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When Tether says “JUMP!” Bitcoin asks “How low?”

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ABSTRACT

While stablecoins such as Tether closely track the peg, there is some evidence for recurring spikes in stablecoins' intraday volatilities rendering stablecoin volatilities unstable (Grobys et al., 2021). Using the Barndorff-Nielsen and Shephard (2006a) methodology, the purpose of our study is to examine whether jumps in Tether have an impact on (subsequent) Bitcoin returns. We retrieve hourly data for Bitcoin and Tether from Bitfinex covering the November 2018 to June 2021 period and encode the binary choice (1 – ‘jump’ and 0 – ‘no jump’) using bi-power variation based on asymptotic distribution theory at 5% significance level for each trading day. Our results show that the joint effect of positive jumps in Tether in association with an 1% increase in Tether returns on the prior day significantly predict negative prices changes in Bitcoin ranging from -3.65% to -8.49% in daily terms. Our results remain robust even after controlling for various other variables.

1. Introduction

Even though there is a wide stream of literature arguing that the leading cryptocurrency (Bitcoin) exhibits safe haven properties and may serve as a tool for portfolio diversification, Baur et al. (2018) assess that Bitcoin (BTC) volatility is extremely high, concluding that its mainly used as speculative investment as opposed to medium of exchange.[1] Due to Bitcoin's failure to serve as a store of value, stablecoins have emerged as a remedy. Tether (USDT), the largest stablecoin in terms of market capitalization, ensures stability by being pegged against the US-dollar. In this regard, two strands of literature have recently emerged. The first focuses on the stability of stablecoins. Specifically, Baur and Hoang (2021) investigate if stablecoins are a safe haven against large negative price changes in BTC, whereas Lyons and Viswanath-Natraj (2019) link stablecoins to fixed exchange rate regimes and explore (*i*) the mechanisms that keep stablecoins stable, and (*ii*) the fundamentals that move the two-sided deviations from the peg. Moreover, another recent study analyzes the returns, volatility and trading volume of the six largest stablecoins and finds that stablecoins are not stable due to too many and too large variations (Hoang and Baur, 2021).

The second body of literature investigates potential price manipulations utilizing stablecoins. In this regard, Wei (2018) is the first

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[1] Recent studies documenting safe haven or portfolio diversification properties are, for instance, Brauneis and Mestel (2019), Lahiani et al. (2021), Liu (2019), Watorek et al. (2021), and Chkili, Ben Rejeb and Arfaoui (2021).

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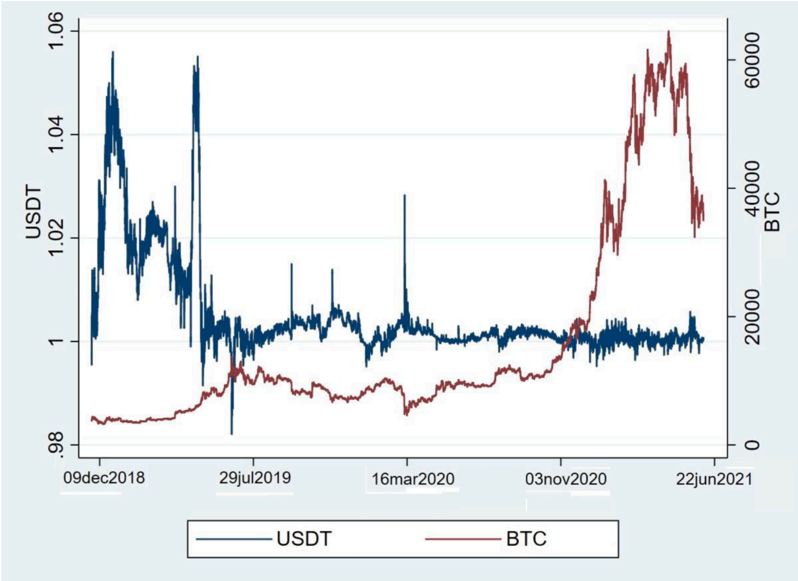

Fig. 1. Bitcoin and Tether prices in hourly frequencies
This figure represents hourly closing price data USDT and BTC over the period from November 2018 to June 2021.

study that investigates USDT and its potential influence on BTC prices. Whereas Wei's (2018) study establishes a link between periods of negative BTC returns and subsequent increased trading volume in USDT, it does not find any evidence for manipulation of BTC prices with USDT. On the contrary, Griffin and Shams (2020) identify such price manipulation and argue that BTC prices are systematically inflated through USDT. Consequently, there does not seem to be a consensus achieved yet on whether or not BTC is manipulated through USDT. Even though stablecoins such as USDT closely track the peg, there is anecdotal evidence for recurring spikes in stablecoins' intraday volatilities rendering their volatility processes unstable (Grobys et al., 2021). Interestingly, there is no study available exploring the impact of jumps in USDT on BTC. Our study remedies this gap.

Our study is the first that explores whether jumps in USDT are Granger-causal for BTC returns. To do so, we first analyze the existence of jumps on each day based on hourly returns. Employing the Barndorff-Nielsen and Shephard (2006a) methodology, we encode the binary choice (1 – 'jump' and 0 – 'no jump') using bi-power variation based on an asymptotic distribution theory at 5% significance level for each trading day. We aggregated hourly data to find the average daily return and clustered three groups (e.g., ''negative jump', 'positive jump', 'no jump') based on the signs of the average daily return. Importantly, our empirical approach also analyzes potential joint effects of jumps in USDT in association with increases in USDT returns.

Our study has some important contributions. First, we extend the current literature on stablecoins by providing some novel evidence on how the BTC process may be influenced through USDT. Whereas the studies from Wei (2018) and Griffin and Shams (2020) relate to the supply-based hypothesis of unbacked digital money inflating cryptocurrency prices, the novel aspect of this study is that it explicitly focuses on analyzing the potential effects of jumps in USDT on BTC. In this regard, our study contributes to the ongoing debate on how stablecoins may potentially influence the price processes of altcoins. Moreover, in finance research, it is widely accepted that Granger-causal effects pose a serious challenge for the efficient market hypothesis. Grobys and Sapkota (2019, p.6) point out that "despite the different views in the literature there currently remains no consensus over the market efficiency of cryptocurrencies." Hence, our study also contributes to the wide strand of literature devoted to investigating the efficiency of the cryptocurrency market.[2] In this respect, our study is the first investigating potential market inefficiency manifested in what we term '*jump-spillovers*' from stablecoin to altcoin. The existence of such spillovers would clearly undermine the efficient market hypothesis.

2. Data and research design

2.1. Data collection

First, we collected hourly data of both USDT and BTC from November 2018 to June 2021 from Bitfinex due to data availability. In our study, we use hourly data for defining jumps which is consistent with Griffin and Shams (2020), who also employ hourly data in their analysis. Since Alexander and Dakos (2020) argue that Bitfinex used to decouple from the other exchanges precisely when the USDT/USD trading initiated in 2015, the data is reliable for further analysis. Furthermore, Griffin and Shams (2020) also find that the quoted prices on Bitfinex accurately reflect the pricing process of USDT. Thus, using data from Bitfinex exchange might be more

[2] A brief overview on the literature is provided in Grobys and Sapkota (2019), for instance.

Table 1
Summary of descriptive statistics.

	USDT Return	BTC Return	USDT Jumps	BTC Jumps
Mean	0.000008	0.0001	0.2100	0.1170
Variance	0.00011	0.0016	0.1660	0.1030
Skewness	−0.310***	−0.185**	1.423***	2.383***
	(0.000)	(0.022)	(0.000)	(0.000)
Kurtosis	13.012***	6.378***	0.024	3.679***
	(0.000)	(0.000)	(0.790)	(0.000)
JB	6526.230***	1569.623***	311.357***	1394.072***
	(0.000)	(0.000)	(0.000)	(0.000)
ERS	−1.002	−2.646***	−8.097***	−9.862***
	(0.316)	(0.008)	(0.000)	(0.000)
$Q^2(20)$	36.479***	11.603**	11.767**	15.985***
	(0.000)	(0.032)	(0.030)	(0.003)
LiMak(20)	308.925***	59.643***	11.767**	15.985***
	(0.000)	(0.000)	(0.030)	(0.003)

This table reports the descriptive statistics for daily data on BTC and USDT returns and jumps. The symbols *, **, *** in the row skewness (kurtosis) indicate statistical significance on the 10%, 5%, or 1% significance level concerning the tests of D'Agostino (1970) or Anscombe and Glynn (1983), respectively. The symbol 'JB' denotes Jarque and Bera (1980) for testing normality. The tests ERS, Q2(20), and LiMak (20) are unit-root test and two weighted portmanteau tests, respectively. The *p*-values are reported in brackets. The data sample covers 992 observations.

reliable than data provided from other exchanges.[3] After retrieving the raw price data, we transformed them into log returns with hourly frequency. Fig. 1 illustrates our hourly data of closing prices for both USDT and BTC over the period from November 2018 to June 2021.

2.2. *Jump identification and research design*

Since we are interested in examining whether jumps in USDT would have an effect on changes in BTC prices, we need to investigate the existence of jumps within each trading day based on hourly returns. Using the Barndorff-Nielsen and Shephard (2006a) methodology, we encode the binary choice (1 – 'jump', 0 – 'no jump') using bi-power variation based on asymptotic distribution theory at 5% significance level for each trading day. The jump analysis proposed in Barndorff-Nielsen and Shephard (2006a) is mainly based on the Brownian semimartingale plus jump (BSMJ) class. Concomitantly, the advantage of using this aforementioned methodology is a non-parametric approach, which fits the variation, jumps, market frictions, and addresses contemporaneous effects (Barndorff-Nielsen and Shephard, 2006b; Christensen et al., 2014). Pragmatically speaking, using this approach to define jumps means to calculate the variability of the difference between realized variance and time-change. The whole process accounts for the Brownian motion and Lévy-based models. A stream of recent studies in financial economics has incorporated those processes. Barndorff-Nielsen and Shephard (2006a) proposed the models by estimating various short memory and long memory Lévy and Brownian motion processes to overcome the contemporaneous shortages.

The process can be summarized in brief as follows. Let N denote a simple (finite) counting process for all t and let c_j represent a nonzero random variable of a standard Brownian motion process denoted as W with càdlàg a function (stochastic processes that admit or even require jumps) and volatility of càdlàg σ. Accordingly, the Brownian motion process of the return series can be written as:

$$Y_t = \int_0^t a_s ds + \int_0^t \sigma_s dW_s + Z_t. \tag{1}$$

Then, the jump process Z assumes that,

$$Z_t = \sum_{j=1}^{N_t} c_j. \tag{2}$$

Theoretically speaking, price variation due to jumps, captured by the Barndorff-Nielsen and Shephard methodology (2006a), is the difference between realized variance (RV_t) and realized bi-power variation (RBV_t) calculated using 60-minute returns (Megaritis et al., 2021). We calculate $RBV_t = \mu_1^{-2} \sum_{i=2}^{n} |r_i| |r_{i-1}|$ and $\mu_1 = \sqrt{2/\pi}$, where r defines as the logarithmic return, that is, $r_i = ln\left(\frac{p_{t+1}}{p_t}\right)$, where p_t denotes the filtered intraday data closing price and n is the number of intraday (60-minute) observations in each daily period. After that, the *Jump* variable in a given day can be defined as:

$$Jump_t = RV_t - RBV_t \tag{3}$$

[3] Our study addresses the arguments raised in Alexander and Dakos (2020), who highlight that coinmarketcap.com denominates price indices in USD instead of USDT. In addition, coinmarketcap.com has non-traded price indices which probably leads to some biased estimations.

Table 2
Prediction of Bitcoin returns with USDT and BTC jumps.

Variables	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
USDT Return$_{(t-1)}$	−0.064 [−0.12]	0.083 [0.147]	1.658 [1.115]	1.775 [1.200]	3.2638*** [3.8670]
USDT No Jumps$_{(t-1)}$		−0.00007 [−0.451]	−0.000 [−1.032]	−0.000 [−1.065]	−0.0003 [−0.9151]
USDT Positive Jumps$_{(t-1)}$		−0.0002 [−1.225]	−0.000 [−1.107]	−0.000 [−1.086]	0.0003 [0.5949]
No USDT Jump$_{(t-1)}$ * USDTR$_{(t-1)}$			−1.561 [−0.963]	−1.677 [−1.043]	−1.6063 [−0.6395]
Positive USDT Jump$_{(t-1)}$ * USDTR$_{(t-1)}$			−3.647* [−1.918]	−3.934** [−1.993]	−8.4857*** [−4.2367]
BTC No Jumps $_{(t-1)}$					0.0001 [0.3680]
BTC Positive Jumps$_{(t-1)}$					0.0003 [0.3420]
BTC No Jumps$_{(t-1)}$ * USDTR $_{(t-1)}$					−1.9573 [−1.0342]
BTC Positive Jumps$_{(t-1)}$ * USDTR$_{(t-1)}$					1.2911 [0.1279]
No USDT Jumps$_{(t-1)}$ * No BTC Jumps$_{(t-1)}$					0.0001 [0.3964]
No USDT Jumps$_{(t-1)}$ * Positive BTC Jumps$_{(t-1)}$					−0.0008 [−0.8372]
Positive USDT Jumps$_{(t-1)}$ * No BTC Jumps$_{(t-1)}$					−0.0008 [−1.2079]
Positive USDT Jumps$_{(t-1)}$ * Positive BTC Jumps$_{(t-1)}$					−0.0002 [−0.1819]
No USDT Jumps$_{(t-1)}$ * No BTC Jumps$_{(t-1)}$ * USDT Return$_{(t-1)}$					0.1112 [0.0359]
No USDT Jumps$_{(t-1)}$ * Positive BTC Jumps$_{(t-1)}$ * USDT Return$_{(t-1)}$					6.3710 [0.5243]
Positive USDT Jumps$_{(t-1)}$ * No BTC Jumps$_{(t-1)}$ * USDT Return$_{(t-1)}$					6.8697**
[2.2992]					
Positive USDT Jumps$_{(t-1)}$ * Positive BTC Jumps$_{(t-1)}$ * USDT Return$_{(t-1)}$					0.0191 [0.0019]
Constant	0.0001* [1.93]	0.0003 [1.232]	0.0003* [1.754]	0.0003* [1.825]	0.0002 [1.0915]
Lagged Bitcoin return control	No	No	No	Yes	Yes
Observations	922	922	922	922	922
R-squared	0.000	0.001	0.004	0.007	0.021

This table reports the results for different model specifications. The dependent variable used in the models is BTC returns. Note that *, **, and *** denote statistical significances on the 10%, 5%, or 1% level. Note that we perform Vector Auto Regressions with interaction terms to test for the existence of a causal relationship. This test strongly confirms Granger-causality ($\chi^2 = 8.364$, df = 4) (see Table A.4 in the appendix for more details). Our results remain robust after controlling for daily, monthly, or yearly effects across five models. Model (1) only considers USDT return as regressor while Model (2) adds USDT jumps as independent variables. Model (3) and (4) account for interaction effects with lagged Bitcoin returns. Finally, Model (5) incorporated all interactions terms even with three components of variables.

We define whether or not $Jump_t$ is significantly different from zero and encode it as binary jump variable (1 – 'jump' and 0 – 'no jump'). Note that this approach is widely used in financial research as documented in Bloom (2009). The main reason for choosing a binary jump variable is to capture whether or not big daily moves exhibit a jump (Shiller, 1981), whereas the magnitude of the jump (e.g., the severity of the jump), might reflect crashes (Kalyvas et al., 2020). Furthermore, the growing literature on jumps in financial markets makes uses binary choice variables (e.g., identifying whether or not a variable exhibits a jump, the economic reason behind their jumps, etc.). Our study offers both views by looking at jumps and return evolutions to predict BTC returns or BTC jumps. Therefore, we consider both returns and jumps as dependent as well as independent variables.

Concomitantly, we aggregated hourly data to compute the average daily return and clustered them into three groups (i.e., 'negative jump', 'positive jump', and 'no jump') based on the signs of average daily return. Using this methodology, we identify 102 jumps in USDT. Table 1 reports the descriptive statistics for USDT and BTC. Additionally, the binary variables for jumps were included. From Table 1 we observe that both of these cryptocurrencies are skewed to the left at a 5% significance level and exhibit extremely fat tails at a 1% significance level. The average number of jumps in USDT is significantly higher than BTC jumps (t-stat = −5.61, $p < 0.01$) by a substantial margin.

3. Results

We employ different model specifications accounting for lagged jumps in USDT or BTC, lagged USDT or BTC returns, and various interactions of those as regressor variables and regress them on BTC returns. Specifically, the first estimation only considers the predictive power of USDT on Bitcoin returns, whereas the sequential estimations add more factors, namely jumps, as well as the interactions of jumps and returns. The results are reported in Table 2. Notably, Table 2 reveals that the joint effect of positive jumps in USDT in association with a 1% increase in USDT returns on day $t-1$ significantly predict negative prices changes in BTC on day t ranging from −3.65% to −8.49% in daily terms. The results remain robust even after controlling for various other variables. Given different model specifications, the evidence suggests that the interaction of positive jumps in USDT with positive USDT returns are

Table 3
Threshold regression models.

Variables	Model (1)	Model (2)
Region 1		
USDT Return$_{(t)}$	3.945* [1.735]	3.665 [1.596]
No Jumps USDT$_{(t)}$	−0.001 [−1.261]	−0.0001 [−0.837]
Positive Jumps USDT$_{(t)}$	−0.001 [−1.064]	−0.001 [−0.992]
No Jumps USDT$_{(t)}$ * USDT Return$_{(t)}$	−3.285 [−1.401]	−3.127 [−1.319]
Positive Jumps USDT$_{(t)}$ * USDT Return$_{(t)}$	−0.617 [−0.192]	0.227 [0.070]
USDT Return$_{(t-1)}$		4.203* [1.819]
No Jumps USDT$_{(t-1)}$		−0.001* [−1.676]
Positive Jumps USDT$_{(t-1)}$		−0.000 [−0.201]
No Jumps USDT$_{(t)}$ * USDT Return$_{(t-1)}$		−4.259* [−1.787]
Positive Jumps USDT$_{(t-1)}$ * USDT Return$_{(t-1)}$		−7.731** [−2.361]
Constant	0.001 [1.552]	0.002** [2.057]
Region2		
USDT Return$_{(t)}$	14.982* [1.874]	9.679 [1.296]
No Jumps USDT$_{(t)}$	−0.000 [−1.181]	−0.0001 [−0.841]
Positive Jumps USDT$_{(t)}$	0.000 [1.228]	0.001 [1.553]
No Jumps USDT$_{(t)}$ * USDT Return$_{(t)}$	−18.257** [−2.236]	−13.805* [−1.825]
Positive Jumps USDT$_{(t)}$ * USDT Return$_{(t)}$	−40.807*** [−4.679]	−35.732*** [−4.333]
USDT Return$_{(t-1)}$		0.978 [0.133]
No Jumps USDT$_{(t-1)}$		−0.0007 [−0.250]
Positive Jumps USDT$_{(t-1)}$		−0.0001 [−0.533]
No Jumps USDT$_{(t)}$ * USDT Return$_{(t-1)}$		2.757 [0.367]
Positive Jumps USDT$_{(t-1)}$ * USDT Return$_{(t-1)}$		−7.878 [−0.965]
Constant	0.0001 [1.516]	0.0004 [1.183]
Threshold regions	15-Jul-19	13-Jul-19
Observation	923	923

This table reports the results for different threshold regression model specifications. (Details for the error term are provided in Table A.3 in the appendix.) The dependent variable used in the models is BTC returns. Note that *, **, and *** denote statistical significance on the 10%, 5%, or 1% level.

Table 4
Logit regression models.

Variables	Model (1)	Model (2)	Model (3)
USDT Return$_{(t)}$	−3792.232 [−1.261]	−4413.573 [−1.472]	−4082.437 [−1.194]
No Jump USDT$_{(t)}$	0.463 [0.750]	0.593 [1.004]	0.569 [0.934]
Positive Jump USDT$_{(t)}$	0.277 [0.368]	0.404 [0.546]	0.332 [0.441]
No Jump USDT$_{(t)}$ * USDT Return$_{(t)}$	4899.653 [1.408]	5878.842* [1.670]	5684.956 [1.499]
Positive Jump USDT$_{(t)}$ * USDT Return$_{(t)}$	8120.493** [2.018]	9144.703** [2.203]	9231.777** [2.114]
USDT Return$_{(t-1)}$		1741.806 [0.320]	1431.535 [0.273]
No Jump USDT$_{(t-1)}$		−0.584 [−1.040]	−0.579 [−1.063]
Positive Jump USDT$_{(t-1)}$		0.197 [0.308]	0.139 [0.222]
No Jump USDT$_{(t-1)}$ * USDT Return$_{(t-1)}$		−1601.489 [−0.279]	−1745.489 [−0.318]
Positive Jump USDT$_{(t-1)}$ * USDT Return$_{(t-1)}$		−33.159 [−0.006]	681.309 [0.119]
USDT Return$_{(t-2)}$			−1224.045 [−0.263]
No Jump USDT$_{(t-2)}$			−0.000 [−0.001]
Positive Jump USDT$_{(t-2)}$			0.831 [1.071]
No Jump USDT$_{(t-2)}$ * USDT Return$_{(t-2)}$			−718.610 [−0.145]
Positive Jump USDT$_{(t-2)}$ * USDT Return $_{(t-2)}$			−26,972.365 [−1.633]
Constant	−3.216*** [−5.392]	−2.942*** [−3.475]	−2.945*** [−2.819]
Pseudo R^2	0.0097	0.0237	0.0355
Observation	923	922	921

This table reports the results for different logit-model specifications. The dependent used in the models is BTC downside jumps. Note that *, **, and *** denote statistical significance on the 10%, 5%, or 1% level.

Granger-causal for BTC returns ($\chi^2 = 8.36$, $df = 4$). An important implication of this result is that the Bitcoin market is inefficient. Our results remain robust when controlling for yearly, monthly, or daily effects across models (1) to (5). The results of the robustness check are reported in Table A.5 in appendix.

Next, we want to have a look whether there is evidence for any contemporaneous effect. It is important to distinguish between contemporaneous effect and Granger-causal effect because in the presence of some extreme contemporaneous effect, Granger-causal effects may be difficult to detect. Indeed, the Granger-causal effect could be an indication of some more extreme event, like a squall could indicate a forthcoming hurricane. Next, accounting for non-linear effects, we also added the squared term of interactions between jumps and returns, and again, test for Granger-causality. Using the optimal lag-order, the results remain robust.[4]

Visual inspection from Fig. 1 provides some anecdotal evidence for that the hourly prices of USDT appear to exhibit much more pronounced volatility before 29th July 2019. Intuitively, given the extremely high volatility of USDT during this period, the predictability of changes in BTC prices using USDT might be poor. Note that Griffin and Shams (2020) point out that the main reason for such a volatile period is that many news concerning changes in reserve policies were released. Therefore, we employed a threshold regression model, allowing us first to choose the best fit threshold region to split our sample into two groups, and second to implicitly control for potential non-linearities (Diks and Wolski, 2016). Unsurprisingly, in line with Griffin and Shams (2020) the threshold regression suggests a manifestation of another regime in the ex-post July 2019 period.

Notably, from Table 3 we observe that in regime 1 there are no significant effects from the interaction between positive USDT jumps with USDT returns on subsequent BTC returns which is manifested in an insignificant coefficient for the term Positive Jumps $USDT_{(t)}$•USDT $Return_{(t)}$ in regime 1 (before threshold region–July 2019). This finding suggests that the contemporaneous joint effect of positive USDT jumps in association with positive USDT returns is not present in the full sample period. On the other hand, we observe from Table 3 that the effect is extremely pronounced in regime 2 (e.g., the ex-post July 2019 period). Specifically, the joint effect of positive USDT jump in association with a 1% positive USDT return significantly predicts contemporaneous changes in BTC prices at a 1% significance level. The effect is negative and economically extremely large, ranging from −35.73% to −40.81%, on average, in daily terms.[5]

Are our results robust? To address this question, we change the research design in some important ways. First, we employ logit regressions to analyze the effects of USDT on specifically large BTC returns, providing us a probabilistic point of view. Second, we define large BTC returns as jumps in the same manner as for USDT using the Barndorff-Nielsen and Shephard (2006a) methodology. This enables us to analyze what we call '*jump-to-jump-effects*'. Third, analyzing the contemporaneous effects from USDT jumps on BTC jumps–while accounting for various interactions like in the earlier analysis–here, we also control for two lags in the USDT process. Hence, our logit model uses the binary choice for BTC downturn jumps (1 – 'jump' and 0 – 'no jump') as the dependent variable.

The Barndorff-Nielsen and Shephard (2006a) methodology identifies 56 negative jumps in BTC, given 450 days of negative BTC returns. Table 4 summarizes our main results of predicting the likelihood for Bitcoin downside jumps. We observe that the coefficients of the interaction effects Positive Jumps $USDT_{(t)}$•USDT $Return_{(t)}$ increase the likelihood of having negative BTC jumps at a 5% significance level. Hence, we infer that our results are robust.

Finally, we follow Baker et al. (2021) and re-identify jumps as an additional robustness check. Accordingly, the jump threshold of USDT can be set as 0.003% per day (note that the average daily USDT return corresponds to −0.0001%). A threshold of 0.003 percent 'up' or 'down' for USDT yields 429 jumps (220 downturn jumps and 209 upward jumps). The correlation of two jump measures is positive and statistically significant ($\rho = 0.109$, p-value < 0.01). Using the lagged term for prediction, our results remain robust.[6] Controlling for Bitcoin or USDT volatility does not change our results (see Table A.2 in the appendix).

4. Conclusion

First, our study provided evidence for the presence of jumps in both cryptocurrencies USDT and BTC. Second, using a predictive model, we found that jumps in USDT are Granger-causal for BTC returns, given that USDT generates a positive return on that day. In Fig. 1 in the appendix, we provide a recent example on this issue. A possible explanation for this phenomenon could be that investors change enormous amounts of BTC to USDT which temporarily might result in an increased demand for Tether resulting in a 'jump'. Then, selling a large amount of BTC could activate stop loss orders resulting in lagged price drops. Next, our study uncovered a contemporaneous effect, where positive USDT jumps in association with a positive USDT return are associated with contemporaneous large negative BTC payoffs, ranging from −35.73% to −40.81%, on average, in daily terms. Hence, we are forced to reject (Urquhart, 2016) hypothesis that Bitcoin is developing toward market efficiency. We argue that our findings may have important implications for future studies that have the objective to uncover the price discovery processes in emerging digital ecosystems. Moreover, future studies are encouraged to explore potential effects stemming from jumps in other stablecoins or to investigate applications of our obtained results for implementing algorithmic investment strategies.

CRediT authorship contribution statement

Klaus Grobys: Conceptualization, Writing – original draft, Validation, Supervision. **Toan Luu Duc Huynh:** Writing – review & editing, Methodology, Validation.

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[4] We acknowledge the thoughtful comment from Reviewer 3.

[5] Note from Table 1 that USDT returns move only marginally. As an example, assuming the USDT return on a jump-day is 0.1%, the model predict decreases in Bitcoin returns, ranging from −3.57% to −4.10%.

[6] The corresponding results are available upon request.

Appendix

Fig. A1.
Table A1.
Table A2.
Table A3.
Table A4.

Fig. A1. Thether jumps and Bitcoin drops.
This screenshot is retrieved from coinmarketcap.com as of April 18, 2021. We see that on April 17, 2021, 11:49 USDT made a 1% move from 1.00 USD to 1.01 USD. Given that USDT returns exhibit a standard deviation of 0.0105, this move corresponds to a 95-sigma event which is, according to our methodology, referred to as a 'jump'. It becomes evident that Bitcoin crashed six hours later. From the chart we observe that on April 18, 2021, 5:49 Bitcoin recorded a negative return of more than −8%.

Table A1

Robustness check predictive power using Baker et al. (2021) classification.

Variables	Model (1)	Model (2)	Model (3)
USDTReturn$_{(t-1)}$	8.083** [1.970]	8.045** [1.963]	8.047** [1.963]
USDT Negative Jump$_{(t-1)}$	0.00002 [0.111]	0.00002 [0.113]	0.00002 [0.112]
USDT Positive Jump$_{(t-2)}$	0.00005 [0.271]	0.00004 [0.315]	0.00005 [0.311]
USDT Negative Jump$_{(t-1)}$ * USDTReturn$_{(t-1)}$	−7.755* [−1.817]	−7.718* [−1.809]	−7.703* [−1.800]
USDT Positive Jump$_{(t-2)}$ * USDTReturn$_{(t-1)}$	−8.896** [−2.121]	−8.892** [−2.121]	−8.910** [−2.123]
Constant	0.0001* [1.821]	0.0001* [1.874]	0.000 [0.091]
Control	No	Yes	Yes
Observations	922	922	922
R-squared	0.004	0.0068	0.007

The dependent variable used in the models is BTC returns. Note that *, **, and *** denote statistical significance on the 10%, 5%, or 1% level. Model (2) controls for lagged Bitcoin returns and Model (3) controls for the time-effect variable. The benchmark of jump is ‘no jump’. The sample consists of 494 days without jump, 209 days exhibiting negative jumps, and 220 days exhibiting positive jumps.

Table A2

Prediction of Bitcoin returns with USDT and BTC jumps with volatility control.

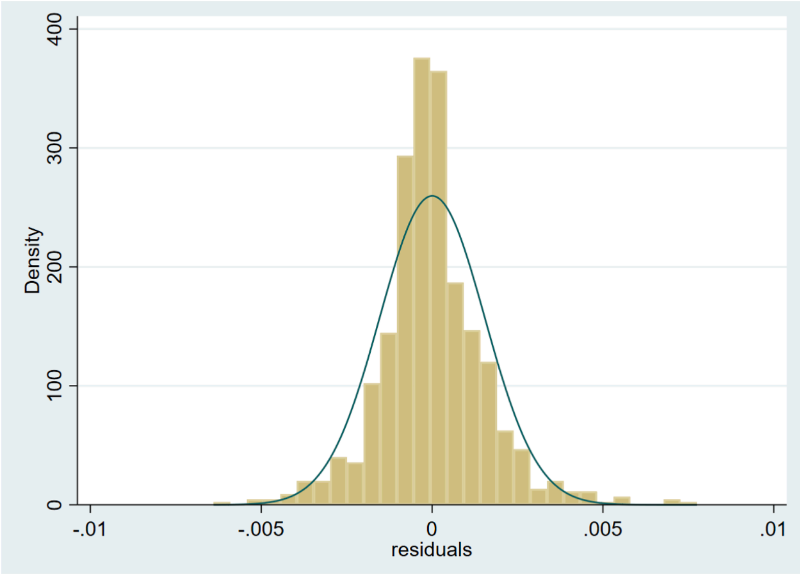
Variables	Model (1)	Model (2)	Model (3)
USDT Return$_{(t-1)}$	3.346*** [3.896]	4.101*** [3.821]	4.226*** [3.970]
USDT No Jumps$_{(t-1)}$	−0.0003 [−0.974]	−0.0004 [−1.144]	−0.0004 [−1.302]
USDT Positive Jumps$_{(t-1)}$	0.0004 [0.682]	0.0003 [0.564]	0.0004 [0.630]
No USDT Jump$_{(t-1)}$ * USDTR$_{(t-1)}$	−1.746 [−0.692]	−2.553 [−0.984]	−2.762 [−1.072]
Positive USDT Jump$_{(t-1)}$ * USDTR$_{(t-1)}$	−10.111** [−2.208]	−10.795** [−2.397]	−12.213*** [−2.742]
BTC No Jumps $_{(t-1)}$	0.0001 [0.334]	0.0001 [0.280]	0.0001 [0.416]
BTC Positive Jumps$_{(t-1)}$	0.0003 [0.341]	0.0003 [0.323]	0.0004 [0.414]
BTC No Jumps$_{(t-1)}$ * USDTR $_{(t-1)}$	−2.011 [−1.060]	−2.256 [−1.183]	−2.262 [−1.202]
BTC Positive Jumps$_{(t-1)}$ * USDTR$_{(t-1)}$	1.259 [0.124]	0.638 [0.063]	−0.136 [−0.013]
No USDT Jumps$_{(t-1)}$ * No BTC Jumps$_{(t-1)}$	0.0002 [0.424]	0.0002 [0.472]	0.0002 [0.612]
No USDT Jumps$_{(t-1)}$ * Positive BTC Jumps$_{(t-1)}$	−0.0008 [−0.831]	−0.0008 [−0.809]	−0.0007 [−0.727]
Positive USDT Jumps$_{(t-1)}$ * No BTC Jumps$_{(t-1)}$	−0.0008 [−1.278]	−0.0008 [−1.195]	−0.0008 [−1.266]
Positive USDT Jumps$_{(t-1)}$ * Positive BTC Jumps$_{(t-1)}$	−0.0003 [−0.235]	−0.0002 [−0.167]	−0.0002 [−0.200]
No USDT Jumps$_{(t-1)}$ * No BTC Jumps$_{(t-1)}$ * USDT Return$_{(t-1)}$	0.237 [0.076]	0.513 [0.165]	0.619 [0.201]
No USDT Jumps$_{(t-1)}$ * Positive BTC Jumps$_{(t-1)}$ * USDT Return$_{(t-1)}$	6.798 [0.560]	7.894 [0.646]	8.557 [0.694]
Positive USDT Jumps$_{(t-1)}$ * No BTC Jumps$_{(t-1)}$ * USDT Return$_{(t-1)}$	8.399* [1.713]	8.035* [1.655]	9.455** [1.978]
Positive USDT Jumps$_{(t-1)}$ * Positive BTC Jumps$_{(t-1)}$ * USDT Return$_{(t-1)}$	1.474 [0.134]	1.571 [0.144]	3.975 [0.356]
Volatility of Bitcoin (based on T-GARCH)	22.189 [0.407]	19.8612 [0.362]	14.097 [0.262]
Volatility of USDT (based on T-GARCH)		3560.477 [1.146]	3687.733 [1.186]
Constant	0.0002 [0.778]	0.0002 [0.862]	0.0002 [0.802]
Lagged Bitcoin return control	No	No	Yes
Observations	922	922	922
R-squared	0.021	0.027	0.027

This table reports the results from different model specifications. The dependent variable is BTC returns. *, **, and *** denote statistical significance on the 10%, 5%, or 1% level. We employed the Threshold GARCH model (T-GARCH) to estimate the volatility for Bitcoin and USDT returns and add them as control variables. Our results remained robust.

Table A5.

Table A6.

Table A3
Statistical treatment for the error term in Threshold regression.



This figure reports the histogram of the error term obtained from the threshold regression (Table 3). The stationary test of the error term is significant at a 1% level (t-statistic = −32.829). Concomitantly, we performed the OLS regression between the error term and the independent variables in Table 3. All coefficients are insignificant. The results are available upon request.

Table A4
Vector Auto Regression for prediction of Bitcoin return.

Variables	Bitcoin Return	Bitcoin Return	Bitcoin Return
Bitcoin Return$_{(t-1)}$	−0.057* [−1.743]	−0.055* [−1.713]	−0.0584* [−1.804]
Bitcoin Return$_{(t-2)}$	0.015 [0.456]	0.006 [0.189]	0.0085 [0.264]
Bitcoin Return$_{(t-3)}$	−0.026 [−0.801]	−0.015 [−0.463]	−0.0150 [−0.465]
Bitcoin Return$_{(t-4)}$	0.095*** [2.905]	0.094*** [2.938]	0.0941*** [2.936]
Positive USDT Jump * USDT Return$_{(t-1)}$ [−1.530]	−2.438 [−1.629]	−2.389 [−1.584]	−2.3045
Positive USDT Jump * USDT Return$_{(t-2)}$	−1.219 [−0.813]	−1.681 [−1.131]	−1.7161 [−1.157]
Positive USDT Jump * USDT Return$_{(t-3)}$	−0.913 [−0.609]	−1.108 [−0.746]	−1.1381 [−0.768]
Positive USDT Jump * USDT Return$_{(t-4)}$	−3.496** [−2.343]	−3.251** [−2.195]	−3.1079** [−2.098]
Positive Jump BTC		0.001*** [6.007]	0.0014*** [6.128]
USDT Return		−0.166 [−0.337]	0.1025 [0.199]
Constant		0.001 [0.166]	0.0015 [0.334]
Time-effect	No	Yes	Yes
Observation	919	919	919
R-square	0.02	0.06	0.01
Adding squared-term of interaction variables	No	No	Yes
VAR Granger	Yes	Yes	Yes

This table reports the results from the Vector Auto Regression model for predicting Bitcoin returns with 4 lagged terms. *, **, and *** denote statistical significance on the 10%, 5%, or 1% level.

Table A.5
Prediction of Bitcoin returns with USDT and BTC jumps with different time-control.

Variables	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
USDT Return(t-1)	3.2638*** [3.8670]	3.2779*** [3.7998]	2.9876*** [3.2985]	3.1077*** [3.5020]	2.9740*** [3.2022]	3.0908*** [3.4037]
USDT No Jumps(t-1)	−0.0003 [−0.9151]	−0.0003 [−0.9116]	−0.0002 [−0.7572]	−0.0003 [−0.9291]	−0.0002 [−0.7501]	−0.0003 [−0.9214]
USDT Positive Jumps(t-1)	0.0003 [0.5949]	0.0003 [0.5975]	0.0004 [0.6658]	0.0004 [0.7686]	0.0004 [0.6693]	0.0004 [0.7730]
No USDT Jump(t-1) * USDTR(t-1)	−1.6063 [−0.6395]	−1.6236 [−0.6465]	−1.2995 [−0.5225]	−1.5184 [−0.6182]	−1.2816 [−0.5121]	−1.4963 [−0.6058]
Positive USDT Jump(t-1) * USDTR (t-1)	−8.485*** [−4.2367]	−8.502*** [−4.2324]	−8.2730*** [−4.0870]	−10.1231*** [−4.1928]	−8.2758*** [−4.1037]	−10.1282*** [−4.2034]
BTC No Jumps (t-1)	0.0001 [0.3680]	0.0001 [0.3752]	0.0001 [0.5370]	0.0002 [0.6806]	0.0001 [0.5398]	0.0002 [0.6834]
BTC Positive Jumps(t-1)	0.0003 [0.3420]	0.0003 [0.3433]	0.0003 [0.3939]	0.0004 [0.4893]	0.0003 [0.3945]	0.0004 [0.4903]
BTC No Jumps(t-1) * USDTR (t-1)	−1.9573 [−1.0342]	−1.9517 [−1.0308]	−1.6166 [−0.8489]	−1.6190 [−0.8626]	−1.5976 [−0.8267]	−1.5954 [−0.8377]
BTC Positive Jumps(t-1) * USDTR(t-1)	1.2911 [0.1279]	1.2657 [0.1253]	0.8484 [0.0861]	0.0541 [0.0054]	0.8399 [0.0855]	0.0429 [0.0043]
No USDT Jumps(t-1) * No BTC Jumps(t-1)	0.0001 [0.3964]	0.0001 [0.3932]	0.0001 [0.2676]	0.0001 [0.4147]	0.0001 [0.2599]	0.0001 [0.4057]
No USDT Jumps(t-1) * Positive BTC Jumps(t-1)	−0.0008 [−0.8372]	−0.0008 [−0.8378]	−0.0009 [−0.9095]	−0.0008 [−0.8219]	−0.0009 [−0.9111]	−0.0008 [−0.8239]
Positive USDT Jumps(t-1) * No BTC Jumps(t-1)	−0.0008 [−1.2079]	−0.0008 [−1.2089]	−0.0008 [−1.2631]	−0.0009 [−1.3673]	−0.0008 [−1.2660]	−0.0009 [−1.3711]
Positive USDT Jumps(t-1) * Positive BTC Jumps(t-1)	−0.0002 [−0.1819]	−0.0002 [−0.1821]	−0.0003 [−0.2245]	−0.0003 [−0.2766]	−0.0003 [−0.2250]	−0.0003 [−0.2773]
No USDT Jumps(t-1) * No BTC Jumps(t-1) * USDT Return(t-1)	0.1112 [0.0359]	0.1079 [0.0348]	−0.2380 [−0.0776]	−0.1153 [−0.0380]	−0.2596 [−0.0840]	−0.1420 [−0.0465]
No USDT Jumps(t-1) * Positive BTC Jumps(t-1) * USDT Return(t-1)	6.3710 [0.5243]	6.4114 [0.5266]	6.6765 [0.5582]	7.4443 [0.6167]	6.6696 [0.5580]	7.4364 [0.6168]
Positive USDT Jumps(t-1) * No BTC Jumps(t-1) * USDT Return(t-1)	6.8697** [2.2992]	6.8407** [2.2787]	6.5889** [2.1770]	8.4399** [2.5703]	6.5825** [2.1713]	8.4336** [2.5686]
Positive USDT Jumps(t-1) * Positive BTC Jumps(t-1) * USDT Return (t-1)	0.0191 [0.0019]	0.0331 [0.0032]	0.4610 [0.0457]	3.3098 [0.3162]	0.4999 [0.0497]	3.3606 [0.3217]
Constant	0.0002 [1.0915]	0.0005 [0.1166]	0.0005 [0.0997]	0.0005 [0.1167]	−0.0318 [−0.0912]	−0.0396 [−0.1131]
Lagged Bitcoin return control	No	Yes	No	Yes	No	Yes
Time-control effects	Yes Daily	Yes Daily	Yes Daily, Monthly	Yes Daily, Monthly	Yes Daily, Monthly, Yearly	Yes Daily, Monthly, Yearly
Observations	922	922	922	922	922	922
R-squared	0.0212	0.0212	0.0219	0.0249	0.022	0.025

This table reports the results from different model specifications. The dependent variable is BTC returns. *, **, and *** denote statistical significances on the 10%, 5%, or 1% level. Concomitantly, we controlled the time-effects with different horizons (e.g., daily, monthly, and yearly).

Table A.6
The lag-order selection criteria.

Lag	LL	LR	AIC	HQIC
0	8118.1		−17.6651	−17.6631
1	8118.46	0.71362	−17.6637	−17.6597
2	8118.54	0.15791	−17.6617	−17.6557
3	8118.78	0.49004	−17.66	−17.652
4	8127.64	17.716*	−17.6771*	−17.6671*

This table reports the lag-order selection statistics for Vector Auto-Regressions accounting for Log likelihood (LL), the Likelihood ratio (LR), the Akaike's Information Criterion (AIC), and the Hannan and Quinn Information Criterion (HQIC).

References

Alexander, C., Dakos, M., 2020. A critical investigation of cryptocurrency data and analysis. Quant. Finance 20 (2), 173–188.
Anscombe, F.J., Glynn, W.J., 1983. Distribution of the Kurtosis Statistic b2 for Normal Samples. Biometrika 1 (70), 227–234.
Baker, S.R., Bloom, N., Davis, S.J., Sammon, M.C., 2021. What triggers stock market jumps? National Bureau Econ. Res. (NBER working paper No. w28687).
Barndorff-Nielsen, O.E., Shephard, N., 2006a. Econometrics of testing for jumps in financial economics using bipower variation. J. Financ. Econom. 4 (1), 1–30.
Barndorff-Nielsen, O.E., Shephard, N., 2006b. Variation, jumps and high frequency data in financial econometrics. Adv. Econ. Econom. Theory and Applications.
Baur, D.G., Hong, K.H., Lee, A.D., 2018. Bitcoin: medium of exchange or speculative assets? J. Inter-national Financ.l Mark., Inst. Money 54, 177–189.

Baur, D.G., Hoang, L.T., 2021. A crypto safe haven against Bitcoin. Finance Res. Lett. 38, 101431.
Hoang, L.T., Baur, D.G., 2021. How stable are stablecoins? Eur. J. Finance (forthcoming).
Bloom, N., 2009. The impact of uncertainty shocks. Econometrica 77 (3), 623–685.
Brauneis, A., Mestel, R., 2019. Cryptocurrency-portfolios in a mean-variance framework. Finance Res. Lett. 28, 259–264.
Chkili, W., Ben Rejeb, A., Arfaoui, M., 2021. Does bitcoin provide hedge to Islamic stock markets for pre- and during COVID-19 outbreak? A comparative analysis with gold. Resour. Policy 74, 102407.
Christensen, K., Oomen, R.C.A., Podolskij, M., 2014. Fact or friction: jumps at ultra high frequency. J. Financ. Econ. 114 (3), 576–599.
D'Agostino, R.B., 1970. Transformation to normality of the null distribution of g1. Biometrika 57, 679–681.
Diks, C., Wolski, M., 2016. Nonlinear Granger causality: guidelines for multivariate analysis. J. Appl. Econom. 31, 1331–1351.
Grobys, K., Sapkota, N., 2019. Cryptocurrencies and Momentum. Econ. Lett. 180, 6–10.
Grobys, K., Kolari, J., Junttila, J.-.P., Sapkota, M., 2021. On the Stability of Stablecoins. J. Empirical Finance 64, 207–223.
Griffin, J.M., Shams, A., 2020. Is Bitcoin Really Untethered? J. Finance 75 (4), 1913–1964.
Kalyvas, A., Papakyriakou, P., Sakkas, A., Urquhart, A., 2020. What drives Bitcoin's price crash risk? Econ. Lett. 191, 108777.
Jarque, C.M., Bera, A.K., 1980. Efficient tests for normality, homoscedasticity and serial independence of regression residuals. Econ. Lett. 6, 255–259.
Lahiani, A., Jeribi, A., Jlassi, N.B., 2021. Nonlinear tail dependence in cryptocurrency-stock market returns: the role of Bitcoin futures. Res. Int. Bus. Finance 56, 101351.
Liu, W., 2019. Portfolio diversification across cryptocurrencies. Finance Res. Lett. 29, 200–205.
Lyons, R.K. and G. Viswanath-Natraj (2019). What Keeps Stable Coins Stable? Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstractid=3508006.
Shiller, R., 1981. Do Stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends. Am. Econ. Rev. 71 (3), 421–437.
Megaritis, A., Vlastakis, N., Triantafyllou, A., 2021. Stock market volatility and jumps in times of uncertainty. J. Int. Money Finance 113, 102355.
Urquhart, A., 2016. The inefficiency of Bitcoin. Econ. Lett. 148, 80– 82.
Wątorek, M., Drożdż, S., Kwapień, J., Minati, L., Oświęcimka, P., Stanuszek, M., 2021. Multiscale characteristics of the emerging global cryptocurrency market. Phys. Rep. 901, 1–82.
Wei, W.C., 2018. The impact of Tether grants on Bitcoin. Econ. Lett. 171, 19–22.