Rating Stablecoins

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Abstract

We construct a rating method to assess the quality of stablecoins. Our evaluation measures for rating include price stability, liquidity, and network effects. In order to normalize values derived from the different measures to the same scale, we use the max normalization and provide its axiomatic characterization. Then we aggregate the normalized scores to a comprehensive rating value by the geometric mean, following the recent idea of welfare economics. Among the stablecoins we examined, we find that USDC is the best stablecoin and that the ranking of market capitalization is not equal to the ranking of rating. Our method is used in the project of Chainsight, which indexes various types of information about crypto assets.

Keywords: Stablecoin, Rating, Cryptocurrency, Time-series analysis, Max normalization

JEL Codes: G0, D7, D6.

1 Introduction

Since the advent of Bitcoin (Nakamoto 2009), one of the main raison d'être of cryptocurrencies has been the independence of any legal tender controlled by the central bank. However, independence does not imply separation. The value of cryptocurrencies and legal tenders can be converted to each other through exchange. A special characteristic of cryptocurrencies is that they can only be transferred on the blockchain that issues them. Stablecoins are expected to overcome this problem.

Any stablecoin is a cryptocurrency issued on a blockchain and pegged with some legal tender. For example, USDC is a cryptocurrency issued on various blockchains and is pegged with the United States Dollar (USD). In this way, USDC on a blockchain smoothly links the value system of USD with the value system on the blockchain.[1] Because of such importance, hundreds of stablecoins have been issued on a variety of blockchains.[2] However, it is not yet clear which stablecoins are superior in what respects. In fact, as far as we know, there does not seem to be rigorous discussion about measures to evaluate stablecoins.

One might think that the most important measure for a stablecoin is its market capitalization. However, market capitalization is not an indicator of convenience or similarity to legal tender. In fact, it does not represent the core properties of stablecoins, such as the degree of price deviation from legal tender, the speed with which the deviation shrinks, or

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[1]Vidal-Tomás (2023) discusses the importance of legal tenders and stablecoins as payment infrastructure.

[2]For example, see, https://coinmarketcap.com/view/stablecoin/

variables on the network effect on a particular blockchain. Given this situation, we shall establish a method to assess the quality of stablecoins based on their properties. Specifically, we evaluate stablecoins based on the average deviation of prices, price volatility, persistence of price deviations, liquidity on DEX, the number of active addresses, and transaction volume. We employ these six items as evaluation measures and give a score to each evaluation measure. We then aggregate six scores so obtained to a comprehensive rating value. Our aggregation function uses geometric mean, and the idea of using it is based on arguments in welfare economics.

A key step in scoring is the normalization of values derived from different evaluation measures. We use the max normalization and provide its axiomatic characterization to clarify its rationale (Theorem 1). We then compute the rating values of several stablecoins, including major and minor ones. Among the stablecoins we examined, we find that USDC is an outstandingly good stablecoin and that the ranking of market capitalization does not coincide with the ranking of rating. Therefore, in order to evaluate the quality of a stablecoin, we need to examine its evaluation measures themselves, rather than its market capitalization. Quantitative comparison is essential for users to make informed choices and for service providers to engage in healthy competition. Our method contributes to making it easier.

The remainder of this paper proceeds as follows. Section 2 introduces evaluation measures. Section 3 defines how to derive easy-to-compare scores for the evaluation measures and how to aggregate the scores into a rating value. Section 4 computes scores and rating values for several stablecoins. Section 5 discusses ways of normalization and briefly explains Theorem 1, which provides an axiomatic foundation of the max normalization. Conclusions are provided in Section 6. A formal mathematical argument for Theorem 1 is summarized in Appendix 1, and how to handle exceptional trouble cases is explained in Appendix 2.

2 Evaluation measures

A *list* is a non-empty set of stablecoins S. Given any stablecoin $s \in S$, a time-series price vector of s is

$$x^s \equiv (x_1^s, x_2^s, \dots, x_T^s) \in \mathbb{R}_+^T.$$

The set $D \equiv \{1, 2, \dots, T\}$ is called the *data collection period*. As usual, the average of the components of x^s is defined by

$$\bar{x}^s \equiv \frac{\sum_{t=1}^T x_t^s}{T}.$$

In most cases, $\bar{x}^s$ is very close to 1 because of the nature of stablecoins, such as $\bar{x}^s = 0.99438$ or 1.00003.

As mentioned in Section 1, market capitalization is often used to evaluate stablecoins, but it does not necessarily indicate their quality or similarity to the associated legal tender. We therefore introduce the following evaluation measures: *average deviation* evaluates the price proximity of each stablecoin with its associated legal tender; *volatility* evaluates price stability over time; *persistence* evaluates the tendency to retain the deviation from one in each period after the deviation; *DEX liquidity* evaluates an exchange liquidity in DEX; *The number of active addresses* and *transaction volume* represent the strength of network effects, which is a key factor of user convenience.[3] The evaluation measures are formally defined as below:

[3]Bakhtiar, Luo, and Adelopo (2023) interpret *the number of active addresses* and *transaction value* as measures of the strength of the network effect.

Average deviation:

$$\texttt{avedev}(x^s) \equiv \frac{1}{T}\sum_{t=1}^{T}|x_t^s - 1|.$$

Usually $\texttt{avedev}(x^s)$ takes a small positive value by nature of stablecoins. For example, the values are

$$(0.0007, 0.00045, 0.00106, 0.01225, 0.00049, 0.025, 0.02659),$$

each of which is the average deviation of USDT, USDC, DAI, TUSD, USDP, USDY, and FeiUSD, respectively, dated at February 9, 2024.[4] In Section 4, we explain details of data and computation.

Volatility:

$$\texttt{volat}(x^s) \equiv \sqrt{\frac{1}{T}\sum_{t=1}^{T}(x_t^s - \bar{x}^s)^2}.$$

Usually $\texttt{volat}(x^s)$ also takes a small positive value by nature of stablecoins.[5] For example, the values are

$$(0.00100819, 0.00076841, 0.00126906, 0.00397111, 0.00070861, 0.00427395, 0.03285081),$$

each of which is the volatility of USDT, USDC, DAI, TUSD, USDP, USDY, and FeiUSD, respectively, dated at February 9, 2024.

Persistence: To measure the persistence of price deviation, we use the absolute value of the first-order autocorrelation of price deviation.

$$\texttt{persis}(x^s) \equiv \left|\frac{\sum_{t=2}^{T}(x_t^s - 1)(x_{t-1}^s - 1)}{\sum_{t=1}^{T}(x_t^s - 1)^2}\right|.$$

It always holds that $\texttt{persis}(x^s) \in [0,1]$ by the definition of persistence. For example, the values are

$$(0.0503, 0.1958, 0.0416, 0.9462, 0.2272, 0.9476, 0.3342),$$

each of which is the persistence of USDT, USDC, DAI, TUSD, USDP, USDY, and FeiUSD, respectively, dated at February 9, 2024.

DEX liquidity: To measure the liquidity of a stablecoin s on a blockchain, we use the amount of s paired with the native currency of the blockchain in the representative DEX pool for swapping.[6] We define *DEX liquidity* of s at $t \in D$ by this amount of s

[4]The values are calculated using the last 30 observations. This applies to the rest of the calculations as well. However, the 30-day period is arbitrary, and the user can choose a different number of days depending on the evaluation horizons.

[5]Esparcia, Escribano, and Jareñot (2024) argue that stablecoins are the most affected tokens after the FTX collapse. Their discussion shows the importance of the instability of stablecoin prices as expressed by volatility.

[6]For example, ETH is the native currency of the Ethereum blockchain, and Uniswap is the most representative DEX.

at t, which is denoted by $y_t^s \geq 0$. Similarly, *DEX liquidity* of s at D is given by

$$\texttt{dexliq}(y^s) \equiv \frac{\sum_{t=1}^{T} y_t^s}{T}.$$

The value $\texttt{dexliq}(y^s)$ can be any non-negative value. For example, the values are

$$(15698575, 98376735, 5375525, 60153, 2298, 98862, 1621),$$

each of which is the DEX liquidity of USDT, USDC, DAI, TUSD, USDP, USDY, and FeiUSD, respectively, dated at February 9, 2024.

Number of active addresses: The number of addresses with at least a certain amount of s at $t \in D$ is denoted by $z_t^s \geq 0$.[7] Let $z \equiv (z_t^s)_{t \in D}$. *The number of active addresses* of s at D is then defined by

$$\texttt{address}(z^s) \equiv \frac{\sum_{t=1}^{T} z_t^s}{T}.$$

The value $\texttt{address}(z^s)$ can be any non-negative integer. For example, the values are

$$(46668, 17467, 1696, 69, 52, 7, 7),$$

each of which is the number of active addresses of USDT, USDC, DAI, TUSD, USDP, USDY, and FeiUSD, respectively, dated at February 9, 2024.

Transaction volume: The transaction volume of s at $t \in D$ is denoted by $w_t^s \geq 0$. Let $w \equiv (w_t^s)_{t \in D}$. *The transaction volume* of s at D is then defined by

$$\texttt{txvol}(w^s) \equiv \frac{\sum_{t=1}^{T} w_t^s}{T}.$$

The value $\texttt{txvol}(w^s)$ can be any non-negative value. For example, the values are

$$(4542711869, 6147130969, 8613315721, 8533759, 5622233, 237568, 99090),$$

each of which is the transaction volume of USDT, USDC, DAI, TUSD, USDP, USDY, and FeiUSD, respectively, dated at February 9, 2024.

3 Scoring and rating

We use the terms *scoring* and *rating* with a clear distinction. *Scoring* refers to the normalized numeration of six evaluation measures, while *rating* refers to the aggregation of six scores into a single, comprehensive evaluation value. This distinction is effective in avoiding confusion between the two types of calculations.

Step 1. Logarithmic transformation

As the six evaluation measures are about different properties of stablecoins, we must normalize the values of the evaluation measures so that they take scores in the unit interval $[0, 1]$. We first explain our method for average deviation.

[7] In Section 4, we set $s = 100$ in our calculations with the data.

We transform

$$\texttt{avedev}(x^s),$$

which is usually a very small value that is close to zero, into the negative of its logarithm with base 10,

$$-\log_{10} \texttt{avedev}(x^s), \tag{1}$$

meaning the number of decimal places where deviation from 1 is shown. For example, if $\texttt{avedev}(x^s) = 0.001$, then $\log_{10} \texttt{avedev}(x^s) = -3$, so that $-\log_{10} \texttt{avedev}(x^s) = 3$.

Note that the smaller the average deviation, volatility, or persistence, the more desirable it is. On the other hand, the larger the DEX liquidity, the number of active users, or transaction volume, the more desirable it is. Therefore we transform each evaluation measure as follows:

$$\begin{aligned}
-\log_{10} \texttt{avedev}(x^s), \\
-\log_{10} \texttt{volat}(x^s), \\
-\log_{10} \texttt{persis}(x^s), \\
\log_{10} \texttt{dexliq}(y^s), \\
\log_{10} \texttt{address}(z^s), \\
\log_{10} \texttt{txvol}(w^s).
\end{aligned}$$

Three important remarks are in order:

- **Reason for using $\log_{10}$:** Network effects play an important role in the adoption of currencies, including stablecoins. Thus, the values of the evaluation measures can differ significantly by a factor of 10^2 or 10^3, not just by a factor of 2 or 3, across various stablecoins. Therefore, to compare the values, it is more appropriate to use $\log_{10}$ to clearly express the difference among the values of various stablecoins.

- **Robustness against strategic manipulation:** Some issuers of a stablecoin may attempt to make false transactions to increase scores. For example, they may do huge transactions within their own addresses to increase $\texttt{txvol}(w^s)$. However, because of the logarithmic transformation of $\texttt{txvol}(w^s)$, increasing $\log_{10} \texttt{txvol}(w^s)$ through such strategic manipulation incurs significant transaction costs. The marginal cost for it also increases drastically as $\log_{10} \texttt{txvol}(w^s)$ increases.

- **How to deal with cases where the logarithmic transformation does not work well:** If $x_t^s = 1$ for all $t \in T$, then $\texttt{avedev}(x^s) = 0$, so that $\log_{10} \texttt{avedev}(x^s)$ is not well-defined. It is hard to imagine that this case actually happens unless the size of T is too small, but whenever it occurs, we simply add a small $\varepsilon > 0$ to $\texttt{avedev}(x^s)$, so that $\log_{10}(\texttt{avedev}(x^s) + \varepsilon)$ is well-defined. The same problem theoretically occurs with volatility and persistence, too. Appendix 2.1 discusses this issue and other theoretically possible but unrealistic issues related to the logarithmic transformation.

Step 2. Max normalization to define scores

Note that

$$\max_{u \in S} -\log_{10} \texttt{avedev}(x^u) \tag{2}$$

denotes the maximum value of (1) among the stablecoins in S. Therefore,

$$\text{score}(\texttt{avedev}(x^s)) \equiv \frac{-\log_{10}\texttt{avedev}(x^s)}{\max_{u\in S} -\log_{10}\texttt{avedev}(x^u)} \tag{3}$$

denotes the normalized value of (1), which is between 0 and 1.

We call this normalization method the *max normalization*. We offer its axiomatic foundation in Section 5.1 and Appendix 1 to explain the rationale of using it. Other types of normalization are discussed in Sections 5.2 and 5.3.

By the max normalization, we define other scores similarly

$$\text{score}(\texttt{volat}(x^s)) \equiv \frac{-\log_{10}\texttt{volat}(x^s)}{\max_{u\in S} -\log_{10}\texttt{volat}(x^u)}, \tag{4}$$

$$\text{score}(\texttt{persis}(x^s)) \equiv \frac{-\log_{10}\texttt{persis}(x^s)}{\max_{u\in S} -\log_{10}\texttt{persis}(x^u)}, \tag{5}$$

$$\text{score}(\texttt{dexliq}(y^s)) \equiv \frac{\log_{10}\texttt{dexliq}(y^s)}{\max_{u\in S} \log_{10}\texttt{dexliq}(y^u)}, \tag{6}$$

$$\text{score}(\texttt{address}(z^s)) \equiv \frac{\log_{10}\texttt{address}(z^s)}{\max_{u\in S} \log_{10}\texttt{address}(z^u)}, \tag{7}$$

$$\text{score}(\texttt{txvol}(w^s)) \equiv \frac{\log_{10}\texttt{txvol}(w^s)}{\max_{u\in S} \log_{10}\texttt{txvol}(w^u)}. \tag{8}$$

We do not need "$-$" to define the scores of (6), (7) and (8) because larger values of $\texttt{dexliq}(y^s)$, $\texttt{address}(z^s)$ and $\texttt{txvol}(w^s)$ are more desirable, unlike (3), (4) and (5).

As an example, Figure 1 shows the transformation from original values to scores on February 9, 2024. Details of the data and computation are explained in Section 4.

	USDT	USDC	DAI	TUSD	USDP	USDY	FeiUSD
Average deviation	0.0007	0.00045	0.00106	0.01225	0.00049	0.025	0.02659
Log-transformed average deviation	3.155150199	3.346626666	2.972854334	1.911846185	3.308623771	1.602059991	1.575243554
Score of average deviation	0.9427852324	1	0.8883137053	0.5712756086	0.9886444176	0.4787089063	0.4706959309

	USDT	USDC	DAI	TUSD	USDP	USDY	FeiUSD
Variance	0.00100819	0.00076841	0.00126906	0.00397111	0.00070861	0.00427395	0.03285081
Log-transformed variance	2.99645813	3.114406694	2.896518736	2.401088589	3.149594789	2.369170348	1.483453915
Score of variance	0.9513789332	0.988827739	0.9196480595	0.7623484131	1	0.7522143345	0.4709983393

	USDT	USDC	DAI	TUSD	USDP	USDY	FeiUSD
Persistence	0.0503	0.1958	0.0416	0.9462	0.2272	0.9476	0.3342
Log-transformed persistence	1.298208735	0.7082131558	1.380683221	0.02400474977	0.643661719	0.02336983718	0.4760565917
Score of persistence	0.9402654537	0.5129439868	1	0.01738613854	0.4661907302	0.01692628462	0.3447978395

	USDT	USDC	DAI	TUSD	USDP	USDY	FeiUSD
DEX liquidity	15698575	98376735	5375525	60153	2298	98862	1621
Log-transfoemed DEX liquidity	7.195860243	7.992892403	6.730420901	4.779257231	3.361415156	4.995029045	3.209818562
Score of DEX liquidity	0.9002823859	1	0.8420507322	0.597938392	0.4205505325	0.6249338528	0.4015841074

	USDT	USDC	DAI	TUSD	USDP	USDY	FeiUSD
The number of active addresses	46668	17467	1696	69	52	7	7
og-transformed number of active addresse	4.669017638	4.242221635	3.229459989	1.839687497	1.719607468	0.8367459656	0.8173449714
Score of the number of active addresses	1	0.9085897643	0.6916786869	0.3940202501	0.3683017716	0.1792124234	0.1750571608

	USDT	USDC	DAI	TUSD	USDP	USDY	FeiUSD
Transaction volume	4542711869	6147130969	8613315721	8533759	5622233	237568	99090
Log-transformed transaction volume	9.657315192	9.788672466	9.935170367	6.931140391	6.749908833	5.375787981	4.996030242
Score of transaction volume	0.9720331746	0.9852546162	1	0.6976367929	0.6793953786	0.541086643	0.502863067

Figure 1: Transformation from original values to scores on February 9, 2024

Step 3. Aggregation to define rating

When calculating a single rating based on multiple evaluation measures, the geometric mean has a beneficial property: a low score on one evaluation measure cannot easily be compensated by a high score on another. The United Nations Development Program calculates the so-called human development index by income, life expectancy, and education levels. Earlier, they used the arithmetic mean to calculate the index; however, in 2010 they switched to using the geometric mean.[8] They made this change because they considered their three evaluation measures to be essential for human life so that none of them can be easily substituted by another one. Similarly, we consider that our six evaluation measures are essential for evaluating stablecoins and define our rating function by the geometric mean as follows:

$$\begin{aligned}\text{rating}(x^s, y^s, z^s, w^s) \equiv\ & \text{score}(\texttt{avedev}(x^s))^{\frac{1}{6}} \cdot \text{score}(\texttt{volat}(x^s))^{\frac{1}{6}} \cdot \text{score}(\texttt{persis}(x^s))^{\frac{1}{6}} \cdot \\ & \text{score}(\texttt{dexliq}(y^s))^{\frac{1}{6}} \cdot \text{score}(\texttt{address}(z^s))^{\frac{1}{6}} \cdot \text{score}(\texttt{txvol}(w^s))^{\frac{1}{6}}, \quad (9)\end{aligned}$$

which is between 0 and 1. In this definition, we assign all criteria an equal weight of $\frac{1}{6}$, reflecting the idea that the evaluation measures are equally important.[9] As an example, Figure 2 shows scores on February 9, 2024.

[8]See, Klugman, Rodríguez and Choi (2011) for a review and Herrero, Martínez, and Villar (2010) and Kawada, Nakamura, and Otani (2019) for properties of the human development index.

[9]Although we have never observed in reality, it is theoretically possible that $a = \texttt{dexliq}(y^s)$, $\texttt{address}(z^s)$, or $\texttt{txvol}(w^s)$ is negative, so that $a^{\frac{1}{6}}$ is not well-defined as a real-value. Then we need to let $a = 0$, so that $a^{\frac{1}{6}} = 0$. This issue is explained in Appendix 2.2.

	USDT	USDC	DAI	TUSD	USDP	USDY	FeiUSD
Rating	0.951	0.877	0.884	0.328	0.604	0.268	0.373
Ranking of rating	1	3	2	6	4	7	5

Figure 2: Rating on February 9, 2024

4 Computation

4.1 List of stablecoins

We compute the scores and ratings of several stablecoins. Our purpose here is not to provide a comprehensive analysis of the assessment of stablecoins, but to help understand our method. In this study, we have selected the following seven stablecoins: USDT, USDC, DAI, TUSD, USDP, USDY, and FeiUSD on the Ethereum network, all of which are pegged to USD.[10] Thus the list of stablecoins is

$$S = \{\text{USDT, USDC, DAI, TUSD, USDP, USDY, FeiUSD}\}.$$

Among the set of stablecoins in CoinMarketCap,[11] USDT, USDC, and DAI consistently hold the top three positions in market capitalization. TUSD is an example that consistently ranks in the top ten. USDY is an example of "middle class" stablecoins that quite often rank in the top twenty. FeiUSD is an example of a rather minor stablecoins, and its market capitalization ranking is always below those of all the stablecoins mentioned above. The ranking of the market capitalization of these stablecoins was always the same as the order of USDT, USDC, DAI, TUSD, USDP, USDY, and FeiUSD during the data measurement period, which is between January 11, 2024 and May 8, 2024.

4.2 Data

Our data are obtained as follows:

- We obtained daily price data x^s from CoinGecko[12] between January 11–May 9, 2024.
- When a user swaps an amount of ETH to a stablecoin s at Uniswap, the Uniswap system selects a "best pool" to minimize the swap's price impact. Our $\texttt{dexliq}(y^s)$ denotes the amount of s in the pool, which is crucial for realizing the price impact. Therefore, we choose this amount as a measure of liquidity. The daily data of the amount are obtained from on-chain data of Uniswap between January 11–May 9, 2024.
- The number of active addresses of s, z^s, is defined as an address with a daily transaction volume with at least 100 units of s. Transaction volume is defined as the daily volume of all transactions of s. These data were collected on-chain between January 11–May 9, 2024.

[10] Chainsight's website also calculates and publishes scores and ratings for many other stablecoins. In this paper, we focus on these seven stablecoins in order to explain our computation results intuitively using line graphs. If the number of stablecoins we deal with increases beyond this, it will be difficult to understand visually using line graphs. Since the aim of this analysis is to explain our method so that readers can understand it, we have taken this approach. `https://docs.chainsight.network/`

[11] `https://coinmarketcap.com/view/stablecoin/`

[12] `https://www.coingecko.com/en/coins/usdc/historical_data`

- The transaction volume of s, w^s, is the daily volume of all transactions. These data were collected on-chain between January 11–May 9, 2024.

4.3 Time-series scores

All of our data are from the period January 11–May 9, 2024, which consists of 120 days. We set $T = 30$. Take any $s \in S$. For any sequence

$$x^s = (x^s_{\text{Jan 11}}, x^s_{\text{Jan 12}}, \ldots, x^s_{\text{May 9}}) \in \mathbb{R}^{120},$$

and any $t \in \{\text{Feb 9, Feb 10}, \ldots, \text{May 9}\}$, we write

$$x^s(t) = (x^s_{t-29}, x^s_{t-28}, \ldots, x^s_t) \in \mathbb{R}^{30},$$

where $t - 29$ denotes 29 days before from time t and January 11 is 29 days before from February 9. For any $s \in S$, the average deviation of s on February 9 is given by

$$\texttt{avedev}(x^s(\text{Feb 9})) = \frac{\sum_{t=\text{Jan 11}}^{\text{Feb 9}} x^s_t}{30}.$$

Following (3), the score of

$$\texttt{avedev}(x^s(t)) \text{ for } t \in \{\text{Feb 9, Feb 10}, \ldots, \text{May 9}\}$$

is

$$\texttt{score}(\texttt{avedev}(x^s(t))) = \frac{-\log_{10}(\texttt{avedev}(x^s(t)))}{\max_{u \in S} -\log_{10}(\texttt{avedev}(x^u(t)))}.$$

Then the time-series scores of the average deviation for s are given by

$$\{\texttt{score}(\texttt{avedev}(x^s(t)))\}_{t=\text{Feb 9}}^{\text{May 9}}.$$

The average deviation for s on any other day, the volatility, and the persistence for s on any day are all defined by the same way.

DEX liquidity, the number of active addresses, and transaction volume for s on any day are defined by the average values over the last 30 days. For example, DEX liquidity for s on February 9 is given by

$$\texttt{dexliq}(y^s(\text{Feb 9})) = \frac{\sum_{t=\text{Jan 11}}^{\text{Feb 9}} y^s_t}{30}.$$

Following (6), the score of

$$\texttt{dexliq}(y^s(t)) \text{ for } t \in \{\text{Feb 9, Feb 10}, \ldots, \text{May 9}\}$$

is

$$\texttt{score}(\texttt{dexliq}(y^s(t))) = \frac{\log_{10}(\texttt{dexliq}(y^s(t)))}{\max_{u \in S} \log_{10}(\texttt{dexliq}(y^u(t)))}.$$

Then the time-series scores of DEX liquidity for s are given by

$$\{\texttt{score}(\texttt{dexliq}(y^s(t)))\}_{t=\text{Feb 9}}^{\text{May 9}},$$

which is in fact the sequence of the scores for the moving average of DEX liquidity. DEX liquidity for s dated on any other day, the number of active addresses, and transaction volume for s dated on any day are all defined by the same way.

4.4 Results

The scores of average deviation, volatility, and persistence dated from February 9 to May 9, 2024, are shown in Figures 3–5. All the detailed scores can be found on the Chainsight website.[13] Compared to persistence, the changes in the scores and score rankings for average deviation and volatility are more moderate. However, given that the ranking of the market capitalization of the seven stablecoins has not changed at all during this measurement period, the change is considerable. In addition, it is clear from looking at TUSD, for example, that the ranking of these scores is not proportional to market capitalization.

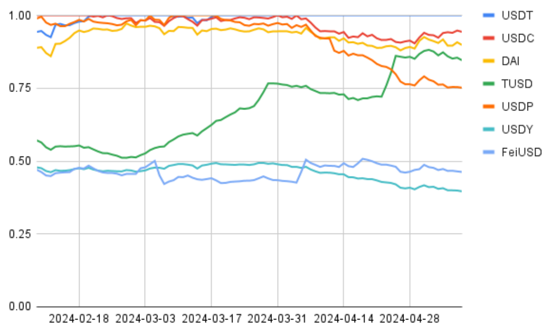

Figure 3: Scores of average deviation

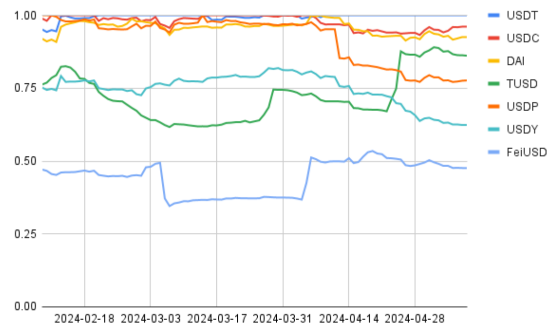

Figure 4: Scores of volatility

On the other hand, the persistence score fluctuates more than the other scores. This is because, by the nature of the definition of persistence, the value changes greatly when the numerator and denominator change in opposite directions.

As shown in shown in Figures 6–8, the scores of DEX liquidity, the number of active addresses, and the transaction volume dated from February 9 to May 9, 2024 are clearly less volatile than the other evaluation measures. Even so, as implied by the fact that the score of USDP for the number of active addresses and its ranking have improved within the measurement period, the scores do change. This change contrasts with the fact that the order of market capitalization remained unchanged among the seven stablecoins within the data measurement period.

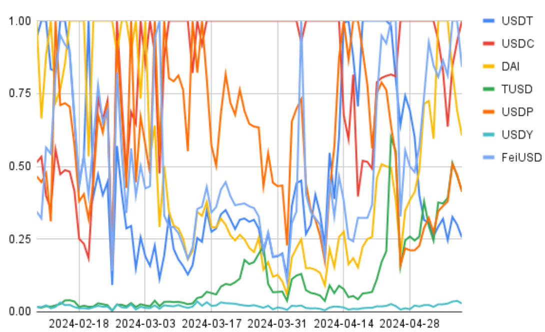

Figure 5: Scores of persistence

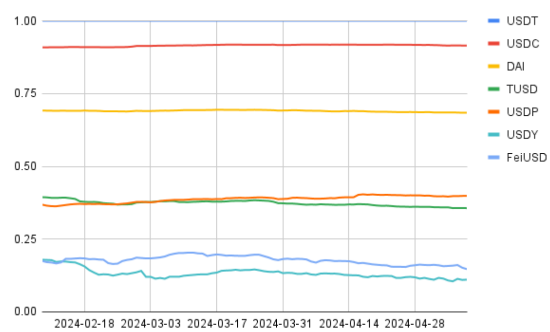

Figure 6: Scores of active addresses

[13] `https://chainsight.network/`

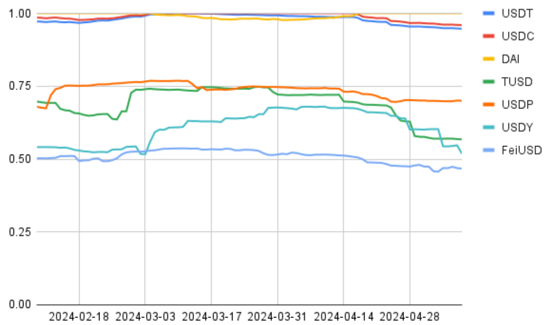

Figure 7: Scores of transaction volume

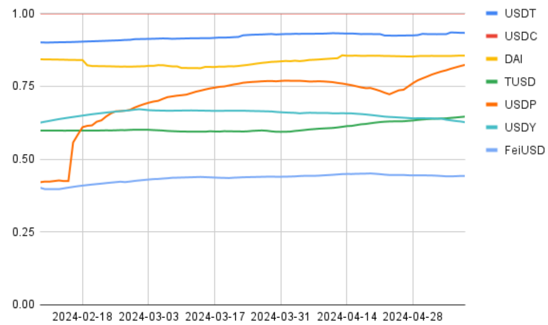

Figure 8: Scores of liquidity

The dynamics of rating based on the six scores are exhibited in Figure 10, while the median and average of rating values are summarized in Figure 11. Out of the 91 days from February 9 to May 9, 2024, USDC was ranked first for 64 days, USDT for 22 days, and DAI for 5 days. Noting that the market capitalization was always in the order of USDT, USDC, and DAI during this period, the ranking of rating and the ranking of market cap are not the same. Furthermore, our results show that USDC is the best stablecoin and that DAI, which may be sometimes overshadowed by the two major stablecoins of USDT and USDC, is also extremely good.

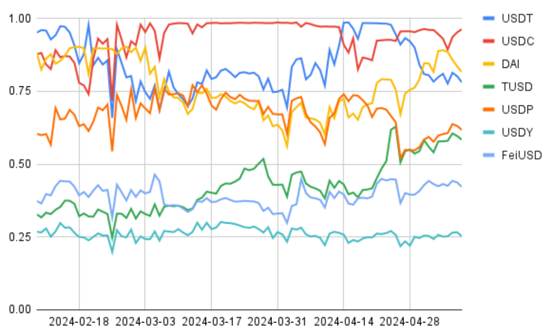

Figure 9: Rating

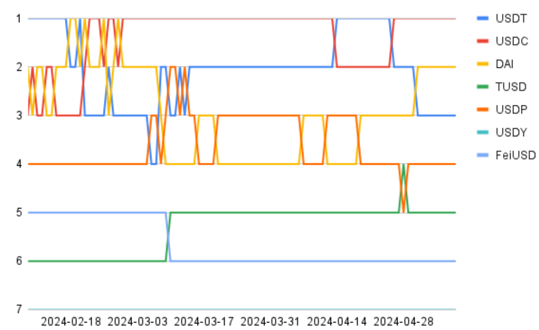

Figure 10: Ranking of rating

	USDT	USDC	DAI	TUSD	USDP	USDY	FeiUSD
Median rating	0.82	0.955	0.747	0.411	0.686	0.261	0.388
Average rating	0.842	0.934	0.768	0.422	0.672	0.261	0.392
Ranking of median/average	2	1	3	5	4	7	6

Figure 11: Median and average of rating values dated from February 9 to May 9, 2024

5 Discussions on normalization

5.1 Rationale of the max normalization

The *max normalization* can be written as a function f that maps each non-negative vector $a = (a_1, \dots, a_k)$ to the normalized vector $f(a) = (f_1(a), \dots, f_k(a))$ such that

$$f_j(a) = \frac{a_j}{\max_{i \in \{1,\dots,k\}} a_i} \text{ for all } j \in S.$$

The max normalization satisfies several desirable properties as normalization functions, which offer the rationale of using it.

The first property is *intensity preservation*, stating that the ratio of differences of inputs is preserved under normalization: for each distinct a_i, a_j, a_k with $a_k \neq a_i, a_j$,

$$\frac{f_k(a) - f_i(a)}{a_k - a_i} = \frac{f_k(a) - f_j(a)}{a_k - a_j}.$$

The second property is *independence of null objects*, stating that adding an extremely low-quality stablecoin k whose unnormalized score a_k is zero to the list does not affect the normalized value of other stablecoins, and the normalized value of a_k is zero: for $a = (a_1, \dots, a_k, a_{k+1})$ with $a_{k+1} = 0$,

$$\begin{aligned} f_j(a) &= f_j(a_1, \dots, a_k) \text{ for all } j = 1, \dots, k, \\ f_{k+1}(a) &= 0. \end{aligned}$$

The third property is the *max-one property*, stating that the value of the stablecoin with the highest parameter is given one:

$$a_j = \max_{i \in \{1,\dots,k\}} a_i \Longrightarrow f_j(a) = 1.$$

The max normalization satisfies *intensity preservation*, *independence of null coins*, and the *max-one property*. In fact, we can establish a much stronger result that the max normalization is the *only* function satisfying the three properties. To prove this result, we need to define the properties more rigorously in a formal model. This will be done in the Appendix 1, but we state the result below for reference:

Theorem 1 (Informal statement). *The max normalization is the only function that satisfies intensity preservation, independence of null objects, and the max-one property.*

5.2 Alternative normalization: ratio to dynamic maximum

For each evaluation measure, the max normalization gives the value 1 to the stablecoin with the maximum value of the evaluation measure during the data collection period. Consequently, even when $f(x^s)$ reduces for all stablecoins through multiple data collection periods, the stablecoin with the maximum value at each data collection period is assigned the value 1. That is, our definition of score($\texttt{avedev}(x^s)$) does not capture such dynamic changes. Below we offer an alternative normalization that captures such changes.

Recall that the data collection period of time-series price data $x^s = (x^s_1, \dots, x^s_T)$ is defined as

$$D = \{1, \dots, T\} \text{ with } T \geq 1.$$

Let $D(1) \equiv D$. There can be "past" data collection periods

$$D(2), \ldots, D(K) \subset \{T-1, T-2, \ldots, 1, 0, -1, -2, -3, \ldots\}$$

and associated data

$$(x_t^s)_{t \in D(2)}, \ldots, (x_t^s)_{t \in D(K)}.$$

Then

$$\max_{k \in \{1,\ldots,K\}} -\log_{10} \texttt{avedev}((x_t^s)_{t \in D(k)}). \tag{10}$$

is the dynamically maximum value of $-\log_{10} \texttt{avedev}((x_t^s)_{t \in D(k)})$ among all data collection periods $D(1), \ldots, D(K)$ for s, and

$$\max_{s \in S} \max_{k \in \{1,\ldots,K\}} -\log_{10} \texttt{avedev}((x_t^s)_{t \in D(k)}).$$

is the maximum value of (10) among the stablecoins in S. Then,

$$\frac{-\log_{10} \texttt{avedev}(x^s)}{\max_{s \in S} \max_{k \in \{1,\ldots,K\}} -\log_{10} \texttt{avedev}((x_t^s)_{t \in D(k)})} \tag{11}$$

is the dynamically normalized score of x^s on the average deviation, which is between 0 and 1. The dynamic normalization of (11) is useful to capture time-series changes in values; however, we use the static normalization of (3) because we are still unclear about how values (11) and (3) can differ, and (3) is easier to use as there is no problem in choosing $D(2), ..., D(K)$. However, in the future with more data and experience, we may shift from static to dynamic normalization or something similar.

5.3 Alternative normalization: quantile

For any $s \in S$, the following set denotes the set of stablecoins whose average deviation is weakly greater than that of s:

$$\{u \in S : \texttt{avedev}(x^u) \geq \texttt{avedev}(x^s)\}.$$

Then

$$\frac{|\{u \in S : \texttt{avedev}(x^u) \geq \texttt{avedev}(x^s)\}|}{|S|} \tag{12}$$

denotes the quantile of s in the decreasing order. This value falls in the range $[0, 1]$, so quantile is also a method of normalization. However, there is a fundamental problem of appropriately selecting a list S. Perhaps we can easily agree that S should contain major stablecoins such as USDT or USDC, but we cannot do it for hundreds of minor stablecoins. Indeed, the boundary of stablecoins is not clear because there are multiple types of peg mechanisms and management organizations.[14] However, the value of (12) highly depends on the choice of S, and hence we do not use this quantile normalization.

[14] For example, whether TerraUSD (UST) on the Terra blockchain is a stablecoin has been debatable because of its exotic peg mechanism, until the collapse of LUNA in May 2022.

6 Conclusion

We have developed a method for rating stablecoins based on their key evaluation measures such as average deviation, volatility, persistence, DEX liquidity, the number of active addresses, and transaction volume. We have transformed those values into an easy-to-compare score using the logarithmic transformation and the max normalization. We then computed rating values by calculating the geometric mean of the scores, following the recent idea of welfare economics. We also established an axiomatic characterization of the max normalization to clarify the rational of using it. Among the stablecoins we examined, USDC is found to be the best stablecoin, and the ranking of market capitalization does not necessarily match the ranking of ratings. Therefore, in order to evaluate the quality of a stablecoin, it is necessary to examine evaluation measures themselves, rather than its market capitalization. As far as we know, this study is the first academically rigorous attempt to rate stablecoins. We hope this study will facilitate further research to assess the quality of stablecoins.

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Appendix 1. Axiomatic characterization of the max normalization

Since the choice of the list S of stablecoins is controversial, we introduce a model with variable lists. The idea of our modelling comes from the theory of axiomatic resource allocation (e.g., Thomson 2003, 2019).

Let $\mathbb{N} = \{1, 2, \ldots\}$ be the set of infinitely many *objects*. A finite set $\hat{S} \subset \mathbb{N}$ is the set of *central objects*, which can be empty or non-empty. A *list* is a non-empty finite set S with $\hat{S} \subset S \subset \mathbb{N}$.

One can interpret that $\mathbb{N}$ is the set of various cryptocurrencies, $\hat{S}$ is the set of cryptocurrencies that everyone recognize as stablecoin such as USDC and USDT, and S is a set of cryptocurrencies that someone may recognize as stablecoin. A positive integer $M \geq 1$ indicates the minimum size of possible S, which can be chosen arbitrary.

Let $\mathscr{S}(M, \hat{S})$ be the set of lists whose size is at least M and contains $\hat{S}$; that is,

$$\mathscr{S}(M, \hat{S}) \equiv \{S \in 2^{\mathbb{N}} \setminus \{\emptyset\} : \hat{S} \subset S \text{ and } M \leq |S| < +\infty\}.$$

Our modelling with $\mathscr{S}(M, \hat{S})$ allows us to simultaneously work with any consideration on $\hat{S}$ and M.

Hereafter, for brevity of notation, we denote $\mathscr{S}(M, \hat{S})$ by $\mathscr{S}$ when there is no danger of confusion. For each $S \in \mathscr{S}$, let

$$D_S \equiv \mathbb{R}^S_+ \setminus \{\mathbf{0}\}$$

be the set of non-negative vectors $a = (a_i)_{i \in S} \in \mathbb{R}^S_+$ satisfying $a_j > 0$ for some $j \in S$, where the uninteresting vector of parameters $\mathbf{0} = (0, 0, \ldots, 0) \in \mathbb{R}^S_+$ is excluded. A *normalization function* on $\mathscr{S}$ is a function

$$f : \bigcup_{S \in \mathscr{S}} D_S \to \bigcup_{S \in \mathscr{S}} [0, 1]^S$$

such that for each $S \in \mathscr{S}$ and each vector of parameters $a \in D_S$, $f(a) = (f_i(a))_{i \in S} \in [0, 1]^S$. The *max normalization* on $\mathscr{S}$ is the normalization function f on $\mathscr{S}$ such that for each $S \in \mathscr{S}$ and each $a \in D_S$,

$$f_j(a) = \frac{a_j}{\max_{i \in S} a_i} \text{ for all } j \in S.$$

We define three axioms of normalization functions on $\mathscr{S}$ satisfied by the max normalization. The interpretation of the axioms has already been explained in Section 5.1.

Axiom 1 (Intensity preservation). *For each $S \in \mathscr{S}$, each $a \in D_S$, and each $i, j, k \in S$, whenever $a_k \neq a_i, a_j$,*

$$\frac{f_k(a) - f_j(a)}{a_k - a_j} = \frac{f_k(a) - f_i(a)}{a_k - a_i}.$$

Axiom 2 (Independence of null objects). *For each $S \in \mathscr{S}$, each $\ell \in \mathbb{N} \setminus S$, and each $a \in D_{S \cup \{\ell\}}$ with $a_\ell = 0$,*

$$f_j(a) = f_j((a_i)_{i \in S}) \text{ for all } j \in S,$$
$$f_\ell(a) = 0.$$

The idea of *independence of null objects* comes from "null claims consistency" in the literature of claims problem (see, Yeh 2008).

Axiom 3 (Max-one property). *For each $S \in \mathscr{S}$ and each $j \in S$, if $a_j = \max_{i \in S} a_i$, then $f_j(a) = 1$.*

We are now in a position to state and prove our axiomatization theorem.

Theorem 1 (Formal statement). *Let $\hat{S} \subset \mathbb{N}$ be any (possibly empty) set of central objects and let $M \geq 1$ be any positive integer. The max normalization is the only normalization function on $\mathscr{S}(M, \hat{S})$ that satisfies intensity preservation, independence of null objects, and the max-one property.*

Proof. Since it is trivial that the max normalization satisfies *intensity preservation*, *independence of null objects*, and *the max-one property*, we only prove the converse statement. Let f be any normalization function on $\mathscr{S}(M, \hat{S})$ satisfying the three axioms. We shall show that f is in fact the max normalization; that is, for each $S \in \mathscr{S}$ and each $a \in D_S$, $f_j(a) = \frac{a_j}{\max_{i \in S} a_i}$ for all $j \in S$.

Case 1. Any $\boldsymbol{S \in \mathscr{S}}$ and $\boldsymbol{a \in D_S}$ satisfying $\boldsymbol{\max_{i \in S} a_i = \min_{i \in S} a_i}$: In this case, by the *max-one property*,

$$f_j(a) = 1 = \frac{a_j}{a_j} = \frac{a_j}{\max_{i \in S} a_i} \text{ for all } j \in S,$$

as desired.

Case 2. Any $\boldsymbol{S \in \mathscr{S}}$ and $\boldsymbol{a \in D_S}$ satisfying $\boldsymbol{\max_{i \in S} a_i > \min_{i \in S} a_i}$:

Step 1. We shall show that there exists a real-value $g(S, a) \in \mathbb{R}$ such that

$$f_i(a) - g(S, a) \cdot a_i = f_j(a) - g(S, a) \cdot a_j \text{ for all } i, j \in S. \tag{13}$$

Let $k, \ell \in S$ be $a_k = \max_{i \in S} a_i$ and $a_\ell = \min_{i \in S} a_i$. Define

$$g(S, a) \equiv \frac{f_k(a) - f_\ell(a)}{a_k - a_\ell}. \tag{14}$$

We separately analyze several types of $j \in S$ below:

- For each $j \in S$ with $j \neq k$ and $a_j = a_k$, by the *max-one property*, $f_j(a) = 1 = f_k(a)$. Therefore,

$$f_j(a) - g(S, a) \cdot a_j = f_k(a) - g(S, a) \cdot a_k. \tag{15}$$

- For each $j \in S$ with $j \neq \ell$ and $a_j < a_k$, by *intensity preservation* and (14),

$$\frac{f_k(a) - f_j(a)}{a_k - a_j} = \frac{f_k(a) - f_\ell(a)}{a_k - a_\ell} = g(S, a),$$

  so that

$$f_j(a) - g(S, a) \cdot a_j = f_k(a) - g(S, a) \cdot a_k. \tag{16}$$

- For ℓ, by (14),

$$f_\ell(a) - g(S, a) \cdot a_\ell = f_k(a) - g(S, a) \cdot a_k. \tag{17}$$

By (15), (16), and (17), we have (13).

Step 2: By Step 1, there exists a real-value $h(S,a) \in \mathbb{R}$ such that

$$h(S,a) = f_j(a) - g(S,a) \cdot a_j \text{ for all } j \in S. \tag{18}$$

Note that

$$f_j(a) = g(S,a) \cdot a_j + h(S,a) \text{ for all } j \in S. \tag{19}$$

In the next step, we shall clarify the forms of g and h.

Step 3: Take any $\ell \in \mathbb{N} \setminus \{S\}$. Let $a_\ell \equiv 0$. Note $S \cup \{\ell\} \in \mathscr{S}$ and $(a, a_\ell) \in D_{S\cup\{\ell\}}$. Since $\max_{i \in S\cup\{\ell\}} a_i > \min_{i \in S\cup\{\ell\}} a_i$, by the same argument as Steps 1 and 2, there exist real-values $h(S \cup \{\ell\}, (a, a_\ell))$ and $g(S \cup \{\ell\}, a)$ such that

$$f_j(a, a_\ell) = h(S \cup \{\ell\}, (a, a_\ell)) \cdot a_j + g(S \cup \{\ell\}, (a, a_\ell)) \text{ for all } j \in S \cup \{\ell\}.$$

By *independence of null objects*,

$$\begin{aligned} &f_j(a, a_\ell) = f_j(a) \text{ for all } j \in S, \\ &f_\ell(a, a_\ell) = 0, \end{aligned}$$

so that

$$\begin{gathered} g(S \cup \{\ell\}, (a, a_\ell)) \cdot a_j + h(S \cup \{\ell\}, (a, a_\ell)) = g(S,a) \cdot a_j + h(S,a) \text{ for all } j \in S, \\ h(S \cup \{\ell\}, (a, a_\ell)) = 0, \end{gathered} \tag{20}$$

which imply

$$g(S \cup \{\ell\}, (a, a_\ell)) \cdot a_j = g(S,a) \cdot a_j + h(S,a) \text{ for all } j \in S. \tag{21}$$

Let $k \in S \cup \{\ell\}$ be such that $a_k = \max_{i \in S\cup\{\ell\}} a_i$. Since $a_\ell = 0$, we have $k \in S$, and so $a_k = \max_{i \in S} a_i$ as well.

By the *max-one property* and (20),

$$1 = f_k(a, a_\ell) = g(S \cup \{\ell\}, (a, a_\ell)) \cdot a_k + h(S \cup \{\ell\}, (a, a_\ell)) = g(S \cup \{\ell\}, (a, a_\ell)) \cdot a_k,$$

so that

$$g(S \cup \{\ell\}, (a, a_\ell)) = \frac{1}{a_k}. \tag{22}$$

Therefore by the fact $a_k = \max_{i \in S} a_i$, (22), and (21),

$$\frac{a_j}{\max_{i \in S} a_i} = \frac{a_j}{a_k} = g(S \cup \{\ell\}, (a, a_\ell)) \cdot a_j = g(S,a) \cdot a_j + h(S,a) = f_j(a) \text{ for all } j \in S,$$

as desired. $\square$

The axioms in Theorem 1 are tight; that is, if any one of them is dropped, then the axiomatic characterization is no longer valid.

- Dropping *intensity preservation*: Let f be the "quantile among positive values" such that for each $S \in \mathscr{S}$, $a \in D_S$, and $j \in S$,

$$f_j(a) = \frac{|\{i \in S : a_j \geq a_i > 0\}|}{|\{i \in S : a_i > 0\}|} \text{ if } a_j > 0,$$
$$f_j(a) = 0 \text{ if } a_j = 0.$$

  This f satisfies all the axioms except *intensity preservation*.

- Dropping *independence of null objects*: Let f be the "min-max normalization" such that for each $S \in \mathscr{S}$, $a \in D_S$, and $j \in S$,

$$f_j(a) = \frac{a_j - \min_{i \in S} a_i}{\max_{i \in S} a_i - \min_{i \in S} a_i}.$$

  This f satisfies all the axioms except *independence of null objects*.

- Dropping *the max-one property*: Let f be a variant of the max normalization such that for each $S \in \mathscr{S}$, $a \in D_S$, and $j \in S$,

$$f_j(a) = q(\sum_{i \in S} a_i) \cdot \frac{a_j}{\max_{i \in S} a_i},$$

  where $q : \mathbb{R}_{++} \to [0,1]$ is any function. Unless $q(\sum_{i \in S} a_i) = 1$ for all $\sum_{i \in S} a_i$, this f satisfies all the axioms except *the max-one property*. A simplest case is a constant function such as $q(\sum_{i \in S} a_i) = 0$ for all $\sum_{i \in S} a_i$.

  This example also suggests that *intensity preservation* and *independence of null objects* do not together imply any well-behaved form of f, since q is allowed to be very strange. For example, consider the following case:

$$q(\sum_{i \in S} a_i) = 1 \text{ if } \sum_{i \in S} a_i \text{ is rational,}$$
$$= 0 \text{ if } \sum_{i \in S} a_i \text{ is irrational.}$$

  The normalization function f seems pathological in this case, but satisfies *intensity preservation* and *independence of null objects*. One may consider that *intensity preservation* is so strong that it implies certain linearity of f, but this f is even discontinuous everywhere and is not Lebesgue measurable on every D_S.

Finally, we remark that Theorem 1 provides a new axiomatization of a certain proportional rule in a new model. For studies on various proportional rules in other models, see, Ju, Miyagawa, and Sakai (2007).

Appendix 2 How to handle exceptional trouble cases

A2.1 Logarithmic transformation

Since our scoring method depends on the logarithmic transformation, it may happen that a value cannot be nicely transformed or be defined. Although such cases can rarely happen, we define how to deal with them.

- Whenever the average deviation, the volatility, or the persistenace is zero, its logarithmic transformation cannot be defined, which causes a trouble to define scores. For average deviation as an example, if $\texttt{avedev}(x^p) = 0$ for some $p \in S$, then for each $s \in S$, we transform x^s by

$$\log_{10} [\texttt{avedev}(x^s) + 0.1]$$

  and calculate all scores as usual. We do the same transformation to volatility and persistence when necessary.

- Whenever DEX liquidity, the number of active addresses, or transaction volume is less than ten, its logarithmic transformation can be negative or undefined, which causes a trouble to define scores. Cases like this may only happen with very minor stablecoins for a short period of time, but here we define how to deal with it. For DEX liquidity as an example, if $\texttt{avedev}(x^p) \in [0, 10)$ for some $p \in S$, then we simply let

$$\texttt{avedev}(x^p) = 10,$$

  so that $\log_{10} \texttt{avedev}(x^p) = 1$, and we calculate all scores as usual.

We do the same transformation to the number of active addresses and transaction volume.

A2.2 Negative scores

It is logically possible that $\texttt{avedev}(x^s) > 1$, although this may happen in unrealistic situations like $[x_t^s > 2 \text{ for all } t \in T]$. In this case,

$$\log_{10} \texttt{avedev}(x^s) > 0,$$

so that the score of average deviation becomes negative:

$$\texttt{score}(\texttt{avedev}(x^s)) = \frac{-\log_{10} \texttt{avedev}(x^s)}{\max_{u \in S} - \log_{10} \texttt{avedev}(x^u)} < 0.$$

This negative score itself is not problematic, but the derived property that

$$\texttt{score}(\texttt{avedev}(x^s))^{\frac{1}{6}}$$

is an imaginary number is problematic, since our rating function (9) is not well-defined as a real-valued function then. However, $\texttt{avedev}(x^s) > 1$ implies that the price of s is greater than 2 on average over the data collection period, and this situation almost never happens with stablecoins. In the unlikely event that it happens, we will simply replace $\texttt{score}(\texttt{avedev}(x^s))$ with zero or a very small positive value, or we may simply remove s from the list S because such an excessively strange stablecoin is not worthy of rating. This negativity problem can theoretically occur for average deviation and volatility, but it is natural to consider that it never happens in reality because of the nature of stablecoins.