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A crypto safe haven against Bitcoin

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ABSTRACT

The design of Bitcoin is closely related to gold which has led to the idea that Bitcoin has gold-like features such as being a store of value and a safe haven. However, given Bitcoin's extreme volatility investors may rather need a safe haven against Bitcoin. We hypothesize that stablecoins provide such a safe haven and analyze high-frequency price changes of the largest stablecoins. We find that they act as safe havens, and Tether showing the strongest effect. The results demonstrate that Bitcoin investors seek out stablecoins when Bitcoin experiences extreme negative prices changes. Since stablecoins react to such price changes they are not stable at all times.

1. Introduction

The volatility of Bitcoin is extreme. Prices do not only fluctuate considerably over longer horizons but also on a daily basis.[1] Harvey [11] documents that the volatility of Bitcoin is around eight times higher than that of stocks. Similar results are observed more recently by Corbet et al. [7] and Smales [13]. Given the excess volatility of Bitcoin, investors may want to hedge the exposure to Bitcoin and seek out a safe haven against extreme price changes of Bitcoin, leading to the question which assets could serve as a safe haven. Interestingly, to the best of our knowledge, there are not many studies that explicitly address this question.[2]

This study examines a special class of cryptocurrencies that could function as safe haven for Bitcoin, i.e. stablecoins.[3] Whilst Baumöhl [2] is a broader study analyzing the connectedness of many cryptocurrencies and forex, our paper focuses on the safe haven property of stablecoins. Thus, we contribute to the understanding on how investors in Bitcoin protect themselves against the extreme volatility of Bitcoin.

Our central hypothesis is that stablecoins provide a crypto safe haven for Bitcoin. Specifically, we examine how stablecoin prices react when Bitcoin experiences extreme negative returns. By design, stablecoins are pegged to other (relatively) stable assets such as gold or the US dollar and thus should have comparatively low volatility. Given the "stable" property, stablecoins should not react to Bitcoin returns even during relatively extreme market conditions and therefore provide a safe haven for Bitcoin. To test this hypothesis,

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[1] The price of Bitcoin increased from $100 in 2014 to more than $19,000 in 2017 with daily variations regularly exceeding $500.

[2] The only study we are aware of is Baumöhl [2] who suggests that XRP can serve as a safe haven for Bitcoin as there is a positive correlation between extreme negative Bitcoin returns (5th quantile) and extreme positive XRP returns (95th quantile) over two trading days but not over longer periods.

[3] Tether is one of the most prominent stablecoins and analyzed by Wei [15].

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we examine whether stablecoins are uncorrelated with average price changes of Bitcoin and with extreme price changes of Bitcoin. The average condition would establish a hedge and the extreme condition would establish a safe haven [5].

The connectedness between Bitcoin and other assets has been extensively studied. Yermack [17] documents that Bitcoin generally shows no return correlation with both international currencies and gold. Using a quantile cross-spectral approach, Baumöhl [2] finds that there are significant negative dependencies between Bitcoin and fiat currencies over short- and long-term horizons. Yi et al. [18] studies the volatility connectedness between cryptocurrencies and finds that Bitcoin is an important but not a dominant net-emitter of the connectedness and that the volatility of smaller cryptocurrencies might also affect that of Bitcoin. Other related studies analyze the safe haven property of Bitcoin (e.g. [4,6,12,14]) or the nexus between Bitcoin and other macro variables such as economic policy uncertainty [9] or market attention [8]. Interestingly, there seems to be no study that considers the linkage between Bitcoin and stablecoins.

We analyze the returns of the six largest stablecoins and their correlation with Bitcoin returns (and four alternative “non-stable” coins[4]) using 1-min returns, hourly returns and daily returns. We find that the “safe haven” property of stablecoins against Bitcoin is relatively strong in some cases, i.e. some stablecoin returns are negatively correlated with extreme negative price changes of Bitcoin. On the one hand, this result confirms our hypothesis that stablecoins can serve as a safe haven for Bitcoin. On the other hand, given the extreme volatility of Bitcoin returns, the significant correlations imply that stablecoins are not always stable contrary to what is implied by their name.

We also identify a trade-off between the properties “stable” and “safe haven”. Stablecoins that positively react to extreme negative Bitcoin returns are strong safe havens but not stable and stablecoins that do not react to extreme negative Bitcoin returns are weak safe havens and stable in relation to Bitcoin. In other words, a strong safe haven property deprives a stablecoin from its “stable” property whereas a weak safe haven is a necessary but not sufficient condition of “stable”.[5]

The rest of the paper is structured as follows. Section 2 describes the data and the methodology, Section 3 presents and discusses the estimation results and Section 4 summarizes the main findings and concludes.

2. Data and methodology

We employ the following econometric model to examine the relationship between stablecoins and Bitcoin during normal and extreme market condition:

$$r_{\text{stablecoin},j} = \alpha_0 + \beta_0 r_{BTC} + \sum_{i=1}^{3} (\alpha_i Dq_i + \beta_i r_{BTC}\ Dq_i) + e_j \tag{1}$$

where $r_{\text{stable coin},j}$ denotes the log return of stablecoin j, r_{BTC} is the log return of BTC and the dummy variable Dq_i equals 1 if r_{BTC} is below the 10%, 5% and 1% quantile for $i = 1, 2, 3$, respectively, and 0 otherwise. The quantiles vary with the return frequency and are smaller in absolute terms for the 1-minute returns than for the hourly returns which are smaller than the daily returns.

Since a stablecoin should not vary and thus not react to Bitcoin returns, all β’s are expected to be zero. If a stablecoin does not react to extreme Bitcoin returns ($\beta_i = 0$ for $i = 1,2,3$), it is also a weak safe haven. On the other hand, if a stablecoin reacts inversely (e.g. $(\sum_{i=0}^{3}\beta_i) < 0$ at the 1% quantile or $(\sum_{i=0}^{J}\beta_i) < 0$ at the Jth% quantile) and thus positively to extreme negative Bitcoin returns the stablecoin is a strong safe haven but not stable.[6] Since investors may react to extreme changes in Bitcoin with a delay or only after significant hourly or daily losses have occurred, we expect the safe haven properties to strengthen from 1-minute to daily returns, i.e. with decreasing return frequencies.

The adopted model is well-established in the safe haven literature and has been used in a number of related studies (e.g. [5,3,16], among many others). We acknowledge that there are several other potential models such as cross-quantilogram of Han et al. [10] or quantile coherency of Baruník and Kley [1].[7] Those models allow to examine tail dependence (e.g. dependence of asset returns when both assets are in the 5% quantile) as well as asymmetric connectedness between assets (e.g. dependence of assets when one asset return is in the 5% quantile and the other in the 95% quantile). However, we argue that standard safe haven test is more general than asymmetric connectedness as the former examines the expected reaction of the potential safe haven asset conditional on extreme negative returns of the base asset, while the latter looks at the connectedness of those assets conditional on both extreme negative returns of the base asset and extreme positive returns of the safe haven asset. Thus, a positive asymmetric connectedness is a sufficient but not a necessary condition for a safe haven.

We include in our analysis the six largest stablecoins, including Tether (USDT), USD Coin (USDC), TrueUSD (TUSD), Paxos Standard Token (PAX), Dai (DAI) and Gemini Dollar (GUSD) based on their market capitalisation.[8] The intraday data is collected from Bitfinex through its API. The sample period starts from 06/12/2018 (the first day for which intra-day data is available) to 22/07/2019 (the day we collected the data), covering 225 trading days. We focus on Bitcoin as the largest cryptocurrency in the econometric analysis and provide other non-stable coins information in the descriptive statistics for comparison.

[4] By “non-stable” coins we mean traditional cryptocurrencies that are not pegged to any stable asset.

[5] An asset that is independent from the extremely volatile Bitcoin is not necessarily stable itself.

[6] Baur and McDermott [3] distinguish between weak and strong safe havens.

[7] We thank an anonymous referee for bringing up this point.

[8] According to https://coinmarketcap.com/.

3. Results

3.1. Descriptive statistics

Table 1 presents the descriptive statistics of hourly returns for six stablecoins and five “non-stable” coins for comparison,[9] namely Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Bitcoin Cash (BCH) and Litecoins (LTC). The statistics show a clear difference between the stablecoins and the “non-stable” coins. The former exhibit mean returns very close to zero whereas the latter exhibit relatively large hourly returns, e.g. Bitcoin displays an hourly return of 0.018% which implies an average daily return of 0.432% and a monthly return of 12.96%. Whilst the mean returns of the stablecoins are very close to zero consistent with the idea of a “stable” coin, the standard deviation of the returns, the minimum and maximum returns are rather large demonstrating that an average return can be misleading. For example, the minimum and maximum returns can reach values of up to 60% for USDC and about 30% for GUSD. These statistics suggest that stablecoins are not stable on a high-frequency (in this case hourly) basis.

Fig. 1 supplements the descriptive statistics of hourly returns with time-series plots of daily stablecoin prices. The plots illustrate that stablecoins regularly deviate from parity with the reference entity. The strongest positive deviations from parity occurred in May 2019 among all stablecoins.

Table 2 presents the hourly (upper triangular) and daily (lower triangular) return correlations (matrix) between all stable and “non-stable” coins for returns (Panel A) and squared returns (Panel B). The estimates show high return correlations among the “non-stable” coins at both the hourly and the daily level (around 0.7–0.8). In contrast, the return correlations among the stablecoins are comparatively low at the hourly level (smaller than 0.1 in general and close to 0 for most stablecoins), but become relatively high at the daily level (>0.2 for most stablecoins and 0.39 between USDT and DAI). The return correlations between stablecoins and “non-stable” coins are generally close to zero for both frequencies except for Tether (USDT) with correlations around 0.2. Given that the “non-stable” coins, Bitcoin in particular, are extremely volatile, such high correlations imply that USDT is not stable at all times. The zero correlations of the other stablecoins with Bitcoin and other non-stable coins are more consistent with “stable” and thus with the term stablecoin. The squared return correlations support the main result derived from the return correlations, i.e. that some stablecoins are positively correlated with some non-stable coins (e.g. USDT, DAI and GUSD with BTC, ETH, XRP, BCH and LTC for hourly frequencies). Interestingly, whilst most squared return correlations are similar to the return correlations there are notable exceptions such as the daily correlations of USDT with TUSD and PAX which are positive and statistically significant in Panel A (lower triangular) but not different from zero in Panel B (lower triangular).

3.2. Regression results

Table 3 presents the estimation results of Eq. (1) using 1-minute returns. The coefficients of r_{BTC} in models (1), (3) and (5) are positive and statistically significant implying that USDT, TUSD and DAI are correlated with BTC during normal market conditions. GUSD in model (6) shows a negative correlation consistent with a hedge against Bitcoin movements.

For extreme Bitcoin returns, three out of six stablecoins exhibit a negative coefficient for some shocks indicating that the stablecoins (USDT, PAX and GUSD) positively react to large negative Bitcoin price changes. Whilst the evidence for the safe haven hypothesis of stablecoins is rather weak, there is stronger evidence against the “stable” hypothesis given the non-zero reaction of stablecoins to one-minute price changes.

However, the weak evidence for the safe haven hypothesis is not surprising as investors may not react to extreme negative 1-min returns with a “flight” to stablecoins but rather delay their reactions to see if the 1-min returns are becoming more extreme over an hour or a day. Hence, we expect a stronger reaction over longer horizons as presented in Table 4 for hourly returns and Table 5 for daily returns.

The estimation results based on the hourly return frequencies indeed show larger coefficients for extreme Bitcoin returns and all stablecoins displaying negative coefficients for the largest negative Bitcoin returns except GUSD which exhibits a positive coefficient. More specifically, whilst USDT is positively correlated with and thus co-moves with Bitcoin for average returns (consistent with the unconditional correlation estimates presented in Table 2) but not for large negative returns, GUSD does not co-move with Bitcoin for average returns but for large negative returns.

The estimates render USDT a safe haven against Bitcoin whilst GUSD is not a safe haven.

For daily returns the coefficient estimates are generally larger and thus the reactions to extreme Bitcoin returns are stronger.[10] However, only Tether (USDT) shows a strong safe haven effect for the most negative Bitcoin returns (1% quantile). All other stablecoins either exhibit an insignificant coefficient consistent with a weak safe haven or a statistically significant positive coefficient estimate inconsistent with a safe haven and a stable coin.

In other words, Tether is a strong safe haven but not stable whilst the other stablecoins (except PAX) are weak safe havens.[11]

[9] The econometric analysis of the safe haven property will focus on Bitcoin as the largest cryptocurrency and the key trigger of flights to quality, in this case flights to stablecoins.

[10] The reactions to average Bitcoin returns are given by β_0 and qualitatively similar to the unconditional correlation estimates presented in Table 2.

[11] We also estimate time-varying correlations using rolling-window correlations and a DCC estimator. The dynamic correlation estimates clearly show that the correlations of stablecoins with Bitcoin are not stable supporting our regression results that stablecoins react to extreme Bitcoin returns and are therefore not stable. Detailed estimation results can be obtained from the authors.

Table 1
Descriptive Statistics. This table presents the descriptive statistics of hourly returns of stablecoins (USDT, USDC, TUSD, PAX, DAI, GUSD) and five largest traditional cryptocurrencies (BTC, ETH, XRP, BCH, LTC). Nobs is the number of observations.

	Mean (%)	Median (%)	Std.Dev (%)	Min (%)	Max (%)	Nobs
USDT	−0.000	0.000	0.112	−1.437	1.293	5426
USDC	−0.001	0.000	1.308	−63.045	67.188	5426
TUSD	−0.000	0.000	0.413	−10.980	12.869	5426
PAX	−0.000	0.000	0.302	−9.220	8.618	5426
DAI	−0.000	0.000	0.426	−3.150	3.622	5426
GUSD	−0.001	0.000	0.783	−33.056	29.025	5426
BTC	0.018	0.011	0.841	−7.798	10.962	5426
ETH	0.013	−0.006	1.116	−13.508	13.629	5426
XRP	−0.002	−0.003	0.998	−9.287	9.361	5426
BCH	0.013	−0.020	1.419	−12.867	14.792	5426
LTC	0.021	0.000	1.220	−14.901	10.863	5426

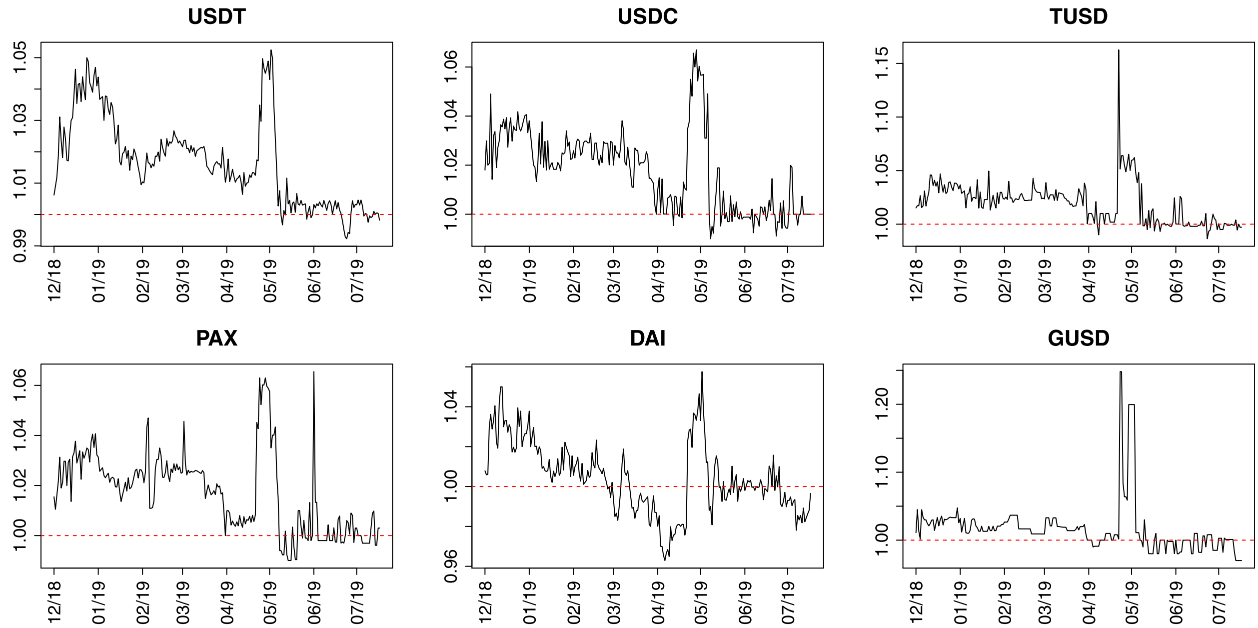

Fig. 1. Daily prices of stablecoins.

4. Summary and concluding remarks

This paper examines the safe haven property of stablecoins against extreme Bitcoin returns. If a stablecoin does not co-move with Bitcoin in times of extreme Bitcoin volatility, the stablecoin does exactly what its name suggests (with regard to Bitcoin), that is, being "stable," and additionally provides a weak safe haven. In contrast, if a stablecoin reacts positively to extreme negative Bitcoin returns, the stablecoin does not live up to its name, that is, being stable, but provides a strong safe haven. If a stablecoin reacts negatively to extreme negative Bitcoin returns, it is neither stable nor a safe haven.

The analysis of high-frequency and low-frequency stablecoin returns illustrates that stablecoins are not consistently and reliably stable at all times. More specifically, when Bitcoin experiences extreme negative returns, stablecoins generally react to these returns rendering them instable during such periods. However, many stablecoins including the largest stablecoin Tether positively react to extreme negative Bitcoin returns offering investors some protection and thus a safe haven. Although stablecoins might not fulfill the initial purpose for which they were created, i.e. being a stable cryptocurrency, they benefit the market in another way by providing investors with a strong crypto safe haven against an extremely volatile Bitcoin and by reducing overall risk in the cryptocurrency market.

Stablecoins are an interesting and potentially important sub-class of cryptocurrencies because they provide safety and stability to a generally very volatile and very risky asset class. Stablecoins could even be more stable than the most stable traditional "safe" assets such as US government bonds if their stability was based on an algorithm rendering them stable by design.

The design of stablecoins and the role of stablecoins as a safe asset may be interesting avenues for future research.

Table 2
Correlation matrix. This table displays the return correlations (Panel A) and squared return correlations (Panel B) between stablecoins and "non-stable" coins. Hourly return correlations are presented in the upper triangular part and daily correlations are presented in the lower triangular part of each correlation matrix. Bold numbers represent statistical significance at the 5% level.

Panel A: return correlations

	USDT	USDC	TUSD	PAX	DAI	GUSD	BTC	ETH	XRP	BCH	LTC
USDT	1	0.01	0.02	**0.09**	**0.08**	0.02	**0.25**	**0.24**	**0.19**	**0.15**	**0.20**
USDC	**0.36**	1	0.02	0.01	0.02	0.00	−0.00	0.00	0.01	0.01	0.02
TUSD	**0.20**	**0.19**	1	**0.08**	**0.05**	−0.00	−0.01	0.01	0.01	−0.00	0.01
PAX	**0.27**	**0.22**	**0.13**	1	0.02	0.01	−0.01	0.02	0.02	0.01	0.02
DAI	**0.39**	**0.25**	**0.28**	0.11	1	−0.02	**0.04**	**0.07**	**0.03**	**0.04**	**0.06**
GUSD	**0.18**	**0.14**	**−0.23**	0.08	**0.14**	1	**−0.03**	**−0.04**	-0.01	**−0.04**	**−0.05**
BTC	**0.15**	−0.04	−0.08	−0.02	0.07	0.09	1	**0.80**	**0.69**	**0.69**	**0.73**
ETH	**0.17**	0.03	−0.10	0.00	0.07	0.07	**0.79**	1	**0.76**	**0.73**	**0.80**
XRP	**0.18**	0.02	−0.04	0.01	0.12	0.07	**0.75**	**0.80**	1	**0.66**	**0.71**
BCH	**0.16**	−0.08	−0.06	0.04	−0.00	0.07	**0.73**	**0.72**	**0.63**	1	**0.71**
LTC	**0.18**	−0.02	−0.08	0.02	0.07	0.09	**0.72**	**0.78**	**0.71**	**0.70**	1

Panel B: squared return correlations

	USDT	USDC	TUSD	PAX	DAI	GUSD	BTC	ETH	XRP	BCH	LTC
USDT	1	−0.00	**0.03**	0.01	**0.18**	0.01	**0.41**	**0.28**	**0.20**	**0.16**	**0.26**
USDC	**0.34**	1	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	0.01	−0.00
TUSD	0.02	**0.22**	1	0.02	0.02	−0.00	0.01	0.01	0.00	0.01	0.00
PAX	0.03	0.03	**0.22**	1	0.02	−0.00	0.03	0.01	0.01	0.01	0.01
DAI	**0.16**	**0.31**	**0.67**	**0.17**	1	−0.00	**0.10**	**0.11**	**0.08**	**0.04**	**0.10**
GUSD	**0.12**	0.08	**0.34**	−0.01	−0.01	1	0.01	0.02	−0.00	**0.03**	**0.06**
BTC	**0.15**	**0.14**	0.01	−0.03	0.07	−0.03	1	**0.65**	**0.48**	**0.50**	**0.63**
ETH	**0.19**	0.11	−0.00	−0.02	0.04	−0.03	**0.54**	1	**0.61**	**0.60**	**0.73**
XRP	**0.10**	0.04	−0.02	0.01	0.10	−0.03	**0.43**	**0.53**	1	**0.51**	**0.55**
BCH	**0.13**	0.02	−0.01	−0.03	−0.02	−0.01	**0.35**	**0.30**	**0.21**	1	**0.61**
LTC	**0.19**	**0.17**	−0.02	−0.03	0.01	−0.03	**0.47**	**0.52**	**0.37**	**0.40**	1

Table 3
Regression results with 1-minute data frequency.

	Dependent variable					
	USDT (1)	USDC (2)	TUSD (3)	PAX (4)	DAI (5)	GUSD (6)
r_{BTC}	0.022***	−0.007	0.009***	0.002	0.024***	− 0.009***
	(0.001)	(0.004)	(0.001)	(0.002)	(0.003)	(0.002)
$r_{BTC} \times$ Dq$_1$(10%)	−0.002	−0.033	−0.015	− 0.061*	−0.017	0.064
	(0.014)	(0.082)	(0.029)	(0.032)	(0.049)	(0.048)
$r_{BTC} \times$ Dq$_2$(5%)	0.009	0.055	−0.005	0.056	−0.008	− 0.091*
	(0.015)	(0.089)	(0.031)	(0.035)	(0.053)	(0.052)
$r_{BTC} \times$ Dq$_3$(1%)	− 0.016***	−0.029	−0.004	−0.016	0.032	0.030
	(0.006)	(0.036)	(0.013)	(0.014)	(0.022)	(0.021)
Constant	− 0.00000***	0.00000	−0.00000	0.00000	−0.00000	0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Observations	322,247	322,247	322,247	322,247	322,247	322,247
R^2	0.004	0.00002	0.0002	0.0001	0.001	0.0001
Adjusted R^2	0.004	−0.00001	0.0002	0.0001	0.001	0.0001

Note: $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Estimates of α_i (Dq_i) not displayed to enhance readability. Model: $r_{\text{stablecoin},j} = \alpha_0 + \beta_0 r_{BTC} + \sum_{i=1}^{3} (\alpha_i Dq_i + \beta_i r_{BTC}\, Dq_i) + e_j$.

CRediT authorship contribution statement

Dirk G. Baur: Conceptualization, Methodology, Formal analysis, Writing - review & editing. **Lai T. Hoang:** Conceptualization, Formal analysis, Methodology, Writing - original draft, Writing - review & editing.

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Table 4
Regression results with hourly data frequency.

	Dependent variable					
	USDT (1)	USDC (2)	TUSD (3)	PAX (4)	DAI (5)	GUSD (6)
r_{BTC}	0.046***	−0.003	0.008	0.004	0.034***	− 0.030*
	(0.002)	(0.029)	(0.009)	(0.007)	(0.009)	(0.017)
r_{BTC} × Dq_1(10%)	−0.042	−0.218	−0.163	0.188	0.012	0.135
	(0.058)	(0.701)	(0.221)	(0.161)	(0.228)	(0.418)
r_{BTC} × Dq_2(5%)	0.046	0.295	0.191	−0.205	0.065	− 0.781*
	(0.061)	(0.733)	(0.231)	(0.169)	(0.238)	(0.437)
r_{BTC} × Dq_3(1%)	− 0.050**	−0.114	− 0.243***	− 0.196***	− 0.184**	0.792***
	(0.021)	(0.257)	(0.081)	(0.059)	(0.084)	(0.153)
Constant	− 0.00005***	−0.00001	−0.00003	−0.00000	−0.00005	−0.00002
	(0.00002)	(0.0002)	(0.0001)	(0.00004)	(0.0001)	(0.0001)
Observations	5426	5426	5426	5426	5426	5426
R^2	0.073	0.0001	0.005	0.008	0.004	0.008
Adjusted R^2	0.072	−0.001	0.003	0.007	0.002	0.007

Note: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. Estimates of α_i (Dq_i) not displayed to enhance readability. Model:$r_{\text{stablecoin},j} = \alpha_0 + \beta_0 r_{BTC} + \sum_{i=1}^{3} (\alpha_i Dq_i + \beta_i r_{BTC}\ Dq_i) + e_j$.

Table 5
Regression results with daily data frequency.

	Dependent variable					
	USDT (1)	USDC (2)	TUSD (3)	PAX (4)	DAI (5)	GUSD (6)
r_{BTC}	0.043***	−0.016	−0.047	0.002	0.0004	0.087
	(0.011)	(0.022)	(0.039)	(0.021)	(0.021)	(0.062)
r_{BTC} × Dq_1(10%)	0.241	0.803**	−0.151	1.633***	0.242	0.441
	(0.192)	(0.395)	(0.706)	(0.391)	(0.389)	(1.129)
r_{BTC} × Dq_2(5%)	−0.205	−0.751	0.612	− 1.510***	−0.076	−1.029
	(0.231)	(0.476)	(0.851)	(0.471)	(0.468)	(1.360)
r_{BTC} × Dq_3(1%)	− 0.718*	−1.004	−1.610	0.720	0.141	0.754
	(0.380)	(0.782)	(1.399)	(0.775)	(0.770)	(2.236)
Constant	− 0.001*	0.0001	0.0004	−0.0003	0.0002	−0.001
	(0.0003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Observations	225	225	225	225	225	225
R^2	0.114	0.030	0.017	0.089	0.023	0.021
Adjusted R^2	0.085	−0.001	−0.015	0.060	−0.009	−0.011

Note: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. Estimates of α_i (Dq_i) not displayed to enhance readability. Model:$r_{\text{stablecoin},j} = \alpha_0 + \beta_0 r_{BTC} + \sum_{i=1}^{3} (\alpha_i Dq_i + \beta_i r_{BTC}\ Dq_i) + e_j$.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.frl.2020.101431

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