzb3VS5JoyKeZZBEYRW	1DUb2YYbQA1jjaNYzVXLZ7ZioEhLXtbUru	5,333,830
1KYiKJEfdJtap9QX2v9BXJMpz2SfU4pgZw	1EMCu5DNMaznDvAgxaVmBCxCyVhSjt3w1i	5,000,000
1KBXtTQnEgU34xXchwvmAoX7o5qZAp3xF	1DUb2YYbQA1jjaNYzVXLZ7ZioEhLXtbUru	5,000,000
1KYiKJEfdJtap9QX2v9BXJMpz2SfU4pgZw	1KBXtTQnEgU34xXchwvmAoX7o5qZAp3xF	5,000,000
1EMCu5DNMaznDvAgxaVmBCxCyVhSjt3w1i	1FoWyxwPXuj4C6abqwhjDWdz6D4PZgYRjA	5,000,000
1AA6iP6hrZfYiacfzb3VS5JoyKeZZBEYRW	1DUb2YYbQA1jjaNYzVXLZ7ZioEhLXtbUru	4,027,980
1AA6iP6hrZfYiacfzb3VS5JoyKeZZBEYRW	1DUb2YYbQA1jjaNYzVXLZ7ZioEhLXtbUru	3,828,360
1AA6iP6hrZfYiacfzb3VS5JoyKeZZBEYRW	1DUb2YYbQA1jjaNYzVXLZ7ZioEhLXtbUru	3,555,890
1AA6iP6hrZfYiacfzb3VS5JoyKeZZBEYRW	1DUb2YYbQA1jjaNYzVXLZ7ZioEhLXtbUru	3,555,880
1AA6iP6hrZfYiacfzb3VS5JoyKeZZBEYRW	1DUb2YYbQA1jjaNYzVXLZ7ZioEhLXtbUru	3,545,320
1AA6iP6hrZfYiacfzb3VS5JoyKeZZBEYRW	1DUb2YYbQA1jjaNYzVXLZ7ZioEhLXtbUru	3,537,010
1AA6iP6hrZfYiacfzb3VS5JoyKeZZBEYRW	1DUb2YYbQA1jjaNYzVXLZ7ZioEhLXtbUru	3,419,270
1AA6iP6hrZfYiacfzb3VS5JoyKeZZBEYRW	1DUb2YYbQA1jjaNYzVXLZ7ZioEhLXtbUru	3,362,360
1AA6iP6hrZfYiacfzb3VS5JoyKeZZBEYRW	1DUb2YYbQA1jjaNYzVXLZ7ZioEhLXtbUru	3,209,250
1J1dCYzS5EerUuJCJ6iJYVPytCMVLXrgM9	1Po1oWkD2LmodfkBYiAktwh76vkF93LKnh	3,044,780
1EMCu5DNMaznDvAgxaVmBCxCyVhSjt3w1i	1FoWyxwPXuj4C6abqwhjDWdz6D4PZgYRjA	3,000,000

Similarly to issuance days, revoke days and extreme *1KY…Zw* net flow days, I ran event studies on interesting days. However, since these are single-day events, the results will be less statistically strong, and it is expected that they are going to be more volatile. For a single-day event study, like the one of the 18th of January, I will calculate abnormal returns (AR) for the period t:

$$AR_t = r_t - E(r_t \mid \text{no 18 January event window})$$

With $t \in [t-5, t+5]$. The results are tabulated below, and they give larger and more volatile abnormal returns, mostly due to the fact that the values are not averaged out with other days given that this is a single-day study. The same calculations are made for abnormal volatility and volume.

Table 9.1.2: Event studies on abnormal returns, volatility and volume around the 18th of January 2018

	Abnormal returns	**Abnormal Volatility**	**Abnormal Volume**
t-5	3.5%	-2.2%	6.7%
t-4	-3.3%	-0.7%	-13.1%
t-3	1.2%	-4.6%	15.1%
t-2	-17.6%	13.5%	40.2%
t-1	-1.8%	-2.3%	0.9%
t	3.4%	-2.4%	-21.6%
t+1	2.0%	-3.8%	-32.5%
t+2	11.4%	5.6%	10.5%
t+3	-9.8%	5.7%	-16.2%
t+4	-5.1%	1.0%	6.9%
t+5	0.3%	-4.3%	-7.6%
Cumulative value t-5, t+5	**-15.7%**	**5.5%**	**-10.7%**
Cumulative value t-5, t-1	**-18.0%**	**3.7%**	**49.7%**
Cumulative value t+1, t+5	**-1.1%**	**4.2%**	**-38.9%**
Cumulative value t-1, t+1	**3.6%**	**-8.4%**	**-53.1%**

Cumulative abnormal returns are negative for the 5-day period before the event, just like for the other multi-day event studies. 2 days after the event there is an 11.4% abnormal BTC return, which is higher than most values of other event studies. Moreover, 2 days before the event there is higher than usual volatility, with the BTC price dropping substantially.

9.2. 22 February 2018

As mentioned earlier, the 22nd of February marked the highest daily average of USDT transactions in the first quarter of 2018 (185k average USDT transaction, 810 million total USDT traded), mainly due to the fact that address *1Gj…Lh* sent 200 million USDT to *1KY…Zw*. No new tokens have been minted this day, however, there have been numerous transactions of over 1 million USDT. Moreover, the 22nd of February is one of the days of extreme *1KY…Zw* net flows. Below is the list of the top 20 transactions by USDT amount on that day. Another noticeable transaction is *1Hc…aZ* sending 166 million USDT to *1LAn…3D*, which is the second highest USDT transaction on that day (as listed in Table 9.2.1 below) and the 5th highest USDT transaction of the entire period examined.

Table 9.2.1: Top 20 USDT transactions by USDT amount on 22/02/2018

Sending Address	Reference Address	Amount
1GjgKbj69hDB7YPQF9KwPEy274jLzBKVLh	1KYiKJEfdJtap9QX2v9BXJMpz2SfU4pgZw	200,000,000
1HckjUpRGcrrRAtFaaCAUaGjsPx9oYmLaZ	1LAnF8h3qMGx3TSwNUHVneBZUEpwE4gu3D	166,310,000
1Co1dhYDeF76DQyEyj4B5JdXF9J7TtfWWE	1A9AUhKv6aLrKGAdwMM9aHXECZM9uQivZK	22,000,000
1Co1dhYDeF76DQyEyj4B5JdXF9J7TtfWWE	1LJjvsEN9ZzeBVPB4XbhS7mxg99gBAPoMB	22,000,000
1Co1dhYDeF76DQyEyj4B5JdXF9J7TtfWWE	1NUyryQe1cQYmqg5bjwWNFXA8T1M6htSQ	22,000,000
1Co1dhYDeF76DQyEyj4B5JdXF9J7TtfWWE	1H48Bp7EGELgnGSVYKdiCuSo6n822mVmHg	22,000,000
1Co1dhYDeF76DQyEyj4B5JdXF9J7TtfWWE	1A6yDZj1241qtGzEeQWRaptxVEhzz5owLP	22,000,000
1Co1dhYDeF76DQyEyj4B5JdXF9J7TtfWWE	1Hi1hyJpUeETGBTQ8aPZ69GBL8xBVV53XP	22,000,000
1Co1dhYDeF76DQyEyj4B5JdXF9J7TtfWWE	17sHnqeQcwvfPneJkmaTBAQEnQN82yi7ye	22,000,000
1Co1dhYDeF76DQyEyj4B5JdXF9J7TtfWWE	1G6jMfQotd6rV8VkMFNx4hPXYHioeBdquf	22,000,000
1Co1dhYDeF76DQyEyj4B5JdXF9J7TtfWWE	1AanEM2PU6GS7krwxaysKP3scwb3fdioyE	22,000,000
1Co1dhYDeF76DQyEyj4B5JdXF9J7TtfWWE	1CEZ4sjk7MUt3LSJi7bRvvbMZvGLWKCa1G	22,000,000
1KBXtTQnEgU34xXchwvmAoX7o5qZAp3xF	1DUb2YYbQA1jjaNYzVXLZ7ZioEhLXtbUru	5,000,000
1KYiKJEfdJtap9QX2v9BXJMpz2SfU4pgZw	1KBXtTQnEgU34xXchwvmAoX7o5qZAp3xF	5,000,000
1KBXtTQnEgU34xXchwvmAoX7o5qZAp3xF	1DUb2YYbQA1jjaNYzVXLZ7ZioEhLXtbUru	3,000,000
1KYiKJEfdJtap9QX2v9BXJMpz2SfU4pgZw	1KBXtTQnEgU34xXchwvmAoX7o5qZAp3xF	3,000,000
1DUb2YYbQA1jjaNYzVXLZ7ZioEhLXtbUru	153saAmBANqkD3t9RMKb2GQXhfQSQWnCPH	2,999,980
1HSjUsmo6zCWc2kDdFXqjfe4CfayrpbmQN	168o1kqNquEJeR9vosUB5fw4eAwcVAgh8P	2,102,050
1KYiKJEfdJtap9QX2v9BXJMpz2SfU4pgZw	17kQoJ3ART6gYif5dPBnJEQqcqDooCxeT7	2,000,000
1Po1oWkD2LmodfkBYiAktwh76vkF93LKnh	12Pch67619NRn3sXKyfsdxrLZ8fCe4Koxh	1,791,230

The results of the event study for this day are tabulated below, again with larger and more volatile abnormal returns, again mostly due to the fact that the values are not averaged out with other days given that this is a single-day study.

Table 9.2.2: Event studies on abnormal returns, volatility and volume around the 22nd of February 2018

	Abnormal returns	Abnormal Volatility	Abnormal Volume
t-5	9.1%	3.5%	18.2%
t-4	-4.3%	0.4%	2.0%
t-3	7.0%	1.4%	-12.3%
t-2	2.4%	-3.2%	27.1%
t-1	-5.6%	1.7%	-4.3%
t	-5.8%	1.9%	-14.6%
t+1	3.8%	-1.9%	-2.8%
t+2	-4.0%	0.1%	-10.2%
t+3	-0.7%	-3.2%	-18.2%
t+4	7.9%	2.2%	25.5%
t+5	4.3%	-1.4%	-3.5%

Cumulative value t-5, t+5	**14.2%**	**1.5%**	**6.9%**
Cumulative value t-5, t-1	**8.7%**	**3.8%**	**30.6%**
Cumulative value t+1, t+5	**11.3%**	**-4.1%**	**-9.1%**
Cumulative value t-1, t+1	**-7.6%**	**1.7%**	**-21.8%**

Abnormal returns around the 22nd of February are highest 5 days before (9.1%) and lowest on the day itself (-5.8%).

9.3. 18 March 2018: the *1Ka…nX* issuance transaction

The 18th of March 2018 is the second-to-last issuance event of the period examined (the last one will be the 20th of March, which will also be the highest USDT transaction of the period examined), when *1Ka…nX* (the other address that issued Tether coins independently of the downstream transactions between *3Mb…XL*, *1Nt…fz* and *1KY…Zw*) issued 100 million USDT to *1Mm…LU*. Both of these addresses did not participate in any other Tether transaction throughout the first quarter of 2018, as displayed in Figure 8.1.

Table 9.3.1: Top 20 USDT transactions by USDT amount on 18/03/2018

Sending Address	**Reference Address**	**Amount**
1Kaecr9gsYjRDJ8AWqZTBjQ6fd7RUwHynX	1MmiapMcvzovzF2dFcfRJN34jyRwJxUYLU	100,000,000
168o1kqNquEJeR9vosUB5fw4eAwcVAgh8P	1LAnF8h3qMGx3TSwNUHVneBZUEpwE4gu3D	27,188,900
168o1kqNquEJeR9vosUB5fw4eAwcVAgh8P	1LAnF8h3qMGx3TSwNUHVneBZUEpwE4gu3D	26,943,500
1MZAayfFJ9Kki2csoYjFVRKHFFSkdoMLtX	1KYiKJEfdJtap9QX2v9BXJMpz2SfU4pgZw	18,000,000
1BtiLqTPDG6M39PVR8rPyWWVSofKSxKr9p	16DauErp8DPDkqTNCvPbzwBHHuhYSTNbDg	9,909,490
1AHeqzQ9VJXAuQu9tTmNqeeo1xgKzFSrTR	1ApkXfxWgJ5CBHzrogVSKz23umMZ32wvNA	4,333,340
1HiGJqkbjW73qfUc29m5S3BNSVVNUA8UQ1	16DauErp8DPDkqTNCvPbzwBHHuhYSTNbDg	4,285,350
1AHeqzQ9VJXAuQu9tTmNqeeo1xgKzFSrTR	1ApkXfxWgJ5CBHzrogVSKz23umMZ32wvNA	3,555,560
1J1dCYzS5EerUuJCJ6iJYVPytCMVLXrgM9	1Po1oWkD2LmodfkBYiAktwh76vkF93LKnh	3,115,160
12coadJtYK5wSxQ74ra9tXmG16nEtM2XDx	1ApkXfxWgJ5CBHzrogVSKz23umMZ32wvNA	3,015,210
1MZAayfFJ9Kki2csoYjFVRKHFFSkdoMLtX	1KYiKJEfdJtap9QX2v9BXJMpz2SfU4pgZw	2,628,980
1MZAayfFJ9Kki2csoYjFVRKHFFSkdoMLtX	1KYiKJEfdJtap9QX2v9BXJMpz2SfU4pgZw	2,595,260
1J1dCYzS5EerUuJCJ6iJYVPytCMVLXrgM9	1Po1oWkD2LmodfkBYiAktwh76vkF93LKnh	2,256,370
1MZAayfFJ9Kki2csoYjFVRKHFFSkdoMLtX	1KYiKJEfdJtap9QX2v9BXJMpz2SfU4pgZw	2,021,040
1MZAayfFJ9Kki2csoYjFVRKHFFSkdoMLtX	1KYiKJEfdJtap9QX2v9BXJMpz2SfU4pgZw	1,923,660
1MZAayfFJ9Kki2csoYjFVRKHFFSkdoMLtX	1KYiKJEfdJtap9QX2v9BXJMpz2SfU4pgZw	1,837,300
1AHeqzQ9VJXAuQu9tTmNqeeo1xgKzFSrTR	1ApkXfxWgJ5CBHzrogVSKz23umMZ32wvNA	1,777,780
1AHeqzQ9VJXAuQu9tTmNqeeo1xgKzFSrTR	1ApkXfxWgJ5CBHzrogVSKz23umMZ32wvNA	1,777,780
1KYiKJEfdJtap9QX2v9BXJMpz2SfU4pgZw	1AHeqzQ9VJXAuQu9tTmNqeeo1xgKzFSrTR	1,777,780
1Po1oWkD2LmodfkBYiAktwh76vkF93LKnh	1AHeqzQ9VJXAuQu9tTmNqeeo1xgKzFSrTR	1,777,780

The results of the event study can be seen in Table 9.3.2 below.

Table 9.3.2: Event studies on abnormal returns, volatility and volume around the 18th of March 2018

	Abnormal returns	Abnormal Volatility	Abnormal Volume
t-5	0.8%	-5.0%	-6.4%
t-4	-9.7%	5.5%	8.2%
t-3	1.2%	-4.7%	7.0%
t-2	1.3%	-4.7%	-24.6%
t-1	-4.3%	0.1%	-16.8%
t	4.7%	-1.3%	41.6%
t+1	5.7%	-0.3%	2.4%
t+2	4.1%	-1.9%	-4.6%
t+3	1.0%	-4.9%	-4.1%
t+4	-1.4%	-2.8%	-7.8%
t+5	2.6%	-3.4%	8.4%
CAA value t-5, t+5	**5.9%**	**-23.4%**	**3.4%**
CAA value t-5, t-1	**-10.8%**	**-8.8%**	**-32.5%**
CAA value t+1, t+5	**12.0%**	**-13.3%**	**-5.7%**
CAA value t-1, t+1	**6.0%**	**-1.5%**	**27.2%**

Increase in returns after the event is noted by the $t+1$, $t+2$, $t+3$ and $t+5$ values, as well as the cumulative returns after the event. There is a noticeable 12% increase in returns dispersed through the 5 days after the event, and a 6% short term increase around the 18th of March, despite lower than usual volatility.

9.4. Comparison between event studies

With the event studies on different types of events, we can compare the results of abnormal returns to assess whether some days have been affected more than others. However, it is crucial to highlight again that the event studies on issuance and extreme *1KY…Zw* net flow days are statistically stronger than the event studies on single day events because of how in the former type of event studies I averaged out results by different days, which allowed me to strengthen the interpretation of results with t tests, whilst the latter type of events are single day events, thus are more volatile and hence have more volatile values.

Below is a comparison table summarising the abnormal returns of each event examined in this report (Table 9.4.1). The cumulative values can give an interesting picture given that throughout the entire event window $(t-5, t+5)$, the only events where the cumulative value is positive (despite the downward trend of BTC during the examined period) are the 22nd of February and 18th of March. These dates are interesting also because throughout the days after the events, these are the only ones where BTC returns increased throughout the 5 days after the event $(t+1, t+5)$, with cumulative 11.3% abnormal returns 5 days after the 22nd of February and 12% cumulative abnormal returns 5 days after the 18th of March (the 0.7% CAAR 5 days after issuance events is not statistically significant). Furthermore, the 22nd of February is the only event where cumulative returns dispersed throughout the 5 days before the event ($t-5, t-1$) are positive (8.7%), whereas on other events BTC tends to be abnormally low before the event. On the 22nd of February, the short run 1 day window ($t-1, t+1$) cumulative abnormal returns are negative (-7.6%), whilst they are positive for the 18th of January (3.6%) and the 18th of March (6%). Specific period results can be summarised as:

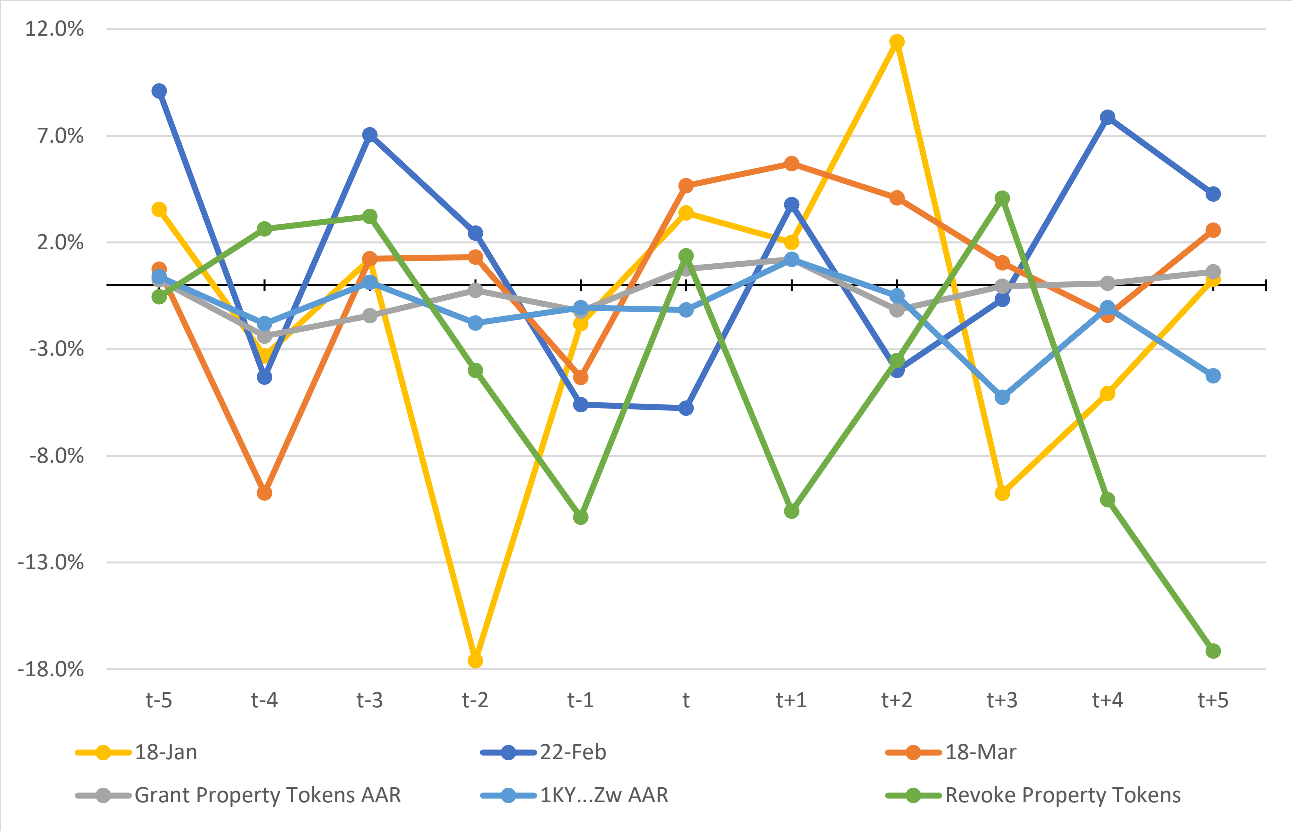
- **18th January:** general fall in BTC returns except for the ($t-1, t+1$) period
- **22nd February:** general increase in BTC returns except for the ($t-1, t+1$) period
- **18th March:** general increase in BTC returns, but a decrease in BTC returns before event, especially 4 days before
- **Issuance days:** slight decrease before event, not statistically significant
- **Revoke event:** general decrease in BTC returns but highly volatile
- ***1KY…Zw* extreme net flow days:** statistically significant fall in returns 3 to 5 days after event

Table 9.4.1: summary results of BTC abnormal returns around event windows

	18-Jan	22-Feb	18-Mar	Grant Property Tokens AAR	Revoke Property Tokens	*1KY…Zw* AAR
t-5	3.5%	9.1%	1%	0.3%	-0.54%	0.4%
t-4	-3.3%	-4.3%	-10%	-2.4%	2.63%	-1.8%
t-3	1.2%	7.0%	1%	-1.4%	3.22%	0.1%
t-2	-17.6%	2.4%	1%	-0.2%	-4.00%	-1.8%
t-1	-1.8%	-5.6%	-4%	-1.2%	-10.89%	-1.1%
t	3.4%	-5.8%	5%	0.8%	1.37%	-1.2%
t+1	2.0%	3.8%	6%	1.2%	-10.60%	1.2%
t+2	11.4%	-4.0%	4%	-1.2%	-3.53%	-0.5%
t+3	-9.8%	-0.7%	1%	-0.1%	4.07%	-5.3%
t+4	-5.1%	7.9%	-1%	0.1%	-10.05%	-1.1%
t+5	0.3%	4.3%	3%	0.6%	-17.15%	-4.2%
Cumulative value: *t-5, t+5*	**-15.7%**	**14.2%**	**5.9%**	**-3.6%**	**-45.5%**	**-15.1%**
Cumulative value: *t-5, t-1*	**-18.0%**	**8.7%**	**-10.8%**	**-5.0%**	**-9.6%**	**-4.1%**
Cumulative value: *t+1, t+5*	**-1.1%**	**11.3%**	**12.0%**	**0.7%**	**-37.3%**	**-9.9%**
Cumulative value: *t-1, t+1*	**3.6%**	**-7.6%**	**6.0%**	**0.7%**	**-20.1%**	**-1.0%**

The graph below is the visual representation of the BTC abnormal returns, which shall be used for illustrative purposes only, given the different sample sizes of event studies, which makes the volatility of values clear: the issuance and extreme *1KY…Zw* net flow days' abnormal returns are much less volatile than the other events, whilst the 18th of January has the largest values at $t-2$ and $t+2$.

Figure 9.4.2: Abnormal returns event studies, $t - 5, t + 5$



10. Conclusive remarks

- The data I used for this assessment covers only the first quarter of 2018, thus it would have benefitted from longer time series data to examine the relationship between Tether and Bitcoin.
- The probabilistic, distributed lag and ARIMA models all align with the fact that there is no statistically significant relationship between USDT volume and the price of Bitcoin: when more USDT is being traded, there is no association with an increase in the price of Bitcoin, and hence there is no evidence that Tether has forecasting power on Bitcoin, within the sample examined.
- The Granger and VAR models align with the same conclusion that USDT has no forecasting power on BTC, and rather, the models with BTC as an explanatory variable and USDT as the dependent variable show a slightly stronger (negative) correlation. This is demonstrated also by the Impulse Response Functions, which show that a shock of USDT has no effect on BTC, whilst a shock of BTC has a weak effect on USDT.
- Issuance days have a weak to no effect on BTC price: this is highlighted both by the Impulse Response Function of issuance days on BTC and by the event study of issuance days, which although highlights the pre-event effect not measured by the IRF, the values do not pass the

t tests, and thus are all statistically not significant. Hence, I did not find any strong evidence that issuing addresses *3Mb…XL* and *1Ka…nX* have had manipulative gains on the price of Bitcoin. This is the same conclusion that the literature on the topic discusses, such as with the study by Lyons and Viswanath-Natraj.

- I found that *1KY…Zw* is an address that participated in interesting transactions associated with the addresses that issue and revoke tokens. When running an event study on days when there have been extreme net transactions from this address, I found that there are statistically significant falls in BTC returns 3 to 5 days after event t, such that the null hypothesis is rejected for $t + 3$ and $t + 5$. These results are more significant than those of the issuance days event study. Although the other values are not statistically significant as we cannot reject the null hypothesis that they are equal to 0, it would be interesting to further examine the activity of this address. Rather than market manipulation, this can suggest portfolio rebalancing under uncertainty.
- Although one could theoretically argue that a predictable lag between issuance and market activity might enable strategic timing, the empirical evidence in this study does not support such a mechanism. In particular, there is no statistically significant pre-event effect on Bitcoin returns around issuance days, nor is there a significant impulse response of Bitcoin to issuance shocks. The delayed effects observed following extreme *1KY…Zw* net flows are more consistent with operational liquidity redistribution and portfolio rebalancing under uncertainty rather than with deliberate price manipulation.
- Out of the period examined, the interesting days of USDT activity are the 18th of January (highest total daily USDT transaction volume), the 30th and 31st of January (some tokens burned and 200 million moved out of *1KY…Zw*), the 22nd of February (highest daily average USDT transaction), the 18th of March (the only time that addresses *1Ka…nX* and *1Mm…LU* participate in a USDT transaction, which is an issuance transaction) and the 20th of March (highest USDT transaction recorded: the 300 million USDT minting transaction from *3Mb…XL*).
- Event studies on singular days (18 January 22 February and 18 March) have larger and more volatile results. The 22nd of February is the only event study with abnormally high cumulative returns before and after event. Nonetheless, single-day event studies must be interpreted with caution.
- In summary, there is no statistically significant relationship between USDT transactions (when both looking at the volume and average transaction size), and my analysis of the data is in agreement with the general literature that USDT issuance events do not have a strong effect on the price of Bitcoin. I believe that further research should be done on longer time series and specific addresses.