Economics Bulletin

Volume 42, Issue 4

Tether points, price stability, and arbitrage efficiency

Huachen Li
Kenyon College

Abstract

Stablecoins rely on secondary market arbitrage to maintain price stability. This paper provides novel evidence about the peg mechanism of the largest stablecoin, Tether. Time-varying estimates of Tether points and speed of convergence of price deviation suggest the arbitrage mechanism has been increasingly effective at maintaining price stability. However, the state of the cryptocurrency market, convertibility, and advances in blockchain technology play an important role in Tether's price stability.

I thank John Conley (editor), three anonymous referees, and Tiezheng Song for their thoughtful comments and suggestions. All remaining errors are my own.

Citation: Huachen Li, (2022) "Tether points, price stability, and arbitrage efficiency", *Economics Bulletin*, Volume 42, Issue 4, pages 2193-2199

Contact: Huachen Li - li8@kenyon.edu.

Submitted: October 19, 2021. **Published:** December 30, 2022.

1. I troductio

Following the boom of the cryptocurrency market, stablecoins have gained much attention by investors, regulators, and researchers. s the largest stablecoin by market capitalization, Tether (USDT) is designed to be pegged at a 1:1 exchange rate to the U.S. Dollar (USD). lthough Tether is issued by a centralized issuer (Tether Limited, TL henceforth), the peg relies on arbitrage in the secondary market. When Tether trades at a premium (discount), arbitrageurs buy (sell) Tether at the parity rate from TL and sell (buy) Tether in the secondary market. This exerts downward (upward) pressure to Tether price towards the parity. Transaction costs and market risks entail a bound of Tether prices over which arbitrage would commence, i.e., Tether arbitrage only takes place when price sufficiently deviates from the peg. I refer to this threshold as the "Tether point".

This paper examines stablecoin arbitrage efficiency and its effect on price stability using Tether data. I ask *(i)* what are the prevailing Tether points, *(ii)* how efficient is the Tether market as measured by the speed of price deviation adjustment, and *(iii)* what factors affect Tether's arbitrage efficiency.

I answer these questions by estimating a rolling window band-threshold utoregressive (Band-T R) model using daily data on Tether prices. This model simultaneously captures the evolution of convergence (i.e., Tether points) and efficiency (i.e., the speed at which excessive price reverts). Following Canjels et al. (2004) and Li (2015), the baseline model is a restricted T R with symmetric thresholds, which implies an optimal arbitrage model. Results from generalized reduced-form models are also provided as a robustness exercise.

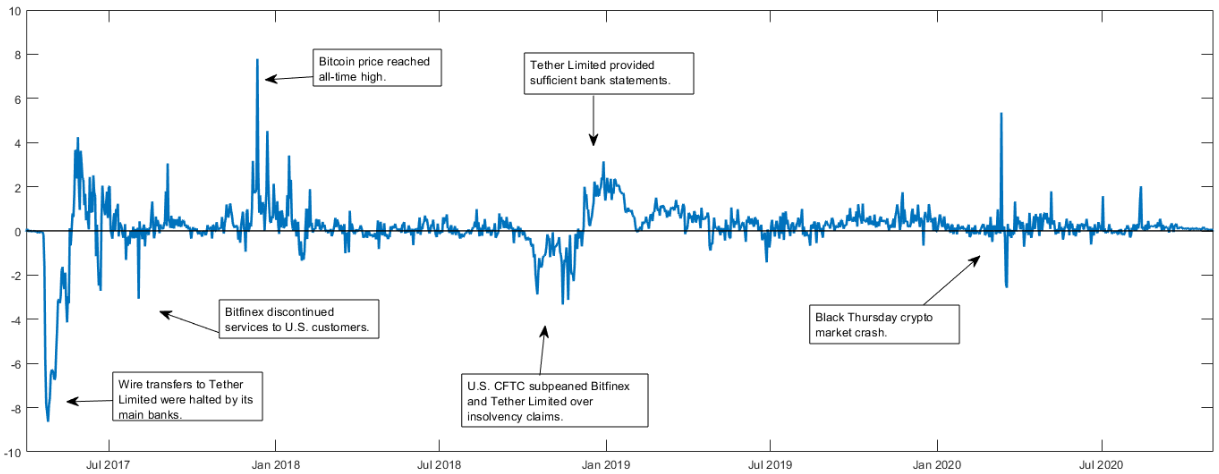
Substantial improvement in Tether's market integration and arbitrage efficiency are found. The full sample estimate of Tether point is 0.23%, but the rolling window results suggest Tether point peaks in 2017 and declines since. This correlates with concerns regarding TL's alleged insolvency and Bitcoin price manipulation scandal in 2017Q4. Similarly, the half-life of excessive price reversion decreases from 6 days in 2018 to about 1 day in 2020. Migration to advanced blockchain technology and restoration of investor confidence are linked to increase in arbitrage efficiency and hence price stability.

To the best of my knowledge, this paper is the first to empirically document the arbitrage mechanism of a stablecoin. Novel time-varying evidence about Tether points and price convergence provides an explanation for volatility in stablecoin prices. These findings contribute to a developing literature on stablecoins (for example, Lyons and Viswanath-Natraj 2020) and present a challenge to the literature that assumes Tether parity always holds (Wei 2018, Baur and Hoang 2020, among others).

2. Backgrou d a d Data

Tether's popularity arises as a low-volatility medium of exchange between crypto- and fiat-currencies. To achieve price stability, TL guarantees convertibility at the 1:1 rate by collateralization of one USD per circulated Tether. Define peg deviation $x_t \equiv (\ _t - 1) \times 100$, where $\ _t$ is Tether price in USD. Figure 1 plots x_t from 4/1/2017 to 11/1/2020 using

Fig. 1. Tether Peg Deviation



Notes: Daily sample is from 2017/04/01 to 2020/11/01. X-axis: sample date; y-axis: percent change.
Source: Coinmarketcap PI.

data from Coinmarketcap's PI.[1] The largest sample deviations are 7.79% above peg and 8.64% below peg. On average, Tether trades at a premium of 0.16% with a standard deviation of 1.10%. Visual inspection and unit root tests suggest x_t is observationally equivalent to an I(0) series.

Figure 1 suggests comovement between peg deviation and state of the cryptocurrency market. For example, claims about TL's insolvency in pril 2017 and November 2018 and Bitcoin price manipulation (Wei 2018) correspond to large discounts in Tether price. Similarly, Bitfinex's service discontinuation to U.S. customers and the recent crypto market crash of March 2020 also link to sizable fluctuations in Tether price. These observations suggest disruptions to the cryptocurrency market could affect Tether's arbitrage mechanism. Thus, documenting the efficiency of Tether's arbitrage mechanism sheds light on the degree of Tether price stability and its functionality as a stablecoin.

3. Model a d Results

3.1. Restricted T R

Consider the following specification

$$\Delta x_t \quad \begin{cases} -\lambda(x_{t\;1} - \gamma) + \epsilon_t^O & \text{when } x_{t\;1} > \gamma \\ \epsilon_t^I & \text{when } |x_{t\;1}| \leq \gamma \\ -\lambda(x_{t\;1} + \gamma) + \epsilon_t^O & \text{when } x_{t\;1} < -\gamma \end{cases}, \tag{1}$$

[1]Daily trading volume of USDT consistently surpasses $10M after 4/1/2017. Note low volume may induce excessive price volatility.

where Δ denotes the first-difference operator, $\epsilon_t^O \sim N(0, \sigma_O^2)$, and $\epsilon_t^I \sim N(0, \sigma_I^2)$. The symmetric threshold $[-\gamma, \gamma]$ is labeled as Tether points. rbitrage is profitable when $|x| - \gamma > 0$, i.e., when marginal revenue of arbitrage exceeds marginal cost. rbitrage flow drives the peg deviation towards the nearest γ at a speed of convergence λ, which measures the fraction of peg deviation adjustment in one day.

Peg deviation is assumed to follow a driftless random walk within Tether points. This is equivalent to no reversion to parity in the middle regime. Heteroskedasticity across regimes is allowed by differentiating the stochastic white noise processes when peg deviation is inside (ϵ_t^I) and outside (ϵ_t^O) the thresholds.

The model is estimated using conditional least squares of the following steps: *(i)* run OLS regression of each regime given values of γ, and *(ii)* conduct a grid search on γ that minimizes the sum of squared residuals of the model. I set a 15% trimming sample for the grid search with a coarseness of 0.001.[2] This results in a dense grid of about one million grid points given the sample size.

First, I estimate (1) with the entire sample. The 15% trimming is equivalent to the restriction that Tether points fall within the interval of $[4.26e \;\; {}^{5}, 0.99]$. The estimated threshold coefficient γ is 0.23. This suggests arbitrage flow begins to work as a price stabilization mechanism when the price deviates more than 23 basis points from parity. Thus, Tether's arbitrage-based peg is, on average, effective as the sample average peg deviation of 0.16% is well within the estimated Tether points.

Exploitable arbitrage opportunities arise frequently. Tether trades at a premium in the upper regime for 585 days and at a discount in the lower regime for 195 days. This leaves the middle regime with 531 days, or 40.5% of the sample. However, these arbitrage opportunities are short-lived. The estimated λ is 0.1834 with a standard error of 0.0169, which corresponds to a half-life of price convergence of 3.42 days.[3] bout 75% of the price deviation in the upper or lower regimes diminishes within a week.

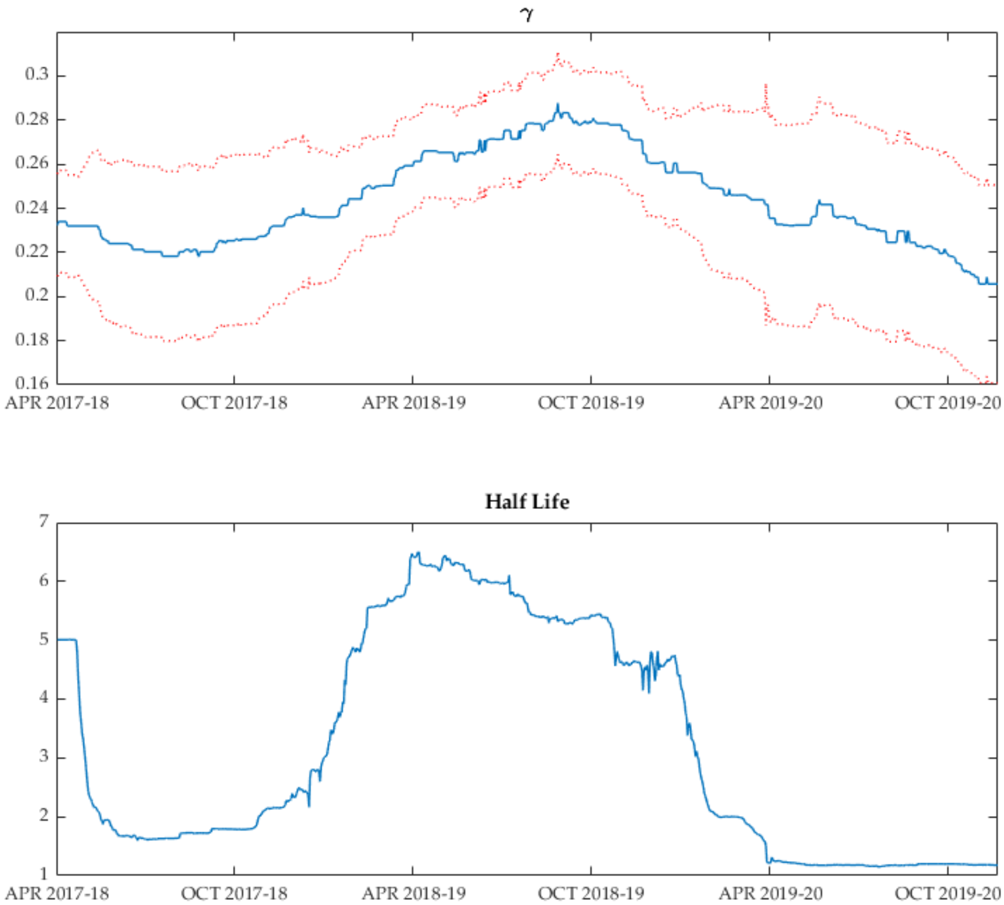
Next, as discussed in Section 2, a natural question is whether or not Tether price stability and arbitrage efficiency evolve over time. I extend the exercise to estimate (1) on a rolling window of fixed length.[4] Figure 2 plots the rolling window estimates in solid blue line and 90% confidence bands in dotted red lines. First, the estimated γ (upper panel) increases in early samples and peaks during the September 2018-2019 sample at 29 basis points. The peak corresponds to a period of low investor confidence when Tether was subpoenaed by the U.S. Commodity Futures Trading Commission for alleged insolvency. Estimated γ declines and reaches the lowest estimate towards the end of the sample as Tether weathered through the crisis. These results are evidence that γ comoves with the

[2] The T R literature suggests trimming values of 5% to 15%. See, for example, Canjels et al. (2004). Different trimming values do not qualitatively alter the results of this paper. ppendix B provides more details on estimation.

[3] The half-life of price convergence, i.e., the number of days for the peg deviation to revert half way to the closest Tether point, is computed as $\tilde{\lambda} \quad \frac{l \quad 0.5)}{l \quad 1 \quad \lambda)}$.

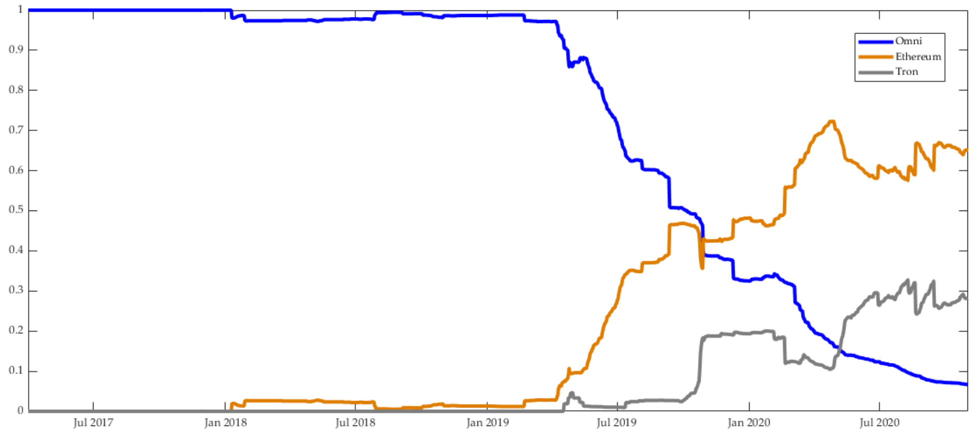
[4] I explore different window sizes between 180 to 540 and settled with 360 observations. This results in 950 rolling window estimates beginning from the sample [4/1/2017, 3/26/2018] and ending at [11/9/2019, 11/1/2020]. Shorter or longer window sizes do not alter the qualitative findings of the exercise. Note a longer window smooths out the trends while a shorter window is sensitive to changes in the data. s suggested by a reviewer, I also report estimates of a time-varying threshold model in ppendix C as a robustness check.

Fig. 2. Rolling Window Restricted T R Estimates



Notes: Rolling window estimates (blue solid line) and 90% confidence bands (red dotted lines) of the threshold coefficient and the half-life of price convergence are plotted. The rolling window size is 360. Half-life is computed as $\tilde{\lambda} \quad \frac{l \quad 0.5)}{l \quad 1 \quad \lambda)}$. The sample period is 4/1/2017 to 11/1/2020. X-axis: Rolling window sample range; y-axis: percentage points ( ) and number of days (half-life).

Fig. 3. Share of Tether in Circulation



Notes: The figure plots Tether per blockchain (Omni in blue, Ethereum in orange, and Tron in gray) as a fraction of total Tether in circulation. The sample period is 4/1/2017 to 11/1/2020. X-axis: sample dates; y-axis: supply share as a fraction.
Source: Coinmetrics PI.

perceived state of Tether.

The lower panel of Figure 2 displays substantial time variation in the half-life of excessive price convergence. The U-shaped movement in the early sample around 2017Q4 has a trough of 2 days. Note a similar trough of γ can be observed around the same time, which correlates with the peak of cryptocurrency bubble of 2017. Following the 2018 crypto market crash and doubts about Tether's insolvency, the half-life slows down by threefold and peaks at over six days in the 2018-2019 samples. These estimates significantly improve during the cryptocurrency boom in 2019 and settle at around one day in the late sample.

doption of new blockchain technology also appears to be important for the decline of half-life. Originally issued on the Omni blockchain, Tether's migration to Ethereum (ERC-20) and Tron (TRC-20) improved arbitrage efficiency because these protocols have faster withdrawal confirmations, among other technological improvements.[5] Figure 3 plots Tether per blockchain as a fraction of total supply. The sharp increase of Tether on Ethereum and Tron since May 2019 reinforces these findings.

In sum, implications of the restricted T R results are threefold. First, economically meaningful time variation in γ and the half-life suggest the state of Tether's solvency matters for both coefficients, but speed of adjustment is more volatile than the estimated Tether points. Second, boom and busts of the cryptocurrency market affect Tether points and half-life in a similar fashion. crypto-market boom (bust) corresponds to lower (higher) Tether points and a shorter (longer) half-life of price adjustment. Third, technological advances in blockchain promote arbitrage efficiency and hence reduce Tether price

[5] The average expected block time for Omni, Ethereum, and Tron protocols are 10 minutes, 19 seconds, and 15 seconds. Block time is the time required to create a new block in a blockchain, i.e., time required to confirm a transaction.

volatility.

3.2. *Unrestricted T R*

s a robustness test, I generalized the previous model to two th order T R models with R regimes and a delay parameter d,

$$x_t \quad \sum_{j \quad 1}^{R}(\beta_{0,j} + \sum_{i \quad 1} \beta_{\ ,j} x_{t \quad i} + \epsilon_{t,j}) \ \ (\gamma_j, x_{t \quad d}), \tag{2}$$

where $\beta_{0,j}$ is the constant, $\beta_{\ ,j}$ represents the regression coefficients on the lags of x_t, $\epsilon_{t,j}$ denotes the region specific error terms, and $(\gamma_j, x_{t \quad d})$ $\quad (\gamma_{j \quad 1} < x_{t \quad d} < \gamma_j)$ is an indicator function that is equal to one if $x_{t \quad d}$ is within the j^{th} region. series of T R models are estimated with $R \leq 3$, $1 \leq \quad \leq 30$, $1 \leq d \leq$, and a 15% trim to be consistent with the baseline model. T R$(3, 2, 1)$ is selected as the optimal model following the advice of IC and BIC.

I first report results from a T R$(3, 2, 1)$ with asymmetric threshold and speed of adjustment.[6] The estimated Tether points are [-0.27%, 0.49%] for the entire sample. This is similar to estimates of the restricted T R. larger upper regime γ^u estimate indicates arbitrageurs require a higher return when the peg deviates positively. This also results in a larger number of samples in the middle regime.

The speed of price adjustment is allowed to be regime dependent. In the upper regime, the estimated β_1 and β_2 are 0.31 with 1% significance. This translates to a half-life of price convergence in the upper regime of 1.45 days. For the lower regime, the estimate of β_1 is 0.85 at 1% confidence level, but β_2 is not accurately estimated. This suggests the half-life in the lower regime is between 4.27 days and 16.98 days. Thus, the average half-life approximates the baseline estimate of 3.4 days, but price deviations converge faster in the upper regime.

The asymmetry of the convergence speed between regimes could be attributed to the design of the arbitrage mechanism. When Tether trades at a premium, TL can purchase and issue new Tether using its own liquidity and sell in the secondary market. In contrast, TL cannot reverse the arbitrage when Tether is trading at a discount. This is because arbitrageurs are to purchase Tether in the secondary market and redeem USD at peg from TL. Thus, asymmetric participation between the regimes could result in the estimated differences in arbitrage efficiency.

Finally, a T R$(3, 2, 1)$ with symmetric threshold and speed of convergence suggests a threshold estimate of 0.20 and half-life of price convergence of 4.6 days. These estimates are qualitatively and quantitatively similar to those of the restricted model. Thus, estimates from both flexible unrestricted T Rs are generally in line with the restricted T R, with the exception of the larger upper regime threshold.

---

[6] ppendix D reports additional estimates of the generalized T R models.

4. Co cludi g Remarks

This paper empirically documents the price stability and market efficiency of Tether, the largest stablecoin since 2017. Threshold autoregression models produce economically meaningful results about Tether points and the evolution of market efficiency. The findings are *(i)* exploitable arbitrage opportunities are frequent and can account for up to 60% of the sample, *(ii)* these arbitrage opportunities diminish quickly as the half-life of excessive price convergence averages about 4 days, and *(iii)* significant time variation exists in the estimated threshold and speed of convergence.

Tether's mechanism to maintain price stability through arbitrage has been effective, but the efficiency depends on the state of the cryptocurrency market and improvement in blockchain technology. This paper sheds light on three factors that keep the peg of stablecoin stable: conversion credibility, blockchain technology, and state of the cryptocurrency market. s stablecoins become a vital part of the cryptocurrency market, these factors are important to optimal stablecoin design. Quantifying the effect of these factors on price stability is another important question which I leave for future research.

Refere ces

Baur, D. G. and Hoang, L. T. (2020). crypto safe haven against bitcoin. *Finance Research Letters*.

Canjels, E., Prakash-Canjels, G., and Taylor, . (2004). Measuring market integration: Foreign exchange arbitrage and the gold standard, 1879-1913. *The Review of Economics and Statistics*, 86(4):868–882.

Hansen, B. E. (2000). Sample splitting and threshold estimation. *Econometrica*, 68:575–603.

Li, L.-F. (2015). Information asymmetry and the speed of adjustment: Debasements in the mid-sixteenth century. *Economic History Review*, 68(4):1203–1225.

Lyons, R. K. and Viswanath-Natraj, G. (2020). What keeps stablecoins stable? *Working Paper*.

Obstfeld, M. and Taylor, . M. (1997). Nonlinear aspects of goods-market arbitrage and adjustment: Heckschers commodity points revisited. *Journal of the Japanese and International Economies*, 11(4):441–479.

Wei, W. C. (2018). The impact of tether grants on bitcoin. *Economics Letters*, 171:19–22.

Zhu, Y., Chen, H., and Min, L. (2019). Threshold models with time-varying threshold values and their application in estimating regime-sensitive taylor rules. *Studies in Nonlinear Dynamics & Econometrics*, (20170114).