DeFi-ying the Fed?

Monetary Policy Transmission to Stablecoin Rates

Andrea Barbon, Jean Barthélemy, Benoit Nguyen*

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Abstract

Does the Federal Reserve's monetary policy transmit to stablecoins pegged to the US dollar? Large stablecoin issuers do not pay interest, but investors can lend stablecoins in Decentralized Finance (DeFi) lending protocols, where interest rates are governed by predetermined interest rate rules enforced by smart contracts. This leads to markedly different interest rates between conventional short-term rates and stablecoins' interest rates. We first document that the recent Federal Reserve's interest rate hiking cycle coincided with falling stablecoin interest rates until July 2022, after which the correlation became positive. To make sense of the observed dynamics, we develop a simple model of DeFi lending and bring it to the data. The model successfully reproduces the observed shift in monetary policy transmission to stablecoin rates.

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*Andrea Barbon is Assistant Professor at the University of St.Gallen, Center for Financial Services Innovation, and the Swiss Finance Institute (andrea.barbon@unisg.ch). Jean Barthélemy is Senior research economist at the Banque de France (jean.barthelemy@banque-france.fr). Benoit Nguyen is Lead Economist at the European Central Bank and Banque de France. (benoit.nguyen@ecb.europa.eu).

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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"*
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> — Vice Chair Michael S. Barr, Federal Reserve Bank of Philadelphia, Sep 8th 2023

Decentralized finance (DeFi) has grown rapidly in a couple of years since 2020, albeit this growth has halted in 2022 in the wake of the crypto-market crash. Nevertheless, DeFi applications such as borrowing, lending, and leveraging without the need for traditional intermediaries and the programmability of money offered by smart contracts may have a durable impact on finance.

Interest rates earned by lending crypto assets in DeFi platforms are an interesting object from a traditional finance point of view. DeFi lending and borrowing rates are set by interest rate models defined and coded in smart contracts. The resulting rates are based on the supply of liquidity and the demand for borrowing, and are not directly influenced like conventional risk-free rates by policy rates, e.g. there is no central bank to set the interest rate or to operate facilities to control the floor and ceiling of market rates, for instance.

This has resulted in the past in a wide disconnect, at least in terms of levels, between stablecoins' interest rates on DeFi and alternatives in traditional finance like bank deposits, MMF shares, or Treasury bills: for instance, in 2021, the average interest rate on USDT, USDC, and DAI was almost 400 bps higher than the effective Fed Funds rate.

This apparent disconnect of a form of privately run digital dollar may reflect differences in risks, eg. remuneration of risks specific to stablecoins as de-peg, or common to crypto markets, such as fails and hacks of the DeFi platforms, volatility in the valuation of the collateral, etc. but it also reflects fundamental mechanisms on the formation of interest rates in DeFi. The recent interest rate hiking cycle of the Federal Reserve offers an experiment on mechanisms at play in the formation of interest rates in DeFi and the potential linkages with conventional financial markets.

Figure 1 displays the evolution of the Fed Fund rate and the 1-year T-Bill rate (solid yellow) as proxies for the risk-free rate, and the average deposit rate across six stablecoin-platform pairs (solid green). It suggests that variations in stablecoins interest rates have been negatively correlated to Tbill yields until mid-2022 and then highly positively correlated. The vertical line on July 1st separates two regimes, motivated by the different relative dynamics between stablecoin rates and the risk-free rate.[1] In the first period, the correlation coefficient between the two rates is strongly negative at -0.54, while it turns positive at 0.68 in the second part of the sample. Further, in most of the first period, the spread between DeFi rates and the risk-free is positive, averaging at 1.9%. On the contrary, in the second period, the spread is negative with an average of -2.9%.

In this paper, we develop a model of liquidity provision that can explain and rationalize the DeFi rate dynamics observed in the data. In a nutshell, we argue two mechanisms are at play: first, one in which investors arbitrage the difference in interest rates between DeFi and conventional markets, and second, one in which the demand for borrowing in DeFi depends on the appetite for leverage, e.g. to invest in other crypto assets like Bitcoin. We show that, depending on which force dominates, the correlation between stablecoin and risk-free rates can be either positive or negative.

To bring the model to the data, our empirical work is based on data available on-chain from two of the most prominent DeFi lending platforms, AAVE and Compound. Leveraging an Ethereum archive node[2], we construct a rich dataset of the available liquidity deposited in the lending pools and the standing borrowing positions for the three most active stablecoins, namely USDC, USDT, and DAI.

We then estimate the key parameters of the model for the six stablecoin-platform pairs with riskfree rates and the demand for borrowing as input variables. The model is able to fit the stablecoin interest rates fairly well and to generate the shift in the monetary policy transmission around July 2022. Before this date, the main determinant of stablecoin rates

[1]Note that the separation line between the 1st and 2nd periods is close to the day in which the two rates cross.

[2]We acknowledge the help and thank Banque de France's Lab for maintaining this node.

was the drop in the demand for borrowing while the main one after is the rise in the riskfree rate.

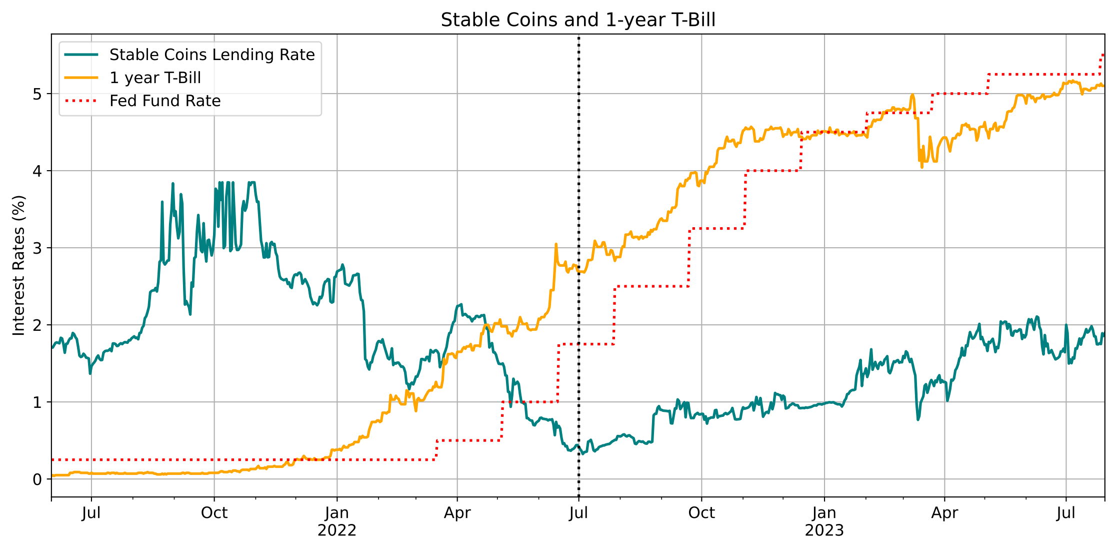

Figure 1: DeFi Rates and US Short-Term Rates The figure displays the time-series evolution of the 1-year T-Bill rates (solid yellow), the FED fund rate (dotted red), and the deposit rate for USD-pegged stablecoins (solid teal). The latter is computed as the daily average across three stablecoins (USDT, USDC, and DAI) and two DeFi lending platforms (Aave v2 and Compound v2) on the Ethereum network. The vertical dotted line denotes a regime shift in the dynamics of the deposit rate in July 2022.

We contribute to the emerging literature on DeFi lending, focusing on the monetary policy passthrough to stablecoin rates. Our paper is closely related to Chaudhary et al. (2023), who investigate the determinants of interest rates in DeFi protocols, both theoretically and empirically. However, their model is fundamentally different since it focuses on demand from speculators while it does not feature liquidity providers. We complement their work by explicitly modeling the supply side and unveiling the crucial role of the risk-free rate as a determinant of stablecoin rates. 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. While they model both the supply and demand sides, the resulting equilibrium rates do not depend on the risk-free rate set by the Central Bank. Gudgeon et al. (2020b) perform an empirical analysis of historical deposit rates for dYdX, Aave, and Compound, finding substantial interest rate parity deviations and a high degree of cross-market dependence. We add to their findings by empirically assessing the relation between DeFi rates and the risk-free rate. Carre and Gabriel (2022) explore the interaction between interest rate models of DeFi lending protocols and the security of the consensus layer in the underlying Proof-of-Stake blockchain. Aramonte et al. (2022) discuss the implications of over-collateralization, including pro-cyclicality and poor financial inclusion. We extend their findings showing that the transmission of monetary policy to DeFi rates can affect the pro-cyclicality of DeFi lending.

On a broader perspective, our paper contributes to the literature on monetary policy pass-through and the dispersion of near-money assets interest rates (Duffie and Krishnamurthy, 2016), the private forms of safe assets (Nagel, 2016; Sunderam, 2015; Kacperczyk et al., 2021) and the transmission mechanisms of monetary policy to asset prices, in particular related to the risk-taking channel of monetary policy (Bernanke and Kuttner, 2005; Borio and Zhu, 2012; Drechsler et al., 2018; Bauer et al., 2023).

The remainder of this paper is organized as follows. Section 2 exposes the DeFi lending protocols and the interest rate determination. Section 3 builds a simple model to account for the possible impact of risk-free rate on DeFi interest rates. Section 4 details the data we extract from the Ethereum archive node and proposes an empirical exercise informed by the model on the link between DeFi and risk-free rates. Finally, in Section 5, we bring the model to the data, and show the model is sufficiently rich to account for the observed dyamics on the DeFi interest rate around the recent Federal Reserve's rate hikes. Section 6 concludes.

2 A Primer on DeFi Lending Protocols

In this section, we briefly describe how DeFi lending protocols work, providing some of the main institutional features and focusing on the determination of interest rates.

DeFi lending protocols DeFi lending protocols are a cornerstone of the decentralized finance ecosystem, enabling users to lend and borrow assets without intermediaries. By leveraging on blockchain technology, these platforms offer transparent, permissionless, and often more competitive interest rates compared to traditional finance. In traditional finance, lenders and borrowers typically engage in direct peer-to-peer interactions. In contrast, DeFi lending platforms operate on a liquidity pool-based model, where lenders deposit assets that become part of a collective pool from which borrowers draw. Within these platforms, 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 —– either in the same or a different crypto-asset —– to secure their borrowing. Should the collateral's value decline, borrowers must provide additional assets. Failing to do so, and upon reaching a predetermined threshold, the collateral is liquidated at a discount, and the loan is automatically settled.

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

Interest Rates Determination Within DeFi lending platforms, there are two primary rates: the *borrow rate*, which borrowers pay, and the *deposit rate*, which lenders earn. These interest rates are not set manually. Instead, they are algorithmically determined by the underlying protocols, ensuring real-time adjustments based on supply and demand dynamics. Borrow rates are a piecewise linear function of this utilization rate (see, for instance, the official Aave documentation). More precisely, they are defined as follows in Aave and Compound, respectively:

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

where u is the utilization rate and α, β are real numbers set by governance vote by the platform itself. $\bar{u} \in (0,1)$ is the targeted utilization rate. Typically, $\beta' >> \beta$ to prevent excessive lending of assets simultaneously. This precaution safeguards against significant price fluctuations in the collateral asset, which could lead to simultaneous mass liquidations or under-collateralized positions. Given that the protocol operates below a utilization rate of 1, it implies that a portion of the funds remains idle within the protocol, thereby "not accruing interest". Yet, given the fungibility of all deposits, interest accrued from borrowers is uniformly distributed to every participant in the pool. As an example, in a USDC pool with a total of 2 deposited tokens and 1 token loaned out at 10% annual interest, the yearly interest payment amounts to 0.1 USDC. This sum is equally distributed among the 2 USDC "providing liquidity", resulting in a return on investment of 0.05 USDC or 5% for lenders. Hence, on platforms like Compound and Aave, the interest earned by lenders is calculated as the deposit rate multiplied by the utilization rate.[3]

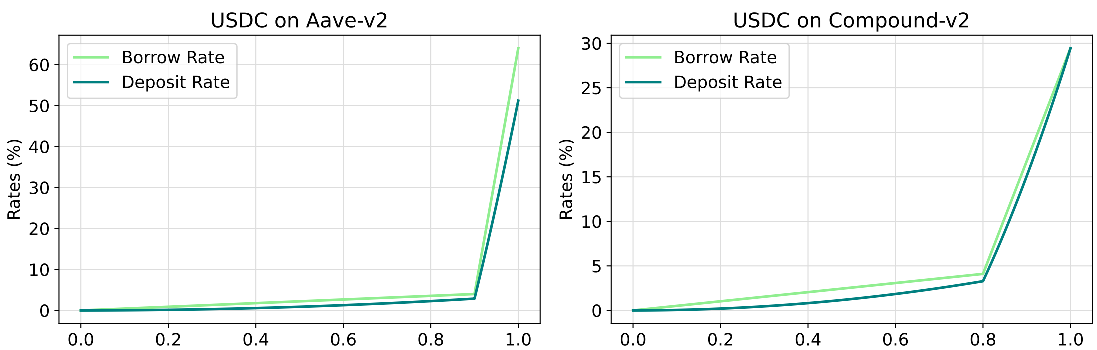

Figure 2: Interest Rate Models. The figure plots the deposit and borrowing rates, annualized and displayed in percentage points, for USDC on Aave and Compound, as a function of the utilization rate.

Risks Lending on DeFi protocols is not a risk-free investment, for at least two reasons. First, if vulnerabilities or bugs are present in the code or logic of underlying smart contracts, the protocol could be breached, resulting in the loss of (part of) the deposited tokens.[4] Second, a sharp decline in the valuation of crypto-assets pledged as collateral may precipitate a cascade of forced liquidations, evoking a scenario analogous to a fire sale. Should the initial

[3]On Maker DAO, the interest rates are set manually by governance on the pools. The "lender" is the platform itself therefore there is no lending interest rate but depositing DAI tokens earns interest through a so-called *Deposit Saving Rates*. The supply does not affect the rates unless the DAO chooses otherwise.

[4]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 on old versions of the Vyper compiler, allowing malicious users to perform re-entrancy attacks.

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. [5]

3 A Simple Model of DeFi Lending

In this section, we propose a model of DeFi lending and borrowing protocols. We abstract from many important features like liquidation, reserves, or governance to focus mainly on the impact of risk-free rate changes on DeFi rates through arbitrage and asset valuation channels. We first derive simple results showing that deposit rates may move due to a fall in demand for borrowing tokens or due to risk-free rate changes, assuming that the demand is exogenous. Then, we solve the model when risky investors optimally use DeFi borrowing to take leveraged positions on risky digital assets (like BTC or ETH). We finally derive testable implications from the model.

3.1 The Role of Liquidity Providers

Environment Time is discrete and indexed by $t \in \{0, 1\}$. There are two types of investors — liquidity providers and risky investors — and two digital assets: a risky digital asset (a crypto-asset) and a risk-free digital asset (a stablecoin).[6] Investors are price takers. A DeFi protocol allows lending and borrowing the risk-free digital asset.

DeFi Protocol The DeFi protocol allows liquidity providers to deposit a quantity S of tokens at a gross rate ρ. With a probability θ a bad event materializes, leading to a lower return of $\rho - \psi$ with $\psi \in (0, 1 + \rho)$. Such a negative scenario can be interpreted in two ways. First, the smart contract representing the liquidity pool is hacked or dysfunctions because of a bug or a vulnerability in the Solidity code, leading to the loss of part of the deposited amount. Second, the value of collateral assets drops significantly, and the proceeds from the

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

[6] We here neglect the risk of de-peg without loss of generality as we introduce a risk on the DeFi platform which is very similar in our setting.

triggered liquidations are not enough to cover the loans completely.

The protocol also allows one to borrow a share of these tokens B at a gross rate ρ^B, unaffected by a potential hack. Both rates are increasing functions of the utilization rate $u = B/S$: $\rho^B = f(u)$ and $\rho = uf(u)$. For analytical tractability, we omit the kink in the presentation of the model and assume a linear formula: $f(u) = \alpha + \beta u$. We also omit the reserve rate that corresponds to an additional spread between the lending and the borrowing rates to manage the protocol's risks. The structural estimation presented in Section 5 will instead account for both the nonlinearity and the reserve rate.

Risky Investors As a first step, we assume that risky investors borrow a fixed amount of stablecoins B at date 0, through the lending platform. In this first presentation of our model, we thus assume an exogenous demand for borrowing stablecoins abstracting from the relationship between B and the risk-free rate ρ^*. We will relax this assumption in subsection 3.2

Liquidity Providers We assume liquidity providers can only invest in stablecoin liquidity provision, by depositing a quantity S of tokens on the DeFi protocol or, alternatively, investing in the risk-free asset. One can think of the risk-free return ρ^* as a measure of the opportunity cost of providing liquidity. Liquidity providers' utility at date 0 is mean-variance and incorporates possible convenience yields resulting from holding stablecoins:

$$u(\tilde{W}, S) = \mathbb{E}\tilde{W} - \frac{\gamma}{2}\mathbb{V}\tilde{W} + w_l \frac{S^{1-\sigma}}{1-\sigma}, \tag{2}$$

where $\tilde{W}$ is the date-1 wealth of liquidity providers, γ measures risk-aversion, w_l is the relative weight of the liquidity services of stablecoin, and σ measures the concavity of the preference for stablecoins.The objective of the liquidity provider is to maximize its utility:

$$\max_{S \geq 0} \quad (\rho - \theta\psi - \rho^*)S - \frac{\theta(1-\theta)}{2}\gamma\psi^2 S^2 + w_l \frac{S^{1-\sigma}}{1-\sigma},$$

The presence of a strictly concave liquidity service ($w_l, \sigma > 0$) allows for a unique interior optimal stablecoin investment S that satisfies the first order condition:[7]

$$\rho - \rho^* - \theta\psi = \theta(1-\theta)\gamma\psi^2 S - w_l S^{-\sigma}. \tag{3}$$

Notice that the deposit rate $\rho = \frac{B}{S} f(\frac{B}{S})$ is strictly decreasing with S. By plugging this function in the optimal portfolio allocation (3), we find that the aggregate demand satisfies:

$$u f(u) - \rho^* - \theta\psi = \theta(1-\theta)\gamma\psi^2 S - w_l S^{-\sigma}. \tag{4}$$

Assuming a fixed demand for stablecoins (B), one can represent the equilibrium as depicted in Figure 3, showing the impact of a risk-free rate increase ρ^* on the equilibrium. The blue line corresponds to the aggregate supply curve defined by equation (4) and the red curve to the aggregate demand curve defined by $u = B/S$ for a given demand B.

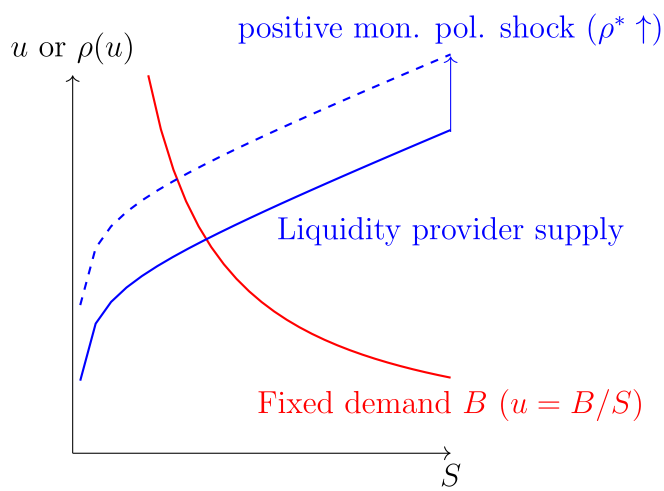

Figure 3: Monetary policy shock with fixed demand. The x-axis stands for the supply of stablecoins; the y-axis stands for the utilization rate u or the borrowing rate $\rho(u)$. The blue curve shows the liquidity providers' optimal supply and the dashed blue curve shows it for a higher riskfree rate ρ^*. The red curve simply corresponds to a fixed demand B. The intersection corresponds to the equilibrium under the assumption that demand is exogenous.

As it is clear from the plot, such an increase leads to a higher utilization rate and higher

[7] We assume perfect competition among liquidity providers, who take the aggregate price ρ as given.

interest rate. The following proposition sums up the key feature of the equilibrium when B is taken as given.

Proposition 1 (Aggregate supply)**.** *The aggregate supply of stablecoins by liquidity providers features the following properties:*

- *For a given borrowed amount B, the stablecoin supply S decreases with ρ^*, while the utilization rate u and the stablecoin deposit rate ρ increase with the risk-free rate ρ^*.*
- *For a given risk-free rate ρ^*, the stablecoin supply S, the utilization rate u, and the stablecoin deposit rate ρ increase with the borrowing demand B.*

Proof. Let us first introduce the key quantities:

$$\lambda = (\alpha + 2\beta u)u \quad \text{ and } \quad \kappa = \frac{\lambda}{\lambda + \theta(1-\theta)\gamma\psi^2 S + w_l \sigma S^{-\sigma}} \in [0,1),$$

where κ is strictly increasing in u, equals 0 for $u = 0$. Full differentiation of equation (4) with $u = B/S$ leads to:

$$(\lambda + \theta(1-\theta)\gamma\psi^2 S + w_l \sigma S^{-\sigma}) d\ln S = -d\rho^* + \lambda d\ln B$$

Therefore we get

$$\begin{aligned} d\ln S &= -\frac{\kappa}{\lambda} d\rho^* + \kappa d\ln B, \\ d\ln u &= \quad \frac{\kappa}{\lambda} d\rho^* + (1-\kappa) d\ln B, \\ d\rho &= \quad \kappa d\rho^* + (1-\kappa)\lambda d\ln B. \end{aligned}$$

We have then the following elasticities with respect to the risk-free rate ρ^*:

$$\frac{\partial \ln S}{\partial \rho^*} = -\frac{\partial \ln u}{\partial \rho^*} = -\frac{\kappa}{\lambda}, \quad \text{ and } \quad \frac{\partial \rho}{\partial \rho^*} = \kappa.$$

Similarly, partial derivation with respect to the borrowing demand B, taking ρ^* as given, leads to:

$$\frac{\partial \ln S}{\partial \ln B} = \kappa, \quad \frac{\partial \ln u}{\partial \ln B} = 1 - \kappa, \quad \text{and} \quad \frac{\partial \rho}{\partial \ln B} = \lambda(1 - \kappa).$$

□

Time-Varying Drivers of Stablecoin Rates According to Proposition 1, stablecoin deposit rates increase with the risk-free rate ρ^* and with the demand for stablecoins B. It is worth noticing that the two forces can have different strengths depending on the state of the economy. To see that, assume $\alpha = 0$. As a consequence, the elasticity $\partial \ln \rho / \partial \ln B$ is exactly $2(1 - \kappa)$, while the partial derivative $\partial \rho / \partial \rho^*$ is equal to κ. So when the first force is weak, the second is strong, and vice-versa. This may rationalize why under some regimes stablecoin rates are mainly driven by changes in B while, under others, they are primarily driven by risk-free rate changes.

Borrowing Constraints Suppose that the liquidity providers face a borrowing constraint. In such a situation, if the risk-free rate ρ^* is sufficiently low given the demand for stablecoins B, then the liquidity providers cannot perfectly arbitrage up to the mean-variance optimal portfolio. Under such a scenario, S is fixed and hence the dynamics of stablecoin rates are completely determined by the demand for stablecoins B and do not depend on the interest rate ρ^*. This is an alternative, yet unnecessary, channel that could explain the shift in the monetary policy transmission we observe in the data.

3.2 Risky Investors

Previous literature highlighted the fact that DeFi lending protocols facilitate speculation in crypto assets and are mainly used by borrowers to take leveraged or short positions (Aramonte et al., 2022; Chaudhary et al., 2023). We therefore model the borrowing demand of risky investors as a function of their expectation of the risk-return tradeoff offered by the unstable crypto asset. More specifically, we assume that risky investors expect a return ρ_U on the unstable coin, with a variance σ_U^2, sufficiently appealing so that they do not invest in risk-free assets. Further, we assume that the only means to borrow and invest more than their initial wealth, W', is to use a DeFi lending protocol — say because collateralization of unstable coins and unsecured lending may be impossible to this class of investors. For simplicity, we assume that there is no return on depositing risky digital assets as collateral in the protocol. The optimization problem faced by the risky investors is the following:[8]

$$\max_U \quad (1+\rho_U)U - B(1+\rho^B) - \frac{\gamma'}{2}\sigma_U^2 U^2, \tag{5}$$

$$\text{s.t } \; W' + B \geq U, \;\; \text{and} \;\; (1-h_U)U \geq B. \tag{6}$$

If interior, this optimization program leads to the standard demand schedule:

$$B = \frac{\rho_U - \rho^B}{\gamma'\sigma_U^2} - W'. \tag{7}$$

The equilibrium is then determined by the intersection of the aggregate demand and the aggregate supply equations:

$$u = \frac{\rho_U - \alpha - W'\gamma'\sigma_U^2}{\gamma'\sigma_U^2 S + \beta}, \tag{8}$$

$$u\rho(u) = \rho^* + \theta\psi + \theta(1-\theta)\gamma\psi^2 S - w_l S^{-\sigma}. \tag{9}$$

The first equation is downward-sloping in the (u, S) locus: B increases by less than one-to-one to a rise in S leading to a fall in the utilization rate (and hence the rate ρ). The limit case with $\beta = 0$ leads to the standard formula for B and the fact that B is independent of the supply S. The second equation is upward-sloping in the (u, S) locus as already studied above. The intersection is unique and coincides with the equilibrium outcome, as depicted in Figure 4.

There are at least two channels through which monetary policy can be transmitted to sta-

[8] As for liquidity providers, we assume that risky investors take the borrowing rate, ρ^B as given.

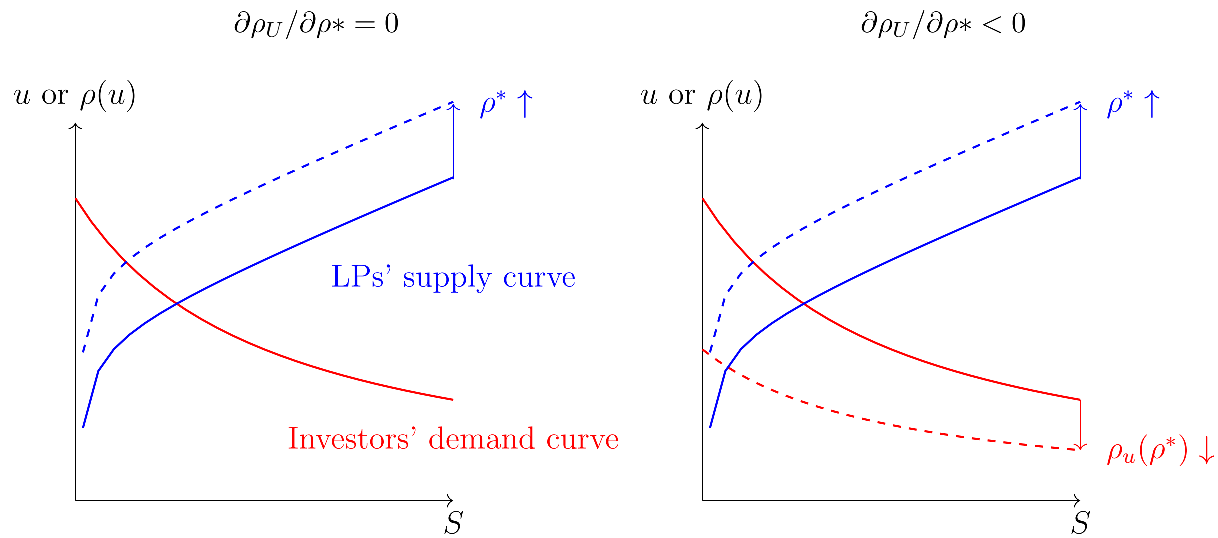

Figure 4: Monetary policy shock with optimal investors. The x-axis stands for the supply of stablecoins; the y-axis stands for the utilization rate or the borrowing rate. The blue curve shows the liquidity provider's optimal supply and the dashed blue curve shows it for a higher risk-free rate ρ^*. The 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.

blecoin rates. First, the supply S depends positively on ρ^*, as in the benchmark case with exogenous B, because of the opportunity cost of investing in liquidity provision. Notice that here, even if this is the only channel through which the risk-free rate affects DeFi, the endogenous reaction of B to ρ^* dampens the response of stablecoin rates to monetary policy shocks. Second, ρ_U may negatively depend on ρ^*, assuming a rate hike reduces the expected return on the risky crypto asset. This leads to a reduction in B and an overall decrease in ρ. The following proposition shows that both forces can dominate:

Proposition 2. *For any risk-free rate ρ^*, there exists a unique equilibrium (S, B). If ρ_U do not depend on ρ^*, then ρ increases with ρ^*. On the contrary, if $\rho_U(\rho^*)$ decreases enough with ρ^*, then ρ is decreasing with ρ^*.*

Proof. First, the existence of a unique solution is given by monotonicity arguments and equations (8) and (9). Second, the impact of a slight change in the risk-free rate can be obtained by partial derivations of these equations. The partial differentiation of equation (8) with respect to ρ^*, assuming that only ρ_u depends on ρ^*, leads to:

$$\frac{\partial S}{\partial \rho^*} = \frac{\frac{\partial \rho_u}{\partial \rho^*}}{\gamma' \sigma_U^2 u} - \frac{S + \beta/(\gamma' \sigma_U^2)}{u} \frac{\partial u}{\partial \rho^*}$$

Then, we plug this formula into the first differentiated supply curve from equation (9) and we get:

$$[\alpha + 2\beta u + \frac{S + \beta/(\gamma' \sigma_U^2)}{u}(\theta(1-\theta)\gamma\psi^2 + w_l \sigma S^{-\sigma-1})]\frac{\partial u}{\partial \rho^*} = 1 + \frac{\frac{\partial \rho_u}{\partial \rho^*}}{\gamma' \sigma_u^2 u}[\theta(1-\theta)\gamma\psi^2 + w_l \sigma S^{-\sigma-1}].$$

The left-hand-side member is positive. The right-hand-side member is positive when ρ_u does not depend on ρ^*. Thus, in this case, $\frac{\partial u}{\partial \rho^*} > 0$, and hence the borrowing rate as well as the deposit rate are increasing with ρ^*. On the contrary, when $-\frac{\partial \rho_u}{\partial \rho^*} > \frac{\gamma' \sigma_u u}{\theta(1-\theta)\gamma\psi^2 + w_l \sigma S^{-\sigma-1}}$ then $\frac{\partial 1u}{\partial \rho^*} < 0$. In particular, this condition is satisfied when:

$$-\frac{\partial \rho_u}{\partial \rho^*} > \frac{\gamma' \sigma_u}{\theta(1-\theta)\gamma\psi^2}. \tag{10}$$

□

Proposition 2 predicts that a risk-free rate increase may lead to a positive or a negative effect on stablecoin rates, as observed in Section 2. This crucially depends on the impact of ρ^* on ρ_U as well as the curvatures of demand and supply curves.

Why can we observe a decoupling of risk-free rate and stablecoin rates? Here, the key driver is the fall in the expected return on the risky asset following an increase in the risk-free rate. Such a fall reduces the willingness to take leverage on the risky asset using the DeFi platform and hence reduces B, if the other side of the market is sufficiently willing to hold stablecoin (ψ sufficiently small) the supply of tokens does not fall as much as the demand and rates decrease.

Testable Implications To test if our model provides a relevant description of the supply side of lending platforms, in Section 5 we perform a structural estimation of the model. We take B and ρ^* as exogenously given, computing the model-implied rates and optimizing the model parameters to achieve the best possible fit of the historical rates. Once the best parameters are estimated, we check whether the model can reasonably fit the data and, in particular, if it can reproduce the difference in the spread dynamics in the two halves of our sample.

Our theory highlights the importance of the deposit rate sensitivity with respect to ρ^*. To estimate that, in Section 4 we regress a proxy for ρ_u on ρ^* and test if the coefficient is negative. Empirically, we use as a proxy for the expected returns on risky crypto assets the funding rates on the BTC-USDT perpetual futures, traded on Binance. A similar proxy is used in Chaudhary et al. (2023).

Is the shift in monetary policy transmission identified in the previous section due to a change in elasticities or large negative shocks on the demand for stablecoins unrelated to the risk-free rates? To tackle this question we check whether we can replicate the fall in B with only ρ^* as input, or whether we need to add ρ_U as an input variable. [TBD]

4 Data and empirical analysis

4.1 Data

We leverage an Ethereum archive node, running at the Banque de France, to collect data on the two most prevalent DeFi lending platforms deployed on the Ethereum blockchain: Aave v2 and Compound v2. For the former, we gather the history of transactions from the Aave Lending Pool smart contract. These include (i) *Deposit* and *Withdraw* transactions, which we use to reconstruct the historical levels of liquidity deposited in the protocol for each stablecoin; (ii) *Borrow* and *Repay* transactions, to reproduce the historical outstanding borrowed amounts by stablecoin. Similarly, we construct historical liquidity levels for Compound, by extracting and processing transactions from the Comptroller contract, and borrowed amounts retrieving transactions from the coin-specific c-token contracts (for instance, the cDAI contract for DAI).

Table 1 provides summary statistics of the main variables from the two DeFi lending plat-

Table 1: Summary Statistics. The table provides summary statistics for the main variables collected from the DeFi lending platforms Aave v2 and Compound v2, broken down by platform and coin, and based on 210,852 observations at an hourly frequency over the period from June 2021 to September 2023. The variables include: the total supply of coins deposited in the liquidity pool by liquidity providers, S, including the amount lent out and that available for lending; the total amount borrowed, B, making up to the total outstanding debt; the utilization rate B/S; the annualized deposit rate, ρ, earned by liquidity providers; the annualized borrow rate, ρ^B, beared by borrowers.

		Aave			Compound		
		DAI	USDC	USDT	DAI	USDC	USDT
Supply S (Billion \$)	Mean	0.814	2.253	0.747	1.687	1.799	0.483
	Std	0.720	1.662	0.332	1.564	1.491	0.253
	Median	0.337	1.447	0.568	0.730	1.004	0.454
Demand B (Billion \$)	Mean	0.582	1.646	0.569	1.182	1.141	0.323
	Std	0.585	1.503	0.302	1.244	1.148	0.197
	Median	0.141	0.589	0.427	0.299	0.356	0.261
Utilisation Rate U (%)	Mean	62.963	66.798	74.144	59.490	55.548	65.067
	Std	15.457	18.665	11.781	14.207	15.348	10.937
	Median	69.737	70.401	75.908	55.872	58.024	64.887
Deposit Rate ρ (%)	Mean	1.761	2.016	2.836	2.223	1.583	2.754
	Std	1.461	2.037	4.727	1.038	1.080	2.609
	Median	1.856	1.790	2.171	1.836	1.500	2.283
Borrow Rate ρ^B (%)	Mean	3.454	3.394	4.448	3.812	3.712	4.671
	Std	2.007	2.513	6.050	0.968	1.525	3.024
	Median	3.548	3.178	3.607	3.553	3.693	4.139

forms, for the three most popular stablecoins pegged to the US Dollar, measured at an hourly frequency over the period from June 2021 to September 2023. These variables include the supplied liquidity S and the total amount borrowed B, expressed in billion US Dollars. Additionally, the table reports statistics on the utilization rate, that is, the ratio of B/S, and the resulting deposit and borrowing rates, expressed in percentage points. The table shows that the two lending platforms enjoy comparable levels of supplied liquidity and borrowing demand, ranging between half a billion and 2.5 billion US Dollars, on average. Some cross-sectional differences can be observed with, for instance, the demand and supply of DAI being significantly higher in Compound, while the USDT and USDT are slightly more represented on Aave. Further, the mean and median utilization rates are similar on the two platforms and across coins, but are roughly 10% higher for USDT. Similarly, mean and median deposit and borrow rates are somewhat comparable across exchanges but are higher for USDT.

Both Aave and Compound have coin-specific interest rate model smart contracts. Those expose public state variables encoding the parameter values for the kink location $\bar{u}$, the intercept α, and the slopes β and β'. For instance, the contract for the USDC model on Compound can be browsed on Etherscan. Thus, the parameter values for each platform-coin pair are collected by calling the appropriate *view* functions on the relevant smart contracts. Further, we collect reserve factors r from the official documentation of each platform.

Table 2: Interest Rate Models. The table provides the parameter values determining the coin-specific interest rate models of Aave v2 and Compound v2. These are collected by calling the appropriate *view* functions on the relevant smart contracts deployed on the Ethereum blockchain. The interest rate models for the two platforms are presented in equation (1).

Coin	Platform	α	β	β'	$\bar{u}$	r
USDT	Compound	0.00	0.05	1.27	0.80	0.08
USDT	Aave	0.00	0.05	0.75	0.90	0.20
USDC	Compound	0.00	0.05	1.27	0.80	0.30
USDC	Aave	0.00	0.04	0.60	0.90	0.20
DAI	Compound	0.00	0.05	1.27	0.80	0.15
DAI	Aave	0.00	0.05	0.75	0.90	0.25

Table 2 displays the obtained values, showing that the intercept α is equal to zero for all platform-coin pairs. The first slope parameter β is almost perfectly homogeneous at 0.05, except for a slightly lower value for USDC on Aave, while the second slopes β' are similar across coins but are much higher on Compound (1.27) than on Aave (0.75 for USDT and DAI, and 0.6 for USDC). Accounting for the different roles of the slope parameters on the two platforms, as expressed in equation (2), all pairs have a similar dependency on the utilization rate below the kink, while the sensitivity above the kink is significantly higher on Aave.[9] This explains why the maximum rates attenable on Compound are significantly lower, as depicted in Figure 2. However, given that the kink location is lower on Compound, there exists a small region next to the kink in which the platform generates higher rates than Aave for a given utilization rate.

[9]To make the slope coefficients comparable, one can define $\hat{\beta} = \beta/\bar{u}$ and $\hat{\beta}' = \beta'/(1-\bar{u})$, thus obtaining the same equations for the two protocols. Given that $\bar{u} = 0.9$ for Aave, the above transformation yields $\hat{\beta} = 0.0625$ and $\hat{\beta}' = 3.75$ for USDT and DAI, and $\hat{\beta} = 0.05$ and $\hat{\beta}' = 3$ for USDC.

Next, we augment the dataset with the daily time series of 1-year TBILL rates from the FRED website, which we use as a proxy for the risk-free rate. Finally, using APIs, we gather daily funding rates for perpetual futures traded on Binance, for BTC and ETH denominated in USDT. The funding rate is defined as the difference between the perpetual contract price and the spot price of the asset. If the perpetual is trading at a premium to the spot market, the funding rate is positive, and vice versa. We hence use the funding rate as a proxy for the expected return of unstable crypto assets ρ_U.

4.2 Empirical Analysis

This section provides some preliminary analysis of the deposit rates provided by DeFi lending platforms. In particular, we provide empirical evidence of their relationships with the expected return on unstable crypto assets and the risk-free rate. For each coin, we run time-series regressions of the deposit rate on the risk-free rate, a dummy indicating the period after July 1st, 2022, and their interaction. We add controls for the VIX index as a proxy for risk aversion, inflation swap to account for inflation expectations, and the funding rate of the BTC-USDC futures on Binance, as a proxy for crypto expected returns. Table 3 reports the results with two proxies for the risk-free rate: the 1-year OIS and the 10-year US Treasury bond yield. For the three stablecoins, and indepently of the risk-free rate used, we find a negative relationship before July 2022 and a strongly significant and positive correlation after. The estimated coefficients imply that the total passthrough after July 2022 is between 10% and 30%, depending on the specific stablecoin. Risk-aversion plays negatively, while inflation expectation plays positively.

To complement the time series analysis, we estimate a VAR model at high frequency, using the changes in 3-month Fed Funds Futures as a plausibly exogenous shock on the risk-free rate. Figure 5 shows the impulse function responses obtained with a hourly-frequency VAR where the shock is assumed to come from the high-frequency changes of the 3-month Fed funds futures, and the shocked variables being the average deposit rate across platforms and stablecoins, the total amount borrowed and supplied on platforms. It confirms again the changing relationship between risk-free rate and DeFi interest rates, but also that this

Table 3: DeFi Rates and Monetary Policy. The table presents regression results for each stablecoin, the dependent variable e.g. $\rho(USDT)$ represents the interest rate at which investors can borrow and lend USDT. OIS 1-year, 10-year US treasury yield, VIX and and 5y5y inflation swaps from Bloomberg. Funding rate BTC is extracted from Binance perpetual futures and represents the difference between the price of the perpetual futures and the spot price. T-stats are reported in parentheses and based on Newey-West standard errors accounting for time-series autocorrelation. Asterisks denote significance levels (***= 1%, **= 5%, *= 10%).

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	$\rho(USDT)$	$\rho(USDC)$	$\rho(DAI)$	$\rho(USDT)$	$\rho(USDC)$	$\rho(DAI)$
OIS 1y × Post Jul-22	0.662***	0.914***	0.675***			
	(2.627)	(3.920)	(3.380)			
OIS 1y	-0.532***	-0.609***	-0.405***			
	(-3.038)	(-4.848)	(-4.333)			
US Treas. 10y × Post Jul-22				0.801**	1.006***	0.741**
				(2.064)	(2.841)	(2.366)
US Treas. 10y				-0.715***	-0.702***	-0.473***
				(-3.000)	(-3.906)	(-3.357)
Post Jul-22	-2.007***	-2.805***	-2.989***	-2.607**	-3.286***	-3.251***
	(-2.955)	(-3.920)	(-4.705)	(-2.344)	(-2.999)	(-3.361)
VIX Index	-0.037***	-0.044***	-0.039***	-0.047***	-0.064***	-0.054***
	(-2.698)	(-3.890)	(-3.994)	(-4.108)	(-6.991)	(-6.511)
Infl. Swap	2.080***	1.843***	1.177***	2.076***	1.660***	1.111***
	(2.879)	(3.675)	(3.597)	(2.892)	(3.158)	(3.042)
Funding Rate (BTC)	0.032**	0.023***	0.006***	0.032**	0.024***	0.007***
	(2.437)	(5.651)	(2.743)	(2.529)	(5.758)	(2.978)
Intercept	-1.265	-1.097	0.855	-0.168	0.570	1.877**
	(-0.720)	(-0.826)	(0.967)	(-0.112)	(0.470)	(2.265)
Observations	791	791	791	791	791	791
R-squared	0.473	0.686	0.826	0.464	0.648	0.803

relationship is significant – albeit in opposite direction – in the two sub-periods.

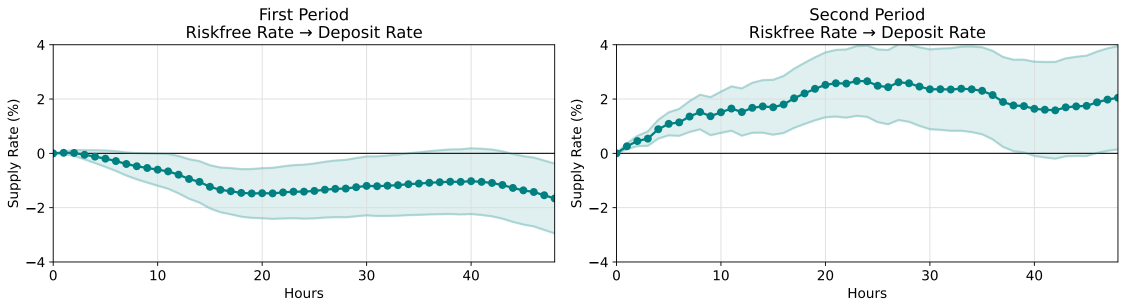

Figure 5: Response to risk-free rate Shocks. The figure plots the cumulative impulse-response functions from a VAR model with 24 lags estimated using data at an hourly frequency. The endogenous variables are log-differentiated, and include: (i) the deposit rate, average across platforms and stablecoins; (ii) the total amount borrowed, in billion USD, summed over the platforms and stablecoins; (iii) the total amount supplied, in billion USD, summed over the platforms and stablecoins; (iii) the risk-free rate, proxied by 3-month Fed funds futures. All variables pass the Augmented Dickey–Fuller test for stationarity.

As noted in Section 3, an important determinant of DeFi rates is the borrowing demand B which, through the lenses of our model, depends on the expected risk-return tradeoff offered by unstable crypto assets. In turn, the current stance of monetary policy is likely to play a role in forming such an expectation, through several channels.[10] To test if expected returns react to changes in the risk-free rate, we use the funding rates on perpetual futures on Bitcoin and Ethereum quoted on Binance as a proxy for the expected return of unstable crypto assets ρ_U. We then run time-series regressions of these funding rates on the risk-free rate.

Results are reported in the first two columns of Table 4, showing that the coefficients on the risk-free rate are negative and highly statistically significant. The estimated coefficients are also economically significant, indicating that a one percentage point increase in the risk-free rate is associated with a 1.17% decrease in the funding rates of perpetual futures on Bitcoin, and a 1.9% decrease in the funding rates of perpetual futures on Ethereum.

Next, we regress the total borrowing demands (for Compound and Aave combined) on the funding rate of perpetual futures. The findings, as delineated in columns (3) and (4) of Table 4, reveal positive and highly significant coefficients across all specifications. Moreover, the economic impacts are noteworthy: a one percentage point augmentation in funding rates cor-

[10]For instance, these include the discount rate channel, the opportunity costs channel, and the portfolio rebalancing channel (Barbon and Gianinazzi, 2019).

Table 4: Crypto Expected Returns. The table provides results from daily time-series regressions estimated over the period from June 2021 to September 2023. T-stats are reported in parentheses and are based on Newey-West standard errors accounting for time-series autocorrelation. Asterisks denote significance levels (***= 1%, **= 5%, *= 10%).

	(1)	(2)	(3)	(4)	(5)
Dep. Variable	Funding Rate (BTC)	Funding Rate (ETH)	Total Borrowing	Total Borrowing	Total Borrowing
Riskfree Rate	-1.165***	-1.858***			-4.483***
	(-2.673)	(-3.975)			(-5.222)
Funding Rate (BTC)			0.317***		
			(4.675)		
Funding Rate (ETH)				0.231***	
				(2.721)	
Intercept	10.225***	10.990***	8.969***	9.819***	22.609***
	(6.035)	(6.961)	(9.409)	(10.443)	(13.813)
Observations	791	791	791	791	791
R-squared	0.049	0.059	0.115	0.129	0.833

relates with a surge in borrowing demand in the order of hundreds of millions of dollars. Such evidence supports the hypothesis that speculative incentives are a primary impetus behind the fluctuations in borrowing demands. Finally, to check if monetary policy is correlated to the DeFi borrowing demand, we regress the total borrowing demand on the risk-free rate. [11] The results, reported in column (5) of Table 4, unveil a negative and highly significant beta coefficient. The economic magnitude is striking, with one percentage increase in the risk-free rate associated with a 4.5 billion dollars decline in the total borrowing demand, on Aave and Compound combined. This result strongly supports the view that the risk-free rate transmits to DeFi rates through a demand channel.

[11] All the reported results are robust to considering coin-specific borrowing demands in place of the total demand.

5 Structural Estimation

In this section, we study the empirical relevance of our model of DeFi lending, assessing its ability to quantitatively match the dynamics of historical stablecoins rates. In particular, we are interested in testing whether our theory can accommodate the two regimes observed in the data, in which the correlation between stablecoin rates and the risk-free rate exhibits different signs. We hence take the model described in Section 3 and bring it to the data, performing a structural estimation of the key model parameters. We start by collecting the values of α, β, β', $\bar{u}$, determining the interest rate models described in Section 2. Notice that, differently from the theoretical exposition, for this empirical exercise we use the complete interest rate models including the kink at $\bar{u}$ giving rise to a non-linear relationship between the utilization rate u and the borrowing rates. Further, deposit rates ρ are calculated by accounting for the reserve ratio r, that is,

$$\rho = uf(u)(1-r).$$

5.1 Univariate test

We then take the time series of borrowing demands B for each platform-coin, resample it at the daily frequency, and merge it with the daily T-Bill rates. Next, for randomized values of the model parameters ψ, θ, σ, and w_l, and taking the historical time series of the borrowing demand B and the risk-free rate ρ^* as exogenous inputs, we compute the model-implied deposit rates by numerically solving equation (4). Finally, we run a standard optimization procedure on the model parameters, separately for each platform-coin pair, to minimize the sum of squared error between the model-implied deposit rate and its empirical counterpart. The risk aversion coefficient is globally set to $\gamma = 5$, but we checked that our results are robust to different values of γ.

Figure 6 displays the model-implied rates (solid light-green) compared to the empirical ones (solid teal). Visually, the results indicate that our model can fit the observed dynamics remarkably well. In particular, the calibrated model shows no difficulty in matching the

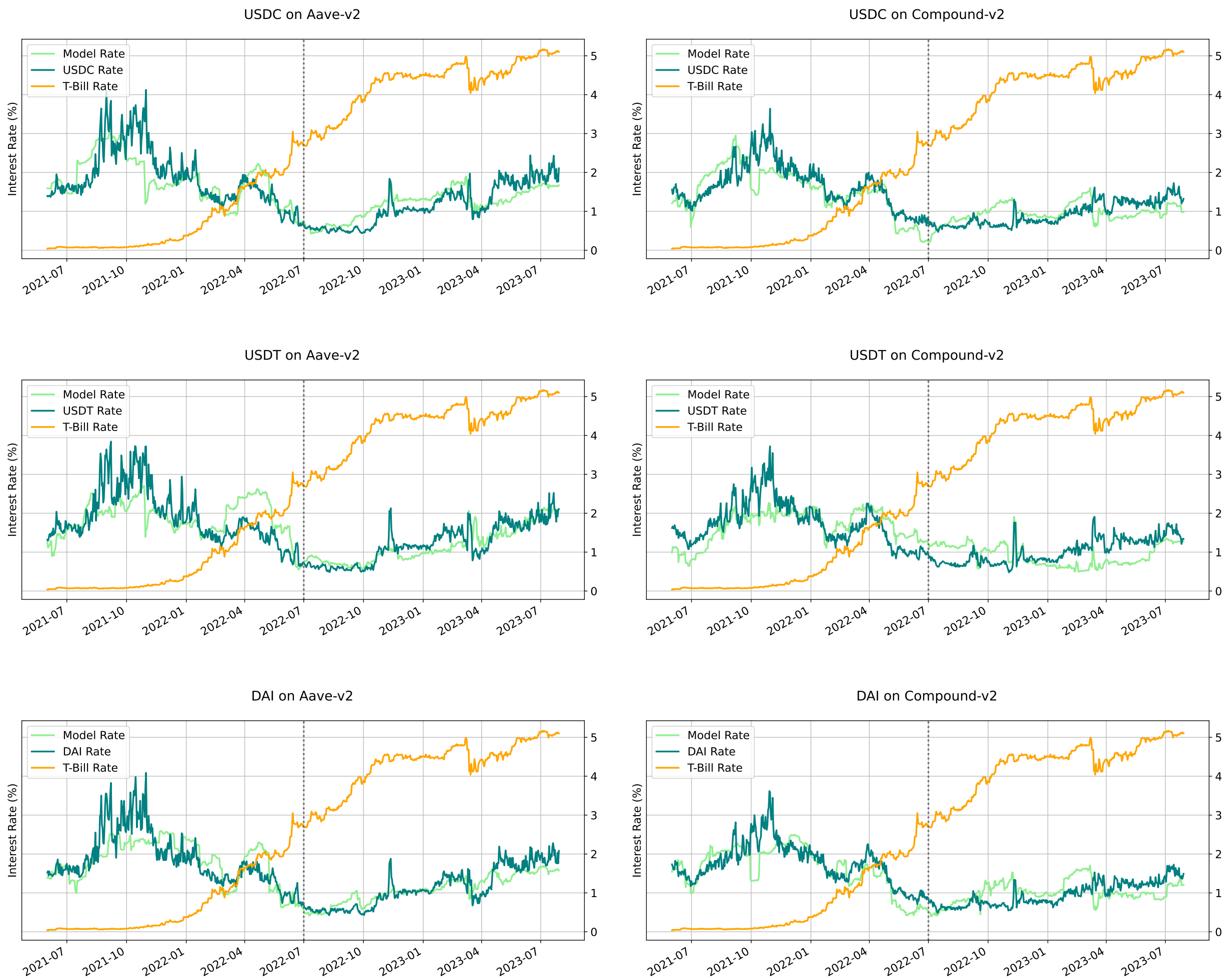

Figure 6: Structural Estimation.

different dynamics of the spread between stablecoin deposit rates and the risk-free rate. In the first part of the sample, before July 2022, the model-implied rates are negatively correlated, with correlation coefficients averaging at -0.46. Conversely, in the second part of the sample, the time series exhibit positive correlations, with an average correlation coefficient of 0.58. Further, when comparing the model-implied rates with the risk-free rate, we observe a spread dynamics consistent with the observational counterpart, with a positive spread in the first half of the sample and a negative spread after July 2021.

Table 5: Estimated Model Parameters.

Coin	Platform	θ	ψ	σ	w_l	RMSE
USDT	Compound	0.053	0.065	0.292	0.137	43 bps
USDT	Aave	0.062	0.041	0.201	0.146	47 bps
USDC	Compound	0.059	0.050	0.583	0.106	38 bps
USDC	Aave	0.031	0.072	0.375	0.088	43 bps
DAI	Compound	0.094	0.035	0.429	0.082	39 bps
DAI	Aave	0.062	0.026	0.274	0.087	40 bps

Table 5 reports the estimated model parameters θ, ψ, σ, and w_l at the platform-coin level, indicating consistent cross-sectional results. Additionally, the last column reports the Root Mean Squared Error (RMSE) of the model-implied deposit rates relative to the historical series, expressed in basis points. The parameter w_l, controlling the importance of the *convenience yield* provided by stablecoins, is consistently estimated as positive across all pairs. Moreover, the estimates are relatively stable across platforms for the same stablecoin. This finding suggests that agents in the DeFi ecosystem enjoy a positive utility from holding stablecoins. These results resonate with those of Gorton et al. (2022), who find a positive trend in the convenience yield of stablecoins. Interestingly, the largest convenience yield is estimated for USDT, which is by far the most important stablecoin by market capitalization and trading volume. The point estimates for ψ and θ are also consistently positive for the entire cross-section, suggesting that liquidity provision in DeFi lending platforms is considered risky by market participants.

5.2 Maximum Likelihood approach [To be continued]

Let us now estimate the full model using a Maximum likelihood approach. We estimate the model assuming that the expected return on the risky digital asset $\rho_{U,t}$ and the opportunity cost of holding stablecoins ρ_t^* are not observable.

We assume that the two unobserved variables follow a AR(1) process:

$$\rho_{U,t} = \lambda \rho_{U,t-1} + \epsilon_t,$$
$$\rho_t^* = \lambda^* \rho_{t-1}^* + \epsilon_t^*,$$

where λ and λ^* are the autocorrelation of the unobserved variables and ϵ_t and ϵ_t^* their respective innovations. The innovations follow a Gaussian law $\mathcal{N}(0_{2\times 1}, \Sigma)$, with Σ the variance-covariance matrix.

We aim at maximizing the log-likelihood conditional on the first observation and assuming zero initial shocks.[12]

We recursively compute the log-likelihood as follows: (i) we initialize the shocks to zero; (ii) at each date $t > 0$, we take as given the vector $(\rho_{u,t-1}, \rho_{t-1}^*, u_t, S_t)$ and infer the value of $(\epsilon_t, \epsilon_t^*)$ and $(\rho_{u,t}, \rho_t^*)$ based on the model and the assumed process of shocks (iii) compute the log-likelihood:

$$\mathcal{L}(Y_T|y_0) = -(T-1)\ln(2\pi\sigma\sigma^*\sqrt{1-c^2}) - \frac{1}{2(1-c^2)}\sum_{t=1}^{T}\left[\left(\frac{\epsilon_t}{\sigma}\right)^2 + \left(\frac{\epsilon_t^*}{\sigma^*}\right)^2 - 2c.\left(\frac{\epsilon_t^*\epsilon_t}{\sigma^*\sigma}\right)\right].$$

The estimated parameters are, as in the univariate test, ψ, θ, σ, w_l, but also those related to the risk-investors side: γ', W', and σ_U and shock processes: σ, σ^*, c, λ, and λ^*.

Notice that at each date $t > 1$, the computation of shocks ϵ_t and ϵ_t^* is straightforward and correspond to the residuals of the demand and the supply curves, equations (8) and (9) as follows:

$$\epsilon_t = ({\gamma'_U}^2 * S_t + \beta)u_t + \alpha + W'\gamma'\sigma_U^2 - \lambda\rho_{U,t-1},$$
$$\epsilon_t^* = u_t\rho(u_t) - \theta\psi - \theta(1-\theta)\gamma\psi^2 S_t + w_l S_t^{-\sigma} - \lambda^*\rho_{t-1}^*.$$

Results Once we have estimated all the parameters of the model, we can then check whether the model-implied shocks are sensible. To do so, we compute the correlation between

[12]Given the large sample size, maximizing the conditional or unconditional likelihood is unlikely to alter the estimation result. For the same reason, the initial values of shocks should not matter much.

the model-implied series and proxies for the opportunity cost of holding stablecoin and the expected return on the risky cryptoasset. For the opportunity cost of holding stablecoin, we consider the US risk-free rate, and for the expected return either the futures funding rates or the Greed & Fear index. Below we report such external validity check.

	Aave-v2			Compound-v2		
Correlation coefficient	USDC	USDT	DAI	USDC	USDT	DAI
(ρ^*, risk-free rate)	95%***	81%***	69%***	96%***	94%***	96%***
(ρ_U, risk-free rate)	-41%***	-41%***	-54%***	-88%***	-92%***	-90%***
(ρ_U, futures funding rates)	41%***	39%***	28%***	42%***	34%***	39%***
(ρ_U, Greed & Fear index)	53%***	39%***	28%***	23%***	3%	17%***

Table 6: Correlation between model-implied shocks and data proxies
(Stars indicate standard significant levels: 10%, 5%, and 1%)

First, Table 6 shows that the estimated shocks ρ^*, which are supposed to stand for the opportunity cost of holding stablecoins, are indeed strongly and positively correlated with the risk-free rate, suggesting that the model effectively captures the arbitrage between holding stablecoin and depositing in a lending platform and holding a US riskfree asset. Second, the last two rows of Table 6 confirm that the other estimated series of shocks effectively capture the appetite for risky digital assets, as proxied by futures funding rates and the Greed & Fear index. Finally, as conjectured in the model section, we detect a strong negative correlation between the expected return ρ_U and the risk-free rate. This finding may result from the fall in interest for cryptos in 2022 while the Fed raised its rates. Overall, these external validity checks confirm that the model effectively captures the two forces we are studying and, in this sense, it is structural.

6 Conclusion and Policy Implications

In this paper, we show that the relationship between conventional risk-free rates and DeFi interest rates relies on two mechanisms: arbitrage between the two markets, which is limited by the high degree of segmentation between the two markets, and the impact of monetary policy on leverage. Our model, calibrated on the data, provides an accurate account of DeFi interest rate dynamics around the recent Federal Reserve interest rate hiking cycle.

From a policymaker's point of view, two questions are in order: Is there a monetary policy case to transmit policy rates to stablecoins? And is there a critical size of DeFi above which the Fed may lose control of monetary policy? In this context, our paper brings a new piece to the debate on remunerating CBDC, as it might provide an anchor to private digital versions of the US dollar, similar to the role of the interest on reserve balance (IORB) in the US money market.

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