To the Graduate Council:
I am submitting herewith a dissertation written by Lebathong (Tim) Dong entitled "Two Essays on the Blockchain Economy." I have examined the final paper copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Finance.

Matthew Serfling, Major Professor

We have read this dissertation
and recommend its acceptance:

Matthew Serfling

Andy Puckett

Hao Zhang

Matthew Henriksson

Accepted for the Council:

Marieke van Puymbroeck

Vice Provost and Dean of the Graduate School

To the Graduate Council:
I am submitting herewith a dissertation written by Lebathong (Tim) Dong entitled "Two Essays on the Blockchain Economy." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Finance.

Matthew Serfling, Major Professor

We have read this dissertation
and recommend its acceptance:

Matthew Serfling

Andy Puckett

Hao Zhang

Matthew Henriksson

Accepted for the Council:

Marieke van Puymbroeck

Vice Provost and Dean of the Graduate School

(Original signatures are on file with official student records.)

Two Essays on the Blockchain Economy

A Dissertation Presented for the

Doctor of Philosophy

Degree

The University of Tennessee, Knoxville

Lebathong (Tim) Dong

May 2026

© by Lebathong (Tim) Dong, 2026
All Rights Reserved.

I would like to dedicate this work to my parents. I began this journey because I wanted to build a better life for them. All of the work presented here began with my belief that finance should be accessible to everyone.

Acknowledgements

There are simply too many people to whom I am indebted. First, I would like to thank my family—my parents and my sister—for their unwavering support, no matter what I chose to do. I would not be here without their unconditional love and encouragement. Next, I would like to thank the members of my dissertation committee, Dr. Matthew Serfling, Dr. Andy Puckett, Dr. Hao Zhang, and Dr. Matthew Henriksson, for their guidance and support throughout my Ph.D. journey. I would also like to thank my co-authors, Dr. Hao Zhang and Dr. Valerie Laturnus, for their excellent collaboration and for believing in me enough to invite me to join their project. Half of this dissertation would not have been possible without Dr. Zhang and Dr. Laturnus. Finally, I would like to thank someone I call "SPLH," who has given me a profoundly new outlook on life and the courage to do anything.

"Be guided by beauty."

Jim Simons

Abstract

This dissertation studies the functioning of credit and governance in decentralized finance (DeFi), with a particular focus on how reputation, incentives, and financial distress shape borrowing behavior and collective decision-making in blockchain-based financial systems. The first chapter develops a theoretical framework for pseudonymous undercollateralized lending, a central challenge in decentralized markets where borrowers can easily create new identities. I propose a mechanism in which borrowers initially access credit through overcollateralized loans and gradually earn eligibility for undercollateralized borrowing by maintaining repayment discipline. Defaulting leads to a temporary loss of access to favorable credit terms, generating an opportunity cost that sustains incentive compatibility even without traditional identity enforcement. The model characterizes conditions under which honest repayment becomes a dominant strategy and provides implications for interest rate design and credit access in DeFi protocols.

The second chapter empirically examines how borrower financial stress influences governance participation in decentralized lending platforms. Using novel data on lending activity and governance voting across major DeFi protocols, the analysis shows that financially exposed users—particularly those facing heightened liquidation risk—participate more actively in governance. Voting intensity rises prior to potential financial distress but declines following liquidation events, suggesting that governance engagement is closely tied to users' economic exposure. These findings highlight

how token-based governance can partially mitigate platform-user conflicts while also introducing short-term incentives that may affect decision quality.

Together, the chapters provide new theoretical and empirical insights into credit formation, incentive design, and governance dynamics in decentralized financial systems, contributing to a deeper understanding of how blockchain-based markets sustain trust and coordination without centralized intermediaries.

Table of Contents

1 Towards Pseudonymous Undercollateralized Loans **1**

1.1 Introduction . . . 3

1.2 Model . . . 9

1.2.1 The setup . . . 9

1.2.2 Payoff functions of possible strategies . . . 10

1.2.3 Participation condition . . . 14

1.2.4 Comparative statics . . . 17

1.2.5 Incorporating market clearing condition . . . 19

1.3 Model calibration and simulation study . . . 20

1.3.1 Model calibration . . . 20

1.3.2 Simulation results . . . 22

1.3.3 Autocorrelated returns and volatility clustering . . . 24

1.4 Practical considerations . . . 26

1.4.1 Multiple wallets . . . 26

1.4.2 Oracle problem . . . 26

1.4.3 No reuse of assets by defaulted borrowers . . . 27

1.4.4 Reputation system . . . 28

1.4.5 Adoption from other services . . . 29

1.4.6 Use of covenants . . . 30

1.5 Undercollateralized loan as an option market . . . 30

1.5.1 USD loan as a call option . . . 31

1.5.2 TOKEN loan as a put-like option . . . 32
1.5.3 Practical application for option-like loans . . . 33
1.6 Conclusion . . . 33
Appendix . . . 35

2 How Do Shareholder Defaults Influence Corporate Governance in DeFi Lending **42**
2.1 Introduction . . . 44
2.2 Some simple Economics of DeFi Lending . . . 48
2.3 Data . . . 50
2.3.1 Variable Construction . . . 50
2.3.2 Descriptive Statistics . . . 52
2.4 Empirical Analysis . . . 53
2.4.1 Effects of Financial Distress on Voter Participation . . . 53
2.4.2 Testing Mechanisms . . . 55
2.5 Conclusion . . . 58
Appendix . . . 58

Bibliography **67**

Appendix **74**
A.1 Mathematical Proofs . . . 74
A.1.1 Proof of Proposition 1.0.A and 1.0.B . . . 74
A.1.2 Proof of Proposition 1.1 . . . 77
A.2 Definitions in DeFi Lending . . . 80

Vita **85**

List of Tables

1.1 Parameter definitions 35

2.1 **Descriptive Summary** This table presents descriptive statistics for the main sample at both the voter and proposal levels. 59

2.2 **Financial Distress on Voter Participation among all Voters** This table presents fixed effects regression results for Equation 2.1. The dependent variable is a dummy equal to 1 if the voter participated in a proposal. The sample includes all voters eligible to vote in proposals on DeFi lending platforms between August 2020 and August 2024. Standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. 60

2.3 **Financial Distress on Voter Participation among all Borrowers** This table presents fixed effects regression results for Equation 2.1. The dependent variable is a dummy equal to 1 if the voter participated in a proposal. The sample includes all borrowers who were eligible to vote on DeFi lending platforms between August 2020 and August 2024. Standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. 61

2.4 **Financial Distress on Voting Participation across Platforms** The dependent variable is a dummy equal to 1 if the voter participated in a proposal. The sample includes all borrowers eligible to vote in proposals on DeFi lending platforms between August 2020 and August 2024. Columns 1 and 2 split the sample based on whether voters borrowed from the same platform in which they vote. Controls include the number of previous liquidations experienced by the voter, the number of executed swaps, the number of proposals previously voted on, and the number of DAOs joined. Standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. . . 62

2.5 **Financial Distress on Voting Participation by Proposal Content** This table presents fixed effects regression results for Equation 2.1. The dependent variable is a dummy equal to 1 if the voter participated in a proposal. The sample includes all borrowers eligible to vote in proposals on DeFi lending platforms between August 2020 and August 2024. Columns 1 and 2 split the sample based on whether the proposal descriptions are loan-related or involve other topics. Columns 3 and 4 split the sample based on whether the proposals are classified as user-favorable. Controls include the number of previous liquidations experienced by the voter, the number of executed swaps, the number of proposals previously voted on, and the number of DAOs joined. Standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. 63

2.6 **Financial Distress on Support for User-Favorable Proposals** This table presents fixed effects regression results for Equation 2.1. The dependent variable is a dummy equal to 1 if the voter supported a user-favorable proposal. The sample includes all borrowers who were eligible to vote on DeFi lending platforms between August 2020 and August 2024. Standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. 64

A.1 **Definitions in DeFi Lending** This table summarizes key definitions used in decentralized lending and describes ten representative lending platforms from the broader 77-platform sample. For each platform, it provides a brief description of the lending mechanism and the endogenous interest-rate setting in these markets, and it outlines the risk-management framework implemented through the platform's governance process. 80

List of Figures

1.1 Borrowers' possible paths 36
1.2 Simulated and numerical interest rate r. 37
1.3 Simulated maximum $\bar{r}$ across different failure rate. 38
1.4 Simulated $\mathbb{E}[H(r) - M(r)]$ in the presence of moral hazard. 39
1.5 Comparative Statics 40
1.6 AR(1)-GARCH(1,1) versus I.I.D returns 41

2.1 **Illustration of a DeFi lending interface.** Users pledge collateral, borrow against it, and actively manage liquidation risk through repayment or additional collateral. Source: Aave. 65
2.2 **Illustration of token-based governance voting.** Governance token holders review proposals on Snapshot and cast token-weighted votes on platform policies. Source: Snapshot. 66

Chapter 1

Towards Pseudonymous Undercollateralized Loans

Abstract. This chapter proposes a design where defaulting borrowers lose access to undercollateralized loans temporarily. I show that under reasonable parameters, always-honest, i.e., paying back the loan, is the dominant strategy. The design works because borrowers are incentivized to keep their access to undercollateralized loans to avoid costly overcollateralized loans and the option to default. My design thus enables trust-minimized undercollateralized lending, increasing access and liquidity of DeFi protocols. The result is robust to practical considerations such as non-zero delinquency rate, autocorrelated returns, volatility clustering, moral hazard, and impatient borrowers. Importantly, even if borrowers are myopic and the mechanism fails, the structure enables a novel, trust-minimized option market.

Keywords: Lending market design, Decentralized Finance, DeFi, Game Theory, Blockchain

JEL Classifications: C7, C72, D4, O31

1.1 Introduction

Ten years since the birth of Ethereum, decentralized finance (DeFi) has seen substantial growth, with its total value locked reaching $123.6 billion in 2025, marking a 41% year-over-year increase,[1] Tether achieving over $1.14 trillion in monthly processing volume,[2] and USDC experiencing a 540% year-over-year increase in on-chain transaction volume to nearly $6 trillion in the second quarter.[3] Nevertheless, DeFi still lacks one important feature: undercollateralized loans, which do not require collateral value to be greater than the loan amount at all times and thus do not expose borrowers to liquidation. Undercollateralized lending is essential for DeFi's growth because it enhances capital efficiency by allowing borrowers to lock up fewer assets, unlocks true liquidity that overcollateralized models fail to provide, and broadens accessibility to users without excess crypto holdings, enabling more productive investments and wider adoption beyond niche crypto enthusiasts. In traditional financial markets, undercollateralized (including unsecured) loans are a cornerstone, representing a substantial portion of lending activity, such as the U.S. consumer unsecured debt market exceeding $4 trillion in credit cards and personal loans alone, and they facilitate economic expansion by enabling individuals and businesses to borrow based on creditworthiness, income, or reputation rather than asset pledges, thereby supporting startups, home purchases, and consumer spending without requiring upfront collateral. The relative harm to DeFi from lacking this feature is significant: it constrains the sector's lending market to roughly $23.6 billion in deposits as of March 2025, dwarfed by traditional unsecured lending markets that are orders of magnitude larger (e.g., global alternative lending at $491 billion in 2025), limits participation to collateral-rich users, locks up capital that could be deployed more productively elsewhere, increases vulnerability to market volatility through

[1] Decentralized Finance (DeFi) Market Statistics 2025
[2] Chainalysis Charts 49% Growth in North American Crypto Adoption
[3] Circle Rides on Strong USDC Adoption: What's the Path Ahead

forced liquidations, and hinders mass adoption by failing to serve underbanked populations or compete with traditional finance's accessibility and scale.

However, building undercollateralized loans in DeFi is challenging because, if the value of the collateral drops below the loan amount, borrowers may rationally choose to default, especially given the absence of legal recourse in a pseudonymous blockchain environment. Consequently, undercollateralized loans have often been deemed impossible in DeFi (Aramonte et al., 2022; John et al., 2022; Harvey and Rabetti, 2023). This limitation not only restricts DeFi's ability to provide liquidity to those who need it most but also leaves vulnerable borrowers susceptible to predatory lending practices, where the constant threat of liquidation can exacerbate financial distress (Packin and Aretz, 2023). Such predatory dynamics are often intertwined with broader systemic issues in traditional finance, including discrimination, which disproportionately affects marginalized groups and perpetuates economic inequality. While DeFi's pseudonymity creates enforcement hurdles for undercollateralized lending, it simultaneously positions DeFi as a powerful tool to mitigate these discriminatory barriers by enabling non-biased, privacy-preserving access to credit. Evidence of discrimination in traditional lending markets is extensive and well-documented across disciplines: for instance, Black small business owners face differential treatment, receiving less encouragement to apply for loans and being more frequently directed toward higher-cost alternative products compared to white counterparts, while minority mortgage applicants are denied at rates up to twice those of white applicants with similar financial profiles, often due to biases in credit scoring and underwriting that lender-reported denial reasons fail to fully explain (e.g., Blanchflower et al. (2003), Pager and Shepherd (2008), Butler et al. (2018)). Undercollateralized loans in DeFi can directly address these challenges in two key ways. First, by reducing or eliminating the need for overcollateralization, they enhance capital efficiency and unlock greater liquidity for borrowers who lack excess assets, fostering broader economic participation. Second, leveraging DeFi's pseudonymous framework on public blockchains preserves borrower privacy, ensuring

lending decisions are based on transparent, automated protocols rather than personal identifiers that could invite bias, thereby promoting non-discriminatory access and inclusivity for underserved populations.

Given the benefits of undercollateralized loans, efforts in designing semi-anonymous credit cards date back at least to Low et al. (1996). However, the system as designed in Low et al. (1996) is only semi-anonymous because it still involves a trusted third party to vouch for the borrower. The rise of DeFi has reignited research into pseudonymous loans. Notably, *TrueFi* is one of the first platforms that allows credit loans. However, *TrueFi* only allows institutional borrowers and requires extensive *Know-Your-Business* procedures. Thus, *TrueFi* operates more like a traditional bank that uses cryptocurrencies. Academic research into designing a credit system includes the works of Jain et al. (2019), Hassija et al. (2020), and Han et al. (2021), among others. These designs often involve uploading users' encrypted credit profiles onto the blockchain and then using *Zero-Knowledge Proofs* to preserve the borrower's privacy while proving their credit score. Nevertheless, if lenders need to query the blockchain to learn about borrowers' credit score, they could simply ask the credit scoring agency via a platform such as *Plaid*.

In this paper, I reconsider the problem of designing an incentive-compatible system that allows for undercollateralized loans in fully decentralized settings. I formulate the problem as an infinitely repeated game between a lender and a borrower, both of whom are pseudonymous. The key difference in my system is that instead of allowing undercollateralized loans immediately, the lending platform permits them only after some given τ years of using overcollateralized loans. If a borrower defaults, he will have to do another τ years of overcollateralized loans before he can borrow undercollateralized loans again. Thus, in the worst-case scenario where there is no market for undercollateralized loans, my proposed system functions precisely like the existing system, which exclusively permits overcollateralized loans. Given τ and other observable parameters, the problem for the lender becomes choosing an interest rate r

that incentivizes honest behavior.[4] An incentive-compatible r should be high enough to incentivize lenders but also be low enough to incentivize repayment by borrowers. The lower bound for r is trivially greater than the rate for overcollateralized loans. However, the upper bound is not as clear. The key result of this paper is a formal formula defining the upper bound of r for undercollateralized loans using only observable and measurable parameters. Relying only on observable and measurable parameters means the model is robust to adverse selection and non-truthful reporting. The model also functions in the presence of moral hazard, provided that the market is efficient and consistent with investors' profit maximization behavior. Once a lower bound and an upper bound are estimated, one can determine whether a pseudonymous undercollateralized lending market is currently feasible.

Given that the paper's goal is to assess whether a pseudonymous undercollateralized loan market is feasible, I adopt a deliberately conservative modeling approach. The model assumes rational agents and independent asset returns, abstracting away from institutional mechanisms that would likely strengthen market viability. In particular, I omit reputation-based incentives, such as the ability to use past borrowing behavior as a signal of creditworthiness, akin to how FICO scores function in traditional credit markets. If such mechanisms were incorporated, borrowers would face stronger incentives to behave honestly in order to preserve future borrowing opportunities. By excluding these reinforcing dynamics, the model isolates the minimal conditions under which such a market could sustain itself. Nevertheless, section 1.4 explores the role of reputation and other practical considerations for completeness.

A key assumption for generating sustainable honest repayment from borrowers, and thus capital supply from lenders, is repeated borrowing. This setup bears a resemblance to the infinitely repeated prisoners' dilemma game, in which a sustainable cooperation equilibrium can be achieved if players anticipate repeated games. Bó (2005), and Dal Bó and Fréchette (2019) provide empirical evidence for this result.

[4] A trivial but infeasible solution is to set $r < 0$, that is, the borrower gets paid to borrow.

Before applying repeated games to this paper's setting, it is important to recognize the cost of defaulting, even if there are no legal consequences. In the proposed system, borrowers cannot borrow undercollateralized loans again immediately after a default. They can only do so after some given number of periods. Hence, the main cost of defaulting is that borrowers must do overcollateralized loans again for τ periods. As explained in Packin and Aretz (2023), overcollateralized loans can be costly to borrowers because they can be liquidated at any time. Furthermore, overcollateralization may result in an opportunity cost to borrowers due to the returns they could have earned with a lower collateral requirement. The cost of losing access to undercollateralized loans is even greater if they default during their overcollateralized periods because of liquidation.

Importantly, while the game is formally modeled as infinitely repeated, the introduction of a finite punishment duration τ renders it effectively equivalent to a finitely repeated game. In particular, the result holds as long as borrowers engage in borrowing for at least $2\tau + 1$ periods (see Appendix A.1.2). This equivalence underscores the practical relevance of the model—borrowers need not participate indefinitely to be incentivized toward honest behavior and to reap its benefits.

The key difference between the game considered in this paper and the classic prisoners' dilemma game is the dynamics of the payoffs. The classic prisoners' dilemma game often involves a fixed payoff matrix. However, since returns are stochastic and the actions of players can depend on ex-post returns, the classic prisoners' dilemma game cannot adequately model the interactions between pseudonymous lenders and pseudonymous borrowers. Solving for a game that involves an infinite number of possible paths presents a challenge. I solve this problem by relying on the assumption that asset returns are independently and identically distributed (i.i.d). Under the i.i.d. assumption, it is sufficient to solve for only an identical subgame (which starts and ends with undercollateralized loans) to determine the condition that a borrower will be honest. Nevertheless, it is important to note that the i.i.d assumption is only needed to derive the semi-analytical solution.

Simulation results show that the proposed system is robust to autocorrelated returns and volatility clustering, modelled using AR(1) and GARCH(1,1) processes.

Overall, I demonstrate the feasibility of pseudonymous undercollateralized lending by designing a market structure that incentivizes borrowers to repay honestly. The proposed design is simple and can be seamlessly integrated into existing DeFi lending platforms. Specifically, a borrower must first complete a series of overcollateralized loans over a predetermined number of periods to establish creditworthiness. Upon meeting this requirement, the borrower gains access to undercollateralized loans. The incentives to repay undercollateralized loans are threefold. First, borrowers seek to avoid the risks associated with overcollateralized loans, particularly the threat of liquidation. Second, overcollateralized loans impose a higher cost of capital due to the higher collateral requirements. Third, the option to default on future undercollateralized loans is valuable, and maintaining this option requires borrowers to repay existing obligations. Importantly, my results do not compete with existing approaches to pseudonymous credit scoring. Rather, the development and adoption of such systems are complementary and will work in tandem with the proposed mechanism to enable true credit-based lending in DeFi.

The model assumes rational and patient agents who seek to maximize long-term expected profits. This intertemporal perspective is crucial to sustaining undercollateralized lending, as it aligns borrower incentives over time. However, the mechanism fails under bounded rationality, i.e., if agents are myopic and prioritize short-term gains. In such cases, borrowers may choose to default on undercollateralized loans, undermining the credit mechanism. Nevertheless, even under bounded rationality, the proposed structure yields a novel and economically meaningful outcome: it effectively transforms into an option market, wherein borrowers purchase the right, but not the obligation, to default in the future. This emergent option-like behavior introduces a new interpretation of undercollateralized lending in DeFi settings with limited strategic foresight. The formal analysis of this result is presented in Section 1.5.

The paper is structured as follows. Section 1.2 presents the main model and all assumptions. Section 1.3 validates the theoretical model with simulation results. I also use simulation to extend the main model to incorporate more complicated cases. Section 1.4 considers practical matters. I argue that the model can perform even better in practice because I impose rather conservative assumptions in the model. Section 1.5 describes what happens if borrowers are impatient. The result is a new option market. Finally, section 1.6 concludes and suggests future research.

1.2 Model

1.2.1 The setup

I consider an infinite game between a lender and a borrower in decentralized settings, e.g., a public blockchain. I now denote the parameters used in the model. Let r be the credit borrowing rate, τ be the number of periods (years) before credit loans are allowed, i be the discount rate or risk-free rate, c be the overcollateral borrowing rate, u be the unobservable borrower's return from using the loan, y be the return the borrower gains from holding his collateral assets (y can be equal to c), k be the collateral-to-loan ratio for overcollateralized loans ($k > 1$), l be the collateral-to-loan ratio for undercollateralized loans ($l \leq 1$), and ρ_t be the stochastic collateral asset's returns. Following the convention, $\bar{\rho}$ denotes the expected collateral assets' return. The only assumption regarding the collateral asset's returns is that they are independently and identically distributed. Thus, the model is robust to the specific form and type of the asset's distribution. In the numerical simulation, I follow the convention and assume a log-normal distribution. Given any distribution for the asset's returns, one can compute the probability of $1 + \rho_t < 1 + r$. This probability will be important in computing the expected payoff for the borrower. The idea here is that if the cost of loan, r, is higher than the asset's return, ρ_t, then it is better to default. Let $F = F(1 + r) = Pr(1 + \rho_t < 1 + r)$ be the aforementioned probability.

Regarding the borrower's return u, I assume that the borrower always attempts to maximize his payoff, regardless of the type of loan he receives. Thus, u is independent of the type of loan. This assumption on u will be relaxed later to allow for the moral hazard problem.

Although the i.i.d returns assumption helps simplify the derivation and allows a semi-analytical solution, it is well-known that financial returns exhibit autocorrelation and volatility clustering. To alleviate this concern, I employ simulation to demonstrate that autocorrelation and volatility clustering do not significantly affect the theoretical results. Section 1.3 describes the simulation procedure in general and 1.3.3 focuses on comparing the case with autocorrelated and volatility clustered returns and the case with i.i.d returns.

Following Rivera et al. (2023), I assume that the lender will lend if the expected interest rate that he receives exceeds his other options. The borrower will borrow every period and will have to honor his debt if he borrows overcollateralized loans, otherwise he may choose to default. Undercollateralized loans require a collateral ratio $l \leq 1$ and cannot be liquidated early by the lender (this helps avoid the problem with predatory lending, as pointed out in Packin and Aretz, 2023).

1.2.2 Payoff functions of possible strategies

Before defining the payoff functions, it is important to review the strategies that players can choose. If the borrower uses overcollateralized loans, he is better off repaying the loan to avoid liquidation. The success of overcollateralized loans in practice provides strong evidence for this. However, the focus of this paper is undercollateralized loans. If the borrower uses undercollateralized loans, then he has a total of four possible strategies: always paying back the debt (*Always-Honest*, or H strategy), always defaulting and creating a new address (*Always-Selfish*, or S strategy), choosing to pay back only when paying back gives higher payoff (*Mixed*, or

M strategy), and choosing to be honest for some fixed N number of periods (*Mixed-Fixed*, or MF strategy). In the M strategy, the borrower will repay the debt only if the value of the collateral is higher than the total cost of debt, which is the principal plus any interest. As a note, L and B subscripts are used to denote the lender's and the borrower's payoff, respectively. Formally, an M-type borrower will repay if and only if:

$$H_B > S_B \Leftrightarrow l(1+\rho_t) > 1+r$$

Before proceeding, I offer two propositions that are useful to reduce the number of strategies that need to be considered, Proposition 1.0.A and 1.0.B.

Proposition 1.0.A. *Let N^* denote the number of honest periods that maximize borrower's payoff. N^* can only be either $N^* = 0$ or $N^* = \infty$.*

Proposition 1.0.B. *The M strategy's expected payoff is at least as high as the S strategy's.*

In Proposition 1.0.A, the first case with $N^* = 0$ is equivalent to the S strategy, in which the borrower never acts honestly; the second case with $N^* = \infty$ is equivalent to the H strategy, in which the borrower always acts honestly. Combining Proposition 1.0.A and 1.0.B, I only need to consider the borrower's payoffs for the H strategy and the M strategy to derive the condition for honest payback.

Payoffs in the case of overcollateralized loans are simple. The lender will receive his principal P back plus interest c:

$$B_L = P(1+c)$$

The borrower will pay back the principal and receive his return u less interest c:

$$B_B = P(u-c)$$

In the case of undercollateralized loans, the payoffs for both the lender and the borrower depend on whether the borrower honor his debt. Nevertheless, because of the reduced requirement in collateral, an undercollateralized loan borrower will have extra capital on which he can earn a yield y, e.g., by lending out the extra assets. This extra return means that even without considering liquidity costs of overcollateralized loans, these loans impose an opportunity cost on borrower through y. The total return from having access to unpledged capital is formally defined by G:

$$G = (k - l)P(1 + y)(1 + \rho)$$

G gives undercollateralized loan borrower yield on the part of his assets that are not pledged as collateral, i.e., $(k - l)P$. These assets earn a yield y and are worth $(1 + \rho)$ in fiat value. An undercollateralized borrower will receive G regardless of whether he pays back the debt or not because G is not part of the loan.

If the borrower pays back the debt, the lender will receive his principal P back plus interest rP:

$$H_L = P(1 + r)$$

An honest undercollateralized loan borrower will receive profits from his investment, $P(1+u)$, pay back the loan $P(1+r)$, get back his collateral which is now worth $lP(1 + \rho)$, and earn the extra yield from unpledged capital G. Formally, the payoff for an honest undercollateralized loan borrower is:

$$H_B = P(1 + u) - P(1 + r) + lP(1 + \rho) + G = Pu - Pr + lP(1 + \rho) + G$$

In case the borrower defaults on his undercollateralized loans, the lender will get the collateral Pl, which has value $Pl(1 + \rho_t)$. Thus, the lender's payoff will be:

$$S_L = Pl(1 + \rho_t)$$

If the borrower defaults on an undercollateralized loan, he will receive profits from his investment, $P(1+u)$ and earn the extra yield from unpledged capital G without paying the loan. However, he will lose his collateral which is now worth $lP(1+\rho)$. Formally, the payoff for a defaulted undercollateralized loan borrower is:

$$S_B = P(1+u) - lP(1+\rho) + G$$

With the payoff functions defined, I can start solving the model. I consider the problem of choosing the credit interest rate r, given all other parameters. Let $H(r) : \mathbb{R} \to \mathbb{R}$ and $M(r) : \mathbb{R} \to \mathbb{R}$ be the total expected payoff from H-strategy and M-strategy, respectively. The payoff function $H(r)$ is given as follows:

$$H(r) = \mathbb{E}\left[\sum_{t=0}^{\infty} H_B \mathrm{e}^{-it}\right] \tag{1.1}$$

where

$$H_B = P\left(u - r + l\rho_t\right) + \left(k - l\right) Py\left(1 + \rho_t\right)$$

For $M(r)$, indicator functions are needed as $M(r)$ depends on borrower's actions, not only in period t, but also in the last τ periods. The function can be described formally as follows:

$$M(r) = \mathbb{E}\left[\sum_{t=0}^{\infty} \left(\mathbb{1}_U \left(\mathbb{1}_H H_B + (1 - \mathbb{1}_H) S_B\right) + (1 - \mathbb{1}_U) B_B\right) \mathrm{e}^{-it}\right] \tag{1.2}$$

where

$$\mathbb{1}_H = \begin{cases} 1, & \text{if } \rho_t > r \\ 0, & \text{otherwise} \end{cases}$$

$$\mathbb{1}_U = \begin{cases} 1, & \text{no default in the last } \tau \text{ periods} \\ 0, & \text{otherwise} \end{cases}$$

$$H_B = Pu - Pr + lP(1+\rho) + G$$

$$S_B = P(1+u) - lP(1+\rho) + G$$

$$G = (k-l)P(1+y)(1+\rho)$$

1.2.3 Participation condition

The borrower should always prefer undercollateralized loans because he has the option to default. The borrower will follow H-strategy if and only if $H(r) > M(r)$. For the lender, if he expects the borrower to default, he will not participate in undercollateralized lending. The lender should be willing to supply capital if he can earn more than some minimum return, r_{min} and he can be assured of honest behavior from the borrower. Given that the lender can earn return c through overcollateralized lending, r_{min} should be at least equal to the overcollateralized loan interest rate c. Overall, the conditions for a feasible pseudonymous and undercollateralized loan market are:

$$r > r_{min} \geq c \tag{1.3}$$

$$\mathbb{E}[H(r) - M(r)] > 0 \tag{1.4}$$

The conditions appear deceptively simple. The main challenge lies in computing $\mathbb{E}[H(r) - M(r)]$. The naive approach is to compute $H(r)$ and $M(r)$ then take the

difference, or to compute the difference $\mathbb{E}[H(r) - M(r)]$ directly. Since the M-type borrower conditions his action on ex-post stochastic returns, computing $M(r)$ requires knowing the joint distribution function of the returns for an infinite number of periods, which is infeasible. A better approach is to focus on the difference $\mathbb{E}[H(r) - M(r)]$ but only up to the *decision node*. A decision node is a period in which the borrower gets access to undercollateralized loans and can decide whether to default. Because this is an extensive form game, one can divide this infinitely repeated game into many identical subgames with the starting node for each subgame being the decision node. The reason why subgames defined in this way are identical follows directly from the assumption that the asset return, ρ_t, is identically and independently distributed. Intuitively, at each decision node, the borrower faces the exact same problem of deciding whether to default because the borrower can disregard any earlier returns. Recall that the borrower is given the option to default only in case of undercollateralized loans. In addition, he can only default once every τ periods. An example subgame for $\tau = 2$ with all possible actions for the M-type borrower is visualized in Figure 1.1. For $\tau = 2$, one needs to consider up to five periods to exhaust all possible interactions. The naive approach of considering only $\tau+1$ periods is not enough because it fails to account for the case when the borrowers who honor their debts still get to choose, while those who default do not (because defaulted borrowers can only do overcollateralized loans for the next τ periods). Another approach that does not work is to apply the options pricing framework. This is what has been used by *BlockScience* team to evaluate the *THORChain* platform's risks.[5] The *THORChain* risk report shows that secured lending without liquidation is akin to selling an American call option. The key difference between my model and *THORChain*'s is the τ overcollateralization periods. *THORChain* does not impose any restriction besides the initial overcollateralization. The platform then allows borrowers to pay back their debt at any time without liquidation. Given that *THORChain* does not allow undercollateralized loans, its settings do not apply to

[5] BlockScience THORChain risk report

this paper. Nevertheless, in 1.5.1 and 1.5.2 I describe how to use loans to construct a trustless option-like contracts, which extends the analyses done in the *THORChain* risk report.

As shown earlier, because the M-type borrower's decision depends on the collateral's returns, the payoff he receives is conditional. That is, for any given period, M-type borrower's expected payoff from being honest is $\mathbb{E}[H_B \mid H_B > S_B]$. The M-type borrower's expected payoff from being selfish is $\mathbb{E}[S_B \mid H_B < S_B]$. In case being honest pays more, the difference between the H-type borrower and the M-type borrower is 0 because both borrowers choose the same action, i.e., to not default. In case defaulting pays more, the difference between the H-type and the M-type borrower is $\mathrm{D}_{HS} = \mathbb{E}\left[H_B - M_B \mid H_B < S_B\right]$. Finally, anytime a borrower defaults, his next τ periods' payoffs are B because he can only do overcollateralized loans and has must pay back the debt. Hence, M-type borrower's expected payoff after defaulting is not conditional: $\mathrm{D}_{HB} = \mathbb{E}\left[H_B - B_B\right]$. I now present the main result of this paper, the condition for which $\mathbb{E}[H(r) - M(r)] > 0$, which guarantees that H-strategy dominates M-strategy, rendering the threat of defaulting not credible.

Proposition 1.1. $\mathbb{E}[H(r) - M(r)] > 0 \Leftrightarrow$

$$\frac{F(\mathrm{D}_{HB}\mathrm{e}^{(-2\tau-1)i}\left(1-F\right)^{\tau+1})}{\left(\mathrm{e}^{i}-1+F\right)\left(\mathrm{e}^{i}-1\right)} + \frac{F\left(\left(-\mathrm{D}_{HB}+\mathrm{D}_{HS}\right)\mathrm{e}^{-i(\tau+1)} - \mathrm{D}_{HS}\mathrm{e}^{-i\tau}\right)\left(1-F\right)^{\tau+1}}{\left(\mathrm{e}^{i}-1+F\right)\left(\mathrm{e}^{i}-1\right)} + \frac{F(\mathrm{D}_{HS}\mathrm{e}^{i} + \mathrm{D}_{HB} - \mathrm{D}_{HS}\mathrm{e}^{-i\tau}\mathrm{D}_{HB})}{\left(\mathrm{e}^{i}-1+F\right)\left(\mathrm{e}^{i}-1\right)} > 0 \tag{1.5}$$

where

$$\begin{aligned} \mathrm{D}_{HS} &= \mathbb{E}\left[H_B - S_B \mid H_B < S_B\right] \\ \mathrm{D}_{HB} &= \mathbb{E}\left[H_B - B_B\right] \end{aligned} \tag{1.6}$$

The full derivation of Proposition 1.1 is presented in Appendix A.1.2. The key to derive the analytical result is to note that while the problem is modeled as an infinitely repeated game, the game "reset" after each default because the borrower is treated as a new user and has to borrow overcollateralized loan again. Thus, the infinitely repeated game is mathematically equivalent to a finitely repeated game. As shown in A.1.2, the result works as long as the borrower is patient for at least $2\tau + 1$ periods.

Proposition 1.1 gives the condition for the dominance of the H-strategy. If the credit interest rate $r > c$ satisfies Ineq. 1.5, it ensures that the expected payoff for the H-strategy is higher than the expected payoff for the M-strategy. This means that it pays more to always be honest and pay back the debt. Note that solving 1.5 involves computing the conditional expectation. Hence, a numerical solver is needed because the distribution of the collateral asset's return, e.g., normal, often does not have a closed form formula.

1.2.4 Comparative statics

As indicated in Table 1.1, the only parameter that is not observable to the lender is the borrower's return u. If u is required in order to price undercollateralized loans, then one needs to have a truthful reporting mechanism or the system cannot work. Fortunately, it is straightforward to show that the inequality in 1.5 does not depend on u. Observe that u drops out of both D_{HS} and D_{HB}. Thus, $\mathbb{E}[H(r) - M(r)]$ does not depend on u. Nevertheless, it is important to note that this result relies on the assumption that u is the optimal return for the borrower, regardless of the type of loan he receives. If the borrower receives a return conditional on the type of loan (undercollateralized versus overcollateralized), then one must know the return on the borrower's loan. This problem can occur under moral hazard, in which the borrower invests differently depending on the type of loan. Modeling moral hazard involves trading off tractability, thus this problem is studied using simulation in Section 1.3.3.

Observe that the loan amount P serves as a scaling factor in the left-hand side of 1.5, meaning that as long as the left-hand side is positive, a higher loan amount only increases the incentive to be honest. This is important because if the formula only works for small P, the market cannot scale.

The overcollateral interest rate c only appears in D_{HB}. Differentiate the LHS of 1.5 w.r.t D_{HB} yields

$$\frac{F\left(\mathrm{e}^{-i(\tau+1)}(1-F)^{\tau+1}-1\right)\left(\mathrm{e}^{-i\tau}-1\right)}{\left(\mathrm{e}^{i}-1+F\right)\left(\mathrm{e}^{i}-1\right)} \geq 0, \quad \forall i>0$$

Thus, $\mathbb{E}[H(r)-M(r)]$ increases with D_{HB}. Intuitively, the advantage of always being honest is avoiding secured loans. Therefore, the larger the difference between the honest payoff in undercollateralized loans and the overcollateralized loans payoff, the larger the incentive to be honest. Observe that the overcollateralized loans' interest rate c appears only in D_{HB} and is positively correlated with D_{HB}. This correlation indicates that increasing c also increases the honest's advantage. This is expected because higher c makes borrowing overcollaterally more expensive, which should encourage borrowers to refrain from defaulting in order to keep the option of borrowing undercollaterally. Other parameters also have the expected sign. A higher credit interest rate r reduces the payoff for honest borrowers since they will have to pay higher price for the credit loans. Selfish borrowers are not affected because they can default. Thus, a higher r reduces the incentive to be honest. The interest borrowers can receive from not having to lock up more assets, y, helps increases the incentive to be honest since honest borrowers can keep receiving y. In the model calibration and simulation section, I assume that $y = c$, meaning that borrowers can become lenders themselves for overcollateralized loans using the extra capital from not having to borrow overcollaterally.

1.2.5 Incorporating market clearing condition

As specified in Table 1.1, the only parameters that need to be identified are τ and r. Previous analysis took τ as given and focused on choosing r (recall from the earlier analysis that P simply scales the payoffs without affecting $\mathbb{E}[H(r) - M(r)]$). I also did not include the market clearing condition to emphasize the possibility of having pseudonymous undercollateralized loans at least for some players, even if not all players get what they want, i.e., the market does not necessarily clear. Nevertheless, incorporating the market clearing condition is straightforward and can help relax the assumption of known τ, albeit at the costs of requiring known forms of capital supply and demand functions. Given the capital supply and demand functions, the market clearing rate, r^*, can be obtained. Assuming τ is not known, given the market clearing interest rate, the condition specified in Proposition 1.1 can then be used to determine τ.

Following Rivera et al. (2023), the capital supply curve, $\mathcal{S}(r)$ can be thought of as the distribution function for the probability of having the lenders' outside interest rate less r. Similarly, the capital demand, $\mathcal{D}(r)$ can be thought of as the distribution function for the probability that borrowers' external interest rate is higher than r. Specifically, $\mathcal{S}(r)$ and $\mathcal{D}(r)$ can have the following forms:

$$\mathcal{S}(r) = 1 - \mathrm{e}^{-z_{\mathcal{S}} r} \tag{1.7}$$

$$\mathcal{D}(r) = \mathrm{e}^{-z_{\mathcal{D}} r} \tag{1.8}$$

where

$$z_f = \text{controls the rate sensitivity for function } f$$

$$r = \text{the pseudonymous credit interest rate}$$

Solving $\mathcal{S}(r) = \mathcal{D}(r)$ gives the market clearing interest rate r^*. Let $\bar{r}$ be the interest rate that satisfies the incentive-compatible condition, as specified in Proposition 1.1.

If $r^* \leq \bar{r}$, an pseudonymous undercollateralized loan market is feasible and is cleared. If $r^* > \bar{r}$, the market will not clear as not enough lenders will be willing to lend at $\bar{r}$ to satisfy the demand. Nevertheless, some lenders may still find $\bar{r}$ attractive enough as $\bar{r}$ is at least feasible, i.e., guaranteeing honest repay.

1.3 Model calibration and simulation study

In this section, I calibrate the model and use Monte Carlo simulation to conduct sensitivity analysis and extend the model to relax some of the initial assumptions.

1.3.1 Model calibration

The discount rate i is assumed to be 2%, following the target inflation rate by the Federal Reserve. The loan amount P is set at $10,000$. The parameter τ is set at 2, which means that a borrower can only use undercollateralized loans after at least 2 years of borrowing overcollaterally. The overcollateral borrowing rate, c, is assumed to be 10%, which is a fairly low interest rate on Bitcoin-backed USD loans.[6] The return that undercollateralized loans borrowers can gain from their extra capital $y = 0.08$. I set $y = 0.08$ because I assume y to be equal to c minus some spread. The collateral-to-loan ratio for overcollateralized loans $k = 2.5$, and the ratio for undercollateralized loans $l = 1$, i.e., the loan is fully-backed initially, with the possibility of being undercollateralized if the collateral decreases in value. The distribution for the collateral asset returns is estimated using the *S&P500*'s annual returns, which are collected from *CRSP*. The reason for choosing *S&P500* instead of a cryptocurrency like *Bitcoin* is because of data limitation. *S&P500* has a much longer history, while *Bitcoin* currently only has a maximum of 14 years of data. In addition, the returns of *Bitcoin* for the early years are not reliable. Regardless, given its extraordinary returns, using *Bitcoin*'s returns would only make the results

[6] Currently the lowest interest rate is 9.5% but requires monthly interest payment and is only for loans of $2 million and above, according to https://strike.me/lending/

stronger, i.e., $\mathbb{E}[H(r)-M(r)]$ is larger if *Bitcoin* is used as collateral. The distribution for the collateral asset is assumed to be log-normal. Note that the model is robust to the specific type of asset's distribution. The decision to use log-normal distribution is purely for conventional purpose and ease of calculation. Using *S&P500*'s annual return from 1925 to 2023, the estimated expected return $\bar{\rho} \approx 11.77\%$. Under these assumptions, the maximum interest rate for undercollateralized loans can be obtained from solving $\mathbb{E}[H(r) - M(r)] = 0$ using the result from Proposition 1.1. The result is $r \approx 20.64\%$, which is roughly the national credit card interest rate at the time of writing. Given this high interest rate, investors who are willing to hold the collateral asset should be interested in providing capital in this undercollateralized lending market because they can earn yields on their capital (similar to selling a put option). The approach to allow loan default as a put option is explored formally in 1.5.2.

Figure 1.5 depicts how undercollateralized loan interest rate, r, changes against key parameters. The plots for u, c, and y are all consistent with the analysis in 1.2.4. Observe that while r increases with τ, the rate of change exhibits diminishing rate. Only the first few τ contributes to raising r. Beyond $\tau = 10$, the effect of τ on r is minimal. This indicates that τ can be chosen by lenders arbitrarily without significantly affecting the r. For the discount rate i, the maximum r decreases in i, suggesting that the model works better when borrowers are more patient. This behavior is consistent with standard results in the infinitely repeated prisoners' dilemma (Bó, 2005). The parameter β is a scalar to scale the risk and return profile of the collateral asset. As can be seen from the graph, higher risks and higher rewards, i.e., higher β, translates into higher upper bound for the undercollateralized loan interest rate r. This theoretical relation between β and r provides insight into how the model can work under moral hazard, in which borrowers may invest differently based on the type of loan that they receive. It is likely that borrowers will prefer high risks high rewards investment when investing with undercollateralized loans. The case with moral hazard is validated and examined thoroughly in 1.3.3.

The next section describes the simulation process and extends the model to more complicated cases.

1.3.2 Simulation results

The simulation study is conducted following the *cadCAD* framework.[7] *cadCAD* stands for *Complex Adaptive Dynamics Computer Aided Design*, which is a Python package for studying complex systems using simulation. *cadCAD* has been applied in practice to study the risks of DeFi platforms, such as *THORChain*. Another reason I choose *cadCAD* is because it is open source, making it easy for readers to replicate the results of this paper.

The simulation employs the payoff functions as specified in 1.2.2. As discussed in 1.3.1, the return of the collateral asset is modeled after the *S&P500* and is assumed to follow a log-normal distribution. Specifically, at the beginning of each period, I sample from a normal distribution with mean ≈ 0.094 and standard deviation ≈ 0.191. I then take the exponential of this sample to get a sample for $1 + \rho_t$. The sampled ρ_t is then used to decide whether the M-type borrower will default and to compute all players' payoffs. All other parameters are as identified in 1.3.1.

One important result from Proposition 1.1 is that the honest advantage does not depend on u, which is unobservable. Figure 1.2 plots the maximum incentive-compatible interest rate $\bar{r}$ ($H(\bar{r}) = M(\bar{r})$) against borrower's return, u. The blue line, $\bar{r}$, results from simulation. To get the simulated $\bar{r}$, for each u, I run the simulation assuming $r = 9\%$ to $r = 15\%$ with 0.1% incremental steps and keep the r such that the absolute difference $\mid \mathbb{E}[H(r) - M(r)] \mid$ is minimized. The values for u range from $u = 1\%$ to $u = 29\%$, with 1% incremental step. For each set of parameters, I run 1,000 simulations for a total of $1,800,000$ simulations. Each simulation is run for 100 periods. The theoretical r is obtained by numerically solving the root of 1.5.

[7] https://cadcad.org/

It can be seen from Figure 1.2 that both approaches produce similar results, confirming Proposition 1.1. The simulated results differ from the theoretical results by only 0.9%. In addition, there is no clear pattern when plotting simulated r against u, confirming that the incentive-compatible credit interest rate, r, is independent from the unobservable u.

Having confirming the theoretical results, I now use simulation to extend the model to include cases that are too complicated for the analytical approach.

Including non-zero probability of failure

As a practical matter, borrowers may fail to pay back not because of their selfishness, but because of unwanted failure. That is, the borrowers cannot pay back even if they want to. This situation hurts both the lenders and the borrowers. Because the market is pseudonymous, there is no way for the lenders to know whether the default was because of selfishness or failure. Hence, any default is treated similarly, and the defaulted borrowers must start the τ overcollateralized loans periods again. If a higher failure rate reduces the honest advantage, then the proposed model may not work during times of distress. Incorporating a non-zero failure rate creates too many possible paths to consider for the analytical approach, hence I use simulation. Assuming the failure is unwanted, the failure rate must be independent from the type loans taken. That is, borrowers face the same failure rate in both over- and undercollateralized loans.

Figure 1.3 plots the simulated maximum incentive-compatible rate, $\bar{r}$, against the failure rate. It is clear that a higher failure rate increases the honest advantage, as evidenced by the higher maximum interest rate r that lenders can charge. This result indicates that the proposed model may perform even better when borrowers face a non-zero probability of failure. The intuition is that borrowers face much harsher consequences when they default on their overcollateralized loans. This is similar to the problem pointed out in Packin and Aretz (2023) regarding predatory lending. Borrowers who are liquidated early lose all their collateral before they have the chance

to pay back. Because of this, borrowers will want to avoid overcollateralized loans if they face a higher default rate, so they may instead default without consequences when they have to.

1.3.3 Autocorrelated returns and volatility clustering

It is well known that short-term financial returns, e.g., daily returns, exhibit autocorrelation and volatility clustering. To demonstrate the model's robustness, I model returns using AR(1) and GARCH(1,1) models to incorporate autocorrelation and volatility clustering. For this simulation, I use similar parameters as in section 1.3.1 except for $\tau = 5$ and failure rate = 1%. The parameter $\tau = 5$ means that users must borrow five consecutive overcollateralized loans before being given the right to borrow undercollateralized loans. This choice is inspired by the "fourth visit" rule, which says that customers become loyal to a brand after their fourth visit.[8] A 1% failure rate means there is a 1% chance that users will not be able to pay back their loans even if they want to, similar to credit card delinquencies. As of the time of writing, the credit card delinquency rate is over 3%, hence my use of 1% for the failure rate is conservative.[9] The parameters for AR(1) and GARCH(1,1) models are estimated from the S&P 500 value-weighted annual returns. Following the rule in A.1.2, I assume that each user borrows 11 loans, avoiding the usual unrealistic assumption that users discount infinite future cash flows. Both the AR(1)-GARCH(1,1) and i.i.d. return experiments are each run 100,000 times. Figure 1.6 shows the distribution of the honest advantage in the proposed model, comparing scenarios with AR(1)-GARCH(1,1) returns and i.i.d. returns. To formally test whether the two distributions are similar, I employ the Kolmogorov-Smirnov test and the Mann-Whitney U test. Both tests fail to reject the null hypothesis even at the 50% significance level, indicating that the two distributions are nearly identical. Other tests of moments such as Levene's test of equal variance and Welch's t-test of

[8] Paytronix fourth-visit rule article

[9] https://fred.stlouisfed.org/series/DRCCLACBS

equal means also give similar results. Thus, I conclude that the proposed model is robust to realistic conditions with non-zero delinquency rates, autocorrelated returns, and volatility clustering.

Moral hazard

The previous analysis assumes that failure is unwanted and thus is independent of loan type. However, without overcollateralization, borrowers may have moral hazard. That is, they may invest in riskier projects in the hope of getting higher rewards when they take out undercollateralized loans. Moral hazard can be detrimental to the lending market because it increases the cost to the lender, forcing the lender to raise the cost of loans (Igawa and Kanatas, 1990; Acharya and Viswanathan, 2011; Ioannidou et al., 2022). In the proposed model, increasing the interest rate also encourages borrowers to default, which may render the model infeasible. Nevertheless, the specific form of moral hazard is important to consider. If all borrowers are rational and the market is efficient, then all investment should have similar risk-adjusted returns. Skeptical readers may question the spread between bond and stock returns a la the "equity premium puzzle". This puzzle can be rationalized to be consistent with optimization behavior by the works of Benartzi and Thaler (1995), Bansal and Coleman (1996), Palomino (1996), and Holmström and Tirole (1998), among others.

The parameter $\beta \geq 1$ is used to represent higher risks and higher rewards by multiplying β with the collateral asset expected return and volatility. I then use simulation to compute the difference in payoffs between honest strategy and mixed strategy, i.e., $\mathbb{E}[H(r) - M(r)]$, across different β's, ranging from $\beta = 2$ to $\beta = 10$ with an incremental step of 1. Figure 1.4 plots simulated $\mathbb{E}[H(r) - M(r)]$ against β. The honest advantage appears to increase with β, confirming the theoretical r and β relation depicted in Figure 1.5. Overall, both theoretical and simulation results confirm that the proposed design is robust to moral hazard.

1.4 Practical considerations

So far the model has imposed rather conservative assumptions. Many of the assumptions are in place to test whether the proposed model can work without widespread adoption and support from the existing infrastructure. In this section, I consider how the proposed system can work in practice and potential attacks. From there I conclude that the model still works, sometimes even better, in practice than in theory.

1.4.1 Multiple wallets

Given the pseudonymous nature of decentralized systems, one concern is that borrowers may create multiple addresses to circumvent the credit building period τ. In practice, a borrower can create a small-value and a high-value wallet. The borrower then act honest in the small-value wallet to build credit and take out a large loan, then use it in his main, high-value wallet. For example, a borrower acts honest with \$10 loan and default a \$1,000,000 loan. The fixed value loan, P, helps avoid this problem. Each chain of loans is tied to a specific value, thus creating multiple wallets does not give any benefit comparing to having one large wallet. Essentially any newly added deposits to the wallet must be overcollateralized for τ periods before being allowed to under collateralize using that new value. Thus, it is not the entire account that becomes able to get undercollateralized loans, it is just the subset of balance that has been used for the τ overcollateralization period. Overall, the P-value loan requirement not only helps simplify the mathematical analysis but also helps prevent the multiple wallets attack.

1.4.2 Oracle problem

The oracle problem, in the context of a decentralized system, refers to the challenge of ensuring the validity of data that is external to the blockchain (John et al., 2022,

Rivera et al., 2023). Any data that is not internally generated by the blockchain cannot inherit the blockchain's security, e.g., credit rating or exchange rate. The main problem with having an oracle is the amount of trust involve. The oracle essentially decides the outcome of the contract. Thus, the oracle can be bribed by either party to lie. This is particularly problematic because the losing party has more incentives to bribe the oracle. For example, consider a bet of some X value between Alice and Bob, and the outcome of the bet is reported by an oracle. Assuming the correct result is that Alice wins and Bob now has to pay her X. Bob is willing to pay the oracle up to X to get the result in his favor. To compete with Bob, Alice has to sacrifice her entire winning value. Thus, the oracle problem affects players unequally and can render any decentralized system no longer trustless. This problem essentially affects all current DeFi lending platforms because they all need to query for current exchange rate to determine contracts' outcomes (Qin et al., 2021, Gudgeon et al., 2020, Al-Breiki et al., 2020).

I claim that my model is robust to the oracle problem. This is because the model does not require both lenders and borrowers to agree on the current exchange rate. Players are free to follow their source of data. The choice to pay back depends entirely on the borrower's best interest, hence there is no reason to bribe a price oracle.

1.4.3 No reuse of assets by defaulted borrowers

In the main model, I allow borrowers to freely send their remaining assets to a new account after defaulting. Thus, borrowers who defaulted can easily rebuild their overcollateralization history. This may not be true in practice because assets on public blockchain, such as *Bitcoin*, can be marked. Tracking assets can be helpful in preventing illicit activities. For example, firms like *Chainalysis*[10] and *Tether*[11] frequently monitor public blockchains and track illegal activities. Once marked, selfish borrowers may find it hard to use their assets in other platforms and services, which

[10] The Chainalysis 2024 Crypto Crime Report
[11] Tether Freezes $225M Linked to Human Trafficking Syndicate Amid DOJ Investigation

can deter them from defaulting in the first place. Even without the adoption from other services, because borrowers cannot reuse assets that were associated with their old account, they will have to acquire new assets to use as collateral, which can be costly.

1.4.4 Reputation system

Besides allowing free reuse of collateral, I also do not consider any credit rating or reputation system. Using the proposed system with any pseudonymous credit rating system should strengthen the incentives to be honest. Perhaps the best example of a working reputation system comes from the dark web merchants. The dark web presents a similar setting to an pseudonymous loan market in which the merchant is the borrower and the buyer is the lender. The buyer sends money to the merchant for some goods and/or services without any guarantee of fulfillment. While some merchants may use an escrow system to enhance trust, doing so simply shifts the point of trust to the escrow. Trust in the dark web is an interesting topic of research on its own. However, perhaps due to data limitations, research in this area remains scarce. Laferrière and Décary-Hétu (2022), and Koutrouli and Tsalgatidou (2012) provide a glimpse into the workings of illegal online marketplaces. Obviously there is no buyer protection or any possibility of recourse for the buyer in case the seller disappears with the money. In these markets, sellers often attempt to instill trust by showing past customers' reviews, appearing professional, and insisting that they are here for the long term to make sustainable profits. Applying to pseudonymous lending market, borrowers may appeal to lenders by showing their history of repaying undercollateralized loans, or they may give more details on how they plan to use the funds. Besides reputation, trust can be built using a *Web-of-Trust* (WoT) (Caronni, 2000). In a WoT, users start with a set of people whom they trust and delegate as their trusted nodes. Users will trust people who are trusted by their trusted nodes. Overtime, a user's WoT can grow into many indirect trusts. One of the largest

applications of WoT is a public blockchain. While a blockchain node can operate trustlessly, any user must first decide which software of the blockchain they want to run. How can a user know that the *Bitcoin* software that they downloaded is not a malicious version While they can check the hash of the software, how can they know the correct hash Before they have the data to verify against, they must first rely on known and trusted users who vouch for the validity of the software. Similarly, large scale open-source projects such as *Debian*, an operating system, relies on trusted community members to avoid malicious code in the system (Wolf and Quiroga, 2018). I emphasize again that the main model does not assume any trust system between the lender and the borrower. Including a trust system only strengthens the result.

1.4.5 Adoption from other services

Adoption of credit rating scores play a major role in their value. For example, *FICO* scores are used by many lenders to evaluate a borrower's creditworthiness. The adoption of *FICO* gives its value since borrowers know that lenders will look at their scores. In my model, I study only the interactions between lenders and borrowers and do not assume the adoption of an pseudonymous undercollateralized loans history as a signal for creditworthiness. Given that borrowers can choose to default in pseudonymous markets, not defaulting should give a very strong signal that they are willing to honor their debts. Thus, if such an pseudonymous undercollateralized loans market is implemented in practice, it is likely that other lending services would want to look at borrowers' pseudonymous loans history. If this were to happen, it should give borrowers a greater incentive to be honest and build a good history of paying back undercollateralized loans.

One reason why I do not consider the benefits of honesty from external lenders is the concern that borrowers may try to fake their undercollateralized loans by lending to themselves to build credit history. This practice is applied not only in DeFi but also

in traditional finance,[12] albeit it is more costly in the latter. Several countermeasures can help detect and deter borrowers from such a practice. Blockchain tracking can map relationships among accounts and determine whether a loan is genuine or the borrower's own loan. Nevertheless, it is important to note that lenders can solve this concern by considering only loans approved by themselves. The downside is that doing so can reduce the model's scalability as borrowers cannot use their credit history with other lenders to borrow from a new lender, meaning that borrowers will be restricted to a set of their frequent lenders.

1.4.6 Use of covenants

The main model does not assume the possibility of having covenants and allowing borrowers to use the funds however they wish. This assumption is conservative because allowing free use of funds opens the door to moral hazard for undercollateralized loans. However, as in traditional loans, DeFi loans conducted using smart contracts can have covenants, which restrict borrowers to only certain activities. The use of covenants in practice can help mitigate moral hazard because lenders can prevent borrowers from spending the funds on high risk activities. Furthermore, borrowers may signal trust to lenders by committing to spend the funds on only activities described in the loan application. Overall, it is likely that covenants can help instill trust and reduce moral hazard in an pseudonymous undercollateralized lending market.

1.5 Undercollateralized loan as an option market

The model relies on the assumption that users maximize their long term expected profit. If users are myopic, the honest incentive conditions will not hold and the best strategy is mixed, i.e., strategic default. Interestingly, this option to default means

[12] One such example is a service called *Self*

one can use these loans to simulate an option market. For the analyses in 1.5.1 and 1.5.2, I assume there are two assets: USD and TOKEN.

1.5.1 USD loan as a call option

I first show that loans can serve both long and short a call option. Consider a borrower who holds $k \cdot S$ TOKEN worth $k \cdot S \cdot p_0$ USD at time 0 ($k \geq 1$ and p_t is the exchange rate between TOKEN and USD at time t). The borrower pledges $k \cdot S$ TOKEN as collateral to borrow $S \cdot p_0$ USD. Without loss of generality, one can ignore the loan's interest here because the interest simply increases k. The initial cost the borrower paid for this option to default is $O_C = (k-1) \cdot S \cdot p_0$ USD. The loan lasts for T periods. At time T, the borrower can choose to pay back the debt and gets back his collateral, which is now worth $k \cdot S \cdot p_T$ USD. Alternatively, the borrower can default and transfer $k \cdot S$ TOKEN to the lender. The payoffs to the borrower are as follows.

If the borrower defaults, he transfers $k \cdot S$ TOKEN to the lender and keeps $S \cdot p_0$ USD. The borrower would want to default if $S \cdot p_0 > k \cdot S \cdot p_T$. If the borrower pays back the loan, he gets back $k \cdot S$ TOKEN and the lender gets back $S \cdot p_0$ USD. Let Y_C denotes the borrower's USD payoffs for this option.

$$Y_C = \begin{cases} (1-k) \cdot S \cdot p_0, & S \cdot p_0 > k \cdot S \cdot p_T \\ k \cdot S \cdot p_T - S \cdot p_0, & S \cdot p_0 \leq k \cdot S \cdot p_T \end{cases}$$

$$\Leftrightarrow Y_C = \begin{cases} (1-k) \cdot S \cdot p_0, & p_T < p_0/k \quad \text{(default, USD gains)} \\ k \cdot S \cdot p_T - S \cdot p_0, & p_T \geq p_0/k \quad \text{(payback, USD gains)} \end{cases}$$

Thus, $(k-1) \cdot S \cdot p_0$ is the premium for this option and p_0/k is the strike price. Because the loss is limited even if price $p_T = 0$ while the profit grows unbounded with p_T, holding this loan is equivalent to going long a call option with p_0/k strike price and matures at time T. For the lender, because he put up a value equivalent to S at

time 0 and will have to take $k \cdot S$ if the borrower defaults at time T, it is similar to going short a put option.

1.5.2 TOKEN loan as a put-like option

Reversing the role of USD and TOKEN and the loan behaves more like a put option, albeit with TOKEN as the numeraire good. Specifically, consider a borrower who holds $k \cdot S$ USD worth $k \cdot S \cdot q_0$ TOKEN at time 0 ($k \geq 1$ and q_t is the exchange rate between USD and TOKEN at time t). The borrower pledges $k \cdot S$ USD as collateral to borrow $S \cdot p_0$ TOKEN. Without loss of generality, one can ignore the loan's interest here because the interest simply increases k. The initial cost the borrower paid for this option to default is $O_P = (k-1) \cdot S \cdot q_0$ TOKEN. The loan lasts for T periods. At time T, the borrower can choose to pay back the debt and gets back his collateral, which is now worth $k \cdot S \cdot q_T$ TOKEN. Alternatively, the borrower can default and transfer $k \cdot S$ USD to the lender. The payoffs to the borrower are as follows.

If the borrower defaults, he transfers $k \cdot S$ USD to the lender and keeps $S \cdot q_0$ TOKEN. The borrower would want to default if $S \cdot q_0 > k \cdot S \cdot q_T$ If the borrower pays back the loan, he gets back $k \cdot S$ USD and the lender gets back $S \cdot q_0$ TOKEN. Let Y_P denotes the borrower's payoffs for this option. Similar to the call option case:

$$Y_P = \begin{cases} (1-k) \cdot S \cdot q_0, & q_T < q_0/k \quad \text{(default, TOKEN gain)} \\ k \cdot S \cdot q_T - S \cdot q_0, & q_T \geq q_0/k \quad \text{(payback, TOKEN gain)} \end{cases}$$

Thus, $(k-1) \cdot S \cdot q_0$ is the premium for this option and q_0/k is the strike price. This option has limited loss and gains as $q_T \to \infty \Leftrightarrow p_T \to 0$, making it behaves similarly to a put option.

1.5.3 Practical application for option-like loans

While these default-allowed loans can behave like options, they are not identical. For both call and put types, the option premium *increases* with the collateral ratio k, meaning that a safer loan (higher k) is a more expensive option contract to the borrower. This means that a market for these options, which targets the case where the model fails, can actually increase the incentives for the borrowers to be honest. In addition, specifically for the put option case, the gain is in TOKEN, not USD, which is beneficial for those who look to accumulate more of the TOKEN. In the case of cryptocurrencies, these entities can include the U.S Government (via the Bitcoin Strategic Reserve), Texas Treasury (via the bill SB21 for Texas Strategic Bitcoin Reserve), or Bitcoin Treasury Companies. The main benefits of using this contract instead of a put option via a centralized exchange is removing counterparty risk and allows more flexibility in constructing the contract.

1.6 Conclusion

In this paper, I show that it is possible to have pseudonymous undercollateralized loans, even under conservative assumptions. Such a market is achieved by setting the interest rate such that it is incentive-compatible for both lenders and borrowers, especially the borrowers, to participate honestly. The model is free from identification issues because all relevant parameters are observable. What distinguishes this paper from prior studies is its focus on the anonymity of market participants in undercollateralized lending, a feature previously deemed unfeasible. Although the model assumes agents maximize their long-term expected profits, even in the presence of myopic behavior, it yields flexible, option-like contracts that harness the core strengths of blockchain systems: trustlessness and global accessibility.

As a direction for future research, although simulation results have confirmed the theoretical predictions, if this market is implemented in practice, it is possible that

players are not aware of the long-term benefits of honesty and deviate from the optimal strategy. Research using primary data, especially real-life implementation, can help show whether a pseudonymous undercollateralized lending market is indeed possible. Given the conservative assumptions in this paper, it is possible that the maximum incentive-compatible interest rate can be higher in practice. A higher maximum interest rate means that the market can be both feasible and achieve market-clearing conditions, i.e., supply = demand. A more efficient upper bound for the incentive-compatible credit rate should prove useful for both academic and industrial uses. In addition, the "failure" case of the model presents an interesting financial product that sits between a loan and an option. I am conducting more research into the implementation of this product.

Appendix

Table 1.1. Parameter definitions

Parameter	Meaning
P	loan amount
r	anonymous credit borrowing rate
τ	number of periods (years) before credit loans are allowed
i	discount or risk-free rate
c	overcollateral borrowing rate
u	unobservable borrower's return from using the loan
y	return the borrower gains from holding his collateral assets
k	collateral-to-loan ratio for overcollateralized loans ($k > 1$)
l	collateral-to-loan ratio for undercollateralized loans ($l \leq 1$)
ρ_t	stochastic collateral assets' return
F	the probability $Pr(\rho_t < r)$
β	risk and return scalar

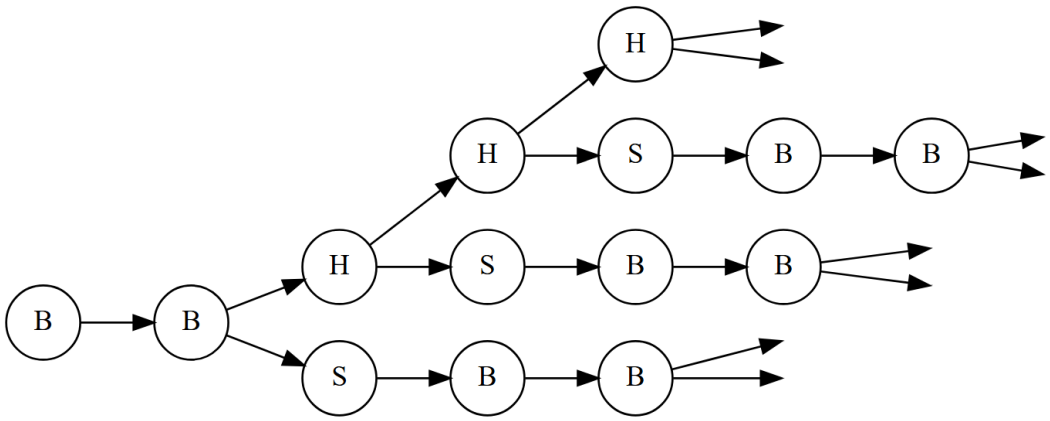


Figure 1.1: Borrowers' possible paths

This figure visualizes possible actions by M-type borrower for $\tau = 2$. Each split (double arrows) represents a decision node, which indicates that the borrower gets to decide whether he will be honest, and receive payoff H, or selfish, and receive payoff S.

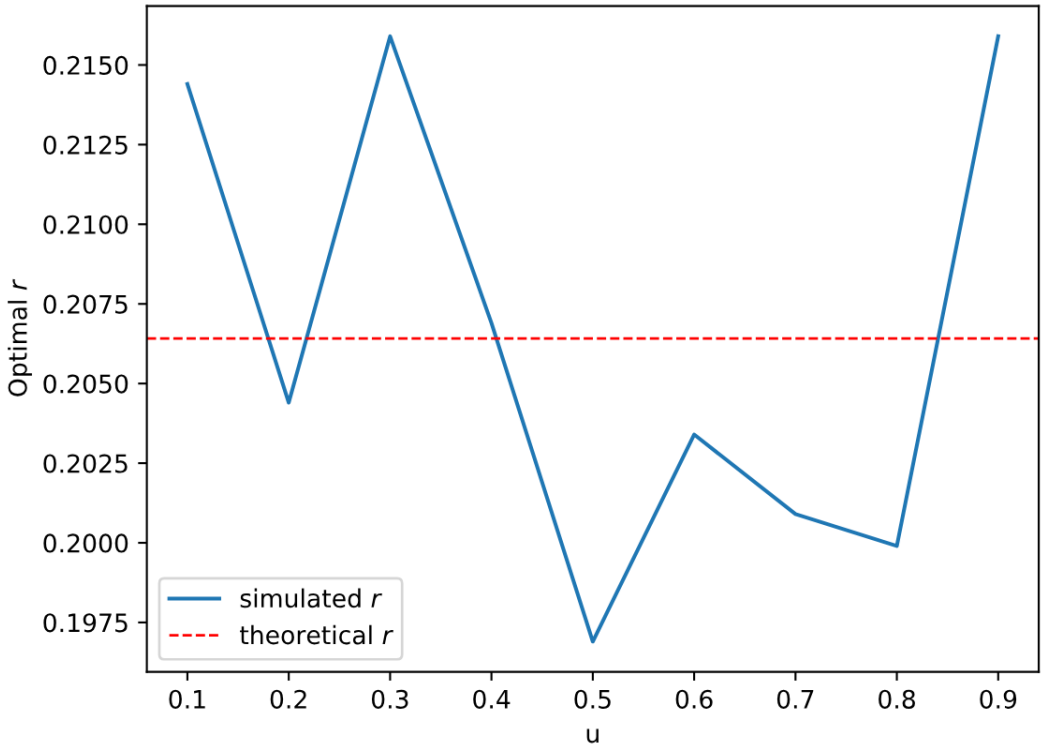


Figure 1.2: Simulated and numerical interest rate r.

This figure compares the simulated r and the theoretical r. The simulated r is derived from simulation while the theoretical r is found by numerically solving $\mathbb{E}[H(r) - M(r)] = 0$ using Proposition 1.1.

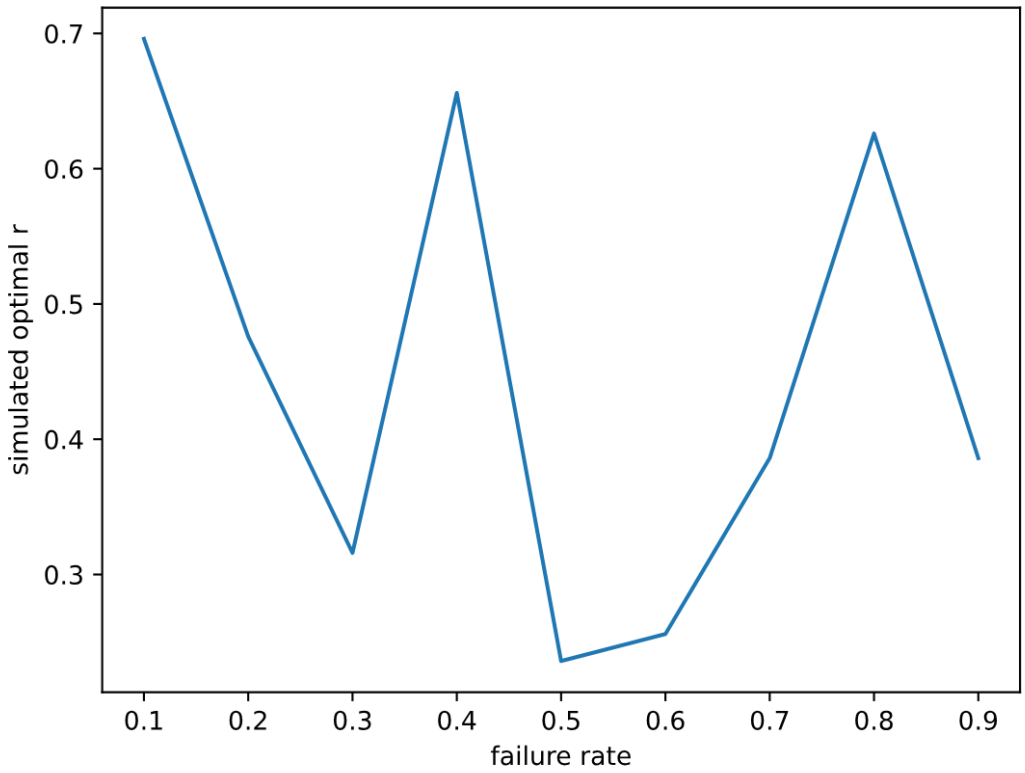


Figure 1.3: Simulated maximum $\bar{r}$ across different failure rate.

This figure shows the optimal (maximum) interest rate r for undercollateralized loans as the failure rate increases. The failure rate is the probability that the borrowers fail to honor their debt even if they want to pay back. The failure rate is similar to the credit card delinquency rate.

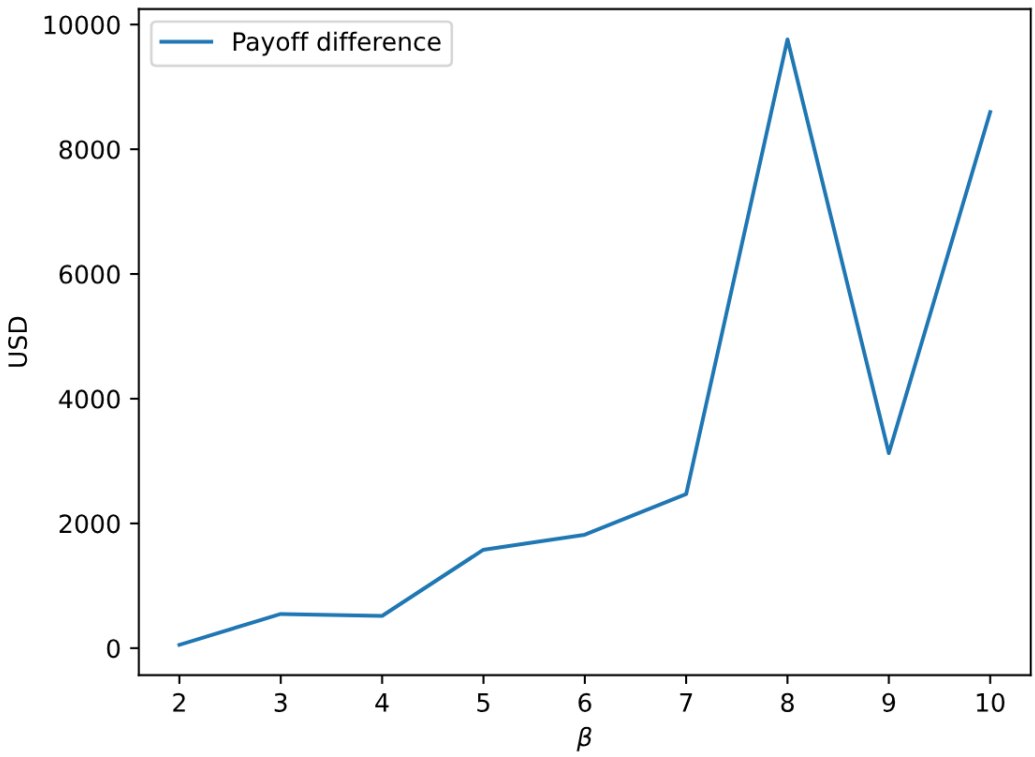


Figure 1.4: Simulated $\mathbb{E}[H(r) - M(r)]$ in the presence of moral hazard.

This figure shows the payoff difference between always-honest strategy and mixed strategy across increasingly risky projects. Under moral hazard, borrowers are assumed to use undercollateralized loans on riskier projects hoping to gain higher profits (higher β investments).

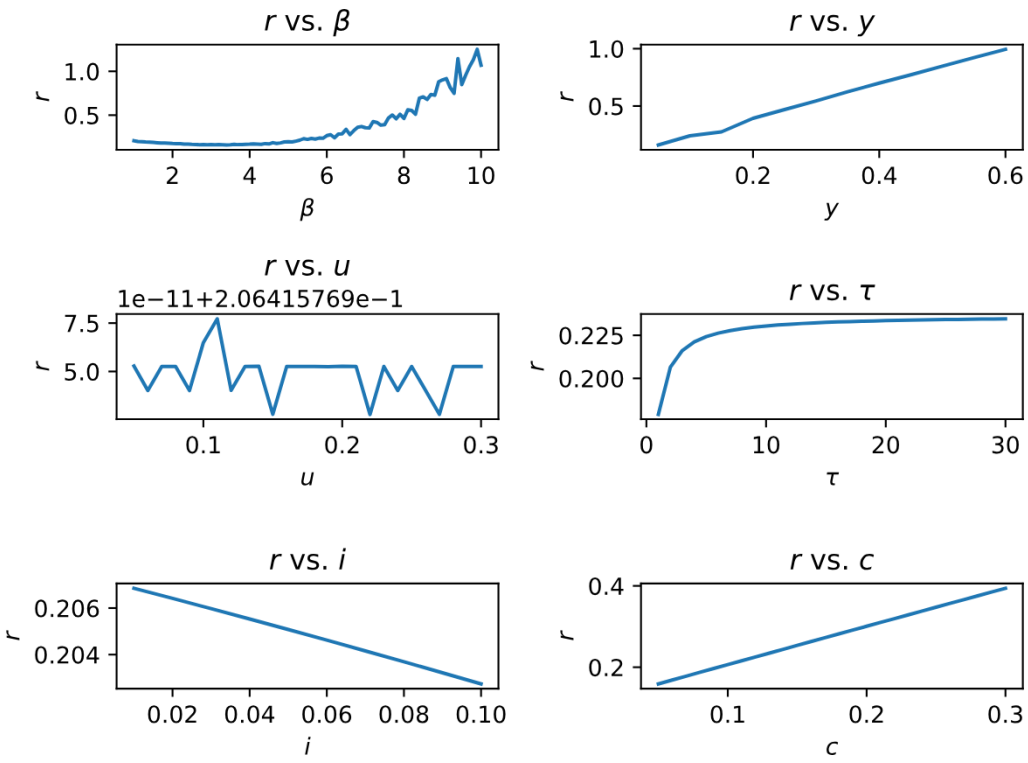


Figure 1.5: Comparative Statics

This figure plots the maximum credit interest rate r against key model parameters. The interest rate r is estimated numerically by solving for the root of 1.5. In each plot, except for the focal parameter, all other parameters are kept constant and as defined in 1.3.1.

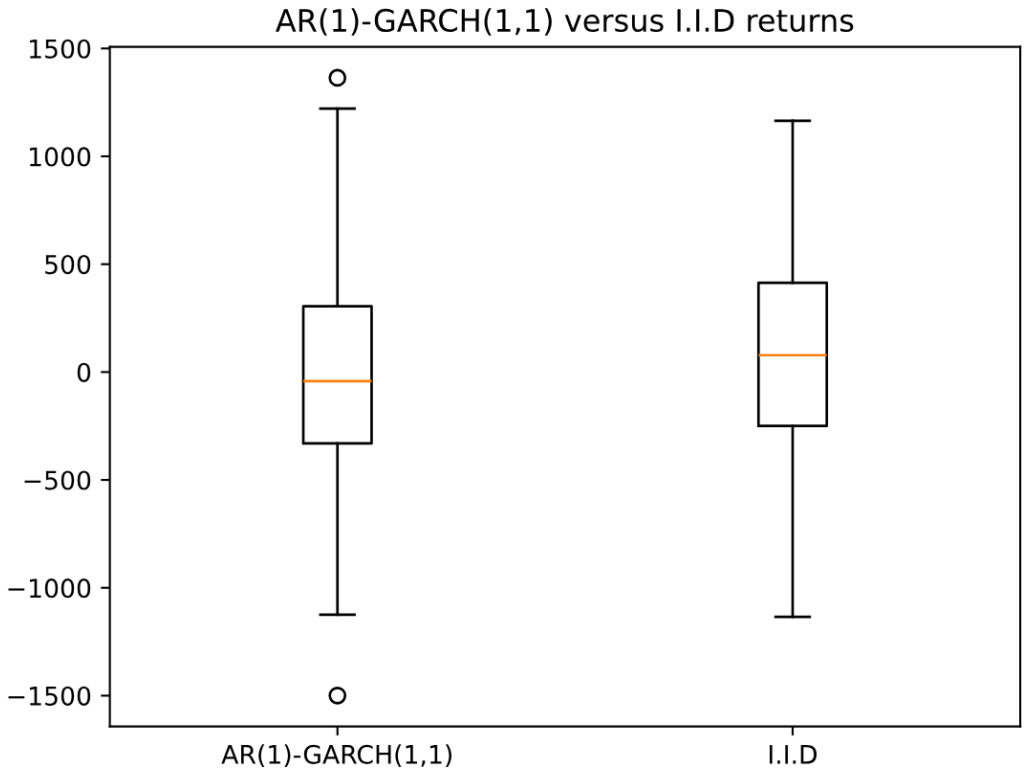


Figure 1.6: AR(1)-GARCH(1,1) versus I.I.D returns

This figure reports the boxplots of the honest advantages from AR(1)-GARCH(1,1) versus i.i.d. returns models. Honest advantage is the difference in payoffs between always-honest strategy and mixed strategy.

Chapter 2

How Do Shareholder Defaults Influence Corporate Governance in DeFi Lending

Abstract. We analyze user voting participation in token-based governance and show how it changes with borrowing activity and financial distress. Using novel user-proposal-level data from 77 DeFi lending platforms, we find that borrowers engage only slightly more in governance than non-borrowers. The key driver is financial distress: borrowers closer to liquidation are significantly more likely to vote, especially on the platform from which they borrowed, on loan-related proposals, and on user-favorable proposals. They are also more likely to support user-favorable proposals. These findings suggest that token-based governance can reflect user preferences, but becomes more short-term driven when tied to active platform use.

JEL Classification: G320, G340, G380, G510

Keywords: Financial Distress, Loan Liquidation, Shareholder Voting, Shareholder Proposals, Corporate Governance, Decentralized Finance

2.1 Introduction

The structural conflict between platform owners and users has become increasingly salient in recent years. In several documented cases, digital platforms such as Amazon, Facebook, and others have adopted policies that shift surplus from users to owners (e.g., by extracting higher rents, reducing quality and data privacy, or weakening competition).[1] The rise of token-based platform governance is often presented as a potential solution to this dilemma because it gives users direct ownership of, and thus decision control over, platform policies (Sockin and Xiong, 2023; Abadi and Brunnermeier, 2024). While prior work emphasizes the potential efficiency gains from decentralizing platform control, it remains unclear whether and when user governance actually mitigates agency conflicts or instead intensifies them.

In this paper, we empirically examine users' incentives to participate in token-based platform governance. We match governance participation with borrowing activity across 77 DeFi lending platforms. Users can borrow overcollateralized loans while simultaneously holding voting power that affects platform policies, including collateral quality, interest rates, reserve policies, and loan-to-value adjustments. Table A.1 in the appendix summarizes key DeFi lending concepts and ten representative protocols from the broader sample.

We address this question by combining four datasets: borrowing activity from 77 DeFi lending platforms, users' daily token holdings on public blockchains, users' swap trades across 15 decentralized exchanges, and governance activity on Snapshot. The final sample contains 13,908,686 voting records on 4,474 proposals between August 2020 and August 2024, including 2,433,195 voting records cast by borrowers.

[1] For instance, Amazon has faced scrutiny for using data from independent sellers to compete against them (see, e.g., the Federal Trade Commission's 2023 lawsuit against Amazon for anticompetitive practices). Facebook's repeated privacy-policy changes have shifted surplus toward advertisers at the expense of users (see the Federal Trade Commission's 2019 fine and the Irish Data Protection Commission's 2023 fine on Facebook for monetizing user data and violating privacy). Apple's App Store policy raised prices and limited user information (see the European Commission's 2024 fine).

We document three main findings. First, borrowing is associated with only a modest increase in governance engagement. Specifically, borrowers vote 0.2 percentage points more often than non-borrowers. Given the average voting participation rate of 27%, this corresponds to about a 1% relative increase. Second, among borrowers, financial distress is a strong driver of participation. Users closer to liquidation are 0.3 percentage points more likely to vote, which corresponds to roughly a 10% increase relative to the 3% baseline participation rate in the borrower sample. Third, this increase is highly targeted. Distressed borrowers are more likely to vote on the platform from which they borrowed, on loan-related proposals, and on user-favorable proposals; they are also more likely to support user-favorable proposals. Taken together, the evidence suggests that token-based governance becomes more short-term driven when it is tied to active platform use.

Our paper contributes to the extensive literature on shareholder voting. Over recent decades, regulatory reforms and charter amendments have enhanced shareholder voting rights, positioning shareholder meetings as critical platforms for corporate governance. Shareholders now vote on a range of strategic and policy decisions, from executive compensation to social and environmental proposals, reflecting a broader shift toward "corporate democracy" Aguilar (2009); Yermack (2010). This evolution has led to a growing body of research examining the determinants and consequences of shareholder voting Iliev et al. (2015); Malenko and Shen (2016); Brav et al. (2022). However, the existing literature has primarily focused on proxy voting where shareholders typically vote through intermediaries (e.g., proxy advisors), leaving a significant gap in our understanding of the factors influencing individual shareholders' voting behaviors.

To fill this gap, we examine *how* and *why* individuals choose to vote, even when it seems puzzling from the perspective of a rational agent Downs (1957); Riker and Ordeshook (1968). In particular, voters often incur higher costs (e.g., time, research, monitoring, etc.) than the expected benefit of winning the vote. This paradox is especially true in transparent settings (like blockchain technology) where voters see

that their individual vote will likely not make a difference. In this vein, we explore how financial distress motivates people to vote.

In fact, personal financial distress can be a driving force behind many decisions. For example, Dittmar and Duchin (2016); Pool et al. (2019); Gopalan et al. (2021); Ring (2023) provide empirical evidence that managers adjust their corporate investment decisions and risk-taking in response to personal wealth losses.

The expected effects on voting, however, are not immediately clear. For instance, in our setting, users facing personal loan default risk may engage more actively in governance, either in the hope of quickly improving their financial situation or to express dissatisfaction. Conversely, they may participate less because financial stress could distract them and reduce their interest in governance. This inattention occurs because investors can process only a limited amount of information at a time and often overlook relevant information when distracted by other priorities or external events Hirshleifer (2001); Hirshleifer and Teoh (2003); Hirshleifer et al. (2011); Kempf et al. (2017). Alternatively, there may be no relationship when users vote for reasons unrelated to their financial situation, for example, when their voting decisions are driven by intrinsic motivation, a sense of duty, or strategic behavior Maug and Rydqvist (2009).

Surprisingly, we know very little on how personal financial loss (or the risk thereof) affects shareholder voting and corporate governance. The main reasons for this are likely data limitations and identification challenges. First, it is extremely difficult to observe a shareholder's personal leverage and risk of defaulting when they decide to vote. Second, even when such data is available, endogeneity issues arise because shareholders often experience financial shocks simultaneously when their firm is financially constrained. We address these challenges by using transaction-level blockchain data that lets us observe borrowing positions, liquidation risk, token holdings, and individual voting decisions at the wallet-proposal level.

Closest to our paper are the studies by McCartney (2021) and Liu et al. (2025), which analyze voter turnout in presidential and other political elections during 2008-2012. McCartney (2021) finds that a 10% decline in local house prices reduces voter turnout by about 1.6 percentage points among homeowners with mortgages. Liu et al. (2025) find that the increase in voter turnout among homeowners who refinanced their mortgages was most pronounced among those with lower incomes and higher debt levels. Their findings are consistent with the view that "financial distress causes stress, distraction, and emotional distress", leading to *lower* voter turnout.

Although our study differs in its institutional setting, it speaks to the same broader question of how personal balance-sheet conditions shape governance participation. Our contribution is that the blockchain setting lets us measure financial distress at the wallet level and link it to the exact proposals that users choose to target. This allows us to show not only that distressed borrowers vote more, but also that they direct that participation toward proposals that are most closely tied to their own borrowing conditions.

Finally, our work contributes to the growing body of literature on Decentralized Finance (DeFi) and its governance design. For instance, Harvey et al. (2021); Makarov and Schoar (2022); John et al. (2023) review the economic mechanisms and institutional features of DeFi in general. We briefly discuss the functioning of DeFi lending in the following chapter, and review the related literature. Theoretical work by Sockin and Xiong (2023); Abadi and Brunnermeier (2024) develops models of token-based platform governance. Both papers argue that granting voting power to platform users can reduce user exploitation (e.g., price discrimination or user data extraction by Amazon, Facebook, and other online platforms) and lead to more user-friendly policies. Cong et al. (2025) present empirical evidence of strategic trading around voting. Our study is complementary. We show that platform users, specifically, borrowers of DeFi lending platforms increase their voting power only when they face financial pressure. In other words, being a user per se does not provide sufficient incentives to participate actively in governance. Instead, default risk, or

being close to a loan liquidation, motivates voting in ways that favor more user-friendly policies, at the expense of shareholder wealth and DeFi platform stability.

The remainder of the paper is structured as follows. section 2.2 provides some simple economics of DeFi lending. section 2.3 introduces the data. Section section 2.4 outlines the methodology and presents the results, and section 2.5 concludes.

2.2 Some simple Economics of DeFi Lending

DeFi lending functions similar to stock pledging Dou et al. (2019); Pan and Qian (2024). In both settings, traders pledge collateral to obtain a loan. This collateral is then monitored against an LTV threshold. If the collateral value falls below this threshold, it can lead to a margin call (and potential forced sale) in stock pledging, and a forced loan liquidation in DeFi.

The key difference lies in intermediation. In stock-pledge loans, a bank or broker acts as an intermediary. This external lender sets the interest rate based on the quality of the collateral and other client-specific factors, and issues margin calls under the contract. In DeFi, there is no traditional intermediary or bilateral negotiation. Instead, the DeFi lending platform functions as a fully automated margin-loan system enforced by smart contracts, i.e., computer code deployed and executed on public blockchains Harvey et al. (2021); John et al. (2023). In DeFi, users typically pledge (i.e., lend) an asset (or a portfolio of assets), in form of cryptocurrencies or tokens, as collateral to a pool and borrow another asset against it. Borrowing incurs a cost in the form of interest payments, while lending generally provides a passive income through the lending interest rate. The borrowing rate is strictly greater than the lending rate, which is why debt increases over time.

[Figure 2.1 about here]

Users manage their loan position by pledging more collateral or repaying the debt. However, as long as the collateral remains above the LTV threshold, the loan can be

maintained indefinitely John et al. (2023). Interest rates within a DeFi lending pool are set algorithmically and adjust with *utilization*. When more borrowers use the pool, rates tend to rise, which incentivizes additional lenders to supply liquidity. When fewer borrowers use the pool, rates tend to fall, making loans cheaper and encouraging more borrowing. If a loan position exceeds the LTV limit (typically 50-80% of the collateral value), it becomes eligible for liquidation, which is then executed by arbitrageurs (see Lehar and Parlour (2022) for an empirical analysis).

Arbitrageurs monitor loan positions that fall below the LTV threshold. When such a liquidation event occurs, they step in, repay the borrower's debt, and in return receive the collateral at a discount, which they can then sell for a profit. Often, loan positions are liquidated only partially, so that only part of the collateral is sold until the loan no longer exceeds the LTV limit. In this scenario, the arbitrageur receives only that portion of the collateral, while the borrower retains the remainder, provided the loan is sufficiently overcollateralized again. In some other application, the DeFi platform itself may seize the collateral to cover the outstanding debt, ensuring that the protocol remains solvent and protecting other users from potential losses. Because such activity is highly profitable, some arbitrageurs, often trading bots, may intentionally increase market volatility to trigger the liquidation of loans that are close to default (see Lehar and Parlour (2023) for an empirical analysis).

Lehar and Parlour (2022); Chiu et al. (2023) further discuss the systemic implications from loan liquidations in DeFi. Heimbach and Huang (2023) provides an empirical analysis of indiviual borrowing activity and finds that borrower leverage does not significantly affect liquidations, as liquidation events appear to be event-driven. Makarov and Schoar (2022); Cornelli et al. (2025) show that DeFi lending is mainly used for leveraged trading. Park and Stinner (2023) documents that participants of DeFi lending platforms leverage stablecoins to earn platform rewards.

2.3 Data

We construct a comprehensive, individual-level panel dataset linking users' borrowing and collateral pledging activities to their participation in token-based governance voting. Specifically, we combine four datasets: borrowing activity from 77 DeFi lending platforms, users' daily token holdings on public blockchains, users' swap trades across 15 decentralized exchanges, and governance activity on Snapshot. The sample period runs from August 2020 to August 2024.

The borrowing dataset, obtained from Flipsidecrypto.xyz, includes each borrower's wallet address, the amounts borrowed and repaid (in $), the value of pledged collateral (in $), an indicator for whether the loan was liquidated, the transaction timestamp, the DeFi platform used, and the underlying blockchain. To determine whether users were eligible to vote, we complement this information with daily wallet-level token holdings from Arkm.com across Arbitrum, Avalanche, Base, Blast, BNB Chain, Ethereum, Linea, Mantle, Optimism, Polygon, and Tron.

Each DeFi platform in our sample is associated with a governance space on Snapshot.org, a popular website for token-based governance. Token holders connect their wallets to verify membership and voting power, and can then propose and vote on governance changes. For each proposal, we observe the proposal description, the duration of the voting period, the participating voters, their voting power, their vote choices, and the final outcome. Across all spaces, we identify 4,474 proposals and 13,908,686 voting records, of which 2,433,195 are cast by borrowers.

[Figure 2.2 about here]

2.3.1 Variable Construction

Our main dependent variables are voting participation (1/0) and support for user-favorable proposals (1/0). To distinguish between active and passive participation, we analyze each borrower's voting history and daily token holdings on public blockchains.

We classify borrowers who hold governance tokens during a proposal's voting period but do not appear in the voting records as having chosen not to participate.
Some proposals allow voters to vote with different types of cryptocurrencies or tokens. In these cases, we check whether the borrower holds any eligible token during the voting period. We also verify that the user's eligible governance-token balance exceeds the voting power of the smallest voter who participated in that proposal. This restriction ensures that users are not classified as non-voters simply because they hold an insufficient number of governance tokens.
Finally, for borrowers who had voting rights but chose not to vote, we infer their potential voting power from their daily balances of the relevant governance tokens.

To measure how voting power is distributed within each proposal, we use the Herfindahl-Hirschman Index (HHI). Higher HHI values indicate that voting power is concentrated among a few voters, with many others holding only small governance token amounts.

Next, we evaluate each borrower's overcollateralized loan position. To proxy for financial distress, we use a distance-to-default measure that computes how far the borrower's collateral value (in $) is from the total amount borrowed (in $). We scale this difference by the volatility of the collateral to reflect the riskiness of the position for user i on day t.

$$\text{Distance-to-Default}_{it} = \frac{\text{Collateral value}_{it} - \text{Borrowing amount}_{it}}{\sigma_{\text{Collateral},it}}$$

In some cases, we observe that borrowers pledge a portfolio of assets in order to manage their loan positions. In such instances, we calculate the average volatility of all collateral assets. To address concerns that pledging cryptocurrencies or tokens as collateral might limit a borrower's ability to vote, we verified that the pledged assets used as collateral are different from the governance tokens that grant voting rights. For instance, the five largest collateral asset by borrowing amount (in $) are Bitcoin BEP2 (BTCB), Ether (ETH), Wrapped BNB (WBNB), Wrapped Beacon

ETH (WBETH), and Wrapped Ether (WETH). These assets are highly liquid native cryptocurrencies or *wrapped* versions backed by native cryptocurrencies, which enable their use across different blockchains and DeFi platforms. As with share pledging, collateralized borrowing in DeFi provide users with liquidity for personal consumption and investment at a relatively low cost without selling the underlying asset, so that they can still participate in any price appreciation.

In some cases, we observe that users pledge governance tokens as collateral to borrow other cryptocurrencies. In these situations, the governance tokens are locked within the lending applications, and users cannot use them for on-chain voting until they withdraw them again.

The most frequently borrowed assets are stablecoins like USD Coin (USDC), USD Coin Bridged (USDC.e), Tether (USDT), and Binance USD (BUSD), which can be used for leveraged trading and arbitrage. For example, stablecoins can be deposited into yield-bearing liquidity pools, also known as yield farms, which function similarly to interest-bearing savings accounts. Additionally, borrowers can pledge their *borrowed* stablecoins back to the DeFi lending platform to earn rewards Park and Stinner (2023). Furthermore, borrowers can use stablecoins to purchase more of the native asset or increase their governance influence by buying additional governance tokens.

2.3.2 Descriptive Statistics

In our sample, shown in Table 2.1, we observe 13,908,686 voting records across 4,474 proposals from August 2020 to August 2024. About 16% of all voting records come from borrowers, and the borrower subsample contains 2,433,195 observations. On average, voters participate in just over two DAOs and about 44 proposals. Borrowers mainly pledge volatile native cryptocurrencies and wrapped versions of them as collateral, while the most frequently borrowed assets are stablecoins such as USDC, USDC.e, USDT, and BUSD.

At the proposal level, voting windows last about four to five days and proposal descriptions contain more than 2,300 words on average. Proposals typically offer three voting options, although some contain many more, and the average HHI is 0.29, indicating that voting power is usually not concentrated in a single wallet. In the proposal-classification sample, 3% of proposals are loan-related and 81% are user-favorable.

2.4 Empirical Analysis

2.4.1 Effects of Financial Distress on Voter Participation

To examine how users vote in token-based governance, we analyze how the personal financial situation of voters who borrow from DeFi lending platforms affects their participation in DAO governance. The key assumption is that borrowers have more skin in the game than non-borrowers and are therefore more committed to participating in governance. However, this commitment may intensify when users experience financial distress or approach liquidation, as they risk losing both their loan and their collateral. On the other hand, it may decrease if users become more focused on their financial problems than on governance.

For our identification strategy, we estimate a voter-fixed effects model,

$$\text{Voting Participation}_{it} = \beta_0 + \beta_1 \cdot \text{Financial Distress}_{it} + \phi_i + \theta_t + \epsilon_{it}, \tag{2.1}$$

where voting participation is set to one if voter i participates in a proposal at time t, and zero otherwise. The main variables of interest are: (i) the log of the borrowing amount, (ii) the log-transformed distance-to-default metric, and (iii) the liquidation value. The voter fixed effect, ϕ_i, controls for voter-specific characteristics (e.g., gender, skills, preferences, beliefs), allowing us to identify within-voter variation in voting behavior across proposals. The proposal fixed effect, θ_t, accounts for unobserved differences between proposals (e.g., content or importance), isolating the effects of

proposal characteristics on voting behavior. Standard errors are clustered at the DAO level to adjust for within-firm correlations.

The first results of this paper are presented in Table 2.2. We find that, on average, voters increase their voting participation by 0.2 percentage points during periods when they borrow. The remaining specifications in Table 2.2 show that this relationship remains robust and even strengthens significantly when borrowers undergo liquidation. Given that the average voting participation is 27%, this result corresponds to a 1% relative increase, suggesting that borrowing does not strongly motivate governance participation.

In Table 2.3, we estimate the relationship among borrowers only, focusing specifically on the effect of voters' risk-taking and the financial pressure they face before liquidation. In column 1 of Table 2.3, we find that voters with a larger distance-to-default (i.e., more financially secure loan position) are less likely to vote, whereas voters closer to liquidation increase their voting participation by 0.3 percentage points on average. In other words, a voter closer to default votes 10.4 percentage points more than the average voter. A similar result is found in column 2, which shows that higher borrowing amounts (due to higher collateral values) are associated with lower voting participation among borrowers. Liquidation events make the average voter slightly less likely to participate, but this effect is marginal.

Taken together, the findings in Table 2.2 and Table 2.3 support our argument that financial distress acts as a strong incentive for governance participation in decentralized platforms. Users facing heightened financial risk are motivated to engage more actively in collective decision-making, instrumentally seeking to protect or recover their economic interests.

Could the results be purely mechanical, in the sense that voters who borrow are algorithmic bots? Through smart contracts and APIs, it is possible to create code that could automate voting participation. This idea can be advantageous for vote delegation, allowing the combined voting power of many small token holders to be

pooled into a single vote. Furthermore, voters (and/or bots) may borrow governance tokens to influence the outcome of a vote Cornelli et al. (2025).

To address these concerns, we verified for our sample that the borrowed tokens are different from the DAO governance tokens, leading us to conclude that our findings are not driven by vote-buying activity. Moreover, if voting activity were automated, we would likely observe constant or even increasing participation rates over time, for instance, to give the impression of high engagement within a DAO. However, our data show that voting participation rates fluctuate over time without following any specific pattern. Moreover, automated voting would also likely result in a concentration of voting power in each proposal, with less diversity in proposal design, content, and outcomes. In contrast, our data reveal significant variability in voting rules, proposal content, and voting options, resulting in more decentralized voting power and a greater diversity of proposals, where automating voting participation is likely more challenging.

2.4.2 Testing Mechanisms

After confirming that shareholders experiencing financial distress are more likely to vote, we further aim to understand why they vote. If voters are indeed motivated by a desire to improve their personal financial situation, our results should be more pronounced for proposals concerning the specific DeFi lending platforms from which voters have borrowed funds.

In column 1 of Table 2.4, we split our main sample to focus on voters who participate in the governance of the same platform from which they have borrowed. Column 2, by contrast, includes only cases where voters participate in the governance of a platform they did not borrow from. This pattern is consistent with our main conjecture that users in financial distress are instrumentally motivated to influence proposals directly affecting their personal financial outcomes. This finding reinforces

the view that DAO governance, unlike traditional corporate or political voting, is strongly driven by self-interest at the intersection of user utility and platform risk.

In this specification, we include several control variables to capture the voter's experience with DeFi. These include the number of past liquidations they have experienced, whether they made any swap trades in the last 20 days, and their governance experience, measured by the number of proposals they previously participated in and the number of DAOs they have joined.

As a result, we find that experiencing more liquidations is associated with lower voting participation. This finding aligns with McCartney (2021) study, which shows that negative financial shocks can discourage political participation. More unexpectedly, we also observe that greater governance experience is linked to a lower likelihood of voting. However, this seemingly counterintuitive result can be explained by trends in the data: DAOs have seen a surge of new participants in recent years, making it appear that experienced users vote less simply because they represent a smaller share of the growing participant base.

Next, we test whether voters specifically target proposals related to loan management or user-favorable outcomes. To do this, we use OpenAI's GPT-4.1 model, a large language model, to classify proposal content into two categories: loan-related proposals (1/0) and user-favorable proposals (1/0). Loan-related proposals refer to those that seek to modify parameters of the DeFi lending platform, such as borrowing requirements, overcollateralization ratios, interest rates, algorithms for determining interest rates, mechanisms for ensuring those rates, or the inclusion of new collateral assets eligible for loans, and include key words like liquidity, collateral, lend, borrow, loan, health ratio, health factor, health rate, and interest rate.

User-favorable proposals primarily focus on whether the proposed changes reduce user costs, increase user rewards, improve user experience, expand access, enhance security and fairness, or lower liquidation risk. The certainty of the model's classification is based on how clearly and transparently the proposal presents supporting evidence.

In Table 2.5, we explore whether the effect of financial distress on voting is more pronounced for certain categories of proposals. Column 1 shows that financially distressed users, proxied by a smaller distance-to-default, are significantly more likely to vote on loan-related proposals. By contrast, this effect is considerably smaller for non-loan-related proposals (-0.006 in Column 1 versus -0.001 in Column 2), and the difference is statistically significant.

Similarly, to test whether this effect is particularly strong for proposals that directly benefit users, we also split the sample by user-favorable proposals. Indeed, we find that the significantly positive effect of financial distress on voting participation is concentrated in proposals that better align with users' preferences.

So far, we have established the main finding of this paper: that voters in riskier financial positions are more likely to participate in governance. This increased turnout appears to be driven by the opportunity to influence proposals that align with user preferences and potentially improve their personal financial outcomes. However, one open question remains: do these financially distressed voters also increase their support for these proposals, or do they participate more frequently only to ultimately vote against them? In other words, while we observe increased voting activity, the direction of that support remains to be fully understood.

To address this question, we extend our analysis by re-estimating the model from Equation 2.1, but with a different outcome variable: instead of voting participation, the dependent variable now captures whether a voter supported a user-favorable proposal (1/0). This variable allows us to examine whether financially distressed voters not only participate more, but also actively support proposals aligned with user interests.

For this test, we analyze individual voting choices, which required limiting the sample to proposals that received both support and opposition votes. This restriction reduced our sample to 1,645 proposals and 41,789 voting records. Despite the smaller sample, our main findings hold under this model specification. In Table 2.6, we find

that voters closer to liquidation are significantly more likely to support user-favorable proposals.

2.5 Conclusion

This paper studies the role of users in token-based governance of DeFi lending platforms and asks when financially exposed users choose to participate. Using a novel wallet-proposal panel, we show that borrowing by itself is associated with only a modest increase in voting participation.

The stronger result is that financial distress matters. Borrowers closer to liquidation are more likely to vote, especially on proposals that are most relevant to their own borrowing conditions: proposals on the platform from which they borrowed, loan-related proposals, and user-favorable proposals. They are also more likely to support user-favorable proposals.

Overall, token-based governance appears capable of reflecting user preferences, but it becomes more short-term driven when governance rights are closely tied to active platform use.

Appendix

Table 2.1. Descriptive Summary
This table presents descriptive statistics for the main sample at both the voter and proposal levels.

	Obs	Mean	SD	Min	P25	Median	P75	Max
A. Voter level								
Voting Participation	13,908,686	0.27	0.44	0.00	0.00	0.00	1.00	1
Borrower	13,908,686	0.16	0.36	0.00	0.00	0.00	0.00	1
Liquidation	13,908,686	0.00	0.06	0.00	0.00	0.00	0.00	1
Borrowing Amount	13,908,686	1.88	99.55	0.00	0.00	0.00	0.00	110,199
Liquidated Value	13,908,686	0.43	64.98	0.00	0.00	0.00	0.00	19,304
#DAOs joined	13,908,686	2.12	1.99	1.00	1.00	1.00	2.00	28
#Proposals voted	13,908,686	43.92	80.63	0.00	5.00	16.00	49.00	1,749
B. Borrower level								
Voting Participation	2,433,195	0.039	0.19	0.00	0.00	0.00	0.00	1.00
log Distance-to-Default	2,433,195	3.46	3.87	0.00	0.00	2.08	5.63	22.98
log Borrowing Amount	2,433,195	4.33	3.79	0.00	1.68	3.36	5.20	15.82
log Liquidation Value	2,433,195	0.63	2.03	0.00	0.00	0.00	0.00	10.51
#Liquidations	2,433,195	0.53	3.74	0.00	0.00	0.00	0.00	176
#Swaps Trades	2,433,195	1.34	28.51	0.00	0.00	0.00	0.00	5,680
#DAOs joined	2,433,195	6.22	3.33	1.00	4.00	6.00	8.00	24
#Proposals voted	2,433,195	13.04	34.77	0.00	0.00	2.00	11.00	624
Support for User-favorable Proposals	42,174	0.51	0.49	0	0	1	1	1
C. Proposal level								
%Voting Participation	4,474	0.023	0.044	0.0	0.0	0.003	0.025	0.5
Avg log Distance-to-Default	4,474	13.20	1.95	0.00	11.93	13.36	14.73	17.91
%Borrowers	4,474	0.27	0.22	0	0.11	0.22	0.36	1
Loan-related Proposal	4,474	0.03	0.17	0	0	0	0	1
User-favorable Proposal	4,474	0.81	0.39	0	1	1	1	1
HHI	4,474	0.29	0.22	0.00	0.15	0.23	0.36	1.0
#Voters	4,474	535	2,000	0	12	38	241	18,546
#Voting Choices	4,474	3.47	5.57	1.00	2.00	2.00	3.00	98
Title Length	4,474	52.57	21.66	1	37	49	66	212
Description Length	4,474	2,394	2,818	1	433	1,374	3,213	26,595
#DAOs	77							

Table 2.2. Financial Distress on Voter Participation among all Voters
This table presents fixed effects regression results for Equation 2.1. The dependent variable is a dummy equal to 1 if the voter participated in a proposal. The sample includes all voters eligible to vote in proposals on DeFi lending platforms between August 2020 and August 2024. Standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable	Voting Participation		
	(1)	(2)	(3)
log Borrowing Amount	0.002***	0.002***	0.002***
	(3.22)	(3.31)	(2.88)
log Liquidation Value		-0.002	-0.004
		(-0.64)	(-1.16)
log Borrowing Amount × log Liquidation Value			0.000**
			(2.21)
Constant	0.266***	0.266***	0.266***
	(910.95)	(862.39)	(786.28)
Voter FE	✓	✓	✓
Proposal FE	✓	✓	✓
Obs	13,862,596	13,862,596	13,862,596
Adj R^2	0.319	0.319	0.319

Table 2.3. Financial Distress on Voter Participation among all Borrowers
This table presents fixed effects regression results for Equation 2.1. The dependent variable is a dummy equal to 1 if the voter participated in a proposal. The sample includes all borrowers who were eligible to vote on DeFi lending platforms between August 2020 and August 2024. Standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable	Voting Participation			
	(1)	(2)	(3)	(4)
log Distance-to-Default	-0.003***			-0.002***
	(-4.31)			(-3.81)
log Borrowing Amount		-0.002***		-0.001
		(-3.90)		(-1.62)
log Liquidation Value			-0.001	-0.001
			(-1.38)	(-1.14)
Constant	0.049***	0.050***	0.040***	0.054***
	(21.94)	(18.40)	(58.94)	(18.30)
Voter FE	✓	✓	✓	✓
Proposal FE	✓	✓	✓	✓
Obs	2,432,900	2,432,900	2,432,900	2,432,900
Adj R^2	0.279	0.279	0.279	0.279

Table 2.4. Financial Distress on Voting Participation across Platforms
The dependent variable is a dummy equal to 1 if the voter participated in a proposal. The sample includes all borrowers eligible to vote in proposals on DeFi lending platforms between August 2020 and August 2024. Columns 1 and 2 split the sample based on whether voters borrowed from the same platform in which they vote. Controls include the number of previous liquidations experienced by the voter, the number of executed swaps, the number of proposals previously voted on, and the number of DAOs joined. Standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable	Voting Participation	
	platform voters borrowed from (=1) vs platform voters did not borrow from (=0)	
	(1)	(2)
log Distance-to-Default	-0.004***	-0.001
	(-39.28)	(-1.33)
log #Liquidations	-0.018***	-0.001
	(-670.00)	(-0.29)
log #Swap Trades	-0.001	-0.000
	(-0.53)	(-0.16)
log #Proposals voted	-0.018***	0.002
	(-61.93)	(0.57)
log #DAOs joined	-0.037***	-0.039***
	(-276.74)	(-5.51)
Constant	0.165***	0.107***
	(239.61)	(6.84)
Voter FE	✓	✓
Proposal FE	✓	✓
Obs	797,401	1,635,411
Adj R^2	0.351	0.283

Table 2.5. Financial Distress on Voting Participation by Proposal Content

This table presents fixed effects regression results for Equation 2.1. The dependent variable is a dummy equal to 1 if the voter participated in a proposal. The sample includes all borrowers eligible to vote in proposals on DeFi lending platforms between August 2020 and August 2024. Columns 1 and 2 split the sample based on whether the proposal descriptions are loan-related or involve other topics. Columns 3 and 4 split the sample based on whether the proposals are classified as user-favorable. Controls include the number of previous liquidations experienced by the voter, the number of executed swaps, the number of proposals previously voted on, and the number of DAOs joined. Standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable	Voting Participation			
	Loan-related (=1) vs other topics (=0)		User-favorable (=1) vs not user-favorable (=0)	
	(1)	(2)	(3)	(4)
log Distance-to-Default	-0.006***	-0.001***	-0.002***	-0.000
	(-5.27)	(-3.30)	(-4.22)	(-0.49)
log #Liquidations	-0.018	-0.005	-0.006	0.002
	(-1.67)	(-1.37)	(-1.50)	(0.51)
log #Swap Trades	-0.001	-0.001	-0.000	-0.002
	(-0.48)	(-0.56)	(-0.45)	(-0.96)
log #Proposal voted	0.026	0.003	0.003	-0.005
	(0.90)	(1.14)	(1.04)	(-0.59)
log #DAOs joined	0.047	-0.043***	-0.042***	-0.035***
	(0.91)	(-7.88)	(-8.49)	(-4.25)
Constant	0.018	0.118***	0.122***	0.111***
	(0.15)	(9.80)	(10.40)	(5.44)
Voter FE	✓	✓	✓	✓
Proposal FE	✓	✓	✓	✓
Obs	53,630	2,377,583	2,255,655	176,238
Adj R^2	0.442	0.274	0.282	0.284

Table 2.6. Financial Distress on Support for User-Favorable Proposals
This table presents fixed effects regression results for Equation 2.1. The dependent variable is a dummy equal to 1 if the voter supported a user-favorable proposal. The sample includes all borrowers who were eligible to vote on DeFi lending platforms between August 2020 and August 2024. Standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable	Support for User-Favorable Proposals (=1)			
	(1)	(2)	(3)	(4)
log Distance-to-Default	-0.004**			-0.002***
	(-2.53)			(-4.14)
log Borrowing Amount		-0.004*		-0.002
		(-1.75)		(-1.07)
log Liquidation Value			-0.005**	-0.003
			(-2.09)	(-1.21)
Constant	0.528***	0.533***	0.520***	0.534***
	(129.92)	(62.39)	(771.68)	(61.54)
Proposal FE	✓	✓	✓	✓
Obs	41,789	41,789	41,789	41,789
Adj R^2	0.924	0.924	0.924	0.924

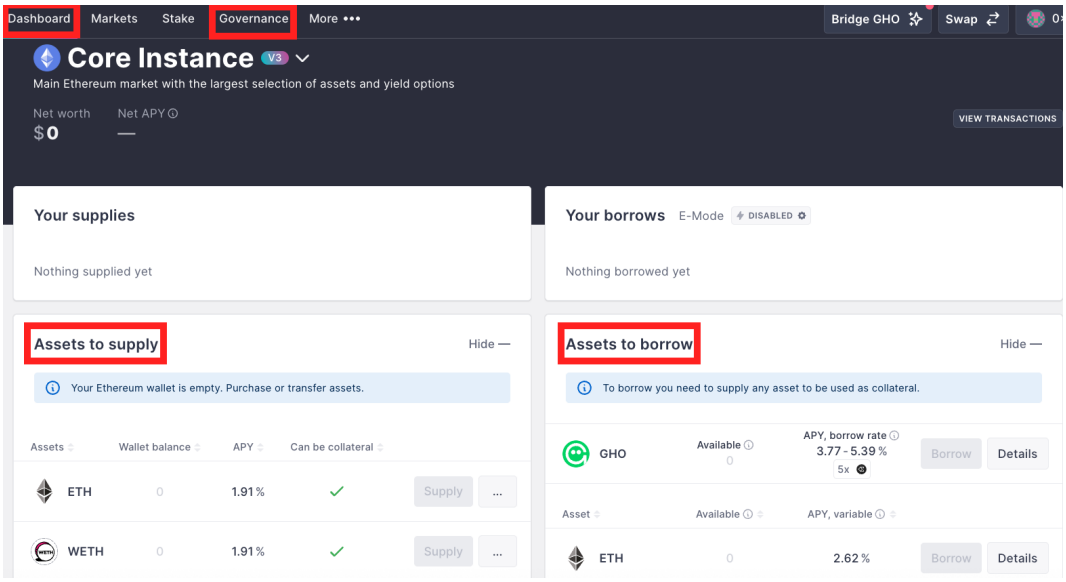


Figure 2.1: Illustration of a DeFi lending interface. Users pledge collateral, borrow against it, and actively manage liquidation risk through repayment or additional collateral. Source: Aave.

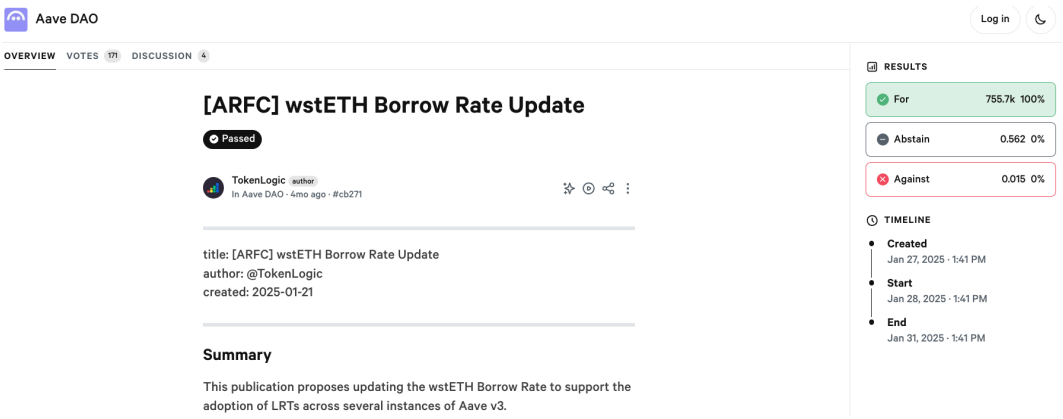


Figure 2.2: Illustration of token-based governance voting. Governance token holders review proposals on Snapshot and cast token-weighted votes on platform policies. Source: Snapshot.

Bibliography

Abadi, J. and Brunnermeier, M. (2024). Token-based platform governance. *Journal of Financial Economics*, 162:103951. 44, 47

Acharya, V. V. and Viswanathan, S. (2011). Leverage, moral hazard, and liquidity. *The Journal of Finance*, 66(1):99–138. 25

Aguilar, L. A. (2009). The power of the shareholder & the rise of corporate democracy. *Speech by U.S. Securities and Exchange Commissioner, New America Alliance Latino Economic Forum*. 45

Al-Breiki, H., Rehman, M. H. U., Salah, K., and Svetinovic, D. (2020). Trustworthy blockchain oracles: Review, comparison, and open research challenges. *IEEE Access*, 8:85675–85685. 27

Aramonte, S., Doerr, S., Huang, W., and Schrimpf, A. (2022). Defi lending: intermediation without information? *Working Paper*. 4

Bansal, R. and Coleman, W. J. (1996). A monetary explanation of the equity premium, term premium, and risk-free rate puzzles. *Journal of Political Economy*, 104(6):1135–1171. 25

Benartzi, S. and Thaler, R. H. (1995). Myopic loss aversion and the equity premium puzzle. *The Quarterly Journal of Economics*, 110(1):73–92. 25

Blanchflower, D. G., Levine, P. B., and Zimmerman, D. J. (2003). Discrimination in the small-business credit market. *Review of Economics and Statistics*, 85(4):930–943. 4

Brav, A., Cain, M., and Zytnick, J. (2022). Retail shareholder participation in the proxy process: Monitoring, engagement, and voting. *Journal of Financial Economics*, 144(2):492–522. 45

Butler, A. W., Mayer, E. J., and Weston, J. P. (2018). Discrimination in the auto loan market. *Working Paper*. 4

Bó, P. D. (2005). Cooperation under the shadow of the future: Experimental evidence from infinitely repeated games. *American Economic Review*, 95(5):1591–1604. 6, 21

Caronni, G. (2000). Walking the web of trust. In *Proceedings IEEE 9th International Workshops on Enabling Technologies: Infrastructure for Collaborative Enterprises (WET ICE 2000)*, ENABL-00. IEEE Comput. Soc. 28

Chiu, J., Ozdenoren, E., Yuan, K., and Zhang, S. (2023). On the fragility of defi lending. *Working Paper*. 49

Cong, L. W., Rabetti, D., Wang, C. C., and Yan, Y. (2025). Centralized governance in decentralized organizations. Technical report. 47

Cornelli, G., Gambacorta, L., Garratt, R., and Reghezza, A. (2025). Why DeFi lending? Evidence from Aave V2. *Journal of Financial Intermediation*. 49, 55

Dal Bó, P. and Fréchette, G. R. (2019). Strategy choice in the infinitely repeated prisoner's dilemma. *American Economic Review*, 109(11):3929–3952. 6

Dittmar, A. and Duchin, R. (2016). Looking in the rearview mirror: The effect of managers' professional experience on corporate financial policy. *Review of Financial Studies*, 29(3):565–602. 46

Dou, Y., Masulis, R. W., and Zein, J. (2019). Shareholder wealth consequences of insider pledging of company stock as collateral for personal loans. *Review of Financial Studies*, 32(12):4810–4854. 48

Downs, A. (1957). An economic theory of political action in a democracy. *Journal of Political Economy*, 65(2):135–150. 45

Gopalan, R., Gormley, T. A., and Kalda, A. (2021). It's not so bad: Director bankruptcy experience and corporate risk-taking. *Journal of Financial Economics*, 142(1):261–292. 46

Gudgeon, L., Werner, S., Perez, D., and Knottenbelt, W. J. (2020). Defi protocols for loanable funds: Interest rates, liquidity and market efficiency. In *Proceedings of the 2nd ACM Conference on Advances in Financial Technologies*, AFT '20. ACM. 27

Han, Y., Chen, H., Qiu, Z., Luo, L., and Qian, G. (2021). A complete privacy-preserving credit score system using blockchain and zero knowledge proof. In *2021 IEEE International Conference on Big Data (Big Data)*. IEEE. 5

Harvey, C. R. and Rabetti, D. (2023). International business and decentralized finance. *Working Paper*. 4

Harvey, C. R., Ramachandran, A., and Santoro, J. (2021). *DeFi and the future of finance*. John Wiley & Sons. 47, 48

Hassija, V., Bansal, G., Chamola, V., Kumar, N., and Guizani, M. (2020). Secure lending: Blockchain and prospect theory-based decentralized credit scoring model. *IEEE Transactions on Network Science and Engineering*, 7(4):2566–2575. 5

Heimbach, L. and Huang, W. (2023). Defi leverage. *Working Paper*. 49

Hirshleifer, D. (2001). Investor psychology and asset pricing. *Journal of Finance*, 56(4):1533–1597. 46

Hirshleifer, D., Lim, S. S., and Teoh, S. H. (2011). Limited investor attention and stock market misreactions to accounting information. *Review of Asset Pricing Studies*, 1(1):35–73. 46

Hirshleifer, D. and Teoh, S. H. (2003). Limited attention, information disclosure, and financial reporting. *Journal of Accounting and Economics*, 36(1-3):337–386. 46

Holmström, B. and Tirole, J. (1998). Private and public supply of liquidity. *Journal of Political Economy*, 106(1):1–40. 25

Igawa, K. and Kanatas, G. (1990). Asymmetric information, collateral, and moral hazard. *The Journal of Financial and Quantitative Analysis*, 25(4):469. 25

Iliev, P., Lins, K. V., Miller, D. P., and Roth, L. (2015). Shareholder voting and corporate governance around the world. *Review of Financial Studies*, 28(8):2167–2202. 45

Ioannidou, V., Pavanini, N., and Peng, Y. (2022). Collateral and asymmetric information in lending markets. *Journal of Financial Economics*, 144(1):93–121. 25

Jain, N., Agrawal, T., Goyal, P., and Hassija, V. (2019). A blockchain-based distributed network for secure credit scoring. In *2019 5th International Conference on Signal Processing, Computing and Control (ISPCC)*. IEEE. 5

John, K., Kogan, L., and Saleh, F. (2022). Smart contracts and decentralized finance. *Working Paper*. 4, 26

John, K., Kogan, L., and Saleh, F. (2023). Smart contracts and decentralized finance. *Annual Review of Financial Economics*, 15(1):523–542. 47, 48, 49

Kempf, E., Manconi, A., and Spalt, O. (2017). Distracted shareholders and corporate actions. *Review of Financial Studies*, 30(5):1660–1695. 46

Koutrouli, E. and Tsalgatidou, A. (2012). Taxonomy of attacks and defense mechanisms in p2p reputation systems—lessons for reputation system designers. *Computer Science Review*, 6(2–3):47–70. 28

Laferrière, D. and Décary-Hétu, D. (2022). Examining the uncharted dark web: Trust signalling on single vendor shops. *Deviant Behavior*, 44(1):37–56. 28

Lehar, A. and Parlour, C. A. (2022). Systemic fragility in decentralized markets. *Working Paper*. 49

Lehar, A. and Parlour, C. A. (2023). Battle of the bots: Flash loans, miner extractable value and efficient settlement. *Working Paper*. 49

Liu, H., McCartney, W. B., Ramcharan, R., Zhang, C., and Zhang, X. (2025). Relieving financial distress increases voter turnout: Evidence from the mortgage market. *Working Paper*. 47

Low, S., Maxemchuk, N., and Paul, S. (1996). Anonymous credit cards and their collusion analysis. *IEEE/ACM Transactions on Networking*, 4(6):809–816. 5

Makarov, I. and Schoar, A. (2022). Cryptocurrencies and decentralized finance (DeFi). *Brookings Papers on Economic Activity*, 2022(1):141–215. 47, 49

Malenko, N. and Shen, Y. (2016). The role of proxy advisory firms: Evidence from a regression-discontinuity design. *Review of Financial Studies*, 29(12):3394–3427. 45

Maug, E. and Rydqvist, K. (2009). Do shareholders vote strategically? voting behavior, proposal screening, and majority rules. *Review of Finance*, 13(1):47–79. 46

McCartney, W. B. (2021). Does household finance affect the political process? Evidence from voter turnout during a housing crisis. *Review of Financial Studies*, 34(2):949–984. 47, 56

Packin, N. G. and Aretz, Y. L. (2023). Crypto native credit score: Between financial inclusion and predatory lending. *Cardozo Law Review*. 4, 7, 10, 23

Pager, D. and Shepherd, H. (2008). The sociology of discrimination: Racial discrimination in employment, housing, credit, and consumer markets. *Annual Review of Sociology*, 34(1):181–209. PMID: 20689680. 4

Palomino, F. (1996). Noise trading in small markets. *The Journal of Finance*, 51(4):1537–1550. 25

Pan, X. and Qian, M. (2024). Firm financing through insider stock pledges. *Review of Finance*, 28(2):621–659. 48

Park, A. and Stinner, J. (2023). Phantom liquidity in decentralized lending. Technical report. 49, 52

Pool, V. K., Stoffman, N., Yonker, S. E., and Zhang, H. (2019). Do shocks to personal wealth affect risk-taking in delegated portfolios? *Review of Financial Studies*, 32(4):1457–1493. 46

Qin, K., Zhou, L., Gamito, P., Jovanovic, P., and Gervais, A. (2021). An empirical study of defi liquidations: incentives, risks, and instabilities. In *Proceedings of the 21st ACM Internet Measurement Conference*, IMC '21. ACM. 27

Riker, W. H. and Ordeshook, P. C. (1968). A theory of the calculus of voting. *American Political Science Review*, 62(1):25–42. 45

Ring, M. A. (2023). Entrepreneurial wealth and employment: Tracing out the effects of a stock market crash. *Journal of Finance*, 78(6):3343–3386. 46

Rivera, T., Saleh, F., and Vandeweyer, Q. (2023). Equilibrium in a defi lending market. *SSRN Electronic Journal*. 10, 19, 27

Sockin, M. and Xiong, W. (2023). Decentralization through tokenization. *Journal of Finance*, 78(1):247–299. 44, 47

Wolf, G. and Quiroga, V. G. (2018). Insights on the large-scale deployment of a curated web-of-trust: the debian project's cryptographic keyring. *Journal of Internet Services and Applications*, 9(1). 29

Yermack, D. (2010). Shareholder voting and corporate governance. *Annual Review of Financial Economics*, 2(1):103–125. 45

Appendix

A.1 Mathematical Proofs

A.1.1 Proof of Proposition 1.0.A and 1.0.B

Proof of Proposition 1.0.A

Proof. Let $N \in \mathbb{N}$ the number of periods that the borrower will be honest after getting access to undercollateralized loans ($N > \tau$). Further, for ease of notation, let $a = \mathrm{e}^{-i}$. After N periods, the borrower will default. To prove Proposition 1.0.A, it is sufficient to show that $\mathbb{E}[MF]$ can only be either always increasing in N or always decreasing in N, $\forall N \in \mathbb{N}$.

Starting from the first period that the borrower receives undercollateralized loans, the expected payoff from MF-strategy can be divided into three parts.

The first part is the gains from being honest for N periods, D_1:

$$D_1 = \sum_{t=0}^{\infty} \left(\sum_{j_1=t(N+\tau+1)+1}^{t(N+\tau+1)+N} a^{j_1} \right) H_B$$

The second part is the gains from all defaults, D_2:

$$D_2 = \sum_{t=0}^{\infty} \left(a^{((t+1)N+t\tau+t+1)} \right) S_B$$

The third part is the gains from all τ periods of overcollateralized loans, D_3:

$$D_3 = \sum_{t=0}^{\infty} \left(\sum_{j_3=t(N+\tau+1)+2}^{(t+1)(N+\tau+1)} a^{j_3} \right) B_B$$

Using Proof by Induction, it can be shown that:

$$\sum_{j=k}^{v} a^j = \frac{a^k - a^{v+1}}{1-a}, \quad \forall k, v \in \mathbb{N}, a \in \mathbb{R}, |a| < 1 \tag{A.1}$$

Thus, D_1, D_2, and D_3 can be expressed as:

$$\begin{aligned} D_1 &= \sum_{t=0}^{\infty} \left(a^{(t(N+\tau+1)+1)} - a^{(t(N+\tau+1)+N+1)} \right) \frac{1}{1-a} H_B \\ &= \frac{a \cdot \left(1 - a^N\right)}{1 - a^{N+\tau+1}} \cdot \left(\frac{1}{1-a} \right) H_B \end{aligned} \tag{A.2}$$

$$\begin{aligned} D_2 &= \sum_{t=0}^{\infty} \left(a^{((t+1)N+t\tau+t+1)} \right) S_B \\ &= \frac{a^{N+1}}{1 - a^{N+\tau+1}} S_B \end{aligned} \tag{A.3}$$

$$\begin{aligned} D_3 &= \sum_{t=0}^{\infty} \left(a^{t(N+\tau+1)+2} - a^{(t+1)(N+\tau+1)+1} a^{j_3} \right) \frac{1}{1-a} B_B \\ &= \frac{a^{N+2} \cdot (1 - a^\tau)}{1 - a^{N+\tau+1}} \cdot \left(\frac{1}{1-a} \right) B_B \end{aligned} \tag{A.4}$$

The second equal sign in each of the above equations can be proven using Proof by Induction. Hence, the expected payoff for MF-strategy, given any value of N is:

$$\begin{aligned} \mathbb{E}[MF] &= \mathbb{E}[D_1 + D_2 + D_3] \\ &= \mathbb{E}\left[\frac{-B_B a^{N+2+\tau} + (-H_B + S_B) a^{N+1} + (B_B - S_B) a^{N+2} + H_B a}{(-1+a)\left(a^{N+\tau+1} - 1\right)} \right] \end{aligned} \tag{A.5}$$

Differentiate A.5 w.r.t N yields:

$$\frac{d\mathbb{E}[MF]}{dN} = \mathbb{E}\left[\frac{\ln(a)\left(\left(B_B - H_B\right)a^{N+2+\tau} + \left(H_B - S_B\right)a^{N+1} - \left(B_B - S_B\right)a^{N+2}\right)}{\left(-1+a\right)\left(a^{N+\tau+1}-1\right)^2}\right] \tag{A.6}$$

$$\begin{aligned}\frac{d\mathbb{E}[MF]}{dN} = 0 \Leftrightarrow\ & \left(B_B - H_B\right)a^{N+2+\tau} \\ & + \left(H_B - S_B\right)a^{N+1} \\ & - \left(B_B - S_B\right)a^{N+2} = 0\end{aligned}$$

However,

$$\begin{aligned}&\left(B_B - H_B\right)a^{N+2+\tau} + \left(H_B - S_B\right)a^{N+1} - \left(B_B - S_B\right)a^{N+2} \\ &= B_B a(a^r - 1) + H_B(1 - a^{1+r}) + S_B(a-1) < 0, \quad \forall B_B, H_B, S_B, i > 0\end{aligned}$$

Thus, $\mathbb{E}[MF]$ does not have a local optimum for $B_B, H_B, S_B, i > 0$, which are the regions of interest. It follows that $\mathbb{E}[MF]$ either always increasing or always decreasing in $N \in \mathbb{N}$ for $B_B, H_B, S_B, i > 0$. □

Proof of Proposition 1.0.B

Proof. Each period that M-type player defaults, he has the same payoff as S-type player, who defaults every period. Thus, to compare the expected payoff between M-type and S-type, it is sufficient to compare when M-type player chooses to repay. Because M-type player only repays if $H_B > S_B$, it follows that in every period that M-type player repays, his payoff is strictly higher than S-type player. In the periods following M-type's payback and S-type's default, M-type can choose to default while S-type must payback his overcollateralized loans. Since the option to default yields a loan cost of 0, and $c > 0$, M-type player receives strictly higher payoff in all τ periods that S-type player must do overcollateralized loans. It follows that M-type player's expected payoff is higher than S-type's expected payoff in all periods. □

A.1.2 Proof of Proposition 1.1

Proof. The considered infinitely repeated game consists of infinite extensive form subgame. Let a subgame be a binary tree that starts with decision node and ends with decision nodes in all possible paths. By the assumption that return ρ_t is independently and identically distributed (i.i.d), it follows that all subgames are identical. Hence, to ensure that $\mathbb{E}[H(r) - M(r) > 0]$, it is sufficient to ensure that the expected differences in payoff between the always honest strategy and all other possible combinations are positive in a subgame.

For an M-type player in a subgame, he can have pure honest path, pure selfish path, and many paths with mixed decisions. I claim that in any identical subgame, the pure honest path and the pure selfish path last up to $\tau + 1$ periods; the strategy with mixed decisions lasts for $2\tau + 1$ periods. To see this, let $t = 0$ for any starting decision node. Because the borrower decides whether to default based on ex-post return, if he defaults, he will receive payoff S at $t = 1$. After τ periods of receiving B, he will be in another decision node. Thus, it takes $\tau + 1$ periods for a borrower who defaulted at $t = 1$ to reach another decision node. If the borrower did not default for the first τ periods, but then defaulted at period $(\tau + 1)$-th, he will need another τ periods to reach a decision node. If he defaulted any time earlier than period τ-th, he must be able reach a decision node earlier. Hence, to ensure that a subgame is identical with all terminal node being decision node, one needs to consider only up to $2\tau + 1$ periods.

Consider an identical subgame with i.i.d collateral asset returns, the probability that an M-type player ends up in the pure honest path is $(1 - F)^{\tau+1}$. If the returns are such that the M-type borrower chooses the pure honest path, his payoff is the same as that of the H-type borrower. Thus, the expected payoff difference for the honest branch is 0.

For the pure selfish path, since I only need to consider one default, the probability of this path is F, which occurs at the period after the starting node. Because M-type borrower only defaults if $\rho_t < r$, the expected payoff for when he defaults is conditional on $\rho_t < r$. The expected difference in payoff between M-type and H-type when M-type defaults is:

$$D_{HS} = \mathbb{E}\left[P\left(l\rho_t + l - r - 1\right) \mid \rho_t < r\right]$$

The expected payoff difference for the selfish branch is then:

$$HS(r) = \left(\mathrm{D}_{HS} \cdot \mathrm{e}^{-i} + \sum_{n=1}^{\tau} \left(\mathrm{D}_{HB} \cdot \mathrm{e}^{-i\cdot(n+1)}\right)\right) \cdot F \tag{A.7}$$

Finally, if the borrower chose to be honest initially, he can then switch to selfish at any point. Let n be the number of periods before the borrower switch to selfish. The probability for the borrower to be in any of the mixed paths is $(1-F)^n F$, i.e., honest for the first n periods then default. Because the borrower always decides ex-post, $n \geq 1$. In addition, since the borrower can default at any time before τ-th period, for the last τ periods are for overcollateralized loans, $n \leq \tau$. The expected payoff difference for any of the τ mixed paths can be described as:

$$\begin{aligned} HM(r) = \sum_{n=1}^{\tau} \Bigg((1-F)^n \cdot F \cdot \Bigg(& \sum_{k=1}^{\tau} \left(\mathrm{D}_{HB} \cdot \mathrm{e}^{-(k+n+1)\cdot i}\right) \\ & + \sum_{j=1}^{n} \left(\mathrm{D}_{HH} \cdot \mathrm{e}^{-i\cdot j}\right) \\ & + \mathrm{D}_{HS} \cdot \mathrm{e}^{-i\cdot(n+1)} \Bigg) \Bigg) \end{aligned} \tag{A.8}$$

Using the result from A.1, $HS(r)$ and $HM(r)$ can be written as:

$$HS(r) = \frac{\left(-\mathrm{e}^{-i(\tau+1)}\mathrm{D}_{HB} + (\mathrm{D}_{HB} - \mathrm{D}_{HS})\,\mathrm{e}^{-i} + \mathrm{D}_{HS}\right) F}{\mathrm{e}^{i} - 1} \tag{A.9}$$

$$\begin{aligned} HM(r) = \frac{F\mathrm{e}^{i}}{(F + \mathrm{e}^{i} - 1)\,(\mathrm{e}^{i} - 1)} \Bigg[& (1-F)^{\tau+1} \left(\mathrm{e}^{i}\mathrm{D}_{HB}\mathrm{e}^{-(2T+3)i} - \mathrm{e}^{i}\mathrm{D}_{HB}\mathrm{e}^{-(T+3)i} \right. \\ & \left. - \mathrm{D}_{HS}\mathrm{e}^{-i(2+T)}\mathrm{e}^{i} + \mathrm{D}_{HS}\mathrm{e}^{-i(2+T)} \right) \\ & - (1-F) \left(\mathrm{e}^{i}\mathrm{D}_{HB}\mathrm{e}^{-(T+3)i} - \mathrm{e}^{i}\mathrm{D}_{HB}\mathrm{e}^{-3i} - \mathrm{D}_{HS}\mathrm{e}^{-2i}\mathrm{e}^{i} + \mathrm{D}_{HS}\mathrm{e}^{-2i} \right) \Bigg] \end{aligned} \tag{A.10}$$

where

$$\begin{aligned} \mathrm{D}_{HS} &= \mathbb{E}\left[H_B - S_B \mid l(1+\rho_t) < 1 + r\right] \\ &= \mathbb{E}\left[P(l(1+\rho_t) - (1+r)) \mid l(1+\rho_t) < 1 + r\right] < 0 \\ \mathrm{D}_{HB} &= \mathbb{E}\left[H_B - B_B\right] \\ &= P\left(c - r + l\bar{\rho}\right) + (k - l)\,Py\,(1+\bar{\rho}) \end{aligned}$$

Taking the sum $HS(r) + HM(r)$ yields the desired result. □

A.2 Definitions in DeFi Lending

Table A.1. Definitions in DeFi Lending

This table summarizes key definitions used in decentralized lending and describes ten representative lending platforms from the broader 77-platform sample. For each platform, it provides a brief description of the lending mechanism and the endogenous interest-rate setting in these markets, and it outlines the risk-management framework implemented through the platform's governance process.

Name	Definition
Decentralized Lending	
Liquidity pool	A single-currency funding market in which lenders deposit cash in the form of cryptocurrencies or tokens and earn a floating return. Borrowers draw the same assets from this market for short- to medium-term credit and pay a floating borrowing rate. Within each liquidity pool, interest rates automatically adjust based on lender supply and borrower demand (known as utilization). When a pool is heavily used, marginal funding becomes scarce, causing borrowing rates to rise and lender yields to increase. When liquidity is abundant, the marginal value of funds falls, causing rates to decline. As such, interest rates are not set administratively, but rather respond mechanically to aggregate funding conditions.
Liquidation	A forced-deleveraging mechanism for a borrower in a liquidity pool, which is analogous to broker margining in derivatives trading or securities lending. When collateral coverage deteriorates (typically due to a decline in collateral value or growth in debt), the position is partially or fully unwound without the borrower's consent in order to restore compliance with solvency constraints (as measured by the loan-to-value (LTV) ratio). Third parties (liquidators) repay part of the borrower's debt and receive collateral at a discount (a liquidation bonus), which compensates them for providing immediacy and for bearing execution and price-impact risk. This mechanism is economically equivalent to a margin call in that it protects lenders by converting collateral into repayment before the position becomes undercollateralized. However, it can create a feedback channel in times of stress because forced sales may amplify downward price pressure.
LTV	A credit constraint that defines maximum leverage as follows, equivalent to a haircut/margin system in securities lending: $\text{LTV} = \frac{\text{Debt}}{\text{Collateral Value}}$. The initial LTV determines how much can be borrowed at origination (or after rebalancing), and a separate liquidation threshold defines the point at which the position is considered unsafe and forced deleveraging begins. For example, with an LTV of 60% and a liquidation threshold of 70%, \$100 of collateral can support a maximum debt of \$60. Liquidation is triggered if the debt exceeds \$70 for the same collateral value, or if the collateral value falls below $\frac{\text{Debt}}{\text{Collateral}} > 0.70$. The lending platform sets effective haircuts (1-LTV) to control default risk under collateral price volatility and market liquidity.
Utilization	A quantity-based measure of liquidity pool tightness: $\text{Utilization} = \frac{\text{Outstanding Loans}}{\text{Total Supplied Liquidity}}$. Utilization is the key state variable for adjusting the endogenous interest rate. High utilization indicates that a large portion of available funds has been allocated to borrowers. Consequently, the marginal cost of borrowing and the marginal return on supplying funds increase. Conversely, low utilization indicates idle liquidity and weak loan demand, causing rates to compress.

Name	Definition
Assets	
Native cryptocurrency	The blockchain's base currency, used to pay transaction fees and secure the system.
Stablecoins	Asset-backed cryptocurrencies designed to track a reference unit of account (typically USD). There exists two dominant structures: (i) Reserve-backed stablecoins issued by an intermediary that holds short-duration safe assets (cash, T-bills) and promises redemption at (near) par. Examples are: USDT, USDC. (ii) Overcollateralized stablecoins that maintain the peg via pledged collateral (typically in cryptocurrency), conservative margins, and automatic liquidation. Examples are: DAI, USDS.
Wrapped currency	A tokenized receipt representing a 1:1 claim on an underlying asset held under a specific custody arrangement. Economically, it is most similar to a deposit receipt. The wrapper issues a transferable claim that can be redeemed for the underlying asset at par. This is conditional on the operational integrity and creditworthiness of the custodian. The main economic purpose is market integration, since the receipt can be used in venues where the underlying asset cannot. The main economic risk is intermediary or operational risk rather than price risk, since the claim is intended to track the asset at a ratio of one to one. For example, wrapped Bitcoin can be used on the Ethereum blockchain since Bitcoin is the native currency of the Bitcoin blockchain.
Market infrastructure	
Layer-1 blockchain	The base settlement system that defines how transactions are settled and how asset ownership records are time-stamped.
Layer-2 blockchain	A cost-reducing overlay that executes transactions off the Layer-1 blockchain and periodically records the aggregated outcomes back to the base settlement layer.
EVM-compatible blockchain	A shared code-execution standard that enables the deployment of the same smart contracts across multiple blockchains. Gnosis, for example, is a separate blockchain with its own settlement rules (consensus) and settlement operators (validators). It is focused on low fees and fast settlement. However, Gnosis is also compatible with Ethereum, meaning Ethereum's smart contracts and wallets can be used on Gnosis.
Decentralized Lending Platforms	
Aave (formerly Eth.lend)	A multi-asset money market in which each asset has its own liquidity pool, i.e., lenders deposit a given asset into a pool, and borrowers draw that same asset from it. Borrowers must pledge collateral worth more than the value of their loans. Within each liquidity pool, interest rates adjust automatically with supply and demand (so-called *utilization*), i.e., when a larger share of the asset is lent out, borrowing costs and lender yields rise, and when liquidity is high, interest rates fall. A single collateral position can support borrowing several different assets at once, each from its own pool, with its own interest rate. If, after a liquidation, an exceptional shortfall remains, Aave first uses its accumulated reserves, funded by a share of interest income. If needed, a dedicated backstop fund, financed by participants who earn rewards for providing this coverage, can be tapped up to a predefined limit. Risk is further contained through per-asset lending LTV and liquidation thresholds, as well as borrow and supply limits.

Name	Definition
Compound	A multi-asset money market with over-collateralized lending and utilization-based interest rates, similar to Aave, but more conservative. In its current design, Compound's markets revolve around a single borrowable base asset (e.g., USDC), i.e., lenders supply that base asset to earn interest, and borrowers pledge other assets as collateral but can borrow only the base asset from that market. To borrow a different asset, a borrower uses a separate Compound market where that asset is the base. Compound retains a portion of borrower interest as reserves within each market, creating a buffer that can absorb residual shortfalls if any debt remains after collateral is sold. Risk is further managed through per-asset LTV limits and liquidation thresholds, and by listing a relatively narrow set of higher-quality collateral assets.
dForce	A multi-asset money market with over-collateralized lending and utilization-based interest rates, where a single collateral position can support borrowing many assets in the same way as Aave. dForce sets aside a portion of interest income as reserves and thus creates a buffer that can help absorb any residual shortfall after liquidations. In extreme cases, governance may also recapitalize the system by issuing or auctioning governance tokens to cover losses. Risk is further managed through per-asset LTV limits and liquidation penalties. dForce also has "close factor" rules that limit how much of a position can be liquidated at once, supply and borrow caps to limit concentration, and an additional parameter that scales borrowing power by the riskiness and liquidity of the borrowed asset (so that borrowing a very liquid, lower-volatility asset is treated more conservatively than borrowing a thinner, more volatile one).
Frax Finance	A pair-based money market, i.e., each market is an isolated two-asset pair in which depositors supply the asset that will be borrowed, while borrowers pledge a different asset as collateral to draw that same deposited asset. Each asset pair is a separate fund that does not share liquidity or default risk. Within each pair, interest rates adjust automatically with supply and demand according to a chosen formula (e.g., Linear, Time-Weighted Variable, or Variable-Rate V2), so interest rates rise when a greater share of available funds is lent out and fall when liquidity is high. Borrowers must keep their LTV below a maximum set per pair (commonly around 75% for volatile pairs and higher for stablecoin-stablecoin pairs). If the threshold is breached, positions are liquidated with liquidators paid a fixed fee. If, after liquidation, an exceptional shortfall remains, the loss is absorbed by lenders in that specific pair. Additional safeguards include per-pair pricing via external data feeds to value collateral and debt, and governance-set parameters for collateralization and liquidations, all applied at the individual-pair level.
Radiant	A multi-asset money market similar to Aave. A special feature of Radiant is that assets can be borrowed and bridged (copied) to another blockchain in one transaction, although deposits remain on the origin blockchain and loans are repaid there, as well. Radiant also offers isolated markets where higher-risk asset pairs are kept in separate pools with their own parameters so issues in one do not spill over to the rest of the system. The platform retains a share of borrower interest as protocol revenue (set by the DAO per pool as a reserve-factor policy), and liquidations apply a 15% penalty that is split between liquidators (7.5%) and a Radiant fund (7.5%). In addition, Radiant operates the another fund as capital buffer that accumulates capital (including a share of protocol revenue) and invests it conservatively.

Name	Definition
Seamless	A Base-native money market similar to Aave. In addition, Seamless offers curated vaults that route deposits into Morpho's isolated markets for passive, risk-scoped yield. Within each pool, interest rates adjust automatically with supply and demand, i.e., the rate rises as a larger share of the pool is lent out and, once usage moves past a target level, it increases more steeply to discourage scarcity. The platform retains a share of borrower interest as protocol reserves (set per market via a reserve-factor policy) and also keeps a portion of each liquidation penalty as a protocol fee, creating a buffer funded by operating income rather than a separate insurance fund. Risk is managed with per-asset LTVs and liquidation thresholds, supply and borrow caps, and "isolation" settings and debt ceilings that limit how much exposure a single collateral type can create.
Silo	A risk-isolated money market in which each supported token has its own self-contained market ("silo") built around that token and a small set of common bridge assets (typically ETH and a stablecoin). Lenders deposit a given asset into its silo's pool and borrowers draw that same asset from that pool, while the bridge assets connect silos so collateral in one market can finance borrowing of those common assets without exposing depositors in other markets to the token's idiosyncratic risk. Within each silo, interest rates adjust automatically with supply and demand; markets choose from several algorithmic models that keep rates relatively low around a target usage range and step them up when usage is high, with the option for fixed-rate configurations in certain specialized markets. Borrowers must remain over-collateralized per market. If a position breaches its limits, liquidations are executed to restore solvency. Core risk limit (e.g., maximum LTV and liquidation thresholds) are set per asset so that each market's parameters reflect that asset's liquidity and volatility, and losses. The platform also retains a defined share of borrower interest as a protocol fee paid to the DAO.
Strike	A multi-asset money market similar to Aave. The platform retains a portion of borrower interest as reserves, building a buffer that can help absorb residual shortfalls after liquidations. Risk is further managed through per-asset LTV limits, partial-liquidation rules that limit how much of a position can be closed at once, and a liquidation bonus paid to liquidators. In emergencies, a designated pause role can temporarily disable selected actions to protect users.
Sturdy	A pair-based money market like Frax Finance. Within each pair, interest rates are set mechanically by supply and demand using a utilization curve. In addition, Sturdy offers an aggregation layer that routes a lender's single-asset deposit across approved pairs and keeps the lender exposed only to the collateral types they have selected. DAO approves the pairs, set per-pair lending caps, and choose (manually or via an automated model) how to allocate funds. The platform collects a fee equal to 10% of the interest paid by borrowers (the remaining 90% flows to lenders). Borrowers must remain over-collateralized at the pair level. Because markets are isolated, any residual shortfall after liquidation would affect only the lenders in the impacted pair rather than being shared across the system. Risk is further managed through per-pair LTV limits, DAO governance, external price feeds and audits specified for each deployment

Name	Definition
Venus	A multi-asset money market on Binance, but similar to Aave. The platform operates a large main pool for major assets and a set of isolated pools, i.e., separate groups of assets with their own settings, so that issues in one pool do not spill over to others. Within each market, interest rates are variable and adjust automatically with supply and demand. Venus uses utilization-based models. A portion of borrower interest is retained as reserves, and each pool (i.e., main and isolated) has its own risk fund that accumulates a percentage of pool income (interest and liquidation proceeds) in USDT and is used to cover any remaining shortfall after liquidations. The risk funds are pool-specific and cannot be used to cover other pools losses. Risk is further managed through per-asset borrowing limits and stricter liquidation thresholds, and a liquidation bonus paid to liquidators. In addition to lending, users may mint the USD-pegged stablecoin VAI against approved collateral, with peg-stability mechanisms supporting convertibility.

Vita

Lebathong (Tim) Dong is a doctoral researcher in Finance at the Haslam College of Business, The University of Tennessee, Knoxville. His research focuses on blockchain-based financial markets, decentralized finance, platform governance, and market design.