Journal of Financial Stability 81 (2025) 101458

Contents lists available at ScienceDirect

Journal of Financial Stability

journal homepage: www.elsevier.com/locate/jfs

A stablecoin that's actually stable: A portfolio optimization approach

Klaus Grobys[a,b,*,1], Juha-Pekka Junttila[c,1], James W. Kolari[d,1]

[a] Finance Research Group, School of Accounting and Finance, University of Vaasa, Wolffintie 34, Vaasa 65200, Finland
[b] Department of Monetary Economics and International Finance, Christian-Albrechts University (CAU) of Kiel, Wilhelm-Seelig-Platz 1, Kiel 24118, Germany
[c] Department of Economics, Accounting and Finance, Oulu Business School, University of Oulu, Erkki Koiso-Kanttilan katu 1, Oulu 90570, Finland
[d] Adam C. Sinn '00 Department of Finance, Mays Business School, Texas A&M University, College Station, TX 77843-4218, United States

ARTICLE INFO

JEL classifications:
C19
C49
C59
G10
G15
G19

Keywords:
Financial technology
Portfolio optimization
Power laws
Stablecoins
Volatility

ABSTRACT

Stablecoins seek to address the high price fluctuations of unbacked cryptocurrencies, such as Bitcoin and Ether. However, recent studies as well as the collapse of stablecoin USTC (Terra) cast doubt on the stability of stablecoins. Using well-known Markowitz portfolio optimization methods, we combine five leading stablecoins into a global minimum variance portfolio that represents a stable aggregate stablecoin (SAS). We find that SAS is much more stable than its constituent stablecoins. Also, in a stress test adding USTC to the portfolio, SAS remains stable with a narrow price range over time. Importantly, the construction of SAS using modern diversification methods has practical implications for the ongoing development of central bank digital currencies (CBDCs).

1. Introduction

Stablecoins are a type of cryptocurrency whose value is pegged to another asset, such as a national fiat currency or commodity (e.g., gold), to maintain a stable price. The main purpose of stablecoins is to provide a more stable medium of exchange than unpegged cryptocurrencies, i.e., altcoins such as Bitcoin and Ether, which are notorious for extraordinarily high volatility. As discussed by Kahya et al. (2021), there are three types of stablecoins: fiat-collateralized, crypto-collateralized, and non-collateralized (algorithmic). To support the value of a fiat-collateralized stablecoin, the entity (issuer) behind the stablecoin maintains a reserve of the underlying asset. For crypto-collateralized stablecoins, the underlying assets are cryptocurrencies. Finally, non-collateralized (algorithmic) stablecoins make use of software algorithms to automatically adjust the supply of stablecoins based on demand with the aim of maintaining a stable price (Grobys et al., 2021).

Despite their name, recent research papers cast doubt on the stability of stablecoins. For example, Hoang and Baur (2021) examine the price stability of stablecoins in absolute (i.e., maintaining a constant value) and relative (with respect to other cryptocurrencies) terms. Their findings demonstrate that stablecoins are not very stable, even though they are more stable than for example Bitcoin. Another study by Grobys et al. (2021) explores the volatility processes of large-cap stablecoins and their stochastic interdependencies with Bitcoin volatility. Surprisingly, as implied by power-law exponents less than 3, their results indicate that the volatilities of stablecoins are statistically unstable. Using high-frequency hourly data, Duan and Urquhart (2023) explore the stability of five large-cap stablecoins via fractional time series analysis.[2] Confirming prior studies, even though deviations from a $1 benchmark are gradually corrected at different speeds, the authors find strong evidence of instability among the stablecoins. Whereas the evidence suggests that BUSD is the most stable stablecoin in terms of the fastest

* Corresponding author at: Finance Research Group, School of Accounting and Finance, University of Vaasa, Wolffintie 34, Vaasa 65200, Finland.
E-mail address: klaus.grobys@uwasa.fi (K. Grobys).

[1] The authors are grateful for the constructive comments provided by the anonymous reviewers, which helped to improve the paper. We would also like to express our sincere thanks to the editor for valuable guidance and for handling the review process with great care and fairness.

[2] Other relevant studies on stablecoins are the ones of Giudici et al. (2022), Ahelegbey and Giudici (2022). Both studies focus on constructing synthetic financial instruments (such as stablecoins or network-based indices) designed to reduce volatility and contagion risks by leveraging diversified, interconnected structures rather than relying on single asset exposures.

https://doi.org/10.1016/j.jfs.2025.101458
Received 27 November 2024; Received in revised form 19 August 2025; Accepted 22 August 2025
Available online 28 August 2025

correction speed, parity deviations for DAI do not converge even in the long-run due to non-stationarity. Corroborating the instability of stablecoins in the academic literature, the TerraUSD (UST) stablecoin collapsed in May 2022. During that month, the price of the Terra crashed from $1.00 on May 3, 2022 to $0.02 on May 31, 2022. According to *The New York Times*, this collapse resulted in losses of approximately USD 40 billion.[3] Due to this episode, Urquhart and Yarovaya (2023) recommended that "… with the collapse of Terra in May 2022 and the regulatory attention stablecoins are attracting, academia needs to pursue studies on how best to design stablecoins …" Urquhart and Yarovaya (2023, p. 4).

In an effort to fill this gap in the literature, we investigate whether Markowitz's (1952) portfolio optimization methods can be used to construct a stable aggregate stablecoin (SAS). A closely related study by Hovanov et al. (2004) shows that a minimum variance basket of major currencies can be combined via Markowitz portfolio methods into a relatively stable aggregate currency (SAC). In their study, the authors introduce a currency invariant index approach to avoid optimization issues with different possible base currencies. By contrast, in the present study, SAS is denominated in U.S. dollars using stablecoins traded in dollars. Unlike Hovanov et al., who utilize daily currency price and return series within each month to compute the variances, we assume that an important source of stablecoin risk is the intraday price variation as opposed to the variation in daily closing prices (see Grobys et al. 2021). Consequently, we employ Parkinson's (1980) range-based variance estimator for five stablecoins that exhibit the largest market capitalizations. These variance estimates are used to build a global minimum variance portfolio (G) of stablecoins. The weights of the stablecoins are optimized using a fixed rolling-time window to ensure that conditional information is available at the time of the portfolio allocation decision. The optimal weights for the asset allocations are estimated on a daily basis to construct a diversified portfolio of stablecoins. To stress test our proposed stable aggregate stablecoin (SAS) under conditions of extreme stablecoin volatility, we add the collapsed stablecoin Terra to the sample of stablecoins in SAS. In our empirical analyses, we focus primarily on range-based variance and price processes. Additionally, due to our expanded dataset of stablecoins, we revisit Grobys et al. (2021) by analyzing the power-law properties of the daily variance processes of stablecoins.

Our study contributes to existing literature in several ways. Ante et al. (2023) document that previous studies on stablecoins fall into three categories: (a) studies on the stability or volatility of different stablecoins, their designs, and safe-haven-properties; (b) the interrelations of stablecoins with other crypto assets and markets, especially Bitcoin; and (c) the relationship of stablecoins to (non-crypto) macroeconomic factors. As discussed above, studies find that stablecoins are more unstable than commonly believed (e.g., Jarno and Kołodziejczyk, 2021; Jeger et al., 2020; Hoang and Baur, 2021). For this reason, consistent with the recommendation of Urquhart and Yarovaya (2023), we seek to design a stablecoin that is stable over time.

From a practical point of view, our empirical analysis is closely related to the current discussions on the development of Central Bank Digital Currencies (CBDCs). In a recent study, Claessens et al. (2024) highlight that the comparison between CBDCs and stablecoins as mediums of exchange contrasts Centralized Finance (CeFi) versus Decentralized Finance (DeFi). They observe that, to realize the full potential of DeFi (like stablecoins), there is a need for CeFi and DeFi to coexist together (see also Ozili, 2022). Furthermore, due to the use of fiat currency as (collateral) assets underlying the stability of stablecoins, implications to financial system stability are important. As stressed by Claessens et al. (2024), given that stablecoins are one of the building blocks of DeFi, there is increasing regulatory scrutiny of their risks with respect to financial stability. In this regard, Aramonte et al. (2021) cautions: "These risks are compounded by the fact that users treat stablecoins as a medium of exchange, although they are neither central bank money nor commercial bank money … as a better substitute for stablecoins, which are privately issued, central bank digital currencies (CBDCs) could support fund transfers with greater efficiency and safety." (Aramonte et al., 2021, p. 33).

As Claessens et al. (2024) argue, while decentralization has its costs and complexities, the simultaneous evolution of CeFi and DeFi can enable better management of financial system risks. While CBDCs offer safety and stability advantages, Defi assets are linked to standard financial assets that can potentially mitigate risks. Consistent with this approach, we believe that these two types of digital currencies can complement one other and thereby create a more integrated and efficient financial system. Consequently, we seek to investigate a basket of stablecoins that is the lowest risk combination of individual stablecoins. Such a stable basket of stablecoins could facilitate their interoperability with CBDCs across different digital currency platforms.

Derived from Markowitz's (1952) Nobel Prize in Economics work on portfolio optimization, a large body of literature exists on the properties of the global minimum-variance portfolio (G). Clarke et al. (2011) observe that, in the wake of the global financial crisis, this minimum-variance portfolio has attracted investor attention. From the literature on equites, it is well known that portfolio G contains low-volatility stocks yielding average market returns.[4] The authors analyze the composition of G portfolios with a focus on the analytic form and parameter values of individual security weights. Their findings suggest G portfolios have high Sharpe ratios with relatively high returns and low total risk.[5]

The present study extends previous research by applying well-known Markowitz optimization methods to the problem of creating a stable aggregate stablecoin (SAS). Even though stablecoins lack variation in daily returns, Grobys et al. (2021) show that intraday price variations are considerable. Taking advantage of intraday data, we construct a global minimum variance-of-variance portfolio using optimally weighted range-based individual stablecoin variances of the five major stablecoins currently traded. These iteratively re-estimated optimal weights are applied to both the range-based stablecoin variance and price processes. The resultant stability of the aggregate stablecoin (SAS) remains robust even in the event of a constituent stablecoin's default.

Concerning the instability of stablecoins, there is emerging literature on power laws in the market for cryptocurrencies. For example, Zhang et al. (2018) examine the heavy tails, autocorrelations, volatility clustering, leverage effects, long-range dependencies, and power-law correlations for eight unpegged cryptocurrencies: Bitcoin (BTC), Dash (DASH), Ethereum (ETH), Litecoin (LTC), NEM (XEM), Stellar (XLM), Monero (XMR), and Ripple (XRP). They find evidence for heavy tails for all cryptocurrencies' returns as well as confirmation of the slow decay of autocorrelations. A recent study by Grobys (2024) employs power-law functions to model the returns on 10 altcoins with the highest market capitalizations as of January 1, 2016. His findings indicate statistically significant evidence for power-law behavior in the vast majority of altcoin returns. In this regard, the only study modeling realized variances of large-cap stablecoins as power laws is by Grobys et al. (2021). Given these studies, a natural question is: Are power laws with undefined second moments manifestations of stablecoin variances? We revisit this issue by studying a considerably larger dataset than used in the study by Grobys et al. (2021).

[3] https://www.nytimes.com/2022/05/18/technology/terra-luna-cryptocurrency-do-kwon.html.

[4] Note that the global minimum-variance portfolio has the unique property that security weights are independent of forecasted or expected returns of individual securities.

[5] More generally, G portfolios have been the subject of numerous methodological studies (e.g., see Best and Grauer, 1992; Bera and Park, 2008; Chow et al., 2016; Bodnar et al., 2017; Xidonas et al., 2017; and others).

Based on Clauset et al.'s (2009) estimation approach for fitting power law functions to five large-cap stablecoins (DAI, USDT, BUSD, TUSD, USDC), our results suggest that the realized variances of stablecoins typically exhibit power-law behavior. In contrast to Grobys et al. (2021), who document that the variances of range-based stablecoin variances are undefined, our findings indicate that we cannot reject the null hypothesis of a universal power-law exponent governing the cross-section of range-based stablecoin variances, viz., $\alpha \approx 2.00$ (p-value 0.7659). Thus, even the theoretical mean of the variance is statistically undefined, which implies that stablecoins behave even more wildly than previously believed. Further evidence suggests that the power-law null hypothesis cannot be rejected for the majority of stablecoin variances.

Based on fitting a standard vector-auto-regressive (VAR) model of order $p = 2$ to the stablecoin variance data, our results suggest that range-based stablecoin variances have statistically significant stochastic interdependencies justifying the adoption of a portfolio optimization approach. Using an iteratively updated portfolio optimization Markowitz (1952) approach, for a set of five large-cap stablecoins, our results show that the global minimum-variance portfolio G, or stable aggregate stablecoin (SAS), exhibits on average a negative sample mean of the variance process. This negative variance is a statistical artifact of the optimization process that allows short positions in stablecoins. As a stress test, we add the collapsed stablecoin USTC to the sample of stablecoins used in the iteratively generated portfolio optimization. Despite the collapse of Terra (USTC) in May 2022, the price process of SAS remains within a narrow range between 0.9991 and 1.0017 corresponding to the 95 % probability interval from January 11, 2021, to March 27, 2024. These results bode well for SAS as a stable basket of stablecoins that is hardened with respect to extreme price instability of a constituent stablecoin.

2. Central bank digital currencies (CBDCs) and stablecoins

2.1. Overview of CBDCs and stablecoins

Central Bank Digital Currencies (CBDCs) and stablecoins represent two innovative yet distinct forms of digital money. CBDCs are state-issued digital tokens regulated by central banks designed to modernize payments and support monetary sovereignty. In contrast, stablecoins are privately issued cryptocurrencies intended to maintain a stable value by being pegged to assets like fiat currencies or commodities. Despite these differences, both instruments seek to provide stability, efficiency, and accessibility in digital transactions (Catalini and de Gortari, 2021; PwC, 2023).[6] CBDCs aim to offer a risk-free digital alternative to cash, promote financial inclusion, and enhance monetary policy transmission. Stablecoins leverage blockchain technology to enable instant settlement and programmable money but are often viewed as riskier due to their private issuance and varying degrees of collateralization (Bellia and Schich, 2020). Recent high-profile failures, such as the collapse of Terra (USTC), have intensified regulatory concerns about their stability (Urquhart and Yarovaya, 2023).

2.2. Risks, regulations, and interoperability

Stablecoins have been criticized for introducing counterparty and operational risks. The Financial Stability Board (Financial Stability Board (FSB), 2022) and G7 Working Group on Stablecoins (2019) have raised alarms regarding reserve management, governance, and systemic risk, particularly for globally significant stablecoins like USDT. Blockchain limitations (e.g., throughput, fees, redemption issues) further challenge their use as payment instruments (Adachi et al., 2022; Dionysopoulos et al., 2024). By comparison, CBDCs are perceived to be safer but not without trade-offs. Potential impacts on the traditional banking sector, privacy concerns, and uncertain user adoption present challenges (Bank of England (BoE), 2019, 2020; Committee on Payments and Market Infrastructures (CPMI), 2018; Niepelt, 2024; Guseva et al., 2024; Di Maggio et al., 2024; Choi and Kim, 2024). Even so, many central banks have begun testing or pilot studies of CBDCs (Areddy, 2021). There is increasing recognition that CBDCs and stablecoins could coexist. Scholars such as Claessens et al. (2024) argue for potential synergies between centralized (CeFi) and decentralized finance (DeFi). Assuming appropriate regulatory frameworks are established (Ozili, 2022), stablecoin strengths in programmability and speed can complement the safety and trust of CBDCs.

2.3. Policy developments and the role of SAS

Recent political developments underscore the relevance of stablecoins. For example, the Trump administration has expressed support for prioritizing private sector innovation in stablecoin development over launching a U.S. CBDC (Banking Dive, 2025). Krause (2025) emphasizes the need for balanced regulation to encourage innovation while mitigating systemic risk. Against this backdrop, a well-structured stablecoin portfolio could play a significant role in future monetary architecture. We propose that a stable aggregate stablecoin (SAS), constructed via Markowitz minimum-variance methods, could serve as a collateral base for CBDCs or as a stability-enhancing component on central banks' balance sheets. This approach offers diversification benefits and dynamic risk management. Given political endorsement and increasing stablecoin market maturity, SAS represents a pragmatic solution to align private innovation with public monetary goals.

2.4. SAS as a design feature for CBDCs

The SAS framework offers several advantages for CBDC design.

- Stability: A diversified SAS reduces exposure to the instability of any single stablecoin.
- Trust and security: By holding only well-collateralized stablecoins, SAS can add credibility to CBDC backing.
- Interoperability: Stablecoins have demonstrated functional integration with both traditional and DeFi systems.
- Efficiency: SAS inherits stablecoins' speed and low-cost settlement, which CBDCs could emulate.

In extreme scenarios wherein private stablecoins become politically entrenched, central banks could use an optimized SAS as part of their asset management strategy. Rather than duplicating infrastructure, CBDCs could leverage innovations from stablecoins while reinforcing regulatory oversight.[7] In summary, the proposed SAS enhances the stability of digital currencies and provides a credible bridge between decentralized innovation and centralized control. This synthesis strengthens the case for SAS-informed CBDC architectures that are resilient, inclusive, and forward-compatible.

3. Data

We download data for the following top five stablecoins in terms of market capitalization from CoinMarketCap.com[8]: DAI, USDT, BUSD, TUSD, and USDC. As shown in Fig. A.1 in the Appendix, these

[6] For an update on recent events in the global adoption of CBDCs, see PwC (2023).

[7] Some precedent exists in the literature for the notion of pegging a digital currency to a basket of assets. For example, a theoretical study by Balvers and McDonald (2021) proposes the creation of a global digital currency that is pegged to a measure of inflation based on a tradable goods basket.

[8] CoinMarketCap.com has been used as a reliable data source in studies such as Liu et al. (2022), Liu and Tsyvinski (2021), and Cong et al. (2021).

stablecoins are key players in the stablecoin market with consistent growth over time. Our sample period is from November 25, 2020 to March 31, 2025. The data include daily low, high, and closing prices. To derive the annualized daily stablecoin variances, the following range-based variance estimator proposed by Parkinson (1980) is employed:

$$\sigma^2_{i,t} = T\frac{1}{4\ln(2)}\left(\ln(H_{i,t}) - \ln(L_{i,t})\right)^2,$$

where $H_{i,t}$ and $L_{i,t}$ are the highest and lowest price for stablecoin i on trading day t, respectively, and $\sigma^2_{i,t}$ is stablecoin i's corresponding annualized realized variance with $T = 364$ trading days per year. We report descriptive statistics for the range-based stablecoin variances in Table 1. As shown there, annualized range-based variances exhibit an extremely high level of heavy tails. For example, excess kurtosis values range between 159.04 (BUSD) and 1536.34 (USDC), which substantially exceeds the kurtosis value of 3 for a normal distribution. In addition, sample means deviate considerably from their median values. For instance, in the case of DAI, the sample mean exceeds its median value by a factor of approximately 325 times. These large disparities suggest that daily stablecoin variances are exposed to extreme events that dominate their overall distribution.

4. Empirical analysis

4.1. How stable are stablecoins? Evidence from power laws

Since heavy tails are typical manifestations of power-law behavior, we follow Grobys et al. (2021) and explore whether the range-based stablecoin variances are governed by power laws. Specifically, we model heavy tails for the range-based stablecoin variances using the following power-law function:

$$p(x) = Cx^{-\alpha}, \tag{1}$$

where $C = (\alpha - 1)x_{MIN}^{\alpha-1}$ with $\alpha \in \{\mathbb{R}_+ | \alpha > 1\}$, x denotes the range-based variance of a stablecoin provided that $x \in \{\mathbb{R}_+ | x_{MIN} \leq x < \infty\}$, x_{MIN} is the cutoff, and α is the magnitude of the corresponding tail exponent.[9] It can be shown that the conditional expectation is defined as:

$$E[X|x > x_{MIN}] = \int_{x_{MIN}}^{\infty} x dp(x)x = \frac{(\alpha - 1)}{(\alpha - 2)}x_{MIN}, \tag{2}$$

and higher moments of order k are defined as:

$$E\left[X^k|x > x_{MIN}\right] = \frac{(\alpha - 1)}{(\alpha - 1 - k)}x^k_{MIN}. \tag{3}$$

From Eqs. (2) and (3), it is evident that the (conditional) theoretical mean only exists for $\alpha > 2$, whereas the (conditional) theoretical variance only exists for $\alpha > 3$. Following Clauset et al. (2009), power-law exponents are estimated using maximum likelihood estimation (MLE):

$$\widehat{\alpha} = 1 + N\left(\sum_{i=1}^{N} \ln\left(\frac{x_i}{x_{MIN}}\right)\right)^{-1} \tag{4}$$

where $\widehat{\alpha}$ denotes the MLE estimator, N is the number of observations exceeding x_{MIN}, and other notation is as before. Clauset et al. derive the corresponding standard deviation of the estimated power-law exponent as:

$$\widehat{\sigma} = \frac{\widehat{\alpha} - 1}{\sqrt{N}} + O\left(\frac{1}{N}\right). \tag{5}$$

[9] Following Clauset et al. (2009), to simplify notation, index i for the respective individual stablecoin variance is dropped.

Following these authors, x_{MIN} is selected with respect to the optimized Kolmogorov-Smirnov (KS) distance D that measures the maximum distance between the cumulative density functions (CDFs) of the data and the fitted power-law model as follows:

$$D = MAX_{x \geq x_{MIN}} |S(x) - P(x)| \tag{6}$$

where $S(x)$ is the CDF of the data for the observation with a value of at least x_{MIN}, and $P(x)$ denotes the CDF for the power-law model that best fits the data in the region $x \geq x_{MIN}$. The estimate for x_{MIN} ($\widehat{x}_{MIN}$) is the value of x_{MIN} that minimizes D. To test the power law model, we employ the goodness-of-fit (GoF) test proposed in Clauset et al. (2009). This test generates a p-value that quantifies the plausibility of the power-law null model by comparing D from Eq. (6) with distance measurements for comparable synthetic data sets drawn from the hypothesized model. The p-value is calculated as the fraction of synthetic distances that exceed D. The power-law null model is not rejected for p-values > 5 %.[10]

Table 2 reports the corresponding estimated exponents for the power-law models. We observe from Table 2 that the estimated power-law exponents vary between $\widehat{\alpha} \approx 1.76$ (DAI) and $\widehat{\alpha} \approx 2.27$ (USDT), such that the range-based stablecoin variances exhibit behavior consistent with infinite variances across the entire cross-section. However, one might argue that the power-law model is a poor description of the data-generating process, thereby rendering invalid statistical inferences derived from the estimated power-law exponents. Considering the p-values for the GoF test, the results from Table 2 show that the power-law models cannot be rejected for the realized variances of DAI, BUSD, and TUSD (i.e., p-values > 0.05). In particular, for the range-based variances of DAI and TUSD, our results suggest that $\widehat{\alpha} \ll 2.00$. Thus, for these stablecoins the infinite-theoretical-variance hypothesis cannot be rejected. Overall, these results indicate that the risk in stablecoin prices, as measured by the range-based variances, is so "wild" that the theoretical means of realized variances are statistically undefined for at least two-out-of-five stablecoins.

4.2. Is there a common exponent governing the variance risk of stablecoins?

Can we identify a common power-law behavior of range-based stablecoin variances? Since the point estimates for the power-law exponents are relatively close to each other, we seek to ascertain whether a common power-law exponent governs the risk of stablecoins. To do so, we propose the following test statistic:

$$\lambda = \boldsymbol{\alpha}^{H\prime}\boldsymbol{\Sigma}_{\alpha}^{-1}\boldsymbol{\alpha}^{H}, \tag{7}$$

where $\boldsymbol{\alpha}^{H\prime} = ((\widehat{\alpha}_{DAI} - q), (\widehat{\alpha}_{USDT} - q), \ldots, (\widehat{\alpha}_{TUSD} - q))$ a 5×1 vector that contains the differences between the estimated power-law exponents and hypothesized common power-law exponent q, and $\boldsymbol{\Sigma}_{\alpha}$ denotes the covariance matrix of the estimated power-law exponent defined as:

[10] The GoF test is described in more detail in (Clauset et al. (2009), pp. 675–678). The skewed-t distribution, while useful in modeling heavy-tailed asset returns, is defined on the full real line and thus not directly applicable to modeling realized variances, which are strictly positive. Power-law models are better suited for capturing the heavy right tails of such non-negative variables.

Table 1
Descriptive statistics for range-based stablecoin variances.

Statistic	DAI	USDT	BUSD	TUSD	USDC	USTC	SAS	SAS*
Min	5.25E − 06	1.31E − 06	1.18E − 05	4.73E − 05	1.18E − 05	0.0002	− 140.9313	− 192.6667
1 % Qnt.	2.10E − 05	1.31E − 06	2.10E − 05	0.0001	2.10E − 05	0.0006	− 0.0006	− 0.0008
2.5 % Qnt.	3.28E − 05	1.31E − 06	3.27E − 05	0.0002	2.10E − 05	0.0013	− 0.0002	− 0.0002
5 % Qnt.	4.72E − 05	5.25E − 06	4.73E − 05	0.0002	3.28E − 05	0.0022	− 6.09E − 05	− 8.41E − 05
10 % Qnt.	4.73E − 05	5.25E − 06	8.39E − 05	0.0002	4.73E − 05	0.0036	− 1.06E − 05	− 1.83E − 05
Median	0.0005	0.0002	0.0003	0.0006	0.0002	0.2662	5.69E − 05	5.46E − 05
90 % Qnt.	0.0023	0.0009	0.0020	0.0025	0.0007	3.1235	0.0005	0.0005
95 % Qnt.	0.0064	0.0017	0.0024	0.0054	0.0016	6.8759	0.0018	0.0018
97.5 % Qnt.	0.0150	0.0020	0.0045	0.0114	0.0020	15.8758	0.0021	0.0021
99 % Qnt.	0.0329	0.0033	0.0146	0.0305	0.0024	54.2043	0.0049	0.0053
Max	224.8839	0.3358	0.0925	0.7083	96.2436	762.7055	2.5783	2.5781
Mean	0.1626	0.0009	0.0013	0.0029	0.0665	3.0575	− 0.0891	− 0.1228
Std Dev	5.7448	0.0102	0.0058	0.0247	2.4491	24.4392	3.5838	4.8990
Kurtosis[a]	1512.6014	787.1917	159.0377	576.4929	1536.3446	629.9561	1540.9615	1541.4155
Skewness	38.7650	26.2215	11.9948	22.5915	39.1879	22.3745	− 39.2737	−39.2825
T	1547	1547	1547	1547	1547	1547	1547	1547

This table reports the descriptive statistics of range-based variance processes for the following stablecoins: DAI, USDT, BUSD, TUSD, USDC, and USTC, as well as the range-based variances for stable aggregate (synthetic) stablecoins SAS and SAS*. To estimate annualized daily stablecoin variances, we employ the range-based variance estimator proposed by Parkinson (1980):

$$\sigma_{i,t}^2 = T\frac{1}{4\ln(2)}\left(\ln(H_{i,t}) - \ln(L_{i,t})\right)^2$$

where $H_{i,t}$ and $L_{i,t}$ denote the highest and lowest price for stablecoin i on trading day t, and $\sigma_{i,t}^2$ is stablecoin i's corresponding annualized range-based variance with $T = 364$ trading days per year. SAS and its augmented version SAS* are constructed as global minimum-variance of variance portfolios using five (DAI, USDT, BUSD, TUSD, USDC) and six (including USTC) stablecoins, respectively. Dynamic portfolio weights are estimated using a 20-day rolling window. Stablecoin price data are obtained from CoinMarketCap.com. Descriptive statistics are reported for the period from January 5, 2021 to March 31, 2025.

[a] Kurtosis is reported in terms of excess kurtosis.

Table 2
Power-law estimates for range-based stablecoin variances.

Stablecoin	DAI	USDT	BUSD	TUSD	USDC	USTC
$\widehat{\alpha}$	1.7599	2.2694	1.8645	1.9357	2.0942	1.8184
$\widehat{x}_{MIN}$	0.0021	0.0004	0.0028	0.0022	0.0003	0.8862
$\widehat{\sigma}$	0.0573	0.0631	0.1098	0.0688	0.0487	0.0394
N	176	405	62	185	504	432
(%T)	(11.38 %)	(26.18 %)	(4.01 %)	(11.96)	(32.58 %)	(27.93 %)
p-value (GoF)	0.9045	0.0490	0.7674	0.9930	0.0117	0.6268

Annualized daily range-based stablecoin variances are modeled using the following power-law function:

$$p(x) = Cx^{-\alpha}$$

where $C = (\alpha - 1)x_{MIN}^{\alpha-1}$ with $\alpha \in \{\mathbb{R}_+ | \alpha > 1\}$, x denotes the respective absolute amount of a range-based stablecoin variance provided $x \in \{\mathbb{R}_+ | x_{MIN} \leq x < \infty\}$, x_{MIN} is the minimum value governed by the power-law process, and α is the magnitude of the corresponding power-law exponent. The tail exponents are estimated as:

$$\widehat{\alpha} = 1 + N\left(\sum_{i=1}^{N} \ln\left(\frac{x_i}{x_{MIN}}\right)\right)^{-1}$$

where $\widehat{\alpha}$ denotes the MLE estimator, N is the number of observations exceeding x_{MIN}, and other notation is as before. The estimate $\widehat{\alpha}$ is selected based on the optimal Kolmogorov–Smirnov (KS) distance D measuring the maximum distance between the cumulative density functions (CDFs) of the data and the fitted power-law model defined as:$D = MAX_{x \geq x_{MIN}} |S(x) - P(x)|$,where $S(x)$ is the CDF of the data for observations with a value of at least x_{MIN}, and $P(x)$ is the CDF for the power-law model that best fits the data for $x \geq x_{MIN}$. The estimate $\widehat{x}_{MIN}$ is the corresponding value of x_{MIN} minimizing D. This table reports the estimates $\widehat{\alpha}$, $\widehat{x}_{\min}$, $\widehat{\sigma}$, and N in absolute and relative terms. The sample period is from period January 5, 2021 to March 31, 2025.

$$\Sigma_\alpha^{-1} = \begin{pmatrix} \widehat{\sigma}^2_{\alpha_{DAI}} & 0 & 0 & 0 & 0 \\ 0 & \widehat{\sigma}^2_{\alpha_{USDT}} & & & \\ 0 & 0 & \ddots & & \vdots \\ 0 & \vdots & 0 & \ddots & 0 \\ 0 & & \cdots & & \widehat{\sigma}^2_{\alpha_{TUSD}} \end{pmatrix},$$

wherein the estimation procedure as given by Eqs. (1)–(6) implies that $COV(\widehat{\alpha}_i, \widehat{\alpha}_j) = 0 \ \ \forall i \neq j$. We implement this test for economically important exponents $\alpha = 1.50$ to $\alpha = 2.50$. The test statistics are iteratively estimated and plotted in Fig. 1. Strikingly, our findings indicate that the function reaches its minimum at $\alpha = 2$. The hypothesis that realized stablecoin variances are governed by the same power-law exponent corresponding to $\alpha = 2.00$ is associated with an estimated test statistic of $\widehat{\lambda} = 2.57$. Since the test statistic is under the null hypothesis distributed as $\chi^2(5)$, the p-value corresponds to 0.7659, so we cannot reject the null hypothesis. That is, from a statistical standpoint, the variance risk of stablecoins is undefined or infinite. Furthermore, because the critical value for the 5 % significance level is $\chi^2_{0.95} = 11.07$, our findings indicate that we cannot reject the null hypothesis of a common power-law exponent for $\alpha \in [1.66; 2.33]$ with corresponding estimated test statistics ranging from $\widehat{\lambda} = 11.55$ and $\widehat{\lambda} = 10.81$.

4.3. *Exploring potential stochastic interdependencies between range-based stablecoin variances*

Are the risks of individual stablecoins interconnected? For this purpose, we perform a vector auto-regression (VAR) of stablecoins' variances. Let us define the 5×1 vector $\boldsymbol{Y}_t = [\sigma^2_{DAI,t}, \sigma^2_{USDT,t}, \sigma^2_{BUSD,t}, \sigma^2_{TUSD,t}, \sigma^2_{USDC,t}]$, where $\sigma^2_{j,t}$ denotes the natural logarithm of range-based stablecoin variance j with $j \in \{DAI, USDT, BUSD, TUSD, USDC\}$. Hence, we can specify a VAR model of order p as:[11]

$$\boldsymbol{Y}_t = \boldsymbol{c} + \boldsymbol{\Gamma}_1 \boldsymbol{Y}_{t-1} + \boldsymbol{\Gamma}_2 \boldsymbol{Y}_{t-2} + \ldots \boldsymbol{\Gamma}_p \boldsymbol{Y}_{t-p} + \boldsymbol{u}_t, \tag{8}$$

where $\boldsymbol{c}$ is a 5×1 vector of constants, $\boldsymbol{\Gamma}_1, \ \boldsymbol{\Gamma}_2, \ldots, \ \boldsymbol{\Gamma}_p$ are parameter matrices of dimension 5×5, and $\boldsymbol{u}_t$ denotes a 5×1 vector of error terms that is assumed to be distributed as $\boldsymbol{u}_t \sim MVN(\boldsymbol{0}, \boldsymbol{\Sigma})$. After fitting a VAR(2) model to the logarithmic stablecoin variance data, Table 3 reports the estimates.[12] Investigating the interdependencies between the realized stablecoin variance of DAI and other stablecoin variances, our results indicate that the lagged realized variances of USDT, TUSD, and USDC have an impact on the realized variance of DAI. Similar evidence is found for the other stablecoin variances. Contrary to the conventional expectation of weak interdependence in stablecoin volatility, our VAR (2) estimates reveal a highly structured system. The R-squared values of up to 0.78 and statistically significant coefficients across multiple lags suggest strong autoregressive behavior and cross-token volatility spillovers. These findings imply that the range-based variances of stablecoins exhibit substantial temporal and cross-sectional dependencies, likely reflecting common shocks, liquidity flows, and synchronized trader behavior. Rather than being purely idiosyncratic, the stablecoin volatilities appear meaningfully interconnected. This observed structure in the variance dynamics motivates our subsequent analysis, in which we examine whether these interdependencies can be leveraged for the stability assessment of our proposed synthetic instrument, i.e. the stable

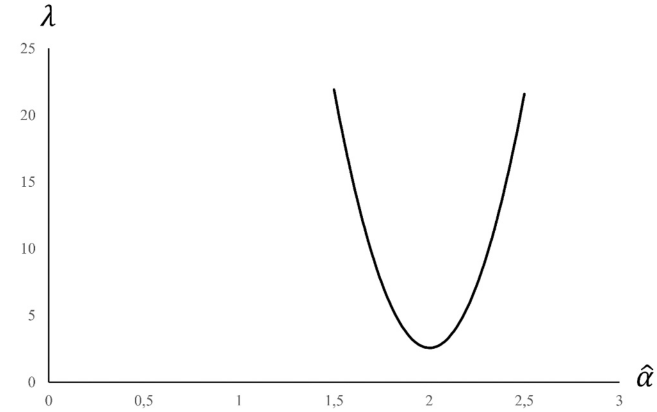


Fig. 1. Testing for a common power-law exponent.
To test for a common power-law exponent governing range-based stablecoin variances, we propose the following test statistic:

$$\lambda = \boldsymbol{\alpha}^{H\prime} \boldsymbol{\Sigma}_\alpha^{-1} \boldsymbol{\alpha}^H$$

,
where $\boldsymbol{\alpha}^{H\prime} = ((\widehat{\alpha}_{DAI} - q), (\widehat{\alpha}_{USDT} - q), \ldots, (\widehat{\alpha}_{TUSD} - q))$ is a 5×1 vector that contains differences between the estimated power-law exponents and hypothesized common power-law exponent q, and $\boldsymbol{\Sigma}_\alpha$ denotes the covariance matrix of the estimated power-law exponents defined as:

$$\Sigma_\alpha^{-1} = \begin{pmatrix} \widehat{\sigma}^2_{\alpha_{DAI}} & 0 & 0 & 0 & 0 \\ 0 & \widehat{\sigma}^2_{\alpha_{USDT}} & & & \\ 0 & 0 & \ddots & & \vdots \\ 0 & \vdots & 0 & \ddots & 0 \\ 0 & & \cdots & & \widehat{\sigma}^2_{\alpha_{TUSD}} \end{pmatrix}$$

.
Because the estimation procedure in Eqs. (1)–(6) implies that $COV(\widehat{\alpha}_i, \widehat{\alpha}_j) = 0 \ \forall i \neq j$, we implement the test for economically important exponents $q = 1.50$ to $q = 2.50$. The estimated test statistics λ for each subsequent test are plotted in the figure.

aggregate stablecoin (SAS).

4.4. *Implementing a stable aggregate stablecoin (SAS)*

Evidence for the stochastic interdependencies between realized individual stablecoin variances supports the construction of an iteratively estimated global minimum variance portfolio of stablecoins (denoted G). In this instance, the G portfolio represents a stable aggregate stablecoin (SAS). Inspired by Markowitz (1952), we estimate dynamic weights $\boldsymbol{w}^{MIN}_{t|\boldsymbol{\Omega}_{t-1}}$ for SAS using five individual range-based stablecoin variances as inputs, rather than the conventional return-based framework. This adaptation is motivated by the fact that the stablecoin return series exhibit minimal variation and near-zero mean, making return-based optimization impractical. Moreover, our analysis reveals that the relevant interdependencies in the system arise from the variance structure, thereby justifying the use of range-based variances as the basis for portfolio construction. Hence, the dynamic weights, $\boldsymbol{w}^{MIN}_{t|\boldsymbol{\Omega}_{t-1}}$, for SAS based on five individual range-based stablecoin variances are defined as:

$$\boldsymbol{w}^{MIN}_{t|\boldsymbol{\Omega}_{t-1}} = \frac{\boldsymbol{\Sigma}^{-1}_{\boldsymbol{\Omega}_{t-1}} \boldsymbol{1}}{\boldsymbol{1}' \boldsymbol{\Sigma}^{-1}_{\boldsymbol{\Omega}_{t-1}} \boldsymbol{1}}, \tag{9}$$

where $\boldsymbol{w}^{MIN}_{t|\boldsymbol{\Omega}_{t-1}}$ denotes a 5×1 vector of (dynamic) weights, $\boldsymbol{\Sigma}^{-1}_{\boldsymbol{\Omega}_{t-1}}$ is the inverse of the range-based stablecoin variances' covariance matrix with

[11] We follow Grobys et al. (2021) by using the natural logarithms of stablecoin variances in the regression model analysis. They observe that this approach normalizes regression residuals by means of removing skewness to some extent.

[12] The motivation for fitting a VAR(2) model is that the partial autocorrelation function (unreported) suggests a lag-order of $p = 1$ for all sample stablecoin variances. This lag structure differs from BUSD with a lag-order of $p = 2$. Results are available upon request from the authors.

Table 3
Estimated vector autoregression (VAR) model for range-based stablecoin variances.

Variable/Stablecoin	DAI	USDT	BUSD	TUSD	USDC
Panel A. Estimated parameters of the fitted VAR(2) model.					
c	**− 2.0944**	**− 2.0922**	**− 1.9131**	**− 2.2355**	**− 2.3950**
$\sigma^2_{DAI,t-1}$	**0.5451**	0.0195	− 0.0054	0.0256	0.0479
$\sigma^2_{USDT,t-1}$	**0.0904**	**0.6676**	**0.0685**	**0.1090**	**0.1730**
$\sigma^2_{BUSD,t-1}$	− 0.0003	− 0.0108	**0.5168**	0.0210	0.0506
$\sigma^2_{TUSD,t-1}$	**− 0.0775**	− 0.0486	− 0.0502	**0.3992**	**− 0.1214**
$\sigma^2_{USDC,t-1}$	0.0240	0.0342	**0.0882**	0.0156	**0.4506**
$\sigma^2_{DAI,t-2}$	**0.3525**	− 0.0497	0.0019	− 0.0151	− 0.0478
$\sigma^2_{USDT,t-2}$	**− 0.0782**	**0.2418**	**− 0.1375**	− 0.0612	− 0.0579
$\sigma^2_{BUSD,t-2}$	0.0306	**− 0.0686**	**0.2769**	0.0433	0.0459
$\sigma^2_{TUSD,t-2}$	− 0.0303	− 0.0332	− 0.0186	**0.2193**	0.0099
$\sigma^2_{USDC,t-2}$	**− 0.1259**	− 0.0134	0.0130	**− 0.0753**	**0.1545**
R-squared	0.7026	0.7878	0.6016	0.3652	0.5087
Panel B. Estimated *t*-statistics for parameter estimates of the fitted VAR(2) model.					
c	− 10.0695	− 10.2277	− 9.2602	− 10.5793	− 11.8633
$\sigma^2_{DAI,t-1}$	19.7555	0.7196	− 0.1961	0.9137	1.7904
$\sigma^2_{USDT,t-1}$	2.8514	21.4012	2.1745	3.3833	5.6189
$\sigma^2_{BUSD,t-1}$	− 0.0102	− 0.3812	18.1223	0.7209	1.8157
$\sigma^2_{TUSD,t-1}$	− 2.6606	− 1.6967	− 1.7347	13.4834	− 4.2921
$\sigma^2_{USDC,t-1}$	0.6845	0.9937	2.5370	0.4377	13.2590
$\sigma^2_{DAI,t-2}$	12.7801	− 1.8324	0.0697	− 0.5406	− 1.7858
$\sigma^2_{USDT,t-2}$	− 2.4744	7.7828	− 4.3814	− 1.9058	− 1.8867
$\sigma^2_{BUSD,t-2}$	1.0606	− 2.4175	9.6675	1.4781	1.6402
$\sigma^2_{TUSD,t-2}$	− 1.0330	− 1.1505	− 0.6384	7.3598	0.3482
$\sigma^2_{USDC,t-2}$	− 3.6158	− 0.3916	0.3769	− 2.1277	4.5700

To explore interdependencies between range-based stablecoin variances, we perform the following vector auto-regression (VAR) of stablecoins variances: $\boldsymbol{Y}_t = \boldsymbol{c} + \boldsymbol{\Gamma}_1\boldsymbol{Y}_{t-1} + \boldsymbol{\Gamma}_2\boldsymbol{Y}_{t-2} + \ldots\boldsymbol{\Gamma}_p\boldsymbol{Y}_{t-p} + \boldsymbol{u}_t,$

$$\boldsymbol{Y}_t = \boldsymbol{c} + \boldsymbol{\Gamma}_1\boldsymbol{Y}_{t-1} + \boldsymbol{\Gamma}_2\boldsymbol{Y}_{t-2} + \ldots\boldsymbol{\Gamma}_p\boldsymbol{Y}_{t-p} + \boldsymbol{u}_t$$

where $\boldsymbol{Y}_t$ is a 5×1 vector defined as $\boldsymbol{Y}_t = [\sigma^2_{DAI,t}, \sigma^2_{USDT,t}, \sigma^2_{BUSD,t}, \sigma^2_{TUSD,t}, \sigma^2_{USDC,t}]$, $\sigma^2_{j,t}$ is the natural logarithm of range-based stablecoin variance j with $j \in \{DAI, USDT, BUSD, TUSD, USDC\}$, $\boldsymbol{c}$ is a 5×1 vector of constants, $\boldsymbol{\Gamma}_1, \boldsymbol{\Gamma}_2, \ldots, \boldsymbol{\Gamma}_p$ are parameter matrices of dimension 5×5, and $\boldsymbol{u}_t$ denotes a 5×1 vector of error terms that is assumed to be distributed as $\boldsymbol{u}_t \sim MVN(\boldsymbol{0}, \boldsymbol{\Sigma})$. This table reports the estimated parameter matrices of a VAR(2) model. The sample period is from period January 5, 2021 to March 31, 2025. **Bold** figures denote statistical significance at a 5 % level.

dimension 5×5, information set $\boldsymbol{\Omega}_{t-1}$ contains the realized variances covering the last $t = 20$ trading days, and $\boldsymbol{1}$ denotes a 5×1 vector of ones. In Eq. (9) the information set $\boldsymbol{\Omega}_{t-1}$ is updated daily and available to the investor at time t. It is important to note that the SAS portfolio is constructed using an out-of-sample approach; that is, weights at time t are estimated using only information available up to time t–1, which ensures that the optimization procedure simulates real-time implementation without look-ahead bias.

While the variances of the individual stablecoins are computed using the range-based Parkinson estimator, the variance of the SAS portfolio is derived from a portfolio-level approach. Specifically, it is computed as the weighted sum of individual range-based variances' covariances (based on the optimized portfolio weights obtained through the minimum-variance framework). Since the optimization procedure allows for short positions (i.e., negative portfolio weights), and given that the covariance matrix is estimated from range-based variance series with heavy-tailed distributions, it is mathematically possible for the portfolio's sample variance to take on negative values. This phenomenon is not a result of applying the Parkinson estimator directly to the SAS price series, but rather an outcome of how portfolio-level risk is constructed from the underlying range-based variance dynamics. Importantly, the occurrence of a negative sample mean for SAS's variance does not imply negative volatility in a physical sense; instead, it reflects the interaction between estimation noise, the presence of short positions, and extreme behavior in the range-based variances typical of stablecoins.

Fig. 2 plots the evolution of the dynamic weights for SAS in the out-of-sample period from January 5, 2021 to March 31, 2025. Optimal weights are re-estimated on a daily basis. The sixth column of Table 1 reports the descriptive statistics for the variance process of SAS. It is notable that, unlike the constituent individual stablecoins, the sample mean of SAS's variance process is negative – a result permitted by the Markowitz framework due to short positions in the optimization.

Fig. 3 plots the time series evolution of the stablecoin price processes under study, and Table 4 reports their descriptive statistics. Panel A of Fig. 3 shows the price processes of DAI, USDT, BUSD, TUSD, and USDC. This panel in conjunction with Table 4 shows that the five individual stablecoin price series vary between 0.9603 and 1.0406 – the minimum and maximum price in USD for one unit of TUSD, respectively. Next, Panel B of Fig. 3 illustrates the price process of USTC, which started to collapse on May 8, 2022. Importantly, Panel C plots the price process of SAS derived from Markowitz's optimization procedure incorporating DAI, USDT, BUSD, TUSD, and USDC. In contrast to Panel A, SAS varies in a narrow range between 0.9898 and 1.0066, which is much narrower than the range of the five single stablecoins.[13] Thus, the SAS portfolio is considerably more stable than its constituent stablecoins.

4.5. Stress testing the stability of SAS in response to the USTC collapse

We next stress test the performance of an augmented SAS that incorporates the collapsed stablecoin USTC in the portfolio of stablecoins.

[13] Note the differences in Y-axis scales for Panels A–C in Fig. 3.

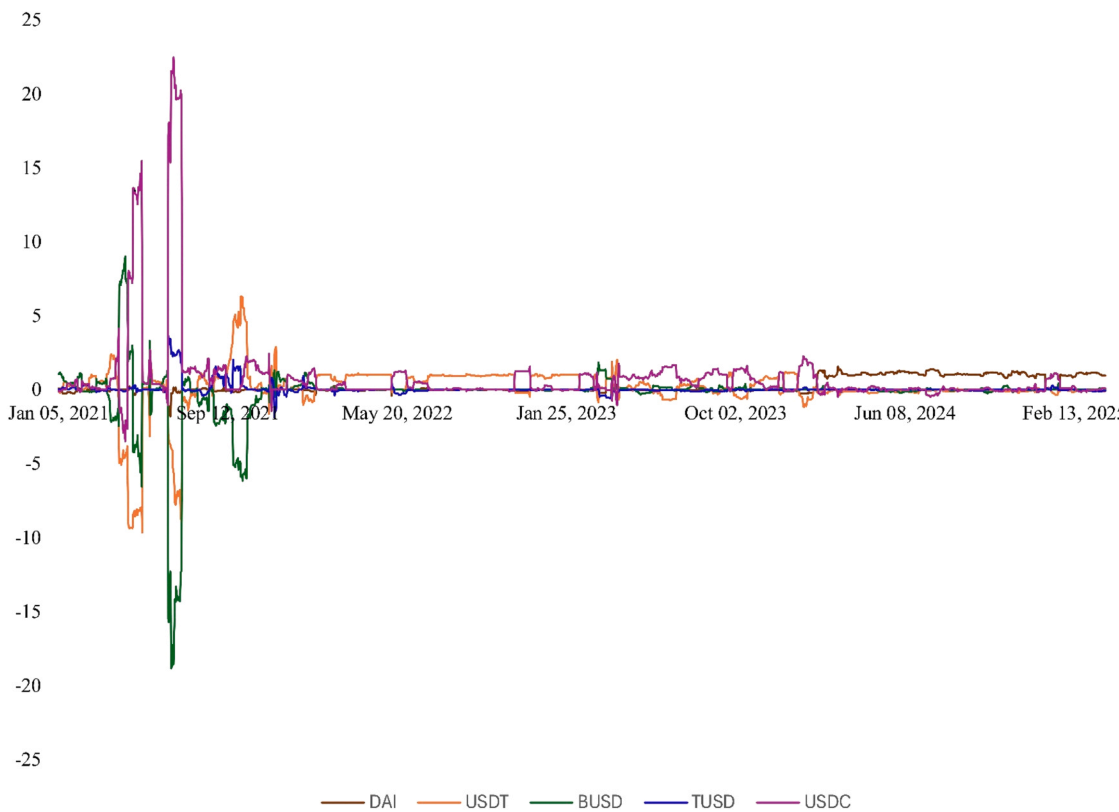


Fig. 2. Dynamic weights for implementing the global minimum-variance of variance portfolio.
This figure plots the evolution of dynamic weights to implement the global minimum-variance of variance portfolio. Weights are estimated daily in the sample period from January 5, 2021 to March 31, 2025.

Table 4 reports the descriptive statistics for the price series of stablecoin USTC and augmented SAS. It is evident that the minimum price for USTC is $p \approx 0$ due to its collapse. Adding USTC to our initial set of five stablecoins, we re-run the optimization procedure outlined in Eq. (9) using all six stablecoins – namely, DAI, USDT, BUSD, TUSD, and USDC as well as collapsed stablecoin USTC. Panel D in Fig. 3 graphs the price process of this augmented SAS (SAS*) derived from Markowitz's optimization procedure. Visual inspection shows that the price processes for SAS and SAS* are virtually identical.

Interestingly, as documented in Table 2 and Panel D of Fig. 1, despite the large price range of USTC from $0.0065 to $1.0421, the SAS* portfolio generates the same narrow price range as SAS, viz., $0.9658 \leq p \leq 1.0066$. The sample averages for USTC and SAS are $0.3344 and $1.0001, respectively. Hence, our results suggest that, despite the inclusion of collapsed stablecoin USTC, SAS* continues to be stable over time. The reason for this stability is that the dynamic weights for the global minimum variance portfolio of stablecoins allow short positions in USTC in the ex-ante crash period and virtually zero-weights for USTC in the ex-post-crash period. These dynamic weights allocated to USTC are illustrated in Fig. 4. This issue is further illustrated in Fig. A.2 in the Appendix, which shows the zoomed-in dynamic weights allocated to USTC during the pre-collapse period. USTC began collapsing on May 8, 2022. The zoomed-in sample period spans from January 1, 2022, to March 31, 2022. This Fig. shows that the optimization framework systematically decreased the weight assigned to USTC well in advance of its eventual de-pegging and collapse, particularly in the beginning of 2022. This decline in weight is not an artifact of retrospective data fitting but rather an endogenous outcome of the model reacting to rising realized variance in USTC a phenomenon consistent with market-based indicators of instability.

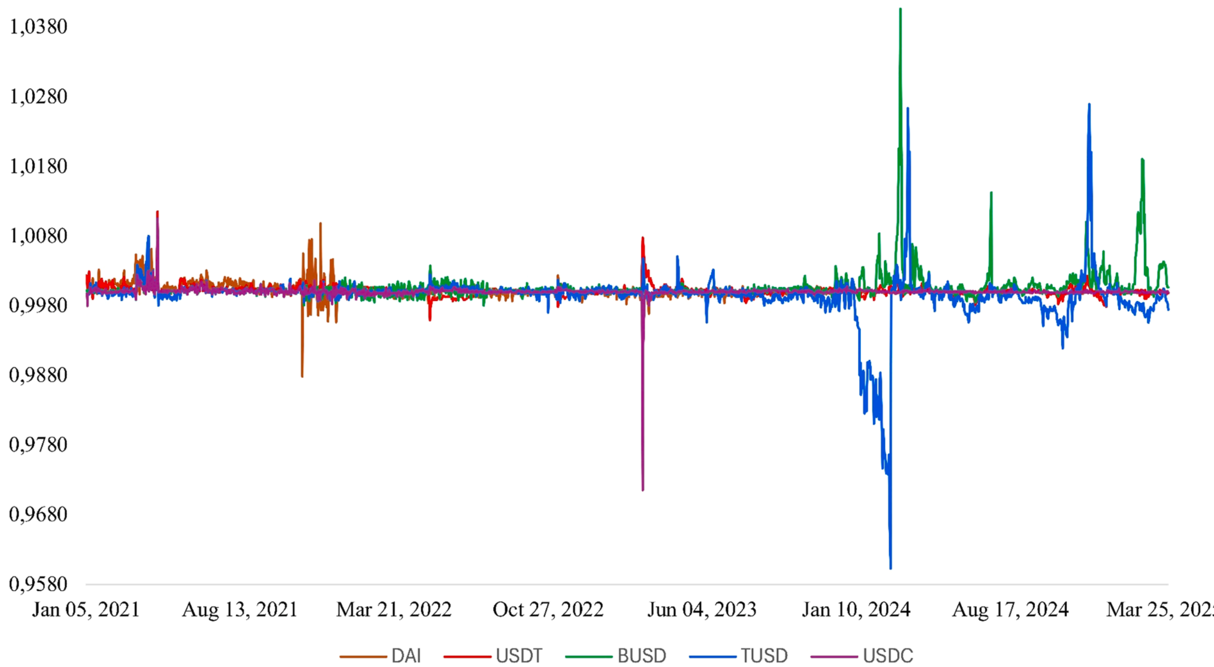
It is important to emphasize that the portfolio optimization framework used to construct SAS is strictly forward-looking and relies solely on data available up to each point in time. The global minimum-variance of variance portfolio is recalculated daily using rolling windows of past realized variance estimates. Consequently, the resulting portfolio weights of variances reflect only historical risk characteristics and do not incorporate any information about future events. In this context, the relatively low weights assigned to USTC prior to its de-pegging event are not the result of hindsight or look-ahead bias. On the contrary, they reflect a data-driven response to growing in-sample volatility exhibited by USTC in the months leading up to its failure. In line with its goal of minimizing the total portfolio risk, the model responds by allocating smaller weights to assets with rising realized variance.[14] This behavior demonstrates that, even without explicit knowledge of impending collapse, the SAS framework automatically mitigates the exposure to emerging instability. Thus, the robustness of SAS is not coincidental but arises directly from the adaptive, risk-sensitive nature of the optimization routine.

4.6. Is SAS robust to changes in the information set used for deriving optimal weights?

In our analyses, the information set $\boldsymbol{\Omega}_{t-1}$ is comprised of the realized variances of the individual stablecoins covering the last $t = 20$ trading days. Here we check the robustness of the results with respect to the chosen information set. More specifically, we restrict $\boldsymbol{\Omega}_{t-1}$ to information on the last 15 or last 10 trading days. Upon replicating the Markowitz optimization methods to construct the augmented SAS including the collapsed stablecoin USTC, we generate dynamically estimated

[14] See Table A.2. in the Appendix, which provides descriptive statistics for historical dynamic weights to quantify the weight differentials across stablecoins.

Panel A. Price processes of DAI, USDT, BUSD, TUSD, and USDC.



Panel B. Price process of USTC.

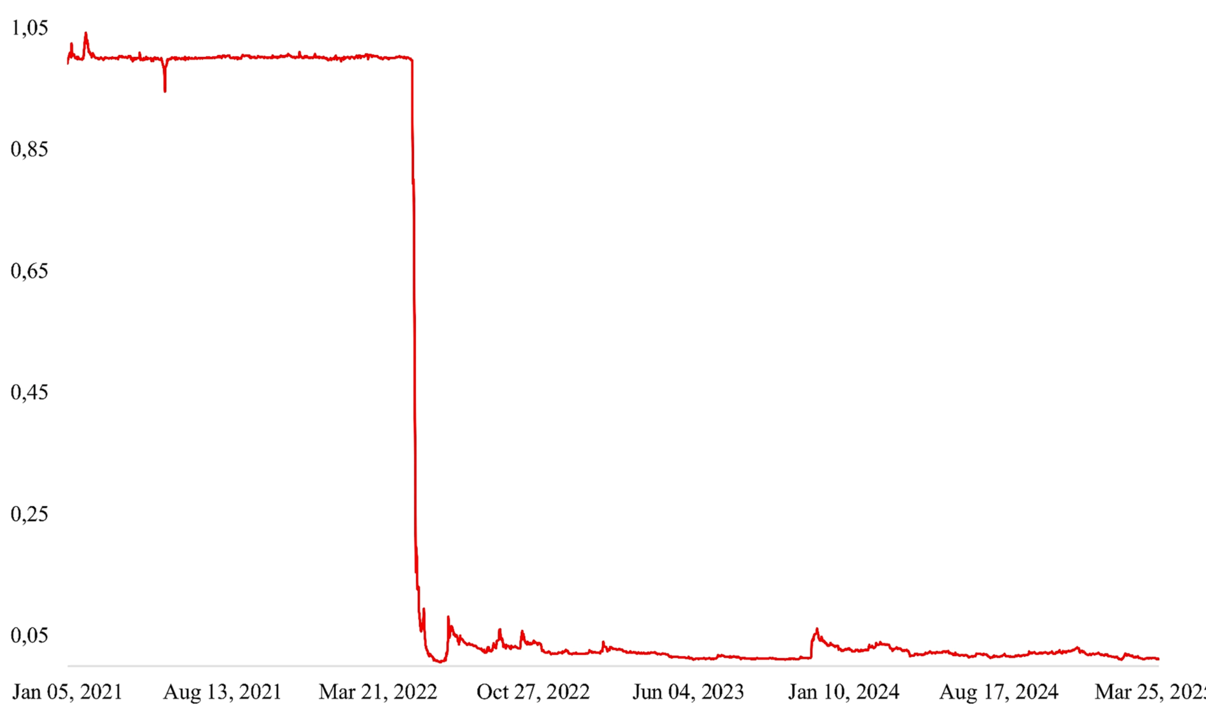
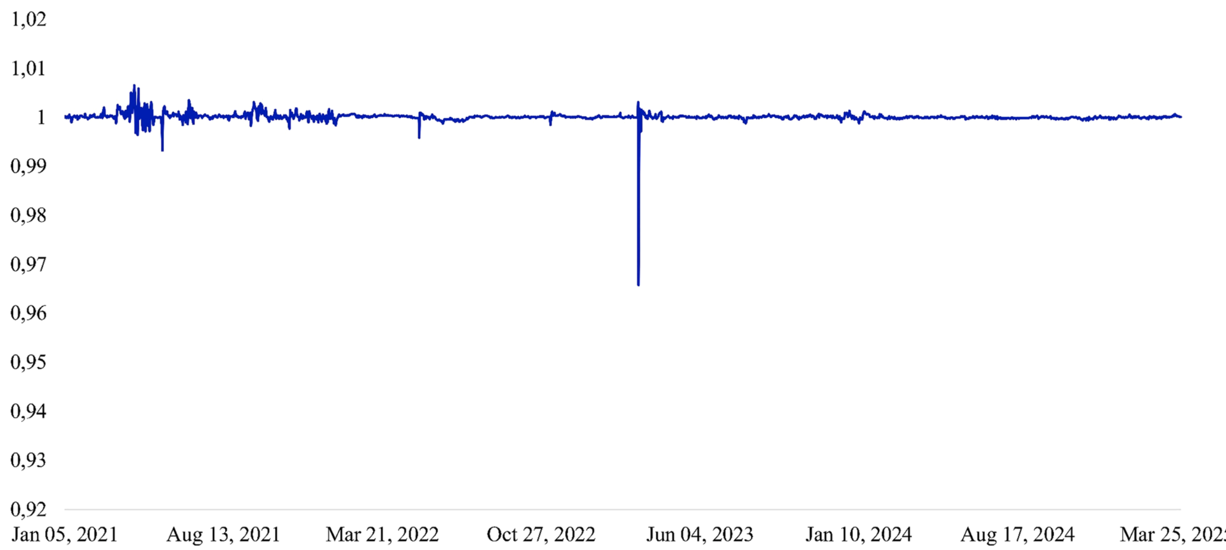


Fig. 3. Evolution of the price processes of various stablecoins including SAS.
This figure plots the evolution of price processes of various stablecoins. Panels A–D plot the price processes of the following stablecoins: (A) DAI, USDT, BUSD, TUSD, and USDC; (B) USTC which started to collapse on May 8, 2022; (C) SAS derived from Markowitz's optimization procedure incorporating DAI, USDT, BUSD, TUSD, and USDC; and (D) an augmented SAS (or SAS*) derived from Markowitz's optimization procedure incorporating DAI, USDT, BUSD, TUSD, and USDC as well as the collapsed stablecoin USTC. The sample period is from January 5, 2021 to March 31, 2025. Panel A. Price processes of DAI, USDT, BUSD, TUSD, and USDC. Panel B. Price process of USTC. Panel C. Price process of SAS based on DAI, USDT, BUSD, TUSD, and USDC. Panel D. Price process of SAS* based on DAI, USDT, BUSD, TUSD, USDC, and USTC.

Panel C. Price process of SAS based on DAI, USDT, BUSD, TUSD, and USDC.



Panel D. Price process of SAS* based on DAI, USDT, BUSD, TUSD, USDC, and USTC.

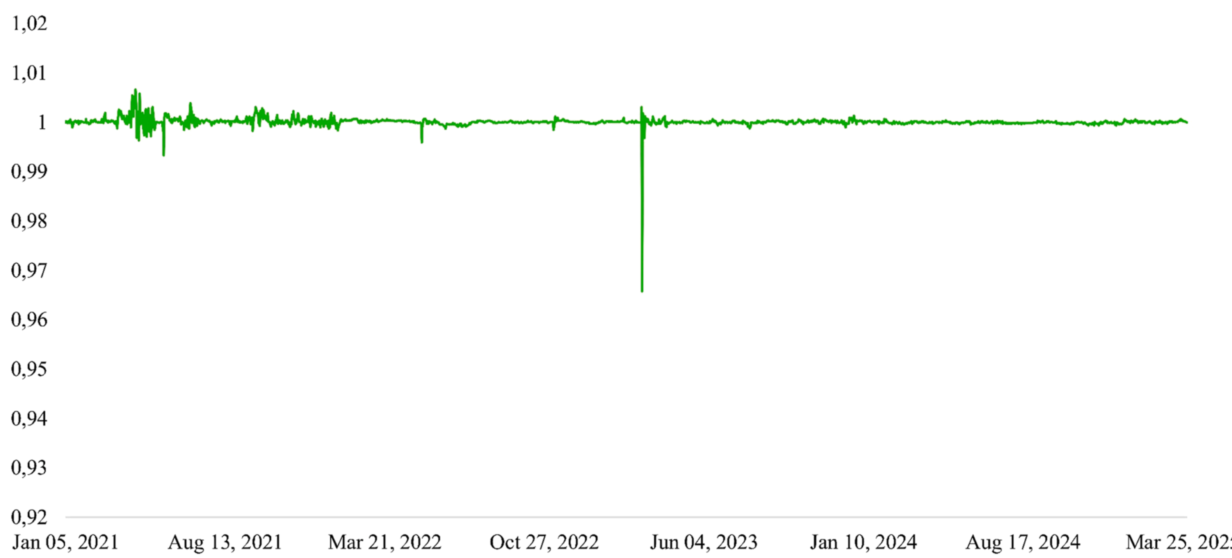


Fig. 3. (*continued*).

optimal weights on a daily basis. Table 5 reports the descriptive statistics for both the realized variance series and price series. Comparatively, the SAS* portfolio exhibits properties similar to our previous analyses. The price series range between \$0.9944 and \$1.0095 when $\mathbf{\Omega}_{t-1}$ is conditioned using the last 15 trading days compared to \$0.9937 and \$1.0069 when $\mathbf{\Omega}_{t-1}$ is based on the last 10 trading days. We infer that our results are robust to alternative information sets used to compute the dynamic weights for constructing the SAS* portfolio.

4.7. Examining data integrity following delisting of BUSD

At the end of November 2023, Binance announced that it would stop supporting BUSD starting on December 15, 2023 and allow redemptions until February 2024. This change raises a concern that BUSD price data from December 15 onward may be less reliable or less valid compared to that of the other stablecoins.[15] Does the delisting of BUSD affect range-based variance analyses incorporating BUSD and thereby alter the composition of portfolio G used to construct SAS? To answer this question, we use the five stablecoin variances (DAI, USDT, BUSD, TUSD, and USDC) and repeat the iteratively re-estimated optimization procedure described in Section 4.4 to derive the dynamic portfolio weights for SAS. However, starting from December 15, 2023, we exclude BUSD from the optimization process. Table 6 reports the descriptive statistics for the full-sample price and variance processes of SAS with this exclusion.[16] When comparing the statistics in Table 6 with those in Tables 1 and 4, we find that the price and variance processes remain statistically indistinguishable. Overall, the key findings remain qualitatively

[15] We thank an anonymous reviewer for pointing out this issue.

[16] Note that in Table A.1 in the Appendix, based on the ex-post sample as of December 15, 2023, we report descriptive statistics for optimized portfolio weights derived from the minimum-variance optimization procedure.

Table 4
Descriptive statistics for price processes of stablecoins and SAS.

Statistic	DAI	USDT	BUSD	TUSD	USDC	USTC	SAS	SAS*
Min	0.9739	0.9959	0.9980	0.9603	0.9715	0.0065	0.9658	0.9658
1 % Qnt.	0.9979	0.9985	0.9987	0.9818	0.9991	0.0101	0.9985	0.9986
2.5 % Qnt.	0.9989	0.9988	0.9991	0.9889	0.9995	0.0115	0.9991	0.9991
5 % Qnt.	0.9992	0.9991	0.9993	0.9965	0.9996	0.0121	0.9995	0.9995
10 % Qnt.	0.9995	0.9994	0.9996	0.9979	0.9998	0.0129	0.9997	0.9997
Median	0.9999	1.0001	1.0002	0.9998	1.0000	0.0264	1.0001	1.0001
90 % Qnt.	1.0011	1.0008	1.0016	1.0008	1.0003	1.0020	1.0005	1.0005
95 % Qnt.	1.0016	1.0011	1.0030	1.0016	1.0004	1.0033	1.0010	1.0010
97.5 % Qnt.	1.0023	1.0016	1.0045	1.0030	1.0007	1.0043	1.0017	1.0017
99 % Qnt.	1.0045	1.0022	1.0100	1.0060	1.0013	1.0075	1.0025	1.0026
Max	1.0103	1.0115	1.0406	1.0269	1.0105	1.0421	1.0066	1.0066
Mean	1.0001	1.0002	1.0006	0.9994	1.0000	0.3344	1.0001	1.0001
Std Dev	0.0012	0.0007	0.0022	0.0037	0.0009	0.4551	0.0011	0.0011
Kurtosis	144.9541	47.1017	108.9439	31.1827	785.9945	− 1.3877	632.8101	631.0231
Skewness	− 5.3461	3.6401	8.4678	− 2.7691	− 22.5258	0.7795	− 19.8127	− 19.7241
T	1547	1547	1547	1547	1547	1547	1547	1547

This table reports descriptive statistics for the price processes of stablecoins DAI, USDT, BUSD, TUSD, and USDC plus collapsed stablecoin USTC. USTC began to collapse on May 8, 2022. The stablecoin portfolio SAS is constructed from DAI, USDT, BUSD, TUSD, and USDC, using a rolling window of 20 days to dynamically re-estimate the weights for an iteratively estimated global minimum variance portfolio of stablecoins. The augmented version, denoted SAS*, incorporates USTC into the set of stablecoins. The sample period is from January 5, 2021, to March 31, 2025.

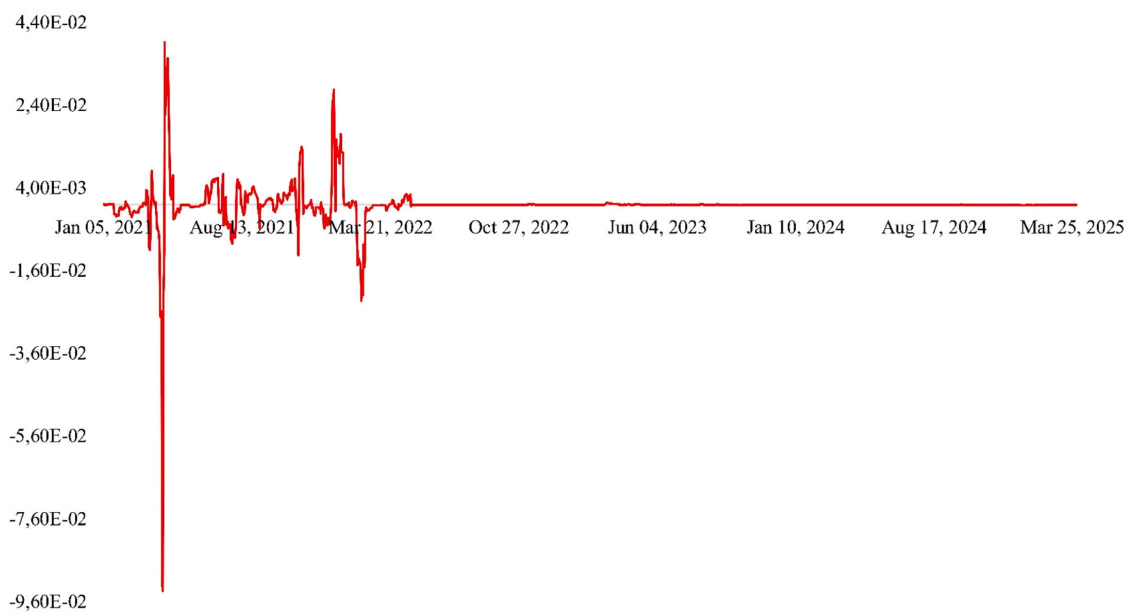


Fig. 4. Evolution of the dynamic weights allocated to collapsed stablecoin USTC.
This figure plots the dynamic weights allocated to USTC over time. USTC started to collapse on May 8, 2022. The sample period is from January 5, 2021 to March 31, 2025.

unchanged, which suggest that the delisting of BUSD did not materially impact our results.

4.8. *Is USTC disconnected from the broader stablecoin market?*

Some reports observe that Terra (USTC) and DAI are not highly correlated that accounts for the stability of SAS* during the Terra crash. As an additional robustness check, we examine the degree of correlation between USTC and other stablecoins in the sample period prior to its collapse. Using range-based variance data, we compute pairwise Pearson correlations between USTC and the other five stablecoins in the sample period from January 5, 2021 to January 5, 2022. The results are reported in Table A.4 in the Appendix. Panel A presents the pairwise sample correlations, and Panel B gives the corresponding *t*-statistics. The average correlation between USTC and other stablecoins is 0.242, which is statistically significant at the 5 % level (p-value ≈ 0.034).[17] Reinforcing the validity of its inclusion in the optimization framework, these results suggest that USTC was meaningfully integrated into the variance dynamics of the stablecoin market prior to its collapse. Hence, SAS stability during the Terra collapse stems from effective variance-based diversification as opposed to the presence of an uncorrelated or isolated component.

[17] Each pairwise correlation between the USTC and other stablecoins is tested for significance using the standard t-distribution transformation: $t = r\sqrt{(n-2)(1-r^2)}$, where r is the sample correlation, and n is the number of observations. The resulting p-values are averaged to summarize the overall statistical significance of the USTC correlation structure.

Table 5
Impact of varying in-sample time window lengths for estimating the global minimum-variance of variance portfolio.

Process	Variance		Price	
Trading Days	10	15	10	15
Minimum	− 5.1237	− 0.0290	0.9937	0.9944
1 % Qnt.	− 0.0016	− 0.0012	0.9978	0.9980
2.5 % Qnt.	− 0.0006	− 0.0003	0.9987	0.9989
5 % Qnt.	− 0.0002	− 0.0001	0.9991	0.9994
10 % Qnt.	− 0.0001	0.0000	0.9995	0.9996
Median	0.0001	0.0001	1.0001	1.0001
90 % Qnt.	0.0007	0.0007	1.0006	1.0005
95 % Qnt.	0.0020	0.0019	1.0010	1.0009
97.5 % Qnt.	0.0040	0.0030	1.0020	1.0018
99 % Qnt.	0.0169	0.0119	1.0030	1.0028
Maximum	1.0016	43.2689	1.0069	1.0095
Mean	− 0.0015	0.0310	1.0001	1.0001
Standard Deviation	0.1479	1.1014	0.0009	0.0008
Excess Kurtosis	956.7336	1534.4466	19.5462	35.0086
Skewness	−28.0921	39.1522	0.2507	2.0388
T	1547	1547	1547	1547

This table reports descriptive statistics for the price processes of SAS as well as augmented SAS (denoted SAS*). SAS is constructed using the following five stablecoins: DesAI, USDT, BUSD, TUSD, and USDC. SAS* includes USTC (which started to collapse on May 8, 2022). The in-sample time window length for estimating the global minimum-variance of variance portfolio is varied between 10 and 15 trading days. The sample period is from January 5, 2021 to March 31, 2025.

Table 6
Descriptive statistics for the full-sample price and variance processes of SAS (BUSD excluded from optimization after December 15, 2023).

Statistic	SAS	
	Price	Variance
Minimum	0.9658	− 140.9313
1 % Qnt.	0.9985	− 0.0006
2.5 % Qnt.	0.9992	− 0.0002
5 % Qnt.	0.9995	− 5.88224E − 05
10 % Qnt.	0.9997	− 8.6568E − 06
Median	1.0001	5.60192E − 05
90 % Qnt.	1.0005	0.0005
95 % Qnt.	1.0010	0.0018
97.5 % Qnt.	1.0017	0.0021
99 % Qnt.	1.0025	0.0051
Maximum	1.0066	2.5783
Mean	1.0001	− 0.0891
Standard Deviation	0.0011	3.5838
Excess Kurtosis	635.9692	1540.9615
Skewness	− 19.8836	− 39.2737
T	1547	1547

This table reports descriptive statistics for the price processes of stable aggregate (synthetic) stablecoin SAS, which is constructed from DAI, USDT, BUSD, TUSD, and USDC. The portfolio is dynamically re-estimated using a 20-day rolling window to iteratively compute the global minimum variance weights. The sample period is from January 5, 2021, to March 31, 2025. BUSD is excluded from the construction of the minimum variance portfolio in the ex-post sample dated December 15, 2023.

5. Discussion

5.1. Empirical alignment with previous findings

To determine the optimal power-law exponents for the range-based annualized daily stablecoin volatilities, Grobys et al. (2021) employ Clauset et al.'s (2009) goodness-of-fit test in combination with trial-and-error. Specifically, searching on the interval $2.00 \leq \alpha \leq 3.50$, the authors select the power-law exponent wherein the goodness-of-fit test does not reject the power-law null model. Examining the same set of stablecoins as in the present study, the authors find that the optimal estimated power-law exponents for stablecoins vary between $\hat{\alpha} = 2.3607$ for USDC volatility and $\hat{\alpha} = 2.9123$ for TUSD volatility. An important implication of their findings is that stablecoins appear unstable due to the sample-specific nature of the estimated volatility. However, it is noteworthy that the authors did not employ the optimal maximum likelihood estimator (MLE) based on distance D in Eq. (6), as proposed by Clauset et al. (2009), when conducting the goodness-of-fit test. Instead, since the null hypothesis was rejected under the MLE, the authors adopted a trial-and-error search method.

The present study utilizes Clauset et al.'s (2009) goodness-of-fit and optimal maximum-likelihood-estimator (MLE) metrics. Because the range-based variances are used in the optimization procedure, our study examines the estimated variances as opposed to volatility. While Grobys et al. (2021) report the power-law exponents to be in the range $2 < \alpha < 3$, which implies that the variance of realized stablecoin volatility is undefined although the theoretical mean exists, we show that the hypotheses of $\alpha < 2.00$ cannot be rejected for the cross section of range-based stablecoin variances. This result implies a more severe statistical property—namely, that even the theoretical mean is not defined. Moreover, the range-based stablecoin variances are governed by the same power-law process with corresponding exponent of $\alpha \approx 2.00$. Contributing to the stablecoin literature, these results point to the presence of a common source of stablecoin risk. By contrast, a recent study of Grobys (2024) suggests that the returns on altcoins often exhibit a theoretically defined variance. Ironically, our results imply that stablecoins are riskier than altcoins. One plausible explanation for this divergence is that even small deviations from the peg are outliers in the data-generating process for stablecoins, whereas altcoins require considerably larger deviations to be outliers due to their relatively high average price fluctuations compared to stablecoins.

Similar to our study, recent research by Giudici et al. (2022) proposes a currency basket-based stablecoin using Markowitz-style optimization. They build a low-volatility fiat-currency basket (the "Librae") and analyze its performance using normalized exchange rate indices and spillover network analysis based on VAR models. While both studies aim to enhance the stability of digital assets through diversification, our practical setups differ substantially. Giudici et al. (2022) work within a macro-financial context that focuses on fiat exchange rates and potential implications for remittance markets. By contrast, our study is grounded in high-frequency range-based stablecoin variances using actual market data for the crypto-based stablecoins traded in USD. Furthermore, our stress-testing framework incorporates the collapse of USTC (i.e., a real domain-specific failure scenario) rather than impulse responses derived from VAR decompositions. These differences reflect distinct target audiences and financial ecosystems – specifically, traditional FX and policy applications in Giudici et al. (2022) versus decentralized finance (DeFi) and crypto-risk modeling in our study. Despite these differences, both papers contribute to the broader effort of improving the design and resilience of stable-value digital instruments.

A related stream of research focuses on systemic risk modeling using high-dimensional VAR frameworks with structural constraints. For instance, Ahelegbey and Giudici (2022) introduce a volatility-based network index of global financial markets using a Bayesian graphical VAR approach with zero constraints in partial covariances. While their method is well-suited for modeling contagion effects across multiple national equity markets, our study focuses on a small set of crypto-based stablecoins, all of which are USD pegged and traded. Accordingly, we rely on range-based variance and covariance estimation techniques tailored to the structure and behavior of these assets.

Lastly, Ante et al. (2023) overview evidence on the interrelation of stablecoins and cryptocurrencies. For example, previous studies investigate the connection between USDT and Bitcoin (e.g., Wei, 2018; Griffin and Shams, 2020; Grobys and Huynh, 2021). Extending prior research, we find statistically significant interdependencies between realized stablecoin variances. Given the first-order autocorrelation for most range-based stablecoin variances, the range-based variance of USDT tends to spill over to other stablecoins, whereas USDT appears to be only influenced by the range-based variance of BUSD. Future research on this interrelation is warranted.

5.2. Implications

In view of the growing role that stablecoins play in decentralized finance (DeFi), collateral management, and payment system, our findings have important implications. The statistical evidence of power-law behavior and infinite variance in the range-based variances of several major stablecoins reveals that these instruments, despite being designed to minimize volatility, can exhibit latent systemic vulnerabilities that are not visible through conventional risk lenses. Infinite variance implies that key statistical assumptions underpinning common risk models (e.g., finite second moments for volatility estimation or distributional normality in Value-at-Risk calculations) do not hold for individual stablecoins.

For technical analysts and quantitative risk managers, our results suggest that stablecoin-related positions, especially when used as low-volatility components in portfolios or as collateral in DeFi protocols, would benefit from alternative modeling approaches that are robust to heavy tails. For example, models rooted in extreme value theory or tempered stable distributions. The finding that stablecoins can be riskier than some altcoins – at least in terms of their statistical variance process – challenges the conventional view that stablecoins serve as safe havens within the crypto ecosystem. Instead, our study implies that even minor, temporary deviations from the $1 peg may serve as signals of structural fragility in the system, especially when such deviations occur under market stress or liquidity fragmentation.

From a regulatory perspective, stablecoin variance processes that are statistically unstable demand more nuanced stress testing frameworks. Current regulatory oversight often focuses on stablecoin reserves and peg mechanisms, but our findings suggest that systemic risk can arise from hidden statistical properties of price fluctuations that could amplify in turbulent conditions. The collapse of USTC is exemplary as a precedent, but our analysis shows that similar risk signatures exist in other stablecoins, regardless of their specific collateral structures. Thus, supervisory authorities and central banks could benefit from integrating heavy-tailed risk assessments into their evaluations of stablecoin resilience, particularly as these instruments become more integrated into traditional financial infrastructure.

For practitioners such as institutional investors, hedge funds, exchanges, and DeFi platform designers, our findings imply that individual stablecoins should not be treated as categorically “safe” assets. The assumption that small peg deviations are benign or self-correcting can be misleading in the presence of fat-tailed variance processes, which are inherently sensitive to outliers. Portfolio managers should reconsider their risk budgets when using individual stablecoins as cash equivalents or volatility dampeners. Similarly, arbitrageurs who rely on short-term stablecoin dislocations could underestimate the downside risk if tail events materialize with higher frequency or severity than expected. For exchanges and smart contract developers, it is prudent to incorporate dynamic risk buffers into liquidity pools and algorithmic pricing mechanisms to absorb unexpected shocks, especially in markets with thin order books or inter-exchange fragmentation.

In sum, a disconnect exists between observed price stability and underlying statistical instability in stablecoins. Given that our findings indicate that their statistical risk profile is relatively volatile, a reassessment of how stablecoins are modeled, monitored, and managed is warranted – both within private institutions and in public oversight regimes.

5.3. Design considerations for SAS

While SAS is derived from robust and widely-accepted Markowitz portfolio optimization techniques, we acknowledge that additional operational details would enhance its practical relevance. Our procedures can be used for constructing algorithmic allocation rules in stablecoin index products by private custodians, fintech platforms, or public institutions such as central banks and regulated financial intermediaries. Although we do not propose a whitepaper or full issuance protocol for SAS, our framework provides a systematic and transparent mechanism for weighting constituent stablecoins to minimize realized risk. In this sense, it represents an initial step toward the design of robust digital assets and cash-comparable digital payment instruments (e.g., CBDCs). Future research is recommended to specify governance structures, redemption mechanisms, and collateral management strategies. Our results show that SAS remains stable even in stress scenarios and, therefore, can serve as a foundation for digital monetary design in decentralized or hybrid systems.

5.4. Distinguishing the surface-level stability from the latent tail risk

A key distinction in our study is surface-level smoothness versus statistical tail risk. While the price range of an individual stablecoin is fairly narrow and fluctuates only minimally around the $1 peg, this observation can be deceptive if the underlying distribution of realized variances is heavy-tailed. Even if the time series looks visually stable for long periods, power law exponents below the threshold of $\alpha = 2$ imply infinite theoretical variance. To illustrate, we simulate two time series: one with a power law exponent of $\alpha = 1.9$ and another with $\alpha = 2.9$. Fig. 5 shows that, although the $\alpha = 1.9$ process may appear smoother, it is more prone to rare but extreme shocks. Conversely, the $\alpha = 2.9$ process, while more volatile on the surface, is statistically more stable. This example demonstrates that a low price range does not necessarily imply robustness. Therefore, relying on the price range alone may underestimate the latent risk embedded in assets like individual stablecoins, which appear stable under normal conditions but are vulnerable to systemic tail events.

5.5. Future research directions

We investigated the top five stablecoins, including USDT, USDC, DAI, BUSD, and TUSD. This selection is based on their consistently high market capitalization and trading volume over the sample period. As shown in Fig. A.3, these five assets rank among the largest and most liquid stablecoins from January 2021 to May 2025. Hence, they dominate the market, thereby mitigating concerns about survivorship bias. A potential extension for future research is the construction of a dynamically composed SAS portfolio with the set of eligible stablecoins updated over time based on liquidity metrics, such as market capitalization, trading volume, or exchange listings. This approach would mimic real-world portfolio construction practices and address the concerns of survivorship bias, particularly as the stablecoin ecosystem continues to evolve. For example, assets like USTC that once held significant market share but later collapsed or BUSD that faced delisting pressures illustrate

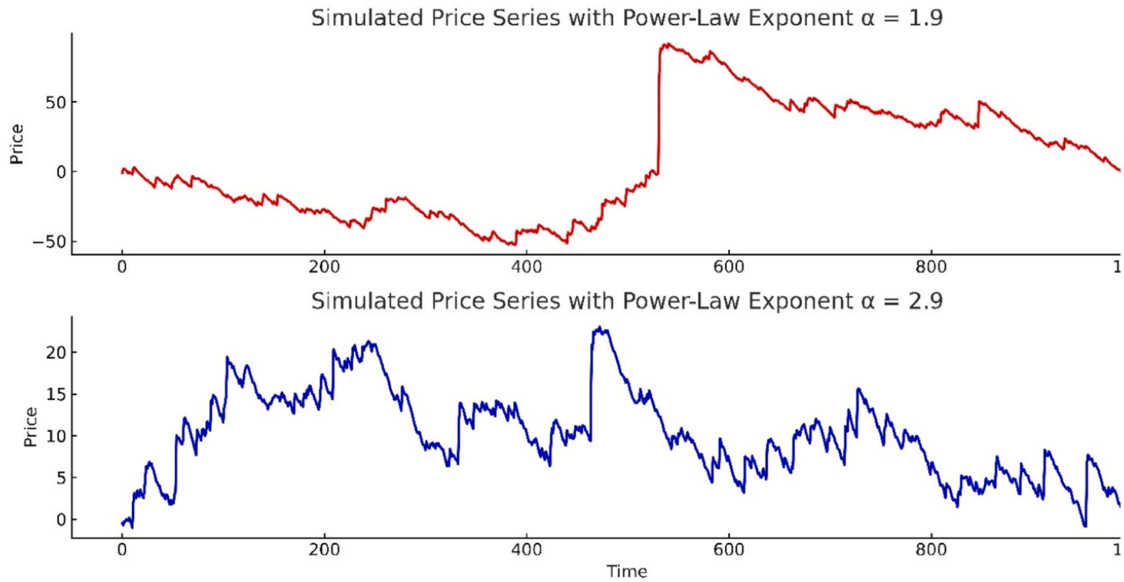


Fig. 5. Power-law simulations.
The top plot illustrates a simulated price process governed by a power-law distribution with an exponent of $\alpha = 1.9$. This exponent implies an infinite theoretical variance, which means that extreme fluctuations are statistically more likely even if infrequent. The series often appears smooth and stable for extended periods and, therefore, gives a false impression of robustness that masks underlying tail risk. In contrast, the bottom plot depicts a price process with a power-law exponent of $\alpha = 2.9$. This value implies a finite variance, such that the process is statistically more stable. However, due to its more frequent but smaller fluctuations, the series appears noisier and more volatile. These examples highlight the difference between statistical stability versus visual stability and demonstrate why surface-level indicators like price range can be misleading when assessing long-term risk exposure.

the dynamic nature of the marketplace. A dynamically updated set of assets could improve the adaptability of the SAS framework to new entrants, market exits, or regulatory changes. While this approach introduces additional complexity, it offers a further test of SAS's performance under changing market conditions.

6. Conclusion

Stablecoins exhibit deviations from their currency pegs that are sufficiently large for power-law models to detect range-based stablecoin variances with theoretically undefined means. Despite this volatility, we show that interdependencies between realized stablecoins variances can be utilized to construct a diversified Markowitz global minimum variance of variance portfolio (G) of stablecoins. Optimal weights for the constituent stablecoins in the proposed stable aggregate stablecoin (SAS) were iteratively updated for five large-cap stablecoins. Our results showed that SAS is much more stable than the individual stablecoins contained therein. Importantly, even if SAS is augmented by including the collapsed stablecoin USTC, the price process of SAS* continued to fall within a narrow price range over time. Thus, portfolio diversification based on a basket of stablecoins appears to effectively harden SAS even to aberrant price behavior of an individual stablecoin. Beyond the construction and empirical analysis of SAS, we explore broader implications for the evolving design of Central Bank Digital Currencies (CBDCs). Drawing on diversification principles, we examine how the stability achieved through SAS could conceptually inform the development of resilient and efficient sovereign digital currencies.

Our stable aggregate stablecoin (SAS) has important implications for CBDC design. Drawing from the SAS model, central banks could enhance CBDC stability by applying diversification principles across reserve assets, thereby reducing volatility and enhancing financial system resilience. This approach allows CBDCs to leverage risk minimization strategies without exposing users to the counterparty risks inherent in private stablecoins. Additionally, by selectively incorporating technological features pioneered by stablecoins, such as instant settlement, CBDCs can offer improved payment efficiency and at the same time preserve regulatory oversight and institutional trust. Consequently, SAS not only demonstrates the potential for creating more stable digital assets but valuable design insights that can inform the development of next-generation sovereign digital currencies.

CRediT authorship contribution statement

Juha-Pekka Junttila: Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization. **Klaus Grobys:** Writing – original draft, Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Kolari James:** Writing – review & editing, Writing – original draft, Validation, Supervision.

Appendix

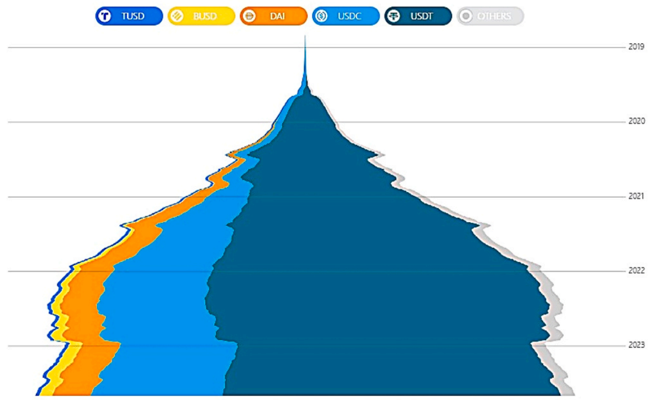


Fig. A.1. Stablecoin growth between 2019 and August 2023. This figure illustrates the growth of stablecoins between 2019 and August 2023. Their total market capitalization exceeds $120 billion as of August 2023.
Source: https://www.moodys.com/web/en/us/about/insights/data-stories/stablecoins-instability.html

Fig. A.2. Zooming in on the evolution of the dynamic weights allocated to the collapsed stablecoin USTC during the pre-collapse period. This figure shows the zoomed-in dynamic weights allocated to USTC during the pre-collapse period. USTC began collapsing on May 8, 2022. The zoomed-in sample period spans from January 1, 2022, to March 31, 2022.

Table A.1
Descriptive statistics of the optimized portfolio weights derived from the minimum-variance optimization procedure based on the ex-post sample as of December 15, 2023.

Panel A. Optimized weights including BUSD.						Panel B. Optimized weights excluding BUSD.				
Statistic	DAI	USDT	TUSD	USDC	BUSD	Statistic	DAI	USDT	TUSD	USDC
Minimum	− 0.2901	− 1.1560	− 0.1024	− 0.5031	− 18.8212	Minimum	− 0.2543	− 1.0595	− 0.0921	− 0.5020
1 % Qnt.	− 0.2649	− 0.9935	− 0.0875	− 0.4091	− 16.0904	1 % Qnt.	− 0.2500	− 0.9271	− 0.0649	− 0.4085
2.5 % Qnt.	− 0.2257	− 0.6462	− 0.0714	− 0.3408	− 14.1530	2.5 % Qnt.	− 0.1937	− 0.6424	− 0.0588	− 0.3569
5 % Qnt.	− 0.0687	− 0.3178	− 0.0647	− 0.2445	− 5.9715	5 % Qnt.	− 0.1051	− 0.3279	− 0.0502	− 0.2506
10 % Qnt.	0.0092	− 0.2072	− 0.0465	− 0.1129	− 4.2596	10 % Qnt.	0.0086	− 0.2056	− 0.0371	− 0.1141
Median	1.0455	− 0.0665	0.0000	0.0388	− 0.0008	Median	1.0407	− 0.0651	− 0.0004	0.0441
90 % Qnt.	1.2318	0.0276	0.0361	0.7044	0.8811	90 % Qnt.	1.1715	0.0273	0.0256	0.7888
95 % Qnt.	1.2986	0.1052	0.0591	1.0982	1.3802	95 % Qnt.	1.3063	0.1305	0.0626	1.1354
97.5 % Qnt.	1.3399	1.1026	0.1420	1.8148	6.7988	97.5 % Qnt.	1.3528	1.0039	0.1477	1.8118
99 % Qnt.	1.3720	1.1495	0.1711	2.0480	7.8461	99 % Qnt.	1.3753	1.0279	0.2096	1.9852
Maximum	1.5794	1.2023	0.2949	2.2525	9.0214	Maximum	1.5754	1.0498	0.2977	2.1812
Mean	0.9210	− 0.0559	0.0018	0.1420	− 0.8339	Mean	0.9072	− 0.0592	0.0018	0.1501
Standard Deviation	0.4233	0.2805	0.0443	0.4507	3.6930	Standard Deviation	0.4169	0.2592	0.0454	0.4485
Excess Kurtosis	1.8477	11.3729	11.4412	8.0188	8.6482	Excess Kurtosis	1.8941	10.4598	14.6581	7.3645
Skewness	− 1.7866	1.9219	2.3439	2.7927	− 2.3289	Skewness	− 1.8149	1.7295	3.2354	2.6982
T	472	472	472	472	472	*T*	472	472	472	472

We construct an iteratively estimated global minimum variance portfolio of stablecoins (denoted G) representing a stable aggregate stablecoin (SAS). For the optimization procedure, we use the stablecoins DAI, USDT, BUSD, TUSD, and USDC. The optimized weights, $\boldsymbol{w}^{MIN}_{t|\Omega_{t-1}}$, for SAS are estimated dynamically as:

$$\boldsymbol{w}^{MIN}_{t|\Omega_{t-1}} = \frac{\boldsymbol{\Sigma}^{-1}_{\Omega_{t-1}}\mathbf{1}}{\mathbf{1}'\boldsymbol{\Sigma}^{-1}_{\Omega_{t-1}}\mathbf{1}},$$

where $w^{MIN}_{t|\Omega_{t-1}}$ denotes a 5 × 1 vector of dynamic portfolio weights, $\Sigma^{-1}_{\Omega_{t-1}}$ is the inverse of the realized stablecoin variances' covariance matrix with dimension 5 × 5, information set Ω_{t-1} contains the realized variances covering the last $t = 20$ trading days, and $\mathbf{1}$ denotes a 5 × 1 vector of ones. The information set Ω_{t-1} is updated daily and available to the investor at time t. This table reports the distribution of the optimized weights $w^{MIN}_{t|\Omega_{t-1}}$ based on out-of-sample forecasts over 472 observations covering the sample period from December 16, 2023 to March 31, 2025. Panel B presents the optimized portfolio weights derived from the minimum-variance optimization procedure excluding BUSD.

Table A.2
Descriptive statistics of the optimized portfolio weights derived from the minimum variance of variance optimization procedure.

Statistic	DAI	USDT	BUSD	TUSD	USDC	USTC
Min	− 1.8835	− 11.1609	− 18.5662	− 1.8139	− 3.5285	− 0.0935
1 % Qnt.	− 0.2544	− 8.9305	− 11.1961	− 0.4192	− 1.0021	− 0.0136
2.5 % Qnt.	− 0.1780	− 5.3594	− 5.0113	− 0.2842	− 0.3339	− 0.0055
5 % Qnt.	− 0.0912	− 0.7051	− 1.8259	− 0.1473	− 0.1267	− 0.0024
10 % Qnt.	− 0.0467	− 0.3160	− 0.4578	− 0.0787	− 0.0581	− 0.0008
Median	0.0000	0.0984	0.0005	− 0.0005	0.1270	0.0000
90 % Qnt.	1.1215	1.0076	0.3394	0.1051	1.3441	0.0008
95 % Qnt.	1.1996	1.0988	0.7498	0.2997	1.6695	0.0033
97.5 % Qnt.	1.2667	1.8849	1.2485	1.0819	7.4562	0.0061
99 % Qnt.	1.3527	4.5394	3.0159	2.4745	18.0880	0.0135
Max	1.5795	6.2852	9.0814	3.8124	22.0335	0.0393
Mean	0.2670	0.1099	− 0.2116	0.0529	0.7820	0.0000
Std Dev	0.5001	1.6769	1.9257	0.3891	2.5906	0.0050
Excess Kurtosis	− 0.0991	18.1318	35.1073	36.8653	37.5505	157.1647
Skewness	0.9010	− 3.3895	− 4.1267	5.3975	5.9471	−7.1115
T	1547	1547	1547	1547	1547	1547

We construct an iteratively estimated global minimum variance of variance portfolio of stablecoins (denoted G) representing a stable aggregate stablecoin (SAS). For the optimization procedure, we use the stablecoins DAI, USDT, BUSD, TUSD, and USDC, in addition to collapsed stablecoin USTC (SAS*). The optimized weights, $w^{MIN}_{t|\Omega_{t-1}}$, for SAS are estimated dynamically as:

$$w^{MIN}_{t|\Omega_{t-1}} = \frac{\Sigma^{-1}_{\Omega_{t-1}}\mathbf{1}}{\mathbf{1}'\Sigma^{-1}_{\Omega_{t-1}}\mathbf{1}},$$

where $w^{MIN}_{t|\Omega_{t-1}}$ denotes a 6 × 1 vector of dynamic portfolio weights, $\Sigma^{-1}_{\Omega_{t-1}}$ is the inverse of the rang-based stablecoin variances' covariance matrix with dimension 6 × 6, information set Ω_{t-1} contains the realized variances covering the last $t = 20$ trading days, and $\mathbf{1}$ denotes a 6 × 1 vector of ones. The information set Ω_{t-1} is updated daily and available to the investor at time t. This table reports the distribution of the optimized weights $w^{MIN}_{t|\Omega_{t-1}}$ based on out-of-sample forecasts with over 1547 observations.

Table A.3
Market capitalization of stablecoins from December 31, 2020 to December 31, 2024

Date	Total Stablecoin Market Cap	DAI	USDT	BUSD	TUSD	USDC	Top-5 in Total	Top-5 in % of Total
Dec 31, 2020	30	1.1	21	1.1	0.28	4	27.5	0.92
Dec 31, 2021	150	9.3	78	14	0.56	42	143.9	0.96
Dec 31, 2022	140	5.5	66	16	1.2	44	132.7	0.95
Dec 31, 2023	205	6	91.6	18	1.8	53	170.4	0.83
Dec 31, 2024	235	6.5	144	20	2	60	232.5	0.99

This table reports the market capitalizations of the stablecoins DAI, USDT, BUSD, TUSD, and USDC as of December 31 for each year from 2020 to 2024. All figures are expressed in billions of U.S. dollars (USD).

Table A.4
Correlation matrix for range-based stablecoin variances

	DAI	USDT	BUSD	TUSD	USDC	USTC
Panel A. Estimated sample period correlation matrix.						
DAI		0.3995***	0.4090***	0.5264***	0.3903***	0.2664***
USDT			0.6293***	0.7028***	0.5263***	0.3731***
BUSD				0.1478***	0.5094***	0.1185**
TUSD					0.1104**	0.3752***
USDC						0.0764
USTC						
Panel B. Estimated *t-statistics for sample period correlations.*						
DAI		8.30	8.54	11.80	8.08	5.27
USDT			15.43	18.82	11.79	7.66
BUSD				2.85	11.28	2.27
TUSD					2.12	7.71
USDC						1.46
USTC						

Statistically significant at 5 % and 1 % levels: ** and ***, respectively.
This table reports the correlation matrix of range-based variance processes for the following stablecoins: DAI, USDT, BUSD, TUSD, USDC, and USTC. To estimate annualized daily stablecoin variances, we employ the range-based variance estimator proposed by Parkinson (1980):

$$\sigma_{i,t}^2 = T\frac{1}{4\ln(2)}\left(\ln(H_{i,t}) - \ln(L_{i,t})\right)^2,$$

where $H_{i,t}$ and $L_{i,t}$ denote the highest and lowest price for stablecoin *i* on trading day *t*, and $\sigma_{i,t}^2$ is stablecoin *i's* corresponding annualized realized variance with $T = 364$ trading days per year. Panel A reports estimates of sample period correlations, and Panel B reports corresponding *t*-statistics. The sample period is from January 5, 2021 to January 5, 2022.

Data availability

Data will be made available on request.

References

Adachi, M., Da Silva, P.B.P., Born, A., Cappuccio, M., Czák-Ludwig, S., Gschossmann, I., Paula, G., Pellicani, A., Philipps, S.M., Plooij, M., Rossteuscher, I., Zeoli, P., 2022. Stablecoins' role in crypto and beyond: functions, risks and policy. In: Macroprudential Bulletin, 18. European Central Bank.
Ahelegbey, A., Giudici, P., 2022. NetVIX - a network volatility index for financial markets. Phys. A: Stat. Mech. Appl. 594, 127017.
Ante, L., Fiedler, I., Willruth, J.M., Steinmetz, F.A., 2023. Systematic literature review of empirical research on stablecoins. FinTech 2, 34–47.
Aramonte, S., Huang, W., Schrimpf, W., A., 2021. DeFi risks and the decentralization illusion. BIS Q. Rev. Bank Int. Settl.
Areddy, J.T., 2021. China creates its own digital currency, a first for major economy. Wall Str. J.
Balvers, R.J., McDonald, B., 2021. Designing a global digital currency. J. Int. Money Financ. 111, 102317.
Bank of England (BoE), 2019. Financial Stability Report July 2019, Issue no. 45: Technical Report, July, 74.
Bank of England (BoE), 2020. Central Bank Digital Currency: Opportunities, Challenges and Design. Technical report, March, 57.
Banking Dive, (2025, January 24). Trump order embraces stablecoins, bars CBDCs. https://www.bankingdive.com/news/trump-order-stablecoin-cbdc/738280/.
Bellia, M., Schich, M., S., 2020. What makes private stablecoins stable? SSRN Electron. J. ISSN 1556-5068.
Bera, K., Park, S.Y., 2008. Optimal portfolio diversification using the maximum entropy principle. Econ. Rev. 27 (46), 484–512.
Best, M.J., Grauer, R.R., 1992. Positively weighted minimum-variance portfolios and the structure of asset expected returns. J. Financ. Quant. Anal. 27 (4), 513–537.
Bodnar, T., Mazur, S., Okhrin, Y., 2017. Bayesian estimation of the global minimum variance portfolio. Eur. J. Oper. Res. 256 (1), 292–307.
Catalini, de Gortari, A., Shah, N., 2021. Some simple economics of stablecoins. Working paper available from SSRN at ⟨https://ssrn.com/abstract=3985699⟩.
Choi, J., Kim, H.H., 2024. Stablecoins and central bank digital currency: challenges and opportunities. Oxf. Res. Encycl. Econ. Financ. https://doi.org/10.1093/acrefore/9780190625979.013.910.
Chow, T.M., Kose, E., Li, R., 2016. The impact of constraints on minimum-variance portfolios. Financ. Anal. J. 72 (2), 52–70.
Claessens, S., Cong, L.W., Moshirian, F., Park, C.-Y., 2024. Opportunities and challenges associated with the development of FinTech and central bank digital currency. J. Financ. Stab. 7, 10128.
Clarke, R.H., Silva, De, Thorley, S., 2011. Minimum-variance portfolio composition. J. Portf. Manag. 37 (2), 31.
Clauset, A., Shalizi, C.R., Newman, M.E., 2009. Power-law distributions in empirical data. SIAM rev. 51 (4), 661–703.
Committee on Payments and Market Infrastructures (CPMI), 2018. Central bank digital currencies. Technical report no. 174, March.
Cong, L.W., Li, Y., Wang, N., 2021. Tokenomics: Dynamic adoption and valuation. Rev. Financ. Stud. 34 (3), 1105–1155.
Di Maggio, M., Ghosh, P., Ghosh, S.K., Wu, A., 2024. Impact of retail CBDC on digital payments and bank deposits: evidence from India. NBER Work. Pap. 32457.
Dionysopoulos, L., Marra, M., Urquhart, A., 2024. Central bank digital currencies: a critical review. Int. Rev. Financ. Anal. 91, 103031.
Duan, K., Urquhart, A., 2023. The instability of stablecoins. Financ. Res. Lett. 52, 103573.
Financial Stability Board (FSB), 2022. Review of the FSB high-level recommendations of the regulation, supervision and oversight of "global stablecoin'' arrangements. Technical report, October.
G7 Working Group on Stablecoins, 2019. Investigating the impact of global stablecoins: technical report, October.
Giudici, P., Leach, T., Pagnottoni, P., 2022. Libra or Librae? Basket based stable coins. Finance Res. Lett. 44, 102504.
Griffin, J.M., Shams, A., 2020. Is Bitcoin really un-tethered? J. Financ. 75 (4), 1913–1964.
Grobys, K., 2024. On co-dependent power-law behavior across cryptocurrencies. Financ. Res. Lett. 63, 105295.
Grobys, K., Huynh, T.L.D., 2021. When tether says "JUMP!" bitcoin asks "how low?". Financ. Res. Lett. 47 (Part A), 102644.
Grobys, K., Junttila, J.-P., Kolari, J.W., Sapkota, N., 2021. On the stability of stablecoins. J. Empir. Financ. 64, 207–223.
Guseva, Y., Gazi, A., Eakeley, D.S., 2024. On the coexistence of stablecoins and central bank digital currencies. Law Contemp. Probl. 87, 91–128.
Hoang, L.T., Baur, D.G., 2021. How stable are stablecoins? Eur. J. Financ. 30 (16), 1–17.
Hovanov, N.V., Kolari, J.W., Sokolov, M.V., 2004. Computing currency invariant indexes with an application to minimum variance currency baskets. J. Econ. Dyn. Control 28 (8), 1481–1504.
Jarno, K., Kołodziejczyk, K., H., 2021. Does the design of stablecoins impact their volatility. J. Risk Financ. Manag. 14 (2), 42. https://doi.org/10.3390/jrfm14020042.
Jeger, C., Rodrigues, B., Scheid, E., Stiller, B., 2020. Analysis of stablecoins during the global COVID-19 pandemic. In: Proceedings of the 2020 s International Conference on Blockchain. Computing and Applications (BCCA), pp. 30–37.
A. Kahya, B. Krishnamachari, S. Yun, 2021. Reducing the Volatility of Cryptocurrencies – A Survey of Stablecoins. Working paper. University of Southern California.
Krause, D., (2025). A Roundtable Discussion on the Trump Administration's Policy on PrivateStablecoins Over a U.S. CBDC (February 12, 2025). Available at SSRN: https://ssrn.com/abstract=5134818 or https://doi.org/10.2139/ssrn.5134818.
Liu, Y., Tsyvinski, A., Wu, X., 2022. Common risk factors in cryptocurrency. J. Finance 77 (2), 1133–1177.
Markowitz, H., 1952. Portfolio selection. J. Financ. 7 (1), 77–91.
Niepelt, D., 2024. Money and banking with reserves and CBDC. J. Financ. 79 (4), 2502–2552.
Ozili, P.K., 2022. Decentralized finance research and developments around the world. J. Bank. Financ. Technol. 6, 117–133.
Parkinson, M., 1980. The extreme value method for estimating the variance of the rate of return. J. Bus. 53 (1), 61–65.
PwC (2023). PwC Global CBDC Index and Stablecoin Overview 2023, November 2023. https://www.pwc.com/gx/en/financial-services/pdf/pwc-global-cbdc-index-and-stablecoin-overview-2023.pdf.
Urquhart, A., Yarovaya, L., 2023. Cryptocurrency research: future directions. Eur. J. Financ. 30 (16), 1–6.
Wei, W.C., 2018. The impact of tether grants on bitcoin. Econ. Lett. 171, 19–22.
Xidonas, P., Hassapis, C., Soulis, J., Samitas, A., 2017. Robust minimum variance portfolio optimization modelling under scenario uncertainty. Econ. Model. 64, 60–71.
Zhang, W., Wang, P., Li, X., Shen, D., 2018. Some stylized facts of the cryptocurrency market. Appl. Econ. 50 (55), 5950–5965.