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DeFi-ying the Fed? Monetary policy transmission to stablecoin deposit rates

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Abstract

Does the Federal Reserve's monetary policy influence the rates on USD-pegged stablecoins? While major stablecoin issuers do not pay interest, investors can earn returns by depositing stablecoins in Decentralized Finance (DeFi) protocols. We document unusually large and persistent spreads between traditional short-term interest rates and DeFi deposit rates, as well as a weak and unstable transmission of policy rate changes. We show that, in the short run, monetary policy shocks can move stablecoin rates in the opposite direction of policy rates, delaying a convergence that occurs only over the medium run. Both the sign of the short-run effect and the speed of convergence depend on the intensity of deleveraging induced by crypto-price reactions relative to the standard interest-rate arbitrage channel — an effect shaped by investors' limited ability to bridge traditional and decentralized finance.

JEL: G14, G23, G29.

Keywords: Stablecoin, Crypto, DeFi.

Non-Technical Summary

While stablecoin issuers do not directly remunerate token holders, investors can deposit stablecoins in Decentralised Finance (DeFi) lending protocols to earn an interest rate analogous to a repo rate in traditional finance. In this paper, we first establish 4 motivating stylised facts. First, DeFi interest rates exhibit unusually large and persistent disconnects from traditional risk-free rates: over 2021-2026, the average spread relative to the Federal funds rate has been approximately 100 bps, but with high volatility, and prolonged periods with DeFi rates materially below policy rates. Second, around monetary policy rate changes, DeFi interest rates sometimes go in the *opposite* direction to policy rate. Third, this pattern seems to be related to the response of Bitcoin returns, and more generally, DeFi rates and Bitcoin returns appear correlated. Fourth, DeFi rates nevertheless converge to risk-free rates in the long run, as confirmed by cointegration tests and error-correction models.

We develop a simple model of DeFi lending that can account for these stylized facts and rationalize why stablecoin rates may react in both directions around a monetary policy rate change. Two main mechanisms are at play: first, depositors having access to both traditional finance and DeFi arbitrage the difference in interest rates, subject to a series of frictions ; second, borrowers adjust their leverage funded in DeFi to size up or deleverage their position in risky crypto assets, like Bitcoin. To test the predictions of the model, we exploit data available on-chain from Aave, the largest DeFi lending protocol. Relying on a Bayesian Proxy-VAR approach, we find that around monetary policy surprises, the leverage channel has considerably delayed the convergence of DeFi interest rates, depending on the initial response of Bitcoin prices to the shock and on the investor base ability to access traditional finance.

To explain the large and persistent spread between risk-free and DeFi interest rates, we investigate the underlying sources in the microstructure of DeFi lending platforms. Using high-frequency and granular blockchain data, we confirm DeFi market functioning is, at this stage, impaired by frictions and by the limited presence of large, active arbitrageurs able to bridge traditional finance and DeFi.

1 Introduction

> *"When an asset is pegged to a government-issued currency, it is a form of private money. When that asset is also used as a means of payment and a store of value, it borrows the trust of the central bank." (...)"Stablecoins are a form of money, and the ultimate source of credibility in money is the central bank. If non-federally regulated stablecoins were to become a widespread means of payment and store of value, they could pose significant risks to financial stability (and) monetary policy"*
>
> — Vice Chair Michael S. Barr, Federal Reserve Bank of Philadelphia, Sep 8th 2023

The rapid growth of tokenized finance has renewed debate on monetary singleness and the ability of central banks to transmit monetary policy across a growing class of tokenized near-money assets. While major stablecoins do not natively bear interest, stablecoin holders can indirectly obtain remuneration by depositing their tokens in decentralized finance (DeFi) lending protocols, which enable collateralized lending and offer interest rates reminiscent of repo rates in secured money markets.

DeFi has experienced successive boom-and-bust cycles since 2020 before resuming rapid growth in 2024, in parallel with a surge in stablecoin capitalization.[1] With total deposits surpassing 50 billion USD in value since August 2025, Aave, the largest DeFi lending protocol, would now rank on par with small-size U.S. deposit-taking institutions.[2] Importantly, DeFi lending protocols are becoming a major way for large trading platforms and centralised exchanges (CEXs) to propose regulatory-compliant forms of remuneration to their users on their stablecoin balances.[3]

DeFi lending protocols set rates independently of any conventional reference rate, relying

[1]Total value locked (TVL) in all DeFi lending protocols – measuring the amount of collateral deposited in lending contracts – reached 86 bn USD in September 2025, more than 5-fold its value of 2023. During the same period, stablecoin capitalization doubled to reach an all-time high of 290 bn USD as of September 2025. Source: `https://defillama.com/`

[2]According to Binance,*"Aave outpaced traditional banks such as SouthState Bank, Valley National Bank, and CIBC Bank USA" in terms of deposit size.*`https://www.binance.com/en/square/post/08-13-2025-aave-surpasses-major-u-s-banks-in-deposit-volume-28241636041274`

[3]DeFi lending protocols like Morpho and Aave are accessible via CEXs, and part of the remuneration options they propose to stablecoin holders, see Huang et al. (2026) for an overview and Section 3.1.

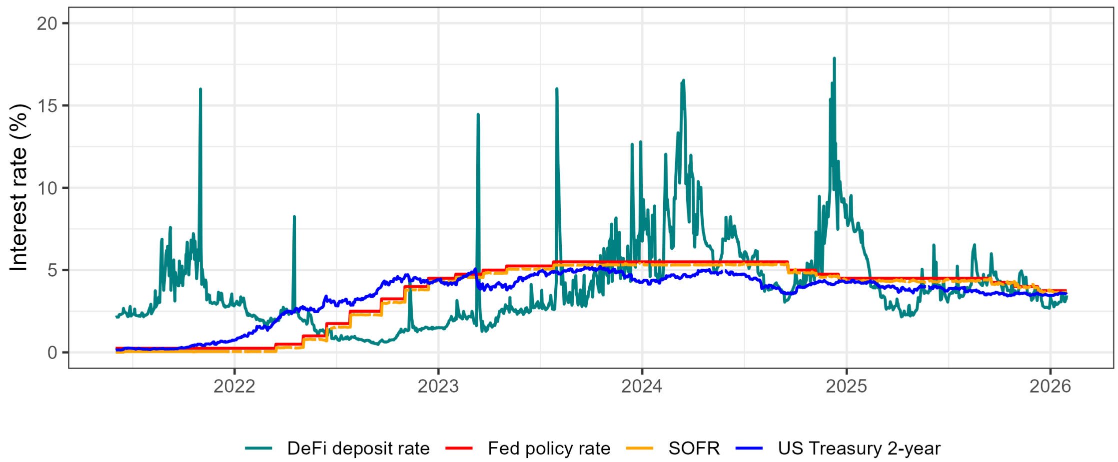
instead on predetermined algorithmic rules. DeFi interest rates depend on the utilization rate — that is, the ratio of borrowed to supplied tokens. This paper examines the transmission of monetary policy to these rates and investigates the factors that may impair such transmission.

We start by documenting four stylized facts on USD-pegged stablecoins' DeFi interest rates.[4] First, these rates exhibit pronounced volatility, with unusually large jumps relative to the Federal Reserve's policy rate, as illustrated in Figure 1, which compares Aave's average deposit rate with benchmark U.S. rates. Over the January 2021–January 2026 period, DeFi deposit rates averaged approximately 100 basis points above the Fed funds target rate. Yet this average masks substantial heterogeneity: between mid-2022 and end-2023, DeFi deposit rates remained persistently and significantly below policy rates, while during the first half of the 2022 tightening cycle, they moved in the opposite direction to policy rates. Second, we find heterogeneous responses to monetary policy rate *changes*, with variations in DeFi interest rates often going in the opposite direction to the policy rate. Third, the spread between DeFi interest rates and U.S. short-term rates is highly correlated to the evolution of Bitcoin price. Fourth, over the long-run, there is, however, a statistically significant convergence of DeFi interest rates to conventional short-term rates. Taken together, these findings point to the presence of multiple forces that delay, weaken, or even invert the standard interest rate transmission channel, whereby policy rates are expected to transmit across monetary instruments through arbitrage.

To rationalize these four stylized facts, we develop a parsimonious model of DeFi liquidity provision to rationalize why stablecoin deposit rates may respond in either direction to changes in monetary policy. In the model, liquidity providers, who differ in their access to traditional financial markets, lend stablecoins to risky investors taking leveraged positions in crypto assets through the DeFi protocol. Two opposing forces govern monetary policy transmission. On the one hand, liquidity providers arbitrage interest rate differentials across DeFi and traditional markets. On the other hand, leveraged investors adjust their demand

[4] In this paper, we mainly focus on DeFi interest rates from the depositors of stablecoins perspective – sometimes referred to as "deposit rates" or "supply rates", terms that may be used interchangeably by lending protocols. In the rest of the paper, unless stated otherwise, DeFi interest rates will always refer to deposit rates earned by depositing stablecoins in lending protocols.

Figure 1: DeFi Interest Rates and US Short-Term Rates



Note: The figure displays the time-series evolution of the volume-weighted average DeFi deposit rate (annualized percentage rate) across stablecoins (USDT, USDC, and DAI) in Aave v2 and v3 on the Ethereum blockchain, compared to Federal Reserve policy rates, the SOFR repo rate and the 2-year U.S. Treasury yield. We switch from Aave v2 to Aave v3 in October 15, 2023, when the Total value locked (TVL) of the latter surpassed the TVL of the former. Source: Aavescan, Bloomberg. Last observation: 30 January 2026.

for stablecoins to size up or deleverage their positions in risky crypto assets, such as Bitcoin or Ether. Monetary policy transmits positively to DeFi rates when the former force dominates, depending also on the fraction of investors able to reallocate funds frictionlessly across markets. Conversely, we observe a negative transmission when the demand for leverage is highly sensitive to policy rate changes.

To assess the transmission of monetary policy to DeFi rates, and hence determine which of these forces dominate, we exploit data available on the Ethereum blockchain. We construct a comprehensive dataset of the aggregate time series of available liquidity and borrowed amounts, the resulting deposit and borrowing rates, and the individual wallet-level liquidity deposited and standing borrowing positions for the three most active stablecoins, namely USDC, USDT, and DAI, in Aave v2 and v3.

First, at a macro-level, we rely on high-frequency price changes around monetary policy announcements to test the overall impact of monetary policy shocks in a Bayesian Proxy-VAR setup. Importantly, we can trace the impact of a monetary policy surprise both on the demand for borrowing and the supply of tokens. Specifically, a restrictive monetary policy shock leads to lower liquidity – as arbitrageurs re-allocate capital to the risk-free asset – hence driving up DeFi rates. At the same time, DeFi borrowing sharply decreases, reflecting the negative impact on risky asset expected returns, including Bitcoin. This confirms that, in the short run, monetary policy has mixed effects on DeFi interest rates due to its impact on the demand for leverage. We find that, over the past five years, around monetary policy decisions, the leverage channel has considerably delayed the convergence of DeFi interest rates to policy rates. This effect is especially pronounced for USDT relative to USDC, which we interpret as reflecting the greater integration of USDC and its holders with traditional finance, consistent with its regulatory compliance in the U.S. and E.U.

Second, we run a series of exercises using wallet-level and high-frequency data to determine the possible factors explaining the large and persistent spreads between risk-free and DeFi interest rates. Starting with an event study of the Silicon Valley Bank failure on March 10, 2023 — which resulted in a fall in USDC demand and a rise in USDT demand in DeFi — we document a sluggish supply response of liquidity providers, confirmed by other demand shocks in our sample, notably more pronounced when transaction costs ("gas fees" in Ethereum) are elevated. These findings confirm that the transmission of monetary policy to DeFi rates is, at this stage, impaired by frictions and by the limited presence of large, active arbitrageurs able to bridge traditional finance and DeFi. In a difference-in-differences setup, we find that liquidity providers who are more integrated and compliant with traditional finance respond more strongly to policy rate changes. This suggests that they act as arbitrageurs between DeFi and the money market.

Overall, our findings suggest that two key factors explain the imperfect transmission of monetary policy to DeFi rates: the limited share of liquidity providers having access to the U.S. traditional financial market, and the high sensitivity of crypto assets to monetary policy changes, which in turn makes the demand for borrowing influenced by monetary policy. We complement these key findings by showing that transaction fees and the limited capital available to liquidity providers may have also contributed to this imperfect transmission.

Our paper is connected to a nascent theoretical literature studying the DeFi lending protocols. Aramonte et al. (2022) describes the functioning and risks of DeFi lending in building highly-leveraged positions. Augustin et al. (2024) detail arbitrage strategies in decentralized finance and the associated risk-returns tradeoffs. Chaudhary et al. (2023) investigates the determinants of interest rates in DeFi protocols with a focus on borrowers and document limits to arbitrage within crypto markets, between DeFi lending and the perpetual futures premium for the ETH/USDT market, due to high trading costs, gas fees, and price impacts. Chiu et al. (2022) propose a dynamic model of DeFi lending with asymmetric information, concluding that the rigidity of the underlying smart contracts may lead to instability and multiple equilibria. In the same vein, Rivera et al. (2023) study the inefficiencies of DeFi interest rate setting compared to competitive lending markets. Our paper contributes to this theoretical literature by highlighting the role of monetary policy via the risk-free rate and risky asset returns in influencing quantities lent and borrowed in DeFi, and by modeling explicitly the frictions at play.

On the empirical side, Gudgeon et al. (2020b) analyse historical deposit rates for dYdX, Aave, and Compound, finding substantial interest rate parity deviations and a high degree of cross-market dependence, illustrative of the frictions at play even within the crypto universe. Heimbach and Huang (2024) exploit granular transaction data on Aave and Compound to compute investor-level leverage ratios and suggest that the demand for leverage is mainly driven by loan-to-value requirements and borrowing costs, as well as crypto market price movements and sentiments. Campello et al. (2025) explore theoretically and empirically the demand for liquidity and safety in DeFi, and find a co-movement of US Treasuries convenience yields with stablecoin convenience yields, attributed to common shifts in liquidity preferences and a response of the stablecoin premium to U.S. Treasury scarcity. Chiu and Danisman (2026) study the Aave v3 protocol from a risk management perspective, investigate the incentives behind leverage positions, and the limited role of liquidation on crypto asset prices. We are, to our knowledge, the first to examine – both theoretically and empirically, using a causal identification strategy – how monetary policy transmits to interest rates in DeFi and how changes in the policy rate affect stablecoin quantities and rates in these markets.

We also contribute to a growing literature assessing the potential interactions between monetary policy and crypto markets. Monetary policy may be affected by stablecoins via different channels. The adoption of stablecoins, through its impact on banks' deposits, may affect the bank lending channel (Caramichael and Liao, 2022; Altavilla et al., 2026) and reinforce the banking system's exposure to international drivers Minesso and Siena (2026). In reverse, crypto markets may be affected by monetary policy. The reaction of Bitcoin price to monetary policy shocks has been previously found to be at best ambivalent (Karau, 2023) if not orthogonal to monetary and macroeconomic news (Benigno and Rosa, 2023). In contrast, in our 2021-2026 sample, we find a strong impact of monetary policy surprises on Bitcoin prices. This finding also resonates with other recent works, for instance Aldasoro et al. (2025), showing that contractionary monetary policy shocks trigger outflows from stablecoins.

In a broader perspective, our paper also builds on the literature on monetary policy passthrough to near-money assets interest rates (Duffie and Krishnamurthy, 2016), including private forms of safe assets (Nagel, 2016; Sunderam, 2015; Kacperczyk et al., 2021), and the transmission mechanisms of monetary policy to asset prices, in particular related to the risk-taking channel of monetary policy (Bernanke and Kuttner, 2005; Borio and Zhu, 2012; Drechsler et al., 2018; Bauer et al., 2023). Drechsler et al. (2017) investigate the drivers of incomplete passthrough to deposit rates in presence of market power in the banking system. By contrast, our paper emphasizes alternative frictions, showing how limits to arbitrage and opposing forces related to the demand for leverage affect the passthrough of policy rates.

The remainder of this paper is organized as follows. Section 2 exposes key stylized facts on the evolution of DeFi deposit rates. Section 3 gives a primer on DeFi lending protocols and explains how interest rates are determined in DeFi. Section 4 builds a simple model to account for the impact of the risk-free rate on DeFi deposit rates and hypothesizes testable channels and predictions. Section 5 details our data sources, and Section 6 tests the impact of monetary policy shocks in a proxy-VAR setup using high-frequency monetary policy shocks for identification – the main empirical test of the model's prediction on monetary policy transmission and main contribution of the paper. To investigate the sluggishness of convergence of DeFi interest rates, we further examine in Section 7 the model's predictions distentangling supply and demand factors and exploiting micro-data at the investor wallet-level to better understand the sources of limits to arbitrage in DeFi lending. Finally, Section

8 concludes and draws policy implications.

2 Motivating stylized facts

In this section, we document four motivating stylized facts on the evolution of DeFi deposit interest rates on USD-pegged stablecoins. These facts are essential for understanding how monetary policy transmits to these rates and form the basis of the analysis developed in the paper.

First fact: A large disconnect from the Fed's policy rates DeFi deposit rates – the average Annual Percentage Rate (APR) for depositing USDC, USDT, and DAI, see Fig. 1 – has experienced *large* and *persistent* disconnects from traditional risk-free rates, *both to the upside and to the downside.*[5] Over the Jan 2021-Jan 2026 period, the DeFi deposit rates have been on average 100 bps above the Fed policy rate, with occasional peaks surpassing 1000 bps. On the contrary, from mid-2022 to the end of 2023, DeFi deposit rates have been on average 160 bps *below* the Fed policy rate. Since mid-2025, the disconnect has been smaller with a standard deviation contained to 75 bps.

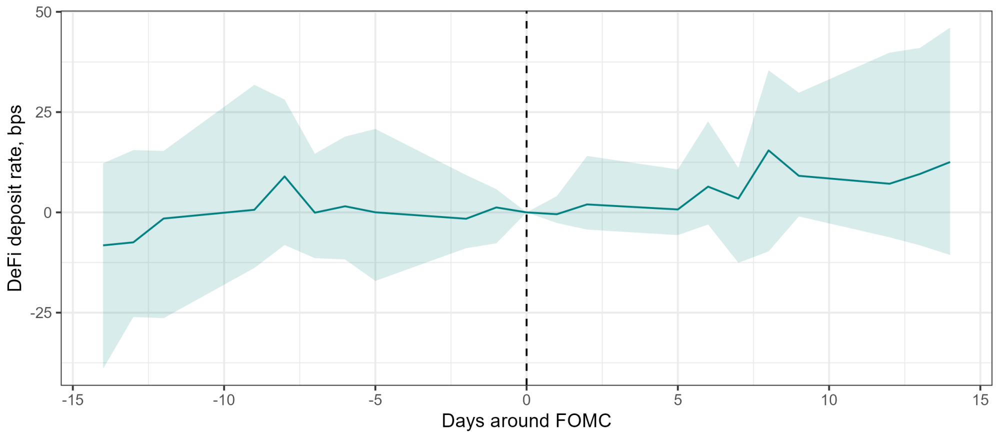
Second fact: Unstable and often negative correlation with policy rate changes From a bird's eye view, as suggested by Figure 1, DeFi deposit rates frequently evolve in an *opposite direction to the risk-free rate.* For example, between March 2022 and July 2023, the Federal Reserve raised policy rates eleven times, totaling an increase of +525 bps. Over the same period, DeFi interest rates fell from 2.5% in March 2022 to 0.5% in September 2022, before gradually returning to 2.5% by July 2023. A similar reversal occurred between September 2024 and December 2024, the Fed cut its policy rate by 100 bps while DeFi rates rose sharply by 600 bps (from 3 to 9%).

Zooming in on narrow event windows around policy rate changes (Fig. 2) reveals a modest

[5]The construction of the data is explained in section 5.

unconditional pass-through: around a median 50-bp rate hike, DeFi interest rates increase by roughly 15 bps after one week, this median point estimate corresponds to a 0.3-to-1 'passthrough'.

Figure 2: DeFi deposit rates around FOMC rate hikes (median rate hike = 50 bps)



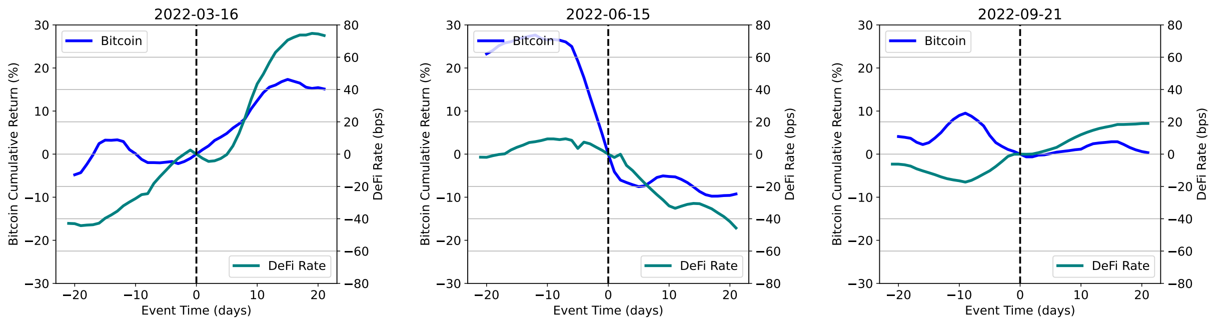
Note: Median and p25/75 DeFi deposit rates for USDC, USDT, DAI in Aave v2/v3 around policy rate hikes, for a median rate hike of 50 bps. Source: Aavescan, Bloomberg, Federal Reserve.

This median response masks however highly heterogeneous responses across individual events and tokens. To showcase the response heterogeneity, Figure 3 presents the path of USDC deposit rates and Bitcoin returns around three selected policy hikes. The left panel shows a significant increase of both series, with the DeFi rate growing by almost 80 basis points and BTC gaining 15%. The central panel, instead, shows an opposite picture, with DeFi rate and BTC dropping sharply. These patterns suggest a relation between BTC prices and DeFi rates. Nevertheless, on the rightmost panel, BTC cumulative returns (starting from the announcement date) are very close to zero, while the DeFi rate increases by 20 basis points, thus suggesting a potential relevance of the arbitrage channel.

Third fact: The strong sensitivity to Bitcoin price dynamics DeFi lending activity and DeFi rates have tended to track Bitcoin price fluctuations more closely than money-market rates, as illustrated by Figures 3 and 4. This relationship is well documented in the literature and is typically associated with the use of DeFi to leverage positions in volatile crypto-assets (Chiu et al., 2022; Heimbach and Huang, 2024), reminiscent of how repo markets are used to build-up leverage in fixed-income markets.

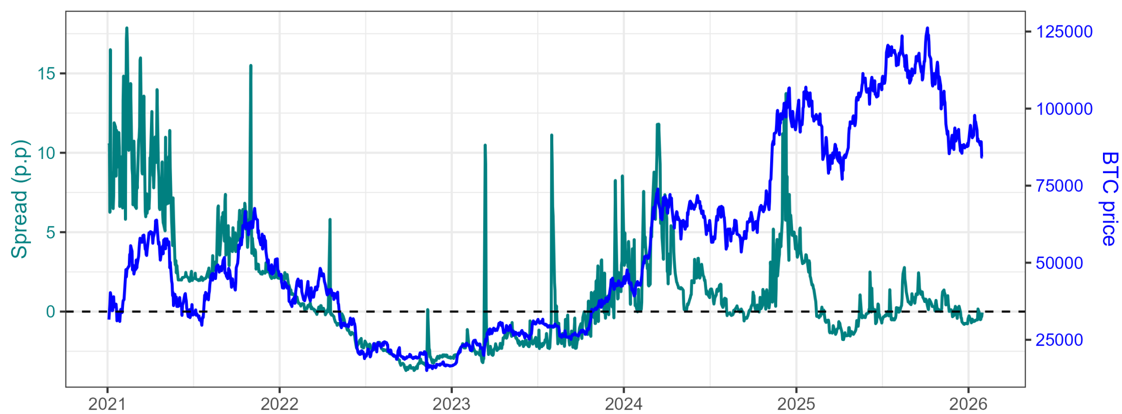
Figure 3: DeFi rates and BTC returns around selected rate hikes

(a) +25 bps (b) +75 bps (c) +75 bps



The figure displays Bitcoin cumulative returns (blue) and the DeFi deposit rate for USDC in Aave (teal), over a ±3 weeks around a monetary policy announcement by the Fed. Both series are normalized to zero on the announcement date and are smoothed using a 7-day moving average. Source: Aavescan, Bloomberg.

Figure 4: Bitcoin price and DeFi deposit rates spread against the US 2-year yield



Note: Spread is computed as the difference between volume-weighted DeFi deposit rates in Aave v2/v3 for USDT, USD and DAI, and the 2-year U.S. Treasury yield. Source: Aavescan, Bloomberg.

Fourth fact: Mean reversion of DeFi spreads Despite the large and persistent disconnect documented above, the spread between DeFi deposit rates and benchmark U.S. rates exhibits strong mean reversion. Because DeFi deposit rates are highly volatile, we rely on weekly averages in order to focus on medium-frequency movements that are more likely to be influenced by monetary policy rather than by transient crypto-specific shocks. Given the relatively short sample period, however, these results should be interpreted with caution. First, Table 7 in the Appendix reports cointegration tests between DeFi deposit rates and U.S. risk-free benchmarks. Over the full sample, cointegration tests frequently reject the null

Table 1: Dynamics of DeFi–Risk-Free Spreads

	DAI	USDC	USDT
Constant	-0.062	-0.081	-0.108
	(0.08)	(0.08)	(0.11)
$spread_{t-1}$	-0.106***	-0.133***	-0.186***
	(0.03)	(0.04)	(0.05)
$\Delta spread_{t-1}$	-0.272***	-0.263**	-0.364***
	(0.08)	(0.10)	(0.12)
$\Delta spread_{t-2}$	-0.159*	-0.140	-0.213**
	(0.08)	(0.09)	(0.08)
$\Delta spread_{t-3}$	-0.108	-0.133**	-0.128*
	(0.07)	(0.07)	(0.07)
$\Delta spread_{t-4}$	0.119	0.199**	-0.070
	(0.11)	(0.08)	(0.06)
$\Delta spread_{t-5}$	0.146***	0.121***	
	(0.05)	(0.05)	
$\Delta \ln BTC_t$	3.357**	5.412***	6.809***
	(1.31)	(1.35)	(2.46)
p (BIC)	5	5	4
Half-life (weeks)	5.0	4.0	2.2
R^2	0.211	0.309	0.284
Observations	259	259	260

The table reports error-correction regressions for DeFi–risk-free spreads constructed relative to SOFR. The dependent variable is the weekly change in the spread. Lag length is selected using the Bayesian Information Criterion. Standard errors (in parentheses) are HAC-robust. ***, **, * denote significance at the 1%, 5%, and 10% levels. Half-lives are computed as $\log(0.5)/\log(\rho)$ with ρ the estimated autoregressive coefficient from an AR(1) regression of the spread.

hypothesis of no cointegration. However, the associated long-run coefficients are economically small and explain only a negligible share of the variation in DeFi deposit rates. However, excluding 2021, a period during which U.S. risk-free rates remained near the zero lower bound while DeFi rates continued to fluctuate substantially, yields markedly different results, as reported in Table 8. Both Engle–Granger and Johansen tests provide strong evidence of cointegration for USDC and USDT, with economically meaningful long-run elasticities close to unity and substantially higher explanatory power.

Second, the spread between DeFi deposit rates and benchmark U.S. money market rates exhibits strong and statistically significant mean reversion. Table 1 reports regressions of the weekly change in the spread vis-à-vis the SOFR rate on its lagged level, lagged changes, and

Bitcoin returns.[6] The coefficient on the lagged spread is negative and statistically significant for all three tokens, providing clear evidence of mean reversion in DeFi deposit rates. As a rough measure of the speed of adjustment, the estimated half-life of shocks to the spread is approximately 5 weeks for DAI, 4 weeks for USDC, and 2.2 weeks for USDT. Finally, Bitcoin returns enter positively and significantly at the 1% level, indicating that fluctuations in cryptocurrency valuations play a meaningful role in shaping the dynamics of DeFi interest rate spreads.

In the next sections, we explain the origin and determination of the DeFi interest rates, build a model to account for these four stylized facts, and bring empirical evidences of the monetary policy transmission to the DeFi deposit rates.

3 Institutional Setup

This subsection first presents the various forms of remuneration available to stablecoin holders. It then briefly details the core functioning of DeFi lending protocols as the one examined in the paper. Finally, we discuss the risks inherent to lending activity.

3.1 Different forms of remuneration: yields, rewards and DeFi deposit rates

From their inception, fiat-backed stablecoin issuers like Circle and Tether excluded to serve interest to their tokens' holders, in part to avoid stablecoins to be classified as securities by the Securities Exchange Commission (SEC), and falling under its jurisdiction. The GENIUS Act further clarified in 2025 a general prohibition for regulated stablecoin issuers from offering any form of interest or yield to stablecoin holders.[7]

[6] An alternative specification using the residual from a long-run regression of DeFi deposit rates on SOFR -rather than the raw spread— yields very similar results and leads to the same conclusions.

[7] Section 4 of GENIUS Act states: *"[N]o permitted payment stablecoin issuer ... shall pay the holder of any payment stablecoin any form of interest or yield (whether in cash, tokens, or other consideration) solely in connection with the holding, use, or retention of such payment stablecoin."*

However, the GENIUS Act does not explicitly prohibit third-parties and affiliates, such as crypto-asset service providers (CASPs), to offer interest-bearing products to stablecoin holders. For example, popular trading platforms like Coinbase, Binance or Kraken all offer *earn products* or *rewards* on certain stablecoin holdings, and the payment service provider PayPal offers *rewards* on PYUSD balances (issued by Paxos Trust Company).

In Europe, MiCA prohibits since 2024 to issuers of e-money tokens (EMTs) and asset-referenced tokens (ARTs) and also to CASPs from granting interest in relation to passive stablecoin tokens' holdings (Garcia Ocampo, 2025; Bindseil, 2025).

However, in all jurisdictions, interest rates generated via DeFi lending protocols like Aave, Morpho or Compound have remained so far largely out of scope of the legislators, as well as unregulated, decentralised yield-bearing stablecoins, such as Ethena's USDe or sUSDS/sDAI issued by the decentralized autonomous organisation (DAO) MakerDAO (now Sky).

Due to this regulatory treatment, major platforms are increasingly using DeFi lending protocols as a yield generation layer to facilitate the access to their users to a remuneration on their stablecoin balances.[8] In that sense, our exploration of DeFi lending protocols and interest rate determination has implications for deposit rates individuals can access through popular apps and not reserved to tech-savvy DeFi participants, magnifying its importance from a macro-finance and monetary policy transmission perspective.

One additional source of value could arise from the use of interest-bearing receipt tokens (e.g., aTokens) as collateral in other DeFi applications. In practice, however, this channel is limited because aTokens are not recursively collateralizable within Aave and have only limited adoption as collateral in other DeFi protocols.

Decentralised protocols in DeFi also sometimes propose incentives, rewards, or redistribute fees to their users, on top of interest rates generated by depositing and lending stablecoins in

[8] For instance Coinbase announced in September 2025 an *"integration with onchain lending protocol Morpho to connect lenders and borrowers on a permissionless basis, all on Base (...) Smart contract wallet will be created by Coinbase to connect to the Morpho protocol via onchain vaults curated by Steakhouse Financial, where the (USDC holdings) will be allocated across different lending markets to optimize returns (...) instantly start earning yield (...) funds are always accessible and can be withdrawn at any time when liquidity permits."* https://www.coinbase.com/en-de/blog/earn-competitive-yields-by-lending-your-usdc

liquidity pools. All of these different ways to generate a remuneration on stablecoin holdings create a constellation of different rates – from different sources, with different properties and risks, as outlined in Figure 18 of the Internet Appendix.

In the next section, we explain how DeFi lending protocols work and how interest rates are determined.

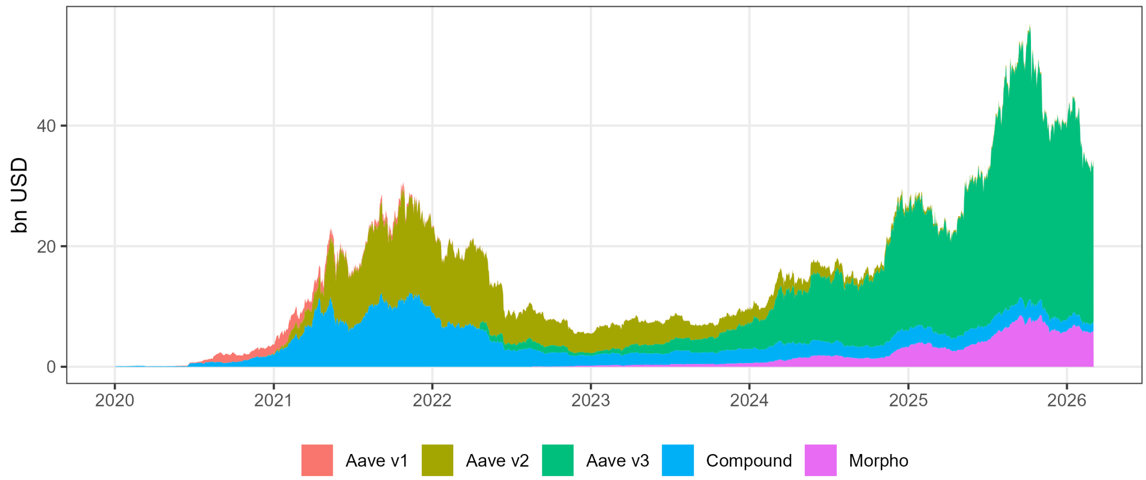
3.2 A primer on DeFi lending protocols

DeFi lending protocols are a cornerstone of the decentralized finance ecosystem, enabling users to lend and borrow crypto assets without intermediaries. DeFi lending protocols generally operate on a liquidity pool-based model, where lenders deposit assets that become part of a collective pool from which borrowers draw. Within these protocols, deposits are fully fungible, as are the borrowing positions. A direct consequence of this system is the elimination of individual credit assessments; all participants face uniform interest rates. To mitigate risk in this environment, positions must be over-collateralized, necessitating borrowers to deposit adequate collateral to secure their borrowing. Should the collateral value decline, borrowers must provide additional assets, or upon reaching a predetermined threshold, the collateral is liquidated at a discount, and the loan is automatically terminated.

The ratio between the total value borrowed and the total value deposited in a pool is called the utilization rate. For instance, if 4 tokens are deposited in the USDC lending pool, and 1 of them is lent out, then the utilization rate is 25% and the remaining liquidity in the pool is equal to 3. In the following, we denote the utilization rate by u.

Interest Rates Determination Within DeFi lending protocols, rates are often referred to as Annual percentage rate (APR) or Annualized Percentage Yields (APY). In the following, we distinguish the *borrow rate*, which borrowers pay, and the *deposit rate*, which lenders earn. These rates are determined by the interest rate model hardcoded in each underlying protocols smart contracts, ensuring real-time adjustments based on supply and demand dynamics. In this paper, we focus on Aave (v2 and v3), the largest DeFi lending protocol (See Fig. 5 for the size of this protocol relative to the overall market).[9]

Figure 5: Total value locked in DeFi lending protocols



The figure displays the time-series evolution of the Total value locked (TVL) in the 5 largest lending protocols from Jan 2020 to February 2026, in billion USD. Data source: DeFiLlama.

In Aave v3, deposit and borrow rates are monotonically increasing function of utilization rate.[10] More precisely, the borrowing rate is given by:

$$f(u) = \begin{cases} \alpha + \beta \frac{u}{\bar{u}} & \text{if } u < \bar{u} \\ \alpha + \beta + \beta' \frac{u - \bar{u}}{1 - \bar{u}} & \text{if } u \geqslant \bar{u} \end{cases} \quad (1)$$

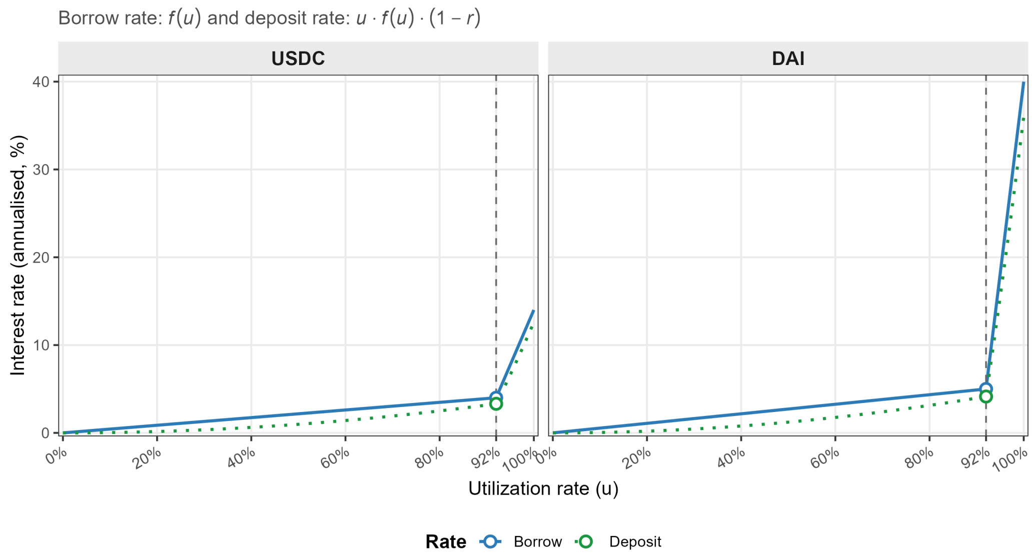
where u is the utilization rate and α, β are parameters set by governance vote by the protocol itself. $\bar{u} \in (0, 1)$ represents the kink in the interest rate function, often labelled as an "optimal utilization rate". Then the deposit rate is the product of the borrowing rate, the utilization rate and $1 - r$ where r is a reserve factor, i.e. a percentage of the interest paid by borrowers that is collected and allocated to the Aave Treasury to manage protocol risk. The resulting deposit rate is thus a piecewise quadratic function of the utilization rate and is strictly

[9] Aave has been by far the largest protocol since 2023. Other protocols like Compound are operating under the same logic, suggesting that our findings could extend also to other protocols.

[10] See the official Aave documentation. A summary on Aave v3 is provided by Chiu and Danisman (2026), who detail the provision by the protocol of interest-rate accruing aTokens to lenders to represent their deposit, and the different modules ("Safety module") which are beyond the scope of this paper. Aave v3 protocol refers to "supply" rather than deposit, we will use these terms interchangeably.

increasing over the domain of definition of $u \in [0, 1]$.

Figure 6: Interest Rate Models



The figure plots the deposit and borrowing rates, annualized and displayed in percentage points, for USDC and DAI in Aave v3 on Ethereum, as a function of the utilization rate, as of March 2025. USDT follows exactly the same parameters than USDC. Interest rate curves can be checked in real time on https://app.aave.com/markets/

On each side of the kink, the slopes $\beta' >> \beta$ incentivize liquidity providers to bring more liquidity to the protocol beyond and borrowers to repay their loans as they are facing increasingly prohibitive rates on their loan position. Without this feature, as $u \to 1$, the available liquidity in the pool — the quantity $(1 - u)S$ approaches zero. Any depositor wishing to withdraw would be unable to do so, creating a situation analogous to a bank run, without any backstop mechanism. This feature also intends to safeguard the protocol against significant price fluctuations in the collateral asset, which could lead to simultaneous mass liquidations of under-collateralized positions.

Aave uses coin-specific smart contracts to define the interest rate models, including the parameter values for the kink location $\bar{u}$, the intercept α, and the slopes β and β', and "reserve factor" r, see Table 2.

Table 2: Interest Rate Model, Aave v3, as of March 2025 (%)

Coin	Platform	α *base rate*	β *slope 1*	β' *slope 2*	$\bar{u}$ *'kink'*	r *reserve factor*
USDT	Aave v3	0	4	10	92	10
USDC	Aave v3	0	4	10	92	10
DAI	Aave v3	0	5	35	92	25

The table provides the current parameter values determining the coin-specific interest rate models of Aave v3. Parameters can be recovered directly in Aave's smart contract in Etherscan, e.g. here for Aave v3: https://etherscan.io/address/0x9ec6F08190DeA04A54f8Afc53Db96134e5E3FdFB for each liquidity pool using the function `getInterestRateData` and specifying the reserve address 0xA0b86991c6218b36c1d19D4a2e9Eb0cE3606eB48 for USDC, 0xdAC17F958D2ee523a2206206994597C13D831ec7 for USDT and 0x6B175474E89094C44Da98b954EedeAC495271d0F for DAI. Coin-specific reserve factors can be found here: https://aave.com/docs/resources/parameters.

3.3 DeFi risks

Deviation of DeFi deposit rates from traditional risk-free rates, especially to the upside, may reflect the pricing of risks inherent to DeFi lending as in traditional-finance credit pricing. In this subsection, we describe the main risks incurred by liquidity providers and borrowers and their potential impact on DeFi deposit rates through the quantities lent and borrowed.

Interest rate risk stems from the fact that DeFi usually work with variable rates, making uncertain ex-ante the remuneration of liquidity providers, especially given the high volatility of rates. All things being equal, higher volatility should command a premium on rates.

Liquidation risk arises from the protocol risk management rules: the risk position of a borrower b at time t is summarized by its *health factor*:

$$H_{b,t} = \frac{\sum_{i \in \mathcal{K}} l^i_{b,t}\, p^i_t\, \mathrm{cf}_i}{\sum_{j \in \mathcal{L}} b^j_{b,t}\, p^j_t}, \tag{2}$$

where $l^i_{b,t}$ and $b^j_{b,t}$ denote the quantities of asset i supplied as collateral and asset j borrowed by user b, respectively; p^i_t is the oracle price of asset i at time t; $\mathcal{K}$ is the set of collateral assets; $\mathcal{L}$ is the set of borrowable assets; and $\mathrm{cf}_i \in (0, 1)$ is the asset-specific *collateral factor* — the collateral value after haircut. Whenever $H_{b,t} < 1$, the position is undercollateralised and can be liquidated by any external actor or automated bot, who repays a fraction of the borrower's debt in exchange for a discounted share of the collateral (Tovanich et al., 2023; Mu et al., 2025; Castillo León and Lehar, 2026; Chiu and Danisman, 2026).

From the liquidity provider perspective, the risk is to recover a lower amount than deposited in case of sharp devaluation in collateral value, resulting from liquidations at lower prices than expected. Specifically, we construct a forward-looking measure of liquidation risk in Aave v2 and v3 by combining market-implied crash probabilities with protocol-level exposures. Crash risk is extracted from BTC and ETH option prices as the risk-neutral probability of a 10% price decline over a one-month horizon. Protocol vulnerability is measured by reconstructing wallet-level collateral and debt positions and estimating the share of loans that would become undercollateralized under such a shock. Expected liquidation risk is then defined as the product of these two components, providing a market-based proxy for systemic risk in decentralized lending. More details on the construction of the metric are provided Section B.3 of the Internet Appendix.

High liquidation risk should command higher rates if depositors are constraining quantities lent, and if borrowers are adjusting less their borrowing demand to expected large collateral valuation changes. Should the initial margin of safety instituted by the protocol prove insufficient to absorb the loss in value, the loans may not be fully repaid, resulting in a net loss for liquidity providers.[11]

Depegging risk of the stablecoin position is not specific to DeFi, but should be priced by depositors when allocating their portfolio in traditional safe assets (Tbill, secured money market) or stablecoins. High depegging risk should command higher DeFi deposit rates if depositors constrain their quantities lent.

Protocol vulnerability, hacks are specific to DeFi and refer to different forms of operational risk when lending and borrowing in DeFi. Vulnerabilities may be exploited in the code or logic of underlying smart contracts, the protocol could be breached, resulting in the loss of

[11] Gudgeon et al. (2020a) use Monte Carlo simulations to show that such a scenario can potentially materialize, with non-zero probability.

(part of) the deposited tokens.[12] Higher operational risks should command a risk premium in DeFi, to the extent depositors will restrict quantities until the interest rates are high enough to remunerate this type of risk.

Figure 19 in the Internet Appendix plots the time series of these four proxies.

The (limited) role of risks To assess the role of risk in shaping DeFi spreads, Table 3 of the Internet Appendix reports the correlations between the average DeFi spread for USDT, USDC, and DAI on Aave v2 and v3 and the four risk proxies discussed above. Together, and in this simple specification, these risks would account for only about one third of the variation in spreads. This estimate should, however, be interpreted with caution, as several of these risk measures are themselves endogenous to the level of DeFi rates and to monetary policy. For instance, rate risk mechanically rises when interest rates are elevated due to the steep slope of the yield function above the so-called "optimal utilization rate", while liquidation risk may correlate with leverage demand —itself potentially influenced by monetary policy.

Taken together, these results suggest that risk factors alone are insufficient to explain DeFi interest spreads. Instead, DeFi markets are shaped by trading frictions and segmentation, which require a deeper examination of investor incentives and the constraints they face —an analysis developed in Section 4.

[12]For instance, on July 30, 2023, several liquidity pools on the decentralized exchange *Curve Finance* were exploited, resulting in approximately $ 70 million in losses. The exploit was based on a vulnerability found in old versions of the Vyper compiler, allowing malicious users to perform re-entrancy attacks.

Table 3: DeFi deposit rates and DeFi risks proxies

This table reports panel regression results of the level of DeFi interest rate spreads on 4 proxies for risk. DeFi spread is defined as the difference in bps between the deposit APR of USDT, USDC and DAI (volume-weighted averaged across Aave v2 and Aave v3), and the 2-year U.S. Treasury yield. Depeg risk proxied by the 5-day moving average of the lowest daily price reached by each coin against the U.S. dollar. Interest rate risk is the 10-day realized volatility of the deposit APR for each coin. Hack risk is proxied by the log of TVL hacked amounts from DeFiLlama. Liquidation risk as defined in section 3.3. Figure 19 plots the time series of these four proxies.

	DeFi spread (bps)				
	(1)	(2)	(3)	(4)	(5)
Liquidation Risk	40.02***				27.81***
	(2.425)				(1.984)
Depeg Risk		3,422.2			3,218.0
		(3,600.5)			(2,819.7)
Hacking Risk			-0.7356		-0.4322
			(0.5921)		(0.4637)
Interest Rate Risk				160.0***	153.6***
				(3.430)	(3.380)
Observations	3,966	3,969	3,969	3,966	3,966
R^2	0.06741	0.00353	0.00369	0.35667	0.38740
Within R^2	0.06433	0.00023	0.00039	0.35455	0.38538
Coin fixed effects	✓	✓	✓	✓	✓

4 A Simple Model of DeFi Lending

In this section, we develop a simple model of DeFi lending and borrowing that yields testable implications for the transmission of monetary policy to stablecoin interest rates. The model builds on the four stylized facts documented in Section 2 and shows how the institutional features of DeFi protocols (Section 3) shape the interaction between the forces driving borrowing demand and stablecoin supply after a monetary-policy shock.

The purpose of the model is to identify the mechanisms through which monetary policy affects DeFi lending rates. In particular, the model isolates two opposing forces. On the supply side, a higher risk-free rate increases the opportunity cost of supplying stablecoins to DeFi protocols. On the demand side, monetary policy affects the profitability and collateral capacity of leveraged investors, thereby influencing their demand for borrowing. We proceed in four steps. First, we derive the supply of stablecoins from liquidity providers. Second, we characterize borrowing demand by leveraged investors. Third, we combine supply and demand to determine the equilibrium utilization rate and lending rate. Finally, we use comparative statics to study how changes in the risk-free rate are transmitted to DeFi rates.

Environment Time is discrete and indexed by $t \in \{0, 1\}$. The economy consists of two types of crypto-investors —liquidity providers and risky investors — and two digital assets: a risky digital asset (a crypto-asset) and a less risky digital asset (a stablecoin). All investors are price takers. Liquidity providers are initially endowed with W units of stablecoins, risky investors with risky assets whose market value is W' possibly depending on the risk-free rate ρ^*. Only risky investors can invest in the risky asset. Through the lending and borrowing of digital assets, the DeFi protocol enables risky investors to take leveraged long positions in the risky asset, while liquidity providers earn revenues by supplying stablecoins.[13]

Liquidity providers are heterogeneous in their access to traditional financial markets. In particular, investing in a risk-free technology that yields a gross return of $1 + \rho^\star$ requires paying a proportional cost $\tau \in [0, 1]$, drawn from a distribution specified below.[14]

Risky investors are also heterogeneous in their initial wealth $W' > 0$, which determines their exposure to collateral constraints. High-wealth investors are unconstrained, whereas low-wealth investors face binding collateral constraints and therefore adjust their investment behavior in response to changes in these constraints.

DeFi Protocol An investor can deposit a token and, if it does so, can borrow another token. We denote by S the quantity of stablecoins deposited and by $B < S$ the quantity borrowed. The DeFi Protocol automatically sets the borrowing and deposit rates as a function of the utilization rate $u = B/S$. Namely, the borrowing rate is $f(u)$, where the function f is piece-wise linear and strictly increasing with the utilization rate. The deposit rate (or *deposit rate*) is given by $\rho = uf(u)(1 - r)$, where $r \in [0, 1)$ is a reserve rate indicating the

[13]Related work shows that DeFi lending protocols primarily facilitate speculative activity in crypto-assets and are mainly used by borrowers to take leveraged long positions (Aramonte et al., 2022; Chaudhary et al., 2023).

[14]This cost should not be interpreted as a literal tax. Rather, it captures, in reduced form, a set of financial frictions or regulatory constraints that limit access to risk-free, dollar-denominated assets, such as U.S. Treasury bills.

share of profits allocated to the platform itself.

When borrowing stablecoins, an investor faces a haircut h_U on the crypto-assets deposited. When depositing a stablecoin, the liquidity provider is exposed to the risk of losing part of the tokens, which we model as follows: with probability $1-\theta$, the liquidity provider can withdraw all its stablecoins at date 1; otherwise, with probability θ, the liquidation process fails, and a fraction ψ of the deposited stablecoins is lost. This is a reduced-form approach to model different specific risks, including: (i) a de-peg event, (ii) a hack or a vulnerability in the smart contracts, (iii) the inability to immediately withdraw due to the lack of non-utilized liquidity in the pool, (iv) liquidation risk, caused by a sudden drop in collateral value leading to bad loans [15]

Assets payoffs The return on the crypto-asset is assumed to be normally distributed with mean $\rho_U(\rho^\star)$, which may depend on the risk-free rate, and variance σ_U^2. Allowing the expected return to vary with $\rho^\star$ captures potential channels through which monetary policy can influence the demand for leverage. The less-risky asset yields no return when it is not deposited on the lending platform.

Liquidity Providers At the beginning of date 0, liquidity providers are endowed with a large stock of stablecoins acquired in an unmodelled past. They can either lend these stablecoins through the DeFi protocol, hold them without lending, or sell them in order to invest in traditional finance. Lending is risky, whereas holding or selling stablecoins is not; hence, liquidity providers choose at most one of the latter two options. Excluding the (mass-

[15] An instance of liquidation risk materialized in April 2026, when some tokens representing staked ETHs where created illegitimately by a hacker exploiting a vulnerability in the a LayerZero-based bridge operated by Kelp DAO. These fraudulently minted (unbacked) tokens were used as collateral in AAVE to borrow real ETH. Once the real nature of the asset was discovered, the collateral value collapsed once the assets were identified as unbacked, leading to large bad loans in the ETH pool. While this is an extreme case, liquidation risk can manifest also during rapid price movements in *proper* collateral assets. See Tovanich et al. (2023) for a detailed and general treatment of liquidation risk. The same event led to a liquidity crunch in stablecoin pools, with the utilization rate hovering at 100% for several days and effectively severely constraining withdrawals due to near-full utilization of the pool. The situation was resolved as the the Aave DAO proposed and implemented a plan to recover the majority of the bad loans in the ETH pool, effectively restoring trust in the platform.

0) indifference case, liquidity providers strictly prefer holding stablecoins to selling them if and only if $(1+\rho^\star)(1-\tau) < 1$.

Liquidity providers' date-0 preferences are represented by a mean–variance utility function, where $\gamma > 0$ denotes their risk aversion coefficient. Their optimization problem is given by:

$$\max_{s \geqslant 0} \quad \left[uf(u)(1-r) - \theta\psi - \max\left(0; (1+\rho^\star)(1-\tau) - 1\right)\right] s - \frac{\theta(1-\theta)}{2}\gamma\psi^2 s^2,$$

where s denotes the individual supply of stablecoins and the term starting with a max corresponds to the net opportunity cost of lending stablecoin through the DeFi platform. We assume perfect competition among liquidity providers, so each liquidity provider takes u as given. The optimal decision of a liquidity provider facing a tax τ satisfies:

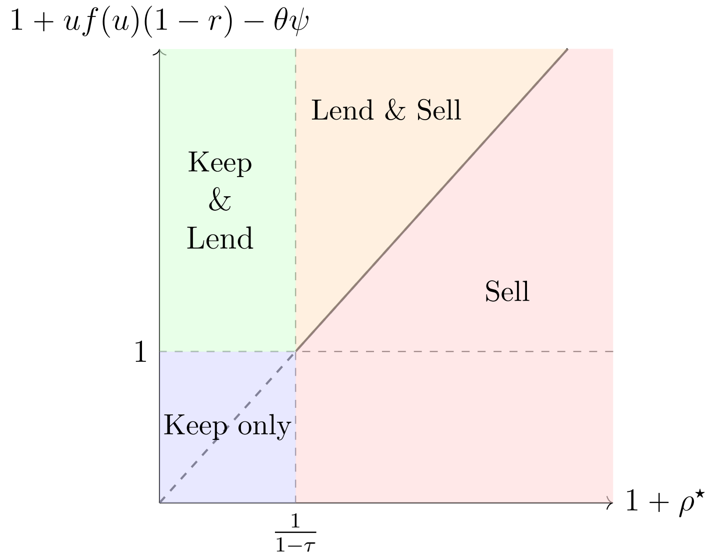
$$s = \max\left\{0;\ \frac{uf(u)(1-r) - \max\left(0; (1+\rho^\star)(1-\tau) - 1\right) - \theta\psi}{\theta(1-\theta)\gamma\psi^2}\right\}. \tag{3}$$

Equation (3) summarizes the liquidity providers' supply decision. Stablecoin supply increases with the DeFi deposit return, $uf(u)(1-r)$, and decreases with expected platform losses, $\theta\psi$, and with the outside option of moving funds into the risk-free asset. Thus, monetary tightening reduces supply whenever it raises the opportunity cost of providing stablecoin liquidity.

The figure 7 shows the optimal portfolio strategy depending on the risk-free rate, the tax τ, and the expected return on lending stablecoins for a given u.

The quantity lent through the DeFi platform depends on the accessibility to traditional finance τ. This tax is distributed as follows. It takes value 0 with probability $1-\mu$ and follows a uniform distribution on $[0,1]$ otherwise. $1-\mu$ hence measures the share of liquidity providers that seamlessly trade on both digital and traditional finance. We also consider a uniform distribution over $[0,1]$ to capture the fact that the portion of liquidity providers who prefer leaving the crypto-ecosystem to invest in traditional finance might increase with investment opportunities in the latter sector, captured by higher $\rho^\star$. The aggregate supply

Figure 7: Optimal liquidity providers' portfolio choice



of stablecoins to the lending platform is given by:[16]

$$S = \begin{cases} \dfrac{uf(u)(1-r) - \theta\psi - \frac{\mu}{2}\frac{(\rho^\star)^2}{1+\rho^\star} - (1-\mu)\rho^\star}{\theta(1-\theta)\gamma\psi^2}, & \text{if} \quad \rho^\star \leqslant uf(u)(1-r) - \theta\psi; \\ \\ \mu\dfrac{2 + uf(u)(1-r) - \theta\psi}{2(1+\rho^\star)} \dfrac{uf(u)(1-r) - \theta\psi}{\theta(1-\theta)\gamma\psi^2}, & \text{otherwise.} \end{cases} \tag{4}$$

First, the aggregate supply of stablecoins is decreasing in the risk-free rate $\rho^\star$ in both cases, and is continuous and strictly increasing in u (notice that the two equations coincide for $\rho^\star = u(f(u)(1-r) - \theta\psi)$.

Second, owing to the limited access to traditional finance, captured by the tax τ, the supply of stablecoins remains strictly positive even when the risk-free return strictly dominates the return from lending. In this case, the risk-free rate affects stablecoin lending only along the extensive margin: a higher risk-free rate reduces the measure of liquidity providers willing to lend, but not the intensive margin, that is, the quantity supplied by an individual liquidity provider. As a result, the sensitivity of stablecoin supply to $\rho^\star$ is lower when DeFi deposit rates are below the risk-free rate, as shown in equation (4).

[16] See B.1.1 of the Internet Appendix for the details.

Risky Investors Through the DeFi protocol, risky investors can borrow stablecoins to buy risky digital asset.[17] For simplicity, we assume that there is no return on depositing risky digital assets as collateral in the protocol. Risky investors are heterogeneous. A fraction ν is endowed with a low initial wealth $\underline{W}(\rho^\star)$, sensitive to the risk-free rate $\rho^\star$, thereby capturing a potential collateral channel of monetary policy.[18] The remaining investors are endowed with sufficiently high initial wealth $\overline{W}$, such that the collateral constraint never binds and any valuation effects of monetary policy are immaterial for their decisions. For a given endowment $W' \in \{\underline{W}(\rho^\star), \overline{W}\}$, the optimization problem faced by a risky investor is as follows:[19]

$$\max_{U,b \geqslant 0} \quad (1+\rho_U(\rho^\star))U - (1+f(u))b - (1+\rho^\star)W' - \frac{\gamma'}{2}\sigma_U^2 U^2,$$

$$\text{s.t} \quad W' + b \geqslant U, \quad \text{and} \quad (1-h_U)U \geqslant b.$$

Assuming that both high- and low-wealth risky investors actively use the DeFi platform in equilibrium and that the collateral constraint is binding for low-wealth investors only, $\frac{1-h_U}{h_U}\overline{W} > \frac{\rho_U(\rho^\star)-f(u)}{\gamma'\sigma_U^2} > \max\{\overline{W}, \frac{1-h_U}{h_U}\underline{W}(\rho^\star)\}$, we get the following aggregate demand for borrowing:

$$B = (1-\nu)\left[\frac{\rho_U(\rho^\star)-f(u)}{\gamma'\sigma_U^2} - \overline{W}\right] + \nu\left[\frac{1-h_U}{h_U}\underline{W}(\rho^\star)\right]. \tag{5}$$

Equation (5) summarizes aggregate borrowing demand. High-wealth investors choose leverage by equating the marginal benefit of exposure to the risky asset with the borrowing cost and risk, whereas low-wealth investors are constrained by collateral requirements. Hence, borrowing demand falls after a rate hike if monetary policy lowers expected crypto returns,

[17] We assume that this is the only way to take such a leveraged position, perhaps because collateralizing unstablecoins and unsecured lending are infeasible for this class of investors.

[18] Because risky investors are endowed with risky assets, changes in the risk-free rate may affect their initial wealth through asset valuation effects, giving rise to a potential collateral channel of monetary policy.

[19] As for liquidity providers, we assume that risky investors take the borrowing rate $f(u)$ as given.

$\rho_U(\rho^\star)$, or reduces collateral capacity, $\underline{W}(\rho^\star)$. In equilibrium and using $u = B/S$, we get the following downward-sloping relationship between S and u:

$$S = \frac{1}{u}\left\{(1-\nu)\left[\frac{\rho_U(\rho^\star) - f(u)}{\gamma'\sigma_U^2} - \overline{W}\right] + \nu\left[\frac{1-h_U}{h_U}\underline{W}(\rho^\star)\right]\right\}. \tag{6}$$

Equilibrium Any symmetric interior equilibrium should satisfy the optimal supply of stablecoins described in (4) and the optimal demand from risky investors outlined in (5). The supply equation is upward-sloping in the (S, u) space because a higher utilization rate raises the lending return required to attract stablecoin deposits. The demand equation is downward-sloping because higher utilization implies a higher borrowing rate, which reduces leveraged borrowing. Their intersection determines the equilibrium utilization rate and, through $\rho = uf(u)(1-r)$, the equilibrium DeFi deposit rate.

By first differentiating the supply and the demand of stablecoins —respectively equations (4) and (6)— we get that monetary policy transmits positively to the utilization rate ($\frac{\partial u}{\partial \rho^\star} > 0$) and hence to stablecoin deposit rates if and only if:[20]

$$\underbrace{(1-\mu)\frac{u^\star}{\theta(1-\theta)\gamma\psi^2} + \mu\rho^\star\frac{u^\star}{\theta(1-\theta)\gamma\psi^2}}_{\text{arbitrage channel}} > \underbrace{\frac{1-\nu}{\gamma'\sigma_U^2}(-\rho_U'(\rho^\star))}_{\text{leverage channel}} + \underbrace{\nu\frac{1-h_U}{h_U}(-\underline{W}'(\rho^\star))}_{\text{collateral channel}}, \tag{7}$$

with $u^\star$ being the equilibrium utilization rate. The comparative statics characterize how equilibrium utilization responds to changes in the risk-free rate. The answer depends on whether the supply-side contraction dominates the demand-side contraction.

The inequality displayed in (7) highlights three channels related to the transmission of monetary policy. First, arbitrage induces a positive transmission channel. Following a rate hike, LPs move capital from DeFi to the risk-free asset, inducing an increase in utilization ratios and hence of DeFi rates. This channel is modulated by the fraction of constrained LPs, denoted by μ. If more LPs are constrained in accessing traditional financial markets, this

[20]This equation is derived when $\rho^\star < uf(u)(1-r) - \theta\psi$, otherwise the right-hand-side member should be replaced by $\frac{S^\star}{1+\rho^\star}$. Such a differentiation is valid as long as the equilibrium rate does not coincide with a kink, which we assume in the following.

creates a friction reducing arbitrage activity and hence the passthrough of monetary policy. The second channel is based on the appetite for leverage, potentially inducing a negative transmission force. If contractionary policy changes are associated with a reduction in the expected returns of risky assets, this lowers the appetite for leverage and thus borrowing demand for stablecoin. In turn, this reduces the utilization ratio and hence DeFi rates. The third channel, a negative force, relies on collateral valuations. If rate hikes reduce the value of available collateral, constrained borrowers are mechanically forced to deleverage. This lowers their demand for stablecoin borrowing and, in turn, puts downward pressure on DeFi interest rates. The strength of this channel depends on the sensitivity of the market value of pledgeable assets to changes in the risk-free rate.[21]

Empirical Implication: *DeFi rates increase with the risk-free rate only if the supply-side effects dominate the demand-side ones. Positive monetary policy shocks reduce supply through the arbitrage channel, modulated by access to traditional finance. On the demand side, borrowing demand falls because of reduced appetite for leverage and lower collateral valuations.*

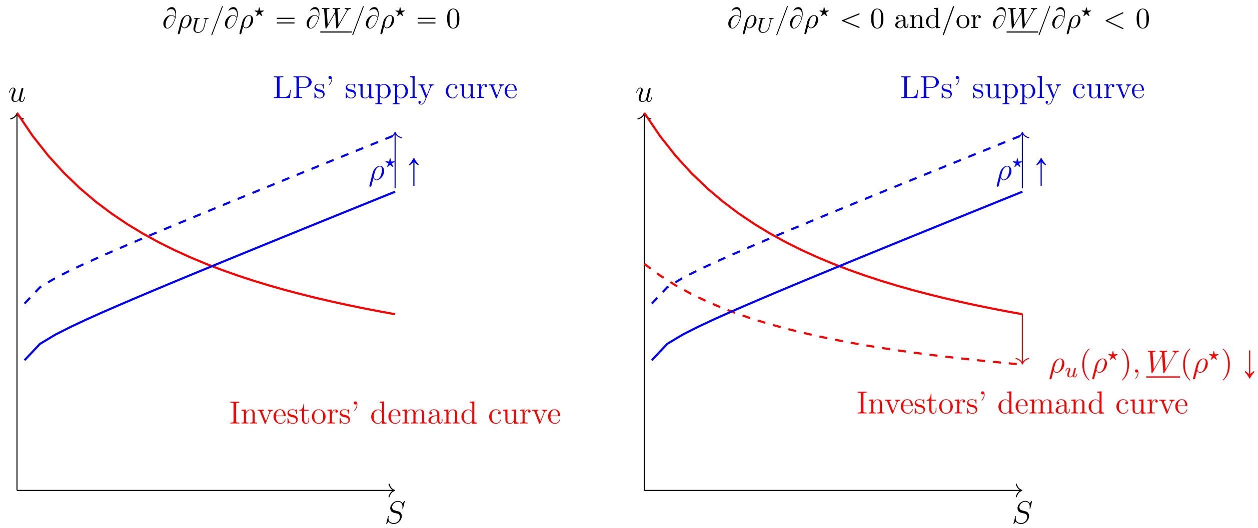
A formal way to see this is the following. When the sensitivities of the expected crypto-asset return and of collateral capacity to the risk-free rate are sufficiently small —that is, when $\rho_U'(\rho^\star)$ and $\underline{W}'(\rho^\star)$ are close to zero— inequality (7) is always satisfied, since the equilibrium utilization rate is bounded away from zero by $u^\star > \theta\psi/f(1)(1-r) \geqslant 0$. Conversely, when these derivatives are sufficiently large in absolute value, the inequality is violated as $u^\star \leqslant 1$.

Three remarks are in order.

First, note that if both the expected return on the risky asset, $\rho(\rho^\star)$, and the collateral capacity of less-wealthy investors, $\underline{W}(\rho^\star)$, are only weakly affected by monetary policy (i.e., their first derivatives with respect to $\rho^\star$ are close to zero), then a monetary policy tightening mechanically increases the utilization rate and deposit rates, and reduces the supply of

[21] For simplicity, we assume that risky investors' initial endowment consists entirely of risky crypto-assets. If investors instead held a portfolio of both stablecoins and risky assets, the strength of the collateral channel would depend not only on the sensitivity of risky-asset prices to the risk-free rate but also on the share of risky crypto-assets in investors' portfolios.

Figure 8: Monetary policy shock with optimal investors



The x-axis stands for the supply of stablecoins; the y-axis stands for the utilization rate or the borrowing rate. The blue curve shows the liquidity provider's optimal supply and the dashed blue curve shows it for a higher risk-free rate $\rho^\star$. The red curve corresponds to the optimal aggregate demand curve. The dashed red curve is when the expected return on the risky digital asset is negatively affected by the risk-free rate increase. The intersections correspond to the equilibrium outcomes.

stablecoins.

Second, when liquidity providers are risk-neutral ($\gamma \to 0$), the deposit rate is determined by those with limited access to traditional finance ($\tau \geqslant 1 - \frac{1}{1+\rho^\star}$, or, to a first-order approximation, $\tau \geqslant \rho^\star$). The equilibrium condition collapses to $uf(u)(1-r) = \theta\psi + 1$ which is independent of the level of the risk-free rate. This outcome is extreme and relies on the assumption that liquidity providers with restricted access to traditional finance possess arbitrarily large wealth. At the opposite extreme, when all liquidity providers have seamless access to traditional finance ($\mu = 0$), the equilibrium deposit rate satisfies $uf(u)(1-r) = \theta\psi + \rho^\star$ implying a one-for-one passthrough of the risk-free rate.

Third, the Figure 8 shows how monetary policy can affect the deposit rate depending on which force dominates. As clear from inequality (7), there are at least three channels through which monetary policy can be transmitted to stablecoin rates. First, the supply S depends negatively on $\rho^\star$: the opportunity cost of investing in liquidity provision increases and the fraction of liquidity providers contemplating investing in traditional finance increases with

$\rho^\star$. Even if this were the only channel through which the risk-free rate affects DeFi, the endogenous reaction of B to $\rho^\star$ dampens the response of stablecoin rates to monetary policy shocks (see the left-panel chart). Second and third, if a rate hike reduces the expected return on the risky crypto asset (ρ_U negatively depends on $\rho^\star$) or/and reduces the collateral value $\underline{W}(\rho^\star)$, a rate hike moves the investors' demand curve down (the red curve) reducing the equilibrium stablecoin deposit rate (see the right-panel chart). The reaction of the DeFi rates to risk-free rate eventually depends on which of these channels dominates.

5 Data

This section first describes the data sources used for the time-series analyses, covering both DeFi and traditional financial markets, and then, taking advantage of the availability of granular blockchain data, presents the investor-level metrics we construct.

5.1 Time series data

Our main source for DeFi data is **Aavescan**, a data platform that provides historical daily lending data including deposit and borrow rates, quantities lent and borrowed, for each liquidity pool.[22] We focus on the Aave v2 and Aave v3 protocols, from 4th January 2021 to 30th January 2026. Aave v2 has been launched on the Ethereum mainnet in December 2020, while Aave v3 has been launched in January 2023.[23]

We restrict our main analysis to the three largest asset-backed stablecoins deposited (USDC, USDT, and DAI), and to contracts deployed on the Ethereum blockchain, by far the most traded, both in Aave v2 and Aave v3.

The data trace out daily time series obtained by tracking 4 types of interaction with Aave's

[22]Aavescan has been widely used as a reference data source in the press and in academic research, see for instance Ma et al. (2025); Li and Mayer (2025).

[23]For simplicity, for our time series, we switch from Aave v2 and Aave v3 in October 15, 2023, when the TVL of the latter surpassed the TVL of the former.

smart contracts [24], i.e.:

- `Deposit` and `Withdraw` transactions cumulated to retrace the liquidity providers' total supplied positions S_t in each lending pool ;
- `Borrow` and `Repay` transactions, cumulated to build the total borrowed quantities B_t in each lending pool

Interest rates are derived from the utilization rate $u_t = \frac{B_t}{S_t}$, and are function of the interest rate model defined for each liquidity pool, as explained in Section 3.2. We recompute average daily deposit interest rates from the Aave smart contracts' `LiquidityIndex`, which tracks the accumulation of interest accrued since the inception of the protocol, including any eventual fees or incentives received, and the daily borrowing interest rates, similarly, using the `VariableBorrowIndex`.[25]

Annual percentage rate (APR) is computed from the indexes at a daily frequency, then annualized, following the formulas[26]:

$$\text{Deposit APR} = \left(\frac{\texttt{LiquidityIndex}_t}{\texttt{LiquidityIndex}_{t-1}} - 1 \right) \times 365$$

$$\text{Borrowing APR} = \left(\frac{\texttt{VariableBorrowIndex}_t}{\texttt{VariableBorrowIndex}_{t-1}} - 1 \right) \times 365$$

Aavescan provides aggregated daily data points recorded at midnight UTC time. For robustness, we double-check the rates and quantities series with our own queries in Dune Analytics.[27] Table 6 reports the descriptive statistics of our rate and quantities variables for

[24] https://etherscan.io/address/0x7d2768dE32b0b80b7a3454c06BdAc94A69DDc7A9

[25] As recommended by Aavescan, *"The interest index (such as Aave's liquidityIndex or variableBorrowIndex) is a number that continuously increases to reflect accumulated interest. By comparing the index values of two different dates you can precisely calculate the interest that has accrued, i.e. the interest earned or owed, fully accounting for compounding and additional sources of income such as flash loan fees."* See also https://aave.com/docs/aave-v3/smart-contracts/pool

[26] Annual percentage yield (APY) can alternatively be used and computed for deposit rates: $\left(\frac{\texttt{LiquidityIndex}_t}{\texttt{LiquidityIndex}_{t-1}} \right)^{365} - 1$

[27] In earlier versions of the paper, we also relied on an Ethereum archive node, running at the Banque de France, which provided times series consistent with Aavescan.

our three stablecoins of interest, USDT, USDC and DAI.

We complement this database with daily time series: BTC and ETH spot prices and BTC and ETH perpetual futures prices from Coindesk, Gas fees from Etherscan, Fear and greed index from Coinmarketcap, stablecoin market cap and DeFi daily hacks (TVL hacked) from DeFiLlama.

Finally, from the traditional finance side, we retrieve from Bloomberg daily time series of U.S. money market rates (SOFR, Fed Funds rate, U.S. T-bill and U.S. Treasuries yields and OIS rates of different maturity), VIX, S&P 500, Nasdaq, and the 5-year and 10-year inflation swaps.

When merging traditional finance and crypto data, we keep U.S. business days, and carry forward traditional finance market data over holidays.

5.2 DeFi wallet-level data

We construct user-level measures of supplied liquidity and borrowing activity on Aave using transaction-level data from Dune Analytics. The raw data consist of all deposit, withdrawal, borrow, and repayment events at the user–asset–day level. The resulting granular dataset is used for two empirical exercises. First, it is key to estimate our measure of liquidation risk, reported in B.3. Second, we use it in Section 7.3 to causally identify LPs reaction around monetary policy changes.

We define net supply flows as the signed sum of all supply-relevant events. In particular, deposits enter positively, while withdrawals enter negatively. In addition, we account for repayments executed using interest-bearing tokens, which mechanically reduce both outstanding debt and supplied balances, and therefore enter negatively in the supply measure. We further incorporate liquidation events affecting collateral positions, which correspond to collateral seizures and are also recorded as negative supply flows. Formally, for user i, asset a, and day t, net supply flow is given by

$$\text{Flow}^S_{iat} = \text{Deposit}_{iat} - \text{Withdraw}_{iat} - \text{RepayWithATokens}_{iat} - \text{LiquidationCollateral}_{iat}.$$

We then construct the stock of supplied liquidity as the cumulative sum of these flows:

$$S_{iat} = \sum_{\tau \leqslant t} \text{Flow}^{S}_{ia\tau}.$$

The same procedure is applied at the hourly frequency to obtain an intraday dataset of supplied liquidity.

Importantly, our construction abstracts from the passive accumulation of interest through Aave's interest-bearing tokens (aTokens). Because interest accrual is smooth and continuous, while our identification for the difference-in-differences analysis described in Section 7.3 relies on high-frequency variation around announcement windows, this omission primarily removes a low-frequency drift component and does not affect the measurement of discrete user-driven flows. A similar argument applies to the other exercises based on wallet-level data.

6 Monetary policy shocks and DeFi deposit rates: a proxy-VAR approach

In this section, we extend our analysis by focusing on the impact of *monetary policy surprises* on DeFi deposit rates, using a proxy-VAR *a la* Mertens and Ravn (2013). We follow the Bayesian estimation approach of Miranda-Agrippino and Ricco (2021) to trace the full impact of monetary policy shocks and, crucially, to check which channels have been dominating in the past 5 years around monetary policy announcements.

Our VAR follows a standard form for coin-specific series, where $\mathbf{Y}_t$ is an $n \times 1$ vector of time series variables, with the main variables of interest being the DeFi deposit rate, the total quantity borrowed, and the total quantity supplied for each stablecoin:

$$\mathbf{A}\mathbf{Y}_t = \sum_{j=1}^{p} \boldsymbol{\alpha}_j \mathbf{Y}_{t-j} + \boldsymbol{\varepsilon}_t, \tag{8}$$

where $\mathbf{A}$ is an $n \times n$ nonsingular matrix of coefficients, $\boldsymbol{\alpha}_j$, $j = 1, .., p$, are $n \times n$ coefficient matrices and $\boldsymbol{\varepsilon}_t$ is an $n \times 1$ vector of structural shocks. An equivalent representation is:

$$\mathbf{Y}_t = \sum_{j=1}^{p} \boldsymbol{\delta}_j \mathbf{Y}_{t-j} + \mathbf{B}\boldsymbol{\varepsilon}_t, \tag{9}$$

where $\mathbf{B} = \mathbf{A}^{-1}$, $\boldsymbol{\delta}_j = \mathbf{A}^{-1}\boldsymbol{\alpha}_j$.

Let the $n \times 1$ vector $\mathbf{u}_t$ denote the reduced-form residuals which are related to the structural shocks by $\mathbf{u}_t = \mathbf{B}\boldsymbol{\varepsilon}_t$.

Since $E[\mathbf{u}_t\mathbf{u}_t'] = \mathbf{B}\mathbf{B}'$, an estimate of the covariance matrix of $\mathbf{u}_t$ provides $n(n+1)/2$ independent identifying restrictions. However, identification of the elements of at least one of the columns of $\mathbf{B}$ requires more identifying restrictions. The instrument z_t is used to identify monetary policy in the impact matrix B. Identification relies on two conditions:

Relevance requires that the instrument z_t is correlated with the monetary policy reduced-form innovation $\mathbf{u}_t^{mp}$:

$$E[z_t \cdot \mathbf{u}_t^{mp}] \;\neq\; 0 \tag{10}$$

Exogeneity requires that z_t is uncorrelated with the $(n-1) \times 1$ vector $\mathbf{u}_t^{\overline{mp}}$ of all other reduced-form innovations in the system:

$$E\Big[z_t \cdot \big(\mathbf{u}_t^{\overline{mp}}\big)'\Big] \;=\; 0 \tag{11}$$

As common in the monetary policy literature, we build the instrument z_t from high-frequency price changes around monetary policy announcements. The input series include high-frequency changes for various interest rates: Fed funds, Eurodollar and Secured Overnight Financing Rate (SOFR) futures; overnight index swap (OIS) rates; and yields on Treasury bonds and Treasury Inflation-Protected Securities (TIPS), following Acosta et al. (2025).[28] The surprises are calculated as the first principal component of these rate changes.

We then estimate the response of DeFi deposit rates and quantities lent and borrowed to

[28] Series made available by the authors in the USMPD database, from the Federal Reserve of San Francisco, Center of Monetary Research.

a monetary policy shock. In our baseline, we use the 2-year U.S. Treasury yield as the policy variable, and high frequency price changes during the "monetary policy statement" window, a 30-minute window around the release of the statement following FOMC meeting. To smooth out volatility in rates while keeping relevance for the instrument, we run this exercise at a weekly frequency, taking end of week data points and weekly average monetary policy surprises.[29]

We follow the Bayesian Proxy-VAR estimation algorithm of Miranda-Agrippino and Ricco (2021), with Normal-Inverse-Wishart priors. Based on a standard lag-length selection criterion (BIC), our proxy-VAR is estimated with a one-week lag. The shock is normalized so that it has a one percentage point (100 bps) effect on the weekly change in the 2-year U.S. Treasury yield. As a robustness test, we run the same specification with the 3-month U.S. Treasury bill rate, with very similar responses in the DeFi deposit rates (Fig. 16). To test for the slow-moving convergence suggested by the ECM in our motivating stylized facts, we trace out the impulse responses over a 52-week horizon. Fig 9 and Fig 10 report the obtained impulse response functions for USDC and USDT.

Three observations stand out from the results:

First, in our sample, Bitcoin returns react similarly to stock markets and are heavily and durably affected by the monetary policy shock. For our leverage channel, this is an important result to note, which conditions the reaction of borrowing demand in DeFi. In terms of the model, this suggests that the expected return on risky crypto asset (ρ_U) strongly declines following a monetary policy shock (rise in ρ^*), which is a prerequisite for the presence of the demand for the leverage channel.

Second, contractionary monetary policy shocks generate an immediate and persistent decline in both aggregate borrowing and aggregate liquidity supply. A one-basis-point increase in the

[29]While high-frequency surprises are a strong instrument at a monthly frequency, the F-statistic mechanically decreases at a weekly frequency due to non-FOMC weeks. In our baseline specification, the F-statistic of the first stage stands at 7, close but slightly below the usual rule-of-thumb threshold for strong instruments. To complement this result and ensure our conclusions are not affected by a weak instrument bias, we also run a monthly frequency specification of our VAR which confirms our main findings, noting, however, that at monthly frequency our sample becomes small and hence is not our preferred specification, see Fig.17.

two-year Treasury yield attributable to monetary policy is associated with an approximately one-percentage-point reduction in both borrowed and supplied quantities at a four-month horizon, representing the peak impulse response. The co-movement of both quantities is consistent with the theoretical transmission channels outlined in Section 4. Critically, the *relative* magnitude of the supply response versus the demand response governs the equilibrium adjustment of DeFi deposit rates.

Third, the dynamic responses to the same monetary policy shock—normalized to a 100-basis-point increase in the two-year U.S. Treasury yield—differ markedly across stablecoins. For USDC, the contraction in liquidity provision exceeds the decline in borrowing demand in the short run — total borrowing declines the first week by 40% while total supply declines by around 50%. — generating an initial increase in utilization rate and in DeFi deposit rates of comparable magnitude to the policy impulse (approximately 100 basis points). Subsequent deleveraging, however, attenuates this pass-through over the following weeks as total borrowing declined by 90% and total supplied by only 80 % before rates eventually converge toward the policy variable over the longer horizon as both supplied and borrowed quantities are returning slowly to pre-shock levels. For USDT, the dynamic is qualitatively distinct: the leverage channel dominates, as borrowing demand contracts more rapidly than liquidity supply in the weeks immediately following the shock. This differential adjustment produces a short-run *decline* in DeFi deposit rates, with convergence to the policy variable occurring only gradually, beyond a 42-week horizon.

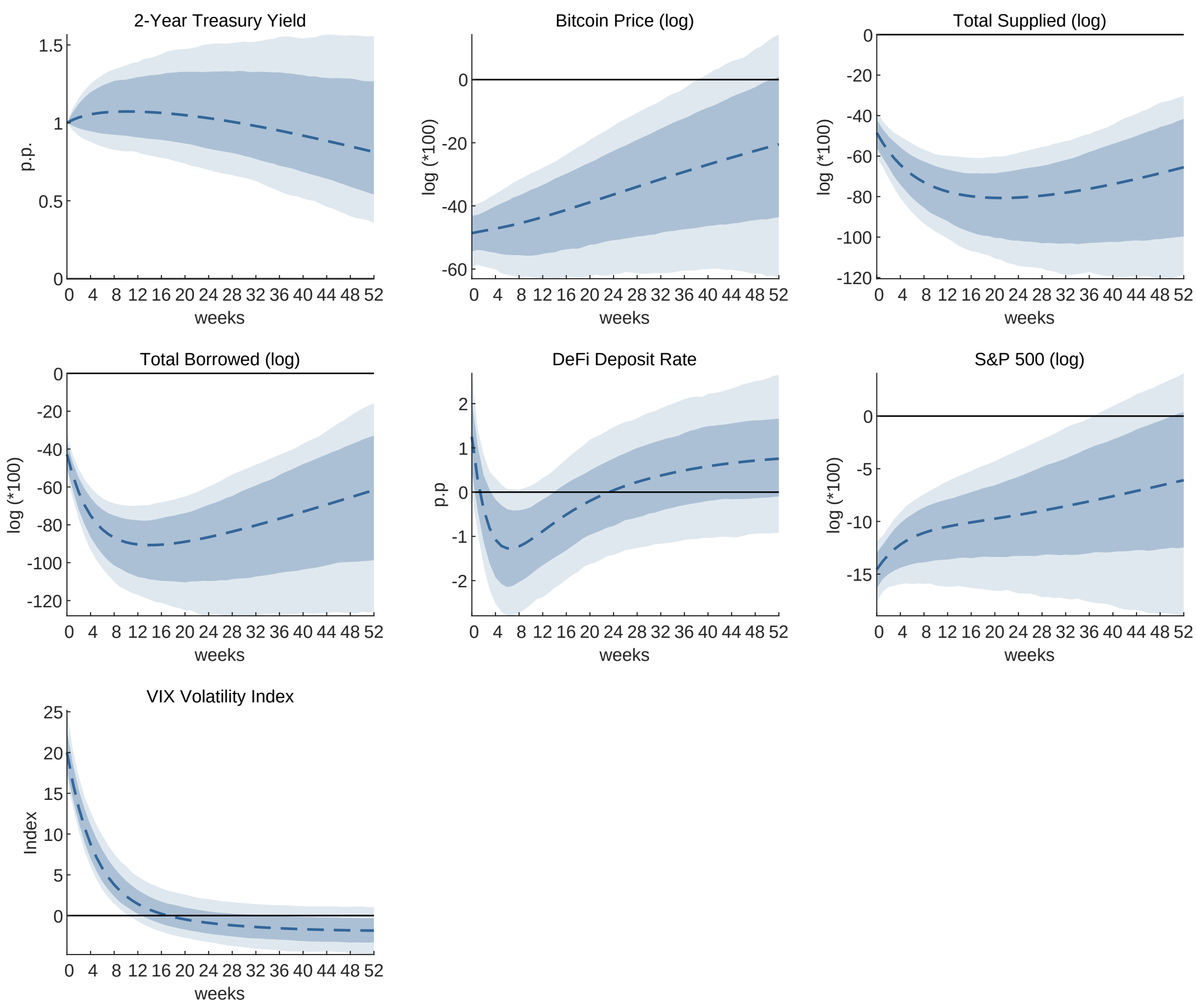
All in all, the proxy-VAR exercise suggests that the full impact of monetary policy shocks is coin- and protocol specific, depending on the relative strength of arbitrage and leverage channels. In both cases, the median response suggests a long-term convergence with the 2-year risk-free rate, but with very long lags, which are significantly shorter for USDC, which is more affected by the interest-rate channel than USDT. While standard arbitrage arguments would predict very similar impulse responses across tokens, the distinct patterns we observe instead point to strong token-level market segmentation. One possible explanation for the heterogeneous responses of USDC and USDT to monetary policy shocks lies in differences in their investor base and different access to traditional finance,[30] as developed in Section 7.3. In that Section, we also report an analysis based on granular data, where we confirm this conjecture by distinguishing categories of liquidity providers according to empirical proxies for their access to traditional finance.

We conjecture that USDC holders are, on average, more deeply integrated into traditional U.S. financial markets, consistent with the fact that USDC is issued by a U.S.-regulated entity. USDT, by contrast, is widely perceived as comparatively opaque and subject to greater counterparty risk, particularly among institutional investors. An alternative and not mutually exclusive explanation pertains to differences in redemption conditions: relatively higher redemption costs for USDT may give rise to systematic differences in investor composition and portfolio behavior across the two tokens.

In Annex A.3, Fig 14 excludes 2021 from the sample, and the results suggest that convergence in rates is faster in the sample starting in 2022, possibly pointing to market immaturity in 2021. Results are unchanged when including liquidation risk and the DXY Index as a proxy for the strength of the U.S. dollar (Fig 15).

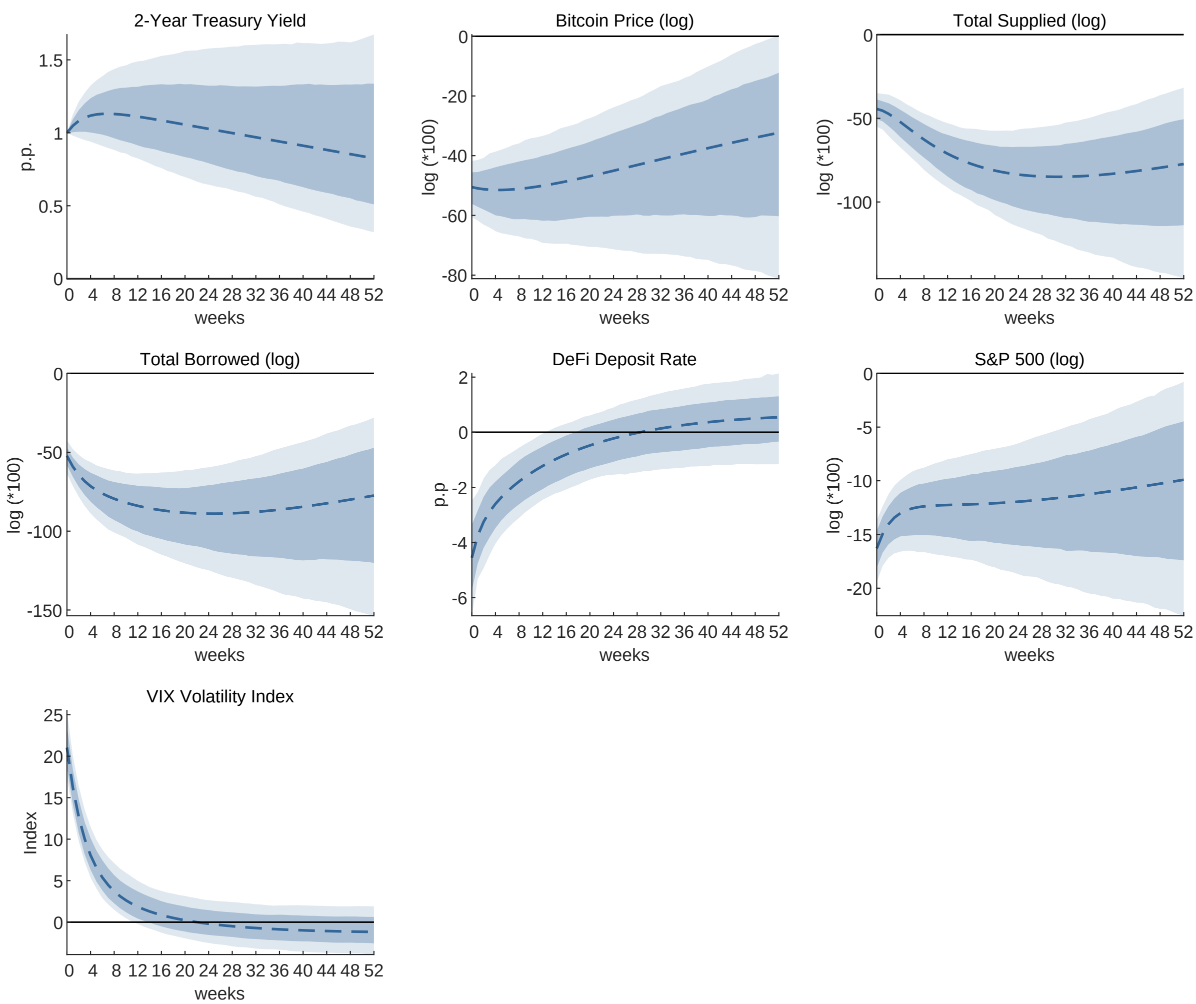
[30] In the model, this heterogeneous impact due to differential access to traditional finance is reflected by the parameter μ.

Figure 9: Impulse responses for USDC



Notes: 7-variable baseline VAR, with 1-week lags (BIC criterion). Shock identified with Acosta et al. (2025) average weekly FOMC statement surprise. The shock is normalized to induce a 100 basis point increase in the 2-year U.S Treasury yield. Sample: January 2021-January 2026. Shaded areas are 90 percent (dark blue) and 68 percent (light blue) posterior coverage bands.

Figure 10: Impulse responses for USDT



Notes: 7-variable baseline VAR, with 1-week lags (BIC criterion). Shock identified with Acosta et al. (2025) average weekly FOMC statement surprise. The shock is normalized to induce a 100 basis point increase in the 2-year U.S Treasury yield. Sample: January 2021-January 2026. Shaded areas are 90 percent (dark blue) and 68 percent (light blue) posterior coverage bands.

7 Investigating the DeFi spread persistence with granular and high-frequency data

In this section, we investigate the sources of the slow convergence of DeFi interets rate spread, exploiting high-frequency and granular wallet-level data from the blockchain. First, we study the March 2023 USDC de-pegging episode around the collapse of Silicon Valley Bank (SVB), using intraday data at the hourly frequency to isolate a demand-driven shock and trace the supply response. Second, we generalize this approach to a set of large, discrete jumps in DeFi deposit rates, classifying them as demand- or supply-driven. Third, we investigate how long it typically takes for DeFi/risk-free spreads to decay following a spike. Fourth, we link spread persistence directly to gas fees by regressing decay times on contemporaneous gas fee levels. Finally, we run a difference-in-differences exercise based on wallet-level data, showing that investors with a better access to traditional finance react more strongly to policy announcements. In line with the model, the heightened response of this type of investors underpins the arbitrage channel of monetary policy transmission.

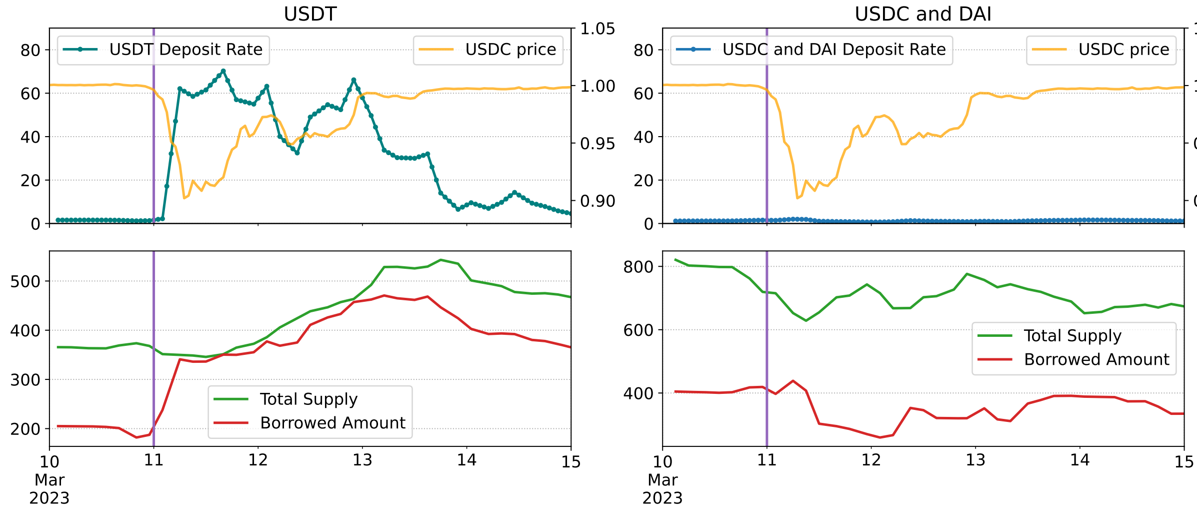
7.1 Anecdotal evidence from SVB shock

Silicon Valley Bank and USDC De-peg We begin with a natural experiment: the collapse of Silicon Valley Bank (SVB) on March 10, 2023, and the subsequent temporary de-pegging of USDC, motivated by the fact that roughly 10% of Circle's treasury was placed in deposits with SVB. This episode offers a clear illustration of how a coin-specific demand shock can propagate across DeFi lending markets.

Using intraday data, Figure 11 traces the response of interest rates and liquidity across major stablecoin pools. In the top-left panel, we observe a sharp spike in DeFi rates for USDT lending, while the top-right panel shows a more muted response in USDC and DAI. The bottom panels document the liquidity dynamics: the USDT pool experienced a surge in borrowing (red line) without an immediate increase in total supply (green line).

A possible explanation is that the increase in USDT borrowing demand reflects arbitrage

Figure 11: DeFi deposit rates and quantities around Silicon Valley Bank failure



Intraday data around the USDC de-peg on March 11, 2023. Top panels show the price of USDC (orange) and DeFi deposit rates for USDT (left) and USDC/DAI (right). Bottom panels display the total supplied liquidity (green) and borrowing volumes (red) in the corresponding pools.

activity. During the depeg, some market participants may have viewed the decline in the USDC price as temporary and sought to take a long position on USDC in anticipation of a recovery toward its $1 peg. To finance this trade, they could borrow USDT and use the proceeds to purchase discounted USDC, effectively betting on the convergence of the stablecoin price back to par. This arbitrage strategy creates additional demand for USDT borrowing even though the initial shock originates from USDC.

Meanwhile, the supply of USDT only gradually increased, leading to high utilization rate and exceptionally elevated deposit rates culminating at more than 60% (in annualized terms). This slow adjustment of supply is consistent with the presence of frictions that delayed capital inflows into the high-yielding USDT pool. For example, incumbent liquidity providers with market power may strategically refrain from expanding their deposits to avoid reducing the return earned on their existing balances.[31]

[31] Another factor behind the slow inflow of additional USDT deposits may have been the perceived increase in the overall riskiness of supplying liquidity to the Aave protocol, including liquidation and protocol-related risks.

The episode underscores how a localized demand shock, possibly driven by leverage demand to exploit available arbitrage opportunities in the broader DeFi space, can create lasting rate distortions when the supply side fails to respond elastically.

7.2 High-frequency DeFi spread analysis and transaction costs

DeFi Rate Jumps and Demand vs. Supply Shocks. To move beyond anecdotal evidence, we systematically identify discrete rate jump events in Aave lending protocol. For each stablecoin, we compute the daily change of the deposit rate and define an event as any observation where the change in the deposit rate exceeds 20 percentage points in absolute value. This procedure yields 89 *rate jump* episodes.

To classify the underlying drivers of these events, we decompose changes in market activity into borrowing (demand) and liquidity provision (supply). Let B_t denote total outstanding debt and S_t total supplied liquidity. For each event, we compute the contemporaneous changes ΔB_t and ΔS_t, and define net liquidity as $\Delta S_t - \Delta B_t$.

For rate increases ($\Delta \rho_t > 20$), a negative net liquidity change ($\Delta S_t - \Delta B_t < 0$) is interpreted as *demand-driven*, reflecting an expansion in borrowing relative to supply that tightens utilization. Conversely, a positive net liquidity change is classified as *supply-driven*, consistent with liquidity inflows. For rate decreases ($\Delta \rho_t < -20$), the classification is inverted: positive net liquidity changes are interpreted as demand-driven (declining borrowing), while negative net liquidity changes indicate supply-driven shocks (liquidity withdrawals).

This classification provides a simple, model-free approach to distinguish whether large interest rate movements are primarily driven by shifts in borrowing demand or liquidity supply in the protocol.

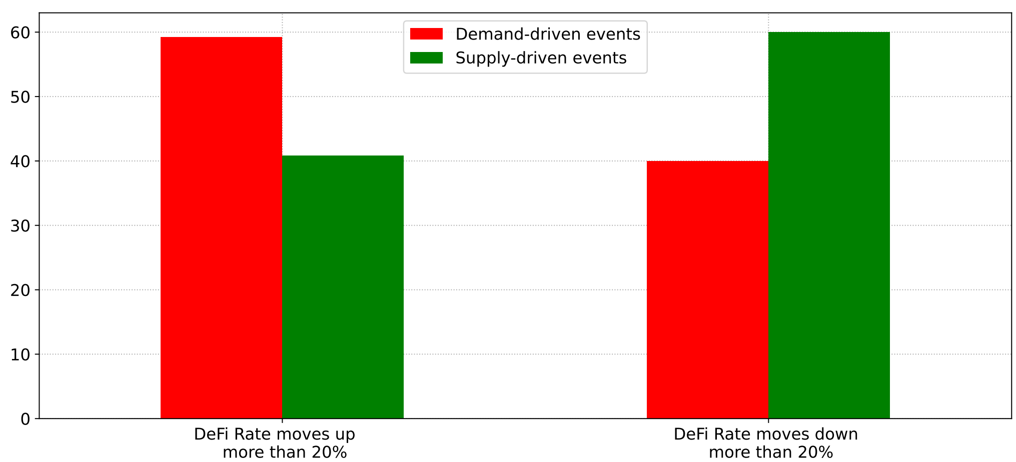
We find that among the 49 large DeFi rate increases, 59% are associated with surging demand, while 41% reflect declining supply. Conversely, among the 40 large DeFi rate decreases, 60% correspond to increased supply and only 40% to declining demand.

Figure 12 summarizes this classification. The left panel shows that rate increases are more likely to stem from a demand shock than from a supply contraction. The right panel confirms the mirror image for rate decreases. This pattern mirrors our findings in the SVB case study and supports the view that demand shocks are a relevant source of rate volatility.

Given that DeFi rates are bounded below by zero and average around 1% in our sample, a decline of 20 percentage points can only occur if rates had previously increased substantially. This pattern is therefore consistent with a dynamic in which an initial demand shock raises rates, followed by a supply response as liquidity providers add funds to the protocol, putting downward pressure on rates.

This observation motivates the following analysis on *Spread Decay*.

Figure 12: Demand and supply Shocks

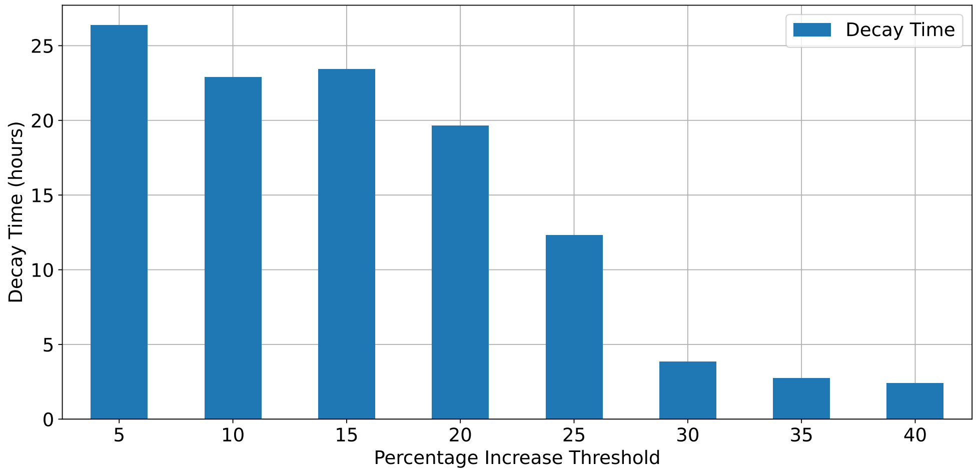


Classification of DeFi rate jumps exceeding $\pm 20\%$ based on net liquidity changes $\Delta S_t - \Delta B_t$. For upward (downward) rate moves, events are classified as demand-driven when net liquidity decreases (increases), and as supply-driven otherwise. Bars report the share of events in each category.

Spread Decay Next, we examine the persistence of the DeFi/risk-free rate spread following sudden increases. Using intraday data, we identify events where the coin-specific absolute spread (difference between the DeFi rate and the risk-free) exceeds a threshold k, with $k \in \{5\%, 10\%, ..., 40\%\}$. For each event, pooling USDT, USDC, and DAI, we measure the number of hours – that we label "decay time" – it takes for the spread to fall back below the same threshold.

Figure 13 displays the average decay time for each threshold. The results confirm a clear

Figure 13: Spread Decay



Average number of hours required for the DeFi/risk-free spread to decay below the threshold k, for values of k ranging from 5% to 40%.

asymmetry: moderate spread increases (e.g., 10–20%) can persist for many hours before mean-reverting. In contrast, very large spread events (above 30%) decay more quickly, likely because the arbitrage opportunity becomes too large to ignore even in the presence of frictions. These findings provide direct evidence of stickiness in the DeFi lending market and point toward an inelastic short-run supply response.

Gas fees and Spread Decay Finally, we explore whether Ethereum gas fees are a binding constraint on liquidity reallocation. For each spread spike event described above, we regress the decay time on the contemporaneous average gas price during the decay window. For each k, we run the specification:

$$\text{Spread Decay}_e = \alpha \; + \; \beta \text{ Gas fees}_e + \varepsilon_e$$

where e runs through all the identified events where the absolute spread exceeds the threshold k. The estimated regression coefficients across the different thresholds are displayed in Table 4. The results indicate a strong positive relationship between gas fees and spread persistence for moderate spread events (5–25%). The explanatory power of gas fees, as reflected in the R^2 values, is substantial in this range. However, for extreme spread movements (30–

40%), the relationship weakens, consistent with the idea that large arbitrage profits outweigh transaction costs.

Table 4: Regressions of spread decay time (in hours) on average gas prices during the decay window. Rows report results for spread thresholds k including estimated coefficients (β) and R2 values.

Threshold	Beta	p-value	R2	N
5%	0.69***	0.00	33%	572
10%	0.38***	0.00	35%	272
15%	0.37***	0.00	50%	135
20%	0.23***	0.00	51%	87
25%	0.12***	0.00	33%	67
30%	0.03*	0.03	10%	47
35%	-0.00	0.95	0%	16
40%	-0.03	0.53	4%	12

β of spread decay time (in hours) on average gas prices during the decay window. Rows report results for spread thresholds k including estimated coefficients (β) and R^2 values.

Overall, the evidence supports the interpretation that gas fees act as friction, preventing capital from flowing quickly into high-yield pools and prolonging DeFi interest rate divergence. The significance of this constraint is further corroborated by the relatively small scale of individual liquidity providers, as illustrated in Figure 20 in the Internet Appendix, which shows the distribution of liquidity provision positions for USDT, USDC and DAI.

7.3 Wallet-level differences-in-differences

In this section, we implement a difference-in-differences (DiD) design built around monetary policy announcements to analyze how LPs with access to traditional financial markets adjust their USDC liquidity relative to other LPs.

First, we identify policy events from changes in the Federal funds target rate: positive changes are hikes, and negative changes are cuts. Around each event, we construct a symmetric event window of 10 days before and 10 days after the announcement. Second, a key challenge is to proxy for investors with access to traditional financial markets. According to our model, those LPs should respond more actively to changes in Fed policy rates, modulating their supply of liquidity. This gives rise to the arbitrage channel of monetary policy transmission. We therefore consider three alternative proxies for such "TradFi" investors.

Our baseline proxy focuses on wallets that use only USDC on Aave and, more strictly, never held USDT or DAI anywhere on-chain over the sample. To enforce this, we use `web3` to query on-chain balances and transfer events and verify whether each wallet ever held USDT or DAI. These wallets are labeled `TradFi` = 1, while all other LPs form the control group. The underlying assumption is that USDC is widely regarded as the regulated stablecoin of choice for institutional investors and, more generally, for participants active in traditional financial markets, in terms of KYC and compliance with GENIUS and MiCAR regulations. We find that there are 8,985 wallets using only USDC in the Ethereum network active in Aave, consisting of 7.29% of LPs active around monetary policy announcements. Taken together, these wallets generate roughly 15% of the volume of USDC in our sample.

We also consider two alternative proxies motivated by the idea that institutional or TradFi-type investors are likely to operate at larger scale and with higher trading intensity. Namely, in specification (4), the `TradFi` dummy identifies wallets in the top decile of the distribution of transaction volumes ("size"), while in specification (5) it identifies wallets in the top decile of transaction frequency ("activeness"). While these proxies may capture more sophisticated or professional traders, they are less easily interpretable: high volume or frequency may also reflect purely crypto-native strategies that do not require access to traditional financial markets.

Third, in order to focus on economic agents, we remove from the sample wallets associated with smart contracts. Following the official Ethereum documentation, we do so by querying each account's bytecode using `web3` and discarding those for which the size of the bytecode is not zero[32]. For each wallet-event window, the outcome variable is the change in log liquidity supplied on Aave, Flow $= \Delta \log_{10}(1+S)$, where S denotes the wallet's cumulative supply position, computed as detailed in Section 5.2. The main DiD regressor is the interaction `post` × `TradFi`, where `post` indicates the period after the announcement. Hikes and cuts are pooled by multiplying the post period dummy with an opposite sign for cuts, so that the coefficient captures whether TradFi investors reduce liquidity after hikes and increase it after cuts, relative to non-TradFi wallets.

The baseline regression is:

$$\text{Flow}_{i,t,e} = \beta\,(\texttt{Post}_{t,e} \times \texttt{TradFi}_i) + \text{FE} + \varepsilon_{i,t,e},$$

where fixed effects (FE) are at the "day" or/and "LP", depending on the specification.

Identification comes from comparing the before-vs-after change around each policy announcement for TradFi wallets to the corresponding change for other LPs.

Results. The results in Table 5 show a clear and robust pattern for the USDC-based proxy. Across specifications (1)–(3), the coefficient on `post` × `TradFi` is negative and statistically significant. This indicates that, relative to other liquidity providers (LPs), LPs with access to traditional finance are more likely to withdraw liquidity from Aave following policy rate hikes and to expand their positions following rate cuts. In economic terms, the estimated coefficients imply that after a rate hike, TradFi investors reduce their liquidity positions by approximately 1 to 2 percentage points more than non-TradFi investors.

Importantly, this pattern remains robust as the specification is progressively strengthened. The result persists when including day fixed effects (column 2), which control for aggregate shocks common to all LPs, and when further adding LP fixed effects (column 3). The latter specification absorbs time-invariant wallet-level heterogeneity as well as common time

[32] Each Ethereum address corresponds to an account. There are two types of accounts: externally owned accounts (EOAs), that is, wallets, and smart contract accounts. EOAs (controlled by private keys) have empty bytecode (size = 0), while smart contract accounts store executable bytecode (size > 0). This filter does not have any significant impact on our results

Table 5: Difference-in-Differences Results

	(1)	(2)	(3)	(4)	(5)
	Flow	Flow	Flow	Flow	Flow
Post × TradFi	-0.018***	-0.019***	-0.013*	-0.001	-0.004
	(-3.046)	(-3.278)	(-1.711)	(-0.200)	(-0.707)
TradFi LP	0.020***	0.017***			
	(5.498)	(4.855)			
Post Period	-0.005*				
	(-1.921)				
Day FE		Yes	Yes	Yes	Yes
LP FE			Yes	Yes	Yes
TradFi Definition	USDC	USDC	USDC	Size	Activeness
N	1,166,298	1,166,298	1,166,298	1,166,298	1,166,298
R^2	0.000	0.002	0.023	0.023	0.023

The dependent variable is the change in log liquidity supplied on AAVE. The `TradFi` dummy is a proxy to indicate investors with access to traditional financial markets. In specifications (1) to (3) the proxy indicates wallets that never held USDT nor DAI during our sample period, thus capturing the notion that USDC is the preferred choice of institutional investors. In specification (4) and (5), the proxy is built by identifying the top decile of the distributions of trade sizes and number of trades, respectively. The `post` dummy indicates the days including and following the monetary policy announcement Standard errors are double clustered by user and day, and are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

trends, reinforcing the interpretation that the estimated effect reflects differential responses to monetary policy actions rather than compositional or aggregate effects.

In contrast, the alternative proxies based on transaction size and activeness (columns 4 and 5) yield coefficients that are small and statistically insignificant, even though the point estimate is still negative. This suggests that these proxies do not successfully isolate investors with meaningful exposure to traditional financial markets.

The fact that the USDC-based proxy delivers strong and consistent results resonates with the VAR evidence discussed above. In that analysis, we show that the arbitrage channel of monetary policy transmission is particularly strong for USDC, whereas it is dominated by the leverage channel for USDT and DAI. This pattern is consistent with a larger presence of investors lacking direct access to traditional finance in USDT and DAI markets, while USDC markets appear more tightly connected to traditional money markets and thus more responsive to arbitrage opportunities between rates.

8 Concluding Remarks and Policy Implications

While we document a substantial disconnect between U.S. risk-free rates and stablecoin deposit rates, our findings nonetheless show that U.S. monetary policy significantly influences stablecoin lending rates through quantities lent and borrowed in DeFi lending protocols. We identify two key economic channels through which monetary policy is transmitted.

First, monetary tightening reduces the demand for leverage and weakens collateral values, jointly lowering borrowing demand following a rate hike. Second, an arbitrage channel operates through investors with access to both traditional and decentralized financial markets: after a rate hike, these investors withdraw stablecoins previously lent via DeFi protocols and reallocate them toward higher-yielding opportunities in U.S. traditional financial markets.

Our empirical results indicate that the first mechanism—operating through leverage demand and collateral valuation—dominates, particularly in the short run and for stablecoins predominantly held by investors with limited access to U.S. traditional financial markets.

In addition, we document significant stickiness on the supply side of stablecoin lending, which helps explain the persistent spread between DeFi deposit rates and risk-free rates. This rigidity is amplified by observable frictions such as transaction fees. As a result, crypto-specific shocks dissipate only gradually and play a central role in driving fluctuations in stablecoin lending rates.

From a policy perspective, two key questions arise: what would be the critical size of DeFi beyond which it would represent an interest rate controllability challenge, and by then do we think the integration of DeFi will be sufficient to rely on market forces and arbitrage to ensure the convergence of rates ? On one hand, the growth of DeFi could well enhance arbitrage, thereby narrowing the disconnect by itself. On the other hand, the demand for leverage may continue to drive rates. A potential game-changer could be the development of remunerated tokenized securities like tokenized T-bills and tokenized MMF, whose interest rates would be more directly influenced by monetary policy rates and which would facilitate on-chain arbitrage. But this greater availability will not necessarily be sufficient, as these instruments generally require KYC and whitelisting, which may still not be the preference of a fraction of the DeFi market players.

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Appendix A: Main Appendix

A.1 Descriptive statistics

Table 6: Descriptive Statistics - DeFi Lending by Stablecoin

Symbol	Variable	Mean	Median	Std. Dev.	p5	p95	n
DAI	Deposit rate (%)	4.15	3.11	3.10	0.81	10.02	1325
	log(B)	18.93	18.66	1.09	17.50	21.15	1325
	log(S)	19.31	18.94	1.01	18.19	21.39	1325
	u (%)	71.29	77.25	18.64	31.66	91.78	1325
USDC	Deposit rate (%)	4.46	3.65	3.28	0.64	10.67	1325
	log(B)	20.77	20.95	1.14	18.70	22.26	1325
	log(S)	21.12	21.15	0.99	19.64	22.47	1325
	u (%)	73.43	79.89	18.85	33.43	92.01	1325
USDT	Deposit rate (%)	4.69	3.55	3.52	1.39	11.50	1325
	log(B)	20.38	20.52	1.28	18.13	22.33	1325
	log(S)	20.71	20.75	1.13	19.17	22.60	1325
	u (%)	74.00	77.84	15.14	39.09	91.22	1325

Macro variables

Variable	Mean	Median	Std. Dev.	p5	p95	n
log(BTC)	10.77	10.76	0.56	9.87	11.62	1325
log(S&P 500)	8.48	8.42	0.18	8.25	8.81	1279
SOFR rate (%)	3.21	4.30	2.13	0.01	5.33	1273
U.S. Treas. 2-year (%)	3.22	3.89	1.66	0.15	4.96	1323
VIX (Index)	19.25	17.95	5.26	12.92	30.11	1307
MP surprises (bps)	0.87	0.73	2.80	-3.56	5.47	40

A.2 Cointegration tests

Table 7: Cointegration Tests by Token and Rate over the whole sample

Rate	Engle-Granger stat	Engle-Granger p-val	Johansen	Crit. 95%	alpha	beta	R2
DAI							
SOFR	-3.39	0.04	23.30	15.49	3.75***	0.12	0.01
Fed Funds (EFFR)	-3.39	0.04	23.01	15.49	3.75***	0.12	0.01
Discount rate	-3.39	0.04	22.19	15.49	3.73***	0.12	0.01
UST 1M	-3.41	0.04	18.47	15.49	3.69***	0.15*	0.01
UST 3M	-3.34	0.05	28.25	15.49	3.91***	0.07	0.00
UST 12M	-3.25	0.06	23.19	15.49	4.34***	-0.05	0.00
UST 2Y	-3.23	0.07	18.10	15.49	4.50***	-0.11	0.00
UST 5Y	-3.23	0.07	16.11	15.49	4.53***	-0.12	0.00
UST 10Y	-3.29	0.06	15.34	15.49	4.09***	0.03	0.00
USDC							
SOFR	-3.09	0.09	26.38	15.49	3.97***	0.15*	0.01
Fed Funds (EFFR)	-3.09	0.09	25.94	15.49	3.97***	0.15*	0.01
Discount rate	-3.09	0.09	25.32	15.49	3.95***	0.15	0.01
UST 1M	-3.11	0.09	20.20	15.49	3.91***	0.17*	0.01
UST 3M	-3.05	0.10	32.17	15.49	4.16***	0.09	0.00
UST 12M	-2.99	0.11	26.34	15.49	4.65***	-0.05	0.00
UST 2Y	-2.96	0.12	19.61	15.49	4.83***	-0.12	0.00
UST 5Y	-2.97	0.12	17.44	15.49	4.81***	-0.11	0.00
UST 10Y	-3.03	0.10	16.79	15.49	4.27***	0.06	0.00
USDT							
SOFR	-3.74	0.02	29.67	15.49	4.78***	-0.03	0.00
Fed Funds (EFFR)	-3.73	0.02	29.99	15.49	4.79***	-0.03	0.00
Discount rate	-3.73	0.02	29.95	15.49	4.79***	-0.03	0.00
UST 1M	-3.74	0.02	25.11	15.49	4.74***	-0.01	0.00
UST 3M	-3.71	0.02	33.16	15.49	4.94***	-0.08	0.00
UST 12M	-3.68	0.02	33.19	15.49	5.43***	-0.22**	0.02
UST 2Y	-3.67	0.02	29.23	15.49	5.67***	-0.30***	0.03
UST 5Y	-3.65	0.02	26.92	15.49	5.93***	-0.39***	0.03
UST 10Y	-3.68	0.02	25.76	15.49	5.70***	-0.29*	0.01

Note: The table reports the results of two standard cointegration tests applied to the long-run relationship between the deposit rate of each stablecoin and a set of interest rate benchmarks at a weekly frequency. For each rate, the long-run equation is first estimated by ordinary least squares (OLS), and the Engle-Granger test is applied to the residuals to assess whether they are stationary, which would indicate cointegration. Finally, the Johansen trace statistic is computed on the corresponding bivariate system; the null hypothesis of no cointegration is rejected when the trace statistic exceeds its 95% critical value (15 in this setting). The coefficients α and β correspond to the intercept and long-run elasticity from the OLS regression; under cointegration, these estimates are known to be super-consistent. However, the significance stars reported for α and β should be interpreted as descriptive indicators of numerical precision rather than as formal parametric inference.

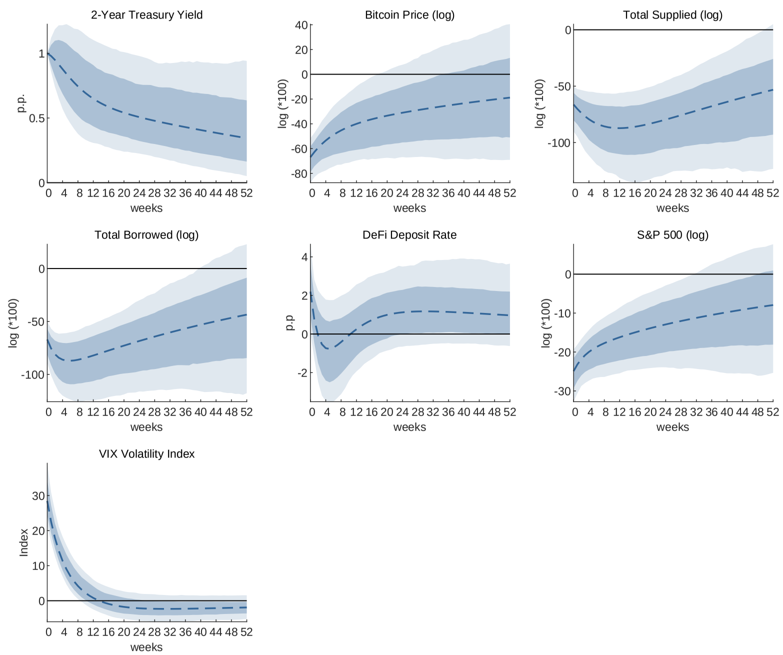
Table 8: Cointegration Tests by Token and Rate outside the ZLB period

Rate	Engle-Granger stat	Engle-Granger p-val	Johansen	Crit. 95%	alpha	beta	R2
			DAI				
SOFR	-2.98	0.12	26.16	15.49	0.69	0.79***	0.22
Fed Funds (EFFR)	-2.97	0.12	25.86	15.49	0.67	0.79***	0.21
Discount rate	-2.97	0.12	25.30	15.49	0.54	0.79***	0.21
UST 1M	-3.04	0.10	21.18	15.49	0.67	0.80***	0.23
UST 3M	-2.91	0.13	32.21	15.49	0.70	0.77***	0.18
UST 12M	-2.78	0.17	29.04	15.49	0.62	0.79***	0.12
UST 2Y	-2.88	0.14	26.13	15.49	-0.56	1.12***	0.14
UST 5Y	-3.15	0.08	26.41	15.49	-2.62***	1.71***	0.19
UST 10Y	-3.14	0.08	23.67	15.49	-2.86***	1.74***	0.20
			USDC				
SOFR	-3.29	0.06	25.93	15.49	0.51	0.90***	0.26
Fed Funds (EFFR)	-3.28	0.06	25.53	15.49	0.50	0.90***	0.26
Discount rate	-3.27	0.06	25.13	15.49	0.35	0.90***	0.25
UST 1M	-3.36	0.05	19.94	15.49	0.53	0.91***	0.27
UST 3M	-3.20	0.07	32.37	15.49	0.56	0.87***	0.22
UST 12M	-3.02	0.11	28.59	15.49	0.54	0.88***	0.14
UST 2Y	-3.12	0.08	24.35	15.49	-0.71	1.22***	0.15
UST 5Y	-3.42	0.04	24.63	15.49	-3.14***	1.92***	0.22
UST 10Y	-3.49	0.03	22.38	15.49	-3.71***	2.03***	0.26
			USDT				
SOFR	-4.32	0.00	36.80	15.49	1.36***	0.71***	0.17
Fed Funds (EFFR)	-4.32	0.00	36.64	15.49	1.35***	0.71***	0.17
Discount rate	-4.31	0.00	36.66	15.49	1.22**	0.71***	0.17
UST 1M	-4.39	0.00	31.74	15.49	1.43***	0.70***	0.18
UST 3M	-4.24	0.00	40.32	15.49	1.34***	0.70***	0.15
UST 12M	-4.10	0.01	40.27	15.49	1.25*	0.73***	0.10
UST 2Y	-4.17	0.00	38.12	15.49	0.14	1.03***	0.12
UST 5Y	-4.37	0.00	38.61	15.49	-1.60*	1.54***	0.15
UST 10Y	-4.35	0.00	36.25	15.49	-1.71*	1.54***	0.16

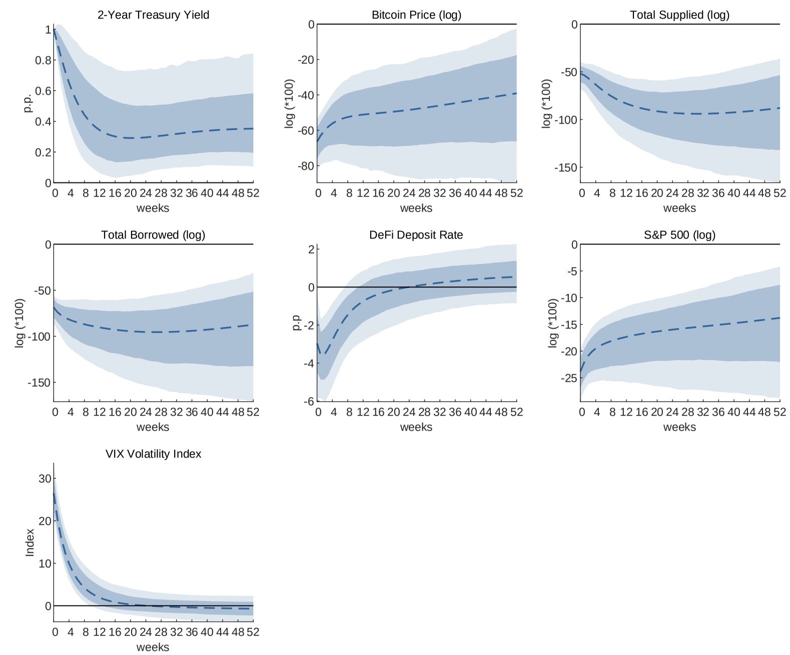
Note: The table reports the results of two standard cointegration tests applied to the long-run relationship between the deposit rate of each stablecoin and a set of interest rate benchmarks at a weekly frequency. We discard 2021, as this year exhibits very few changes in risk-free rates substantially affecting the results of cointegration tests. For each rate, the long-run equation is first estimated by ordinary least squares (OLS), and the Engle-Granger test is applied to the residuals to assess whether they are stationary, which would indicate cointegration. Finally, the Johansen trace statistic is computed on the corresponding bivariate system; the null hypothesis of no cointegration is rejected when the trace statistic exceeds its 95% critical value (15 in this setting). The coefficients α and β correspond to the intercept and long-run elasticity from the OLS regression; under cointegration, these estimates are known to be super-consistent. However, the significance stars reported for α and β should be interpreted as descriptive indicators of numerical precision rather than as formal parametric inference.

A.3 Additional specifications

Figure 14: Impulse responses - excluding 2021



(a) USDC

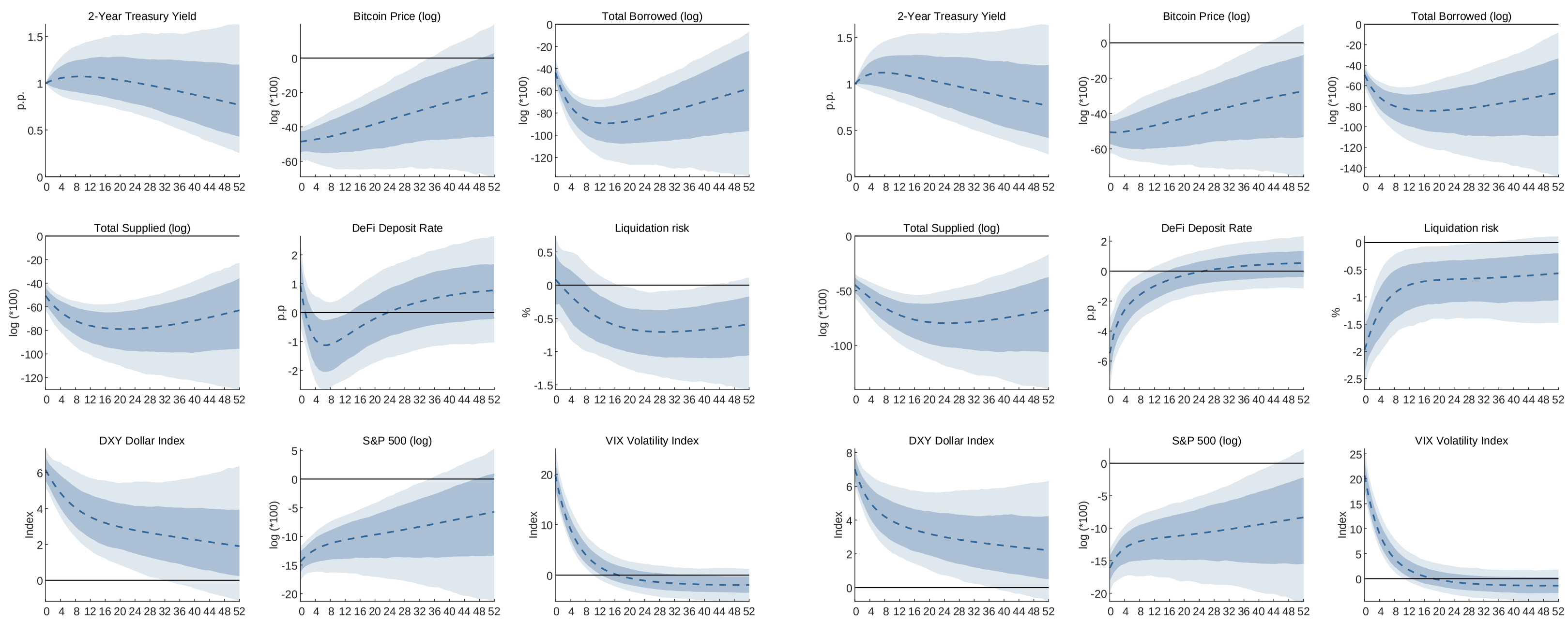


(b) USDT

Notes: 7-variable baseline VAR, with 1-week lags (BIC criterion). Shock identified with Acosta et al. (2025) average weekly FOMC statement surprise. The shock is normalized to induce a 100 basis point increase in the 2-year U.S Treasury yield. Sample: January 2022-January 2026. Shaded areas are 90 percent (dark blue) and 68 percent (light blue) posterior coverage bands.

Figure 15: Impulse responses - Liquidation Risk and DXY Index

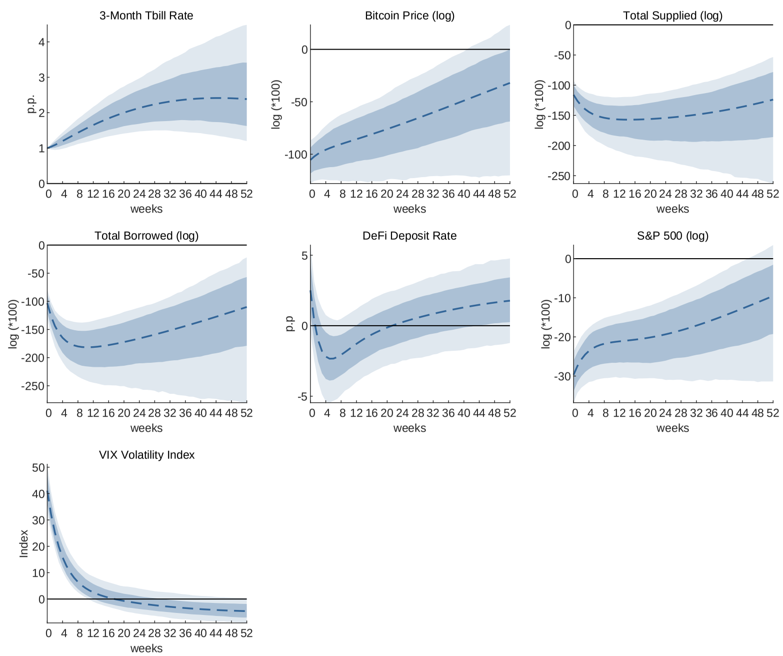
(a) USDC **(b)** USDT



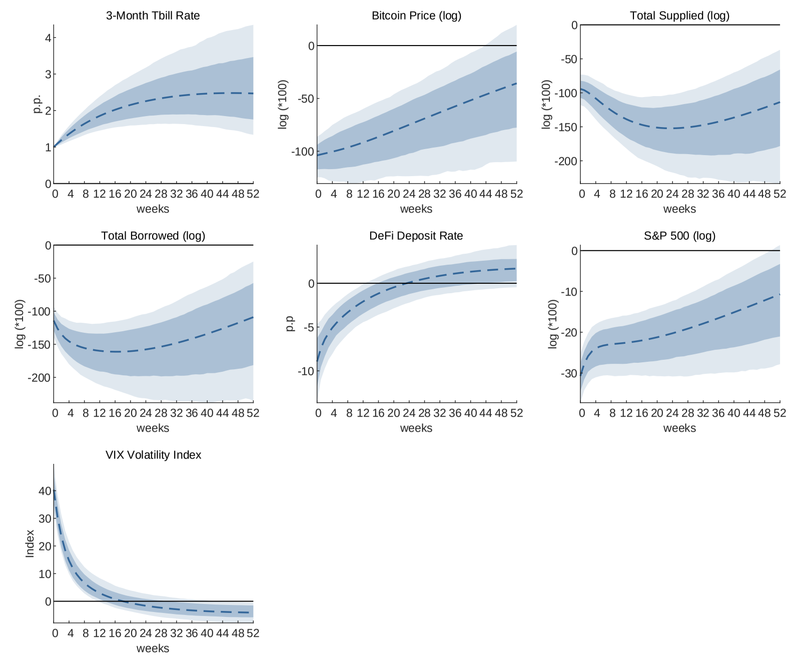
Notes: 7-variable baseline VAR, with 1-week lags (BIC criterion). Shock identified with Acosta et al. (2025) average weekly FOMC statement surprise. The shock is normalized to induce a 100 basis point increase in the 2-year U.S Treasury yield. Sample: January 2022-January 2026. Shaded areas are 90 percent (dark blue) and 68 percent (light blue) posterior coverage bands.

Figure 16: Impulse responses - 3-month Tbill as policy variable

(a) USDC



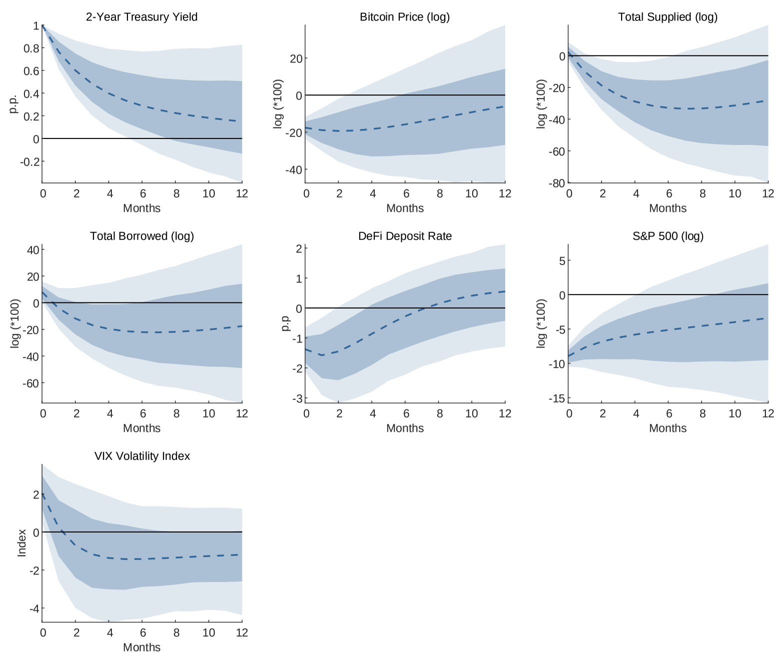
(b) USDT



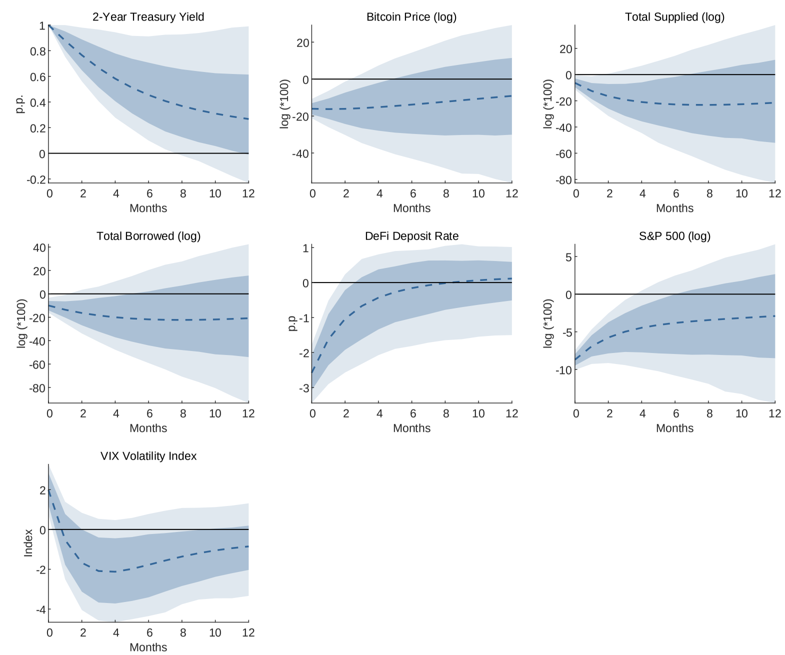
Notes: 7-variable baseline VAR, with 1-week lags (BIC criterion). Shock identified with Acosta et al. (2025) average weekly FOMC statement surprise. The shock is normalized to induce a 100 basis point increase in the 3-month U.S. Treasury Bill yield. Sample: January 2022-January 2026. Shaded areas are 90 percent (dark blue) and 68 percent (light blue) posterior coverage bands.

Figure 17: Impulse responses - Monthly data

(a) USDC



(b) USDT



Notes: 7-variable baseline VAR, with 1-month lags (BIC criterion). Shock identified with Acosta et al. (2025) average monthly FOMC statement surprise. The shock is normalized to induce a 100 basis point increase in the 2-year U.S Treasury yield. Sample: January 2022-January 2026. Shaded areas are 90 percent (dark blue) and 68 percent (light blue) posterior coverage bands.

Appendix B: Internet Appendix

B.1 More on the model

In this section, we begin by providing the key computations that underpin the model's main results. We then present a simple extension of the baseline model when liquidity providers are not atomistic and compete imperfectly.

B.1.1 Derivations of model's main results

We denote by $\Delta = 1-\tau$ the wedge due to taxes, so that the post-tax risk-free rate is $\Delta(1+\rho^\star)$. Further, $D = \theta(1-\theta)\gamma\psi^2$.
When the stablecoin deposit rate adjusted for risks is higher than the risk-free rate, i.e., $\rho^\star \leqslant \rho - \theta\psi$ with $rho = uf(u)(1-r)$, we have

$$
\begin{aligned}
S \cdot D &= (1-\mu)\left(1+\rho-\theta\psi-(1+\rho^\star)\right) + \mu\left(1+\rho-\theta\psi - \int_0^{1/(1+\rho^\star)} 1 d\Delta - \int_{1/(1+\rho^\star)}^{1} (1+\rho^\star)\Delta d\Delta\right) \\
&= 1+\rho-\theta\psi-(1-\mu)(1+\rho^\star) - \mu/(1+\rho^\star) - \mu(1+\rho^\star)[\Delta^2/2]_{1/(1+\rho^\star)}^{1} \\
&= 1+\rho-\theta\psi-(1-\mu)(1+\rho^\star) - \mu/(1+\rho^\star) - \frac{\mu}{2}(1+\rho^\star)[1-1/(1+\rho^\star)^2] \\
&= 1+\rho-\theta\psi-(1-\mu)(1+\rho^\star) - \mu/(1+\rho^\star) - \frac{\mu}{2}[1+\rho^\star-1/(1+\rho^\star)] \\
&= 1+\rho-\theta\psi-(1-\mu)(1+\rho^\star) - \frac{\mu}{2}[1+\rho^\star+1/(1+\rho^\star)] \\
&= \rho-\theta\psi-(1-\mu)\rho^\star - \frac{\mu}{2}[\rho^\star+1/(1+\rho^\star)-1] \\
&= \rho-\theta\psi-(1-\mu)\rho^\star - \frac{\mu}{2}\frac{(\rho^\star)^2}{1+\rho^\star} \\
&\sim \rho-\theta\psi-(1-\mu)\rho^\star - \frac{\mu}{2}[\rho^\star]^2
\end{aligned}
$$

When $\rho^\star \geqslant \rho - \theta\psi$, intead, we have

$$\begin{aligned}
S \cdot D &= (1-\mu)0 + \mu \left(\int_0^{1/(1+\rho^\star)} \frac{1+\rho-\theta\psi-1}{\theta(1-\theta)\gamma\psi^2} d\Delta + \int_{1/(1+\rho^\star)}^{(1+\rho-\theta\psi)/(1+\rho^\star)} \frac{1+\rho-\theta\psi-\Delta(1+\rho^\star)}{\theta(1-\theta)\gamma\psi^2} d\Delta \right) \\
&= (1-\mu)0 + \mu \left(\int_0^{(1+\rho-\theta\psi)/(1+\rho^\star)} \frac{\rho-\theta\psi}{\theta(1-\theta)\gamma\psi^2} d\Delta + \int_{1/(1+\rho^\star)}^{(1+\rho-\theta\psi)/(1+\rho^\star)} \frac{1-\Delta(1+\rho^\star)}{\theta(1-\theta)\gamma\psi^2} d\Delta \right) \\
&= \frac{\mu}{\theta(1-\theta)\gamma\psi^2} \left(\frac{\rho-\theta\psi}{1+\rho^\star}(1+\rho-\theta\psi) + \left[\Delta - \frac{\Delta^2}{2}(1+\rho^\star) \right]_{1/(1+\rho^\star)}^{(1+\rho-\theta\psi)/(1+\rho^\star)} \right) \\
&= \frac{\mu}{\theta(1-\theta)\gamma\psi^2} \left(\frac{\rho-\theta\psi}{1+\rho^\star}(2+\rho-\theta\psi) - \frac{1}{2(1+\rho^\star)} \left((1+\rho-\theta\psi)^2 - 1 \right) \right) \\
&= \frac{\mu(\rho-\theta\psi)}{\theta(1-\theta)\gamma\psi^2} \frac{2+\rho-\theta\psi}{2(1+\rho^\star)}
\end{aligned}$$

B.1.2 Imperfect Competition among liquidity providers

In this subsection, we extend the baseline model to account for imperfect competition due to large liquidity providers. To simplify the exposition, we assume that the liquidity providers are risk-neutral making their decision independent of the risky investors' decision and that there is no reserve rate, $r = 0$. We also abstract for the friction limiting the access to traditional financial, that is, we assume $\mu = 0$. In the pure and perfect competition case, the deposit rate is determined in equilibrium as:

$$uf(u) = \rho^* + \theta\psi. \tag{12}$$

Imperfect competition To introduce imperfect competition, we assume a finite number of symmetric liquidity providers, $n > 2$. For simplicity we also assume a linear yield function. Given other liquidity providers' lending S_{-1} and risky investors borrowing B (with $S_{-1} > B$), the optimization program of a liquidity provider is:

$$\max_{S \geqslant 0} \left[\frac{B}{S+S_{-1}} f\left(\frac{B}{S+S_{-1}}\right) - \theta\psi - \rho^* \right] S, \tag{13}$$

which yields the interior solution:

$$(uf(u) - \theta\psi - \rho^*) + \frac{S}{S + S_{-1}}(-u)(uf'(u) + f(u)) = 0, \tag{14}$$

As in symmetric equilibrium $S = S_{-1}/(n-1)$, we get:

$$uf(u) = \frac{n}{n-2}(\rho^* + \psi\theta).$$

Testable implication: The higher the concentration (low n), the higher the deposit rate, the larger the impact of the risk-free rate on deposit rate.

The intuition goes as follows. When concentration is higher, lenders have more monopoly power so they can charge a higher markup between the marginal gain $uf(u)$ and the marginal cost $\rho^* + \psi\theta$. As a consequence, the deposit rate is more sensitive to monetary policy.

This testable implication omits two important features that may matter in practice: (i) the dynamics dimension may lead to lower rather than higher pass-through due to imperfect competition; (ii) the kink in the yield function can be strategically used by lenders to get higher profits—and especially when utilization rate is high.

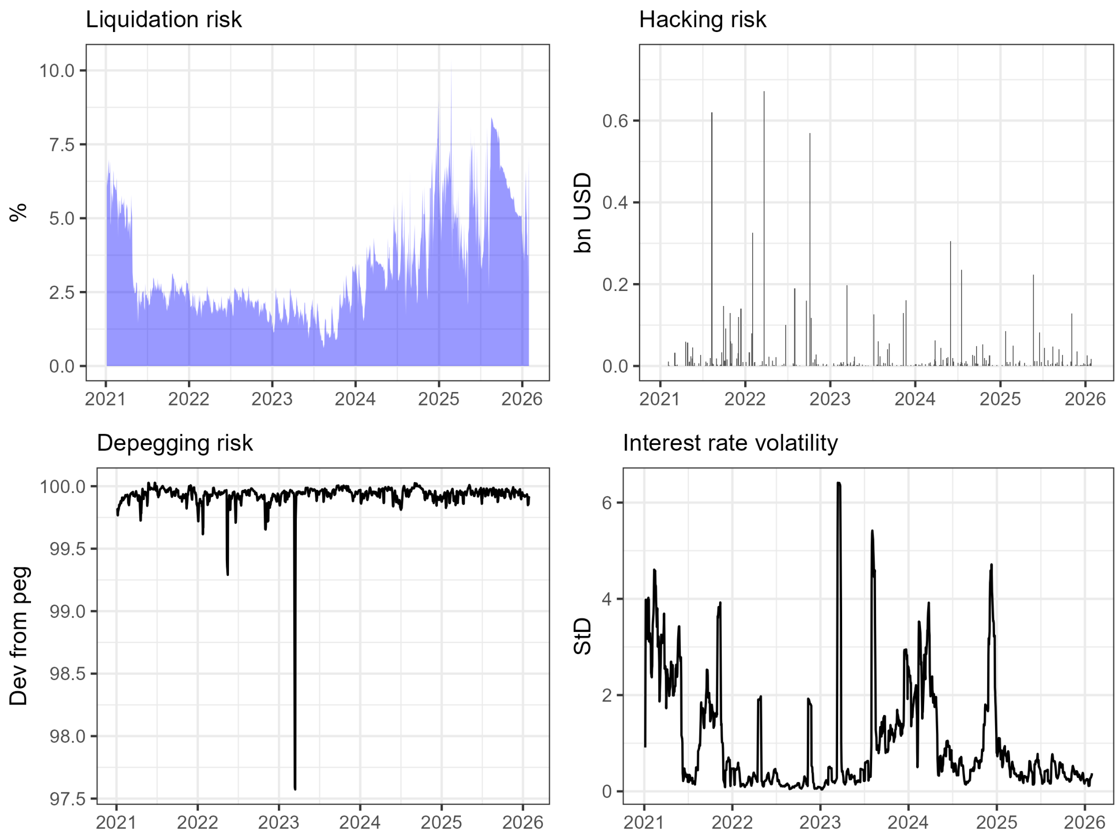
B.2 Additional figures

Figure 18: Yield generation on USD-pegged stablecoins

	Non yield-bearing Stablecoins (USDC, USDT, EURC...)	**Yield-bearing Stablecoins** (Ethena USDe, DAI (via DSR))
Native Yield (paid to the tokens' holders by the issuers)	0% (MiCA, GENIUS)	e.g. Ethena sUSDE: 12.1% (with protocol incentives)
Rewards/Staking (paid by platforms or protocols e.g. Coinbase, Kraken)	e.g. on Coinbase 3.50% (GENIUS) / 0% (MiCA)	e.g. Dai Savings Rate 3.75%
DeFi lending (rates paid to depositors in lending protocols e.g. aave, Morpho)	e.g. Aave: 1.6-4.25 % on USDC incl. incentives and rewards	e.g. Aave: 1-4.5 % on USDe incl. incentives and rewards

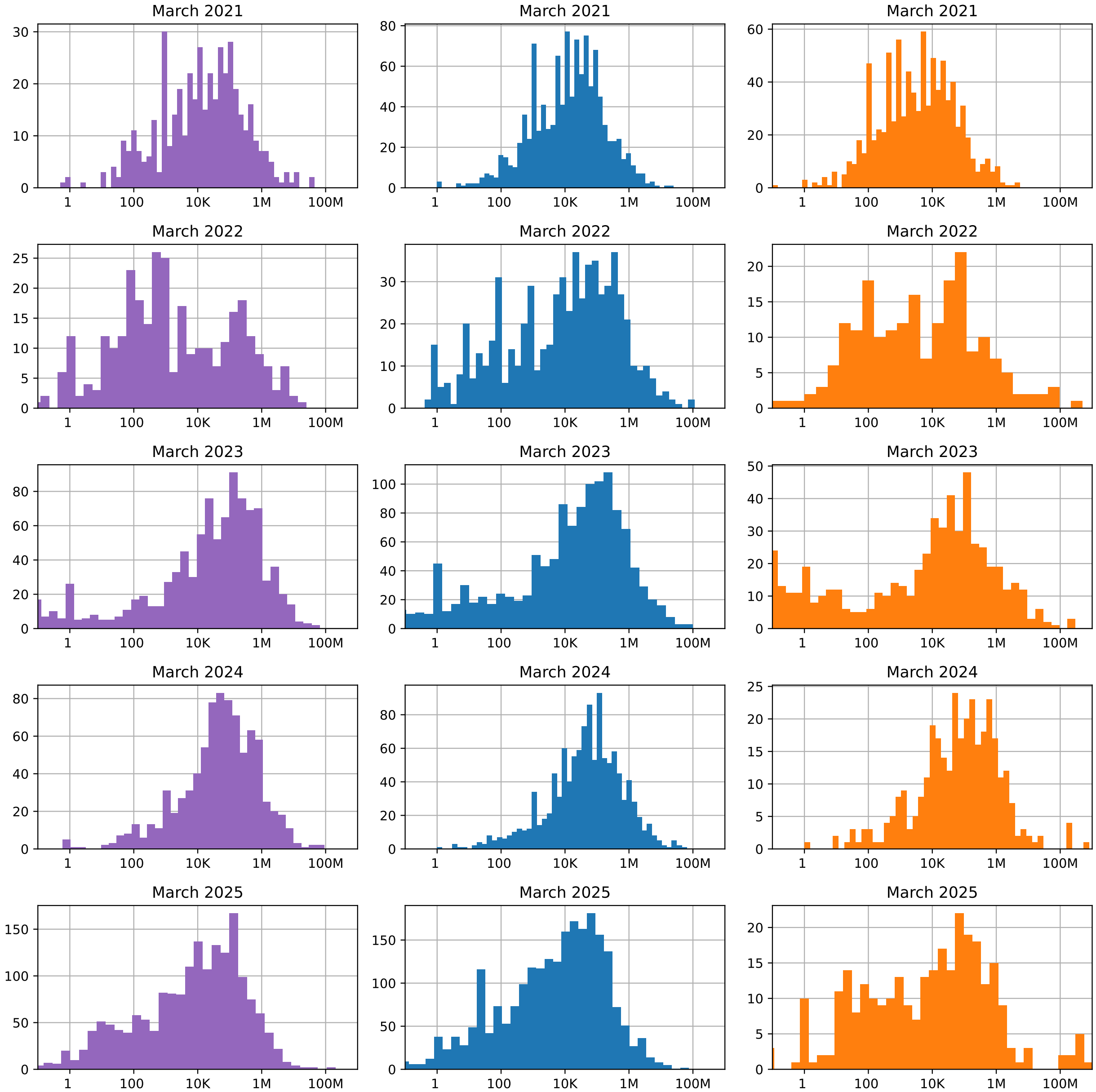
Note: Range of yields observed as of March 2025 for stablecoins, across chains and protocols. In MiCAR, crypto-asset service providers (CASPs) may borrow stablecoins and pay interest to lenders, provided that such remuneration is not linked only to passive holdings of stabelcoin tokens. This table does not reflect the latest discussions on CLARITY Act. Source: DeFiLlama, Aavescan, RWA.xyz, protocols' websites.

Figure 19: DeFi risks proxies



Liquidation risk, averaged across major stablecoins (USDC, USDT, DAI). The measure combines option-implied crash probabilities for BTC and ETH (10% price drop over a one-month horizon), with protocol-level loss exposure on Aave, computed from wallet-level positions under a 10% collateral shock. The resulting metric reflects a forward-looking, market-based proxy for systemic risk in decentralized lending. The series is expressed in percentage units of percentage loss relative to the total amount of deposited liquidity. Hack risks is proxied by the Hacked TVL reported in DeFiLlama, in billion USD. Depegging risk is the 5-day moving average of the lowest price reached by USDC, USDT and DAI. Interest rate risk is the 10-day rolling standard deviation of DeFi deposit rates.

Figure 20: Distribution of liquidity positions size across coins and years



End-of-month shapshots of the distribution of liquidity positions size across coins and years, on a logarithmic scale. The vertical axis is the frequency and the horizontal axis is the deposited amound in US Dollars. The left column refers to USDT, the middle one refers to USDC, and the righmost one refers to DAI.

B.3 Computation of Liquidation Risk

This appendix contains a detailed description of the construction of the liquidation risk metric.

B.3.1 Option-Implied Crash Probabilities

We start by constructing a forward-looking measure of crash risk from option prices on Bitcoin (BTC) and Ethereum (ETH) traded on Deribit. The measure captures the risk-neutral probability of a large negative return over a one-month horizon.

We use end-of-day quotes for European put options. For each day t, we retain out-of-the-money (OTM) contracts with strike $K < S_t$, where S_t denotes the underlying spot price. Option prices are expressed in USD and aggregated at the daily frequency using median quotes.

To obtain a constant maturity, we restrict our attention to options with a time-to-maturity between 20 and 40 days and select, for each day, the most liquid expiration.

Our approach exploits the mapping between option prices and the risk-neutral distribution of future prices (Breeden and Litzenberger, 1978). Rather than estimating second derivatives of option prices, we recover tail probabilities using a numerically stable, first-derivative approximation.

Let $P(K)$ denote the price of a European put with strike K. We approximate the slope of the price function using local finite differences:

$$\frac{\partial P}{\partial K} \approx \frac{P(K_+) - P(K_-)}{K_+ - K_-},$$

where K_- and K_+ denote the adjacent strikes.

Let $\alpha = K/S_t$ denote moneyness. The risk-neutral cumulative probability of returns below $\alpha - 1$ is given by:

$$\mathbb{Q}_t\big(R < \alpha - 1\big) = \alpha \left(\frac{\partial P}{\partial K} - \frac{P(K)}{K} \right),$$

which follows from no-arbitrage restrictions linking option prices to state prices. We truncate negative values to zero.

We interpolate the estimated cumulative distribution across strikes to obtain a smooth mapping from return thresholds to probabilities. The crash probability is defined as:

$$\text{CrashProb}_t = \mathbb{Q}_t \left(R_{t,t+1M} < -10\% \right).$$

In implementation, we interpolate over a grid of return thresholds and extract the value at -10%. The measure reflects risk-neutral, rather than physical, probabilities and therefore embeds both expected downside risk and compensation for bearing tail risk. It provides a market-based, forward-looking proxy for extreme downside risk, closely related to option-implied tail risk measures studied in Bakshi et al. (2003).

B.3.2 Bad loans under a collateral price shock

We next translate market-implied crash risk into protocol-level credit losses. Using wallet-level data from Aave v3, we estimate, for each day, the amount of debt that would become undercollateralized following a sudden 10% decline in the price of the collateral asset. Our procedure is closely related in spirit to the wallet-level stress-testing approach in Tovanich et al. (2023).

We combine three data sources. First, we obtain wallet-level borrowing, repayment, supply, withdrawal, and liquidation events from Aave v3 data retrieved from Dune Analytics. Second, we merge these positions with daily token prices in USD. Third, we use reserve-level information on outstanding variable debt to scale bad loans by the size of the protocol's credit exposure.

We restrict attention to economically meaningful borrowers. Specifically, we retain addresses with cumulative borrowing volume above a minimum threshold and reconstruct, for each wallet and each token, the time series of outstanding supplied and borrowed balances by cumulating past actions.

For each wallet, we recover the stock of collateral and debt from the sequence of on-chain actions. Supplies increase collateral positions, while withdrawals reduce them. Borrows increase debt positions, while repayments and liquidations reduce them. Let $\mathrm{Dep}_{u,j,t}$ denote wallet u's end-of-day collateral holdings in token j, and let $\mathrm{Bor}_{u,j,t}$ denote the corresponding end-of-day debt position. These quantities are obtained by cumulatively summing all past flows at the wallet-token level and truncating negative balances at zero.

We then value all positions in USD using contemporaneous token prices. For collateral positions, we impose a stress scenario in which the value of BTC- and ETH-linked collateral falls by 10%. Formally, if $p_{j,t}$ denotes the token price on day t, stressed collateral values are computed as

$$\widetilde{\mathrm{DepUSD}}_{u,j,t} = 0.9 \times \mathrm{Dep}_{u,j,t} \times p_{j,t},$$

while debt values remain at

$$\mathrm{BorUSD}_{u,j,t} = \mathrm{Bor}_{u,j,t} \times p_{j,t}.$$

Following the stress test, we aggregate each wallet's collateral and debt across tokens:

$$\widetilde{\mathrm{DepUSD}}_{u,t} = \sum_j \widetilde{\mathrm{DepUSD}}_{u,j,t}, \qquad \mathrm{BorUSD}_{u,t} = \sum_j \mathrm{BorUSD}_{u,j,t}.$$

A wallet is treated as generating bad debt when stressed collateral is insufficient to cover its outstanding debt, inclusive of liquidation costs. Let λ denote the liquidation bonus. In the baseline implementation, we set

$$\lambda = 0.05.$$

The fraction of a wallet's debt that becomes bad is then

$$\mathrm{BadShare}_{u,t} = \max\left\{0,\ 1 - \frac{\widetilde{\mathrm{DepUSD}}_{u,t}}{(1+\lambda)\mathrm{BorUSD}_{u,t}}\right\},$$

capped at one. The dollar value of bad loans for wallet u on day t is therefore

$$\mathrm{BadLoan}_{u,t} = \mathrm{BadShare}_{u,t} \cdot \mathrm{BorUSD}_{u,t}.$$

Aggregating across wallets yields total bad loans on day t:

$$\mathrm{BadLoans}_t = \sum_u \mathrm{BadLoan}_{u,t}.$$

To express losses relative to protocol size, we divide aggregate bad loans by total outstanding variable debt on the corresponding reserves:

$$\text{BadLoanPct}_t = \frac{\text{BadLoans}_t}{\text{TotalBorrowed}_t}.$$

This produces a daily measure of the share of protocol debt that would become impaired under a 10% collateral price shock.

This measure captures the cross-sectional fragility of Aave's borrower base to abrupt declines in collateral values. Because it is constructed from wallet-level exposures, it incorporates both leverage and heterogeneity in balance-sheet composition. Combined with the option-implied crash probability from the previous subsection, it yields a forward-looking proxy for liquidation risk that reflects both the likelihood of a sharp market decline and the losses such a decline would generate within the lending protocol.

B.3.3 Expected liquidation risk

We combine the option-implied crash probability with the protocol-level loss given a price shock to obtain a forward-looking proxy for expected liquidation risk.

Let CrashProb_t denote the risk-neutral probability of a 10% price decline over the next month, as constructed in Section A.1. Let BadLoanPct_t denote the fraction of protocol debt that becomes impaired under such a shock, as constructed in Section A.2.

We define expected liquidation risk as:

$$\text{LiqRisk}_t = \text{CrashProb}_t \times \text{BadLoanPct}_t.$$

This measure can be interpreted as a reduced-form proxy for the expected share of protocol debt that would become impaired due to a sudden decline in collateral values. It combines the likelihood of a large adverse price movement and the cross-sectional vulnerability of borrower balance sheets to such a shock. Note that this can be seen as a lower bound for the real liquidation risk, since using a 10% threshold for bad loans does not include the full conditional loss.

The construction parallels standard expected loss decompositions in credit risk, where expected losses equal the product of default probabilities and loss-given-default. In our setting, the option-implied crash probability plays the role of a forward-looking default likelihood, while the bad loan share captures the loss conditional on a crash.

Because the crash probability is risk-neutral, the measure embeds both expectations and risk premia. As a result, LiqRisk_t should be interpreted as a market-based measure of perceived liquidation risk rather than a purely physical expectation. At the same time, the loss component is constructed from realized on-chain positions and therefore reflects the actual distribution of leverage in the protocol.

Taken together, the measure provides a forward-looking proxy for systemic risk in decentralized lending, capturing both market-wide tail risk and protocol-specific fragility.

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