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Rate Discovery in Decentralised Lending

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Abstract

This paper introduces a novel framework for rate discovery in decentralised finance (DeFi), focusing on the unique challenges and opportunities within decentralised lending platforms. We explore the mechanisms of interest rate formation in a decentralised environment, without traditional banking institutions' control. By leveraging lending pool dynamics, we propose a method that integrates borrowers' risk profiles with market liquidity conditions to determine fair borrowing rates without third-party involvement. Our model aims to offer a transparent and reliable solution for rate discovery in DeFi. Through a series of simulations, we demonstrate the potential of our framework to improve lending practices in the DeFi ecosystem, making it a viable and competitive alternative to conventional financial systems. The findings suggest that our approach not only enhances the transparency and fairness of the lending process but also encourages a more informed participation of lenders and borrowers, ultimately contributing to the stability and growth of the DeFi market.

Keywords: *Lending, Blockchain, DeFi, Interest Rate*

JEL Classifications: *G20, G23*

List of Symbols

Symbol	Description
R_0	Minimum interest rate (base rate)
R_{slope1}	Interest rate slope below optimal utilisation
R_{slope2}	Interest rate slope above optimal utilisation
U	Utilisation rate
$U_{optimal}$	Optimal utilisation rate
R_t	Borrowing rate at time t
r^*	True value borrowing rate (market rate)
r_i	Tick-specific borrowing rate
ROI	Borrower's maximum acceptable borrowing rate
K	Target loan amount
$D_{LP_{B,\tau}}$	Total deposit amount (TVL) in borrower's lending pool
CD_{r_i}	Cumulative deposit volume up to tick r_i
RR	Recovery rate upon default
$p_{d,k}$	Borrower's default probability assessed by lender k

Introduction

The determination of interest rates in financial markets is a process influenced by a variety of factors, ranging from individual creditworthiness to broader macroeconomic conditions. Traditional financial systems have long relied on intermediaries, such as banks, to assess borrower risk and set interest rates accordingly. However, this reliance on centralised institutions introduces challenges related to information asymmetry [1, 2], where lenders possess less information than borrowers, leading to potential inefficiencies and inequities in lending practices.

Decentralised finance (DeFi) represents a significant departure from traditional financial systems, offering a decentralised approach to lending that eliminates the need for trusted third-party intermediaries. By leveraging blockchain technology, DeFi platforms enable peer-to-peer transactions and lending agreements, thereby democratising access to financial services. However, the decentralised nature of DeFi also introduces unique challenges, particularly in determining fair and transparent borrowing rates in the absence of centralised control.

This paper aims to address these challenges by proposing a theoretical framework for interest rate discovery within the DeFi ecosystem. Our approach builds upon existing literature on credit rationing, information asymmetry, and auction theory, extending these concepts to the decentralised context. By examining the dynamics of lending pools and integrating borrowers' risk profiles with market liquidity conditions, we seek to develop a model that facilitates equitable rate determination without intermediary involvement.

Central to our framework is the concept of an auction mechanism, where lending rates are determined through a competitive bidding process among liquidity providers. This mechanism is designed to reflect the true market value of borrowing rates, taking into account both the borrower's risk profile and prevailing market conditions. Through a series of simulations, we explore the potential of our framework to enhance transparency and fairness in DeFi lending practices.

The findings suggest that our model not only aligns incentives between lenders and borrowers but also fosters a more informed and stable lending environment. By encouraging the disclosure of financial information and leveraging market dynamics, our approach contributes to the theoretical discourse on financial decentralisation and offers insights into the potential of DeFi to provide reliable lending and borrowing options in a decentralised manner.

Moreover, this paper delves into the implications of our proposed framework for the broader financial ecosystem, examining its potential to address long-standing issues related to information asymmetry and credit rationing. By advancing our understanding of decentralised rate discovery mechanisms, we aim to contribute to the ongoing evolution of DeFi and its integration into the global financial landscape.

Interest Rate Model in DeFi

Lending protocols such as Aave, Compound, Maker DAO, and dYdX have established a robust foundation for the lending market in DeFi [3]. They enable cryptocurrency holders to earn interest on their assets in a permissionless manner, thereby democratising access to financial services.

A pivotal aspect of these protocols is the determination of borrowing rates, which is intricately linked to the concept of utilisation rate. The utilisation rate, denoted as U is a metric that quantifies the proportion of supplied assets that are currently borrowed within a lending pool. Mathematically, it is expressed as:

$$U = \frac{Total\ Borrows}{Total\ Supplies}$$

This rate serves as an indicator of the availability of capital within the pool, with higher utilisation rates signifying greater demand for borrowing relative to the supply of assets. The utilisation rate is fundamental in managing liquidity risk within the protocol, as it influences borrowing and lending behaviours through dynamic interest rate adjustments.

The interest rate model employed by these protocols is algorithmically designed to optimise capital utilisation and manage liquidity risk. Specifically, the borrowing interest rates are derived from the utilisation rate through a piecewise linear function. According to Aave's documentation, the interest rate model is defined as follows:

- if $U \leq U_{optimal}$, $R_t = R_0 + \frac{U_t}{U_{optimal}} R_{slope1}$
- if $U > U_{optimal}$, $R_t = R_0 + R_{slope1} + \frac{U_t - U_{optimal}}{1 - U_{optimal}} R_{slope2}$

where,

- R_0 is the minimum interest rate charged to borrowers when the utilisation rate is at its lowest. It represents the baseline cost of borrowing, irrespective of the demand for the asset. It is typically set to cover the basic operational costs and risks associated with lending.
- R_{slope1} determines the rate of increase in the interest rate as the utilisation rate rises from 0% to the optimal utilisation rate. It reflects how sensitive the interest rate is to changes in utilisation within this range. A steeper slope indicates a more rapid increase in the interest rate as utilisation increases, incentivising borrowers to repay their loans or suppliers to provide more liquidity as demand rises.
- R_{slope_2} governs the rate of increase in the interest rate when the utilisation rate exceeds the optimal utilisation rate. It is generally steeper than to discourage high utilisation, which could lead to liquidity shortages. A higher ensures that as the pool becomes more utilised, the cost of borrowing increases significantly, encouraging repayments and additional supply to maintain liquidity.

The model parameters (R_0, $U_{optimal}$, R_{slope1}) are asset dependent. The interest rate parameters of assets with lower liquidity levels are more conservative. Model's parameters can also be subject to change depending on market conditions.

By understanding and effectively managing the utilisation rate, DeFi protocols can incentivise behaviours that support liquidity and optimise capital allocation, thereby enhancing the overall functionality and reliability of the decentralised lending ecosystem.

The current landscape of decentralised finance (DeFi) lending is primarily focused on highly collateralised borrowing, where borrowers must provide collateral equal to or greater than the borrowed amount. This approach ensures repayment and minimises default risk by enabling the sale of collateral in case of extreme market fluctuations [4]. The borrowing rate is influenced by liquidity in the pool, rather than reflecting the financial health of the borrower; it is more indicative of liquidity and market risk. Hence, when considering over-collateralised lending, the extent to which DeFi lending protocols facilitate true borrowing – where an agent gets into a position of net debt – is limited, creating a gap compared to traditional finance (TradFi) offerings.

To bridge this gap, a potential solution involves reducing the on-chain collateral requirement by replacing it with off-chain collateral that can be materialised through the creation of a dedicated Special Purpose Vehicle (SPV). Rather than having the corporation serve as the legal obligor, an SPV structure leverages the advantages of traditional securitisation frameworks. It does this by collateralising the loan with a diversified asset portfolio within an SPV and subjecting these assets to eligibility criteria, robust portfolio covenants, and comprehensive legal recourse. Another solution lies in the tokenisation of off-chain assets, allowing them to serve as collateral on-chain. By making the collateral ratio variable, we preserve the signalling role of collateral quality while enabling more flexible borrowing conditions [1]. By reducing the on-chain over-collateralisation requirement, we introduce default risk, posing a challenge in determining a borrowing rate that accurately reflects the borrower's financial risk without relying on a third party or arbitrarily adding a risk premium to the existing algorithmic rate model.

While Aave and Compound use algorithmic interest rate curves based on utilisation, protocols that do not rely on on-chain over-collateralisation – like Notional, Maple Finance, or Goldfinch – involve fixed-rate lending through centralised negotiations or credit committee assessments. Our approach introduces decentralised, transparent rate formation suitable for unsecured lending at scale.

The following section details our structured approach to decentralised rate discovery. It includes the implementation of an auction, proposed as a method to accurately reflect credit risk in addition to enabling fixed borrowing rates, which are more suitable for most borrowing use cases.

Lending Pools Framework to Enable a Decentralised Rate Discovery

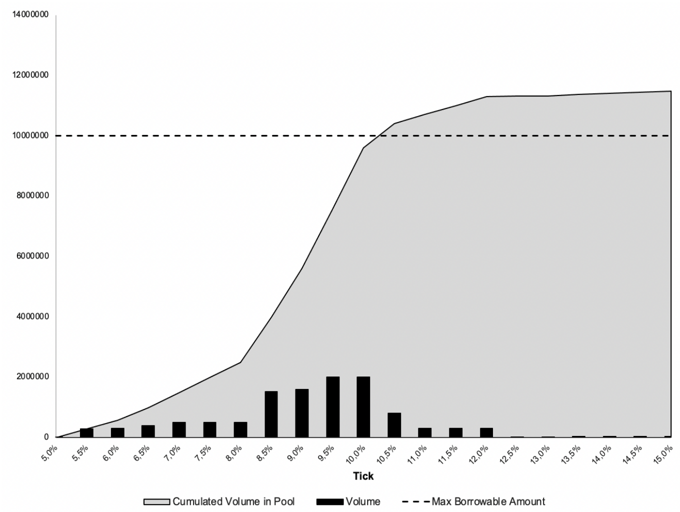
The lending process is initiated by the creation of a lending pool on-chain. These pools are tailored to individual borrowers and possess distinct characteristics, including the desired loan type, loan amount K, maturity period, and token type. We denote $LP_{B,\tau}$ as a lending pool assigned to a borrower B, and $D_{LP_{B,\tau}}$ represents the total deposit amount within that particular pool.

Pre-Pool Opening Phase

In order to deter borrowers from creating idle lending pools, it is required that borrowers lock a deposit before the opening of the pool. The size of the deposit is determined by a fraction of the desired borrowed amount. Once the borrower successfully borrows from their pool, the deposit will be returned to them. However, in cases where the borrower does not end up borrowing from their pool despite the pool being filled up, the deposit will be distributed among the liquidity providers of that particular pool. This constraint ensures that borrowers have an interest in utilising the lending pool, as they risk losing their deposit if they do not borrow from it.

Lending Pool as a Set of Ticks

To enable an on-chain rate discovery, we propose to implement an auction process enabled by the division of lending pools into a series of ticks. Each tick represents a sub-pool of funds within the borrower's pool, and corresponds to a specific lending rate. Liquidity providers, when contributing to the pool, select their lending rate, and their funds are allocated to the corresponding tick. For instance, if a liquidity provider opts for a 5% rate, their funds find placement in the 5% tick of the borrower's lending pool. The visual representation below offers a clearer depiction of the lending pool design:



The integration of auctions and ticks in decentralised lending frameworks offers several advantages over traditional DeFi models like Aave. Auctions facilitate market-driven rate discovery by leveraging competitive bidding [5, 6], ensuring rates reflect true market values and enhancing transparency and fairness [7, 8]. The use of ticks allows for granular rate adjustments, dynamically aligning lending rates with market conditions [9, 10] and incentivising information disclosure. This approach can lower transaction costs [11] by streamlining the lending process.

The pool opening marks the beginning of the book-building phase.

Book-Building Phase

The book-building phase is time-limited; its duration is set in the pool's characteristics. During this phase, liquidity providers can freely deposit into the lending pool at the lending rate of their choice. They are free to update their lending rate. Additionally, liquidity providers can freely withdraw their funds as their funds have not yet been borrowed.

The ticks can be transposed to a limit order book restricted to the bid side. The bids are limit orders, and the bond issuance is a sell market order. Consider a zero-coupon bond auction where a bond unit delivers 100 at maturity. Let's assume a lending pool with lending rates of $r_1, \cdots, r_n$, with T being the bond maturity, $p_1, \cdots, p_n$ the implied bid prices and $d_1, \cdots d_n$ representing the amount of deposit available in each tick. We can derive the following bids:

Order Book Representation

Side	Rate	Deposit Available	Implied Bid Price	Implied Buyable Bond Units
bid	r_1	d_1	$p_1 = 100/(1+r_1)^T$	d_1/p_1
bid	r_i	d_i	$p_i = 100/(1+r_i)^T$	d_i/p_i
bid	r_n	d_n	$p_n = 100/(1+r_n)^T$	d_n/p_n

where,

$$0 < r_1 < r_i < r_n, and\ d_i \geq 0 \quad \forall i \in [0, n]$$

It is important to note that pools should not be limited in size; therefore, even if the amount in the pool is higher than the target amount to be borrowed, any lender can still add liquidity to the lending pool and challenge the lending rates until the end of the book-building phase. This creates market dynamics, rate competition, and gives access to a market rate discovery for borrowers.

During the book-building phase, the borrower is not yet authorised to borrow from their pool. They must wait for the end of the book-building phase to make sure all the commits have been gathered and are final.

Loan Origination Phase

After the conclusion of the book-building phase, liquidity providers are unable to make any further deposits or withdrawals. During the origination phase, borrowers can borrow a predetermined amount of K tokens from their pool. The borrower cannot borrow more or less than this agreed-upon amount, unless there is insufficient liquidity in the pool (i.e., if $D_{LP_{B,\tau}} \leq K$). The origination phase has a specific time limit corresponding to the duration set in the characteristics of the pool.

Lenders are provided with their chosen lending rate, resembling a form of discriminatory auction where the winning participants pay their bid prices [12]. It is essential to emphasise that, given the on-chain nature of bids, the auction is not sealed but open, fostering transparency and accessibility. The borrowing rate is simply the lowest volume-weighted rate that corresponds to the amount borrowed. It is derived from the ticks and is the result of the amount available in each tick. The borrowing rate is fixed and does not change during the life period of the loan.

The choice of discriminatory matching over uniform matching is motivated by the tick model's ability to establish an order book for the secondary market while maintaining consistent mechanisms within smart contracts. A borrowing event is likened to a selling event, and secondary prices can be derived from discounted future cash flow.

Monostori [13] suggests that the choice of auction format can significantly impact the behaviour of bidders and the functioning of the primary market. Monostori's findings indicate that uniform-price auctions tend to attract a larger number of bidders and enhance the role of the primary market compared to discriminatory-price auctions [14]. However, a deeper analysis of discriminatory-price auctions reveals potential advantages, such as ensuring continuity of financing, reducing volatility on the primary market, and preventing collusion. This is supported by Morales-Camargo et al. [15], who argue in favour of discriminatory auctions, contrary to the conclusions drawn by proponents of uniform-price auctions. Furthermore, Goldreich [16] highlights the susceptibility of uniform-price auctions to overbidding, as participants attempt to signal the secondary market, indicating potential drawbacks of this format. Additionally, Myers et al. [17] emphasise the increased risk of collusion in uniform auctions, particularly in repeated settings, due to the payoff irrelevance of infra-marginal bids. It is crucial to acknowledge that the advantages of each auction format may vary based on specific market conditions and the objectives of the issuer. This is in line with the study by Beierlein and Katô [18], which highlights the trade-offs between auction formats, indicating that uniform-price auctions achieve lower award concentration and higher average revenues but experience higher revenue variance compared to discriminatory-price auctions. Therefore, Monostori's article concludes that the choice between auction formats should be carefully considered based on the specific context and desired outcomes. Hence, the decision to prefer discriminatory matching over uniform for practical reasons does not contradict observed choices in Monostori's article [13].

The decision to have bidders select lending rates instead of primary and secondary bond prices is driven by several factors, with a particular emphasis on the implications for gas consumption. Gas, in the context of blockchain, refers to the computational effort required to execute operations. In decentralised finance, every transaction, including the continuous updating of bid prices, incurs a cost in gas, which can accumulate significantly over time. By choosing to base the system on lending rates, the protocol significantly reduces the frequency and complexity of transactions that lenders need to perform. This is because lenders no longer need to continually update bid prices throughout the loan term, a process that can consume substantial amounts of gas due to the repeated and complex calculations involved. Instead, bid prices can be easily derived from the lending rate and the remaining time until maturity, simplifying the transaction process. This approach not only conserves gas, thereby minimising operational costs for users, but also contributes to the overall effectiveness of the smart contract implementation.

Loan Life Period

Depending on the type of loan, borrowers are required to make principal and interest payments either before or at maturity.

Throughout the loan duration, lenders with unused funds in the pool can withdraw their remaining amount at any time. This allows for the withdrawal of pre-maturity interest payments and instalment payments. Once the final payment is made, all liquidity providers can freely withdraw their funds from the lending pool.

In the next section, we will evaluate the equilibrium of our proposed rate model, analysing its stability and performance in various scenarios.

Modelling the Rate Discovery

Rate Discovery Game Framework

Our approach to rate discovery is, in fact, an open multi-unit auction, casting the borrower as the seller and lenders as bidders, and that can be formalised as an extensive form game. In this context, the seller offers multiple units for sale, and each bidder assigns a valuation to the units on offer. The game unfolds with the borrower declaring the desired borrowing amount. Subsequently, lenders deposit an amount into the tick that aligns with their preference and information and submit bids for the number of units they wish to purchase. The game concludes on the specified borrowing date, with units allocated to winning bidders, and successful bidders remit the amount of their bid to the seller.

Our game model comprises the following components:

- **Players:** One borrower, N lenders.
- **Action Sets:**
  - A_{lender} = {*does not deposit, deposits any amount between 1 and K at a rate in the range* r_1 *to* r_n*, updates the rate of an existing position*}
  - $A_{borrower}$ = {*borrows K, does not borrow*}
- **Choice Nodes:** Lenders are free to deposit and/or update their rate until the end of the book-building phase. The borrower cannot perform any action before the end of that phase.
- **Terminal Nodes:** At the end of the book-building phase, the borrower can either borrow or not borrow.

  We make the following assumptions:

- A borrower who has placed a significant amount as collateral and is a repeat borrower, thus being cautious about reputation risk. This implies that the borrower will not default maliciously and that there is no incentive for them to borrow regardless of the borrowing rate.
- The borrower expects to make a certain return on investment (ROI) on the borrowed amount, and any additional cost from borrowing is priced into the ROI. The ROI corresponds to the borrower's reserve rate, which is the maximum rate that they are willing to accept for each unit. If the reserve rate is too low, there may not be enough lenders willing to bid at or below that rate, and the auction will not generate any revenue. If the reserve rate is too high, the borrower may not get the maximum revenue possible.
- The ROI is known by the lenders, or the borrower discloses a maximum rate at which they'd be willing to borrow, which is representative of the ROI. The assumption that borrowers' reserve rates (ROI) are known to lenders may be supported through verifiable disclosures. In practice, this could be enabled by cryptographic tools such as zero-knowledge proofs, DAO-approved financial statements, or decentralised credit scoring protocols. These mechanisms would allow borrowers to demonstrate expected returns without compromising decentralisation or privacy.
- We assume heterogeneous beliefs among lenders. Each lender k associates a default probability $p_{d,k}$ to the borrower which remains constant throughout the game. The assumption of heterogeneous beliefs among bidders is well-supported by the literature. Ockenfels and Roth [19] discuss the incidence of multiple bidding and its relation to late bidding, indicating that bidders may have varying beliefs about the auctioned item, leading to diverse bidding behaviours. Li and Zheng [20] develop an empirical model of entry and bidding controlling for unobserved auction heterogeneity, highlighting the presence of diverse beliefs among bidders in auction settings. Krasnokutskaya [21] and Decarolis [22] emphasise the importance of considering unobserved auction heterogeneity and the impact of asymmetric information, which can be indicative of heterogeneous beliefs among bidders. Moreover, Crosetto et al. [23] provide evidence that individual belief reports can be rationalised by subjective beliefs that differ from the objective truth, further supporting the presence of diverse beliefs among bidders in auction scenarios.
- We define RR as the recovery rate, the estimated per cent of the loan that will still be repaid to creditors in the event of default or bankruptcy.
- We set the risk-free rate to zero without loss of generality.
- As borrowing time is known and lenders have the ability to update their rate, we assume that lenders choose their lending rate with the knowledge of all the choices made by others. This implies that we are considering a finite perfect information game, and at least one pure strategy Nash equilibrium exists.

Objective Definition

To evaluate the suitability of our rate discovery, we must first define our objectives. While some auction models are assessed based on the expected revenue of the auctioneer, our objectives are as follows:

- Convergence: We aim to understand the mechanism that links the borrowing rate to the borrower's default probability that is assessed by the market.
- Speed of Convergence: Literature has shown that in centralised lending processes, banks can fail to discriminate between risky and non-risky borrowers [1, 2]. In decentralised lending, borrowers are compelled to provide their own information since there is no third party to furnish it. In the early 1980s, particularly in works by Milgrom [24] and in collaboration with Weber [25], significant advancements were made in auction theory. This research explored scenarios involving both private and common values, within reasonably straightforward mathematical conditions governing bidder information and value distribution. Milgrom's comprehensive analysis shed light on instances where sellers could potentially increase their revenues by sharing expert appraisals, like authenticity certificates or inspection protocols, with prospective bidders [26]. We will try to assess whether our rate discovery model can serve as an incentive for borrowers to provide more information, thus enabling their borrowing rate to converge more rapidly.

We proceed to assess our model equilibrium and evaluate whether it corresponds to lenders depositing in a tick that represents their true valuation of the borrower's default probability.

Multi-Unit Game with n Players and Perfect Information

In this section, we present a multi-unit model that captures the rate discovery process that we described in the first section.

Game Description

The game involves one borrower and N lenders. The borrower can choose to either borrow K or not borrow, while lenders can deposit any amount from 1 to K in the tick of their choice. There are n ticks.

Utility Functions

We define as d_i the deposit amount in tick r_i and CD_i, the cumulative volume up to tick r_i starting from the lowest tick. We assume that the lenders and the borrower have perfect information about the state of the pool at all times.

Lenders

For lender k and tick r_i,

$$u_{lender_k}(deposit\ m\ at\ r_i, borrower\ borrows)$$

$$= m \times \left[(1 - p_{d,k}) \times r_i - p_{d,k} \times (1 - RR)\right] \times 1_{CD_{r_i} \leq K}$$

where $p_{d,k}$ is the default probability evaluated by lender k, and RR is the recovery rate.

Borrower

$$u_{borrower}(borrows) = K \times (ROI - \sum \delta_i \times r_i)$$

where

$$(\delta_1, \delta_2, \dots, \delta_n) = argmin \sum_{\delta_i \leq d_i} \delta_i \times r_i$$

$$such\ that\ \sum \delta_i = K$$

Equilibrium

Let $r_{borrowing}$ be the rate that corresponds to the one that would have been achieved if the borrower were to borrow K in the current state. We observe that in the case where the total value in the pool is lower than K, it is a strictly dominant strategy for all lenders to deposit at the rate that corresponds to the borrower's ROI as it maximises their utility function. However, if the total value in the pool exceeds K, the lenders are incentivised to deposit at a lower rate. If a certain percentage of the lenders are willing to lower their rate, in that case, they will lower their rate as low as they need in order to guarantee matching. We can derive an analogy between our model and the model described by Ausubel [27], who proposes an ascending-bid auction for multiple objects. Nonetheless, in our model, the bids (both the lending rate and the deposit amount) are updated not because the auctioneer raises the price but because bidders might want to lower their bidding rate to ensure matching. In the Ausubel auction, sincere bidding is an ex-post equilibrium [28] meaning that it is in the best interest of each bidder to submit sincere bids and accurately reveal their valuations for the items they want. In hindsight, after the auction concludes, no bidder could have achieved a better outcome by submitting dishonest or manipulative bids. The auction's design encourages truthful bidding, making it a strategy-proof mechanism. In our model, lenders will only be inclined to lend at their 'true value rate' r^* if their true value rate is below ROI and $CD_{r^*+rate\ spacing} > K$. Overall, this requirement for lenders to deposit at their true value implies that the pool's total value must significantly exceed the amount to be borrowed, which leads to challenges in terms of capital efficiency.

Numerical Illustration

To illustrate the equilibrium of our game, we perform a numerical illustration and consider two types of borrowers. Borrower A that provides an extensive amount of information to prospective lenders and borrower B that provides a regular amount of information. We assume that they both have the exact same level of risk and have the same true default probability.

We use the following parameters:

- Order book range from 2% to 18%, rate spacing of 0.5%.

- Target loan amount: 100,000.
- Declared reserve rate 15%: the borrower declares that they will only be willing to borrow if their borrowing rate is lower than or equal to 15%.
- Recovery rate 30%.
- Lenders deposit sequentially in the pool. They choose their rate in order to maximise their utility function based on the status of the pool at deposit time.
- They can only deposit once in the pool, but can update their rate later. One deposit corresponds to one time stamp.
- Lenders can freely update their rate based on the other lenders' bids until the end of the auction, based on their utility function.
- For simplicity, the amount deposited by each lender is the same and does not change throughout the duration of the book-building phase. It differs for Borrower A and Borrower B as explained below.

We use the same default probability distribution across lenders and use a normal distribution centred on the actual default probability and a standard deviation of 1%. Hence, each lender k evaluates a default probability $p_{d,k}$ that follows a normal distribution and has an associated r_k^* such that

$$r_k^* = \left(\frac{p_{d,k} \times (1 - RR)}{1 - p_{d,k}}\right)^+ \times 0.005$$

As both borrowers have the same risk profile, we use the same parameters as for borrower A, i.e., mean 12%, standard deviation 1% which corresponds to an average r^* of 10%. The average r^* is considered the true market value borrowing rate.

To account for increased risk aversion for Borrower B and lower uncertainty for Borrower A, we model differently the lenders' bidding behaviour. Esö and Szentes [29] argue that in auctions, information plays a crucial role in attracting bidders. They discuss how the level of information affects bidder participation and the optimal strategy for the seller in disclosing information. From their research, we can derive that an auction with more information on the valued item will attract more bidders compared to an auction with less information. Cohen and Einav [30] conducted research on risk preferences by analysing deductible choices in insurance. Although their study focuses on insurance deductibles, it provides insights into risk aversion and decision-making under uncertainty. In their benchmark model, they assume that individuals have full information about their risk exposure and level of risk aversion. This assumption implies that individuals with more information are better equipped to assess their risk profile accurately. Therefore, a risk-averse agent with more information on the borrower would be more likely to choose a lower lending rate. Hinz and Spann [31] found that the amount and dispersion of information significantly impact bidding behaviour. They demonstrate that more information and greater dispersion of information lead to more competitive bidding behaviour. Additionally, they highlight the importance of betweenness centrality in the social network context, indicating that individuals who are well-connected and have access to diverse information sources are more likely to exhibit competitive bidding behaviour.

To reflect these findings, we assume that Borrower B's pool attracts 30% less liquidity in the same time period and that lenders in Borrower B's pool are less prone to updating their lending rate after depositing into the pool. At every new deposit, we assume that 30% of existing lenders update their rate based on the order book evolution for Borrower A and 15% for Borrower B.

Our goal is to illustrate whether the borrowing rate converges to the market value and the speed of convergence.

Analysis

Borrowing Rate

Time	TVL	Average Rate (%)	Std (%)
20	100,000	15	0
40	200,000	11.22	0.05
100	500,000	9.75	0.06

Borrower A

Time	TVL		Average Rate (%)	Std (%)
20	60,000		15	0
40	120,000		14.07	0.05
100	300,000		9.82	0.06

Borrower B

Convergence

After running the simulations, we observe that, with a significant amount of TVL and time, our model allows convergence as both borrowers are able to reach the market value borrowing rate of 10%. Lenders' lending rates converge to their respective r^* for both borrowers.

Speed of Convergence

For Borrower A, the average borrowing rates are 15%, 11.22%, and 9.75% for TVL levels of 100,000, 250,000, and 500,000, respectively. For Borrower B, the average borrowing rates are 15%, 14.07%, and 9.82% for TVL levels of 60,000, 120,000, and 300,000, respectively. Borrower A reaches the market value borrowing rate faster and with a lower amount of TVL, illustrating that, given the same level of risk, Borrower A is able to achieve their true borrowing rate faster by providing more information to potential lenders. Lenders' lending rates converge to their respective r^* at a greater speed for Borrower A than for Borrower B. It is also fair to assume that by providing less information, Borrower B will attract fewer bidders than

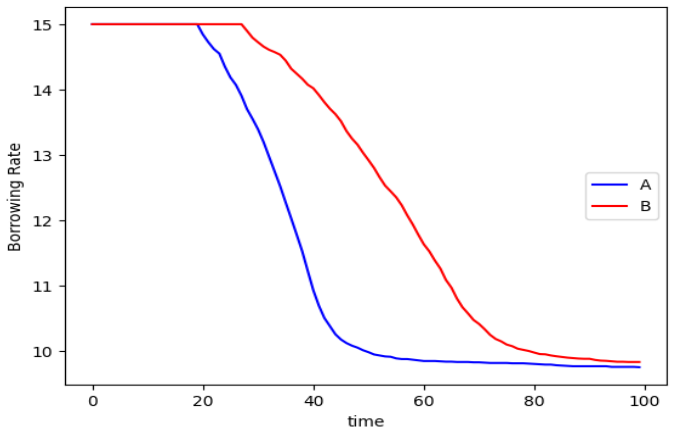
Borrower A for the same duration, so Borrower B's lending rate will be even more impacted.

Gas Consideration

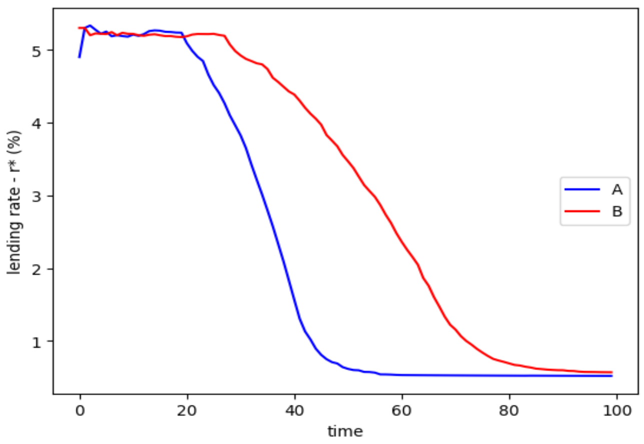
Our proposed mechanism offers accurate rate discovery at the expense of high gas requirements and frequent interactions. Given the gas costs on Ethereum L1, implementation would likely benefit from Layer 2 solutions (e.g., Optimism, Arbitrum) or dedicated app chains. Additionally, batching transactions and limiting update frequency could help reduce operational costs without significantly compromising convergence.

Gas and Capital Efficiency

The simulations illustrate that the rate model is not optimal in terms of capital efficiency, as a substantial amount of Total Value Locked (TVL) is required to reach the true value. However, it is worth noting that the required amount of TVL would sharply reduce if we were to increase the amount of update rate actions. We arbitrarily chose a 30% update rate among existing lenders at each deposit for Borrower A and 15% for Borrower B. Since capital is a scarce resource, we will explore in the next section how we can alleviate this constraint.



Evolution of Theoretical Borrowing Rate



Evolution of Lending Rate vs R Star

Multi-Unit Game with n Players and Imperfect Information

Game Description

In order to address the high capital efficiency, we introduce uncertainty in the amount to be borrowed and thus move to an incomplete information model. We introduce a Bayesian model where the borrower is faced with three business opportunities:

- Type 1: probability q_1, high liquidity needs: they will borrow K_1
- Type 2: probability q_2, medium: they will borrow K_2
- Type 3: probability q_3, low: they will borrow K_3

with $K_1 > K_2 > K_3$.

We also make the following assumptions:

- The lenders are unaware of the borrower's type.
- All lenders associate the same probability q to each opportunity, leading to r^*, the lowest rate at which the lender would be willing to lend to maintain a positive utility function.
- The reserve price / ROI on each business opportunity remains constant.

Utility Functions

The utility function of the lenders and the borrower are now as follows:

Lenders

For lender k and tick r_i,

$$u_{lender_k}(deposit\ m\ at\ r_i, borrower\ borrows)$$

$$= q_1 \times m \times [(1 - p_{default}) \times r_i \quad + p_{d,k} \times (1 - RR)] \times 1_{CD_{r_i} \leq K_1}$$
$$+ q_2 \times m \times [(1 - p_{default}) \times r_i + p_{d,k} \times (1 - RR)] \times 1_{CD_{r_i} \leq K_2}$$
$$+ q_3 \times m \times [(1 - p_{default}) \times r_i$$
$$+ p_{d,k} \times (1 - RR)] \times 1_{CD_{r_i} \leq K_3}$$

Borrower

$$u_{borrower}(borrows\quad M) = 1/(M) \times \sum \delta_i \times r_i$$

where

$$(\delta_1, \delta_2, \ldots, \delta_k) = argmin \sum_{\delta_i < d_i} \delta_i \times r_i$$

$$such\ that\ \sum \delta_i = M$$

Numerical Illustration

We consider the same two different borrowers. Borrower A provides an extensive amount of information to prospective lenders and borrower B provides a low amount of information. We use the following parameters:

- Order book range from 2% to 20%, rate spacing of 0.5%.
- Target loan amount
  - 100,000 with probability 33%
  - 50,000 with probability 33%
  - 20,000 with probability 33%
- Declared reserve rate 15%.
- Recovery rate 30%.
- Lenders deposit sequentially in the pool. They choose their rate in order to maximise their utility function based on the status of the pool at deposit time.
- They can only deposit once in the pool, but can update their rate later. One deposit corresponds to one time stamp.
- Lenders can freely update their rate based on the other lenders' bids until the end of the auction. Their decision is also driven by their utility function.
- For simplicity, the amount deposited by each lender is the same. It differs for borrower A and borrower B as explained below.

As for the previous simulation, depending on the borrower, we modelise differently the default probability distribution evaluated by the lenders and use the same parameters: mean 12%, standard deviation 1% which corresponds to a theoretical borrowing rate of 8%.

Analysis

Convergence and Speed of Convergence

Borrowing Rate

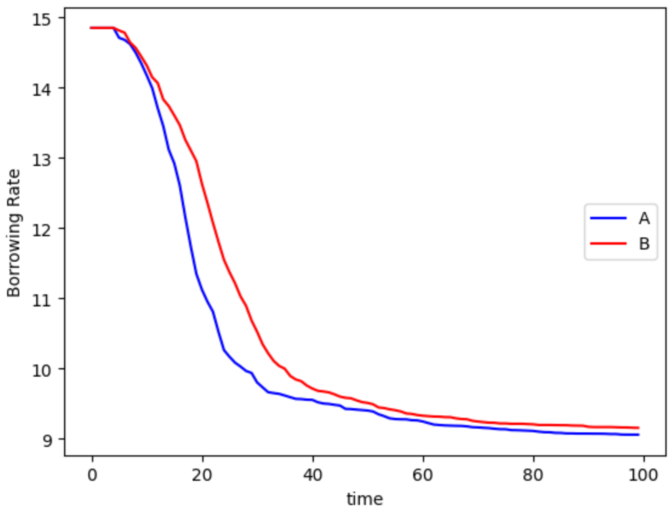
Time	TVL	Average Rate (%)	Std (%)
10	50,000	14.34	0
20	100,000	11.34	0
40	200,000	9.55	0.05
100	500,000	9.05	0.06

Borrower A

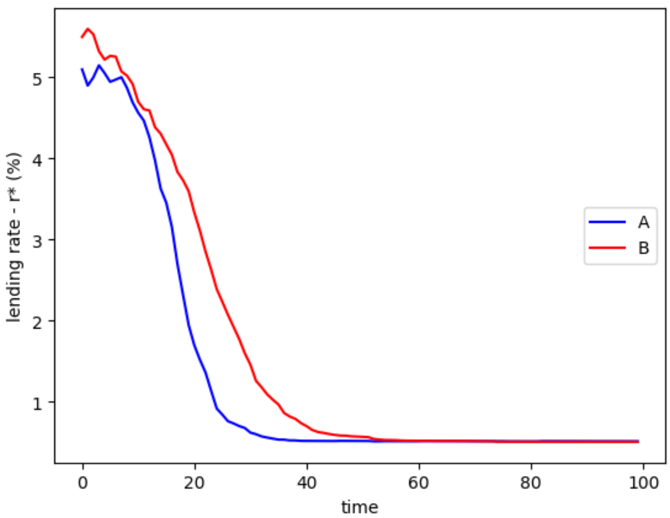
Time	TVL	Average Rate (%)	Std (%)
10	30,000	14.44	0
20	60,000	12.95	0
40	120,000	9.76	0.05
100	300,000	9.15	0.06

Borrower B

For borrower A, the average borrowing rates at time intervals of 10, 20, 40, and 100 are 14.34%, 11.34%, 9.55%, and 9.05%, respectively. For borrower B, the average borrowing rates at time intervals of 10, 20, 40, and 100 are 14.44%, 12.95%, 9.76%, and 9.15%, respectively. Similarly to the previous model, borrower A enjoys lower average borrowing rates across all time intervals thanks to their higher TVL and more frequent bid updates. By providing more information to their potential lenders, the borrowers are able to lower their borrowing rate and reach their true borrowing rate at a faster pace i.e., with a lower amount of TVL.



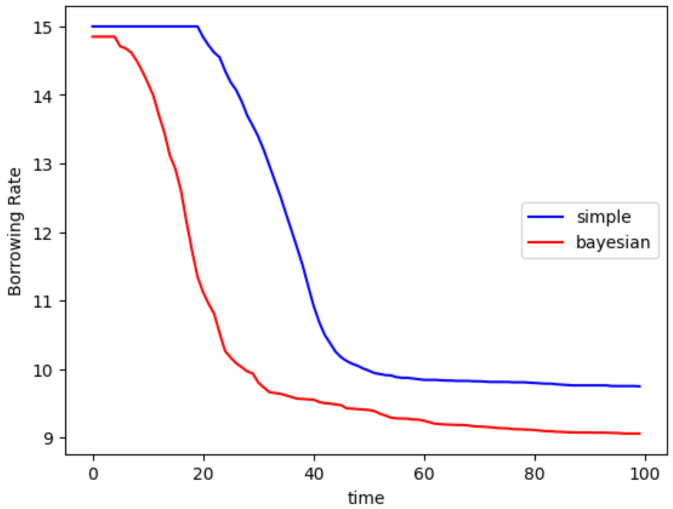
Evolution of Theoretical Borrowing Rate



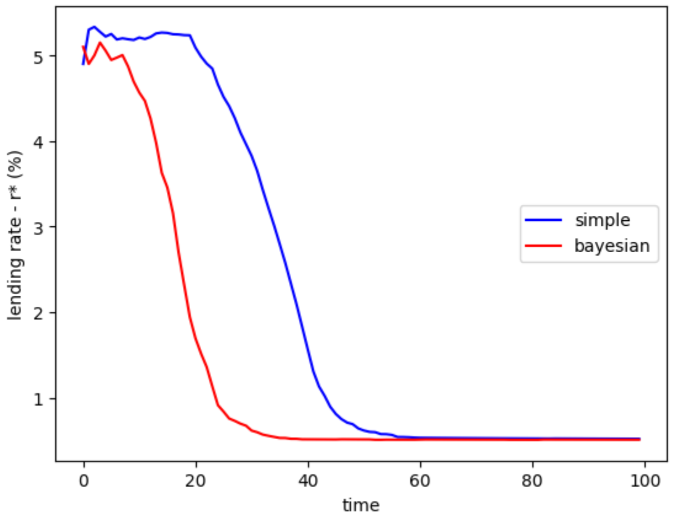
Evolution of Lending Rate vs R Star

Comparison with Previous Model

Compared with the previous model, we can visualise that adding uncertainty on the amount borrowed allows one to reach the true borrowing rate with a lower amount of TVL. This model operates with lower capital. Adding uncertainty of the amount borrowed allows a faster convergence to the market average lending rate.



Evolution of Theoretical Borrowing Rate (Borrower A)



Evolution of Lending Rate vs R Star (Borrower A)

Model Representation Limitations

Borrower's Creditworthiness

The numerical simulations assume perfect information about the borrower's creditworthiness and difference in lender's assessment of default probability only coming from lender's expertise and information. This is a strong assumption that relies on the fact that decentralised systems allow full transparency so if we consider DAO as borrowers, it is fair to assume that we have full transparency on their creditworthiness. DAOs operate on blockchain technology, which allows for complete visibility of their financial transactions and governance decisions, making it reasonable to assume full transparency regarding their creditworthiness. For instance, a DAO's smart contracts and on-chain activity can be publicly audited, providing lenders with comprehensive insights into the organisation's financial health and operational history.

However, this assumption becomes more tenuous when applied to 'traditional' borrowers, such as individuals or conventional businesses. These entities may not operate on blockchain platforms and thus do not benefit from the same level of automated transparency. For example, a small business seeking a loan in a DeFi platform might not have its financial records or operational data readily accessible on a blockchain, making it challenging for lenders to assess creditworthiness with the same degree of confidence as they would with a DAO.

Stiglitz and Weiss [2] argue that when there is imperfect information, lenders may not be willing to lend to all borrowers who are willing to pay the market interest rate. Stiglitz and Weiss suggest that governments can address credit rationing by providing more information about borrowers' creditworthiness, either directly or through institutions such as credit bureaus. This can help lenders make more informed lending decisions and reduce the need for credit rationing. In decentralised finance, this can be replicated by creating a data room accessible to all potential lenders where the borrowers could freely disclose all their financial documents. A limitation would be to verify the validity of the documents and ensure that everything has been shared.

Unknown Borrowed Amount

Our simulations on the Bayesian model assume that lenders have the same evaluation of the amount borrowed. When looking at a sequential open multi-unit auction, if the number of units to be sold is unknown to the bidders, it can potentially influence their bidding behaviour and make it more difficult for them to bid their true values. Each bidder has their own assumption on the number of units to be sold. The uncertainty about the number of units to be sold affects the bidders' beliefs about the strategies of the other bidders, which in turn can affect their optimal bidding strategy.

However, if the bidders have a common understanding or prior knowledge about the distribution of the number of units to be sold, they may still be able to bid their true values. For example, if the bidders know that the number of units to be sold follows a certain distribution, such as a uniform distribution, they may be able to use this information to determine their optimal bidding strategy and bid their true values. This is the case in our illustrative example. In the case of a recurrent borrower, the estimate of the amount of bidding to be sold can be based on prior knowledge and behaviour, thus improving the bidding process.

Market Frictions

While our model assumes rational actors, real-world DeFi markets often exhibit behaviours such as strategic underbidding, front-running, and lazy participation. These frictions can distort rate discovery and impact the efficiency of auctions. Future work may incorporate mechanisms such as anti-sniping rules or incentive alignment tools to mitigate such effects.

Lenders' Interactions

The model illustration assumes that lenders make their lending decisions independently and do not take into account the actions of other lenders. However, in reality, lenders may re-evaluate their assessment of a borrower's default probability based on the actions of other lenders. This is because lenders may have access to different information or expertise, and their decisions may influence the borrower's financial position.

For example, if one lender decides to increase their exposure to a borrower, other lenders may perceive this as a positive signal and decide to increase their exposure as well. Alternatively, if one lender decides to reduce their exposure to a borrower, other lenders may perceive this as a negative signal and decide to reduce their exposure as well. This can lead to a cascade effect where lenders' actions reinforce each other and lead to a concentration of exposure to certain borrowers.

The impact of lenders' interactions on credit markets has been widely studied in the finance literature. Martin and Ventura [32] show how banks' decisions to lend to each other can lead to systemic risk and banking crises. In the context of decentralised lending, lenders' interactions may also play a significant role in determining the efficiency and stability of the lending market.

One way to address the issue of lenders' interactions is to introduce mechanisms that encourage lenders to share information and collaborate. For example, lenders could be incentivised to share their expertise or data about borrowers, or to form coalitions that jointly assess borrowers' creditworthiness. Such mechanisms could lead to a more efficient allocation of credit and reduce the risk of cascading defaults. However, implementing such mechanisms would require overcoming coordination and free-riding problems, as well as ensuring that lenders do not collude to manipulate the lending market.

Conclusion

This paper provides a significant advance in decentralised finance by proposing a framework for rate discovery that accurately reflects a borrower's probability of default. The model enhances our understanding of lending efficiency in DeFi while promoting a transparent and flexible borrowing environment. Encouraging the disclosure of financial information aligns incentives between borrowers and lenders, fostering trust across decentralised lending markets. This approach has the potential to broaden the scope of DeFi lending, making it a more viable and competitive alternative to traditional financial institutions.

While our model assumes rational actors, real-world DeFi markets often exhibit behaviours such as strategic underbidding, front-running, and passive participation. These frictions can distort rate discovery and reduce the efficiency of auction mechanisms. Future work could explore the implementation of this model on existing platforms, evaluating its performance under practical constraints. Additionally, incorporating mechanisms such as anti-sniping rules, dynamic bidding penalties, or incentive alignment tools could help mitigate these market inefficiencies. Such enhancements will be essential to assess the model's full impact and scalability in real-world financial environments.

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