Journal of Digital Economy 4 (2025) 268–288

Contents lists available at ScienceDirect

Journal of Digital Economy

journal homepage: www.keaipublishing.com/en/journals/journal-of-digital-economy

Stablecoin market growth and sensitivity to interbank lending rates: Projections for wholesale CBDC adoption

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ARTICLE INFO

JEL classification:
E42
E52
G23

Keywords:
Stablecoins
Central bank digital currency
Interbank lending rates
Cryptocurrency markets
Monetary policy

ABSTRACT

This paper investigates the sensitivities of the stablecoin market by analysing daily data using a set of widely recognised financial indicators. Focusing on Tether and USD Coin (USDC), which together account for approximately 90 percent of the stablecoin market capitalisation, we find that the two coins respond differently to macro-financial conditions. Tether appears to be influenced by a broader range of indicators, while USDC shows pronounced sensitivity to the Secured Overnight Financing Rate (SOFR). These behavioural differences likely reflect variations in collateral composition, market integration, and the internal reserve management practices of the issuers. Using non-linear analytical methods, including quantile regression and decision tree models, we assess the distinct dynamic relationships between stablecoin value and key financial indicators. Based on these findings, we can support a framework for wholesale central bank digital currencies (wCBDCs) that can enhance the effectiveness of monetary policy transmission or respond more flexibly during liquidity shocks.

1. Introduction

We chose to investigate stablecoins by utilising Tether and USDC time series as together these currencies represent almost 90 % of the stablecoin market capitalisation; Tether 70 %, and USDC 19 % of the market capitalisation, respectively (Nicolle, 2024). By investigating these stablecoins using financial indicators, we aim to better understand their responses to macroeconomic changes and potentially make predictions for the rollout of wCBDCs. WCBDCs are a digital liability of the central bank, denominated in the national unit of account and issued solely to regulated financial institutions. Like today's reserves, it would settle inter-bank and other wholesale transactions by debiting and crediting participants' balances at the central bank (BIS, 2021; Bank of England, 2020A).

Even with novel stablecoin statutes now in force such as the EU's Markets in Crypto-assets Regulation (MiCA) from 2024, which brings e-money and asset-referenced tokens under a unified consumer-protection regime (European Parliament and Council, 2023) and the United States' GENIUS Act of 2025 (U.S. Senate, 2025; Lang, 2025), which mandates 1:1 reserves, monthly disclosures and federal licensing for “payment stable-coins”, wCBDCs remain relevant. These new laws are majorly aimed at retail-payment tokens, whereas wCBDCs would serve regulated financial institutions and, preserve the central bank's ability to operate the asset risk-assessed money-multiplier system: commercial banks could continue to expand settlement balances against eligible deposits and assets while the central bank manages system-wide liquidity and safeguards financial stability (BIS, 2021; Bank of England, 2020).

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Peer review under responsibility of Editorial Board of Journal of Digital Economy.

https://doi.org/10.1016/j.jdec.2025.08.004
Received 6 July 2025; Received in revised form 17 August 2025; Accepted 29 August 2025

USDC is backed predominantly by cash and short-term U.S. Treasury securities, making it more responsive to changes in SOFR, which influences the yield on these treasuries or repos. This transparency and regulatory compliance, combined with its widespread use in the decentralised finance (DeFi) sector and by institutional investors, heighten its sensitivity to fluctuations in financial indicators like SOFR. With this indicator that relates to wholesale lending, we could use this to make projections for wholesale CBDCs adaptation. In contrast, Tether holds a wider selection of instruments as collateral. USDC and Tether collateral related operational divergences can give us a natural experiment in how collateral quality and disclosure affect liquidity, collateral quality variance and reaction to policy rates.

Both coins promise one-for-one redemption, yet episodes like the March 2023 USDC de-peg reveal that this promise holds only if collateral is valued continuously and liquidity backstops exist (Howcroft and Jaiswal, 2023). We proxy these fragilities by modelling how the coins respond to shocks in SOFR, Treasury bill yields and equity volatility. Bank of International discussion letter shows that asset-backed stable-coins can fail the tests of singleness, elasticity and integrity during stress (BIS, 2025A).[1]

The introduction of wholesale CBDCs can mitigate or solve interbank lending challenges (Accenture, 2024). Furthermore, we understand that stablecoins can contribute positively to overall market liquidity, but also carry various risks including credit, asset-liability mismatch and operational risk(BIS, 2019). The nature of the risky assets owned by a traditional bank can affect their provision of and type of liquidity (Dang et al., 2017) This appears to hold up also relating to stablecoin asset collateralisation, which quality will have differing effects during market events. The study corroborates that stablecoins can exhibit sensitivities to t-bills, interbank lending and even equity market movements. Aldasoro et al. (2023) analyse the on-chain "stablecoin" and off-chain "euro-dollar" deposit parity, noting that these correlate more with assets within their respective systems. Our results also indicate that while stablecoins are considered safe-haven instruments, they do not serve this role for the entire financial market. Aldasoro et al. (2023) consider the liquidity features of the stablecoins, but usually these are studied for their stability or collateralisation (e.g. Watsky et al., 2024; Lyons and Viswanath-Natraj, 2023). Our study therefore extends the debate by testing whether the interaction between collateral composition and liquidity explains stable-coins' behaviour, and by asking whether this could guide the calibration of a wholesale CBDC repo facility. Stablecoins also seem to exhibit a dynamic between liquidity and collateral that is similar to banks typically. After all, the money markets are there to provide liquidity (Holmstrom et al., 2015).

Furthermore, wholesale central bank digital currencies (wCBDCs) can operate alongside tokenised assets to facilitate more transparent and efficient transaction processing. By enabling delivery-versus-payment (DvP) to occur within a single on-chain instruction, wCBDCs support automated settlement while reducing reconciliation burdens and operational complexity. This combination of programmable central bank money and tokenised wholesale assets has the potential to enhance liquidity provision and improve the resilience of financial market infrastructure (BIS, 2025A; BIS & Federal Reserve Bank of New York, 2025; Committee on Payments and Market Infrastructures, 2023).

Considering the correlation between SOFR and stablecoins, we seek to understand if we can empirically learn about this dynamic for the wCBDC instrument design process. As Acharya and Rajan (2022) state, during periods of stress, healthy banks may prefer to attract flight-to-safety deposits rather than lend in the interbank market, due to concerns about the quality of debt associated with interbank lending. This, in turn, will not help companies meet their financing needs and will subsequently have a wide economic impact. Companies seek to secure financing, particularly during periods of uncertainty when firms actively seek buffer funding to weather financial stress and maintain operations (BIS, 2025B).

A growing body of time series research now examines stable-coins from several angles. For instance Ma et al. (2025) fit a structural model to daily creation and redemption flows together with price spreads, showing that tightly centralised arbitrage narrows the peg yet heightens simulated run risk; our focus on conditional growth-rate distributions extends their systemic-risk insight by tracing how macro-financial shocks propagate even when no outright run occurs. Jin et al. (2023) analyse panel survey data from Ethereum traders and find that on-chain liquidity, rather than classical risk–return considerations, drives stable-coin adoption, a behavioural result that supports including liquidity-sensitive variables such as the Secured Overnight Financing Rate (SOFR) in our empirical design. Lee et al. (2025) forecast de-pegging episodes with an non-linear classifier trained on high-frequency prices, volumes and sentiment; our quantile-regression framework complements this machine-learning strand by capturing the full conditional distribution of market-capitalisation growth and thereby informing early-warning thresholds relevant to a prospective wholesale central-bank digital currency collateral facility.

The remainder of the paper proceeds as follows. Section 2 describes our data, detailing the construction of daily market-capitalisation growth rates for Tether, USDC and the combined stable-coin universe, alongside macro-financial covariates such as SOFR, Treasury-bill returns, VIX and commodity indices. Section 3 sets out the empirical methodology, combining mean-based OLS, quantile regression and decision-tree models, and justifies each against the non-Gaussian diagnostics revealed by Q–Q plots. Section 4 presents the core results, highlighting the asymmetric sensitivity of stable-coin growth to wholesale funding costs and equity-market volatility. Section 5 provides robustness checks, including Granger-causality tests and machine-learning forecasts, while Section 6 discusses policy implications for the design of a wCBDC repo facility with tokenised-asset collateral. Section 7 concludes.

[1] The BIS sets three foundational tests for any form of money. Singleness means every unit is accepted at par that is the same quality and standard of other units. Elasticity is the capacity of the system to expand or contract settlement liquidity on demand so large-sized payments keep flowing even in stress. Integrity requires robust safeguards – KYC/AML, sanctions compliance, audit trails, to keep illicit finance out of the payment rails. Asset-backed stable-coins typically fail all three tests in turbulent markets (BIS, 2025A).

2. Data and methodology

We investigate three stablecoin market capitalisation growth rates as a proxy for their adaptation and use. Namely, we will use market cap growth rates of Tether, USDC and then one combined from them both.

We model daily growth rates and returns to mitigate non-stationarity:

$$g_{i,t} = \left(MC_{i,t} - MC_{i,t-1}\right) \ / \ MC_{i,t-1} \tag{1}$$

where $g_{,t}$ denotes the market capitalisation growth rate of i observation at time t, and $MC_{i,t}$ is the market capitalisation of stablecoin i at time t.

$$r_{j,t} = 100 \times \left[\ln\left(P_{j,t}\right) - \ln\left(P_{j,t-1}\right)\right] \tag{2}$$

where $P_{j,t}$ is the price of asset j at time t. The return is expressed in percentages.

We decided to inspect the market growth rates; as Fig. 1 evidences, the log market capitalisation transformation may not be a good indicator of how the SOFR rate may have affected the stablecoin market base growth rate. In fact, after completing initial analysis of OLS estimator modelling with log transformed market capitalisation dependent variables, we see that these specifications exhibited high levels of autocorrelation marked by low Durbin-Watson results. This prompted us to focus on modelling market cap growth rates using the first differences from daily market capitalisations observations. Furthermore, a quantile regression approach is employed to estimate the effects at different points of the conditional distribution of the market cap growth rates, specifically the 25th, 50th, and 75th percentiles. This is to better investigate non-linear relationships. It is particularly useful in identifying the impacts under different market conditions, such as low, median, and high growth scenarios, especially as the digital asset market is known for its exponential growth rates. This is evident in Table 3, which presents descriptive statistics showing that the growth rates of the stablecoin market exhibit high excess skewness."

We transform the price series of indices and assets into return series to facilitate comparability and mitigate non-stationarity. In addition, lag structures are applied to the financial indicators within the regression models to account for potential delayed effects and improve the robustness of the estimations.

We employ a range of indicators to proxy key macro-financial conditions relevant to stablecoin behaviour. The VIX index is used as a proxy for market uncertainty, while total returns on U.S. Treasury bills represent the risk-free rate. The Secured Overnight Financing Rate (SOFR) serves as an indicator of banks' risk appetite in short-term funding markets. In the digital asset space, Ethereum is used as a proxy for alternative cryptocurrencies (altcoins). For commodity exposure, we include the Goldman Sachs Commodity Index (GSCI) as a broad energy benchmark, and the Goldman Sachs Softs Index to capture price movements in soft commodities often linked to broader inflationary pressures. Data was sourced from the Bloomberg Terminal, while cryptocurrency and stablecoin data were obtained via the CoinGecko API. Further details on each variable are provided in Table 1. All prices are denominated in US dollars.

The time series is selected from the launch of SOFR Bloomberg total return index March 2, 2020 to January 31, 2024. SOFR also compounds during weekends, so the index prices during holidays and weekends (New York Fed, 2022). This is useful, as stablecoins as well as cryptos trade and price everyday of the week.

As shown in Table 2, the prices of both Tether (USDT) and USD Coin (USDC) exhibit mean values close to parity, at approximately 1.001 and 1.000 respectively. Their standard deviations are low (around 0.002), consistent with their design as stablecoins. Both display minimal skewness but relatively high kurtosis, suggesting a tight clustering around the mean with occasional extreme deviations. In contrast, S&P 500 (SPX) returns show a small positive mean (0.074), whereas VIX returns exhibit a negative mean (−0.259), indicating a general tendency towards increasing market volatility during the sample period. The S&P GSCI Commodity Index (SPGSCI) and the S&P GSCI Softs Index (SPGSSF) also display notable variability, with mean returns of 0.095 and 0.079, respectively. Bitcoin (BTC) and Ethereum (ETH) returns demonstrate higher average values (0.187 and 0.285), but also much larger standard deviations (3.891 and 5.080), underscoring the pronounced volatility associated with these assets. The skewness and kurtosis values for ETH, in particular, indicate the presence of extreme price movements. Overall, the sample reflects a period characterised by broad upward trends in financial markets.

Table 3 presents summary statistics for combined market growth, as well as individual growth rates for Tether and USDC. All three series exhibit positive mean values: 0.331 for combined market growth, 0.323 for Tether, and 0.377 for USDC. These growth rates display considerable variability, particularly in the case of Tether, which has a notably high standard deviation of 1.700. The extreme skewness and kurtosis values further indicate the presence of occasional substantial surges in market growth, pointing to periods of rapid expansion. The mean log market capitalisation of Tether is 24.608, with a standard deviation of 0.750, suggesting moderate variability over the sample period. Bitcoin and Ethereum show higher average log market capitalisations, at 26.951 and 25.845 respectively, with similarly moderate standard deviations, reflecting a strong and sustained market presence. The skewness and kurtosis statistics for these variables suggest distributions that are broadly normal, though Tether and USDC again display signs of deviation from normality. The actual market capitalisations of Tether and USDC show greater variability. The mean market cap for Tether is 59.289, compared to 27.733 for USDC, but with a much higher standard deviation for Tether (26.803), indicating more pronounced fluctuations in value. The skewness and kurtosis values further highlight the presence of extreme observations, particularly for Tether, which is consistent with episodes of abrupt growth or contraction in market size.

The correlation matrix presented in Table 4 provides several insights that support the validity of the dataset. As expected, the S&P 500 Index exhibits a strong negative correlation with the VIX Index, consistent with the established inverse relationship between

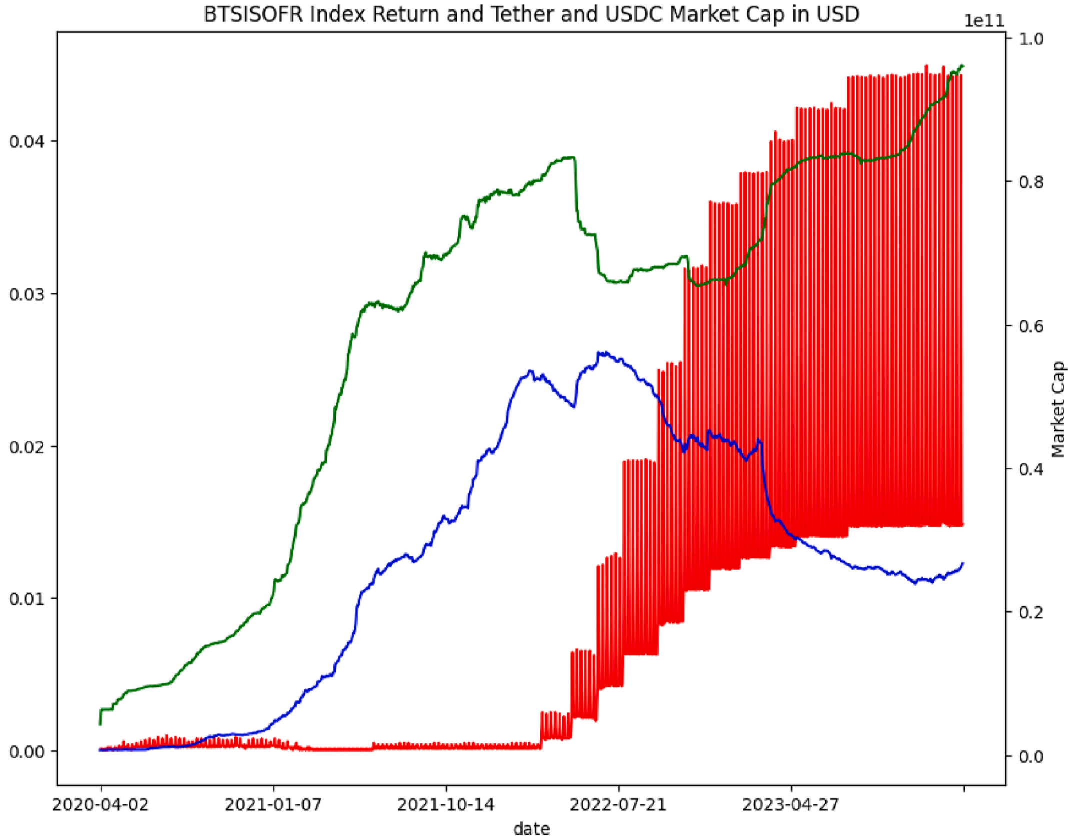

Fig. 1. SOFR Index Return vs Tether Market Capitalisation in Dollars
Notes: The chart displays the BTSSOFR Index Return (RED), aligned with the left y-axis, which represents daily return values. Tether Market Capitalisation (GREEN) and USDC Market Capitalisation (BLUE) are plotted against the right y-axis, representing market capitalisation in US dollars (USD).

equity performance and market volatility. Additionally, Bitcoin and Ethereum returns display a high positive correlation, indicating that these leading cryptocurrencies tend to move in tandem. This relationship extends to their market capitalisations, which are also strongly correlated, suggesting that shifts in market sentiment and investment flows commonly affect both assets in a similar manner. The S&P GSCI Commodity Index and the S&P 500 Index show a moderate positive correlation, pointing to some degree of alignment between commodity and equity market returns. This implies that shared macroeconomic factors may influence both asset classes. While the correlation between VIX returns and Tether growth is not particularly strong, it is negative, suggesting that periods of increased market volatility may be associated with a slight reduction in Tether's growth.

2.1. Diagnostic role of the Q-Q plots

Before selecting an estimation technique, we examined the empirical distributions of the daily market-capitalisation growth rates for the combined stable-coin market, USDC, and Tether. Figs. 2–4 present quantile-quantile (Q-Q) plots that compare each series with the theoretical normal distribution. In all three cases the plotted quantiles diverge markedly from the 45° reference line, with pronounced S-shaped patterns and long upper- and lower-tail excursions. These departures confirm the visual evidence of excess skewness and leptokurtosis already documented in the descriptive statistics (Table 3 shows kurtosis values well above three for every series). Together, the Q-Q plots and summary moments demonstrate that the conditional distribution of growth rates is neither Gaussian nor homoscedastic, and that the degree of departure varies across the distribution's centre and tails.

Because ordinary least-squares (OLS) regression targets the conditional mean, it can mask such heterogeneity and provide an incomplete picture when the response variable exhibits heavy tails or asymmetric behaviour. Quantile regression, by contrast, estimates conditional quantiles directly and therefore captures the entire distribution, allowing the slope coefficients to differ at, for example, the 25th, 50th and 75th percentiles. The pronounced tail deviations revealed by the Q-Q plots thus serve as a diagnostic test motivating the use of quantile regression: they indicate that the marginal effects of our financial-market covariates are likely to vary across low-, median- and high-growth episodes, a hypothesis that is subsequently confirmed by the differing sign and magnitude of the coefficient estimates reported in Tables 5–7

Table 1
Variable definitions.

Variables	Description
Tether (USDT)	Tether is a stablecoin pegged to the U.S. dollar that has the largest market capitalisation and seeks to offer 1:1 conversion. The peg to the dollar efficiency can be viewed in Figure A.2 in Appendix.
USD Coin (USDC)	USDC stablecoin is pegged to the U.S. dollar that seeks to offer 1:1 conversion.The peg to the dollar efficiency can be viewed in Figure A.2 in Appendix.
Bitcoin (BTC)	Bitcoin has the largest market capitalisation of any cryptocurrency.
Ethereum (ETH)	A leading altcoin, cryptocurrency and blockchain platform. Ethereum has smart contract functionality and influences the DeFi space.
BTSISOFR Index	This index tracks the performance of the Secured Overnight Financing Rate (SOFR), reflecting interbank lending rates. Launched on March 2, 2020 to replace LIBOR, it serves as a benchmark for the cost of wholesale borrowing. Due to avoiding the noise and volatility that can occur during these initial launch periods caused by e.g. operational issues, the data sample is selected to start a month after. Appendix Fig. A.1 exhibits this.
I00078MX Index	The Bloomberg unhedged 1–3 month U.S. Treasury notes index. This index is used as a data proxy for the risk-free rate.
S&P GSCI (SPGSCI)	The S&P Goldman Sachs Commodity Index, which tracks global commodities. Changes in commodity prices may reflect broader economic environments, especially the changes in the energy prices.
S&P GSF (SPGSSF)	The S&P Global Soft Commodities Funds Index. The S&P GSCI Softs index is a sub-index of the S&P GSCI that measures the performance of only the soft commodities, weighted on a world production basis. This can be used as a broad proxy for daily pricing inflation expectations.
S&P 500 Index (SPX)	An equity benchmark index tracking the performance of 500 leading U.S. companies. Its performance is used as a proxy for broad economic health.
VIX	The Volatility Index, measuring market expectations of near-term volatility. A higher VIX indicates greater uncertainty. It is constructed from weighted prices of a select S&P 500 call and put options and this implied 30-day volatility proxy is then annualised.

Table 2
Descriptive table prices and returns.

Variables	count	mean	std	min	25 %	50 %	75 %	max	skew.	kurt.
Tether price	1000	1.001	0.002	0.982	1	1	1.001	1.011	0.106	11.658
USDC price	1000	1	0.002	0.981	1	1	1.001	1.011	−0.745	12.203
SPX return	943	0.074	1.157	−6.075	−0.545	0.085	0.745	6.797	−0.181	3.024
VIX return	957	−0.259	6.884	−22.035	−4.35	−0.888	3.232	48.021	0.974	4.452
SPGSCI return	943	0.095	1.526	−12.523	−0.63	0.149	0.949	5.659	−0.978	7.392
SPGSSF return	943	0.079	1.201	−4.75	−0.692	0.034	0.879	3.545	−0.062	0.209
I00078MX return	999	−0.026	0.751	−3.127	−0.474	−0.032	0.37	3.663	0.299	1.674
BTSISOFR return	999	0.007	0.011	0	0	0.001	0.013	0.045	1.986	3.818
Tether return	999	0	0.245	−1.973	−0.084	0.001	0.082	1.645	−0.32	9.576
USDC return	999	0	0.25	−1.585	−0.095	0.004	0.095	1.926	0.134	10.466
BTC return	999	0.187	3.891	−17.252	−1.524	0.083	2.043	17.603	−0.239	2.661
ETH return	999	0.285	5.08	−30.52	−2.015	0.236	2.882	26.942	−0.338	4.674

Notes:The data sample is captured between the dates 2/04/02020 - January 31, 2024.

Table 3
Descriptive statistics market cap growth rates and log market capitalisations.

Variables	count	mean	std	min	25 %	50 %	75 %	max	skew.	kurt.
Tether price	1000	1.001	0.002	0.982	1	1	1.001	1.011	0.106	11.658
USDC price	1000	1	0.002	0.981	1	1	1.001	1.011	−0.745	12.203
SPX return	943	0.074	1.157	−6.075	−0.545	0.085	0.745	6.797	−0.181	3.024
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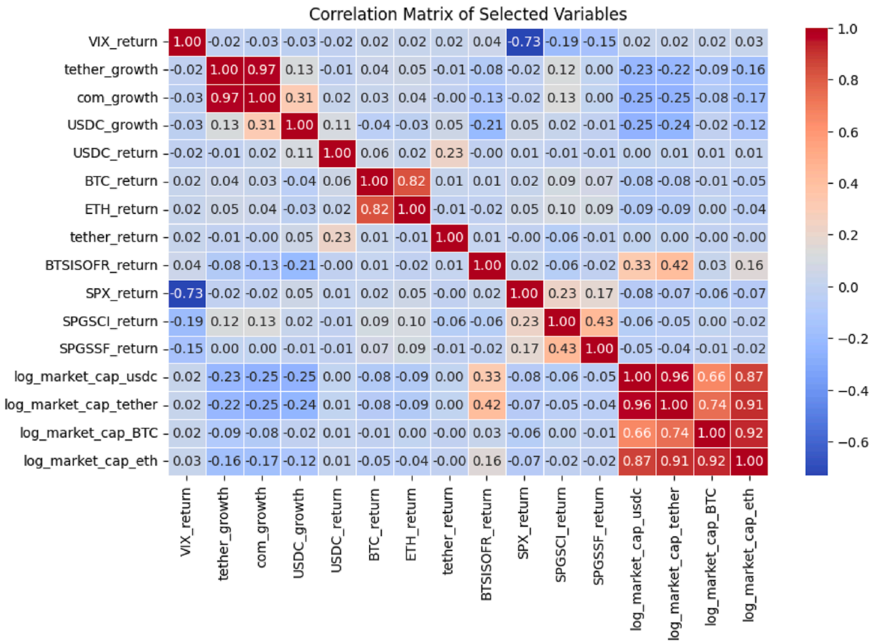
ETH return	999	0.285	5.08	−30.52	−2.015	0.236	2.882	26.942	−0.338	4.674

Notes: The data sample is captured between the dates 2/04/02020, to January 31, 2024.

2.2. The quantile regression specification

This study employs quantile regression, alongside ordinary least squares (OLS) and decision tree methods, to examine the magnitude and significance of the effects of selected financial indicators on the growth rates of stablecoin market capitalisations (see Table 8). The analysis focuses on the influence of returns from Bitcoin, Ethereum, and various traditional financial indices, as well as the logarithmic market capitalisations of Bitcoin and Ethereum, which are included to control for size effects. TThe regression models incorporate lagged returns of up to five periods for the following variables: Bitcoin (BTC), Ethereum (ETH), the Bloomberg Short-Term

Table 4
Variable correlation matrix.



	VIX_return	tether_growth	com_growth	USDC_growth	USDC_return	BTC_return	ETH_return	tether_return	BTSISOFR_return	SPX_return	SPGSCI_return	SPGSSF_return	log_market_cap_usdc	log_market_cap_tether	log_market_cap_BTC	log_market_cap_eth
VIX_return	1.00	-0.02	-0.03	-0.03	-0.02	0.02	0.02	0.02	0.04	-0.73	-0.19	-0.15	0.02	0.02	0.02	0.03
tether_growth	-0.02	1.00	0.97	0.13	-0.01	0.04	0.05	-0.01	-0.08	-0.02	0.12	0.00	-0.23	-0.22	-0.09	-0.16
com_growth	-0.03	0.97	1.00	0.31	0.02	0.03	0.04	-0.00	-0.13	-0.02	0.13	0.00	-0.25	-0.25	-0.08	-0.17
USDC_growth	-0.03	0.13	0.31	1.00	0.11	-0.04	-0.03	0.05	-0.21	0.05	0.02	-0.01	-0.25	-0.24	-0.02	-0.12
USDC_return	-0.02	-0.01	0.02	0.11	1.00	0.06	0.02	0.23	-0.00	0.01	-0.01	-0.01	0.00	0.01	0.01	0.01
BTC_return	0.02	0.04	0.03	-0.04	0.06	1.00	0.82	0.01	0.01	0.02	0.09	0.07	-0.08	-0.08	-0.01	-0.05
ETH_return	0.02	0.05	0.04	-0.03	0.02	0.82	1.00	-0.01	-0.02	0.05	0.10	0.09	-0.09	-0.09	0.00	-0.04
tether_return	0.02	-0.01	-0.00	0.05	0.23	0.01	-0.01	1.00	0.01	-0.00	-0.06	-0.01	0.00	0.00	-0.00	-0.00
BTSISOFR_return	0.04	-0.08	-0.13	-0.21	-0.00	0.01	-0.02	0.01	1.00	0.02	-0.06	-0.02	0.33	0.42	0.03	0.16
SPX_return	-0.73	-0.02	-0.02	0.05	0.01	0.02	0.05	-0.00	0.02	1.00	0.23	0.17	-0.08	-0.07	-0.06	-0.07
SPGSCI_return	-0.19	0.12	0.13	0.02	-0.01	0.09	0.10	-0.06	-0.06	0.23	1.00	0.43	-0.06	-0.05	0.00	-0.02
SPGSSF_return	-0.15	0.00	0.00	-0.01	-0.01	0.07	0.09	-0.01	-0.02	0.17	0.43	1.00	-0.05	-0.04	-0.01	-0.02
log_market_cap_usdc	0.02	-0.23	-0.25	-0.25	0.00	-0.08	-0.09	0.00	0.33	-0.08	-0.06	-0.05	1.00	0.96	0.66	0.87
log_market_cap_tether	0.02	-0.22	-0.25	-0.24	0.01	-0.08	-0.09	0.00	0.42	-0.07	-0.05	-0.04	0.96	1.00	0.74	0.91
log_market_cap_BTC	0.02	-0.09	-0.08	-0.02	0.01	-0.01	0.00	-0.00	0.03	-0.06	0.00	-0.01	0.66	0.74	1.00	0.92
log_market_cap_eth	0.03	-0.16	-0.17	-0.12	0.01	-0.05	-0.04	-0.00	0.16	-0.07	-0.02	-0.02	0.87	0.91	0.92	1.00

Notes:The data sample is captured between the dates 2/04/02020, to January 31, 2024.

Bank Yield Index (BTSISOFR), Bloomberg Commodity Index (I00078MX), S&P GSCI (SPGSCI), S&P GSCI Softs Index (SPGSSF), S&P 500 Index (SPX), and the VIX volatility index. These models assess their respective impacts on the growth of the combined stablecoin market, as well as on USDC and Tether individually. These regressions also include the log of market capitalizations of Bitcoin and Ethereum to control for the size effect. The model parameters are estimated using a sample of 858 observations. o control for the size effect. This is particularly useful for capturing the asymmetric effects of explanatory variables, such as the BTSISOFR, which may have

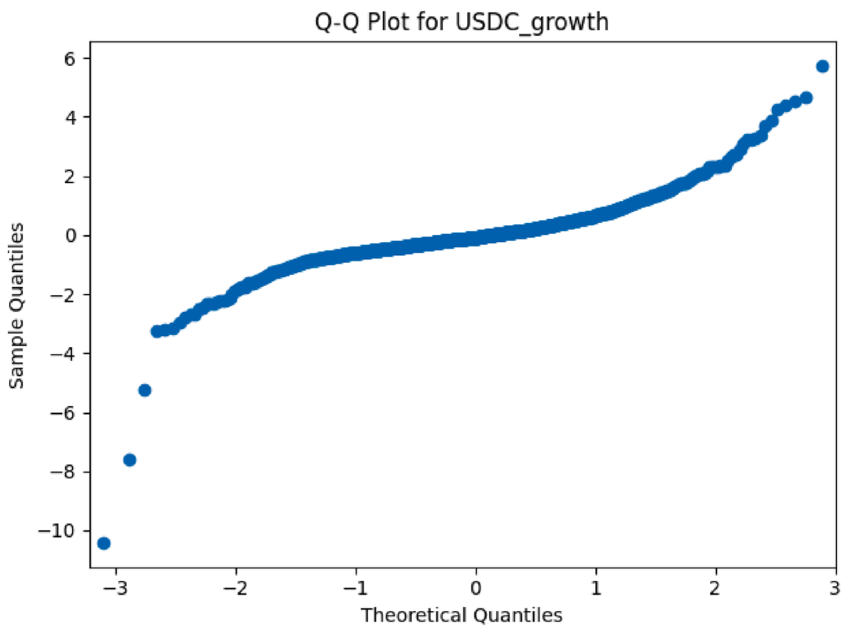


Fig. 2. Q-Q Plot USDC growth.

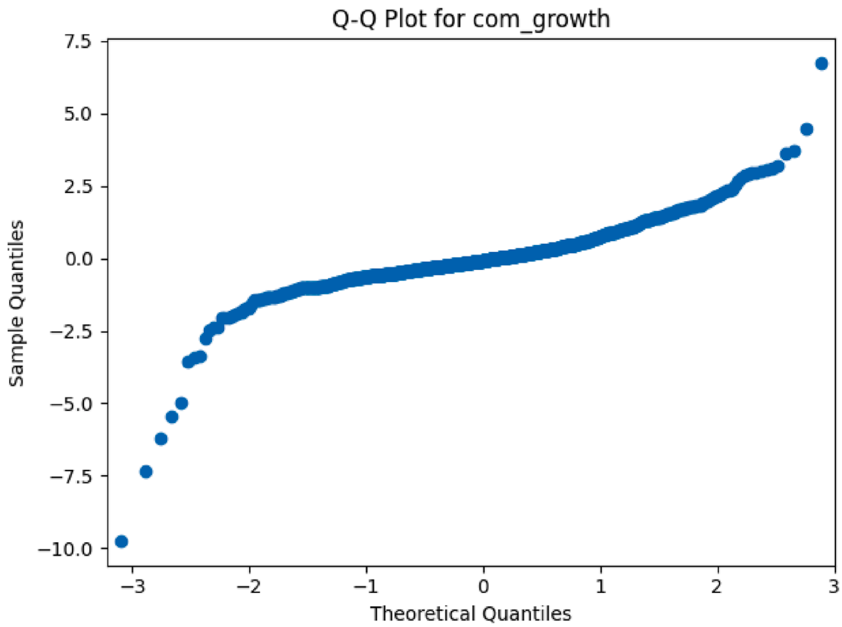


Fig. 3. Q-Q Plot combined stablecoin growth.

a greater impact at either the upper or lower ends of the growth distribution. Such effects may not be adequately identified using a standard mean-based OLS model, making quantile regression especially appropriate for this context.

For robustness we first estimate a mean-based OLS specification with five daily lags of each predictor:

$$g_{\mathrm{i,t}} = \alpha_{\mathrm{i}} + \Sigma_{\mathrm{k=1}}\ 5\ \beta_{1,\mathrm{k}}\ r_{\mathrm{BTC,t-k}} + \Sigma_{\mathrm{k=1}}\ 5\ \beta_{2,\mathrm{k}}\ r_{\mathrm{ETH,t-k}} + \Sigma_{\mathrm{k=1}}\ 5\ \beta_{3,\mathrm{k}}\ r_{\mathrm{SOFR,t-k}} + \cdots + \gamma_1\ \ln(MC\mathrm{BTC}^{\mathrm{t}}) + \gamma_2\ \ln(MC\mathrm{ETH}^{\mathrm{t}}) + \varepsilon_{\mathrm{i,t}} \tag{3}$$

where $g_{i\ t}$ denotes the market capitalisation growth rate of i observation at time t, each Σ term gathers the five-day lags of key return series: Bitcoin (^{r}BTC,$_{t\text{-}k}$), Ether (^{r}ETH,$_{t\text{-}k}$), the Secured Overnight Financing Rate (^{r}SOFR$_{,t\text{-}k}$), and several additional asset classes; commodity futures (I00078MX), broad commodities (SPGSCI), soft commodities (SPGSSF), U.S. equities (SPX), and implied equity volatility (VIX). The coefficients γ_1 and γ_2 capture the long-run elasticities with respect to the logarithms of Bitcoin and Ether market capitalisation, respectively. And finally, εi,t is an idiosyncratic error term that contains all remaining influences on $g_{i,t}$.

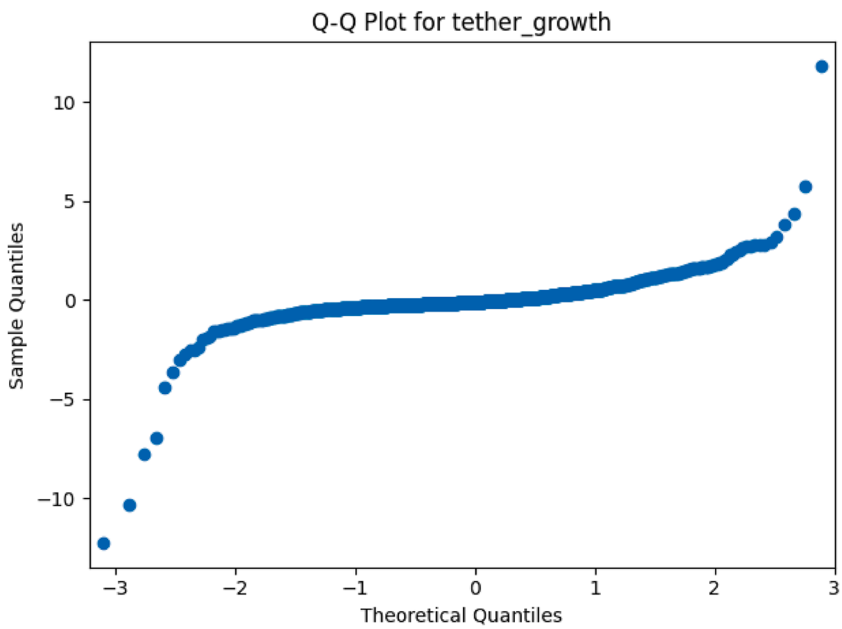


Fig. 4. Q-Q Plot Tether growth.

Table 5
Quantile regression of combined stablecoin market cap growth rate.

	Dependent variable: com growth		
Variables	**25th Quantile**	**50th Quantile**	**75th Quantile**
	(1)	(2)	(3)
BTC_return_lag1	0.002	0.001	−0.003
	(0.005)	(0.005)	(0.007)
BTC_return_lag2	0.008	−0.005	−0.005
	(0.005)	(0.005)	(0.007)
BTC_return_lag3	−0.002	0.002	−0.009
	(0.005)	(0.005)	(0.007)
BTC_return_lag4	−0.002	0.002	0.003
	(0.005)	(0.005)	(0.007)
BTC_return_lag5	−0.017***	−0.019***	−0.025***
	(0.005)	(0.005)	(0.007)
BTSISOFR_return_lag1	−1.561	−3.424**	−6.225***
	(1.392)	(1.332)	(1.747)
BTSISOFR_return_lag2	0.081	−1.799	−2.807
	(1.428)	(1.316)	(1.765)
BTSISOFR_return_lag3	0.042	−1.810	−4.710***
	(1.380)	(1.330)	(1.786)
BTSISOFR_return_lag4	−1.356	−1.878	−3.786**
	(1.379)	(1.331)	(1.779)
BTSISOFR_return_lag5	0.987	2.030	3.163*
	(1.375)	(1.331)	(1.714)
ETH_return_lag1	0.009**	−0.000	0.004
	(0.004)	(0.004)	(0.006)
ETH_return_lag2	0.001	0.006	0.009
	(0.004)	(0.004)	(0.006)
ETH_return_lag3	0.002	0.002	0.010*
	(0.004)	(0.004)	(0.006)
ETH_return_lag4	0.007*	0.003	0.001
	(0.004)	(0.004)	(0.006)
ETH_return_lag5	0.015***	0.015***	0.016***
	(0.004)	(0.004)	(0.006)
I00078MX_return_lag1	−0.007	0.008	−0.021
	(0.017)	(0.016)	(0.021)
I00078MX_return_lag2	−0.016	−0.022	−0.052**
	(0.017)	(0.016)	(0.021)
I00078MX_return_lag3	−0.017	0.014	−0.020
	(0.016)	(0.016)	(0.021)
I00078MX_return_lag4	−0.022	0.008	0.009
	(0.016)	(0.015)	(0.021)
I00078MX_return_lag5	−0.027*	0.009	0.035*
	(0.016)	(0.015)	(0.020)
SPGSCI_return_lag1	−0.009	0.005	0.001
	(0.010)	(0.008)	(0.009)
SPGSCI_return_lag2	−0.005	−0.007	−0.010
	(0.009)	(0.008)	(0.011)
SPGSCI_return_lag3	0.004	0.002	−0.010
	(0.009)	(0.008)	(0.010)
SPGSSF_return_lag1	0.008	0.006	0.017
	(0.011)	(0.010)	(0.014)
SPGSSF_return_lag2	0.016	0.013	0.028**
	(0.011)	(0.010)	(0.014)
SPGSSF_return_lag3	−0.014	0.016	0.039***
	(0.011)	(0.010)	(0.013)
SPGSSF_return_lag4	0.013	0.007	−0.005
	(0.010)	(0.009)	(0.012)
SPX_return_lag1	−0.023	−0.030**	−0.041**
	(0.016)	(0.015)	(0.020)
SPX_return_lag2	0.005	0.016	−0.004
	(0.018)	(0.015)	(0.020)
SPX_return_lag3	0.028*	0.004	0.069***
	(0.016)	(0.015)	(0.020)
SPX_return_lag4	0.000	0.001	−0.001
	(0.016)	(0.015)	(0.019)
VIX_return_lag1	−0.005**	−0.005**	−0.006*
	(0.003)	(0.002)	(0.003)
VIX_return_lag2	0.005*	0.005**	0.002
	(0.003)	(0.002)	(0.003)

(*continued on next page*)

Table 5 (*continued*)

	Dependent variable: com growth		
VIX_return_lag3	0.005**	0.002	0.013***
	(0.002)	(0.002)	(0.004)
VIX_return_lag4	−0.000	−0.001	−0.003
	(0.002)	(0.002)	(0.003)
VIX_return_lag5	0.001	−0.001	0.001
	(0.002)	(0.002)	(0.002)
log_market_cap_BTC	0.496***	0.712***	1.064***
	(0.063)	(0.058)	(0.078)
log_market_cap_eth	−0.346***	−0.508***	−0.846***
	(0.044)	(0.040)	(0.052)
Observations	835	835	835
Pseudo R^2	0.075	0.128	0.191
Residual Std. Error	0.855 (df = 796)	0.785 (df = 796)	0.782 (df = 796)
F Statistic	nan*** (df = 38; 796)	nan*** (df = 38; 796)	nan*** (df = 38; 796)

Notes: 838 observations between 2/04/02020, to January 31, 2024. P-values are set as following: $p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

To capture heterogeneous effects across the potential conditional distribution of growth we estimate the following quantile regression:

$$Qg\_(i,t)\ (\tau \mid X\_(t)\ ) = \alpha\_(i)\ (\tau) + \Sigma\_(k=1)\ \ 5\ \beta(\tau)'\ X\_(t\text{-}k)\quad \text{with } \tau \in \{0.25, 0.50, 0.75\} \tag{4}$$

where τ is the quantile level ($0 < \tau < 1$) for which the conditional quantile is estimated, αi is the stablecoin-specific intercept capturing unconditional mean growth, β is the slope of each quantiles. The predictor vector $X_{t\text{-}k}$ contains the same lagged returns and contemporaneous log-market-capitalisations as in Equation (3).

3. Results

Table 5 presents the quantile regression results for the growth rate of the combined stablecoin market. The findings indicate that Bitcoin and Ethereum returns exert significant but opposing effects on stablecoin market growth, consistent with observations in Anadu et al. (2024). Specifically, Bitcoin returns are positively associated with stablecoin market growth, whereas Ethereum returns exhibit a negative association, particularly with Tether.Furthermore, the logarithmic market capitalisation of Ethereum is found to have a significantly negative relationship with stablecoin growth rates, while Bitcoin's market capitalisation displays a significant positive effect. These contrasting impacts suggest that the market capitalisations of Bitcoin and Ethereum influence stablecoin expansion in divergent ways.

At higher quantiles of stablecoin market growth, the BTSISOFR shows a strong negative correlation, indicating that higher short-term funding rates are associated with a contraction in stablecoin market expansion during periods of elevated growth.

Quantile Regression of Combined, USDC, and Tether Market Cap Growth Rate.

Similarly to Table 5 results, we see again in Table 6 results that at higher growth rates, the BTSISOFR has a large negative correlation.

The results presented in Tables 5 and 6 are reaffirmed in Table 7, particularly the finding that BTSISOFR exhibits a strong negative correlation with stablecoin growth at higher quantiles. In addition, the I00078MX Index, which serves as a proxy for short-term U.S. Treasury notes, shows a significant negative effect on Tether's growth rate. Tether growth also demonstrates a negative correlation with the first lag of the S&P 500 Index, suggesting that declines in equity performance may precede contractions in Tether market expansion. Furthermore, Tether growth rates are found to correlate with Bitcoin and Ethereum returns across different quantiles and lag structures, though these relationships warrant further investigation to determine their consistency and significance. Consistent with earlier findings, Tether growth is significantly and positively associated with Bitcoin market capitalisation, while showing a significant negative relationship with Ethereum market capitalisation. These contrasting effects may reflect differing risk profiles or perceived “safe asset” roles within the digital asset ecosystem and potentially also in relation to broader financial markets.

4. Robustness

Given the presence of non-linear patterns in the tails of the growth rate distributions, as illustrated in Figs. 2–4, decision tree models are employed to explore potential non-linear relationships and interactions among the explanatory variables. This method allows for the identification of complex structures that may not be captured by linear models.

In addition, Granger causality tests are conducted to assess the dynamic relationships between variables and to provide insights into potential directional causality. For comparison and completeness, results from ordinary least squares (OLS) regression models for the three stablecoin growth rates are presented in Table A.1 in the Appendix.

Table 6
Quantile regression of USDC market cap growth rate.

	Dependent variable: USDC growth		
Variables	**25th Quantile**	**50th Quantile**	**75th Quantile**
	(1)	(2)	(3)
BTC_return_lag1	−0.002	0.005	−0.007
	(0.012)	(0.012)	(0.015)
BTC_return_lag2	−0.014	−0.007	0.000
	(0.011)	(0.011)	(0.015)
BTC_return_lag3	−0.027**	−0.007	−0.048***
	(0.012)	(0.011)	(0.015)
BTC_return_lag4	−0.017	−0.021*	−0.039**
	(0.012)	(0.012)	(0.015)
BTC_return_lag5	−0.038***	−0.038***	−0.056***
	(0.012)	(0.012)	(0.016)
BTSISOFR_return_lag1	−4.532	−8.146***	−12.178***
	(3.011)	(3.054)	(3.952)
BTSISOFR_return_lag2	−1.707	−5.870*	−10.236***
	(3.078)	(3.017)	(3.904)
BTSISOFR_return_lag3	−0.957	−3.777	−10.439**
	(3.020)	(3.050)	(4.065)
BTSISOFR_return_lag4	−5.855*	−3.133	−6.644*
	(2.998)	(3.051)	(3.815)
BTSISOFR_return_lag5	−1.240	4.741	4.122
	(2.953)	(3.051)	(3.885)
ETH_return_lag1	−0.002	−0.025***	−0.012
	(0.009)	(0.009)	(0.012)
ETH_return_lag2	−0.010	−0.005	−0.001
	(0.009)	(0.009)	(0.012)
ETH_return_lag3	0.012	−0.007	0.004
	(0.009)	(0.009)	(0.011)
ETH_return_lag4	0.004	−0.003	−0.002
	(0.009)	(0.009)	(0.013)
ETH_return_lag5	0.008	0.004	0.020
	(0.009)	(0.009)	(0.013)
I00078MX_return_lag1	−0.011	−0.056	0.017
	(0.038)	(0.036)	(0.046)
I00078MX_return_lag2	0.044	0.009	0.048
	(0.036)	(0.036)	(0.047)
I00078MX_return_lag3	0.009	0.036	0.083*
	(0.038)	(0.036)	(0.046)
I00078MX_return_lag4	0.012	−0.015	−0.017
	(0.035)	(0.035)	(0.046)
I00078MX_return_lag5	−0.055	−0.020	0.028
	(0.036)	(0.034)	(0.042)
SPGSCI_return_lag1	0.014	0.005	0.050**
	(0.022)	(0.018)	(0.020)
SPGSCI_return_lag2	0.040**	−0.003	−0.007
	(0.019)	(0.018)	(0.021)
SPGSCI_return_lag3	−0.000	−0.009	0.027
	(0.020)	(0.019)	(0.022)
SPGSSF_return_lag1	−0.006	0.037	−0.020
	(0.024)	(0.023)	(0.029)
SPGSSF_return_lag2	−0.019	0.020	−0.002
	(0.023)	(0.023)	(0.030)
SPGSSF_return_lag3	0.005	0.018	0.030
	(0.023)	(0.023)	(0.029)
SPGSSF_return_lag4	0.002	−0.004	0.029
	(0.021)	(0.021)	(0.026)
SPX_return_lag1	−0.025	−0.053	−0.103**
	(0.037)	(0.035)	(0.045)
SPX_return_lag2	0.019	0.071**	0.050
	(0.035)	(0.035)	(0.045)
SPX_return_lag3	−0.006	0.040	0.061
	(0.035)	(0.036)	(0.048)
SPX_return_lag4	0.019	0.010	0.054
	(0.035)	(0.034)	(0.042)
VIX_return_lag1	−0.004	−0.009*	−0.025***
	(0.006)	(0.006)	(0.008)
VIX_return_lag2	0.006	0.012**	0.011
	(0.005)	(0.006)	(0.007)

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Table 6 (*continued*)

	Dependent variable: USDC growth		
VIX_return_lag3	0.005	0.006	0.015**
	(0.005)	(0.006)	(0.008)
VIX_return_lag4	0.003	0.003	0.014**
	(0.006)	(0.005)	(0.007)
VIX_return_lag5	0.004	−0.004	−0.005
	(0.004)	(0.004)	(0.006)
log_market_cap_BTC	0.762***	1.207***	1.889***
	(0.136)	(0.133)	(0.167)
log_market_cap_eth	−0.422***	−0.782***	−1.523***
	(0.094)	(0.091)	(0.113)
Observations	835	835	835
Pseudo R^2	0.069	0.102	0.167
Residual Std. Error	1.614 (df = 796)	1.476 (df = 796)	1.522 (df = 796)
F Statistic	nan*** (df = 38; 796)	nan*** (df = 38; 796)	nan*** (df = 38; 796)

Notes: 858 observations between 2/04/02020, to January 31, 2024. P-values are set: $p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

4.1. Decision tree

In the decision tree modelling described, the log transformed market capitalisation (‘combined’), USDC and Tether are set as the dependent variable. The independent variables influencing this growth rate include 'I00078MX', 'BTSISOFR', 'log market cap eth', 'BTC return', 'ETH return', 'log market cap BTC', 'USDC price', and 'Tether price'. The variables were selected as they price also on weekends and holidays and there are no challenges with the missing values. We will be using MAE, MSE and MRSE to assess the fit of the model.

We define the decision-tree regression predictor equation as in Noguer i Alonso (2024) and we format it as follows:

$$\hat{S}_{i,t} = T(X_t) = \sum_{m=1}^{M} c_m \, 1\{X_t \in R_m\} \tag{5}$$

where $\hat{S}_{i,t}$ is the predicted value for observation i at time t, m is index running from 1 to M, identifying each terminal node and T is the decision-tree mapping with partitions the predictor space. M is number of terminal nodes (leaves), regions R_m and assigns mean response c_m to each leaf. R_m is the– m-th terminal region (hyper-rectangle) of the partition defined by the tree. Also, c_m is the constant predicted value for all observations that fall into region R_m. This is typically the average of the target variable for the training samples in that region. $\{X_t \in R_m\}$ is the indicator function that returns 1 if X_t is in region R_m, and 0 otherwise.

The data are split into training (80 %) and testing (20 %) sets using a random state for reproducibility. A decision tree regressor is then instantiated and fitted to the training data. The structure and decision rules of the trained tree are visualised, with a limited depth to simplify the interpretation, allowing for an immediate understanding of the key variables influencing the dependent variable at the initial decision nodes.

This methodological approach leverages the decision tree's capability to model non-linear relationships and interactions between variables, providing a clear and interpretable model that elucidates the primary factors driving changes in stablecoin market capitalisation growth.

Fig. 5 denotes BTSISOFR relevance in predicting the target variable in specific branches of the data. The threshold values indicate how slight changes in BTSISOFR returns can significantly impact the predicted values. Bitcoin market capitalisation is another important variable, especially in the left subtree. The model further refines predictions based on the size of Bitcoin's market cap, suggesting that Bitcoin's market size has a substantial impact as well. The Ethereum appears to be the most significant variable in predicting the target variable, as it is used for the initial split. This indicates that the size of the Ethereum market cap is a crucial determinant in the stablecoin market. We will analyse the stablecoin market sizes individually.

In Fig. 6, the regression decision tree begins by splitting on the log market cap of Ethereum at a threshold of 25.556, indicating its primary importance in predicting log USDC market capitalisation. The left branch further splits based on the I00078MX return and then the log market cap of Bitcoin, revealing the layered influence of these financial metrics. The right branch focuses on the log market cap of Bitcoin and BTSISOFR returns, underscoring their critical roles in the model.

In Fig. 7, the initial split is based on the log market cap of Ethereum with a threshold of 25.556, highlighting its primary influence on the target variable. The left branch further divides by the log market cap of Bitcoin and Ethereum, reflecting their substantial roles in fine-tuning predictions. The right branch focuses on the I00078MX, the short term treasury notes return and subsequent log market caps of Bitcoin and Ethereum, illustrating their layered impact.

Through this sub-sample analysis we can see that interbank lending rates have a higher impact on USDC market growth than Tether. Also, notable is the short-term treasury notes on Tether market growth. In the combined stablecoin market capitalisation the interbank lending has a higher total impact.

Table 7
Quantile regression of Tether market cap growth rate.

	Dependent variable: Tether growth		
Variables	**25th Quantile**	**50th Quantile**	**75th Quantile**
	(1)	(2)	(3)
BTC_return_lag1	−0.004	−0.002	0.014**
	(0.005)	(0.004)	(0.007)
BTC_return_lag2	0.002	−0.004	−0.014*
	(0.004)	(0.004)	(0.007)
BTC_return_lag3	0.015***	0.007*	−0.014**
	(0.005)	(0.004)	(0.006)
BTC_return_lag4	0.017***	0.011**	0.012*
	(0.004)	(0.004)	(0.007)
BTC_return_lag5	−0.012***	−0.004	−0.014**
	(0.004)	(0.004)	(0.007)
BTSISOFR_return_lag1	0.485	−1.676	−4.796***
	(1.179)	(1.148)	(1.743)
BTSISOFR_return_lag2	1.680	−0.432	−3.539**
	(1.191)	(1.134)	(1.672)
BTSISOFR_return_lag3	0.860	−0.541	−3.799**
	(1.174)	(1.147)	(1.775)
BTSISOFR_return_lag4	−0.381	−1.897*	−3.271*
	(1.197)	(1.147)	(1.786)
BTSISOFR_return_lag5	0.665	2.076*	4.311**
	(1.207)	(1.147)	(1.670)
ETH_return_lag1	0.011***	0.005	−0.001
	(0.004)	(0.003)	(0.006)
ETH_return_lag2	0.009***	0.016***	0.021***
	(0.003)	(0.003)	(0.006)
ETH_return_lag3	−0.006*	0.001	0.016***
	(0.003)	(0.003)	(0.005)
ETH_return_lag4	−0.002	0.004	0.007
	(0.003)	(0.003)	(0.005)
ETH_return_lag5	0.016***	0.009***	0.017***
	(0.003)	(0.003)	(0.006)
I00078MX_return_lag1	−0.003	−0.019	−0.039*
	(0.014)	(0.014)	(0.021)
I00078MX_return_lag2	−0.020	−0.023*	−0.071***
	(0.015)	(0.014)	(0.021)
I00078MX_return_lag3	−0.019	−0.009	−0.041*
	(0.014)	(0.014)	(0.022)
I00078MX_return_lag4	−0.010	−0.005	−0.016
	(0.014)	(0.013)	(0.021)
I00078MX_return_lag5	−0.008	0.005	0.013
	(0.013)	(0.013)	(0.020)
Intercept	−1.028*	−2.383***	−3.057***
	(0.599)	(0.598)	(0.957)
SPGSCI_return_lag1	0.000	0.001	−0.003
	(0.008)	(0.007)	(0.010)
SPGSCI_return_lag2	−0.010	−0.015**	0.006
	(0.007)	(0.007)	(0.011)
SPGSCI_return_lag3	0.001	0.005	−0.012
	(0.008)	(0.007)	(0.010)
SPGSSF_return_lag1	−0.004	0.000	−0.002
	(0.009)	(0.009)	(0.013)
SPGSSF_return_lag2	0.007	0.017*	0.020
	(0.010)	(0.009)	(0.013)
SPGSSF_return_lag3	0.001	0.003	0.022*
	(0.009)	(0.009)	(0.013)
SPGSSF_return_lag4	0.026***	0.010	0.002
	(0.009)	(0.008)	(0.012)
SPX_return_lag1	−0.021	−0.008	−0.042**
	(0.014)	(0.013)	(0.019)
SPX_return_lag2	0.011	0.016	−0.008
	(0.015)	(0.013)	(0.019)
SPX_return_lag3	0.009	−0.002	0.008
	(0.014)	(0.013)	(0.020)
SPX_return_lag4	−0.006	0.005	−0.009
	(0.014)	(0.013)	(0.019)
VIX_return_lag1	−0.003*	−0.003	−0.006*
	(0.002)	(0.002)	(0.003)

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Table 7 (*continued*)

	Dependent variable: Tether growth		
VIX_return_lag2	0.004*	0.004**	0.006*
	(0.002)	(0.002)	(0.003)
VIX_return_lag3	0.002	0.002	0.006
	(0.002)	(0.002)	(0.003)
VIX_return_lag4	−0.001	0.002	−0.004
	(0.002)	(0.002)	(0.003)
VIX_return_lag5	−0.001	0.002	0.003
	(0.002)	(0.002)	(0.002)
log_market_cap_BTC	0.223***	0.420***	0.708***
	(0.050)	(0.050)	(0.079)
log_market_cap_eth	−0.195***	−0.340***	−0.600***
	(0.035)	(0.034)	(0.053)
Observations	835	835	835
Pseudo R^2	0.058	0.089	0.155
Residual Std. Error	0.883 (df = 796)	0.825 (df = 796)	0.819 (df = 796)
F Statistic	nan*** (df = 38; 796)	nan*** (df = 38; 796)	nan*** (df = 38; 796)

Notes: 858 observations between 2/04/02020, to January 31, 2024. P-values are set as following: $p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

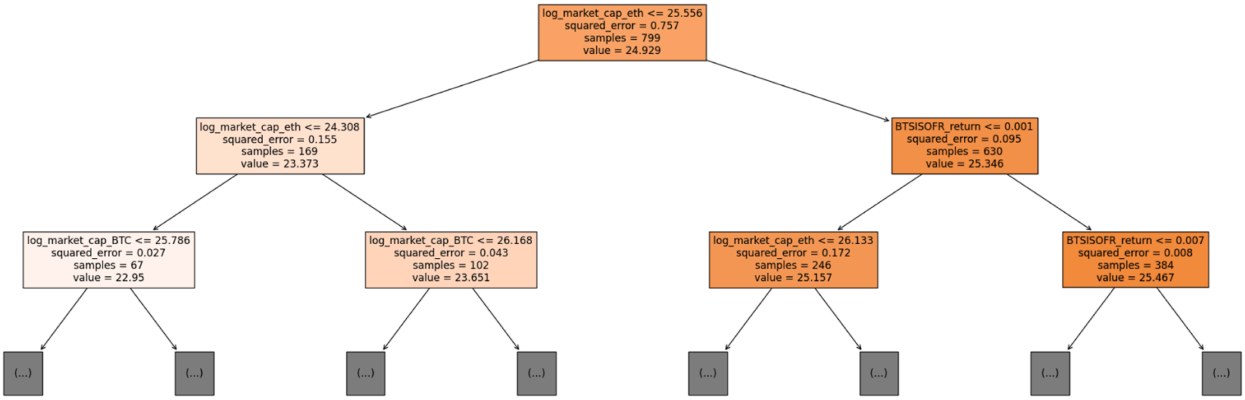

Fig. 5. Decision tree on log combined market capitalisation growth rate.
Notes: 1000 observations between 2/04/02020, to January 31, 2024.

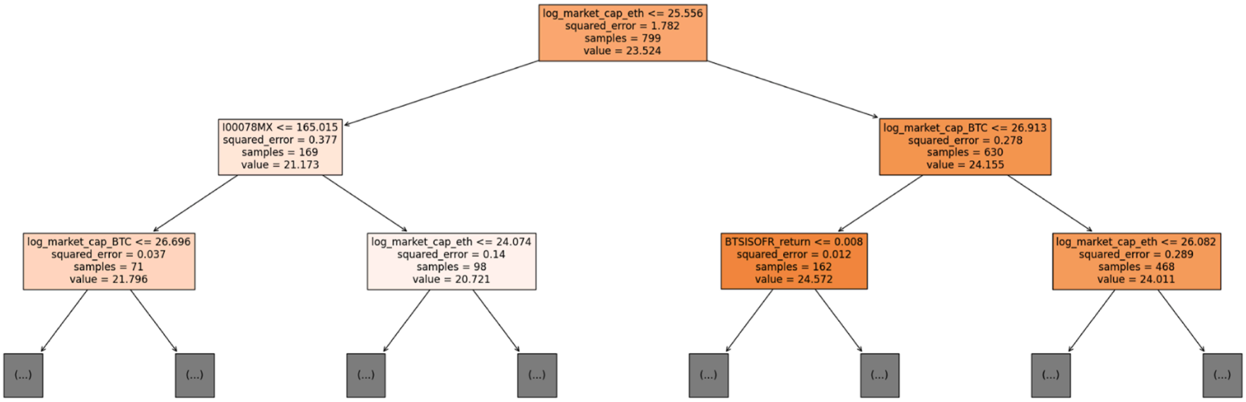

Fig. 6. Decision tree on the log USDC market capitalisation.
Notes: 999 observations between 2/04/02020, to January 31, 2024.

4.2. Granger causality test

Beside magnitude and significance of correlations, we also need to analyse causality relationships for designing wCBDCs instruments. We will conduct a Granger-causality test in order to do so. We set the maximum lag parameter based on the Akaike Information Criterion (AIC), as recommended in the article by Toda and Yamamoto (1995), *Statistical Inference in Vector Autoregressions*

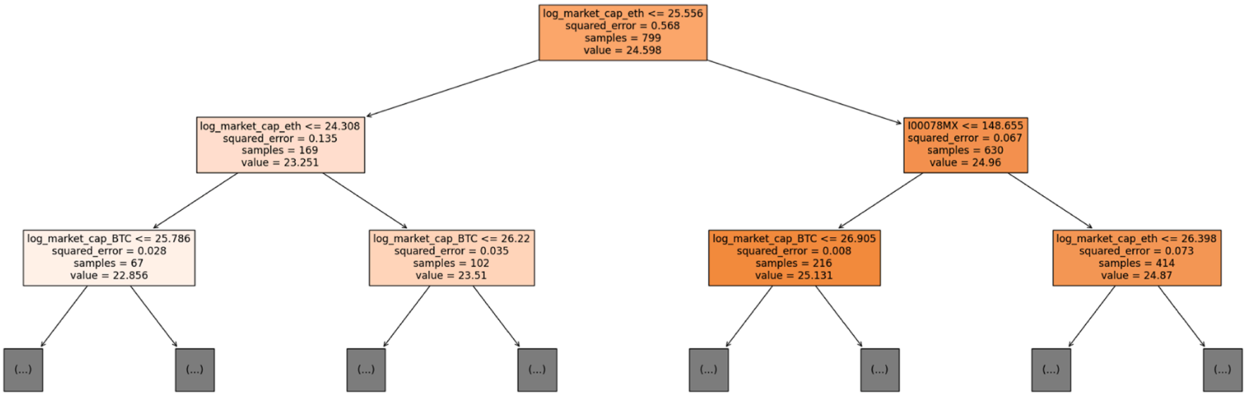

Fig. 7. Decision tree on the log Tether market capitalisation
Notes: 1000 observations between 2/04/02020, to January 31, 2024.

Table 8
Granger Causality test 1.

A. Stablecoin combined growth rate ~ SOFR return.

Lag	F-Statistic	p-value	Critical Value (1 %)	Significant at 1 %	Critical Value (5 %)	Significant at 5 %
1	54.130703	3.919244e-13	6.61	True	4.96	True
2	24.190788	5.523745e-11	6.61	True	4.96	True
3	11.958955	1.073909e-07	6.61	True	4.96	True
4	7.604703	4.919008e-06	6.61	True	4.96	True
5	4.212170	8.571213e-04	6.61	True	4.96	True

B. SOFR return ~ Stablecoin combined growth rate.

Lag	F-Statistic	p-value	Critical Value (1 %)	Significant at 1 %	Critical Value (5 %)	Significant at 5 %
1	7.631123	0.005843	6.61	True	4.96	True
2	5.795693	0.003145	6.61	False	4.96	True
3	3.389874	0.017551	6.61	False	4.96	False
4	2.333865	0.054002	6.61	False	4.96	False
5	3.089792	0.008959	6.61	True	4.96	False

Notes: 1000 observations between April 2, 2020, to January 31, 2024.

with Possibly Integrated Processes. The decision to reject or fail to reject the null hypothesis is based on the p-values obtained from these tests. The significance of the Granger causality tests is assessed at conventional levels (e.g., 1 %, 5 %). Critical values for these tests are obtained from standard F-distribution tables, corresponding to the degrees of freedom implied by the model specifications and the sample size. Results from the Granger-causality tests are shown below and the left variable is the tested dependent variable, and the right variable is the “independent variable”.

Here we specify the Granger-causality, Vector Autoregression (VAR) test equation first showing stablecoin growth being caused by SOFR rates:

$$g_{i,t} = \sum_{k=1}^{p} \varphi_k \, g_{i,t-k} + \sum_{k=1}^{p} \theta_k \, r_{SOFR,t-k} + u_t \tag{6}$$

where the null hypothesis: H_0: $\theta_1 = \cdots = \theta_p = 0$ tests whether SOFR returns do not Granger-cause stablecoin growth $g_{i,t}$. Here φ_k denotes autoregressive coefficient on lag k of $g_{i,t}$ in the VAR equation, θ_k represents the coefficient on lag k of SOFR returns in the VAR and P denotes the number of lags. The term u_t is the error term We then reverse the equation to test whether SOFR returns are Granger-caused by stablecoin growth utilising the null hypothesis test. The results are discussed in the following section.

The results from Granger-causality test 1A indicate the presence of correlation between the variables; however, SOFR returns appear to Granger-cause the combined stablecoin market growth rate over a longer horizon with a higher level of statistical significance. This suggests that movements in short-term funding rates may precede changes in stablecoin market expansion. Both variables also appear to respond to common underlying factors. These can be such as the policy rate decisions by the Federal Reserve or inflation. Indriawan et al. (2021) find that the SOFR aligns more closely with Federal Reserve policy targets than the predecessor LIBOR, and that also short-term market rates are more responsive to the SOFR.

5. Discussion and sought impact

This paper seeks to provide a well determined within-scope solution based on empirical data to help to design an effective intermediary financial instrument or mechanism to improve liquidity in financial markets and more importantly, access to finance in the economy. Through the design of the wCBDCs, there is a potential to offer faster, more transparent and more effective alternative to current practices. For example, the dependency on governmental intermediary institutions such as the Bank of England, through its Sterling Monetary Framework and Discount Window Facility, or the European Central Bank, through its Targeted Longer-Term Refinancing Operations (TLTROs) and Emergency Liquidity Assistance (ELA) or or the US Federal Home Loan Banks intervention, during financial stress. This wCBDC mechanism could facilitate interbank lending or transactions with more focus and transparency.

The USDC collateral fund is managed by Blackrock (Blackrock, 2024; Circle, 2024), and it holds 61.4 % U.S. Treasury Repos from U. S. banks and U.S. Treasuries 38.%. The collateral fund also has separately USD4bn as bank cash reserves. The USDC was over-collaterased: it had $32.6B in circulation and $32.8B in reserves (Circle, 2024). This is where the business model case is made for Circle, the annualised yield on the short-term assets is 5.27 %, and the management charge by Blackrock and other fees constitute 0.21 % gross expense ratio. Roughly speaking USD32bn USDC in circulation will make Circle around USD1.4bn income annually from treasuries and repos. Interestingly, Circle. The most notable recent de-peg of USD0.88 took place during the collapse of Silicon Valley Bank where Circle had cash bank deposits and subsequent run of USDC in March 9–10th 2023 (Anadu et al., 2024). The USDC then had a 20 % cash allocation.

The USDC reserve exposures, as breakdown in Table 9, corroborate our asset impact effect findings relating to repo exposures. Circle provides reserve breakdown on a weekly basis.

On the other hand, as in Table 10, Tether appears to have a wider collateralisation base and the exposures corroborate our asset impact effect findings relating to Bitcoin, GSCI and SP500 index exposures as well as bank repos. Interestingly, when the stock market goes up, Tether may become over-collateralized. Tether only reports its holdings quarterly. They are audited by BDO.

Noting that reserve backed stablecoins are already widely used in crypto financing and market liquidity (Aldasoro et al., 2023), we should focus the study on these features for which wCBDC attributes could be most applicable. Therefore, innovating a wCBDC interbank lending/market feature that can be tagged with specific portfolio assets through potential tokenisation could improve the ability of banks to borrow and transact. This, in turn, could enhance monetary liquidity by ensuring that deposits are actively being lent out. Additionally, fast syndication among banks could help stabilise the monetary system and contribute to the transparency and price discovery of collateralized debt.

Table 9
USDC reserve exposures.

Reserve Type	Amount bn (USD)	Percentage
Cash & Bank Deposits	4.0	12.20 %
U.S. Treasury Bills	17.7	53.89 %
Overnight Reverse Repurchase Agreements	11.1	33.91 %
Total	32.8	100

Notes: Sourced from Circle and Blackrock websites as of Jun 30, 2024. The reserves are as of June 27, 2024.

Table 10
Tether reserve exposures.

Reserve Type	Amount bn (USD)	Percentage
Primary Categories		
Cash & Cash Equivalents & Other Short-Term Deposits	92.7	84.05 %
Corporate Bonds	0.0	0.02 %
Precious Metals	3.7	3.31 %
Bitcoins	5.4	4.87 %
Other Investments	3.8	3.45 %
Secured Loans (None To Affiliated Entities)	4.7	4.29 %
Total	110.3	100 %
Sub-Categories of Cash & Cash Equivalents		
U.S. Treasury Bills	74.0	79.88 %
Overnight Reverse Repurchase Agreements	11.3	12.20 %
Term Reverse Repurchase Agreements	0.8	0.90 %
Money Market Funds	6.3	6.77 %
Cash & Bank Deposits	0.1	0.11 %
Non-U.S. Treasury Bills	0.1	0.13 %
Total	92.7	100 %

Notes: Sourced from Tether (2024) websites as of Jun 30, 2024 and the reserves are as of March 31, 2024.

In liquidity shocks, there could be the feature that wCBDC repo assets, that are of wider asset based, can be purchased and settled a few times a day to avoid large asset price haircuts. The study findings show that there are optimums that wCBDC can use for reserve allocation to enhance liquidity and that broader assets, that is as long as they are liquid and have price forming transparency, can be included in the reserves and traded at a degree. There is a benefit to having a feature on how often reserve exposures can be bought and sold in the market. Gellert and Schlögl (2021) find that SOFR records abrupt jumps around Federal Open Market Committee announcements, showing that short-term funding rates respond almost immediately to changes in monetary policy. This evidence suggests that a wCBDC collateral framework could help manage suddenly larger SOFR movements and adjust haircuts or liquidity requirements in real time, helping banks manage their funding risk when market conditions shift quickly after policy decisions.

Further, key advantage is the possibility of atomic settlement (BIS, 2025A) of wCBDC and tokenised assets. Once each counterparty has approved the payment message, the platform updates every participating bank's account simultaneously and the settlement on the central bank balance sheet; if any leg of the transfer cannot proceed, no balances move at all. This delivery-versus-payment (DvP) mechanism links asset transfer and payment within a single operation, thereby reducing counterparty risk, removing the need for escrow arrangements, and limiting reconciliation and post-trade procedures. Consequently, atomic processing strengthens the functioning of the inter-bank market and can reduce reliance on central-bank backstops. After all, central bank backstops, such as emergency liquidity assistance or standing repo facilities, are used as responses to stabilise financial markets when interbank lending breaks down. The integration of atomic settlement with wCBDCs and tokenised assets may also enable more targeted and timely central bank interventions in periods of market stress.

Pfister (2024) contends that a wCBDC would allow authorities to implement capital-flow controls more swiftly and precisely, while Bear et al. (2024) show that embedding a wCBDC in a tokenised-asset settlement layer delivers immediate finality and faster mobilisation of collateral, thereby bolstering intraday liquidity. When considering wider implementation of wCBDC-tokenisation-DvP system, the range of eligible collateral can be widened during periods of market stress. Building on Tether's diversified reserve model that responses to SOFR to a lesser extent compared to USDC, a wCBDC repo facility could accept tokenised investment-grade corporate bonds, covered bonds, commodities or equity portfolios rather than restricting collateral to short-term Treasury bills. Evidence from the Hong Kong Monetary Authority shows that tokenised bonds trade with bid–ask spreads about 8.5 per cent narrower than comparable conventional bonds, indicating superior liquidity and faster price discovery (Hong Kong Monetary Authority, 2023). An IMF staff note reaches similar conclusions, suggesting that tokenisation can expand useable collateral pools and lower frictions in repo markets (Agur et al., 2025). Provided that reliable price oracles and haircut schedules are embedded, a broader collateral choice during market distress could widen banks' funding options and enhance the targeted inter-bank liquidity. This faster response system could further help reduce the need for taxpayer-funded bailout during market distresses. The wCBDC-tokenisation-DvP system architecture can provide a two-pronged safety net: it accommodates gradual policy adjustments under normal conditions and delivers rapid support when an exogenous systemic risk event emerges.

The United States and the euro area are advancing towards more automated systems to facilitate settlement of tokenised assets in central-bank money whether this will be wCBDCs or not, their institutional contexts diverge considerably. Because the United States and the euro area operate under different legal and supervisory frameworks, the roll-out of a wholesale CBDC, tokenised assets and delivery versus payment (DvP) settlement will follow distinct paths. In the United States, the Federal Reserve can rely on nationwide banking statutes and on the amended Uniform Commercial Code, which already defines “controllable electronic records” and clarifies how digital assets can serve as collateral. A single sequence of steps that covers finalising the policy mandate, adapting Fedwire interfaces and issuing supervisory guidance would therefore be sufficient to support a wCBDC and tokenised-asset DvP platform (Board of Governors of the Federal Reserve System, 2023; Uniform Law Commission, 2022). In the euro area, despite national variation in banking statutes, significant progress has been made through ECB-led pilot programmes and national experiments. The Banque de France, for example, has conducted various wCBDC trials since 2020, focusing on securities settlement and cross-border applications (Banque de France, 2023). Furthermore, the ECB's 2024 exploratory programme processed more than €1.5 billion across 200 transactions with 64 market participants using distributed-ledger technology (European Central Bank, 2024). To address the legal fragmentation, the European Commission introduced a legislative package in 2023 that seeks to provide the ECB with a clear mandate for digital euro issuance and harmonise national legal frameworks (European Commission, 2023). In both jurisdictions, the combination of wCBDCs and tokenised asset framework's successful implementation will depend on tailoring solutions to each system's legal and institutional constraints. Accordingly, the United States can advance through a mainly federal, single-issuer process, whereas the euro area must complete a multi-step programme of legal alignment before full deployment of a wCBDC-enabled atomic DvP system becomes feasible.

Further analysis could examine the technological infrastructure required to support a wholesale CBDC system. This includes assessing suitable collateral assets such as tokenised government bonds, investment-grade credit and real asset tokens, alongside dynamic intervention tools like haircut schedules and intraday liquidity thresholds. Legal harmonisation across jurisdictions will also be important to establish clear definitions, ownership rights and a sound regulatory foundation for wCBDC adoption.

6. Conclusion

This study contributes to the discussion on wCBDCs by linking stablecoin reserve composition to market sensitivities and macro-financial transmission. For this, we have introduced a new financial indicator to study stablecoin collateral; the SOFR rate. We see that higher interbank interest rates have affected the growth rate of this novel market capitalisation. We see that USDC is more sensitive to increase in the SOFR rates compared to Tether. But appear to have been affected by SOFR in distinct market situations. It appears that increase of SOFR rate has been correlated with moderated stablecoin market adoption and growth. However, we see stronger relationships between Tether and broader financial market indicators such as S&P500, short term treasury notes and Goldman Sachs Commodity Index. At higher inter-bank lending rates, market capitalisation of stablecoins, and cryptocurrencies is lower. The dynamic relationship and causation, nevertheless, moves from uncertainty and risk appetite affecting banks and then the short-term wholesale lending rates. These findings suggest that wCBDC designers can model the effects of different collateral mixes on stablecoin stability by applying tokenised assets within an atomic-settlement framework. During normal conditions a narrow set of high-quality collateral may be adequate, whereas in periods of market stress the framework could accommodate a wider pool of liquid, transparently priced assets. These advancements could improve the banking system stability and further minimise the need for tax payer bail-outs.

CRediT authorship contribution statement

Tatja Karkkainen: Writing – review & editing, Writing – original draft, Formal analysis. **John Paul Broussard:** Writing – original draft, Resources, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendices

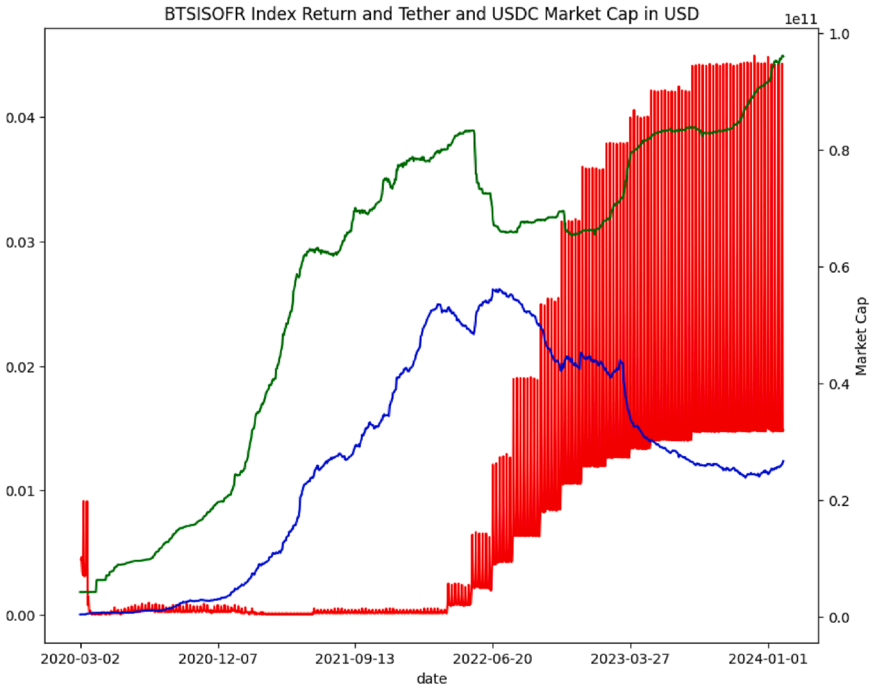

Fig. A.1. SOFR launch volatility.
Notes: BTSISOFR Index Return (RED) and Tether (GREEN) and USDC Market Cap in USD (BLUE). The data is sourced from Bloomberg using BTSISOFR index and Coingecko stablecoin database. The daily data sample is between 2020/03/02–2024/01/31 which is 1000 observations.

Table A1
OLS Estimator Regression Results of Stable Coin Market Growth. Combined, USDC and Tether Market Growth are computed individually

Variables	Combined	USDC	Tether
	(1)	(2)	(3)
BTC_return_lag1	0.010	−0.029	0.017
	(0.012)	(0.023)	(0.012)
BTC_return_lag2	−0.002	−0.021	0.003
	(0.012)	(0.023)	(0.012)
BTC_return_lag3	−0.022*	−0.050**	−0.013
	(0.012)	(0.023)	(0.012)
BTC_return_lag4	0.007	−0.014	0.022*

(continued on next page)

Table A1 (*continued*)

Variables	Combined	USDC	Tether
	(1)	(2)	(3)
	(0.012)	(0.023)	(0.013)
BTC_return_lag5	−0.032***	−0.054**	−0.025**
	(0.012)	(0.023)	(0.013)
BTSISOFR_return	−7.234***	−18.174***	−2.703
	(2.494)	(4.788)	(2.572)
ETH_return_lag1	0.002	−0.008	0.008
	(0.010)	(0.018)	(0.010)
ETH_return_lag2	0.008	−0.018	0.018*
	(0.009)	(0.018)	(0.010)
ETH_return_lag3	0.024***	0.014	0.027***
	(0.009)	(0.018)	(0.010)
ETH_return_lag4	0.008	−0.009	0.014
	(0.010)	(0.019)	(0.010)
ETH_return_lag5	0.029***	0.016	0.035***
	(0.010)	(0.018)	(0.010)
I00078MX_return_lag1	−0.035	−0.078	−0.023
	(0.038)	(0.073)	(0.039)
I00078MX_return_lag2	−0.053	0.015	−0.062
	(0.038)	(0.073)	(0.039)
I00078MX_return_lag3	−0.028	−0.014	−0.036
	(0.038)	(0.073)	(0.039)
I00078MX_return_lag4	−0.052	−0.146**	−0.038
	(0.037)	(0.071)	(0.038)
I00078MX_return_lag5	0.036	0.052	0.034
	(0.036)	(0.069)	(0.037)
Intercept	−6.196***	−12.847***	−3.490**
	(1.659)	(3.186)	(1.712)
SPGSCI_return_lag1	0.037*	0.046	0.031
	(0.019)	(0.037)	(0.020)
SPGSCI_return_lag2	−0.073***	0.042	−0.095***
	(0.019)	(0.037)	(0.020)
SPGSCI_return_lag3	−0.034*	0.006	−0.037*
	(0.019)	(0.037)	(0.020)
SPGSSF_return_lag1	0.013	−0.048	0.014
	(0.024)	(0.047)	(0.025)
SPGSSF_return_lag2	0.039	−0.027	0.046*
	(0.024)	(0.047)	(0.025)
SPGSSF_return_lag3	0.014	0.073	−0.002
	(0.024)	(0.047)	(0.025)
SPGSSF_return_lag4	0.006	0.051	−0.005
	(0.022)	(0.043)	(0.023)
SPX_return_lag1	−0.069*	−0.179***	−0.063*
	(0.036)	(0.069)	(0.037)
SPX_return_lag2	−0.033	0.100	−0.052
	(0.037)	(0.070)	(0.038)
SPX_return_lag3	0.018	−0.021	0.035
	(0.037)	(0.071)	(0.038)
SPX_return_lag4	0.029	0.050	0.020
	(0.035)	(0.067)	(0.036)
VIX_return_lag1	−0.017***	−0.037***	−0.012**
	(0.006)	(0.011)	(0.006)
VIX_return_lag2	−0.001	0.016	−0.002
	(0.006)	(0.011)	(0.006)
VIX_return_lag3	0.010*	0.007	0.013**
	(0.006)	(0.011)	(0.006)
VIX_return_lag4	0.001	0.018*	−0.002
	(0.006)	(0.011)	(0.006)
VIX_return_lag5	0.002	0.008	0.003
	(0.004)	(0.008)	(0.004)
log_market_cap_BTC	1.022***	1.682***	0.777***
	(0.136)	(0.261)	(0.140)
log_market_cap_eth	−0.813***	−1.238***	−0.664***
	(0.093)	(0.178)	(0.096)
Observations	835	835	835
R^2	0.212	0.154	0.225
Adjusted R^2	0.178	0.119	0.192
Residual Std. Error	0.743 (df = 800)	1.426 (df = 800)	0.766 (df = 800)
F Statistic	6.321*** (df = 34; 800)	4.298*** (df = 34; 800)	6.842*** (df = 34; 800)

Notes: 858 observations between 2/04/02020, to January 31, 2024. P-values are set as following: p < 0.1; **p < 0.05; ***p < 0.01.

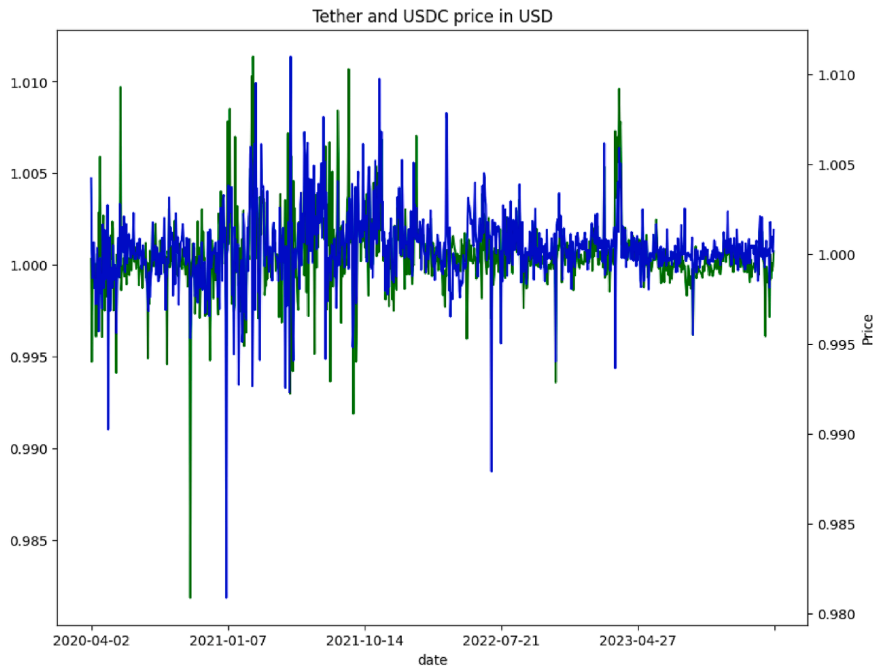

Fig. A2. Tether and USDC price in USD
Notes: 1000 observations between 2/04/02020, to January 31, 2024.

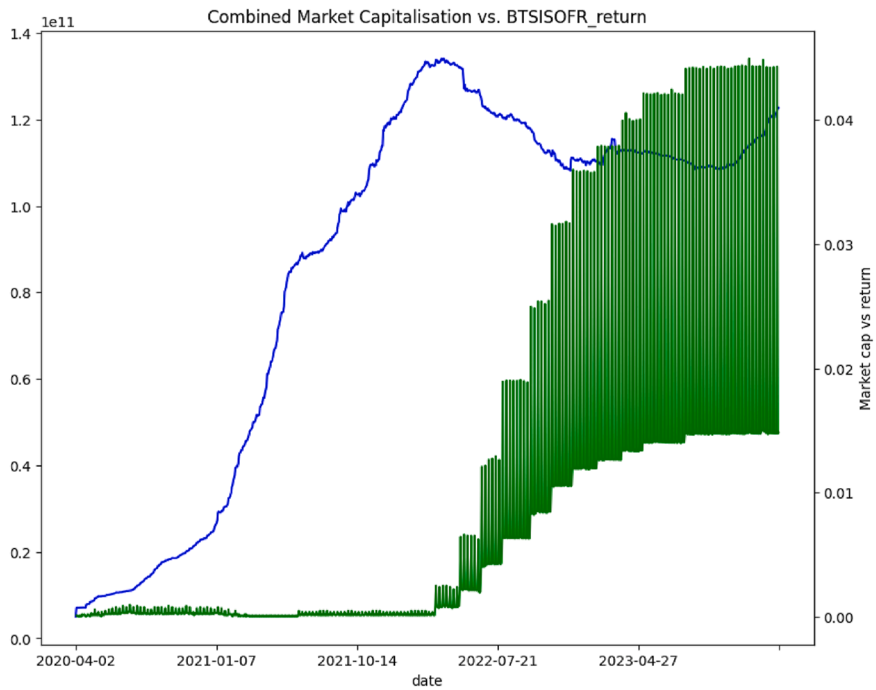

Fig. A3. Combined market capitalisation vs. SOFR return
Notes: 1000 observations between 2/03/02020, to January 31, 2024.

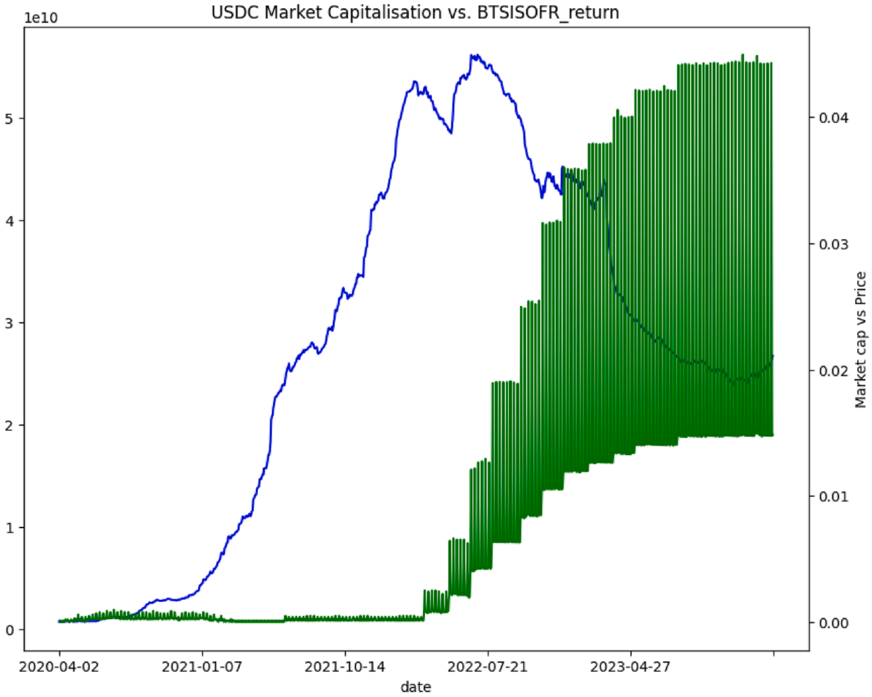

Fig. A4. USDC market capitalisation vs. SOFR return
Notes: 1000 observations between 2/03/02020, to January 31, 2024.

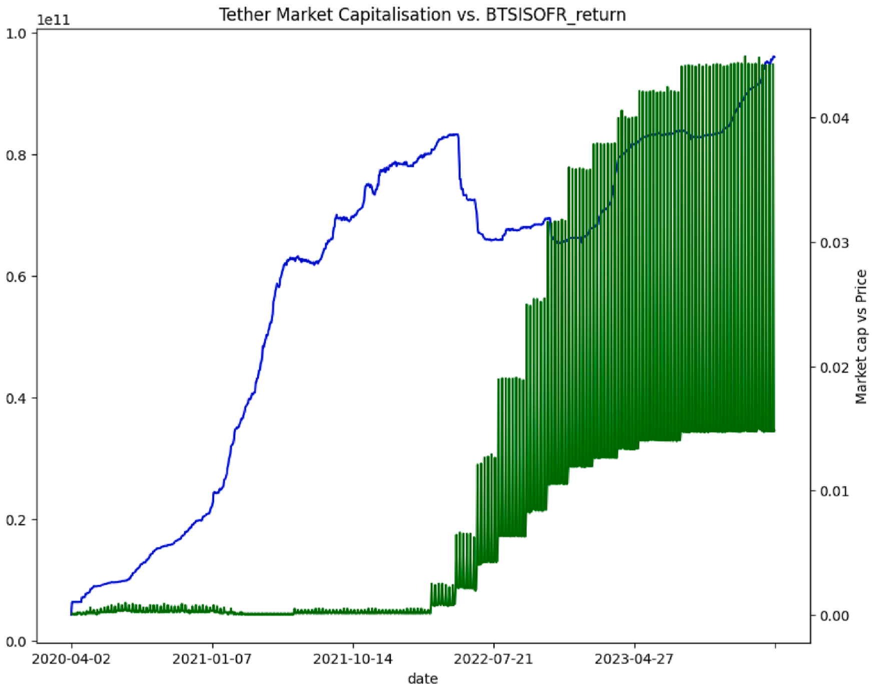

Fig. A5. Tether market capitalisation vs. SOFR return
Notes: 1000 observations between 2/03/02020, to January 31, 2024.

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