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The instability of stablecoins

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ABSTRACT

This paper examines the stability of the five largest stablecoins in terms of market capitalization through a fractional time series analysis. By using hourly data of Tether, USDC, Binance USD, DAI and PAX Dollar, we find strong evidence of instability of stablecoins, although these deviations from the $1 mark are gradually corrected at different speeds for all stablecoins except for DAI. For the latter, the deviations do not converge even in the long-run due to non-stationarity of the differentiated series between its price and the $1 mark. BUSD is found as the most stable stablecoin with the fastest correction speed. Further rolling-window analysis shows that stability of different stablecoins exhibits strong co-movement and time-variation.

1. Introduction

Cryptocurrencies are growing in terms of attention and popularity, with increasing investors trading these new innovative assets. Stablecoins are a brand of cryptocurrency that are pegged to fiat currencies or assets that are relatively stable, such as the US dollar. They are designed by maintaining a peg (usually one-to-one) with an official numeraire, and hence are ideal for investors who want to realize their profits into a safe asset while not leaving the cryptocurrency ecosystem, as well as their settlement speed and faster transfer of funds between different entities.

Recently, stablecoins have faced criticism and unwanted attention due to ongoing empirical evidence on stablecoins' instability depicted by large dependence between stablecoins and other cryptocurrencies including Bitcoin Grobys and Huynh (2021), Kristoufek (2021). This therefore raises a question of how stable they actually are? However, there exists little literature studying the stability of stablecoins, where (Grobys et al., 2021) show that stablecoins are unstable due to infinite theoretical variances of their volatility while Bitcoin volatility is instead statistically stable. They also find that Bitcoin exhibits volatility spillover effects on stablecoins. Hoang and Baur (2022) find strong evidence of excess price variations of stablecoins while also noting a correlation between trading volumes of stablecoins and Bitcoin. In addition, existing limited applications mainly focus on the presence of stability of stablecoins, failing to answer whether the instability, if any, can be corrected and the corresponding correction speed.

This paper advances the literature by studying the stability of the five largest stablecoins in terms of market capitalization by analyzing stationarity of deviations of the stablecoins price from the $1 mark. (In)stability and the correction speeds can be investigated by measuring the fractional integration order of the differentiated series. By employing intra-day data, we find that stablecoins show different extents of deviations from the $1 value, indicating clear evidence of instability. Except for DAI, the other four stablecoins become stable in the long-run as their deviations diminish gradually over time. Binance USD (BUSD) is found to be the most stable one with the highest correction speed, while DAI is the least stable and its deviations from $1 cannot be corrected instead.[1] Rolling-window analysis depicts a co-movement of such deviations across different stablecoins, which stability further depicts an evident variation over time.

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[1] DAI is the only one of our stablecoins that is not minted by a central organization.

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Table 1
Descriptive statistics of stablecoins prices.

Name	Ticker	Market cap	Start date	End date	No. obs	Mean	Median	Std. Dev	Max	Min
Tether	USDT	$74.1 billion	17/02/2018	18/05/2022	37248	1.0016	1.0007	0.0052	1.0868	0.9485
USD Coin	USDC	$52.3 billion	24/10/2018	18/05/2022	31272	1.0029	1.0004	0.0060	1.0565	0.9578
Binance USD	BUSD	$18.4 billion	20/09/2019	18/05/2022	23320	1.0012	1.0002	0.0347	6.2885	0.9552
DAI	DAI	$6.5 billion	22/22/2019	18/05/2022	21814	1.0035	1.0011	0.0077	1.1224	0.9464
PAX Dollar	USDP	$0.95 billion	28/09/2018	18/05/2022	31898	1.0024	1.0009	0.0053	1.0691	0.6124

Table 2
Stability feature of stablecoins. This table summarizes the stationarity of y_t (i.e., the differentiated series of stablecoin price and $1) and the associated stability feature of the target stablecoin with various d values.

d value	Memory pattern of y_t	Stationarity of y_t	Stability of stablecoin
$d = 0$	Short	Stationary	Stable
$0 < d < 0.5$	Long	Stationary	Stable
$0.5 \leq d < 1$	Long	Non-stationary	Unstable
$d = 1$	Permanent	Non-stationary, unit root process	Unstable
$d > 1$	Permanent, explosion	Non-stationary, explosive process	Unstable

Table 3
Estimation of fractional integration order (d) of the five stablecoins examined at various bandwidths.

Bandwidth	Tether	USDC	BUSD	DAI	PAX
0.4	0.3093	0.2700	0.1734	0.3688	0.3050
0.5	0.3996	0.3582	0.2656	0.4621	0.3586
0.6	0.4608	0.4195	0.3240	0.5285	0.3986
0.7	0.4880	0.4457	0.3562	0.5500	0.4004
0.8	0.4710	0.4407	0.3514	0.5358	0.3784

The rest of this paper is organized as follows. Section 2 outlines the data and methodology while Section 3 presents our results. Finally, Section 4 provides conclusions.

2. Data and methodology

2.1. Data

We collect data from Glassnode[2] which provides details on various cryptocurrencies including stablecoins. Glassnode is a blockchain data and intelligence provider that generates innovative on-chain metrics and tools for digital asset stakeholders, and has been used in previous studies such as (Urquhart, 2021). We collect open, high, low and close prices of five of the largest stablecoins, namely Tether (USDT), USD Coin (USDC), Binance USD (BUSD), DAI and Pax Dollar (USDP) from 24th October 2018 to 18th May 2022.[3] The total market capitalization of the stablecoin market is over $180 billion and the five coins we study capture over 90% of the market. The start date of each stablecoin is due to data availability and we employ hourly data as this is the highest frequency available on Glassnode. Using hourly data enables us to study the intraday stability of stablecoins which is an unexplored area of research.

Table 1 reports descriptive statistics of our stablecoins where we show that the total market capitalization of our five stablecoins is over $150 billion. What is noticeable is that the mean price for each stablecoin is not exactly $1 but varies from $1.0012 for BUSD to $1.0035 for USDP. This indicates that there must be some periods in which these stablecoins are not close to their $1 peg. Such a deviation pattern is also reflected in the positive and relatively high standard deviation of their prices, as well as the maximum and minimum values. Specifically, BUSD has a maximum price of $6.2885 where the other stablecoins do not have a maximum never have a price over $1.13. In terms of minimum values, USDP has a minimum value of $0.6124 while the other stablecoins do not fall lower than $0.94. Therefore, from our basic descriptive statistics of the prices of our stablecoins, we can see that stablecoins often deviate from the $1 peg and there is some variation in their prices.

2 www.glassnode.com
3 According to www.coinmarketcap.com as of 19th May 2022, the top 7 largest stablecoins in terms of market capitalization are USDT, USDC, BUSD, DAI, TUSD, UST and USDP. However Glassnode does not provide data on TUST or UST and therefore we cannot include them in our analysis.

Table 4
Additional estimation of fractional integration order (d) of the five stablecoins examined at various bandwidths (Dropping the first 20% of the sample).

Bandwidth	Tether	USDC	BUSD	DAI	PAX
0.4	0.3571	0.2506	0.2133	0.3487	0.2664
0.5	0.4312	0.3120	0.2789	0.4400	0.3152
0.6	0.4791	0.3876	0.2969	0.4884	0.3528
0.7	0.5021	0.4254	0.3367	0.5139	0.3629
0.8	0.4836	0.4258	0.3240	0.4917	0.3492

2.2. Methodology

2.2.1. Fractional integration order and stability

A time series (y_t) with a positive integration order (d) is formulated as

$$(1-L)^d y_t = \psi(L)\varepsilon_t \tag{1}$$

where $(1-L)^d$ is the difference operator of order d. $\sum_{j=0}^{\infty} |\psi(L^j)| < \infty$ to ensure that y_t is stationary after differentiating d times. $\varepsilon_t \sim iid(0, \sigma^2)$. Unlike conventional assumption of integer d, it is relaxed to be any positive real number as either an integer or a fraction. The integration order (d) of y_t, i.e., difference between $1 and prices of a target stablecoin in our case, characterizes its stationarity, shedding light on 'stability' of the stablecoin Duan et al. (2021).

Extending to the fractional domain, y_t is known to be stationary so long as $d < 1/2$ rather than in the domain of integer as $d = 0$. Given the fact that a stablecoin is 'stable' only when its price dynamics converge to $1 in the long-run, such the convergence can be examined by analyzing whether the differentiated series of the target price and $1 (i.e., y_t) is stationary. That is, the stablecoin is stable only when d of y_t is less than 1/2, indicating that the short-run deviation from the pegged $1 can be corrected in the long-run. The greater the d, the higher correction speed and more stable the target stablecoin would be. In contrast, the stablecoin is unstable if the d value of y_t is greater than 1/2. The following Table 2 summarizes the stability property of a target stablecoin associated with various d values of y.

2.2.2. Local Whittle estimator

While log periodogram (LP) regression and local Whittle (LW) estimation are the two commonly used semi-parametric d estimators, LW estimation that involves numerical methods is known to be more efficient than LP regression (Phillips and Shimotsu, 2004). Developed by Robinson (1995), LW estimator starts by minimizing the below objective function.

$$Q_m(G,d) = \frac{1}{m}\sum_{i=1}^{m}\left[log(G\lambda_j^{-2d}) + 1/GI_{(1-L)^d Y_t}(\lambda_j)\right] \tag{2}$$

Concentrating $Q_m(G,d)$ with regard to G, the LW estimator of d is defined as

$$\hat{d} = \underset{d\in[\Delta_1,\Delta_2]}{\arg\min}\, R(d) \tag{3}$$

where m is the truncation parameter of the function, Δ_1 and Δ_2 define lower and upper bounds of admissible values of d such that $-1/2 < \Delta_1 < \Delta_2 < +\infty$, and

$$R(d) = log\hat{G}(d) - 2d\frac{1}{m}\sum_{i=1}^{m} log(\lambda_i) \tag{4}$$

Following Robinson (1995), LW estimator is consistent for $d \in (-1/2, 1)$ and asymptotically normally distributed for $d \in (-1/2, 3/4)$. As a further extension by Phillips and Shimotsu (2004), LW estimator has a normal limit distribution for $d \in [3/4, 1)$, and a mixed normal limit distribution for $d = 1$.

3. Empirical results

3.1. Price clustering

Following (Berk et al., 2017) we study the frequency price clustering for all hourly prices. We use three decimal places around the $1 and report the frequency of the hourly closing stablecoin prices in Fig. 1. We can see that BUSD is the most successful at closing each hour at $1.000, with nearly 50% of all closing hourly prices at $1.000. Only 23% of hourly closing prices are at $1.000 for DAI suggesting that out of the five stablecoins, it is the worst at keeping at the $1.000 price. We also note that across all five stablecoins, closing prices are not normally distributed around the $1.000 mark. Specifically, all stablecoins appear to show positive skewness with more observations greater than $1.000 rather than less than $1.000. This indicates that stablecoins tend to be overpriced more of the time rather than be underpriced. We also show that USDC and DAI have more extreme values than the other three stablecoins, with 13% and 14% of their observations less than $0.988 or greater than $1.012 respectively, indicating their large volatility.

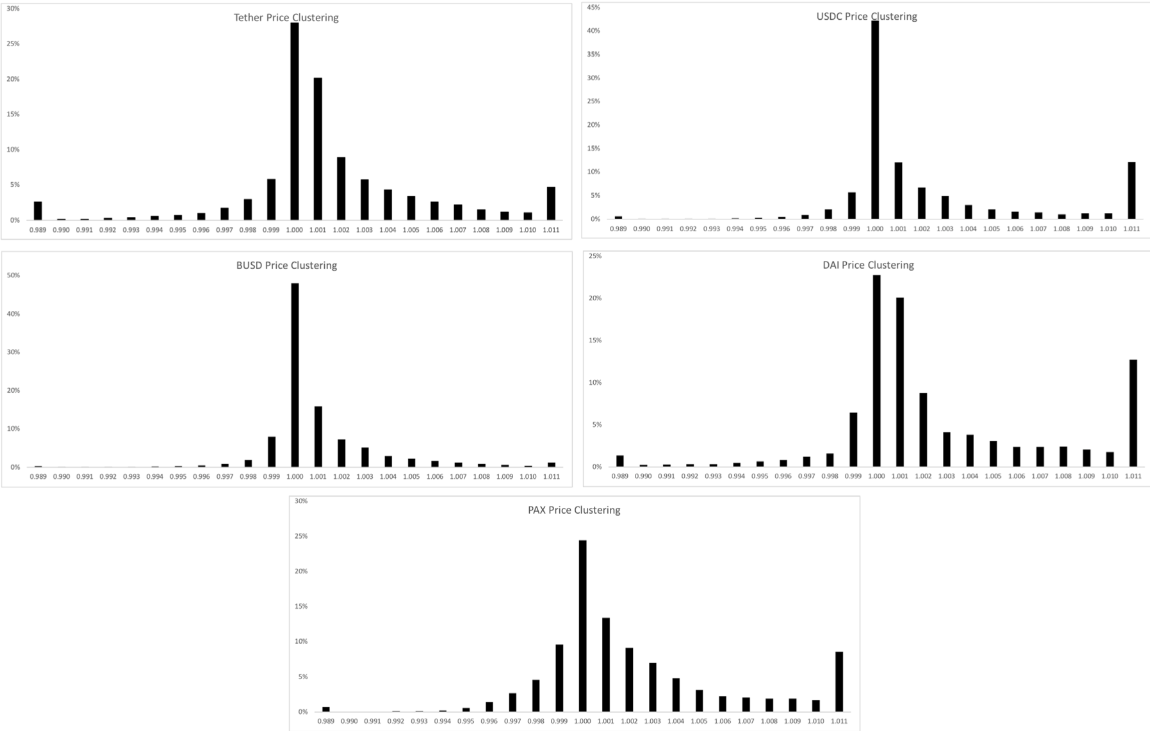

Fig. 1. This figure presents the percentage price clustering of hourly stablecoin closing prices. Specifically, we report the percentage of times that price of each stablecoin closes on a specific price. Note that first (last) x-axis value includes any closing price that is lower (high) than that price.

3.2. (In)stability: Evidence from fractional time series analysis

The previous analysis provided evidence of stablecoins deviating away from their $1.000 mark. To provide further statistical evidence of (in)stability, we study the fractional integration order (d) of the difference between the price of stablecoins and the $1.000 mark where they should converge to. We report d values of the differentiated series of five target stablecoins at various bandwidths estimated by using the Local Whittle method in Table 3.[4] Overall, within the sample of our high frequency dataset, the average d value for each stablecoin at nearly all bandwidth is less than 0.5 except for DAI at higher bandwidths, indicating that most of the stablecoins under research can converge to stability in the long run. In specific, DAI is found to be unstable with its d value greater than 0.5, showing that its short-run deviation cannot converge in the long-run. The other four stablecoins possess stable feature with their d values less than 0.5 at various conditions, and BUSD is shown to be the most stable one with the lowest d value. Among the four stable stablecoins, the orderly ranking of the ones with higher convergence speeds towards the pegged $1 is BUSD, PAX, USDC, and Tether.

By far, our finding is drawn based on an average setting of the data sample, which might loss information that the stability feature of stablecoins could vary over time. To study the underlying time-variation of the stability of each of the target stablecoins, a rolling window estimation for d is further conducted where the window size is constantly set as one week. The time-varying d series estimated by the LW estimator with bandwidth 0.7 is then plotted in Fig. 2. Specifically, the d value of the five stablecoins tends to be highly correlated at the start of the sample period but there appears to be large differences of d around August 2020 and in early 2021 when the Bitcoin bull run of 2021 was beginning. There is also quite a large deviation in values of d in the periods when stablecoins have the highest and the lowest magnitudes of d, respectively. In line with our results in Table 3, BUSD is shown to have the largest number of rolling-windows, i.e., more than 70% of the total windows, where BUSD is stable with d less than 1/2. DAI is found to be the most unstable one where only around 36% of all the rolling window have its d less than 1/2. Overall, the results of dynamic rolling-window analysis are consistent with the static analysis, and further indicate that there exists a co-movement between the deviations from $1.000 of the five stablecoins, and the stability of stablecoins tends to vary dramatically over time.

[4] To select the optimal bandwidth within a wide range of 0.4–0.8, we have followed Kumar and Okimoto (2007) by comparing the sample mean squared error (MSE) of the calculation of the fractional integration order d using different bandwidths through simulation. The bandwidth 0.7 is then selected due to its lowest MSE among others.

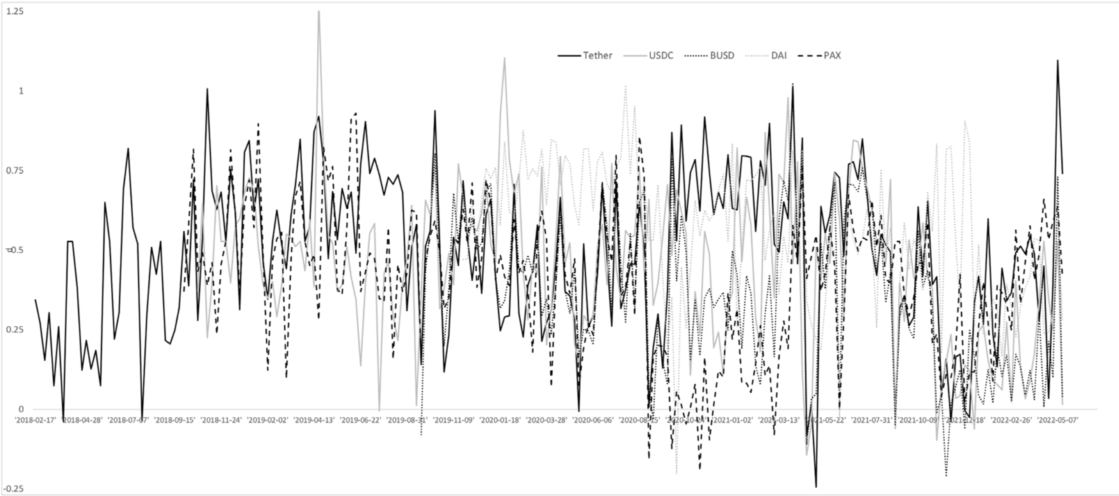

Fig. 2. This figure presents the fractional integration over time of our five stablecoins.

3.3. Robustness

As pointed out by one of the reviewers, stablecoins typically exhibit high volatility in the initial period after their launch. Therefore it would be interesting to include a robustness check to see how the results look like after excluding the first 20% of the sample. Table 4 reports our findings and it is clear that our results remain consistent thereafter that price deviations from $1 tend to converge for all the stablecoins except for DAI, which features instability with its associated d being greater than 0.5. BUSD is the most stablecoin, indicating that its price convergence towards $1 is relatively quicker than others under research.

4. Summary and conclusions

This paper examines stability of stablecoins by testing stationarity of the differentiated series of the target stablecoin's price and the $1 mark using the fractional time series analysis. We find that while the five stablecoins show clear deviations from their pegged $1, most of such deviations can be corrected towards stability with different speeds except for DAI. Rolling-window analysis shows that there is a co-movement of the extent of deviation of stablecoins' prices from $1, and such the (in)stability features an evident variation over time. In future research, we suggest the literature addresses the differences between stablecoins and the corresponding determinants. Future research could also examine how the collapse of the Terra stablecoins has impacted the market for stablecoins.

But why is DAI the least stable of our stablecoins. DAI is quite different to the other stablecoins we study. DAI maintains its value not by being backed by U.S. dollars custodied by a company, but by using collateralized debt denominated in ether (ETH), Ethereum's cryptocurrency. DAI is decentralized, which means that no centralized organization controls the supply of new DAIs in circulation. The Maker Protocol, through smart contracts running on Ethereum, enables borrowers to lock ETH and other crypto assets, thus collateralizing it, in order to generate new DAI tokens in the form of loans. If borrowers wish to recover the locked ETH, they will have to return the DAI to the protocol and pay a fee. In the event of liquidation, the Maker Protocol will take the collateral and sell it using an internal market-based auction mechanism. Due to its design, the supply of DAI cannot be altered by any party in the network. Rather, it is maintained through a system of smart contracts designed to dynamically respond to changes in the market price of the assets in its contracts. So these characteristics may explain why DAI is the least stable of our stablecoins.

Our paper has not included Terra, which was a popular stablecoin that collapsed in May 2022 as we wanted to study the stability of stablecoins that are still in use, in order to provide some implications for users of these assets. The impact of the Terra collapse on the market is still relatively unknown but given, at the time of writing, it has been 6 months since the collapse, future research could study the impact that Terra had on the market, specifically how other stablecoins reacted and which (if any) stablecoins became more popular since the collapse of Terra.

CRediT authorship contribution statement

Kun Duan: Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Andrew Urquhart:** Methodology, Formal analysis, Data curation, Writing – original draft, Writing – review & editing.

Data availability

The data that has been used is confidential.

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