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DeFi-ying the Fed? Monetary Policy Transmission to Stablecoin Deposit Rates

Andrea Barbon, Jean Barthélemy & Benoit Nguyen[1]

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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 DeFi deposit 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.

Keywords: Stablecoin, Crypto-assets, DeFi, Monetary Policy Transmission

JEL classification: G14, G23, G29

[1] Barbon: University of St.Gallen, Center for Financial Services Innovation, and the Swiss Finance Institute (andrea.barbon@unisg.ch). Barthélemy: Banque de France (jean.barthelemy@banque-france.fr). Nguyen: Banque de France (benoit.nguyen@banque-france.fr). We thank Rashad Ahmed, Bruno Biais, Anthony Lee Zhang, Maxi Guennewig and an anonymous referee for their insightful feedback. We are grateful to Carlo Altavilla, Angela Gallo, Martina Fraschini, Wenqian Huang, Vincent Maurin, Marco Pinchetti and Xin Zhang for their discussions. We also thank the participants of Torino Decentralized Finance Conference 2026, EABCN Workshop on Digital Assets and Monetary Policy Transmission, the Bocconi-CEPR-ECB Conference on future of payments 2025, the 2nd SAFE-CEPR Frankfurt Hub International Conference, Warwick Gillmore Centre DeFi & Digital Currencies Conference, the SNB-CIF 2025 Conference on Cryptoassets and Financial Innovation, the 2024 Knut Wicksell Conference on Crypto and Fintech, the Banque de France 2023 Digital Finance Research Conference, and the St. Gallen Financial Economics Workshop for the valuable comments and feedback, and Riho-Marten Pallum and Thomas Martignon for their excellent research assistance.

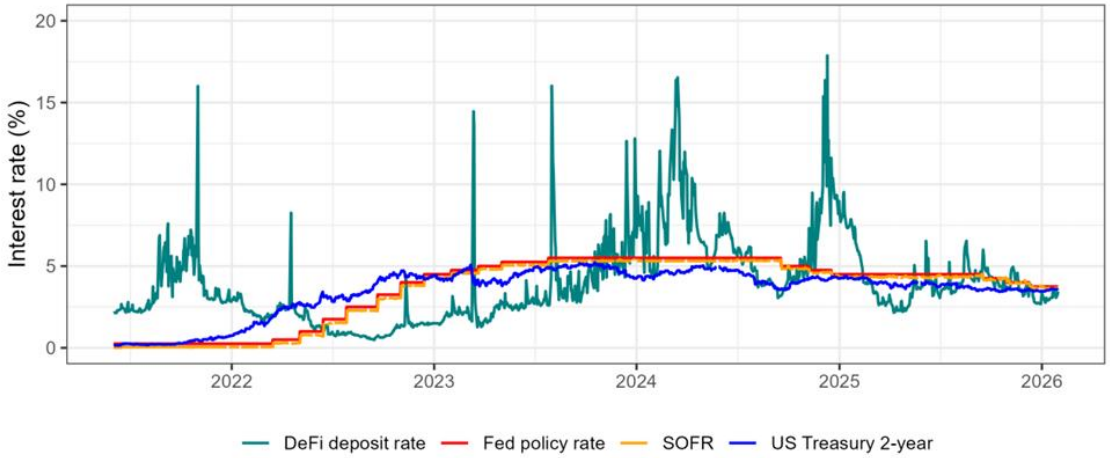
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NON-TECHNICAL SUMMARY

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. This paper explores the Fed's monetary policy transmission to these deposit rates.

In this paper, we first establish four 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 (as illustrated in Figure 1). 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.

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 on 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.

We then 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.

La DeFi défie-t-elle la Fed ? Transmission de la politique monétaire aux taux de rémunération des dépôts en stablecoins

RÉSUMÉ

La politique monétaire de la Réserve fédérale influence-t-elle les taux de rémunération des stablecoins en dollar américain ? Bien que les principaux émetteurs de stablecoins ne versent pas d'intérêts, les investisseurs peuvent obtenir un rendement en les déposant dans des protocoles de finance décentralisée (DeFi). Nous mettons en évidence des écarts exceptionnellement élevés et persistants entre les taux d'intérêt de court terme traditionnels et les taux de dépôt offerts par la DeFi, ainsi qu'une transmission faible et instable des variations des taux directeurs. Nos résultats montrent qu'à court terme, un choc de politique monétaire peut faire évoluer les taux de dépôts en stablecoins dans le sens opposé aux taux directeurs, retardant ainsi une convergence qui ne s'opère qu'à moyen terme. Le signe de l'effet à court terme comme la vitesse de convergence dépendent de l'ampleur du désendettement induit par les réactions des prix des crypto-actifs, relativement au canal traditionnel d'arbitrage des taux d'intérêt. Ce dernier effet est lui-même conditionné par la capacité limitée des investisseurs à effectuer des arbitrages entre finance traditionnelle et finance décentralisée.

Mots-clés : stablecoin, crypto-actifs, finance décentralisée, transmission de la politique monétaire

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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, Tarashev, and Wang (2026) for an overview and Section 3.1.

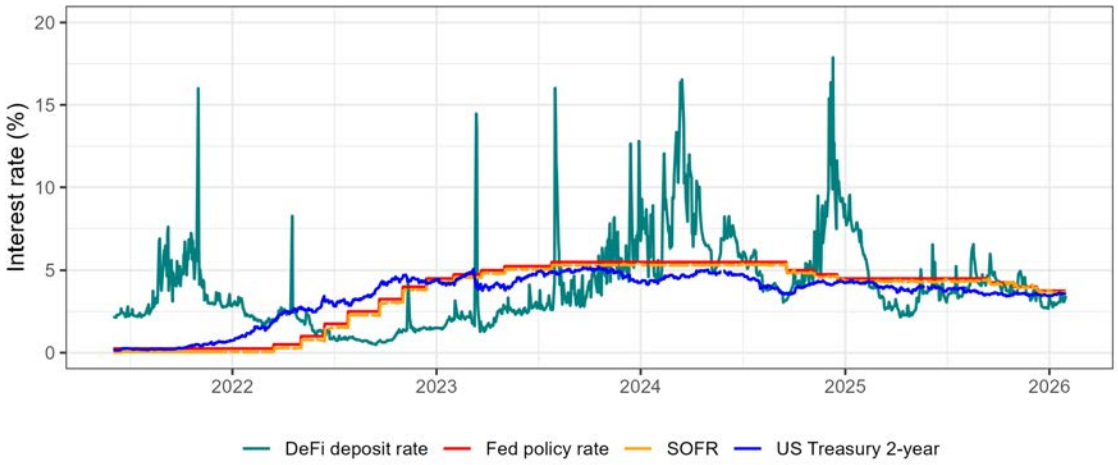
instead on predetermined algorithmic rules. DeFi deposit rates depend on the utilization rate — that is, the ratio of borrowed to supplied tokens. This paper examines the transmission of monetary policy to these rates and investigates the factors that may impair such transmission.

We start by documenting four stylized facts on USD-pegged stablecoins' DeFi deposit 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 deposit rates often going in the opposite direction to the policy rate. Third, the spread between DeFi deposit 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 deposit 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 account for these four stylized facts and the possibility that stablecoin deposit rates may respond in either direction to monetary policy shocks, we develop a parsimonious model of DeFi lending and borrowing. 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 the rates earned by depositors of stablecoins – sometimes referred to as "deposit rates", "supply rates", or "lending rates". In the rest of the paper "DeFi deposit rates" (or *DeFi rates* for short) will always refer to deposit rates earned by depositing stablecoins in decentralized lending protocols.

Figure 1: DeFi Deposit 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 deposit 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 DeFi 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 identify the overall impact of monetary policy shocks in a Bayesian Proxy-VAR setup. Importantly, this approach allows us to trace the effects of a monetary policy shock on both borrowing demand and stablecoin supply.

We find that, around monetary policy decisions over the past five years, both the arbitrage channel and the deleveraging channel are present across the stablecoins in our sample and jointly shape the overall dynamics of the deposit DeFi rate response to monetary policy shocks. A restrictive monetary policy shock reduces the supply of stablecoins, as arbitrageurs reallocate capital toward risk-free assets, putting upward pressure on DeFi rates. At the same time, DeFi borrowing declines sharply, reflecting the negative effect of tighter monetary policy on risky-asset expected returns, including Bitcoin.

Overall, we find that DeFi deposit rates decline on impact following a monetary policy shock and then gradually converge toward levels consistent with the long-run cointegration relationship between risk-free rates and DeFi deposit rates. This dynamic suggests that, in the short-run, the deleveraging channel dominates the arbitrage channel. Monetary policy tightening therefore reduces lending and borrowing activity not only because higher rates discourage leverage, but because lower expected returns on risky crypto assets diminish the demand for leveraged positions. The predominance of the deleveraging channel over the arbitrage one also points to the presence of significant financial frictions that hinder conventional arbitrage, an issue that we explore in more detail using micro-level data.

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 deposit 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 show that liquidity providers who deposit stablecoins in DeFi protocols and who are more integrated and compliant with traditional finance respond more strongly to policy rate changes compared to those more distant to traditional finance. This suggests that the weak arbitrage channel in the short run that we observe after a monetary policy shock at a macro-level could result

from an insufficient share of large liquidity providers with an access to traditional safe-assets markets.

Using a difference-in-differences design, we show that liquidity providers supplying stablecoins to DeFi lending protocols and exhibiting stronger integration with, and compliance with, traditional financial markets respond more strongly to policy rate changes than those more distant from traditional finance. This finding suggests that the weak arbitrage channel observed at the aggregate level in the short run following a monetary policy shock may reflect the limited presence of large liquidity providers with effective access to traditional safe-asset markets.

Overall, our findings suggest that two key factors explain the imperfect transmission of monetary policy to DeFi rates. First, liquidity providers do react following a monetary policy shock but face high frictions, suggesting that only a small share has a cheap, rapid, and effective access to traditional U.S. financial markets. Second, borrowers respond strongly by deleveraging their positions, consistent with the high sensitivity of crypto-asset prices to monetary policy changes. Together, these forces weaken the arbitrage channel while amplifying the deleveraging channel, thereby shaping the counter-intuitive short-run response of DeFi rates to monetary policy.

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, Chen-Zhang, and Shin (2024) detail arbitrage strategies in decentralized finance and the associated risk-returns tradeoffs. Chaudhary, Kozhan, and Viswanath-Natraj (2023) study the equilibrium determinants of DeFi deposit rates using transaction-level data from Compound. They show that leverage demand and speculative beliefs are associated with interest-rate differentials between stablecoins and risky cryptoassets, while gas fees and other trading costs generate wide arbitrage bounds between DeFi lending and perpetual-futures markets. We build on these insights by studying the monetary-policy dimension of DeFi deposit rates: how policy-rate changes transmit to stablecoin deposit rates and how the supply-side arbitrage response interacts with leverage-driven demand. 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, Saleh, and Vandeweyer (2023) study the inefficiencies of DeFi lending protocols compared to centralized 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) use granular data from DeFi lending platforms to compute investor-level leverage ratios and suggest that the demand for leverage is driven by loan-to-value requirements, borrowing costs, and crypto market price movements and sentiment. We build on their results to assess how leverage demand impact monetary policy transmission. 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 study theoretically and empirically the transmission of monetary policy to DeFi deposit rates and to decompose the forces that can generate, for some stablecoins, a short-run response opposite to the policy-rate change.

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 or-

thogonal to monetary and macroeconomic news (Benigno and Rosa 2023). In contrast, in our 2021-2026 sample, we find a strong impact of monetary policy shocks 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. Consistently, Kyriazis et al. (2023) find that unexpected Fed tightenings lead to negative Bitcoin price adjustment. They also provide early reduced-form evidence that monetary policy surprises affect DeFi borrowing rates, outstanding debt, and total value locked.

In a broader perspective, our paper also builds on the literature on monetary policy pass-through to near-money assets interest rates (Duffie and Krishnamurthy 2016), including private forms of safe assets (Nagel 2016; Sunderam 2015; Kacperczyk, Pérignon, and Vuillemey 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, Savov, and Schnabl 2018; Bauer, Bernanke, and Milstein 2023). Drechsler, Savov, and Schnabl (2017) document incomplete pass-through to bank deposit rates and attribute it to banks' deposit-market power. By contrast, we document incomplete pass-through in DeFi lending, where traditional deposit-market power is absent, and show how limits to arbitrage and leverage-driven demand can weaken the transmission of policy rates to stablecoin deposit 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 deposit 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.

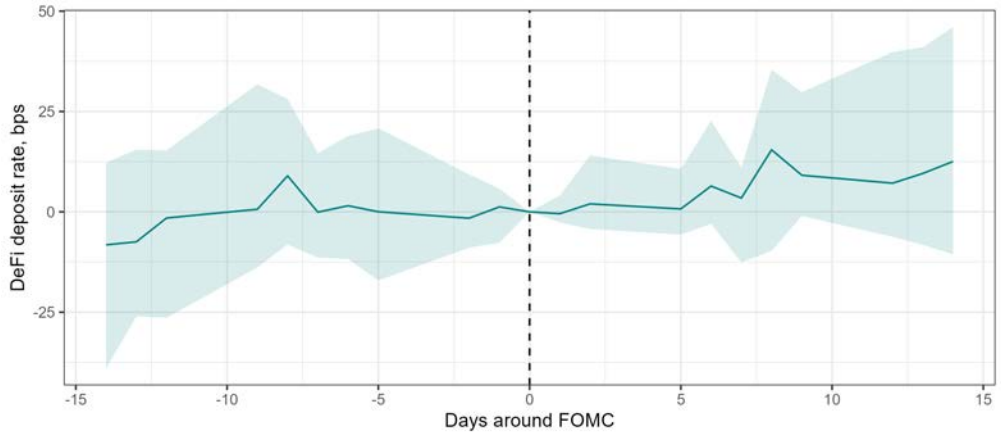
Second fact: Unstable and often negative correlation with policy rate changes From a bird's eye view, as suggested by Figure 1, DeFi deposit rates frequently evolve in an *opposite direction to the risk-free rate*. For example, between March 2022 and July 2023, the Federal Reserve raised policy rates eleven times, totaling an increase of +525 bps. Over the same period, DeFi deposit 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 deposit 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)

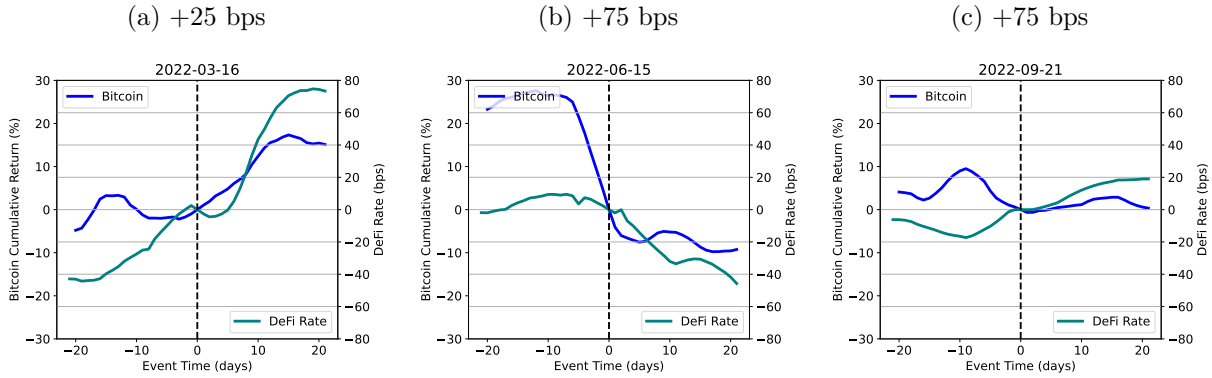


Note: Median and p25/75 DeFi deposit rates for USDC, USDT, DAI in Aave v2/v3 around policy rate hikes, for a median rate hike of 50 bps. Source: Aavescan, Bloomberg, Federal Reserve.

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.

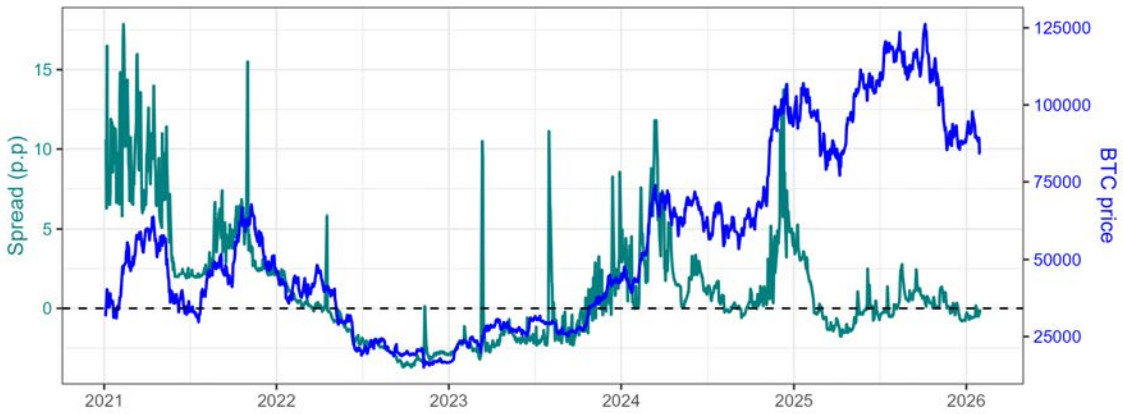
Third fact: The strong sensitivity to Bitcoin price dynamics DeFi lending activity and DeFi rates have tended to track Bitcoin price fluctuations more closely than money-market rates, as illustrated by Figures 3 and 4. This relationship is well documented in the literature and is typically associated 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



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, USDC 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

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.

U.S. risk-free benchmarks. Over the full sample, cointegration tests frequently reject the null 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 deposit rate spreads.

In the next sections, we explain the origin and determination of the DeFi deposit 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

[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.

any form of interest or yield to stablecoin holders.[7]

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 electronic 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

[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."*

[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

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 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 17 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

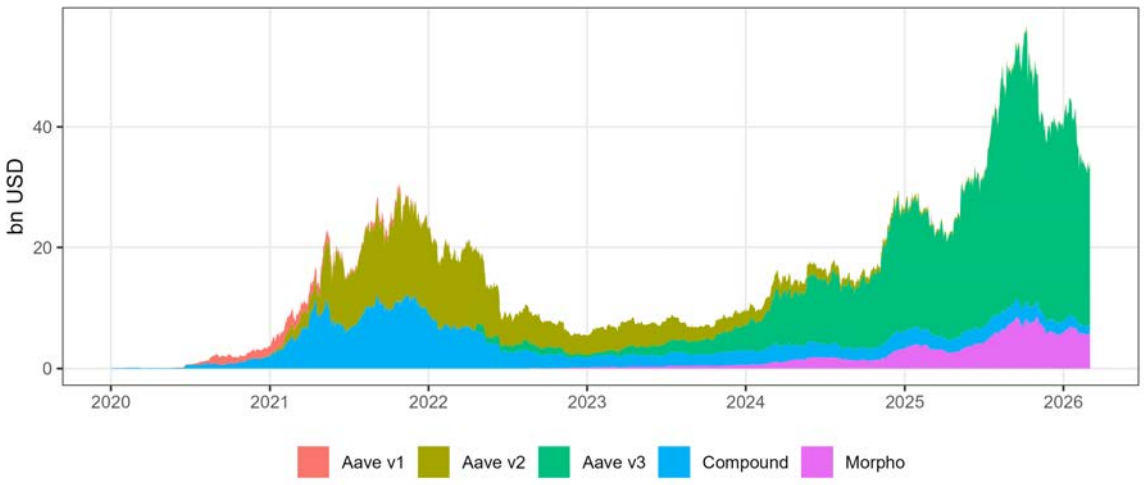
DeFi lending protocols are a cornerstone of the decentralized finance ecosystem, enabling users to lend and borrow crypto assets without intermediaries. DeFi lending protocols generally operate on a liquidity pool-based model, where lenders deposit assets that become part of a collective pool from which 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 $f(u)$ paid by borrowers is given by:

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

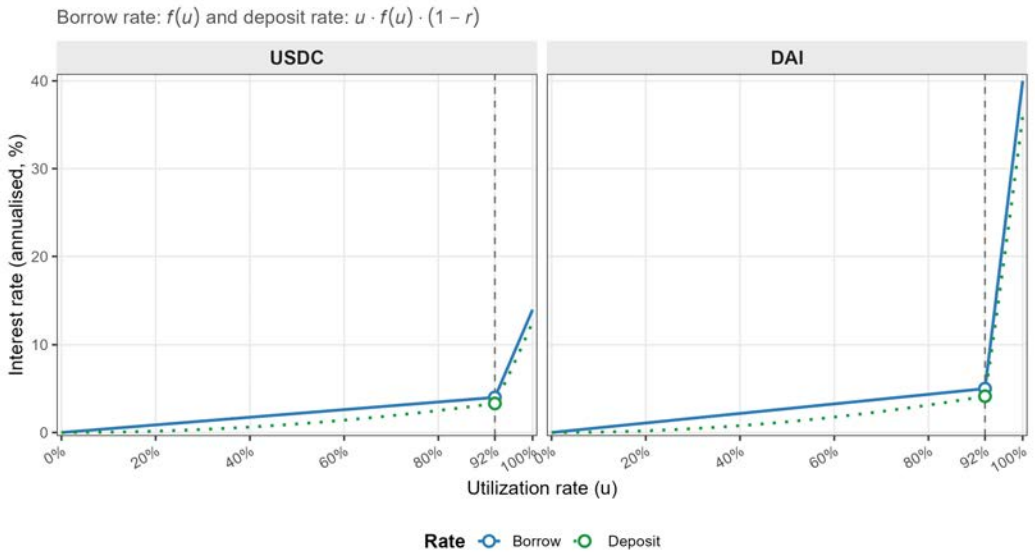
where u is the utilization rate and α, β are parameters set by governance vote by the protocol itself. $\bar{u} \in (0, 1)$ represents the kink in the interest rate function, often labelled as an "optimal utilization rate". Then the DeFi deposit rate ρ is the product of the borrowing rate, the

[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.

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

Figure 6: Interest Rate Models



The figure plots the DeFi 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 both sides of the kink, the steeper slopes ($\beta' >> \beta$) incentivize liquidity providers to supply additional liquidity beyond the kink, while encouraging borrowers to repay their loans as they face increasingly prohibitive borrowing rates. Without this feature, as $u \to 1$, the available liquidity in the pool – the quantity $(1 - u) \cdot S$ 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 works 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, Tovanich, and Prat 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 (T-bill or 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 18 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 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 deposit 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 18 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 deposit rates (or *DeFi rates* for short). 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 deposit 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 deposit 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 $\rho^* \geqslant 0$. 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 that we call a "tax" and denote by $\tau \in [0, 1]$, 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 DeFi deposit rate (or

[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, Kozhan, and Viswanath-Natraj 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.

for short *DeFi rate*) is given by $\rho = uf(u)(1-r)$, where $r \in [0,1)$ is a reserve rate indicating the share of profits retained by 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, 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:

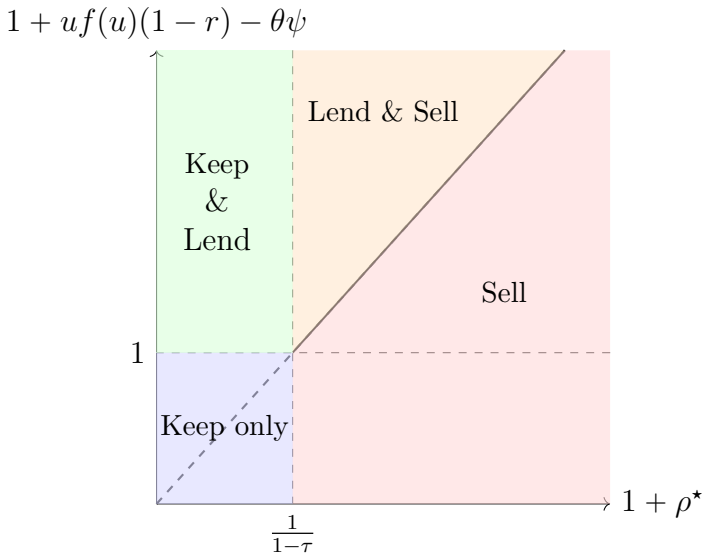
$$s=\max\left\{0;\ \frac{uf(u)(1-r)-\max\left(0;(1+\rho^\star)(1-\tau)-1\right)-\theta\psi}{\theta(1-\theta)\gamma\psi^2}\right\}. \tag{3}$$

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]

$$S = \begin{cases} \dfrac{uf(u)(1-r) - \theta\psi - \frac{\mu}{2}\frac{(\rho^\star)^2}{1+\rho^\star} - (1-\mu)\rho^\star}{\theta(1-\theta)\gamma\psi^2}, & \text{if} \quad \rho^\star \leqslant uf(u)(1-r) - \theta\psi; \\ \mu\dfrac{2 + uf(u)(1-r) - \theta\psi}{2(1+\rho^\star)} \max\left\{0; \dfrac{uf(u)(1-r) - \theta\psi}{\theta(1-\theta)\gamma\psi^2}\right\}, & \text{otherwise.} \end{cases} \tag{4}$$

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 provided that $uf(u)(1-r) > \theta\psi$.[17]

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 as long as the DeFi rate covers the expected loss $uf(u)(1-r) > \theta\psi$. 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

[16] See B.1.1 of the Internet Appendix for the details.
[17] The two equations coincide for $\rho^\star = u(f(u)(1-r) - \theta\psi$, proving the continuity of S with respect to u.

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).

Risky Investors Through the DeFi protocol, risky investors can borrow stablecoins to buy risky digital asset.[18] 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.[19] 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:[20]

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

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

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, $\frac{\overline{W}}{h_U} > \frac{\rho_U(\rho^\star)-f(u)}{\gamma'\sigma_U^2} > \max\{\overline{W}, \frac{\underline{W}(\rho^\star)}{h_U}\}$, 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

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

[19] 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.

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

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, $\rho_U(\rho^\star)$, 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:[21]

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

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,

[21] 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. Further, the term $\mu\rho^\star$ in the *arbitrage channel* expression is a first-order approximation for $\rho^\star$ close to zero, while the full expression equals $\mu\rho^\star(2+\rho^\star)/2(1+\rho^\star)^2$.

liquidity providers 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 liquidity providers, denoted by μ. If more of them are constrained in accessing traditional financial markets, this 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 deposit rates. The strength of this channel depends on the sensitivity of the market value of pledgeable assets to changes in the risk-free rate.[22]

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.*

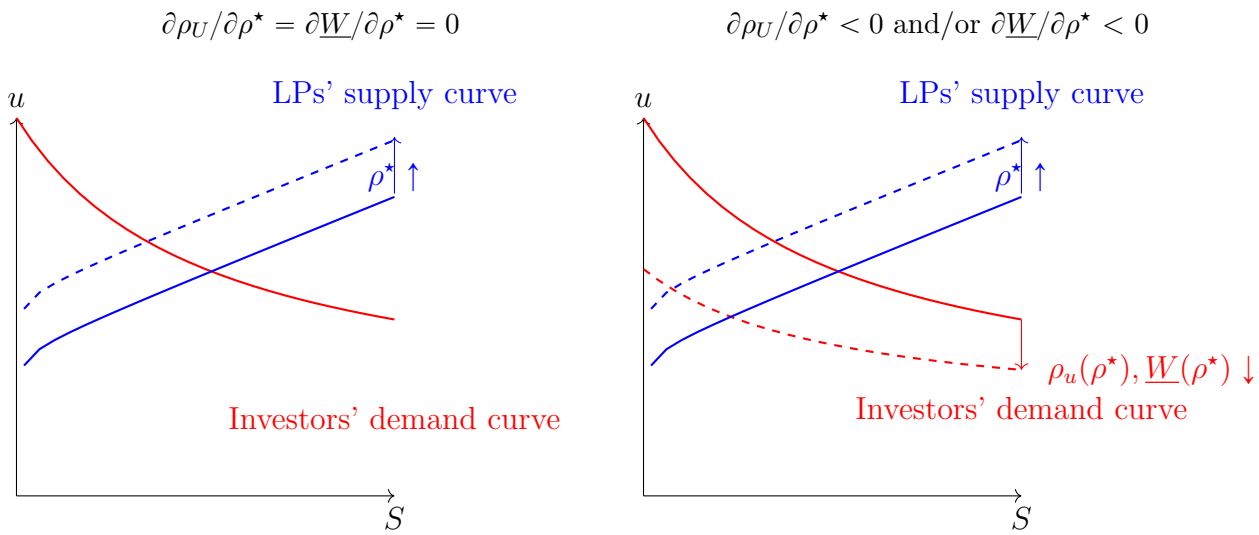
A formal way to see this is the following. When the sensitivities of the expected crypto-asset return and of collateral capacity to the risk-free rate are sufficiently small —that is, when $\rho_U'(\rho^\star)$ and $\underline{W}'(\rho^\star)$ are close to zero— inequality (7) is always satisfied, since 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 ca-

[22]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.

pacity 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 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 $uf(u)(1-r) = \theta\psi$ 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 DeFi deposit 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 DeFi deposit 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.[23] 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.[24]

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

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

[24] 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.

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 smart contracts [25], 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`.[26]

Annual percentage rate (APR) is computed from the indexes at a daily frequency, then annualized, following the formulas[27]:

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

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

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

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

[26] 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

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

Analytics.[28] Table 6 reports the descriptive statistics of our rate and quantities variables for 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 liquidity providers 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

[28] 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.

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.

6.1 Proxy-VAR approach

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 instrument z_t by exploiting high-frequency

price changes around monetary policy announcements.

We use monetary policy surprises developed by Jarociński and Karadi (2020). Surprises are measured by the first principal component of changes in interest rate derivatives with horizons from 1 month to 1 year (MP1, FF4, ED2, ED3, ED4) in a half-hour window starting 10 minutes before and ending 20 minutes after the FOMC announcement. Surprises are decomposed in pure monetary policy shocks and central bank information effect, using sign restrictions.

We then estimate the response of DeFi deposit rates and quantities lent and borrowed (in log) to a monetary policy shock. In our baseline, we use the 2-year U.S. Treasury yield as the policy variable and include the S&P 500 and the VIX as controls.[29] To smooth out volatility in rates while keeping relevance for the instrument, we run this exercise at a monthly frequency.[30] The first stage F-stat with the 2-year Treasury yield as policy variable is at 11.5, above the usual $F > 10$ rule-of-thumb threshold.

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-month lag. The shock is normalized so that it has a 25-bps instantaneous effect on the 2-year U.S. Treasury yield. To test for the slow-moving convergence suggested by the ECM in our motivating stylized facts, we trace out the impulse responses over a 1-year horizon. Figs. 9 and 10 report the impulse responses obtained for USDC and USDT. Fig.14 in Annex reports the response for DAI.

6.2 VAR results

Three observations stand out from the Impulse Response Functions obtained by the proxy-VAR.

[29] To the extent the DeFi interest rate are determined by borrowing and supply but not by the log-transformed DeFi quantities, DeFi rates are informative in this setup and the VAR is not affected by collinearity. We confirm that the results are robust in a specification with 5-variables keeping only the DeFi rate, see Fig. 15.

[30] For robustness, we also run a weekly frequency VAR, with qualitatively similar results, see in the online appendix Fig.20.

First, in our sample, the Bitcoin price reacts similarly to the stock markets and is 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 stablecoin supply. A 25-basis point increase in the two-year Treasury yield attributable to monetary policy is associated with an approximately 10 percent reduction in both borrowed and supplied quantities over a four-to five month horizon, representing the peak impulse response. The co-movement of both quantities is consistent with the theoretical transmission channels outlined in Section 4 and suggests that both the arbitrage and the delaveraging channels are at play. Critically, the *relative* magnitude of the supply response versus the demand response governs the equilibrium adjustment of DeFi deposit rates.

Third, in our baseline monthly-frequency proxy-VAR, DeFi deposit rates exhibit qualitatively similar responses to monetary policy across all three stablecoins. Following a monetary policy shock, deposit rates decline on impact before gradually converging toward a positive long-run level, although this level is not statistically different from zero. This pattern suggests that the deleveraging channel dominates in the short run, with borrowing contracting more strongly than supply. However, this effect is short-lived. Over time, the arbitrage channel becomes increasingly important and eventually offsets, or even dominates, the deleveraging effect.

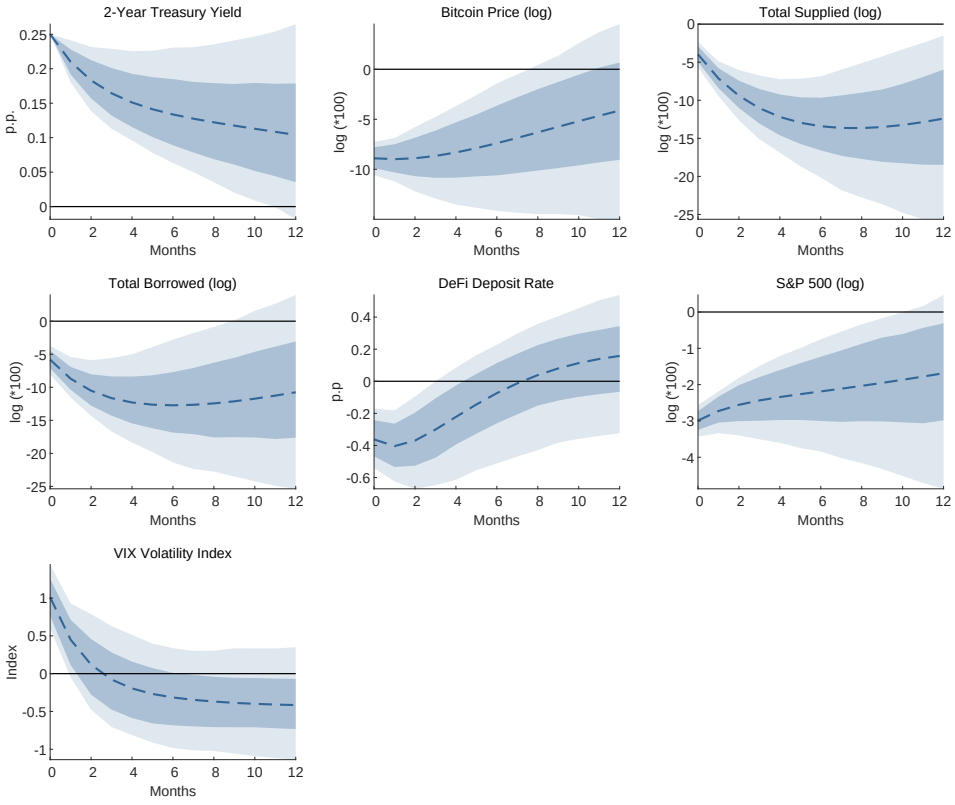
How can this result be interpreted through the lens of the model developed in Section 4? Equation (7) implies that the DeFi deposit rate falls after a monetary policy shock when the returns of investing in risky crypto-assets decline and arbitrage remains limited. The sharp declines in Bitcoin prices and total borrowing point to a strong deleveraging channel, while the milder response of total supply suggests limits to arbitrage on the demand side. In the model, these limits come from DeFi-specific risks, captured by θ, or restricted access to traditional financial markets, captured by μ. We provide evidence on the frictions underlying

this limited supply response in Section 7.

Overall, the proxy-VAR exercise suggests that deleveraging forces dominate in the short run. An important implication of this finding is that lending and borrowing activity in DeFi declines as the risk-free rate increases, even when DeFi rates do not immediately adjust to risk-free rates. The contraction in lending activity is driven not by higher financing costs, but rather by weaker borrowing demand, reflecting reduced opportunities to earn excess returns on borrowed funds.

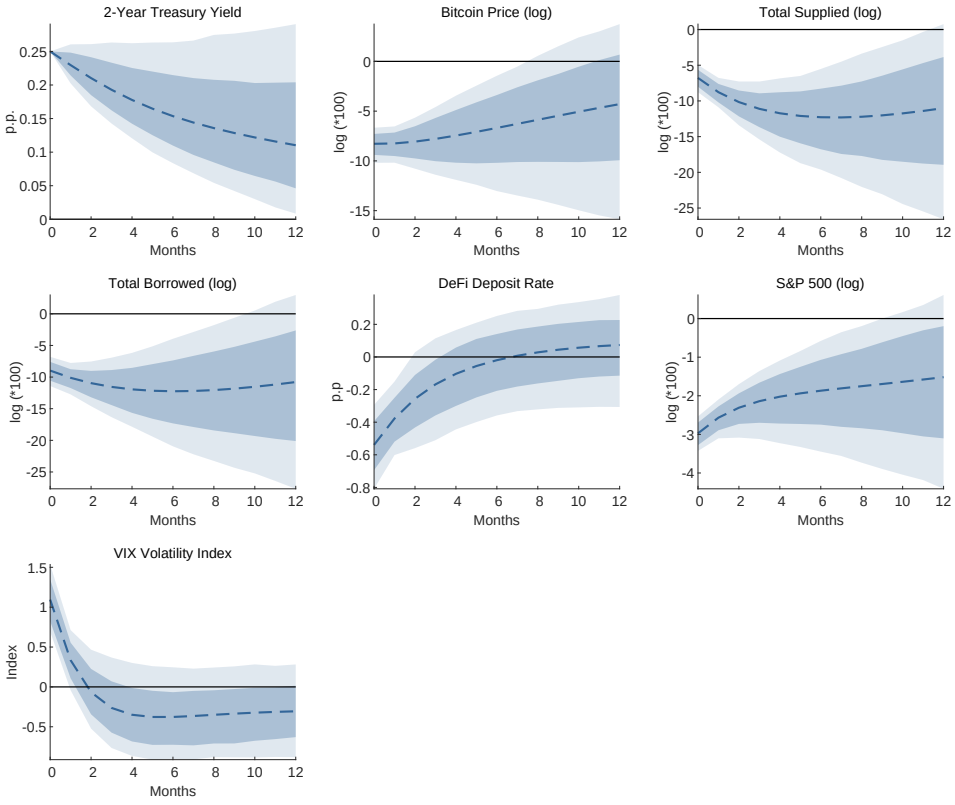
In Annex A, as a robustness exercise, we run the same specification with the 3-month U.S. Treasury bill rate, with very similar responses in the DeFi deposit rates (Fig.16). In addition, we run a 5-variable specification excluding DeFi quantity variables, which confirms the response of the DeFi rate (Fig.15). In the online appendix, we report for robustness a specification at weekly frequency, more volatile on impact, but exhibiting the same strong deleveraging pattern (Fig 20) and a specification including liquidation risk and the DXY Index as a proxy for the strength of the U.S. dollar (Fig 21). Both confirm our pattern for the DeFi rate response to a monetary policy shock.

Figure 9: Impulse responses for USDC



Notes: 7-variable baseline VAR, with 1 lag (BIC criterion). Shocks from Jarociński and Karadi (2020) using monthly-aggregated monetary policy surprises purged from information effect (Poor man's sign restrictions). First stage F-stat = 11.5 is above the usual weak instrument threshold. The shock is normalized to induce a 25 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 lag (BIC criterion). Shocks from Jarociński and Karadi (2020) using monthly-aggregated monetary policy surprises purged from information effect (Poor man's sign restrictions). First stage F-stat = 11.5 is above the usual weak instrument threshold. The shock is normalized to induce a 25 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 interest rate spreads, 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 better access to traditional finance react more strongly to policy announcements. In line with the model, the increased response of this type of investors underpins the arbitrage channel of monetary policy transmission.

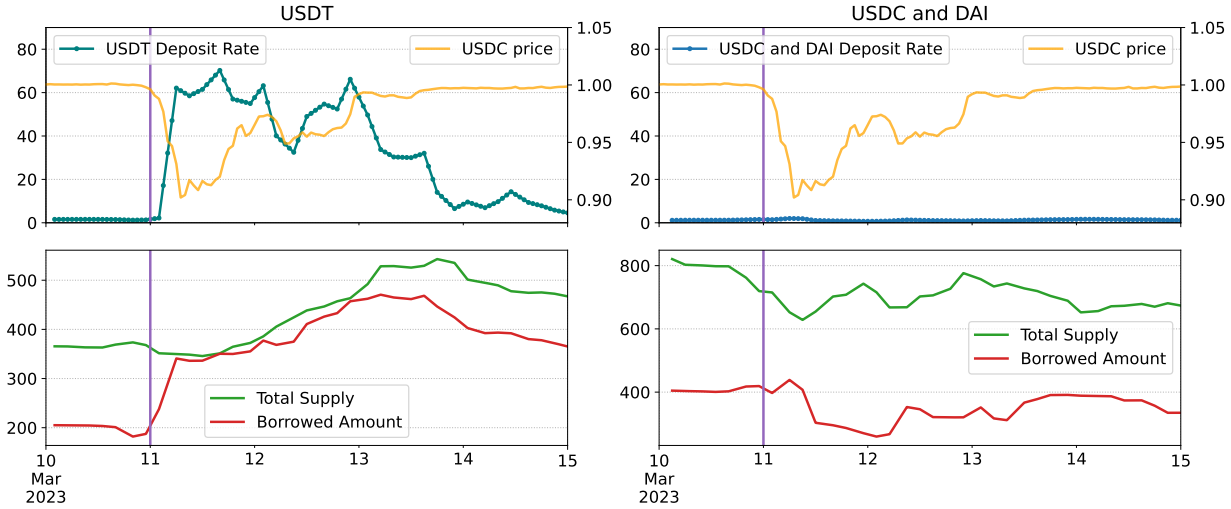
7.1 Anecdotal Evidence from SVB Shock

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 for the observed pattern is that market participants who expected

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.

USDC to recover toward its peg used their USDC holdings as collateral to borrow USDT rather than sell USDC at a loss. This allowed them to obtain liquidity while retaining exposure to a USDC recovery; some may also have used the borrowed USDT to purchase discounted USDC and increase that exposure. Thus, although the shock originated in USDC, it surfaced in the protocol as a higher demand for USDT borrowing rather than a withdrawal of USDC liquidity.

Meanwhile, the supply of USDT only gradually increased, leading to a high utilization rate and exceptionally elevated deposit rates that culminated 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 does not respond elastically.

7.2 High-Frequency DeFi Spread Analysis and Transaction Costs

DeFi Rate Jumps and Demand vs. Supply Shocks. To go beyond anecdotal evidence, we systematically identify discrete rate jump events in the 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 supply. Let Δb_t and Δs_t denote the contemporaneous changes in outstanding borrowing and supplied liquidity, respectively. For rate increases, we classify an event as demand-driven when $\Delta b_t + \Delta s_t > 0$, indicating that the increase in borrowing dominates any contraction in supply and as supply-driven otherwise. For rate decreases, the classification is reversed: events with $\Delta b_t + \Delta s_t < 0$ are classified as demand-driven, reflecting a relatively stronger decline in borrowing, while the remaining events are classified as supply-driven.

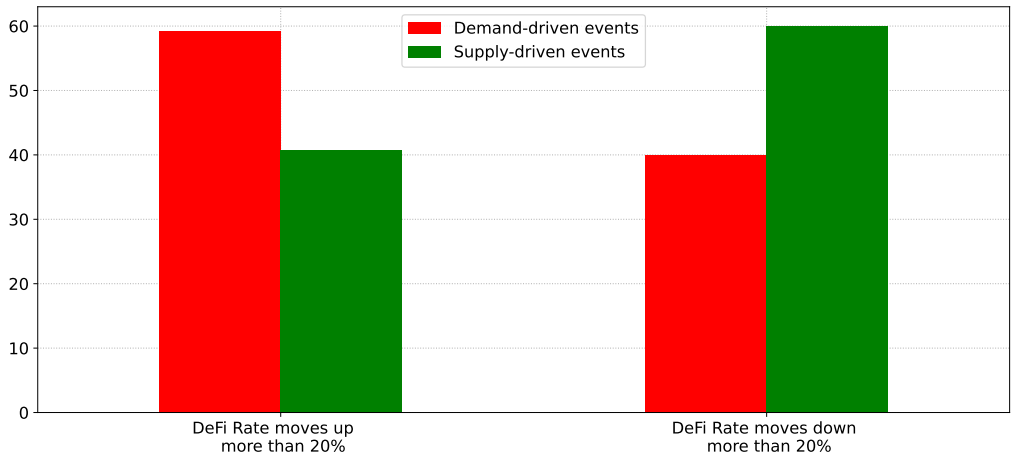
We find that 29 of the 49 large DeFi rate increases are classified as demand-driven, corresponding to 59% of the events (95% confidence interval: 45–72%). Among the 40 large rate decreases, 24 are classified as supply-driven, corresponding to 60% of the events (95% confidence interval: 45–74%). Neither proportion is statistically distinguishable from 50%. Nevertheless, the same qualitative ordering is obtained using alternative thresholds of 10, 15, 25, and 30 percentage points.

Figure 12 summarizes this classification. Point estimates suggest that large rate increases are more frequently associated with demand shocks, whereas large rate decreases are more frequently associated with supply expansions. Although neither share is statistically distinguishable from 50%, the pattern is consistent with the SVB case study.

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

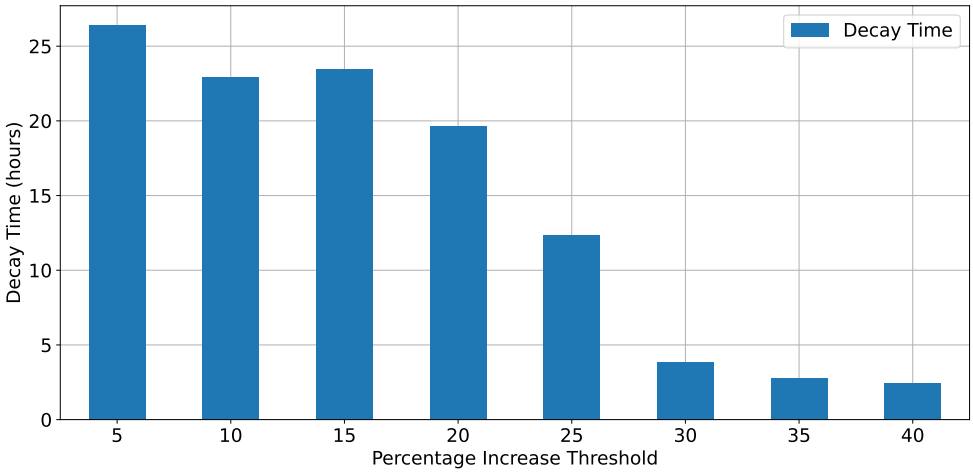


Classification of DeFi rate jumps exceeding 20 percentage points in absolute value. For upward (downward) rate movements, events are classified as demand-driven when $\Delta b_t + \Delta s_t > 0$ (< 0), and as supply-driven otherwise. Bars report the share of events in each category.

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 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, pos-

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%.

sibly because the arbitrage opportunity becomes too large to be ignored, even in the presence of frictions.

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 for the different thresholds are shown 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.

For extreme spread movements (30–40%), the coefficients become statistically insignificant. However, these regressions contain only 12–16 observations. We therefore cannot distinguish whether the loss of significance reflects a reduced role for transaction costs or simply low

statistical power.

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 R^2 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

Taken together, the relatively long decay times and the positive relationship between gas fees and persistence for moderate spread events are consistent with stickiness in the DeFi lending market and an inelastic short-run supply response. Gas fees act as a friction, preventing capital from flowing quickly into high-yield pools and prolonging DeFi deposit rate divergence.

This interpretation is further supported by the relatively small scale of individual liquidity providers, as illustrated in Figure 19 in the Internet Appendix, since fixed transaction costs are likely to weigh more heavily on smaller positions.

7.3 Wallet-Level Differences-in-Differences

The proxy-VAR evidence supports the idea that the leverage channel dominates in the short-run, with borrowed amounts dropping more than liquidity supply. This pattern does not rule out that the arbitrage channel is relevant, through the supply side. In particular our model predicts that liquidity providers with easier access to traditional financial markets

should deliver a stronger response to monetary policy changes. We test this prediction using wallet-level variation in liquidity provision around monetary policy announcements. To do so, we implement a difference-in-differences (DiD) design built around monetary policy announcements to analyze how liquidity providers with access to traditional financial markets adjust their USDC liquidity relative to other liquidity providers.

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, these liquidity providers 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 liquidity providers 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 liquidity providers active around monetary policy announcements. Taken together, these wallets generate roughly 15% of the volume of USDC in our sample.

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 $= \Delta \ln(1 + S)$, where S denotes the wallet's cumulative supply position, computed as detailed in Section 5.2. The main DiD regressor is the interaction $\texttt{post} \times \texttt{TradFi}$, 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:

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

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

Identification comes from comparing the before-vs-after change around each policy announcement for TradFi wallets to the corresponding changes for other liquidity providers. Our empirical strategy requires that, absent the policy announcement, changes in USDC liquidity provision would have followed parallel trends for USDC-only wallets and other liquidity providers. The event-study estimates in Figure 22 of the Internet Appendix support this assumption: the pre-announcement coefficients fluctuate around zero and are individually statistically insignificant. The coefficient β measures the difference between the two groups' pre-to-post announcement changes, with the sign reversed for rate cuts. A negative coefficient therefore indicates that USDC-only wallets reduce liquidity provision more strongly after hikes and increase it more after cuts, consistent with the arbitrage channel.

Results. The results in Table 5 show a clear and robust pattern for the USDC-based proxy. Across specifications (1)–(3), the coefficient on $\texttt{post} \times \texttt{TradFi}$ is negative and statistically significant. This indicates that, relative to other liquidity providers (LPs), LPs with access to

[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)
				Placebo
Post × TradFi	–0.018***	–0.019***	–0.013*	–0.006
	(–3.046)	(–3.278)	(–1.711)	(–0.922)
TradFi LP	0.020***	0.017***		0.024***
	(5.498)	(4.855)		(4.603)
Post Period	–0.005*			–0.013***
	(–1.921)			(–4.339)
Day FE		Yes	Yes	
LP FE			Yes	
N	1,166,298	1,166,298	1,166,298	1,123,605
R^2	0.000	0.002	0.023	0.000

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. Specification (4) reports results from a Placebo test, where the event dates are shifted backward by 10 days. 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. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

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 estimates imply that, following a rate hike, TradFi investors reduce their supplied liquidity by approximately 3–4% 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 trends, reinforcing the interpretation that the estimated effect reflects differential responses to monetary policy actions rather than compositional or aggregate effects.

The stronger response of USDC-only wallets is consistent with an arbitrage channel operating among liquidity providers with closer links to traditional financial markets. This mechanism can coexist with the aggregate dominance of deleveraging, as deposit rates may fall following monetary tightening when the contraction in borrowing demand outweighs the reduction in liquidity supply. Taken together, the difference-in-differences and VAR evidence suggests that the deleveraging channel dominates because only a limited share of liquidity providers can arbitrage frictionlessly across traditional and decentralized financial markets.

Design validation. To check if the baseline estimates are driven by pre-existing differential trends or anticipation, we conduct a placebo test in which we shift each event date backward by ten days. That is, we produce a placebo window from day -20 to day 0, centered on a placebo event at day -10. The interaction coefficient is statistically insignificant (column (4) of Table 5), suggesting that the baseline result is not driven by pre-trends or anticipation.

We also estimate a dynamic event-study specification using two-day event-time bins interacted with the `TradFi` indicator. Figure 22 in the Internet Appendix reports the coefficients and their 90% confidence intervals. The pre-event estimates fluctuate around zero and are individually insignificant, whereas the post-event estimates are predominantly negative and larger in absolute magnitude. This pattern is consistent with TradFi LPs reducing liquidity provision more than non-TradFi LPs following a rate hike.

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 DeFi deposit rates for stablecoins 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.

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 DeFi deposit 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 the 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.

References

Aldasoro, Iñaki, Giulio Cornelli, Massimo Ferrari Minesso, Leonardo Gambacorta, and Maurizio Michael Habib 2025. "Stablecoins, money market funds and monetary policy". *Economics Letters* 247, 112203. https://doi.org/10.1016/j.econlet.2025.112203.

Altavilla, Carlo, Miguel Boucinha, Lorenzo Burlon, Ramon Adalid, Roberta Fortes, and Franziska Maruhn 2026. "Stablecoins and monetary policy transmission". *ECB Working Paper Series No 3199*.

Aramonte, Sirio, Sebastian Doerr, Wenqian Huang, and Andreas Schrimpf 2022. "Defi lending: intermediation without information?". Technical report, Bank for International Settlements.

Augustin, Patrick, Roy Chen-Zhang, and Donghwa Shin 2024. "Reaching for yield in decentralized financial markets". *LawFin Working Paper No. 39*.

Bakshi, Gurdip, Nikunj Kapadia, and Dilip Madan 2003. "Stock return characteristics, skew laws, and the differential pricing of individual equity options". *Review of Financial Studies* 16, no. 1, 101–143.

Bauer, Michael D., Ben S. Bernanke, and Eric Milstein 2023. "Risk appetite and the risk-taking channel of monetary policy". *Journal of Economic Perspectives* 37, no. 1, 77–100. https://doi.org/10.1257/jep.37.1.77.

Benigno, Gianluca, and Carlo Rosa 2023. "The bitcoin-macro disconnect". *Federal Reserve Bank of New York Staff Reports, no. 1052*.

Bernanke, Ben S., and Kenneth N. Kuttner 2005. "What explains the stock market's reaction to federal reserve policy?". *The Journal of Finance* 60, no. 3, 1221–1257.

Bindseil, Ulrich 2025. "Stablecoin regulation revisited: Is prohibiting remuneration the solution?". SUERF Policy Brief, SUERF.

Borio, Claudio, and Haibin Zhu 2012. "Capital regulation, risk-taking and monetary policy: A missing link in the transmission mechanism?". *Journal of Financial Stability* 8, no. 4, 236–251. https://doi.org/10.1016/j.jfs.2011.12.003.

Breeden, Douglas T, and Robert H Litzenberger 1978. "Prices of state-contingent claims implicit in option prices". *Journal of Business* 51, no. 4, 621–651.

Campello, Murillo, Angela Gallo, Lira Mota, and Tammaro Terracciano 2025. "Demand for safety in the crypto ecosystem". *mimeo*.

Caramichael, John, and Gordon Y. Liao 2022. "Stablecoins: Growth potential and impact on banking". *International Finance Discussion Papers* 2022.0, no. 1334, 1–26.

Castillo León, Jaime, and Alfred Lehar 2026. "What data have told us about decentralized finance". *Journal of Corporate Finance* 96, 102916. https://doi.org/10.1016/j.jcorpfin.2025.102916.

Chaudhary, Amit, Roman Kozhan, and Ganesh Viswanath-Natraj 2023. "Interest rate parity in decentralized finance". *WBS Finance Group Research Paper Forthcoming*.

Chiu, Jonathan, and Furkan Danisman 2026. "DeFi lending: Returns, leverage, and liquidation risk". Staff Analytical Paper 2026-13, Bank of Canada.

Chiu, Jonathan, Emre Ozdenoren, Kathy Yuan, and Shengxing Zhang 2022. "On the fragility of defi lending". *Available at SSRN 4328481*.

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl 2017. "The deposits channel of monetary policy". *The Quarterly Journal of Economics* 132, no. 4, 1819–1876. https://doi.org/10.1093/qje/qjx019.

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl 2018. "A model of monetary policy and risk premia". *The Journal of Finance* 73, no. 1, 317–373. https://doi.org/10.1111/jofi.12539.

Duffie, Darrell, and Arvind Krishnamurthy 2016. "Passthrough efficiency in the fed's new monetary policy setting". In *Designing Resilient Monetary Policy Frameworks for the Future. Federal Reserve Bank of Kansas City, Jackson Hole Symposium*, pages 1815–1847.

Garcia Ocampo, Denise 2025. "Stablecoin-related yields: Some regulatory approaches". FSI Brief 27, Bank for International Settlements (BIS), Financial Stability Institute.

Gudgeon, Lewis, Daniel Perez, Dominik Harz, Benjamin Livshits, and Arthur Gervais 2020a. "The decentralized financial crisis". In *2020 crypto valley conference on blockchain technology (CVCBT)*, pages 1–15. IEEE.

Gudgeon, Lewis, Sam Werner, Daniel Perez, and William J Knottenbelt 2020b. "Defi protocols for loanable funds: Interest rates, liquidity and market efficiency". In *Proceedings of the 2nd ACM Conference on Advances in Financial Technologies*, pages 92–112.

Heimbach, Lioba, and Wenqian Huang 2024. "Defi leverage". *BIS Working PapersNo 1171*. https://doi.org/10.2139/ssrn.4459384.

Huang, Wenqian, Nikola Tarashev, and Xingyi Wang 2026. "Stablecoin remuneration on centralised exchanges". BIS Bulletin No 125, Bank for International Settlements.

Jarociński, Marek, and Peter Karadi 2020. "Deconstructing monetary policy surprises - the role of information shocks". *American Economic Journal: Macroeconomics* 12, no. 2, 1–43. https://doi.org/10.1257/mac.20180090.

Kacperczyk, Marcin, Christophe Pérignon, and Guillaume Vuillemey 2021. "The private production of safe assets". *The Journal of Finance* 76, no. 2, 495–535. https://doi.org/10.1111/jofi.12997.

Karau, Sören 2023. "Monetary policy and bitcoin". *Journal of International Money and Finance* 137, 102880. https://doi.org/10.1016/j.jimonfin.2023.102880.

Kyriazis, Antzelos, Iason Ofeidis, Georgios Palaiokrassas, and Leandros Tassiulas 2023. "Monetary policy, digital assets, and defi activity". *arXiv preprint arXiv:2302.10252*.

Li, Ye, and Simon Mayer 2025. "Financial intermediation with fragile seigniorage: A dynamic model of stablecoin issuers". Working paper, Fisher College of Business. https://doi.org/10.2139/ssrn.3757083.

Ma, Yiming, Yao Zeng, and Anthony Lee Zhang 2025. "Stablecoin runs and the centralization of arbitrage". Working Paper 2025-76, University of Chicago, Becker Friedman Institute for Economics. NBER Working Paper No. w33882.

Mertens, Karel, and Morten O. Ravn 2013. "The dynamic effects of personal and corporate income tax changes in the united states". *American Economic Review* 103, no. 4 (June), 1212–47. https://doi.org/10.1257/aer.103.4.1212.

Minesso, Massimo Ferrari, and Daniele Siena 2026. "Private money and public debt. u.s. stablecoins and the global safe asset channel". *ECB Working Papers Series No 3174*.

Miranda-Agrippino, Silvia, and Giovanni Ricco 2021. "The transmission of monetary policy shocks". *American Economic Journal: Macroeconomics* 13, no. 3 (July), 74–107. https://doi.org/10.1257/mac.20180124.

Mu, Boyang, Natkamon Tovanich, and Julien Prat 2025. "Do you care about your positions? Users under liquidation risk in decentralized lending protocol". In *IEEE International Conference on Blockchain and Cryptocurrency (ICBC)*, Pisa, Italy. HAL preprint hal-05041569. https://doi.org/10.1109/ICBC64466.2025.11114495.

Nagel, Stefan 2016. "The liquidity premium of near-money assets". *Quarterly Journal of Economics* 131, no. 4, 1927–1971. https://doi.org/10.1093/qje/qjw028.

Rivera, Thomas J., Fahad Saleh, and Quentin Vandeweyer 2023. "Equilibrium in a DeFi lending market". Working paper. https://doi.org/10.2139/ssrn.4389890.

Sunderam, Adi 2015. "Money creation and the shadow banking system". *Review of Financial Studies* 28, no. 4, 939–977. https://doi.org/10.1093/rfs/hhu083.

Tovanich, Natkamon, Myriam Kassoul, Simon Weidenholzer, and Julien Prat 2023. "Contagion in decentralized lending protocols: A case study of compound". In *Proceedings of the 2023 Workshop on Decentralized Finance and Security*, pages 55–63.

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

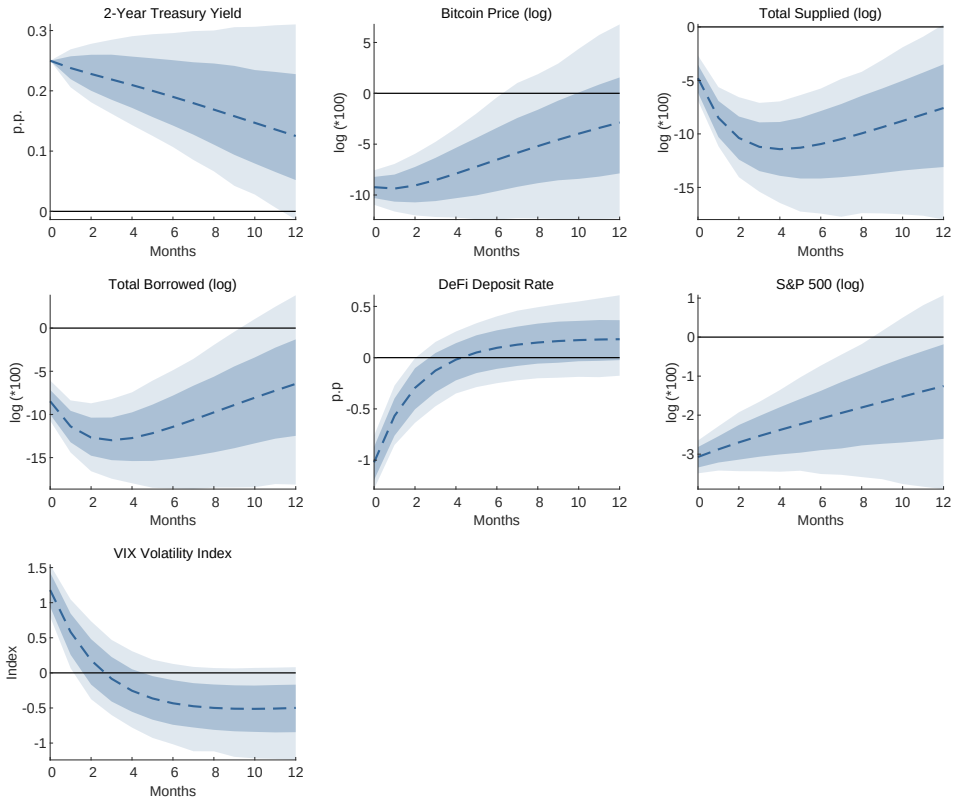
Note: The table reports the results of two standard cointegration tests applied to the long-run relationship between the deposit rate of each stablecoin and a set of interest rate benchmarks at a weekly frequency. For each rate, the long-run equation is first estimated by ordinary least squares (OLS), 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.

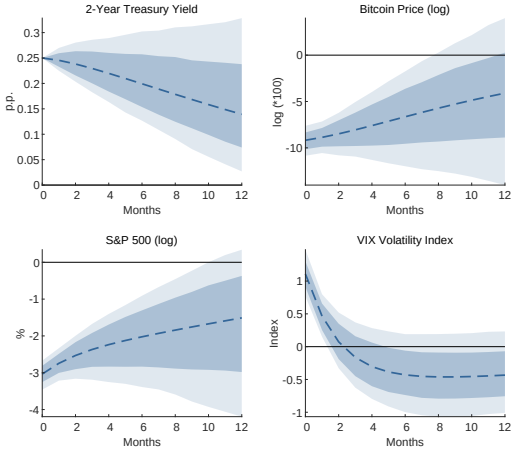
Figure 14: Impulse responses for DAI



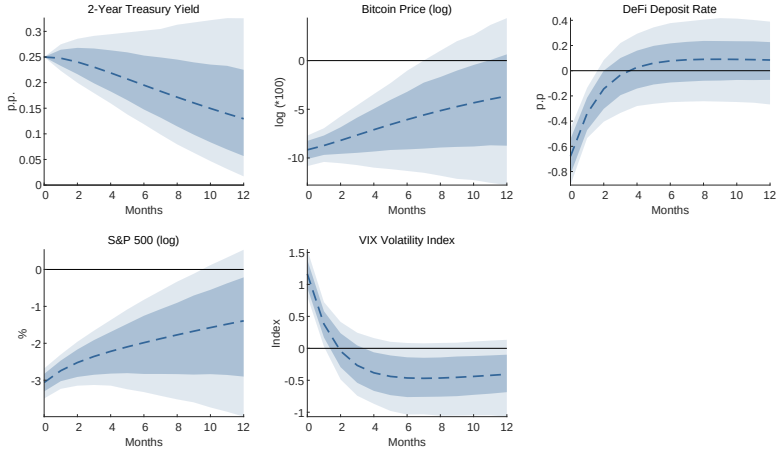
Notes: 7-variable baseline VAR, with 1 lag (BIC criterion). Shocks from Jarociński and Karadi (2020) using monthly-aggregated monetary policy surprises purged from information effect (Poor man's sign restrictions). First stage F-stat = 11.5 is above the usual weak instrument threshold. The shock is normalized to induce a 25 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 15: Impulse responses - 5-variables robustness check

(a) USDC



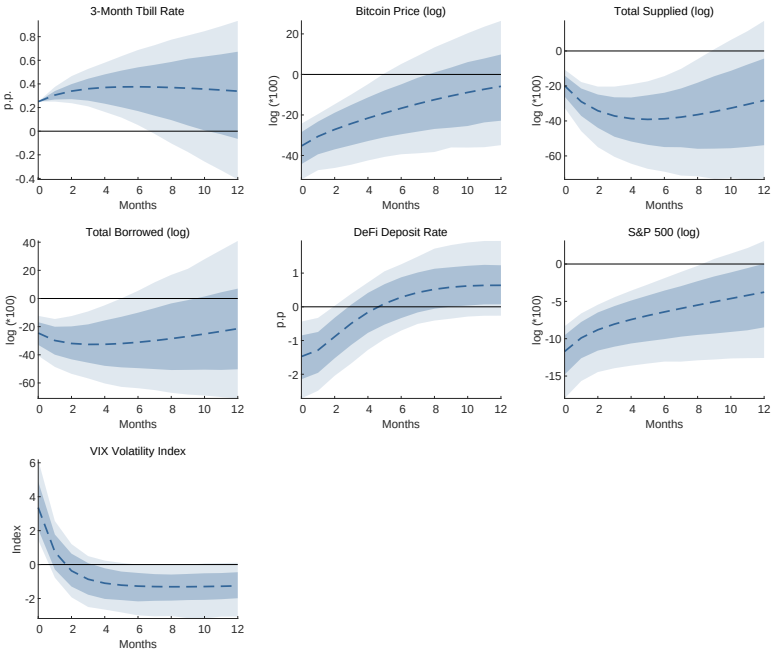
(b) USDT



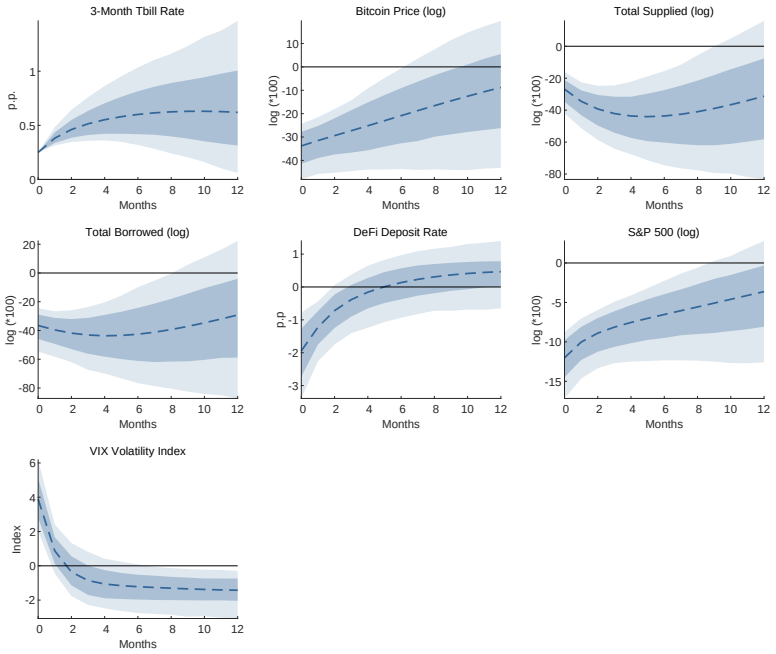
Notes: 5-variable baseline VAR, with 1 lag (BIC criterion). Shocks from Jarociński and Karadi (2020) using monthly-aggregated monetary policy surprises purged from information effect (Poor man's sign restrictions). First stage F-stat = 11.5 is above the usual weak instrument threshold. The shock is normalized to induce a 25 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 16: Impulse responses - 3-month Tbill as policy variable

(a) USDC



(b) USDT



Notes: 7-variable baseline VAR, with 1 lag (BIC criterion). Shocks from Jarociński and Karadi (2020) using monthly-aggregated monetary policy surprises purged from information effect (Poor man's sign restrictions). First stage F-stat = 13.3. The shock is normalized to induce a 25 basis point increase in the 3-month U.S. Treasury Bill yield. Sample: January 2021-January 2026. Shaded areas are 90 percent (dark blue) and 68 percent (light blue) posterior coverage bands.

Appendix B. Supplementary 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

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

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:

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

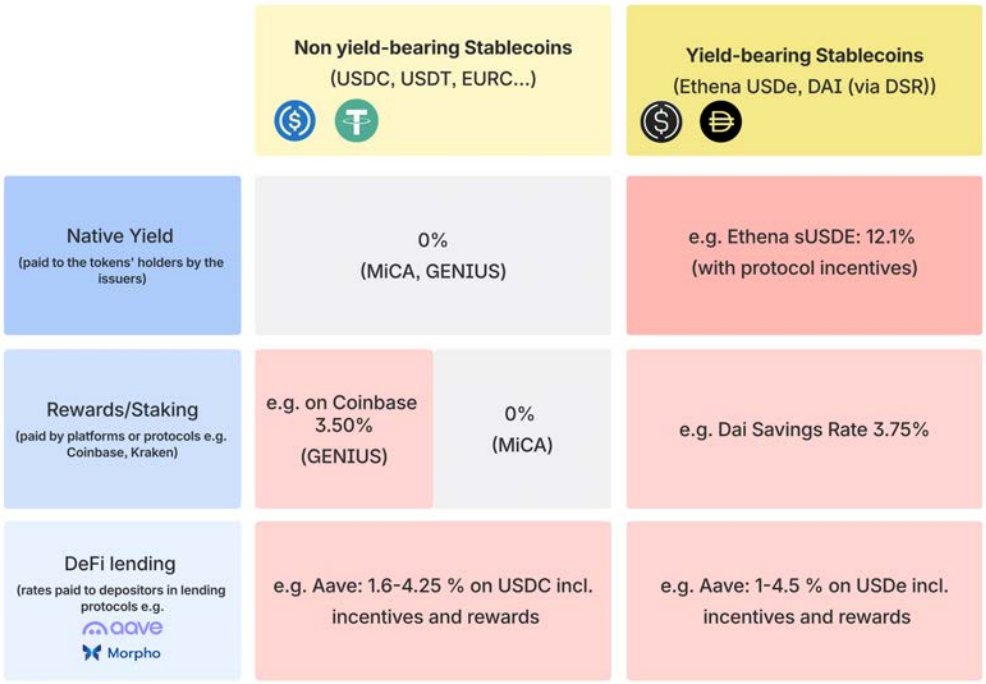
Testable implication: The higher the concentration (low n), the higher the deposit rate, the larger the impact of the risk-free rate on deposit rate.

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.

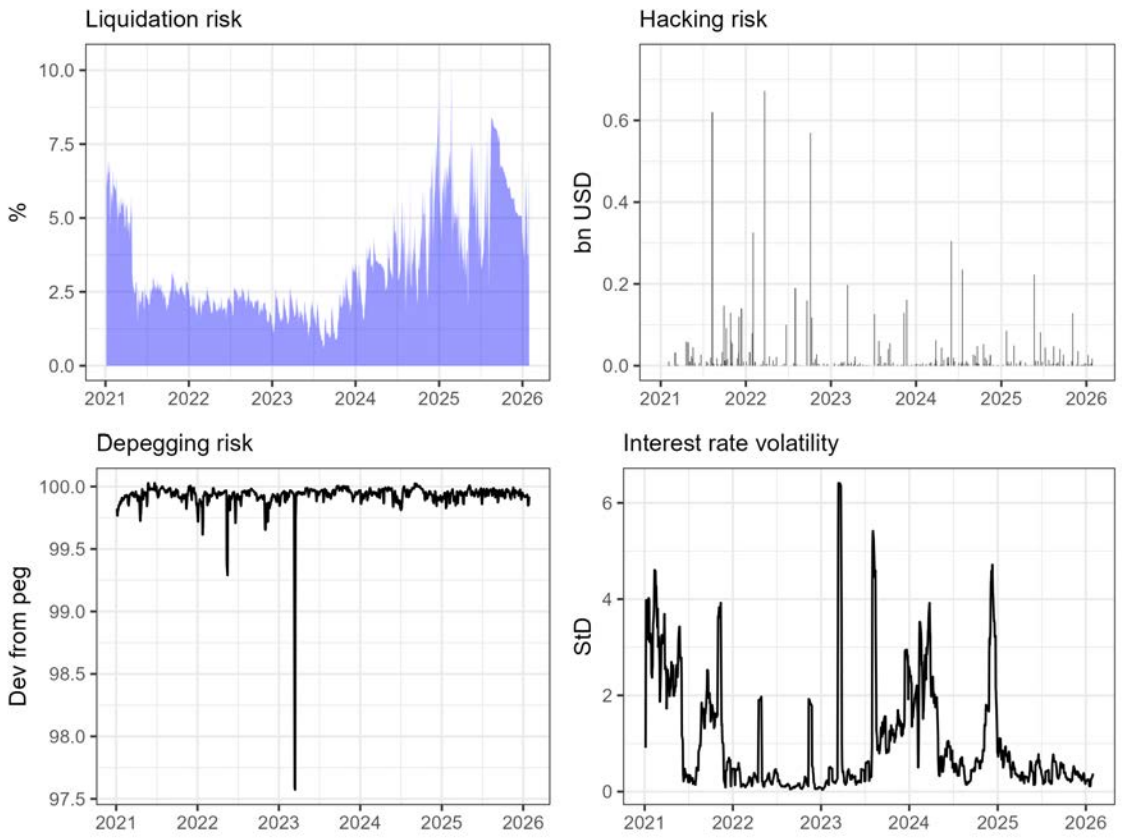
B.2 Additional Figures

Figure 17: Yield generation on USD-pegged stablecoins



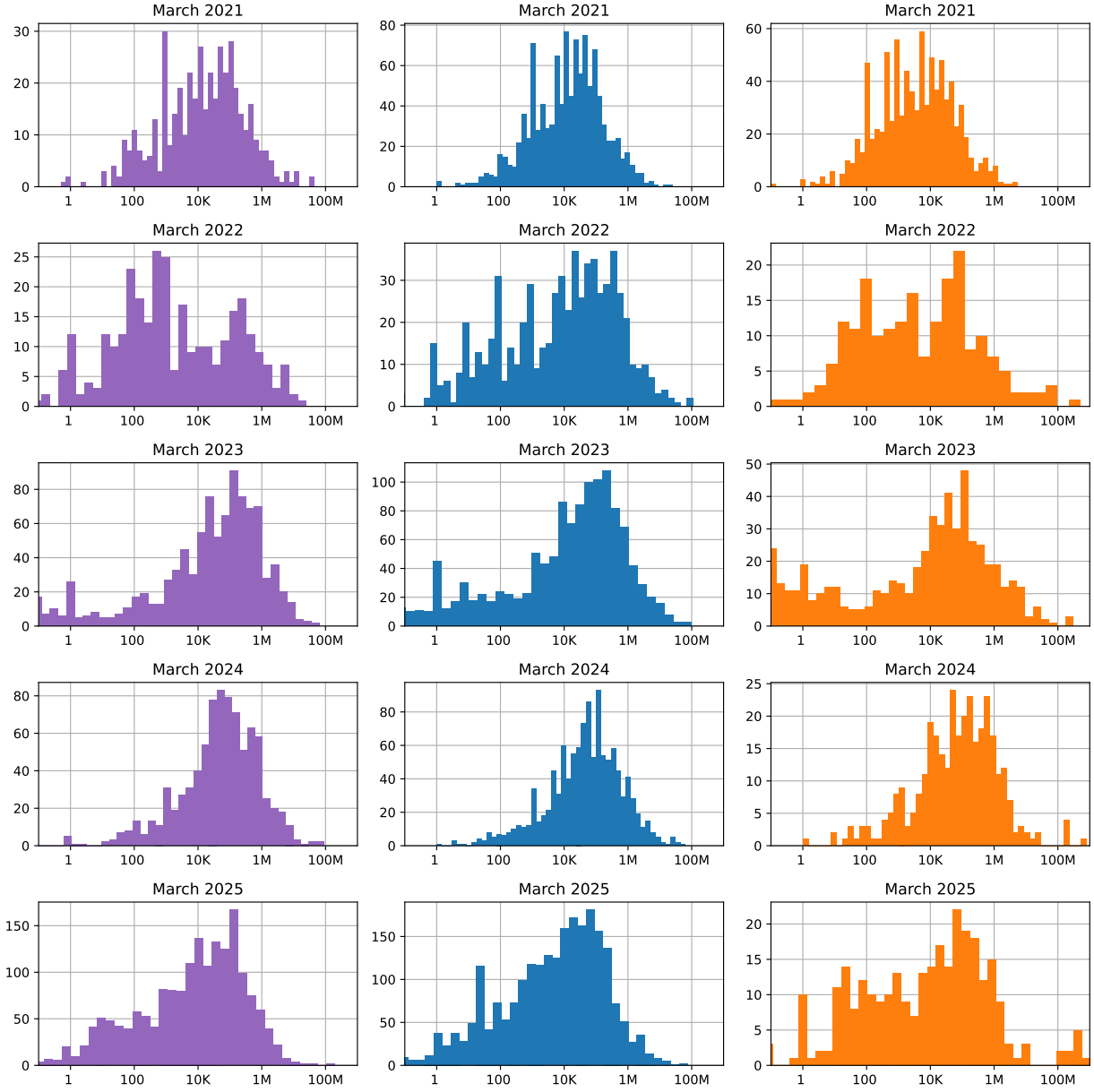
Note: Range of yields observed as of March 2025 for stablecoins, across chains and protocols. In MiCAR, crypto-asset service providers (CASPs) may borrow stablecoins and pay interest to lenders, provided that such remuneration is not linked only to passive holdings of stabelcoin tokens. This table does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

Figure 18: 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.

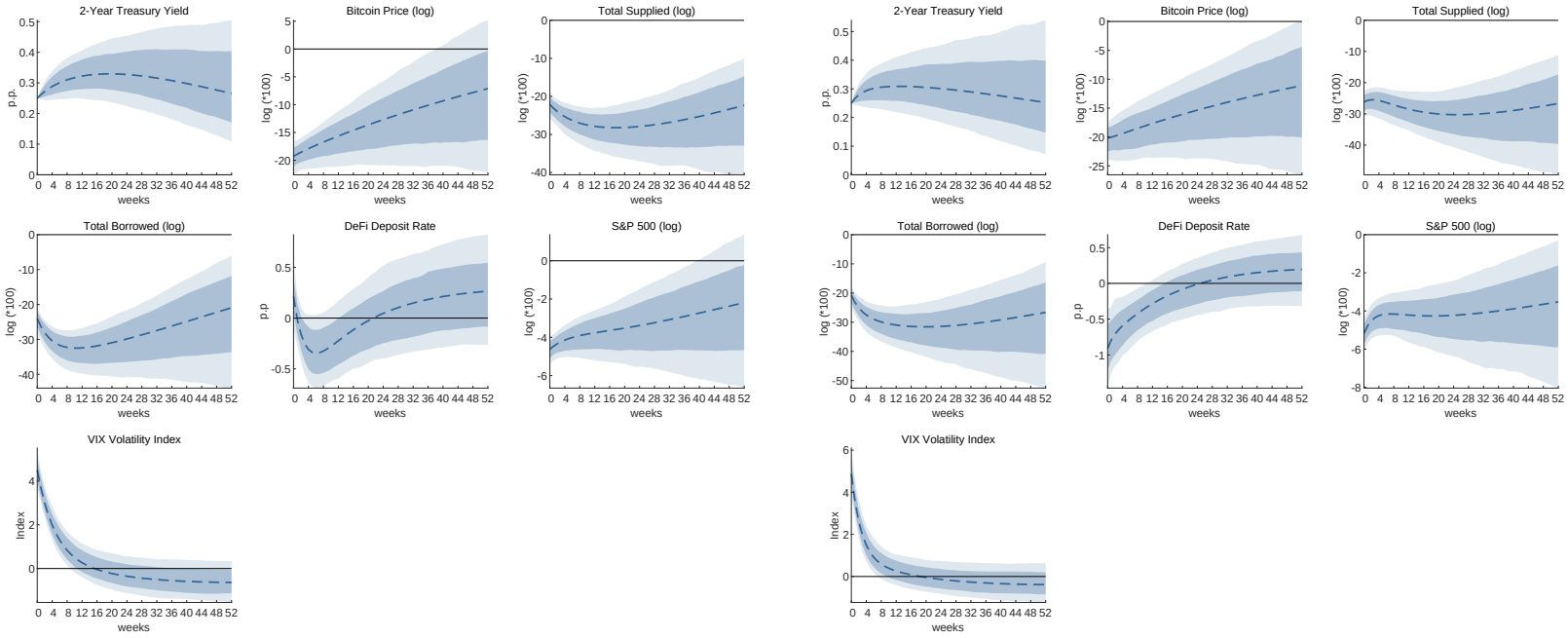
Figure 19: Distribution of liquidity positions size across coins and years



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.

Figure 20: Impulse responses - weekly frequency robustness check

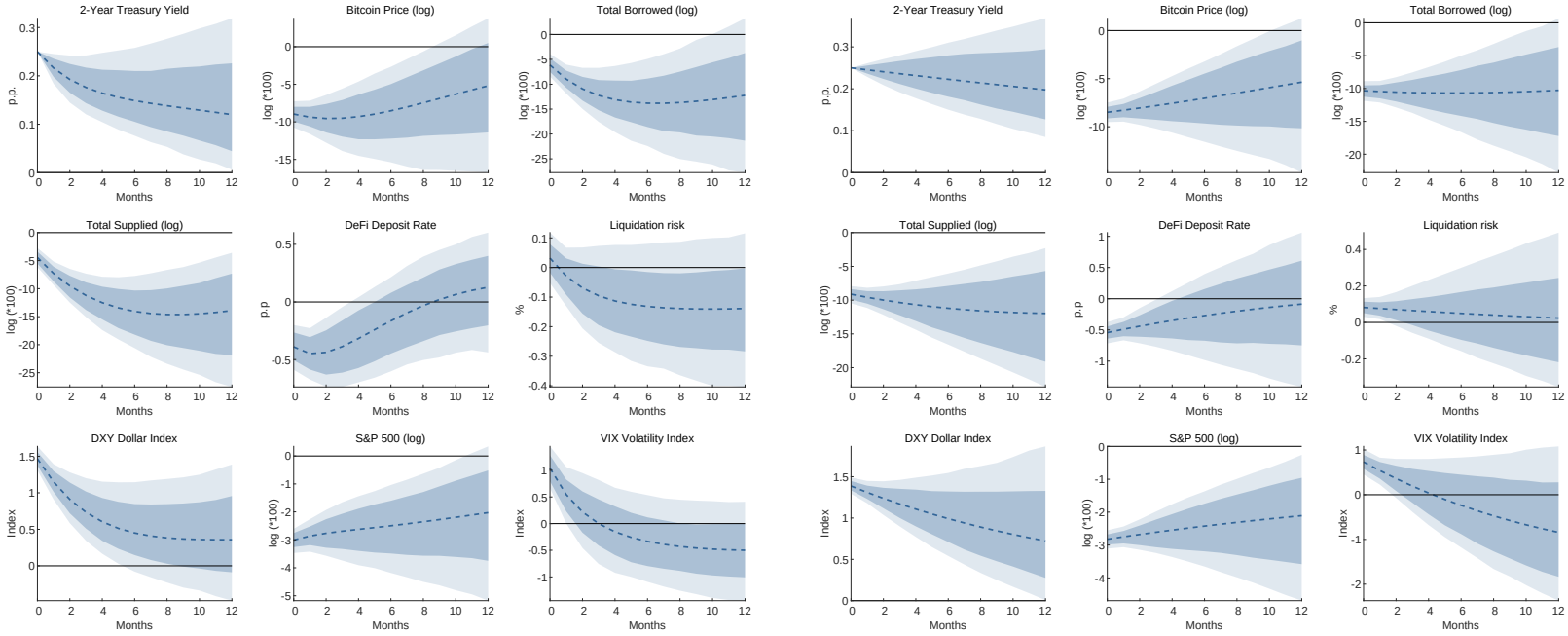
(a) USDC **(b)** USDT



Notes: 7-variable baseline VAR, with 1 lag (BIC criterion). Shocks from Jarociński and Karadi (2020) using weekly-aggregated monetary policy surprises purged from information effect (Poor man's sign restrictions). First stage F-stat = 16.7. The shock is normalized to induce a 25 basis point increase in the 3-month U.S. Treasury Bill yield. Sample: January 2021-January 2026. Shaded areas are 90 percent (dark blue) and 68 percent (light blue) posterior coverage bands.

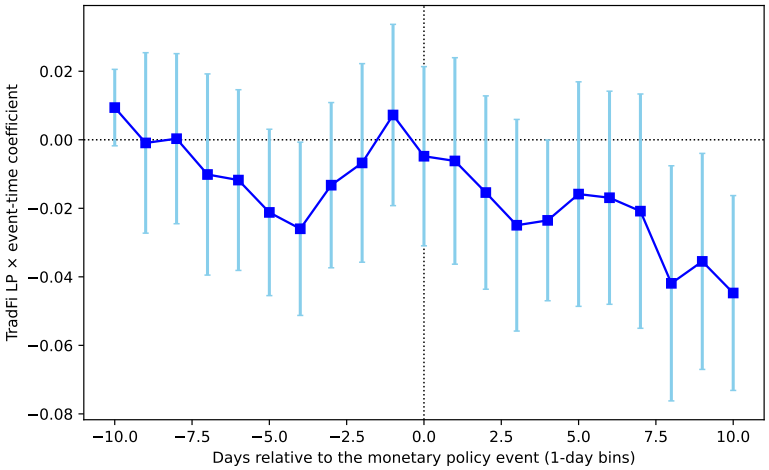
Figure 21: Impulse responses - Liquidation Risk and DXY Index

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



Notes: 7-variable baseline VAR, with 1 lag (BIC criterion). Shocks from Jarociński and Karadi (2020) using monthly-aggregated monetary policy surprises purged from information effect (Poor man's sign restrictions). First stage F-stat = 11.5 is above the usual weak instrument threshold. The shock is normalized to induce a 25 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 22: Dynamic response around monetary policy events.



Notes: The figure reports the estimated coefficients on the interactions between the TradFi LP indicator and event-time indicators, analogue to the specification reported in Table 5 with day-dummies around the policy rate event. The dummy takes value -1 for the rate cuts in the sample. A negative coefficent indicates that USDC-only wallets reduce liquidity provision more strongly after a rate hike and increase it mor after a cut. The error bars represent 90% confidence intervals. The vertical dotted line indicates the event date.

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, Kapadia, and Madan (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 $\text{Dep}_{u,j,t}$ denote wallet u's end-of-day collateral holdings in token j, and let $\text{Bor}_{u,j,t}$ 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

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

while debt values remain at

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

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

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

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

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

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

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

Aggregating across wallets yields total bad loans on day t:

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

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.