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Essays on Lending, Rate Discovery, and Token Price Drivers in Decentralized Finance

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Charlotte Eli

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Composition du jury :

Fabrice RIVA Professeur, Université Paris Dauphine-PSL	*Président du jury*
Alexis COLLOMB Professeur, CNAM	*Rapporteur*
Sonia JIMENEZ-GARCES Professeur, Université Grenobles Alpes & Grenoble INP	*Rapporteur*
Bastien TEINTURIER Directeur Technique, Lightning Network	*Examinateur*
Hervé ALEXANDRE Professeur, Université Paris Dauphine-PSL	*Directeur de thèse*

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Résumé

Cette thèse explore les fondements économiques et comportementaux de la finance décentralisée (DeFi), un champ en pleine expansion où les fonctions de prêt, d'emprunt et de fixation des taux d'intérêt sont assurées par des contrats intelligents plutôt que par des institutions financières. À travers trois essais complémentaires, ce travail analyse la conception des protocoles de crédit décentralisés, la formation des taux d'intérêt dans des marchés automatisés et les déterminants fondamentaux et comportementaux de la valorisation des tokens DeFi.

Le premier essai examine l'architecture du protocole Atlendis, qui permet des prêts non ou partiellement collatéralisés grâce à l'articulation entre souscription off-chain et exécution on-chain. Le deuxième propose un modèle théorique de découverte de taux basé sur une approche de jeu multi-unités, identifiant les conditions d'efficience et les frictions propres aux marchés décentralisés. Le troisième évalue empiriquement les facteurs économiques et comportementaux influençant les rendements des tokens, révélant le rôle central du sentiment des investisseurs et de la liquidité on-chain dans la dynamique des prix.

En combinant ingénierie financière, modélisation théorique et analyse empirique, cette recherche met en lumière les mécanismes par lesquels la DeFi redéfinit l'intermédiation, la formation des prix et la gouvernance financière dans un environnement transparent et programmable.

Mots clés : Finance décentralisée, blockchain, crédit, taux d'intérêt, contrats intelli-

gents, intermédiation financière, comportement des investisseurs, tokens DeFi, économie numérique, marchés financiers décentralisés.

Abstract

This dissertation investigates the economic and behavioral foundations of decentralized finance (DeFi) where lending, borrowing, and rate discovery are executed by smart contracts rather than traditional financial institutions. Through three complementary essays, it analyzes the design of decentralized credit protocols, the formation of interest rates in decentralized markets, and the fundamental and behavioral drivers of DeFi token valuation.

The first essay examines the Atlendis protocol, which enables non- or partially-collateralized lending by combining off-chain underwriting with on-chain execution. The second develops a theoretical model of decentralized rate discovery based on a multi-unit game framework, identifying the conditions for efficiency and the frictions specific to these markets. The third provides an empirical analysis of DeFi token returns, showing that investor sentiment, liquidity dynamics, and behavioral factors play a significant role in price formation alongside economic fundamentals.

By bridging financial engineering, theoretical modeling, and empirical research, this thesis sheds light on how DeFi reshapes intermediation, price formation, and governance in a transparent, programmable financial environment.

Keywords : Decentralized finance, blockchain, lending, interest rates, smart contracts, financial intermediation, investor behavior, DeFi tokens, digital economy, decentralized markets.

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Glossary

composability Interoperability property allowing protocols (e.g., stablecoins, DEXs, lending pools) to plug into each other like "money Legos," increasing both efficiency and systemic linkages

ERC-20 Fungible token standard for transferable balances (e.g., stablecoins, governance tokens)

ERC-4626 Tokenized vault standard for yield-bearing assets

ERC-721 Non-fungible token standard representing unique positions or assets

governance risk Risk arising from token-holder or delegated control of parameters and upgrades; includes misaligned incentives and voter concentration

health factor A solvency metric (used e.g., in Aave); positions are safe if $HF > 1$ and liquidatable if $HF \leq 1$

impermanent loss A temporary reduction in a liquidity provider's portfolio value compared with holding the same assets, caused by automatic rebalancing in an automated market maker when relative prices change.

interest rate model Utilization-based or piecewise (kinked) curves embedded in smart contracts that map pool utilization and liquidity to borrow/supply rates

lending pool Smart contract that autonomously manages deposits and borrows for a given asset; interest rates are set algorithmically from the interaction of liquidity suppliers and borrowers

liquidation Process by which third-party liquidators repay (part of) a borrower's debt when risk thresholds are breached in exchange for collateral at a discount (a "liqui-

dation bonus")

liquidation bonus Discount α applied to seized collateral to compensate liquidators who repay debt during liquidation events

liquidation threshold Protocol parameter θ at which a position becomes eligible for liquidation when $D/C \geq \theta$

loan-to-value Ratio LTV $= D/C$ with a protocol-imposed maximum $\text{LTV}_{\max}$; a buffer relative to the liquidation threshold mitigates small price moves

oracle Mechanism that brings off-chain data (e.g., prices) on-chain; designs range from centralized to decentralized aggregators; oracle failures can induce insolvency or unfair liquidations

over-collateralization Requirement that the market value of posted collateral exceeds outstanding debt, used in pseudonymous settings to substitute for legal enforcement and lower default risk

Proof of Stake Consensus where validators bond stake and are penalized for equivocation; used by Ethereum since 2022

Proof of Work Consensus where miners expend computational work to secure the ledger (e.g., Bitcoin)

smart contract A self-executing program on a blockchain that runs automatically when predefined conditions are met. It enforces agreements without intermediaries, enabling decentralized applications and asset management.

smart contract risk Risk of code vulnerabilities, upgrade errors, or governance capture impacting protocol solvency or user funds

Total Value Locked (TVL) Aggregate value of assets supplied to a protocol; often used as a proxy for adoption/liquidity depth, but not necessarily predictive of token returns

utilization Share of pool liquidity that is currently borrowed; a key state variable driving the algorithmic rate in pool-based lending

Introduction Générale

1 Contexte et motivation

Au cours des cinq dernières années, la finance décentralisée (aussi appelée DeFi) s'est affirmée comme l'une des innovations les plus marquantes issues des technologies blockchain. Elle désigne un ensemble de services financiers reposant sur du code appelé contrats intelligents (smart contracts en anglais), déployé sur des blockchains publiques et accessible à tous. En supprimant la nécessité d'un intermédiaire de confiance, la DeFi se positionne comme une alternative au système bancaire et financier traditionnel. Les transactions y sont exécutées automatiquement par le code, selon des règles transparentes et immuables, garantissant une gouvernance ouverte et décentralisée. Depuis son émergence, cet écosystème a attiré plusieurs centaines de milliards de dollars d'actifs, témoignant d'une croissance rapide et d'un intérêt soutenu des acteurs économiques et technologiques. L'architecture de la DeFi permet en outre une interopérabilité avancée entre les applications, ouvrant la voie à de nouvelles formes de prêt, d'emprunt et d'échange d'actifs numériques. L'ensemble repose sur des blockchains programmables servant de support au développement d'applications décentralisées (DApps), parmi lesquelles Ethereum demeure la plus utilisée et la plus influente.

La DeFi se distingue par plusieurs caractéristiques qui en font un modèle singulier au regard de la finance traditionnelle. Elle est d'abord publique et accessible à tous : toute personne disposant d'une connexion Internet et d'une adresse sur une blockchain compatible, telle qu'Ethereum, peut y participer sans autorisation préalable ni intermédiaire

institutionnel. Cette ouverture universelle constitue l'un de ses fondements essentiels. L'écosystème est également interopérable : les protocoles sont conçus pour interagir entre eux, formant un réseau intégré où la coopération technique prime souvent sur la concurrence. La programmabilité de la DeFi repose sur l'usage de smart contracts qui exécutent automatiquement les opérations prévues par leur code, sans intervention humaine. Enfin, sa résilience découle de l'infrastructure décentralisée des blockchains, dont la nature immuable et infalsifiable garantit la continuité et la sécurité des services, tout en réduisant la dépendance à des acteurs centralisés.

L'essor de la finance décentralisée trouve son origine dans un constat bien établi : l'accès aux services financiers demeure fortement conditionné par des facteurs économiques et géographiques. L'inclusion financière représente pourtant un levier essentiel d'inclusion sociale. Une personne dépourvue de compte bancaire ou d'accès au crédit se retrouve souvent exclue du système économique. Si dans les économies développées, le taux de bancarisation est proche de la saturation, de nombreux pays, notamment en Afrique et en Amérique du Sud, demeurent confrontés à une inflation persistante, à un manque d'institutions financières et à l'absence de services financiers. Dans ce contexte, la DeFi est parfois perçue comme une transformation profonde du système financier, porteuse d'une promesse d'inclusion accrue fondée sur des principes radicalement différents de ceux de la finance traditionnelle.

Parmi les différents domaines d'application de la DeFi, les marchés du crédit occupent une place centrale. Ils remplissent des fonctions économiques fondamentales : transformer l'épargne en investissement, allouer le capital entre agents et gérer la répartition intertemporelle des ressources. Dans leur forme traditionnelle, ces activités sont assurées par des intermédiaires financiers qui mobilisent leur bilan pour prêter à long terme des fonds empruntés à court terme. Ces intermédiaires évaluent la solvabilité, gèrent le risque de liquidité et exercent une fonction de transformation de maturité dans un cadre réglementé et institutionnel structuré.

La finance décentralisée bouleverse cette architecture. Elle introduit une forme d'intermédiation sans institution, où les fonctions de prêt, d'emprunt et de règlement sont assu-

rées par des smart contracts. Ces derniers définissent les règles selon lesquelles les actifs peuvent être déposés, empruntés ou liquidés, et exécutent automatiquement ces opérations. La confiance n'est plus accordée à une entité, mais au code lui-même. L'accès y est dit permissionless : tout détenteur d'actifs numériques peut interagir avec les protocoles sans condition d'identité ni autorisation préalable. Comme en finance traditionnelle, les marchés du crédit jouent un rôle structurant au sein de la DeFi. Les protocoles de prêt décentralisés mettent directement en relation emprunteurs et prêteurs de crypto-actifs, sans intermédiaire centralisé. Les utilisateurs peuvent emprunter ou déposer des actifs numériques pour générer des intérêts, ces derniers étant versés dans le même crypto-actif que celui prêté. La détermination des taux d'intérêt repose sur des mécanismes algorithmiques : lorsque la demande d'emprunt pour un actif augmente, le taux associé s'ajuste automatiquement à la hausse. Au cœur de ces protocoles se trouvent les lending pools (pools de liquidité), des smart contracts qui gèrent de manière autonome l'ensemble des opérations de prêt et d'emprunt.

Pour les économistes, cette évolution représente un véritable changement de paradigme. Les mécanismes de crédit traditionnels reposent sur trois piliers : la confiance institutionnelle, l'exécution juridique des contrats et la garantie publique implicite du système financier. Aucun de ces éléments n'existe nativement dans la DeFi. Les règles d'exécution y sont codées dans des contrats automatisés, les garanties sont numériques et la solvabilité repose sur des collatéraux enregistrés on-chain plutôt que sur une surveillance externe. Ce déplacement conceptuel pose une question fondamentale : le crédit peut-il exister sans droit, et si oui, selon quelles logiques économiques ?

Les marchés de prêt décentralisés illustrent pleinement cette tension. La plupart reposent sur la sursécurisation (over-collateralization) : pour emprunter 100 unités d'un actif, il faut immobiliser entre 120 et 150 unités en garantie. Ce modèle réduit le risque de défaut, mais limite la création de crédit et exclut les agents à faible capital initial. À l'inverse, de nouvelles approches explorent des formes de crédit partiellement garanti, combinant évaluation du risque hors-chaîne et mécanismes on-chain. Ces innovations soulèvent plusieurs questions théoriques : comment déterminer un taux d'intérêt sans marché monétaire central ? Comment évaluer le risque d'un emprunteur anonyme ? Et comment assurer la

liquidité dans un marché fonctionnant en continu, sans prêteur en dernier ressort ?

Ces marchés ont désormais atteint plusieurs dizaines de milliards de dollars d'encours et influencent la formation des taux d'intérêt sur blockchain. Ils participent à la création d'effets de levier financiers utilisés tant par des investisseurs particuliers qu'institutionnels. Leur émergence récente fait que la recherche académique n'en couvre encore qu'une partie. Si certaines études se concentrent sur leur architecture technique [Schär, 2021 ; Harvey, 2020], peu explorent leurs fondements économiques : la formation des taux, la répartition du risque, la coordination entre agents ou encore l'influence des comportements dans la valorisation des actifs.

Cette thèse s'inscrit dans ce champ de recherche émergent. Elle n'a pas pour objectif de promouvoir la DeFi comme une alternative supérieure à la finance traditionnelle, mais d'en analyser les mécanismes économiques. Elle cherche à comprendre comment le crédit peut fonctionner lorsque son exécution est algorithmique, que la participation est ouverte, et que la confiance repose sur le code plutôt que sur les institutions. L'objectif est de contribuer à la compréhension des conditions d'efficience, de stabilité et de soutenabilité de ces nouveaux marchés du crédit décentralisés.

Au-delà de ses promesses économiques et sociales, la DeFi constitue également un objet scientifique singulier, dont la transparence et la traçabilité en font un terrain d'étude inédit.

2 La DeFi comme laboratoire empirique

Au-delà de son intérêt conceptuel, la finance décentralisée constitue un environnement de recherche d'une richesse inédite. Chaque opération effectuée sur une blockchain publique y laisse une trace horodatée, vérifiable et accessible à tous. Ces registres distribués forment ainsi des bases de données transparentes permettant d'observer, avec un niveau de détail sans précédent, des comportements économiques à l'échelle microstructurelle. Autrement dit, la DeFi offre aux chercheurs un système financier ouvert et intégralement observable,

où il est possible de reconstituer l'ensemble des opérations (dépôts, prêts, remboursements et liquidations) directement à partir des données inscrites sur la blockchain.

Cette transparence ouvre la voie à de nouvelles approches empiriques, tout en posant des défis méthodologiques importants. L'anonymat des adresses empêche d'identifier les acteurs : il est impossible de distinguer un investisseur institutionnel d'un particulier, ou même d'un automate exécutant des transactions programmées. De plus, les interactions réalisées off-chain, comme la négociation préalable d'un accord de crédit, la stratégie d'allocation du capital ou la gestion du risque, échappent à l'observation directe. À cela s'ajoute l'évolution rapide des protocoles, qui complique la construction d'échantillons homogènes et comparables dans le temps.

Malgré ces limites, les données on-chain ouvrent un champ d'investigation empirique considérable. Elles permettent d'examiner des questions jusqu'alors difficilement accessibles : comment la liquidité réagit-elle aux variations de rendement ? Comment les taux s'ajustent-ils face à des chocs de marché ? Quels sont les mécanismes précis de transmission et de contagion du risque entre protocoles interconnectés ? Autrefois abordées principalement par la modélisation théorique ou l'analyse agrégée, ces dynamiques peuvent désormais être observées et mesurées empiriquement dans un environnement transparent, automatisé et programmable.

Ainsi, la DeFi peut être considérée comme un véritable « laboratoire naturel » de l'intermédiation financière. Elle permet d'analyser la manière dont des agents anonymes interagissent sous contrainte de liquidité, comment les taux se forment dans des marchés entièrement algorithmiques, et comment les comportements agrégés influencent la stabilité du système. Ce cadre offre une opportunité unique de rapprocher théorie économique, conception de mécanismes et observation empirique, tout en renouvelant les outils d'analyse des dynamiques financières contemporaines.

3 Problématique et structure de la recherche

Cette thèse a été menée parallèlement à mon activité professionnelle en tant que cofondatrice d'Atlendis, un protocole de prêt décentralisé. Cette double expérience a apporté à la fois une inspiration conceptuelle et un ancrage pratique, donnant lieu à des contributions situées à la croisée de l'innovation appliquée et de la recherche académique.

Tout au long de ce travail, plusieurs dimensions des marchés de prêt en DeFi sont examinées. Parmi les questions abordées figurent les choix de conception possibles lorsque les contrats financiers doivent être mis en œuvre dans un environnement soumis à de fortes contraintes computationnelles et économiques. Il s'agit aussi de comprendre comment fixer des taux d'intérêt lorsque la découverte des prix doit être assurée par du code autonome plutôt que par des institutions centralisées. Enfin, la thèse s'intéresse aux facteurs fondamentaux et comportementaux qui déterminent la valeur des tokens, c'est-à-dire des actifs numériques utilisés comme instruments d'échange et de gouvernance dans ces systèmes.

L'étude des dimensions comportementales s'explique par la structure même des marchés décentralisés. Contrairement aux marchés financiers traditionnels, façonnés par des régimes d'information normalisés, une transparence réglementaire et une forte présence d'investisseurs institutionnels, les environnements DeFi se caractérisent par une base de participants hétérogène comprenant une proportion importante d'utilisateurs particuliers. Par ailleurs, l'absence de normes de publication et la complexité des protocoles contribuent à des inefficiences informationnelles qui amplifient le rôle du sentiment et des récits collectifs dans la formation des prix. Dans ce contexte, les biais comportementaux ne se contentent pas de compléter les modèles de valorisation fondamentale : ils constituent une dimension essentielle à l'analyse des dynamiques de marché et à la compréhension de la prévisibilité des rendements des tokens [Shiller, 2017 ; Barberis, 1998].

Cette thèse aborde ces questions à travers trois essais complémentaires consacrés au fonctionnement des marchés de crédit décentralisés, depuis leur conception structurelle jusqu'à leurs dynamiques de marché. Ensemble, ces travaux combinent l'analyse de l'architecture des protocoles, la modélisation théorique et l'étude empirique, afin d'offrir une vision in-

tégrée du fonctionnement des marchés du crédit lorsque ceux-ci sont gouvernés par des contrats intelligents.

Le premier essai porte sur la conception du protocole Atlendis, une plateforme de prêt qui, contrairement à des protocoles tels qu'Aave ou Compound, ne repose pas sur la surcollatéralisation on-chain. L'éligibilité des emprunteurs et l'évaluation du risque de crédit y sont effectuées off-chain, souvent à travers des accords juridiques, des systèmes de réputation ou d'autres formes de souscription, tandis que l'émission, l'appariement et le remboursement des prêts sont entièrement automatisés par des smart contracts. Au-delà de la description d'un système fonctionnel, cet essai utilise le processus de conception comme cadre d'analyse pour explorer la manière dont l'intermédiation financière doit s'adapter aux contraintes d'une blockchain publique. Les choix relatifs à la structure des pools de liquidité, aux mécanismes de tarification ou à l'alignement des incitations ne peuvent être séparés des considérations techniques liées aux coûts de transaction ou à la complexité computationnelle. Le design qui en résulte illustre l'interaction entre ingénierie financière et contraintes d'infrastructure, et montre comment ces contraintes délimitent l'espace des architectures possibles.

Sur cette base, le deuxième essai propose un modèle théorique de découverte du taux d'intérêt. En considérant le mécanisme de lending pool décrit précédemment comme un jeu multi-unités impliquant des prêteurs hétérogènes, le modèle identifie les conditions dans lesquelles une formation de prix efficiente et transparente peut émerger, ainsi que les frictions susceptibles d'altérer cet équilibre. Cet essai établit un lien entre la microstructure des lending pools à paliers de taux et la littérature sur la théorie des jeux et la conception de marchés. La formation du prix y est envisagée comme le résultat d'interactions stratégiques entre participants disposant d'informations incomplètes et de préférences différenciées en matière de risque et de rendement. Le modèle met en évidence la structure d'équilibre qui en découle et analyse comment ces caractéristiques influencent le taux d'intérêt, la répartition du capital et l'efficacité du marché.

Le troisième essai s'intéresse aux déterminants fondamentaux et comportementaux des rendements des tokens DeFi. À l'aide d'approches analytiques et économétriques, il éva-

lue le pouvoir explicatif des variables issues de la finance traditionnelle, telles que des métriques de marché, en les comparant à des variables comportementales et à des facteurs spécifiques à la DeFi. Ce travail part du constat que les tokens DeFi présentent des dynamiques de prix sensiblement différentes de celles des actifs financiers classiques. En l'absence de modèles de valorisation standardisés et de normes de transparence homogènes, les acteurs du marché s'appuient souvent sur des proxys, des récits ou des signaux sociaux pour former leurs anticipations. Ces éléments comportementaux deviennent ainsi des moteurs importants de la valorisation des tokens, en complément des métriques de marché. L'étude apporte des éclairages nouveaux sur l'efficience informationnelle des marchés de tokens et contribue à une meilleure compréhension des mécanismes de formation des prix dans un environnement décentralisé.

Pris ensemble, ces trois essais examinent les mécanismes sous-jacents aux marchés du crédit décentralisés. Ils associent analyse technique des protocoles, modélisation théorique et investigation empirique pour comprendre comment les marchés fonctionnent, comment les prix s'y forment et comment les comportements des participants influencent leurs équilibres. Ce travail vise ainsi à contribuer à une meilleure compréhension de la finance décentralisée et de la place qu'elle occupe dans l'évolution des systèmes financiers contemporains. Il propose d'en analyser les fondements économiques et comportementaux afin d'éclairer les conditions dans lesquelles ces nouveaux mécanismes d'intermédiation peuvent s'intégrer durablement dans l'écosystème financier global.

General Introduction

1 Context and Motivation

Over the past five years, decentralized finance (DeFi) has emerged as one of the most significant innovations in blockchain technologies. It refers to a set of financial services based on open-source smart contracts, deployed on public blockchains and accessible to all. By removing the need for a trusted intermediary, DeFi positions itself as an alternative to the traditional banking and financial system. Transactions are executed automatically by code under transparent and immutable rules, which supports open and decentralized governance. Since its emergence, this ecosystem has attracted several hundreds of billions of dollars in assets, reflecting rapid growth and sustained interest from economic and technological actors. DeFi's architecture also enables advanced interoperability across applications, opening the way to new forms of lending, borrowing, and trading of digital assets. It relies on programmable blockchains that support the development of decentralized applications (DApps), among which Ethereum remains the most widely used and influential.

DeFi displays several features that make it distinct from traditional finance. It is public and permissionless : anyone with an Internet connection and an address on a compatible blockchain, such as Ethereum, can participate without prior authorization or institutional intermediation. This openness is one of its core principles. The ecosystem is also interoperable : protocols are designed to interact with one another, forming an integrated network in which technical cooperation often prevails over competition. DeFi is programmable

through smart contracts, which execute predefined operations automatically without human intervention. Finally, it is resilient thanks to decentralized blockchain infrastructure whose immutable and tamper-resistant nature supports continuity and security of services while reducing dependence on centralized actors.

The rise of DeFi stems from a well-known fact : access to financial services remains strongly shaped by economic and geographic factors. Financial inclusion is a key driver of social inclusion. Individuals without a bank account or access to credit are often excluded from the economic system. While banking penetration is close to saturation in advanced economies, many countries, notably in Africa and South America, still face persistent inflation, limited financial institutions, and a lack of basic services. In this context, DeFi is sometimes viewed as a deep transformation of the financial system that could foster broader inclusion based on principles that differ from those of conventional finance.

Among DeFi's applications, credit markets occupy a central place. They perform core economic functions : transforming savings into investment, allocating capital across agents, and managing intertemporal resources. In their traditional form, these activities are carried out by financial intermediaries such as banks, funds, or credit institutions. These intermediaries use their balance sheets to lend long term with short-term funding. They assess borrower solvency, manage liquidity risk, and perform maturity transformation within a structured legal and regulatory framework.

DeFi reshapes this architecture. It introduces intermediation without institutions, where lending, borrowing, and settlement are carried out by smart contracts. These contracts set the rules under which assets can be deposited, borrowed, or liquidated, and they execute these operations automatically. Trust shifts from an entity to the code itself. Access is permissionless : any holder of digital assets can interact with protocols without identity requirements or prior authorization. As in traditional finance, credit markets are a structuring component within DeFi. Decentralized lending protocols directly connect borrowers and lenders of crypto-assets without a centralized intermediary. Users can borrow assets or deposit them to earn interest, which is paid in the same crypto-asset that was supplied. Interest rates are set by algorithmic mechanisms : when borrowing demand for an asset

rises, the associated rate adjusts upward. At the core of these protocols are lending pools (liquidity pools), smart contracts that autonomously manage all lending and borrowing operations.

For economists, this shift represents a genuine change in paradigm. Traditional credit mechanisms rest on three pillars : institutional trust, legal enforcement of contracts, and an implicit public backstop to the financial system. None of these elements exists natively in DeFi. Execution rules are encoded in automated contracts, collateral is digital, and solvency relies on on-chain collateral rather than external supervision. This conceptual move raises a fundamental question : can credit exist without legal enforcement, and if so, under what economic logic ?

Decentralized lending markets illustrate this tension. Most rely on over-collateralization : to borrow 100 units of an asset, borrowers must post between 120 and 150 units as collateral. This model reduces default risk but limits credit creation and excludes agents with low initial capital. In response, new approaches explore partially secured credit that combines off-chain risk assessment with on-chain mechanisms. These innovations raise several theoretical questions. How should interest rates be determined without a central money market ? How can the risk of an anonymous borrower be assessed ? And how can liquidity be maintained in a market that operates continuously without a lender of last resort ?

These markets now manage assets in the tens of billions of dollars and influence interest rate formation on blockchains. They support the creation of financial leverage used by both retail and institutional investors. Their recent emergence means that academic research still covers only part of them. While some studies focus on technical architecture [Schär, 2021 ; Harvey, 2020], fewer examine the economic foundations : rate formation, risk sharing, coordination across agents, or the role of behavior in asset valuation.

This thesis contributes to this emerging field. It does not aim to promote DeFi as superior to traditional finance. It seeks to analyze its economic mechanisms. The objective is to understand how credit can function when execution is algorithmic, participation is open, and trust rests on code rather than institutions. The goal is to clarify the conditions for

efficiency, stability, and sustainability in these new decentralized credit markets.

Beyond its economic and social promise, DeFi is also a distinctive scientific object. Its transparency and traceability make it an unprecedented field for empirical study.

2 DeFi as an Empirical Laboratory

Beyond its conceptual interest, DeFi offers an unusually rich research environment. Every operation on a public blockchain leaves a timestamped, verifiable, and publicly accessible record. These distributed ledgers form transparent databases that allow observation of economic behavior at a microstructural level with unprecedented detail. In other words, DeFi provides researchers with an open and fully observable financial system in which deposits, loans, repayments, and liquidations can be reconstructed directly from on-chain data.

This transparency enables new empirical approaches but also raises methodological challenges. Address anonymity prevents identification of actors. It is not possible to distinguish an institutional investor from a retail user or from an automated agent. In addition, off-chain interactions such as pre-loan negotiations, capital allocation decisions, or risk management are not directly observable. Rapid protocol evolution further complicates the construction of homogeneous and time-consistent samples.

Despite these limits, on-chain data open a wide empirical agenda. They allow researchers to examine questions that were previously difficult to address. How does liquidity respond to changes in yields ? How do rates adjust to market shocks ? Through what channels does risk propagate across interconnected protocols ? These dynamics, once studied mainly through theory or aggregated data, can now be observed and measured empirically in a transparent, automated, and programmable environment.

DeFi can thus be viewed as a natural laboratory for intermediation. It makes it possible to analyze how anonymous agents interact under liquidity constraints, how rates form

in fully algorithmic markets, and how aggregate behavior affects system stability. This setting creates an opportunity to bring together economic theory, mechanism design, and empirical observation, and to renew the analytical tools used to study financial dynamics.

3 Research Problem and Structure

This thesis was conducted in parallel with my professional work as a cofounder of Atlendis, a decentralized lending protocol. This dual engagement provided conceptual insights and practical grounding, and led to contributions at the intersection of applied innovation and academic research.

Throughout the thesis, several dimensions of DeFi lending are examined. The analysis considers design choices when financial contracts must be implemented under tight computational and economic constraints. It studies how to set lending rates when price discovery is governed by autonomous code rather than centralized institutions. It also investigates the fundamental and behavioral factors that determine the value of the tokens that support these systems.

The focus on behavioral dimensions follows from the structure of decentralized markets. Unlike traditional financial markets shaped by standardized disclosure, regulatory transparency, and a strong presence of institutional investors, DeFi environments feature a heterogeneous participant base with a significant share of retail users. The absence of reporting standards and the complexity of protocol fundamentals contribute to informational inefficiencies that amplify the role of sentiment and narratives in price formation. In this context, behavioral biases do not merely complement fundamental valuation models. They are essential to understanding market dynamics and the predictability of token returns [Shiller, 2017 ; Barberis, 1998].

The thesis addresses these questions through three complementary essays on decentralized credit markets, from structural design to market dynamics. Together, they combine protocol-level analysis, theoretical modeling, and empirical evidence to provide an inte-

grated view of how credit markets function when governed by smart contracts.

The first essay analyzes the design of the Atlendis protocol. Unlike platforms such as Aave or Compound, Atlendis does not require on-chain over-collateralization. Borrower eligibility and credit risk are assessed off-chain, often through legal agreements, reputation systems, or other forms of underwriting, while loan origination, matching, and repayment are executed by smart contracts. Beyond describing a working system, the essay uses the design process to examine how financial intermediation adapts to the practical realities of a public blockchain environment. Choices on pool structure, pricing mechanisms, and incentive alignment cannot be separated from technical considerations such as gas costs, state storage, and computational complexity. The resulting design shows how financial engineering interacts with infrastructure constraints and how these constraints shape the feasible space of protocol architectures.

Building on this foundation, the second essay develops a theoretical model of rate discovery. It frames the lending-pool mechanism described above as a multi-unit game with heterogeneous lenders. The model identifies the conditions under which transparent and efficient pricing can emerge and the frictions that may distort outcomes. It connects the microstructure of tick-based lending pools to the literature on game theory and market design. Price formation arises from strategic interaction among participants with incomplete information and different risk-return preferences and capital constraints. The model characterizes the resulting equilibrium and studies how these features shape the interest rate, the allocation of lending capital, and overall market efficiency.

The third essay examines the fundamental and behavioral drivers of DeFi token returns. Using analytical and econometric methods, it tests the explanatory power of market metrics alongside behavioral indicators and DeFi-specific variables. The analysis starts from the observation that DeFi tokens display price dynamics that differ from those of traditional assets. In the absence of standardized valuation models and consistent disclosure, market participants often rely on proxies, narratives, and social signals to form expectations. Behavioral variables can therefore be powerful drivers of token returns, in addition to market metrics. The study offers new insights into the informational efficiency of token

markets and into price formation in a decentralized environment.

Taken together, the three essays examine the mechanisms that underpin decentralized credit markets. They combine technical analysis of protocols, theoretical modeling, and empirical investigation to understand how these markets operate, how prices form, and how participant behavior shapes outcomes. The aim is to contribute to a clearer understanding of decentralized finance and its place in the evolution of contemporary financial systems. The thesis analyzes the economic and behavioral foundations of these mechanisms to clarify the conditions under which new forms of intermediation can integrate sustainably into the broader financial ecosystem.

Foundations of Decentralized Finance

This chapter lays the conceptual groundwork for the rest of the thesis. It introduces the technological and economic building blocks behind decentralized finance, from blockchain infrastructure to lending protocols. The goal is to provide the necessary context to understand the subsequent analytical and empirical sections.

1 From Blockchain to Decentralized Finance

Decentralized finance (DeFi) did not emerge as a single innovation, but as a gradual evolution of blockchain technology, cryptographic trust systems, and dissatisfaction with traditional financial infrastructure. Understanding DeFi requires first understanding how value was transferred without intermediaries in Bitcoin, how Ethereum introduced programmable contracts, and how these technologies enabled financial markets to operate without central authorities.

1.1 Bitcoin and Trustless Value Transfer

Bitcoin, introduced by [Nakamoto, 2008], enables peer-to-peer payments without relying on banks or central authorities. It uses a public blockchain to record valid transactions in a

transparent and tamper-resistant way.This innovation marked the beginning of blockchain technology, establishing a framework for decentralized record-keeping that later systems would expand upon.

The system represented a new model for digital ownership and value exchange. It establishes digital scarcity through a fixed and transparent issuance schedule, hard-capped at twenty-one million coins. Network integrity is maintained through cryptographic verification and decentralized agreement achieved via proof-of-work mining, ensuring that no single participant controls the ledger. Bitcoin demonstrates that economic incentives and computational effort can secure a distributed system, making manipulation prohibitively costly. Ownership of coins is defined by cryptographic key pairs, giving users direct control over their assets without intermediaries.

Bitcoin's functionality is intentionally limited. Its scripting language allows only simple transactions and basic conditions, such as multi-signature or time locks. More complex financial activities, like lending, derivatives, or automated contract, are not possible. Building such systems requires greater programmability.

1.2 Ethereum and Programmable Smart Contracts

Ethereum extends Bitcoin's model by introducing smart contracts that can be described as pieces of code executed on the blockchain when predefined conditions are met [Buterin, 2014]. This innovation transforms the blockchain from a payment network into a general-purpose platform for decentralized applications. It enables code itself to define, verify, and enforce agreements.

Smart contracts enable the automatic execution of agreements without traditional intermediaries, the issuance of digital assets such as tokens representing money, equity, or governance rights, and composability among protocols that function as modular financial components.

These capabilities make it possible to build on-chain versions of exchanges, lending plat-

forms, stable currencies, and derivatives. This development laid the foundation for what became known as decentralized finance (DeFi).

1.3 Emergence of DeFi

Traditional finance depends on intermediaries such as banks, brokers, and clearinghouses. These institutions record ownership, enforce contracts, and manage credit relationships. Decentralized finance (DeFi) replaces many of these functions with software protocols that operate on public blockchains.

DeFi does not eliminate trust ; it redistributes it. Instead of relying on banks or states, users rely on open-source code, distributed consensus, and economic incentives that align participants' behavior. Trust is placed in transparent systems rather than institutional authorities.

The emergence of DeFi is driven by several structural motivations. Public blockchains make transactions and balances verifiable by anyone, increasing transparency. They are censorship-resistant, since no central authority can freeze assets or restrict access. Their global reach allows anyone with an internet connection to save, borrow, or trade without needing a bank account. Automation through smart contracts reduces the need for human oversight and enables continuous operation of financial logic.

These characteristics are especially appealing in settings where financial infrastructure is inefficient, exclusionary, or vulnerable to political control. In some economies, banking services remain limited or costly, leaving large segments of the population unbanked. In others, capital controls or currency instability undermine confidence in local institutions. DeFi offers an alternative that is open by design, operating independently of borders and local regulation. It provides predictable rules encoded in software, allowing users to interact under the same conditions regardless of jurisdiction.

Before exploring lending and interest rate mechanisms, we must understand the technological components that make DeFi possible : blockchains, smart contracts, tokens, and

oracle systems. This is the focus of the next section.

2 Core Technologies Enabling Decentralized Finance

Decentralized finance relies on a stack of technological components that together allow financial services to operate without centralized institutions. At its foundation is the blockchain, which provides a shared ledger and settlement layer. On top of this, smart contracts encode financial logic, tokens represent assets, and oracle networks supply external data such as asset prices.

2.1 Blockchain as a Settlement Layer

Blockchains function as distributed ledgers where all network participants maintain a synchronized record of transactions.

2.1.1 Consensus Mechanisms

Consensus is the process by which nodes agree on the state of the ledger. Two mechanisms dominate current blockchain networks. Proof of Work (PoW), used by Bitcoin, secures the network through computational effort : miners solve cryptographic puzzles, and the energy they expend deters manipulation. Proof of Stake (PoS), used by Ethereum since 2022, replaces energy expenditure with collateral. Validators lock cryptocurrency as a stake, risking its loss if they behave dishonestly. Both mechanisms ensure that confirmed transactions are effectively immutable, a property essential for reliable financial settlement.

2.2 Smart Contracts

Smart contracts are autonomous programs stored on a blockchain that execute predefined logic without intermediaries. In the context of DeFi, they handle core financial operations such as lending, trading, and interest accrual. Their execution is deterministic, meaning all nodes compute the same result when given identical input. Once deployed, contracts are immutable unless upgrade logic has been built in, and they can hold or transfer funds directly without relying on institutions. This combination of autonomy and transparency enables financial systems that operate continuously and predictably.

Examples include automated lending pools, decentralized exchanges, and stablecoin issuance protocols, where code replaces many of the functions traditionally managed by banks or clearinghouses.

2.3 Tokens and Digital Asset Standards

Ethereum introduced standardized token frameworks that simplify the creation of new digital assets. The most common standard, ERC-20, defines fungible tokens used for stablecoins such as USDC and DAI or for governance tokens like AAVE and COMP. ERC-721 defines unique, non-fungible tokens (NFTs) used to represent specific assets or positions, including collateralized loans or digital collectibles. A more recent standard, ERC-4626, supports tokenized vaults for yield-bearing assets.

In lending protocols, users who deposit funds often receive tokenized claims, such as cTokens or aTokens, that represent their share of a liquidity pool and automatically track accrued interest. These token standards allow assets and positions to move seamlessly between applications.

2.4 Oracles : Bringing Off-Chain Data On-Chain

Blockchains cannot access external data by themselves. Oracles bridge this gap by delivering information such as asset prices, interest rates, or exchange rates to smart contracts. Some oracles are centralized, operated by a single entity, which simplifies deployment but introduces trust dependencies. Others, such as Chainlink, aggregate data from multiple independent sources to reduce manipulation risk. A third approach uses on-chain time-weighted average prices (TWAP) derived from decentralized exchanges.

Oracles are crucial for DeFi applications that depend on real-world data, particularly lending protocols where they determine collateral values and trigger liquidations. Inaccurate or delayed price feeds can lead to insolvencies or unfair liquidations, making oracle design a critical element of system stability.

2.5 Composability and Interoperability

DeFi protocols are inherently modular. Lending platforms, decentralized exchanges, and stablecoins interact like interlocking components. This high degree of composability accelerates innovation but also creates interdependence. A failure in one protocol can quickly propagate through others, amplifying systemic risk across the ecosystem.

3 Financial Primitives in Decentralized Finance

Decentralized finance (DeFi) reproduces core financial services such as trading, lending, and asset issuance through smart contracts rather than intermediaries. These basic building blocks are referred to as financial primitives. They form the foundation of more complex applications through composability. This section introduces the main DeFi primitives.

3.1 Decentralized Exchanges (DEXs)

Decentralized exchanges allow users to trade tokens directly from their wallets without centralized brokers or custodians.

3.1.1 Automated Market Makers (AMMs)

Most DEXs use automated market makers rather than order books. A liquidity pool holds two assets, and their relative price is determined by a function such as the constant product rule [Adams, 2020] :

$$x \cdot y = k,$$

where x and y denote token reserves in the pool and k remains constant. Traders change the ratio of reserves, and prices adjust automatically according to

$$p = \frac{dy}{dx} = \frac{y}{x}.$$

Liquidity providers deposit both assets into the pool and earn a share of trading fees. However, they are exposed to impermanent loss, a reduction in value relative to simply holding the two assets outside the pool. This occurs because, as market prices move, the AMM continuously rebalances the pool's composition, leaving liquidity providers with a different mix of tokens. The loss remains impermanent as long as prices return to their original ratio but becomes realized when liquidity is withdrawn.

3.1.2 Order Book Models

Some decentralized exchanges adopt an order book model similar to traditional trading platforms. Users place limit and market orders, but maintaining these orders directly on-chain is costly and inefficient. To reduce transaction overhead, most systems therefore keep order books off-chain while performing trade settlement and custody on-chain.

3.2 Stablecoins

Stablecoins are tokens designed to maintain a stable value, typically pegged to the U.S. dollar. They provide a reliable unit of account for trading, lending, and accounting across DeFi applications.

3.2.1 Fiat-Backed Stablecoins

Centralized issuers such as Circle and Tether hold fiat reserves and issue tokens like USDC and USDT. These stablecoins offer high liquidity but introduce custodial and regulatory risks, as users must trust the issuer's reserve management and compliance practices.

3.2.2 Crypto-Collateralized Stablecoins

Protocols such as MakerDAO issue decentralized stablecoins (e.g., DAI) by allowing users to lock crypto assets as collateral and mint new tokens. The system maintains solvency through over-collateralization and automated liquidations managed by smart contracts. When the value of collateral falls below a threshold, it is auctioned to liquidators who purchase it using DAI. The DAI paid by liquidators is sent back into the MakerDAO system and burned, cancelling the corresponding debt and keeping the overall supply fully backed.

3.2.3 Algorithmic Stablecoins

Algorithmic stablecoins attempt to maintain a price peg through programmed supply adjustments rather than full collateralization. When the token trades above its target price, supply expands ; when it falls below, supply contracts. Designs that rely entirely on market confidence are highly fragile, as illustrated by the collapse of TerraUSD in 2022 [Various, 2022]. More recent models combine algorithmic control with partial collateralization or dynamic redemption mechanisms, reducing but not eliminating the associated risks.

3.3 Synthetic Assets and Derivatives

Synthetic asset platforms, such as Synthetix, create tokens that track external prices of assets like equities, commodities, or indices. Users lock collateral to mint these synths, while oracles provide price data. Synthetic assets expand market access but depend critically on accurate and timely oracle feeds.

DeFi has also developed derivatives markets that replicate traditional financial instruments through smart contracts. Perpetual futures enable continuous leveraged trading without fixed maturities, while on-chain options allow decentralized hedging and exposure to asset volatility. Other designs explore interest rate swaps and yield-curve instruments, extending decentralized finance beyond spot markets. These derivatives operate without clearinghouses or brokers, relying instead on algorithmic pricing, collateral management, and on-chain settlement.

3.4 Liquidity Mining

Liquidity mining refers to the distribution of governance or reward tokens to users who supply liquidity, stake assets, or borrow funds within a protocol. It emerged as a mechanism to accelerate early adoption by aligning user incentives with network growth. Participants earn tokens that often grant governance rights or a share of protocol fees, effectively turning users into stakeholders.

These incentives help bootstrap liquidity in new markets, improve price stability, and attract trading volume. However, they can also distort behavior. High short-term yields encourage speculative inflows that may withdraw once rewards decline, leaving liquidity fragmented or volatile. In some cases, the cost of token issuance exceeds the long-term value retained by the protocol, creating unsustainable cycles of growth and contraction.

Over time, liquidity mining has evolved toward more targeted and measured designs, such as rewards linked to real usage, dynamic emission schedules, or liquidity-directed governance mechanisms. Despite these refinements, balancing user incentives with sustainable

protocol economics remains one of the central challenges in decentralized finance.

3.5 Lending as the Core Primitive

Lending protocols form the foundation of DeFi credit markets. Users deposit assets into a liquidity pool and receive interest-bearing tokens in return. Borrowers draw loans against collateral, and interest rates adjust dynamically based on utilization. Because there is no legal recourse or identity-based credit scoring, most loans are over-collateralized to ensure solvency.

The following section examines lending mechanisms in greater detail, as they represent the economic core of DeFi and the primary focus of this thesis.

4 Lending in Decentralized Finance

Lending is a foundational pillar of decentralized finance (DeFi). While decentralized exchanges enable trading and stablecoins provide a stable unit of account, lending protocols create on-chain credit markets, determine interest rates, and allocate capital over time. They account for the largest share of total value locked (TVL) in DeFi and remain the main mechanism through which users earn yield on idle assets.

Unlike traditional banking, which transforms deposits into loans through balance-sheet intermediation, DeFi lending operates through smart contracts that pool liquidity and automate collateral management. This design allows borrowing and lending to occur without centralized institutions, replacing credit assessment and enforcement with algorithmic rules and transparent collateralization. The resulting markets provide continuous rate discovery and form the basis for leverage, liquidity, and monetary dynamics across the broader DeFi ecosystem.

4.1 Over-Collateralized Lending : Logic and Design

Unlike traditional lending, DeFi protocols cannot rely on identity verification, legal contracts, or debt recovery through courts. To mitigate credit risk, loans are therefore over-collateralized : borrowers must deposit assets whose value exceeds the amount borrowed.

4.1.1 Collateral Ratio and Liquidation Threshold

A central measure is the loan-to-value ratio (LTV), defined as :

$$\text{LTV} = \frac{D}{C},$$

where D is the borrowed amount expressed in monetary terms (typically USD) and C is the collateral value. Protocols impose a maximum allowable ratio, $LTV_{\max}$, such that

$$\frac{D}{C} \leq LTV_{\max}.$$

If collateral prices fall and the ratio rises beyond a second parameter, the liquidation threshold, the position becomes eligible for liquidation. This condition can be written as :

$$\frac{D}{C} \geq \theta,$$

where θ denotes the liquidation threshold. In practice, $\theta > LTV_{\max}$ to provide a buffer against minor price movements.

When liquidation occurs, third-party liquidators repay the borrower's debt and receive the corresponding collateral at a discount. Let α denote the liquidation bonus : if D is the outstanding debt, the liquidator receives

$$C_{\text{seized}} = D \cdot (1 + \alpha),$$

thereby earning a small profit for restoring the system's solvency.

Over-collateralization substitutes for legal enforcement mechanisms. In the absence of identity, reputation, or court-enforced recovery, collateral must always cover the debt in full to ensure solvency.

4.1.2 Economic Implications

The requirement to lock excess collateral has several implications. First, it reduces capital efficiency, as borrowers must immobilize more value than they receive. Second, it introduces *reflexivity* : declining collateral prices can push positions toward liquidation, amplifying downward price pressure and volatility. Third, the absence of maturity transformation means lending protocols cannot create credit beyond the deposited capital, avoiding traditional bank-run dynamics, though they remain exposed to liquidity shocks from correlated liquidations or collateral withdrawals.

Although over-collateralized lending appears inefficient, it provides important functionality. It enables users to obtain liquidity without selling their assets, to take leveraged market positions, and to participate in decentralized credit markets transparently. In systems such as MakerDAO, the borrowing process also serves as the mechanism for stablecoin issuance, giving it both a monetary and financial role.

Despite these limitations, over-collateralized lending has proven resilient in practice. MakerDAO, the first large-scale implementation, successfully liquidated positions during extreme market stress in March 2020, demonstrating that algorithmic collateral management can preserve solvency even under high volatility [Maker Foundation, 2020].

4.2 Architecture of Lending Protocols

Although implementation details differ, most large DeFi lending protocols follow a common architectural structure. They share a pool-based approach to liquidity but differ in governance, collateral management, and interest rate mechanisms.

4.2.1 Pool-Based Lending (Compound and Aave)

In protocols such as Compound and Aave, users supply assets into liquidity pools. Borrowers draw loans from these pooled assets by posting collateral. There is no peer-to-peer (P2P) matching ; instead, liquidity providers (lenders) are exposed to the aggregated borrowing activity of the protocol.

A lender supplying asset X receives an interest-bearing token representing their claim on the pool :

— Compound issues *cTokens* (e.g. `cDAI`), such that the exchange rate between cToken and the underlying asset increases over time.

— Aave issues *aTokens* (e.g. `aUSDC`), whose balance increases continuously in the user's wallet to reflect accrued interest.

The value of these tokens evolves according to :

$$\text{Balance}(t) = \text{Balance}(0) \cdot (1 + r_s \cdot t),$$

where r_s is the supply rate. In practice, interest is accrued per block.

4.3 Interest Rate Models

In DeFi lending protocols, interest rates are not set by central banks or market-makers but are derived algorithmically based on supply and demand conditions. The central variable is the **utilization rate** U, defined as :

$$U = \frac{B}{S},$$

where B is the total borrowed amount and S is the total supplied amount in a pool.

4.3.1 Linear Interest Rate Model

The simplest model sets the borrowing rate r_b as a linear function of utilization :

$$r_b(U) = r_0 + m \cdot U,$$

where r_0 is the base rate (when no funds are borrowed), and m determines sensitivity to demand. The supply rate r_s is derived by :

$$r_s = r_b \cdot U \cdot (1 - \gamma),$$

where γ is the protocol's reserve factor.

This model is intuitive but fails to capture sharp increases in risk when liquidity becomes scarce (high utilization).

4.3.2 Kinked (Piecewise Linear) Interest Rate Model

To better reflect liquidity risk, protocols like Compound V2 and Aave use a piecewise linear function with an inflexion point at target utilization U^*. The borrowing rate is :

$$r_b(U) = \begin{cases} r_0 + m_1 \cdot U & \text{if } U \leq U^*, \\ r_0 + m_1 \cdot U^* + m_2 \cdot (U - U^*) & \text{if } U > U^*, \end{cases}$$

where $m_2 > m_1$ to strongly penalize high utilization. This encourages borrowers to repay when liquidity becomes scarce.

This model implicitly embeds a liquidity premium : as available deposits approach zero, the marginal cost of borrowing rises sharply. This is analogous to liquidity stress in inter-bank markets, where interest rates spike when institutions hoard reserves.

Supply rates derive from :

$$r_s = r_b \cdot U \cdot (1 - \gamma),$$

ensuring that lenders receive a share of interest proportional to the extent their funds are used.

4.4 Liquidation Mechanisms

Liquidation is the core mechanism that ensures solvency in over-collateralized lending systems. Because there is no legal enforcement or credit scoring, lending protocols must guarantee that the value of collateral always exceeds the value of outstanding debt. This is achieved through automatic liquidation when a borrower's health factor falls below a predefined threshold.

4.4.1 Health Factor

The health factor (HF) in Aave is a solvency metric that measures how safe a borrowing position is relative to its collateral. It is defined as :

$$\text{HF} = \frac{\sum_i (C_i \cdot LT_i)}{D}$$

where :

— C_i is the current market value of collateral asset i,

— LT_i is the liquidation threshold associated with asset i,

— D is the total value of the debt (including accrued interest), expressed in the same currency.

A position is considered safe when $\text{HF} > 1$. If $\text{HF} < 1$, the position becomes eligible for liquidation.

4.4.2 Liquidation Process

When a position breaches the threshold, external actors (liquidators) can repay part of the borrower's outstanding debt and receive a proportional amount of collateral at a discount. If α is the liquidation bonus (e.g. 5%), the liquidator receives :

$$C_{\text{seized}} = D_{\text{repaid}} \cdot (1 + \alpha).$$

Protocols allow partial liquidations to reduce systemic stress. Typically, only up to 50% of the debt can be liquidated per transaction. This avoids unnecessarily closing fully collateralized positions.

4.4.3 Systemic Risk and Cascading Liquidations

Liquidations can create reflexive feedback loops that amplify market stress :

1. Declining collateral prices push loan-to-value ratios above liquidation thresholds.
2. Protocols or liquidators sell collateral (such as ETH) to repay outstanding debt.
3. These sales exert additional downward pressure on prices, triggering further liquidations.

The process resembles margin calls in traditional finance but unfolds much faster due to programmatic execution and on-chain leverage. If market liquidity is thin, this dynamic can escalate into widespread deleveraging across protocols, spreading volatility throughout the system.

5 Risks in Decentralized Finance

Decentralized finance introduces a new financial architecture based on programmable contracts and open participation. While this reduces reliance on traditional intermediaries, it creates novel sources of fragility that do not exist in conventional finance. Risk is

no longer centered around bank insolvency or maturity mismatch, but around software security, oracle manipulation, governance capture, and coordination failures.

5.1 Smart Contract Risk

Smart contracts encode the core financial logic of DeFi protocols, including collateral management, interest accumulation, and liquidation procedures. Errors in this code can lead to irreversible losses, as transactions executed on-chain cannot be reversed. Typical vulnerabilities include reentrancy attacks, where an attacker repeatedly triggers contract calls before the initial transaction settles, allowing funds to be drained or balances altered. Arithmetic errors, such as integer overflows or underflows, can also distort token balances or interest calculations. Finally, access control flaws may permit unauthorized entities to change critical parameters or invoke privileged functions.

Once deployed, smart contracts are difficult to modify unless upgrade mechanisms are built into their architecture. This immutability limits governance manipulation but increases the potential cost of coding errors. Formal verification, independent audits, and bug bounty programs have become standard methods of risk mitigation, although none can fully eliminate the possibility of failure.

5.2 User Interface Exploitation Risk

In addition to smart contract vulnerabilities, users of decentralized finance (DeFi) protocols face risks originating from the exploitation of user interfaces. Although core protocol logic is executed on-chain, most users interact with these systems through web-based front ends that facilitate wallet connections and transaction initiation.

If an attacker compromises a protocol's website or injects malicious code into its interface, users can be deceived into approving unauthorized transactions that transfer assets directly from their wallets. Such attacks may occur through DNS hijacking, phishing domains, or manipulation of front-end JavaScript code. Because wallet interactions are often

signed by the user, these transactions appear legitimate on-chain, making recovery nearly impossible.

User interface exploitation can lead to substantial losses for individuals and can erode trust in otherwise secure protocols. It highlights the distinction between the security of on-chain contracts and that of the off-chain infrastructure used to access them.

5.3 Oracle Risk

Lending protocols rely on price oracles to determine collateral values and to trigger liquidations when necessary. If an oracle provides inaccurate data or is manipulated, the system can malfunction. Healthy positions may be liquidated unnecessarily, while undercollateralized loans may remain open, creating bad debt. In extreme cases, attackers can distort prices on low-liquidity markets to extract value from lending pools.

To reduce these risks, protocols use decentralized oracle networks that aggregate data from multiple sources. Some rely on time-weighted average prices from decentralized exchanges to smooth short-term volatility. Others implement sanity checks and short update delays to prevent flash crash manipulation. Despite these safeguards, oracle failure and manipulation remain among the most common causes of financial loss in decentralized finance.

5.4 Governance Risk

Most DeFi protocols are governed by decentralized autonomous organizations (DAOs). Token holders vote on parameters such as collateral factors, liquidation thresholds, interest rate models, supported assets, and the allocation of treasury funds. This structure distributes decision-making power across participants and aligns governance with protocol ownership.

However, governance itself introduces new risks. Large token holders can dominate voting outcomes, concentrating influence in a few hands. Low participation rates often lead to

voter apathy, allowing a small minority to control major decisions. In some cases, attackers have borrowed governance tokens temporarily to manipulate proposals in their favor.

These vulnerabilities can be mitigated through mechanisms such as time-locks on parameter changes, quorum and participation thresholds, or multisignature emergency controls. Each measure, however, reintroduces some degree of centralization, illustrating the trade-off between security, efficiency, and decentralized governance.

6 Real-World Assets and the Convergence with Traditional Finance

While DeFi initially evolved around crypto-native assets such as ETH and stablecoins, an increasing share of activity now involves the integration of real-world assets (RWAs). These include tokenized government bonds, invoices, revenue streams, and short-term credit instruments. The trend reflects a broader convergence between decentralized and traditional finance, where blockchain infrastructure is used to settle, collateralize, and fractionalize claims on real economic value.

6.1 Tokenization of Real-World Assets (RWA)

Tokenization is the process of creating a blockchain-based representation of an off-chain asset. For a tokenized asset to function reliably, three elements are essential : a legally enforceable claim on the underlying asset, sound custodial or asset management arrangements, and transparent mechanisms for issuance and redemption.

In practice, tokenization has taken several forms. Tokenized Treasury bills allow investors to hold on-chain representations of short-term government debt. Tokenized invoices or trade receivables enable businesses to finance working capital by issuing claims that can later serve as collateral. Real estate and revenue-sharing tokens extend the model to fractional ownership of income-generating properties or future cash flows. By integrating

such instruments, DeFi protocols can provide collateral with lower volatility than ETH or BTC and offer yields that more closely follow traditional interest rates.

The incorporation of real-world assets addresses several structural limitations of crypto-native DeFi. Collateral volatility remains a persistent issue, as the prices of crypto assets fluctuate sharply and trigger frequent liquidations ; RWAs provide a more stable base of collateral. During market downturns, on-chain lending activity slows and yields decline, but RWAs supply external sources of return independent of crypto market cycles. Their introduction also facilitates participation by institutional investors, who require exposure to identifiable cash flows and instruments compliant with financial regulation.

These advantages come at the cost of increased centralization. Tokenization depends on trusted custodians, legal contracts, and off-chain asset management, reintroducing elements of traditional finance into an otherwise decentralized system.

6.2 Credit Risk and Re-Centralization

The integration of RWAs reintroduces several centralized risk layers. Custodial risk arises because the assets are held by regulated entities, and investors depend on proper asset segregation and reporting. Legal enforcement remains jurisdiction-dependent ; in the event of default, recovery depends on off-chain legal systems rather than on-chain mechanisms. Governance discretion also plays a larger role, as decentralized organizations must approve whitelists, evaluate counterparties, and set concentration limits.

RWA protocols therefore operate in a hybrid zone where decentralized coordination co-exists with traditional legal infrastructure. The balance between on-chain transparency and off-chain trust becomes a central design challenge.

The inclusion of real-world assets marks a shift in DeFi from experimental financial engineering toward integration with established capital markets. This evolution brings several implications. Credit risk, largely absent from crypto-collateralized lending, reappears as borrowers may default on real-world obligations. Interest rates become increasingly linked

to macroeconomic conditions and central bank policy, as yields on tokenized instruments track those of their traditional counterparts. Regulatory convergence also accelerates, requiring compliance with securities law, disclosure standards, and anti–money-laundering rules.

Together, these developments suggest that DeFi is moving toward a model of hybrid finance, where programmable infrastructure supports assets and contracts anchored in the real economy.

7 Conclusion

Decentralized finance has emerged as a new layer of financial infrastructure built on public blockchains. It replaces traditional intermediaries with open-source smart contracts and enables users to lend, borrow, exchange, and issue assets without relying on banks or clearing institutions. This chapter introduced the conceptual and technological foundations of DeFi and examined how these components converge to create on-chain credit markets.

A key observation from this chapter is that lending protocols do not rely on a central authority to set interest rates. Instead, borrowing costs emerge endogenously from the interaction between liquidity suppliers and borrowers, according to mathematical rate models embedded in smart contracts. In practice, rates vary across protocols, assets, and market conditions. They are influenced by liquidity, collateral composition, and expectations of risk.

This analysis also highlights the limits of fully over-collateralized systems. While they ensure solvency and transparency, they exclude most real-world borrowers and constrain credit expansion to crypto-native collateral. The recent emergence of hybrid protocols seeks to overcome this barrier by connecting on-chain liquidity with off-chain credit opportunities. Such designs integrate real-world assets and legal contracts while preserving on-chain transparency and automated settlement.

Atlendis represents one such hybrid design. It introduces a model where decentralized liquidity can be allocated to real-world enterprises under predefined contractual conditions and supported by tokenized collateral. The next chapter examines the Atlendis whitepaper in detail, analyzing how its architecture integrates DeFi mechanisms with conventional credit practices and what this implies for the evolution of decentralized lending.

Chapitre 1

Atlendis Whitepaper

Objectives

This chapter introduces Atlendis, a decentralized lending protocol designed to facilitate credit access for real-world companies through a combination of off-chain underwriting and on-chain execution. It details the protocol's architecture, mechanisms, and governance model to illustrate how decentralized finance can extend beyond crypto-native use cases into real-economy applications.

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1 Introduction

Lending protocols such as Compound, Aave, and Maker have established the foundation of decentralized credit markets ; yet, their reliance on on-chain over-collateralization significantly limits their ability to provide genuine debt financing. This essay addresses that gap by examining the design of a protocol, Atlendis, that enables lending without on-chain overcollateralization by using borrower-specific pools and a tick-based rate mechanism. While grounded in the architecture of an operational protocol, the objective of this essay is to formalize design choices and to illustrate how they create incentives for transparent and competitive rate setting.

A central dimension of the paper lies in understanding the constraints imposed by blockchain infrastructure on protocol design at the time of writing. When implemented on Ethereum in 2021/2022, protocol mechanisms had to account for gas costs, state storage limitations, and execution complexity. These factors restricted the feasible set of lending mechanisms. Documenting these constraints provides insight into how decentralized infrastructure conditions financial innovation. Protocol design reflects trade-offs inherent to smart-contract development and illustrates the evolving relationship between financial engineering and blockchain infrastructure. It is important to note that the analyses and discussions presented here reflect the state of decentralised finance and the protocol's development as they stood in 2022. Since then, the DeFi ecosystem has continued to evolve, and incorporating these more recent developments falls beyond the scope of this work.

The essay focuses on Atlendis V2, the second version of the protocol, deployed on the Polygon blockchain in July 2022. Through its lending pools, Atlendis offers two categories of credit instruments : loans [2] and revolving credit lines [3], each of which can be structured to reflect the borrower's needs, financial constraints, and opportunities.

Contents

Sections 2 and 3 were intended to be independent and self-sufficient. They can be read as two distinct and stand-alone sections.

2 Loans

2.1 Defining Loan Types on Atlendis

In order to serve a wide range of use cases, two different loan types are available on the Atlendis protocol : **bullet loan** and **installment loan**. We will start by defining each of them.

2.1.1 Bullet Loans

In financial theory, a bullet loan is a debt contract in which repayment of the principal is deferred until maturity, while interest may either accrue in full or be paid periodically. Such instruments are common in traditional credit markets, particularly for projects that generate delayed cash flows, such as infrastructure or research investments. On the protocol, bullet loans are adapted to decentralized execution, where smart contracts ensure continuous accrual of interest and automatic settlement at maturity. Compared to traditional markets, on-chain enforcement of repayment limits renegotiation but ensures automatic settlement.

Two variants of bullet loans are available on the Atlendis protocol. In a **zero-payment bullet loan**, interest accrues over time and the borrower repays both principal and accrued interest as a lump sum at maturity. On the protocol, interest is compounded per second. In an **interest-only bullet loan**, the borrower makes regular interest payments during the life of the loan, reducing the final payment at maturity to the principal alone.

Example 2.1. *Let's consider a* $10,000$ *zero payment bullet loan with a one year maturity*

and an annual interest rate of 6%. *The borrower must repay* 10,600 *at maturity.*

Example 2.2. *Let's consider a* 10,000 *interest-only bullet loan with a one year maturity, monthly payments and an annual interest rate of* 6%. *The borrower must repay* 50 *monthly and* 10,050 *at maturity.*

2.1.2 Installment Loans

Installment loans are contracts in which repayment occurs through regular installments that combine principal and interest. They are typically suited to borrowers generating stable cash flows. Within the protocol, installment loans extend this contract form to a decentralized environment, where repayment schedules are enforced on-chain.

For each installment, the payment includes both interest and principal, with the exact amount determined by the loan size, interest rate, and duration :

$$\text{Installment Amount} = P \cdot r \cdot \frac{(1+r)^n}{(1+r)^n - 1},$$

where P is the principal, r the interest rate, and n the number of periods. Repayment occurs according to the schedule specified in the lending pool's parameters.

Example 2.3. *Considering a loan of* 1,000 *with 1 year duration and monthly payments at a* 6% *rate. The installment payment amount equals to*

$$\textit{Monthly Installment Amount} = 1,000 \times \frac{0.005 \times (1+0.005)^{12}}{(1+0.005)^{12} - 1} = 86.06$$

2.1.3 Choice of Loan Type

The choice of loan type by the borrower depends on the maturity of the loan and the immediate cash generated by the investment. Bullet loans will be favored by entities that don't generate immediate cash-flow from their investment. Installment loans will be preferred by entities that are able to generate immediate cash-flow from their investment as they have an incentive to smooth out their monthly payments.

2.2 Loan Origination

In traditional credit markets, loan origination involves screening, underwriting, and pricing, often through centralized intermediaries. In decentralized settings, these functions are replaced by transparent rules encoded in smart contracts.

Let's break down the different phases that come with the origination of a loan on Atlendis.

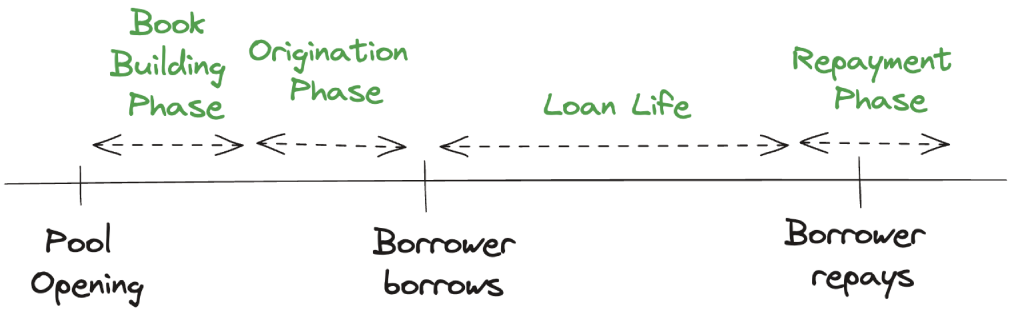

FIGURE 1.1 – Phases of the loan origination process in the Atlendis protocol. The figure illustrates the sequential steps from pre-pool borrower assessment to on-chain capital deployment : (1) off-chain borrower onboarding and credit evaluation, (2) lending pool opening and activation of the rate-based order book, (3) book-building phase where lenders submit rate–amount offers across ticks, and (4) loan origination, during which the smart contract matches the borrower's demand with available liquidity at the lowest interest rates.

2.2.1 Pre-Pool Opening

Each origination begins with a pre-pool deposit requirement from the borrower designed to discourage unused pool creation. The amount locked corresponds to a percentage of the targeted borrowed amount. The deposit will be returned to the borrower once they borrow from their pools. However, the deposit will be distributed to the pool's lenders in the case where the borrower ends up not borrowing from their pool.

2.2.2 Lending Pool Opening

Atlendis' loans are materialized by the creation of lending pools. Atlendis' lending pools are borrower-specific and have their own specificities. The borrowing rates are discovered via a limit order book specific to each lending pool.

Set of Ticks

To enable the borrowing rate discovery, Atlendis sets up a discriminatory auction process via the creation of sub-pools called **tick**. A tick is a sub-pool of funds within the borrower's pool that corresponds to a specific lending rate. Every lending pool is composed of multiple ticks. When adding liquidity to the pool, lenders choose their lending rate and their funds are then placed into the corresponding tick. This effectively translates lenders' risk-return preferences into a decentralized limit order book.

Example 2.4. *If a lender is willing to lend to a borrower at* 5%*, their funds will be placed in the* 5% *tick of the borrower's lending pool.*

Here is a visual representation of a lending pool on Atlendis :

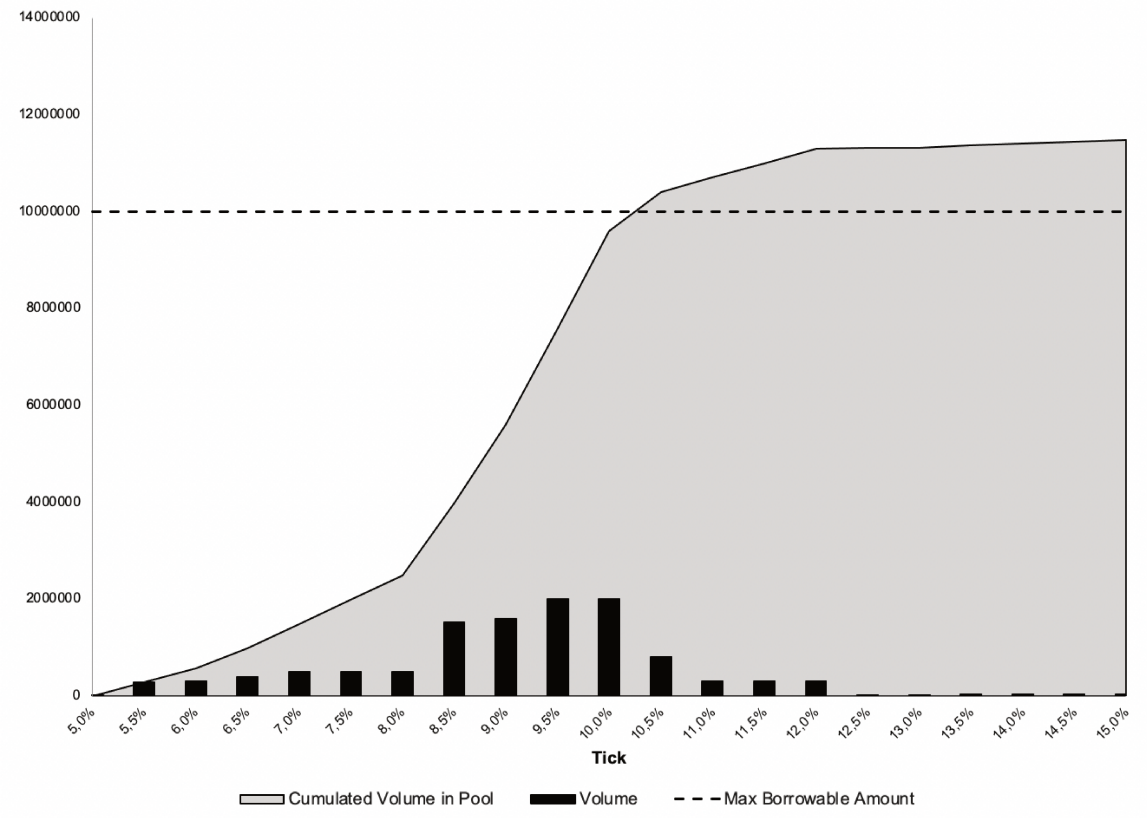

FIGURE 1.2 – Structure of a borrower's pool on Atlendis and how it is built from individual ticks. Each tick represents a specific interest rate at which lenders make funds available. The pool aggregates these ticks to form an on-chain order book used to match borrower demand with available liquidity.

Since lenders have the ability to set their own lending rate, they can actively determine the level of risk they are willing to assume relative to the potential return. This mechanism allows heterogeneous lenders to reveal their risk-return preferences. This design is motivated by the absence of a central authority to set borrowing costs. Decentralization makes it necessary to establish a mechanism through which rates emerge endogenously from the interaction of market participants.

Pool Specificities

Each lending pool has its own specificities, fixed in accordance with the borrower. The pool's parameters are encoded in smart contracts and apply uniformly to all participants, ensuring that rules are transparent and automatically enforced. Pool parameters are inputs

of the smart contract function responsible for initializing the pool's configuration. The parameters are as follows :

- Loan type : bullet loans (zero payment and interest only) or installment loans plus additional characteristics if required. For instance, payment frequency is required for interest payment bullet loans and installment loans.
- Assets in the pool : each pool is composed of only one type of asset, for instance USDC.
- Maturity.
- Target amount range : it corresponds to target amount to be borrowed (upper bound) and minimum amount to be borrowed (lower bound). The amount borrowed should be within that range.
- Tick range and rate spacing : the lending rates that can be chosen by the lenders when depositing into the pool must remain within a preset range. The upper and lower bounds are fixed in accordance with the borrower. The rate spacing between two ticks is also a characteristic of the lending pool. A low rate spacing gives more flexibility to the lenders, but increases the amount of gas costs paid by the borrower when borrowing from their pool.
- Late repayment fee : In the event of late repayment, a penalty fee will be paid by the borrower to discourage late repayment. The late payment penalty varies depending on the loan type. This will be detailed in a dedicated section (see section 3.3.2 below).
- Book building phase duration, origination phase duration and repayment phase duration.

The choice of these parameters influences the lenders' behavior with the pool. The pools are opened with their own characteristics, and they are clearly stated to encourage participation in the pool. Note that pools are not limited in size.

2.2.3 Book Building Phase

The first phase after the opening of the lending pool is called the **book building phase**. It is limited in time, and its duration corresponds to the book building phase duration set in the pool's characteristics. Lenders act as liquidity providers, allocating capital in exchange for compensation that reflects risk and maturity. Lenders' rights and options are translated into programmable actions enforced by smart contracts.

During this phase, lenders are allowed to perform the following actions :

1. **Deposit** : lenders can freely deposit into the lending pool at the lending rate of their choice. In exchange, they will receive an NFT with original artwork that represents their **position** : pool's identifier, amount deposited and chosen lending rate.
2. **Update Rate** : lenders can freely update their lending rate during this phase. Their position will be updated accordingly.
3. **Withdraw** : as their position has not yet been borrowed by the borrower, the lenders can freely withdraw their funds if they want.

It's important to note that pools are not limited in size, therefore, even if the amount in pool is higher than the target amount to be borrowed, any lender can add liquidity to the lending pool during the book building phase and challenge the lending rates. This creates market dynamics and gives access to a fair market rate discovery for borrowers.

During the book building phase, the borrower is not yet authorized to borrow from their pool. They must wait for the end of the book building phase to make sure all the commits have been gathered and are final. Unlike in traditional finance, where a bid is an expression of intent, here the commitment must be backed by an actual deposit. This is necessary because participants are often anonymous, there is no centralized intermediary to enforce promises, and the protocol cannot rely on non-binding offers. Locking the funds ensures that committed liquidity is genuinely available once the lending phase begins.

2.2.4 Origination Phase

Once the book building phase is terminated, the lenders can no longer update or withdraw their commitment. No action can be performed during this phase by the lenders.

During the **origination phase**, the borrower can freely borrow from their pool. The amount borrowed must be less than or equal to the target amount but greater than the minimum amount. The borrower may not borrow less than the minimum amount unless there is insufficient liquidity in the pool (see 2.2.4).

The origination phase is limited in time, and its duration corresponds to the origination phase duration set in the pool's characteristics.

Borrowing Rate

The borrowing rate is simply the lowest volume-weighted rate that corresponds to the amount borrowed. It is derived from the ticks and is the result of the amount available in each tick. To determine this rate, the smart contract iterates over the order book until the required amount is reached, and the more ticks it needs to process, the higher the gas cost of the transaction. The borrowing rate does not change during the life period of the loan.

Let T be the loan's maturity, K the amount borrowed, d_i the amount available in tick i, d_i^b the amount borrowed in tick i, the borrowing rate r_b set at loan origination time is the following :

$$r_b = \frac{1}{K} \min_{d_b^i} \sum r_i \times d_i^b$$

such that :

$$\begin{cases} 0 \leq d_i^b \leq d_i \\ \sum d_i^b = K \end{cases}$$

In the case of bullet loans without interest payment, the borrower must repay $K \times (1+r_b)^T$ at maturity, each tick receives $d_i^b \times (1+r_i)^T$. The position status and amount that should be received at maturity can be deducted from the position's tick and the amount deposited.

Example 2.5. *Let's consider a bullet loan lending pool without interest payment and one year maturity. A lender that deposits in the* 5% *tick wishes to make a return of* 5% *on their investment. By depositing* 100 *into the* 5% *tick of a lending pool, the lender is expecting to receive* 105 *in one year if all their deposit ends up being borrowed. Let's say a borrower borrows 100 from* 5% *tick and 100 from* 6% *tick, the borrowing rate is* 5.5%*. At maturity, lenders in* 5% *tick receive 105 and lenders in* 6% *tick receive 106.*

Loan Cancellation

The origination phase has a set termination date. If the borrower ends up not borrowing from their pool at the end of the loan origination period, their locked deposit will be distributed to the lenders as a compensation. The portion of the locked deposit distributed to lenders is proportional to the amount in the pool vs. the target amount. If there is more in the pool than the target amount, the lenders in lower ticks are prioritized over lenders in higher ticks. After that, the borrower can no longer interact with their pool. The lenders are free to withdraw their funds and their portion of the compensation.

Minimum Target Not Reached

If there is less in the pool than the minimum borrowable amount, the borrower can decide to either borrow the total amount available in the pool or to cancel the loan origination. In that case, the borrower won't get penalized and will be able to retrieve their entire locked deposit.

2.3 Loan Life Period and Repayment Period

Depending on the type of the loan, the repayment of principal and interest takes place before maturity and/or at maturity.

During the life period of the loan, lenders that have some unborrowed funds can freely withdraw their unused funds from the pool. This means that any interest payment or installment payment pre-maturity are withdrawable. All lenders can freely withdraw the full amount from the lending pool following the final payment.

2.3.1 Bullet Loans

Standard Repayment

The principal and (remaining) interest are repaid at maturity. The repayment must happen during a time window close to maturity that is called the repayment period. The repayment window takes place before the maturity date.

Example 2.6. *Let's consider a loan that expires on the 1st of April at 2pm with a repayment period of two days. The borrower can repay the loan without enduring a penalty between March 30th at 2pm and April 1st at 2pm.*

If existing, the interest payable before maturity must be paid at the set interest payment date. However, if the borrower misses one interest payment, they have the ability to repay the missing interest up to the next interest payment due date without incurring a penalty fee.

Late Repayment

If the amount due at maturity (principal + (remaining) interest) is not repaid during the repayment period, a penalty fee will be applied that corresponds to the interest accrued past the maturity date at a mark-up interest rate defined as the late repayment rate.

Example 2.7. *Let's consider a loan that expires on the 1st of April at 2pm with a repayment period of two days. The borrower can repay the loan without enduring a penalty between March 30th at 2pm and April 1st at 2pm. If the borrower repays the loan on April 3rd at 2pm instead, they must repay two additional days of interest at the mark-up rate (late repayment rate).*

No penalty will be applied in case of one late interest payment. However, if the borrower misses more than two interest payments, it will be decided by the governance to place the pool into the nonstandard repayment procedure (see Appendix - Non Standard Repayment Procedure) in accordance with the terms of the Master Loan Agreement.

2.3.2 Installment Loans

Standard Repayment

The periodic payment must be made at the set installment date. The payment must happen during a payment window preceding the installment date.

Example 2.8. *Let's consider a loan with monthly payment on the 3rd of each month with a repayment period of 48 hours. The borrower must make their payment between the 1st and 3rd of each month.*

Late Repayment

If the borrower repays one installment amount late, a penalty will be applied that corresponds to additional interest accrued at a mark up rate.

Example 2.9. *Let's consider a loan with monthly payment of* 150 *on the 1st of each month with a repayment period of 48 hours and a late repayment fee of* 20%*. If the borrower pays one of their monthly payment 15 days late, they will have to pay a penalty fee of*

$$Penalty = 150\left[\left(1+\frac{0.20}{365}\right)^{15}-1\right]$$

2.4 Protocol Fees

Fee structures serve both to sustain the platform and to influence participant behavior. In centralized markets, these may take the form of spreads, origination charges, or management fees. In the protocol, fees are encoded ex ante in smart contracts and apply symmetrically across participants, ensuring transparency.

There are two types of fees on Atlendis that go to Atlendis' treasury.

2.4.1 Borrowing Fee

At borrow time, a fee defined as the borrowing fee is applied to the borrower. It corresponds to a fixed percentage applied on the amount borrowed. The current borrowing fee on Atlendis corresponds to a 1% annualized rate.

Example 2.10. *A borrower that borrows* 100 *for 1 year, only receives* 99 *at borrow time, the rest is sent to Atlendis' treasury.*

2.4.2 Interest Fee

At repayment time, an interest fee is applied to the interest earned by lenders. The current interest fee rate corresponds to 10% meaning that a 10% cut is applied to the interest earned by lenders.

Example 2.11. *A lender, who lent* 100 *at a* 6% *for one year, receives* 105.4 *at maturity.*

2.5 Computation Approximation

On-chain computation consumes gas because each arithmetic operation executed by a smart contract requires computational resources from network validators. More complex operations therefore lead to higher transaction costs. In addition to computation, gas also accounts for other resource usage such as memory access and data storage. Approximating

these functions reduces the computational load, which helps keep transactions efficient and economically viable

Power functions are thus approximated using a 1st Order Taylor Series. For instance, when computing actualization factors and repayment amount, we use the following approximation :

$$(1+r)^{\Delta T} = 1 + \Delta T \times r$$

where r is the rate per second and ΔT is the number of seconds until maturity. This approximation effectively turns the calculations into a simple interest formula, as it linearizes the annual compounding effect by only considering the first-order term.

3 Revolving Credit Lines

Revolving credit lines are a well-established financial instrument, often used by firms to manage short-term liquidity needs. In traditional banking, they provide flexible access to credit up to a specified limit, with interest charged only on the drawn balance.

3.1 Defining Revolving Credit Lines on Atlendis

Within the protocol, revolving credit lines are implemented as a series of successive bullet loans, initiated each time the borrower draws from the pool. At any point, the borrower can use their line of credit and borrow funds up to the preset maximum borrowable amount. Every time the borrower uses their credit line, this initializes a new borrow cycle with a set end date defined as the maturity date. The borrowed amount plus interest must be repaid at maturity. If the full borrow capacity has not been used and the loan has not yet matured, the borrower has the ability to further borrow from their liquidity pool. However, it does not change the initial maturity date. Once the principal and interest have been repaid at maturity, the borrower is able to initiate a new borrow cycle. In a way, Atlendis' revolving credit lines lending pool enables successive bullet loans with the same maturity. This mechanism reproduces the flexibility of traditional revolving facilities

while embedding execution and enforcement in smart contracts.

Example 3.1. *Let's consider a borrower that has access to a revolving credit line on Atlendis with one month maturity and* $10,000$ *maximum borrowable amount. On January 1st, the borrower borrows* $5,000$ *from their revolving credit line at a* 4% *interest rate. This initiates a borrow cycle that will end on January 31st. On January 15th, the borrower borrows an additional* $2,500$ *at a* 5% *interest rate and finally* $1,000$ *on January 30th at a* 7% *interest rate. On January 31st, the borrower must repay*

$$5,000 \times (1 + 4\%/365)^{30/365} + 2,500 \times (1 + 5\%/365)^{15/365} + 1,000 \times (1 + 7\%/365)^{1/365}$$

The choice to implement revolving credit lines as successive bullet loans rather than as continuously revolving facilities stems from both technical and practical considerations. Smart contracts cannot easily enforce repayment without a predefined due date, which makes a fixed maturity essential for reliable execution. At the same time, this structure allows borrowers to choose pools with maturities that best match their financing needs, preserving much of the flexibility of traditional credit lines while remaining compatible with on-chain constraints. One might question why protocols such as Aave do not require a maturity date. The key difference lies in the design : Aave relies on onchain overcollateralization and on-chain liquidation mechanisms to secure repayment, which removes the need for a predefined end date. In contrast, Atlendis being a credit-based lending cannot rely solely on collateral enforcement, making a fixed maturity an essential part of risk management and contract execution.

3.2 Atlendis' Lending Pools

Atlendis' revolving credit lines are materialized by the creation of lending pool's. Atlendis' lending pools are borrower-specific.

3.2.1 Set of Ticks - Order Book

To enable the borrowing rate discovery, Atlendis sets up a discriminatory auction process via the creation of sub-pools called ticks. Lending pools are split into multiple ticks. A tick is a sub-pool of funds within the borrower's pool that corresponds to a specific lending rate. When adding liquidity to the pool, lenders choose their lending rate and their funds are then placed into the corresponding tick.

Example 3.2. *If a lender is willing to lend to a borrower at* 5%*, their funds will be placed in the* 5% *tick.*

Here is a visual representation of a lending pool with ticks on Atlendis :

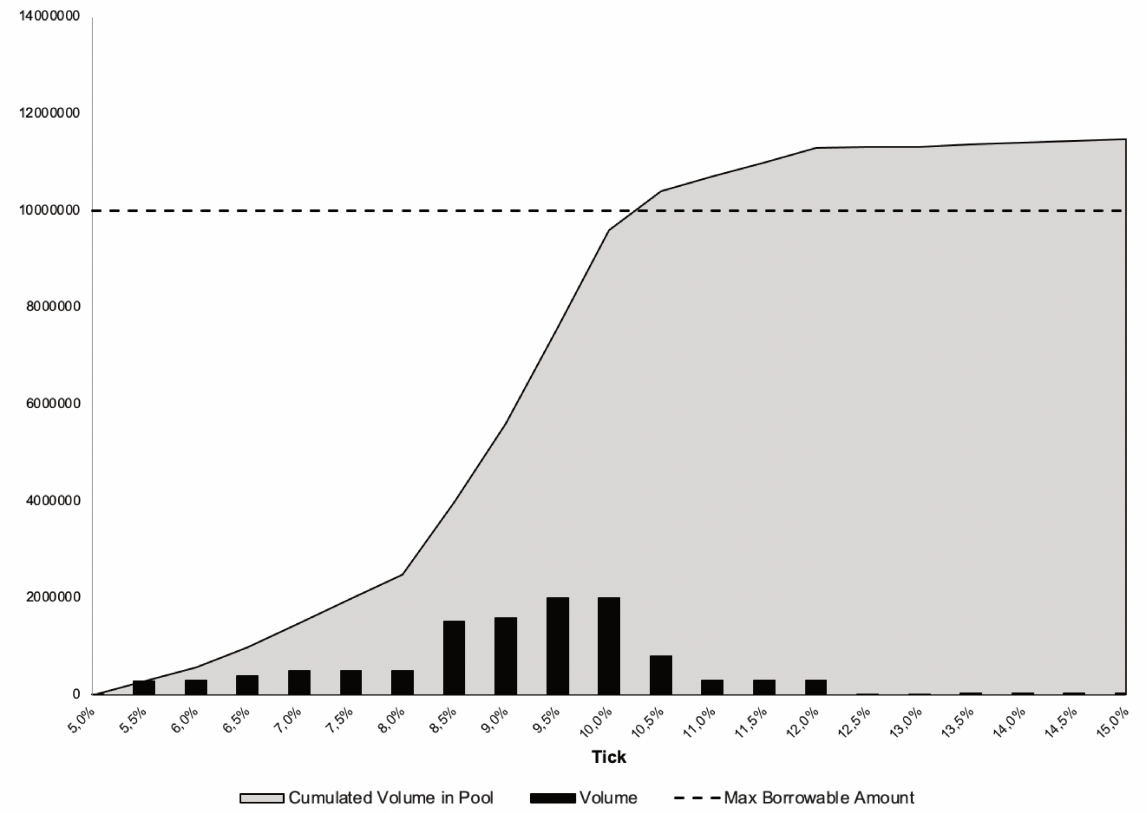

FIGURE 1.3 – Structure of a borrower's pool on Atlendis. The pool is built from individual ticks, where each tick corresponds to a specific interest rate and available liquidity. Together, these ticks form the on-chain order book from which borrower demand is filled.

As lenders have the possibility to set their own lending rate, they are able to choose the amount of risk they are willing to take for the level of potential return.

3.2.2 Transposing Ticks to an Order Book

The lending pool's ticks can be transposed to a limit order book. We define the actualization factor as the amount that the lender would be willing to lend now to receive 1 at maturity. The actualizaton factor is derived from the position's tick rate and maturity, or the time remaining until maturity if the loan is ongoing.

Example 3.3. *A lender who deposits in the* 5% *tick wishes to make a return of* 5% *on their loan. They are thus willing to lend* 100 *to receive* 105 *in one year. If they were to replace someone else halfway through maturity who had a borrowed position, they would be willing to replace their position for* $\frac{\textit{position value at maturity}}{(1+0.05)^{1/2}}$*, where* $1/(1+0.05)^{1/2}$ *is the actualization factor.*

Let's consider a borrower's lending pool with maturity T, let $r_1, \cdots, r_n$ be the ticks' rates and $d_t^1, \cdots d_t^n$ the amount of deposit available in each tick at time t. We can derive the following bid order book :

Side	Rate	Deposit Available	Actualization Factor
bid	r_1^t	d_1^t	F_1^t
bid	$\vdots$	$\vdots$	$\vdots$
$\vdots$	r_i^t	d_i^t	F_i^t
$\vdots$	$\vdots$	$\vdots$	$\vdots$
bid	r_n^t	d_n^t	F_n^t

where :

— $F_i^t = 1/(1+r_i^t)^{\Delta T}$ is the actualization factor, and $\Delta T = T - t$ is the time remaining until maturity.

— $0 \leq r_1^t \leq r_i^t \leq r_n^t$,

— $F_1^t \geq F_i^t \geq F_n^t \geq 0$,

— and $d_i^t \geq 0 \ \forall$ i in $[1, n]$.

Having a limit order book where lenders set their rate enables both the loan origination and lenders' exits. The exit mechanisms will be further described in the section (3.4.5). Depositing into a pool can be perceived as placing a pending buy limit order to buy future bonds. The implied bid prices and quantities can be derived from the amount deposited and the chosen lending rate. Unlike in traditional finance, where a bid is an expression of intent, here the commitment must be backed by an actual deposit. This is necessary because participants are often anonymous, there is no centralized intermediary to enforce promises, and the protocol cannot rely on non-binding offers. Locking the funds ensures that committed liquidity is genuinely available once the lending phase begins.

Pool Specificities

Each lending pool has its own specificities, fixed in accordance with the borrower. The pool's parameters are encoded in smart contracts and apply uniformly to all participants, ensuring that rules are transparent and automatically enforced. Pool parameters are inputs of the smart contract function responsible for initializing the pool's configuration. The parameters are as follows :

— Assets in the pool : each pool is composed of only one asset type, for instance USDC.

— Maturity.

— Max borrowable amount : it corresponds to the maximum amount that the borrower can withdraw from their pool.

— Tick range and rate spacing : the lending rates, that can be chosen by lenders when depositing into the pool, must remain within a preset range. The upper and lower bounds are fixed in accordance with the borrower. The rate spacing between two ticks is also a characteristic of the lending pool. A low rate spacing gives more flexibility to the lenders, but increases the amount of gas costs paid by the borrower when borrowing from their pool.

— Repayment period duration (see section 3.3.2).

— Late repayment fee : in the event of late repayment, a penalty fee will be paid by the borrower to discourage late repayment. This is detailed in a dedicated section

below (see section 3.3.3).

— freeze period duration : optional period pre-maturity that prevents lenders from withdrawing liquidity from the pool during that specific period (see section 3.3.4).

— Fees parameters (see section 3.5).

— Optional features : this pertains to the availability of specific functionalities such as rollover, exit, and early repayment options within the pool. The activation of these features is at the discretion of the borrower, as detailed in the respective sections (see 3.3.4, 3.4.5, 3.3.5).

The choice of these parameters influences the lenders' behavior with the pool. The pools are opened with their own characteristics and they are clearly stated to encourage participation in the pool. Note that pools are not limited in size. The pool's parameters are encoded in smart contracts and apply uniformly to all participants, ensuring that rules are transparent and automatically enforced.

3.3 Borrower Side

3.3.1 Borrowing

Fixed Borrowing Rate

The borrowing rate is simply the lowest volume-weighted rate that corresponds to the amount borrowed. It is derived from the ticks and is the result of the amount available in each tick. To determine this rate, the smart contract iterates over the order book until the required amount is reached, and the more ticks it needs to process, the higher the gas cost of the transaction. The borrowing rate does not change during the life period of the loan.

Let T be the maturity, K the amount borrowed, d_i the amount available in the tick i, d_i^b the amount borrowed in the tick i, the borrowing rate r_b is the following :

$$r_b = \frac{1}{K} \min_{d_b^i} \sum r_i \times d_i^b$$

such that :

$$\begin{cases} 0 \leq d_i^b \leq d_i \\ \sum d_i^b = K \end{cases}$$

The borrower must repay $K \times (1 + r_b)^T$ at maturity, each tick receives $d_i^b \times (1 + r_i)^T$. The position status and amount that should be received at maturity can be deducted from the position's tick and amount deposited.

Example 3.4. *Let's consider a borrower with a revolving credit line that has a one year maturity. A lender that deposits in the* 5% *tick wishes to make a return of* 5% *on their investment. By depositing* 100 *into the* 5% *tick of a lending pool, the lender is expecting to receive* 105 *in one year if all their deposit ends up being borrowed. Let's say a borrower borrows 100 from the* 5% *tick and 100 from the* 6% *tick, the borrowing rate is* 5.5%*. At maturity, lenders in the* 5% *tick receive 105 and lenders in the* 6% *tick receive 106.*

Further Borrowing

If the full borrow capacity has not been used and the loan has not yet matured, the borrower has the ability to further borrow from their liquidity pool. However, it does not change the initial maturity date.

3.3.2 Repayment

The repayment must happen during a time period (defined as the **repayment period**) preceding the maturity date.

3.3.3 Late Repayment

If the borrower misses their repayment period, a penalty fee will be applied that corresponds to the interest accrued past the maturity date at a mark-up interest rate defined as the late repayment rate. While these penalties mirror traditional credit contracts, their enforcement on-chain ensures automatic execution but reduces contractual flexibility, illustrating the trade-off between algorithmic enforcement and discretionary renegotiation.

3.3.4 Rolling Over

At maturity, the borrower has the ability to roll over their loans allowing them to start a new borrow cycle immediately, thanks to the embedded rollover function. However, there is no guarantee that the terms of the loans will remain the same for the two borrow cycle. The borrowing rate will most probably be different and the amount available to be borrowed might differ depending on market conditions.

In order to guarantee the amount that can be rolled over and the borrowing rate, a specific feature can be activated at the borrower's request. It introduces a relatively short **freeze period** pre-maturity that prevents lenders from withdrawing liquidity from the pool during that specific period. Even though rolling over will be made possible for all pools, that specific feature will be pool dependent.

3.3.5 Early Repayment

At pool's creation, the borrower has the possibility to ask for an early repayment option that could happen in the standard course of the pool's life. However, as this feature removes the possibility for sellers to exit the pools during a borrow cycle, this specific feature won't be made available for all pools and will only be activated at the borrower's request.

3.4 Lender Side

Lenders act as liquidity providers, allocating capital in exchange for compensation that reflects risk and maturity. In centralized markets, their rights and exit options are governed by contract terms and secondary market liquidity. Within the protocol, these functions are translated into programmable actions enforced by smart contracts. Actions available to lenders on Atlendis replicate the traditional spectrum of lender rights—deposit, withdraw, renegotiate, or sell—within a rule-based and automated environment.

3.4.1 Deposit

At any point in time, lenders can freely deposit into the lending pool of their choice at their chosen lending rate, as long as it remains within the pool's tick range. In exchange, they will receive an NFT with some original artwork that represents their **position** : pool's identifier, amount deposited, chosen lending rate. Atlendis' position NFTs are non-transferable.

The funds in lenders' positions can become borrowed on three occasions :

— The borrower initiates a new borrow cycle.

— The borrower further borrows from their pool.

— A lender with borrowed funds wants to exit the pool (see 3.4.5).

In the meantime, at the lender's request (see staking section 4), capital that is not actively being loaned out can be used to provide liquidity on a third-party yield provider.

It's important to note that pools are not limited in size, therefore, even if the amount in the pool is higher than the maximum borrowable amount, any lender can add liquidity to the lending pool and challenge the lending rates. This creates market dynamics and gives access to a fair market rate discovery for borrowers and exiting lenders. In effect, deposits act as binding limit orders, making the pool resemble a continuous order-driven market.

3.4.2 Withdraw

As long as their position is not borrowed, lenders can either totally or partially withdraw funds in their positions. For partially borrowed positions, the lender can withdraw the totality of the unborrowed funds.

Lender APY following Withdraw

Lenders that have had some funds borrowed (either through the borrower borrowing or other lenders exiting) and that don't exit before maturity, realize an APY that corresponds exactly to their chosen lending rate during the time that their position was borrowed. It is important to note that interest are compounded between two borrow cycles, this means that Atlendis' lenders earn interest on their realized interest.

Example 3.5. *Let's say a lender deposits* 100 *in the* 5% *tick of a lending pool with one month maturity. If the borrower borrows from their pool for a 6 month period without any interruption and the lender's position has been borrowed every time. The lender's position after 6 months equals* $100 \times (1 + 5\%/12)^6 = 102.53$ *which corresponds to a* 5% *APY.*

3.4.3 Rate Update

As long as their position is not borrowed, lenders can freely change their lending rate. Their position will be updated accordingly.

3.4.4 Opt Out

A lender with a borrowed position who doesn't want to exit their position in the current market conditions but would rather wait for the loan to mature, can choose to signal their position as exiting. Their position will remain unchanged until maturity. However, if a new borrow cycle is initiated before the withdrawal of deposited funds, their funds won't be used, preventing them from being involved in a new loan. This ensures predictability

in the withdrawn amount. The lenders can withdraw their initial deposit plus the interest earned on Atlendis that corresponds to their set rate, and the interest earned on the third-party yield provider. The lenders are not subject to the current market conditions. Opting out is only permitted on borrowed positions and is irreversible.

3.4.5 Exit

Secondary markets for debt instruments are critical for providing lenders with liquidity before maturity. In conventional finance, such markets rely on bilateral transfers or exchange-based trading. In the protocol, liquidity is achieved through an exit mechanism that enables lenders with borrowed positions to close them early under transparent, rule-based conditions.

When exiting a position with loaned out capital, the exiting lender enables lenders with non-borrowed positions to replace them as lenders. There is no position transfer, the exiting lender's position is burnt and the replacing lender's positions are updated accordingly. The amount received by the exiting lender depends on the market conditions, hence the order book. The matching engine ensures that replacement occurs in order of rate competitiveness and deposit epoch, prioritizing earlier commitments. This design substitutes peer-to-peer negotiation with algorithmic matching, reducing counterparty risk but introducing dependence on pool liquidity and rate dispersion. As such, it reflects both the opportunities and limitations of on-chain secondary credit markets.

Let's consider a lender A that deposited at a rate r_A, is expecting to receive q_A at maturity and wishes to exit their position at time t. Let's consider that the current state of the limit order book on Atlendis is :

Side	Rate	Deposit Available	Actualization Factor
bid	r_1^t	d_1^t	F_1^t
bid	$\vdots$	$\vdots$	$\vdots$
$\vdots$	r_i^t	d_i^t	F_i^t
$\vdots$	$\vdots$	$\vdots$	$\vdots$
bid	r_n^t	d_n^t	F_n^t

where :

$$\begin{cases} F_i^t = 1/(1+r_i^t)^{\Delta T} \text{ is the actualization factor} \\ \Delta T \text{ is the time remaining until maturity.} \\ 0 \leq r_1^t \leq r_i^t \leq r_n^t, \\ F_1^t \geq F_i^t \geq F_n^t \geq 0, \\ \text{and } d_i^t \geq 0 \ \forall i \in [0,n]. \end{cases}$$

By exiting their position, they will receive :

$$\sum_i F_i^t \times q_{i,A} \tag{1.1}$$

where $q_A^1, \cdots, q_A^i, \cdots$ correspond to

$$\text{argmax}_{q_{i,A}} \sum F_i^t \times q_{i,A}$$

such that

$$\begin{cases} 0 \leq q_{i,A} \leq d_i^t / F^{i_t} \\ \text{and } \sum q_{i,A} = q_A \end{cases}$$

In the case where there is not enough liquidity to exit the position, the lender can decide to either partially exit their position or wait for better market conditions. Note that opted out positions cannot be exited. The position's holder shall wait for the loan termination

and is free to withdraw after repayment.

The choice of a tick-based order book rather than a price-based one is motivated by the need to allow continuous price updates without requiring any action from lenders. Unlike in traditional finance, updating bids on-chain consumes gas, so frequent manual updates are impractical. A tick-based structure solves this by enabling automatic price adjustment through the actualization factor, which determines the effective bid price.

Lender APY following Exit

If lenders exit their position before maturity, their realized APY can slightly differ from their chosen lending rate, as their APR on the last borrow cycle will depend on market conditions. Indeed, for an exiting lender to be able to realize their desired APY, they must have their position replaced by remaining lenders that asked for the same tick rates. If a lender exits at a lower rate than the position's tick rate, they will realize a higher APY than the position tick rate. However, if there is no liquidity at the same rate or lower, then they will have to give up part of their yield to make up for the desired rate of the remaining lenders. The lowest PnL that can be achieved for the lender who set a rate r, and was expecting to receive q at maturity after being borrowed at time t_1 and exists at time t_2 is the following :

To illustrate this, we will consider a simple example and four different scenarios.

Example 3.6. *Let's consider the following :*

- *Alice deposits 100 at rate of* 6%*.*
- *The borrower borrows 100 at* 6% *for a maturity of one year. The borrower must thus repay 106 at maturity.*
- *Half through the time to maturity, Alice wants to exit.*

and four different example scenarios.

Scenario 1

There is not enough liquidity left in the pool, Alice cannot exit.

Scenario 2

— *After the loan started, Bob had deposited at* 6% .

— *Bob's position doesn't have any borrowed funds. Given the fact that Bob wants to lend at* 6%*, that there is still half a year left until maturity and that the borrower will repay 106 at maturity, in order to realize the* 6% *on the remaining time to maturity, he is willing to lend* $106/(1+6\%)^{1/2} = 102.95$ *where* $(1/2)$ *corresponds to the time left until maturity.*

— *Alice receives* 102.95 *minus an exit cost taken by Atlendis (for simplification purposes here, we'll assume it's zero). Her PnL is* $(102.95 - 100) = 2.95$*, her realized APY is* 6%*.*

— *At maturity Bob receives 106, his PnL is* $(106 - 102.95) = 3.05$*, his realized APY is* 6%*.*

Scenario 3

— *After the loan started, Bob had deposited at* 5% .

— *Bob's position doesn't have any borrowed funds. Given the fact that Bob wants to lend at* 5%*, that there is still half a year left until maturity and that the borrower will repay 106 at maturity, in order to realize the* 5% *on the remaining time to maturity, he is willing to lend* $106/(1+5\%)^{1/2} = 103.45$ *where* $(1/2)$ *corresponds to the time left until maturity.*

— *Alice receives 103.45 minus an exit cost taken by Atlendis (for simplification purposes here, we'll assume it's zero). Her PnL is* $(103.45 - 100) = 3.45$*, her realized APY is* 6.8%*.*

— *At maturity Bob receives 106, his PnL is* $(106 - 103.45)$*, his realized APY is* 5%*.*

Scenario 4

— *After the loan started, Bob had deposited at* 7%*.*

— *Bob's position doesn't have any borrowed funds. Given the fact that Bob wants to lend at* 7%*, that there is still half a year left until maturity and that the borrower will repay 106 at maturity, in order to realize the* 7% *on the remaining time to maturity, he is willing to lend* $106/(1+7\%)^{1/2} = 102.47$ *where* $(1/2)$ *corresponds to the time left until maturity.*

— *Alice receives 102.47 minus an exit cost taken by Atlendis (for simplification purposes here, we'll assume it's zero). Her PnL is* $(102.47 - 100) = 2.47$*, her realized APY is* 4.9%*.*

— *At maturity Bob receives 106, his PnL is* $(106 - 102.47) = 3.53$*, his realized APY is* 7%*.*

Summary

Bob's Deposit Rate	Alice PnL	Bob PnL	Alice APY	Bob APY
6% = Alice's rate	2.95	3.05	6%	6%
$5\% \leq$ Alice's rate	3.45	2.55	6.8%	5%
$7\% \geq$ Alice's rate	2.47	3.53	4.9%	7%

Adjustment

When an exit occurs, computations of the replacement positions' value at repayment are based on the theoretical original loan amount, which could slightly disadvantage replacing lenders as they would not realize interest on the already accrued interest. To ensure that the replacing lenders receive their desired annual percentage yield (APY), exiting lenders must compensate for this difference.

Example 3.7. *Coming back to example 3.6, scenario 2, to make sure Bob realizes a PnL of*

$$100 \times (1 + 6\%) - 100 \times (1 + 6\%)^{1/2}$$

and not

$$100 \times (1 + 6\%)^{1/2} - 100$$

Alice is required to compensate the unaccrued interest when exiting, enabling Bob to realize his desired APY at maturity. The difference here represents 0.087*. Hence Alice receives* $102.95 - 0.087 = 102.86$ *when exiting and Bob receives* 106 *at maturity.*

Hence recalling the exiting amount formula 1.1, the amount received at exit time is actually the following :

$$\sum_i F_i^t \times q_{i,A} - \sum_i (q_{i,A} - q_{i,A} \times F_i^t) - (q_{i,A} \times F_i^t - q_{i,A} \times F_i^0)$$

where $q_{1,A}, \cdots, _{i,A}, \cdots$ correspond to

$$\text{argmax}_{q_{i,A}} \sum F_i^t \times q_{i,A}$$

such that

$$\begin{cases} 0 \leq q_{i,A} \leq d_i^t / F_t^i \\ \text{and } \sum q_{i,A} = q_A \end{cases}$$

3.4.6 Matching Engine

Order matching is a central element of market microstructure, where the allocation of orders across time and price influences both liquidity and price efficiency. In traditional limit order markets, priority is typically given to best price and then to order arrival time. The protocol adopts a similar logic through its matching engine, implemented entirely on-chain.

Lenders are prioritized first by their chosen rate (lowest rates matched first) and then by the epoch of their deposit, which reflects the time of entry into the pool. An epoch corresponds to a period of time between two borrowing (or further borrowing) actions. Any deposits before an initial borrow correspond to the same epoch. Any deposits past the initial borrow date correspond to a new epoch. The same applies to further borrow actions. When matching the borrower (or accommodating exiting lenders) and lenders, lenders are matched firstly according to their tick's rate (the lower first), and secondly according to their deposit's epoch (the early depositors first). Within the same tick, lenders are matched in a priority order that corresponds to their epoch, meaning that depositors in the tick's oldest epochs are matched first. All epochs are merged at repayment time.

Example 3.8. *Let's consider a borrower with a revolving credit line pool with a* $2,000$ *borrow capacity. Let's say Alice deposited* $1,000$ *in the 5% tick and the borrower borrowed* 500 *from their pool. Let's say Bob deposited in the 5% tick past the initial borrow. Alice*

and Bob's deposits are not part of the same epoch, as Bob's deposit came after the initial borrow date. If the borrower further borrows an additional 500*, only Alice's deposit will be used. However, if the borrower borrows* 750*, both deposits will be used (an additional* 500 *of Alice's deposit and* 250 *of Bob's deposit). Once the borrower repays, both deposits are now part of the same epoch, meaning that if the borrower borrows again, Alice and Bob will be matched proportionally to the amount they provided to the tick's epoch vs. the rest. Note that if Bob had deposited in the 4% tick, his deposit would have been prioritized over Alice's deposit, as it would have been placed at a more favorable rate than Alice's.*

3.5 Protocol Fees

There are four types of fees on Atlendis that go to Atlendis' treasury.

3.5.1 Borrowing Fee

At borrow time, a fee defined as the borrowing fee is applied to the borrower. This corresponds to a fixed percentage applied on the amount borrowed. The current borrowing fee on Atlendis corresponds to a 1% annualized rate.

Example 3.9. *A borrower that borrows* 100 *for 1 year, only receives* 99 *at borrow time, the* 1% *is sent to Atlendis' treasury.*

3.5.2 Interest Fee

At repay time, an interest fee is applied to interest earned by lenders. The current interest fee rate corresponds to 10% meaning that a 10% cut is applied to interest earned by lenders. Interest fees go to Atlendis' treasury.

Example 3.10. *A lender, who lent* 100 *at a* 6% *for one year, receives* 105.4 *at maturity.*

3.5.3 Withdrawal Fee

At withdraw time, a fee is applied to the withdrawn amount. The current withdrawal fee on Atlendis corresponds to $15bp$. Withdrawal fees go to Atlendis' treasury.

3.5.4 Exit Fee

An exit fee is applied to exiting positions. It corresponds to a % applied on the position value. It increases closer to maturity to discourage exiting right before maturity.

Let t be the time elasped since the beginning of the loan cycle and T be the pool's maturity, the current exit fee rate is the following :

$$\begin{cases} 0.25\% + \frac{(0.75\% - 0.25\%)}{0.9} \times t/T \text{ if } t/T \leq 0.9 \\ \\ 0.75\% + \frac{(20\% - 0.75\%)}{0.1} \times (t/T - 0.9) \text{ if } t/T > 0.9 \end{cases} \tag{1.2}$$

with

— initial fee 0.25%.

— first cliff duration 0.9.

— final fee end first cliff 0.75%.

— final fee end second cliff 10%.

Parameters are subject to evolution. Exit fees have the possibility to be redistributed to the remaining lenders via the reward module.

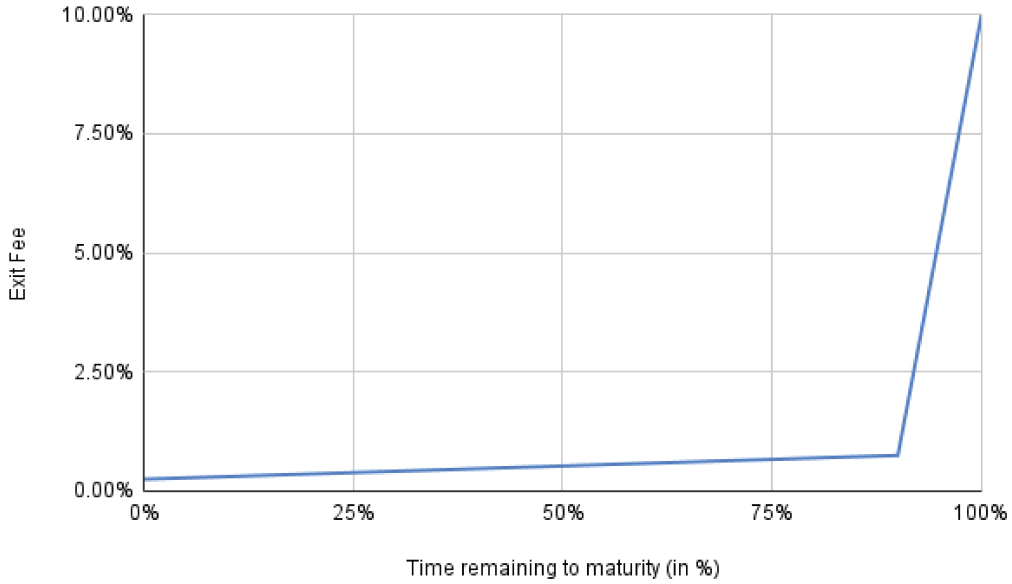

FIGURE 1.4 – Exit fee structure in the Atlendis protocol. The chart shows how the exit fee evolves depending on when a lender withdraws their funds relative to the loan cycle. Withdrawing closer to loan origination triggers a higher fee, while waiting until later stages reduces or removes it.

3.6 Computations Approximation

On-chain computation consumes gas because each arithmetic operation executed by a smart contract requires computational resources from network validators. More complex operations therefore lead to higher transaction costs. In addition to computation, gas also accounts for other resource usage such as memory access and data storage. Approximating these functions reduces the computational load, which helps keep transactions efficient and economically viable

Power functions are thus approximated using a 1st Order Taylor Series. For instance, when computing actualization factors and repayment amount, we use the following approximation :

$$(1+r)^{\Delta T} = 1 + \Delta T \times r$$

where r is the rate per second and ΔT is the number of seconds until maturity. This approximation effectively turns the calculations into a simple interest formula, as it linearizes

the annual compounding effect by only considering the first-order term.

4 Reward / Staking Module

4.1 Defining Liquidity Mining

Liquidity bootstrapping is the primary challenge for new DeFi protocols. TVL measures the overall value of assets currently staked or locked in a specific protocol, and a higher TVL usually signifies greater trust and usage by the community. Protocols face a chicken-and-egg problem : attracting liquidity without substantial TVL (Total Value Locked) is difficult, as existing TVL is a key investment criterion for most DeFi investors.

Some protocols bypass this issue by negotiating off-chain deals to secure their first early adopters. Most, however, implement liquidity mining programs, which subsidize liquidity by distributing incentives via protocol-native tokens. These tokens typically grant holders governance rights over key protocol decisions.

Pioneering lending protocols, such as Aave and Compound, have implemented successful incentive schemes for their lending pools.

4.1.1 History

Liquidity mining was introduced in mid-2020 by projects like Compound and Balancer. These programs encouraged participation through token distribution. Yield farming's popularity quickly grew, enabling liquidity providers to increase their returns on crypto-assets. This led to a proliferation of DeFi projects launching their own yield farming programs with varied tokenomics to attract liquidity. As DeFi evolved, yield farming became more sophisticated, with increasingly complex approaches and refined economic parameters. Yield farming has played a crucial role in the expansion and adoption of DeFi, serving as a powerful marketing tool in an increasingly competitive landscape. Compound (COMP) and Yearn (YFI) are two examples of projects with innovative tokenomics mo-

dels. However, these strategies have limitations, as "yield farmers" often withdraw their liquidity once the incentive program ends.

A more recent approach has been to distribute points instead of tokens or untransferable tokens, which can later be converted to token equivalents at an unknown conversion rate. This allows projects to incentivize liquidity from the start without the risk of launching a token prematurely, setting in stone the project's tokenomics, or concentrating too much governance power. It also helps generate early interest in the protocol and acts as an effective user acquisition strategy.

4.1.2 Aave Liquidity Mining Program

Aave is considered as a foundational lending protocol, serving as a base layer for multiple more recent protocols. As of September 2024, Aave's total value locked (TVL) is $21 billion, with a peak of $32 billion in October 2021. Its native token, AAVE, serves as a governance token, allowing holders to vote on key decisions and serving as mean to align various stakeholders within the Aave ecosystem.

The Aave protocol incentivizes participation through scheduled distributions from the Aave Reserve, rewarding both liquidity providers and users via its Protocol Ecosystem Incentives. As described in [Park, 2024], the AAVE token was launched in September 2020 through a migration from the protocol's original LEND token. Aave allocated 18.75% of the total token supply to incentives over a period of 391 days, with rewards distributed almost evenly between borrowers and lenders. These liquidity mining programs proved effective in attracting capital and expanding Aave's market share across multiple networks. For example, the launch of liquidity mining on Polygon led to a notable increase in total value locked (TVL) and strengthened Aave's position within the Polygon ecosystem.

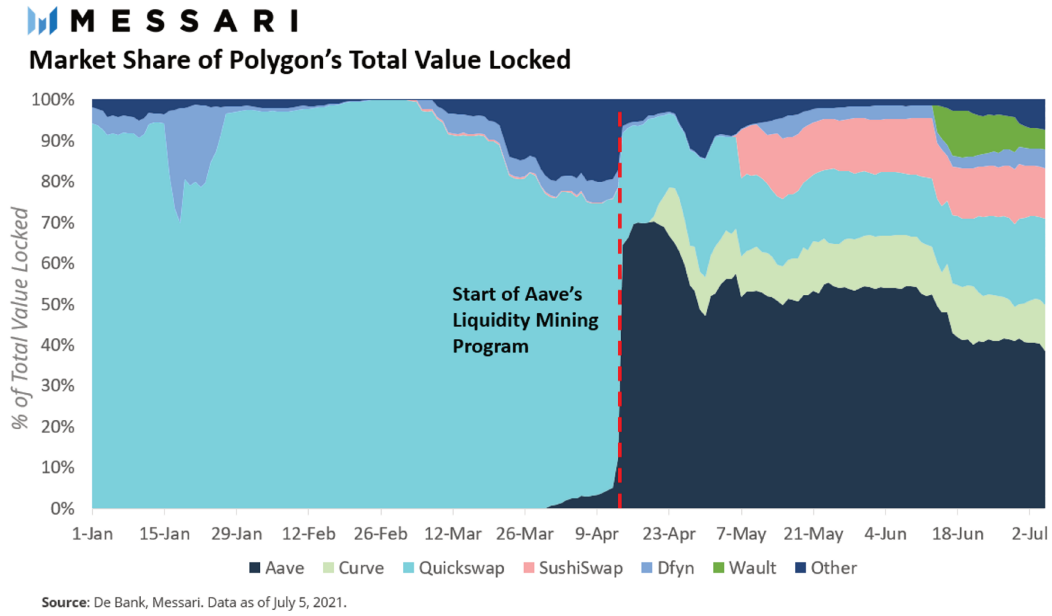

FIGURE 1.5 – Total value locked (TVL) on Aave deployed on the Polygon network. The chart shows how deposited liquidity evolves over time, reflecting user participation and lending activity on this specific deployment of the protocol.

4.1.3 Liquidity Mining Limitations

While liquidity mining programs are highly efficient at attracting liquidity, their discontinuation often leads to withdrawals as the protocol's associated yields decrease. Ideally, the protocol will have grown large enough to become self-sustaining, with a total value locked high enough to attract unincentivized liquidity but it's not always the case. Liquidity that exits after the program ends is typically from token hunters who are only interested in the additional yield provided by the token distribution, rather than the governance power associated with the tokens. These individuals sell the tokens as soon as possible, which creates selling pressure.

Another detrimental behavior is the use of looping strategies, where users amplify returns by repeatedly supplying and borrowing the same crypto assets. This method, often used to increase APY, involves depositing assets into a DeFi platform, borrowing against them, then re-supplying the borrowed assets as collateral to take out more loans, repeating this cycle multiple times. Platforms like Contango offer opportunities for amplified

returns through looping strategies, but these do not come without inherent risks. Looping strategies can boost liquidity rewards for LPs but come at the expense of the protocol, as they contribute to what is referred to as phantom liquidity [Park, 2024]. According to their study, phantom liquidity accounts for 18% of deposits and 31% of loans, with peaks reaching above 80%, and up to 25% of total deposits can be classified as phantom liquidity.

Next, we explore how a liquidity mining program could be adapted to Atlendis auction-based lending pool.

4.2 Defining Atlendis' Reward Modules

Atlendis' Reward Modules was not designed as a reward module per se, but rather as a collection of individual reward modules with their own properties (distribution schedule and tokens distributed). Each lending pool has its own reward module and collection of individual reward modules available to lenders in the pools who wish to stake their positions.

We define as $RM_t^{PoolXYZ}$, the set of all the rewards modules available on Atlendis Pool XYZ at time t and $RM_{i,t}^{PoolXYZ}$, a specific reward module i in place at time t. The number of rewards module n_t is not fixed, it evolves with time depending on liquidity mining programs in place and the business opportunities. Hence Atlendis' Reward Module for Pool XYZ corresponds to

$$RM_t^{PoolXYZ} = (RM_{1,t}^{PoolXYZ}, \cdots RM_{i,t}^{PoolXYZ}, \cdots RM_{n_t,t}^{PoolXYZ}).$$

We distinguish two types of reward modules : continuous reward module and term reward module. They differentiate in the way rewards are distributed.

4.2.1 Continuous Reward Module

As its name suggests, continuous rewards are distributed continuously and not in one-shot at a set date. They can be claimed continuously. There are currently two implementations of continuous rewards that satisfy different use cases.

Fixed Distribution Rate

The amount of tokens distributed to the stakers per unit of time is fixed. It doesn't grow with the total amount staked for instance. It is distributed to stakers continuously, proportionally to what their staked positions are worth in relation to the rest of the staked positions.

Example 4.1. *Let* $10,000$ *be the amount of tokens distributed per day in a set reward module. A staker, with a staked position that represents* $1/10$ *of the staked positions, is entitled to receive* $1,000$ *per day. If the total amount staked evolves and their position decreases to* $1/12$ *of the staked pool, the staker starts earning* 833 *from that day. As rewards are distributed continuously, their past rewards accumulated at a rate of* $1,000$ *per day are still theirs even if they haven't yet been claimed.*

Custodian Rewards

The rewards come from a third-party, for instance a yield provider. The amount of rewards claimable depends on the amount of rewards generated on the custodian by all the staked positions. It is also distributed to stakers continuously, proportionally to what their staked position is worth in relation to the rest of the staked positions.

4.2.2 Term Rewards Module

Term rewards are delivered in one-shot and can only be claimed after a set term date. At staking time, the user must commit to a staking duration defined as the locking period.

The locking period determines the date at which the term rewards become claimable. The position is not locked per se, but if the user unstakes their position before the set term date, they are not entitled to claim their term rewards.

Unlike continuous rewards, the amount of claimable rewards does not depend on the position value vs. the rest of the staked position, but only on the position value itself on which a distribution rate subject to a multiplier is applied.

There are currently two implementations of term rewards that satisfy different use cases.

Distribution Rate as a Function of Locking Period

The distribution rate applied during the staking period is subject to a multiplier that depends on the duration of the locking period. The higher the locking period, the higher the multiplier.

The position rewards are computed as :

$$\text{position rewards} = \text{position value} \times \text{distribution rate} \times \frac{\text{multiplier}}{\text{base multiplier}} \times \text{locking duration}. \tag{1.3}$$

The multiplier is defined as :

$$\begin{aligned} \text{multiplier} = \text{base multiplier} \\ + (\text{max multiplier} - \text{base multiplier}) \\ \times \frac{(\text{locking duration} - \text{min locking duration})}{(\text{max locking duration} - \text{min locking duration})}. \end{aligned} \tag{1.4}$$

Distribution Rate as a Function of Locking Period and Lending Rate

The distribution rate applied during the staking period is subject to a multiplier that depends on the duration of the locking period and the position's lending rate. The multiplier increases with the duration of the locking period but decreases with the position's lending rate.

The position rewards are computed as :

$$\text{position rewards} = \text{position value} \times \text{distribution rate} \times \frac{\text{multiplier}}{\text{base multiplier}} \times \text{locking duration}. \tag{1.5}$$

The multiplier is defined as :

$$\begin{aligned} \text{multiplier} = \text{base multiplier} &+ (\text{max multiplier} - \text{base multiplier}) \\ &\times \frac{(\text{locking duration} - \text{min locking duration})}{(\text{max locking duration} - \text{min locking duration})} \\ &\times \frac{(\text{max rate} - \text{rate})}{\text{max rate}}. \end{aligned} \tag{1.6}$$

4.3 Users Actions

4.3.1 Staking

Definition

Lenders have the possibility to stake their position in a lending pool via its corresponding reward module. In exchange for their position NFT, they receive a staked position NFT that represents their position staked on the reward module.

By staking their position, the users are automatically entitled to all the rewards currently available in the lending pool's reward module. If new reward modules are introduced, the stakers will have to update their staking to become eligible for these new reward modules (see section 4.3.4).

Locking Duration

Staking of positions in **revolving credit line' pools** allow the stakers to choose their locking duration. It is done at staking time and directly impacts the amount of term rewards that they will be entitled to get. Note that the stakers have the liberty of choosing a locking duration of zero but by doing so, they will only be entitled to continuous rewards.

Staking of positions in **loans' pools** does not allow the stakers to choose their locking duration. It is enforced by the smart contracts and corresponds to the amount of time left in the book building phase plus the loan maturity. This insures two things :

— Early depositors in the pool during the book building phase are rewarded more than later depositors. This is important as early participation is crucial to reach the pool's target and achieve a proper rate discovery. It is easier to feel confident supplying liquidity to a pool when a lot of other lenders have already deposited into it.

— The rewards are only claimable at the loan's maturity date. This ensures that lenders who only provide liquidity during the book building phase but withdraw their capital right before the end of that phase do not benefit from the term rewards.

4.3.2 Unstaking

By unstaking their position, stakers exchange their staked position for their original position plus the rewards that they are entitled to, meaning both continuous and term rewards if they haven't been previously claimed. The staked position NFTs are then burnt.

Unstaking can be done at any time. However, if unstaking happens before the end of the locking period set at staking time, the staker must give up their term rewards but their continuous rewards remain unaffected. The locking period must thus be chosen wisely at staking time to avoid this scenario.

4.3.3 Claim Rewards

The users can claim their due rewards at any point in time. If claiming happens before the end of the locking period, only the continuous rewards are claimable. All rewards are claimable after that.

4.3.4 Staking Update

The stakers have the ability to update their staking status to renew their staking duration at the end of the locking period or to become eligible for new reward modules introduced after the initial staking time. In the latter case, note that it does not change the initial locking period for the pre-existing term rewards.

4.3.5 Additional Constraints on RCL Positions

To avoid malicious actors only seeking rewards without the intention of providing borrowable liquidity, some restrictions have been introduced on users' actions on their revolving credit lines' pools' positions. They are as follows :

— A opted out position cannot be staked, nor staking updated.

— A position cannot be opted out if the remaining time in the locking period is higher than the remaining time to maturity (+ a small buffer). The user could unstake their position, stake again for the remaining time to maturity, and opt out their position instead.

— By opting out their position, the staker ceases to benefit from future continuous rewards.

5 Governance

Governance mechanisms are essential to decentralized finance, as they replace the role of centralized oversight with distributed decision-making [Buterin, 2017]. The literature emphasizes the inherent trade-offs between efficiency, inclusiveness, and incentive alignment in such systems [Schär, 2021].

5.1 Aave Governance Model

The AAVE governance system is a multi-layered, complex framework that allows token holders to participate in various aspects of the protocol, including market creation and termination, risk parameter adjustments, ecosystem reserve usage, and the construction of the Safety Module, which protects users in the event of a shortfall. Governance is carried out through the Aave Improvement Proposal (AIP) process and forums that encourage communication between stakeholders. The tokenomics model is designed to incentivize active participation in Aave's governance decisions.

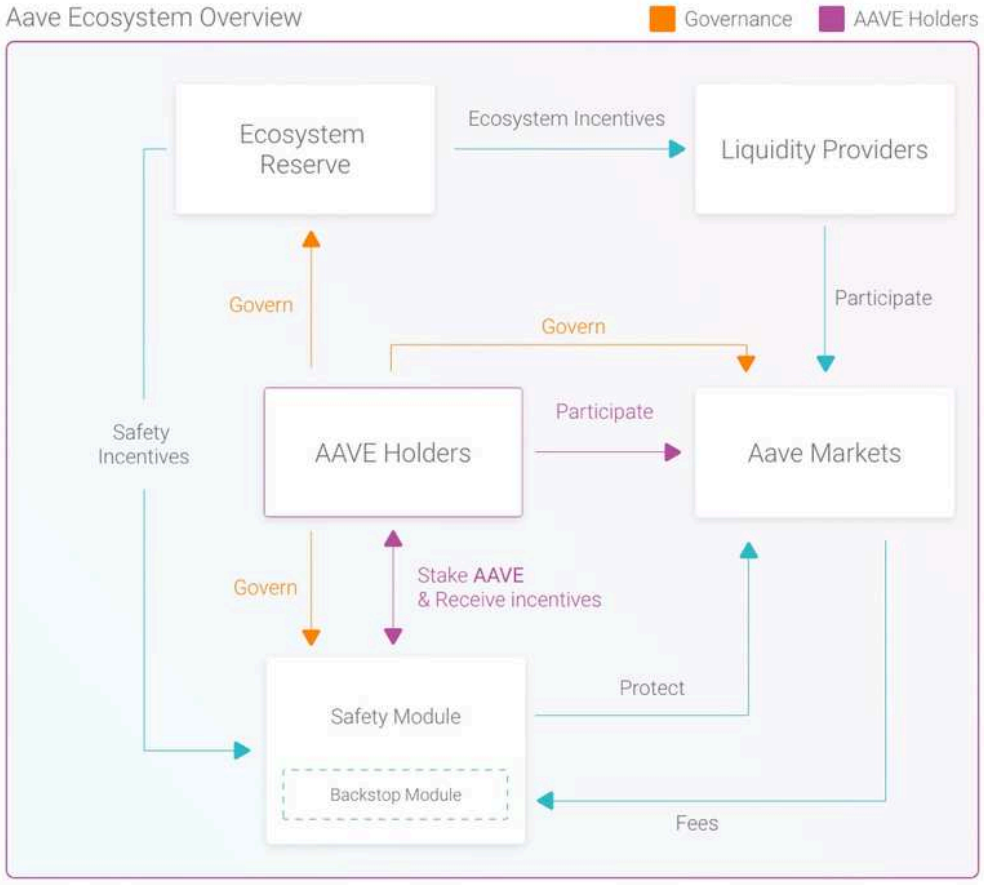

FIGURE 1.6 – Overview of Aave's lending mechanism. The diagram shows how users supply assets to a liquidity pool and receive interest-bearing aTokens, while borrowers can take loans against posted collateral. Smart contracts manage deposits, borrowing, interest rates, and liquidations automatically.

5.2 Atlendis Governance

Atlendis' governance module reflects these tensions by granting stakeholders authority over parameter updates, non-standard repayment procedures, and treasury management.

Key decisions, such as the activation of early repayment features or the resolution of delinquent loans, are determined collectively. Atlendis Governance has important privileges in the protocol, and constitutes a point of failure. For these reasons, what the governance address can and can not do should be understood by users.

Governance actions can be separated into four categories :

— Maintain protocol : deploy new products factories, upgrade contracts etc

— Pool day to day operations : deploy pools, allow and disallow users addresses (borrowers, lenders, fees operator)

— Manage Pool parameters : change pool parameters (for example update maximum borrowable amount, update minimum deposit amount)

— Handle Pools non standard resolution paths : start and execute non standard repayment procedure (see Appendix - Non Standard Repayment Procedure), and start and execute rescue procedure

Note that the two non standard resolution paths are the only instances in which governance might have access to users funds, mainly to recover them in case of unforeseen issues. For that reason, these operations are behind timelocks, which means that there will have to be a fixed amount of time between the starting of the procedures and their execution, leaving the time for users that don't agree with the procedures to manage their positions accordingly.

For all the reasons described above, governance addresses management is very sensitive and will be handled with great attention by the Atlendis Labs team.

6 Conclusion

This essay has explored the design of a decentralized lending protocol that seeks to go beyond the onchain overcollateralized models common in DeFi markets. By examining the architecture of Atlendis and its main components, it shows how core credit intermediation functions can be adapted to a permissionless, algorithmic setting.

A key takeaway from this analysis is the significant impact of technological constraints on protocol design. Choices related to pricing mechanisms, liquidity management, and user incentives are shaped by the economic and computational limits of public blockchains, including gas costs, storage capacity, and execution complexity. These factors define what is technically feasible and require trade-offs between flexibility, efficiency, and security, which differ in important ways from those in traditional financial systems.

With the evolution of blockchain since the design of this protocol, greater scalability and lower transaction costs have expanded the range of viable design choices. Yet the fundamental challenge remains the same : translating financial mechanisms into forms that are robust, transparent, and efficient under decentralized execution.

In summary, the design of Atlendis shows that lending without on-chain overcollateralization is possible when off-chain credit processes are combined with decentralized execution. This chapter also shows how financial mechanisms need to adapt to the technical limits of blockchain, which influence the range of possible protocol designs. The next essay builds on these ideas by formalizing the tick-based lending mechanism as a multi-unit auction and studying its main properties.

Chapitre 2

Rate Discovery in Decentralized Lending

Objectives

This chapter presents a novel framework for interest rate discovery within the decentralized finance (DeFi) ecosystem, addressing the theoretical and practical challenges inherent in decentralized lending mechanisms. By examining the dynamics of lending pools and the integration of borrowers' risk profiles with market liquidity conditions, we propose a model that facilitates the determination of equitable borrowing rates without reliance on intermediaries. Our approach seeks to elucidate the underlying mechanisms of rate formation in a decentralized context, thereby contributing to the theoretical discourse on financial decentralization. Through simulation-based analysis, we explore the potential of our framework to enhance transparency and fairness in DeFi lending practices. The findings suggest that our model not only aligns incentives between lenders and borrowers but also fosters a more informed and stable lending environment, offering a robust alternative to traditional financial systems.

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1 Introduction

The determination of interest rates in financial markets is a multifaceted process influenced by a variety of factors, ranging from individual creditworthiness to broader macroeconomic conditions. Traditional financial systems have long relied on intermediaries, such as banks, to assess borrower risk and set interest rates accordingly. However, this reliance on centralized institutions introduces challenges related to information asymmetry [Bester, 1985 ; Stiglitz, 1981], where lenders possess more information than borrowers, leading to potential inefficiencies and inequities in lending practices.

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

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

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

The findings suggest that our model not only aligns incentives between lenders and borro-

wers but also fosters a more informed and stable lending environment. By encouraging the disclosure of financial information and leveraging market dynamics, our approach contributes to the theoretical discourse on financial decentralization and offers insights into the potential of DeFi to provide reliable lending and borrowing options in a decentralized manner. Moreover, this paper delves into the implications of our proposed framework for the broader financial ecosystem, examining its potential to address longstanding issues related to information asymmetry and credit rationing. By advancing our understanding of decentralized rate discovery mechanisms, we aim to contribute to the ongoing evolution of DeFi and its integration into the global financial landscape.

List of Symbols

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

2 Interest Rate Model in DeFi

Lending protocols such as Aave, Compound, MakerDAO, and dYdX have established a robust foundation for the lending market in DeFi [Xu, 2021]. These protocols signify a substantial advancement for DeFi, given the critical role of lending operations in the economy. They enable cryptocurrency holders to earn interest on their assets in a permissionless manner, thereby democratizing access to financial services.

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

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

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

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

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

where :

R_0 is the minimum interest rate charged to borrowers when the utilization rate is at

its lowest. It represents the baseline cost of borrowing, irrespective of the demand for the asset. The base rate is typically set to cover the basic operational costs and risks associated with lending.

R_{slope_1} determines the rate of increase in the interest rate as the utilization rate rises from 0% to the optimal utilization rate . It reflects how sensitive the interest rate is to changes in utilization within this range. A steeper slope indicates a more rapid increase in the interest rate as utilization increases, incentivizing borrowers to repay their loans or suppliers to provide more liquidity as demand rises.

R_{slope_2} governs the rate of increase in the interest rate when the utilization rate exceeds the optimal utilization rate). It is generally steeper than to discourage high utilization, which could lead to liquidity shortages. A higher ensures that as the pool becomes more utilized, the cost of borrowing increases significantly, encouraging repayments and additional supply to maintain liquidity.

The model parameters (R_0, U_{optimal}, R_{slope_1}) are asset dependent. The interest rates parameters of assets with lower liquidity levels are more conservative. Model's parameters can also be subject to change depending on market conditions.

By understanding and effectively managing the utilization rate, DeFi protocols can incentivize behaviors that support liquidity and optimize capital allocation, thereby enhancing the overall functionality and reliability of the decentralized lending ecosystem.

The current landscape of decentralized finance (DeFi) lending is primarily focused on highly collateralized borrowing, where borrowers must provide collateral equal to or greater than the borrowed amount. This approach ensures repayment and minimizes default risk by enabling the sale of collateral in case of extreme market fluctuations [Qin, 2021]. The borrowing rate is influenced by liquidity in the pool, rather than reflecting the financial health of the borrower ; it is more indicative of liquidity and market risk. Hence, when considering over-collateralized lending, the extent to which DeFi lending protocols facilitate true borrowing, where an agent gets into a position of net debt, is limited, creating a gap compared to traditional finance (TradFi) offerings.

To bridge this gap, a potential solution involves reducing the on-chain collateral requirement by replacing it with off-chain collateral that can be materialized through the creation of a dedicated Special Purpose Vehicle (SPV). Rather than having the corporation serve as the legal obligor, an SPV structure leverages the advantages of traditional securitization frameworks. It does this by collateralizing the loan with a diversified asset portfolio within an SPV and subjecting these assets to eligibility criteria, robust portfolio covenants, and comprehensive legal recourse. Another solution lies in the tokenization of off-chain assets, allowing them to serve as collateral on-chain. By making the collateral ratio variable, we preserve the signaling role of collateral quality while enabling more flexible borrowing conditions [Bester, 1985]. By reducing the on-chain over-collateralization requirement, we introduce default risk, posing a challenge in determining a borrowing rate that accurately reflects the borrower's financial risk without relying on a third party or arbitrarily adding a risk premium to the existing algorithmic rate model.

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

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

3 Lending Pools Framework to Enable a Decentralized Rate Discovery

The lending process is initiated by the creation of a lending pool on-chain. These pools are tailored to individual borrowers and possess distinct characteristics, including the desired

loan type, loan amount K, maturity period, and token type. We denote $LP_{B,\tau}$ as a lending pool assigned to borrower B, and $D_{LP_{B,\tau}}$ represents the total deposit amount within that particular pool.

3.1 Pre-Pool Opening Phase

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

3.2 Lending Pool as a Set of Ticks

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

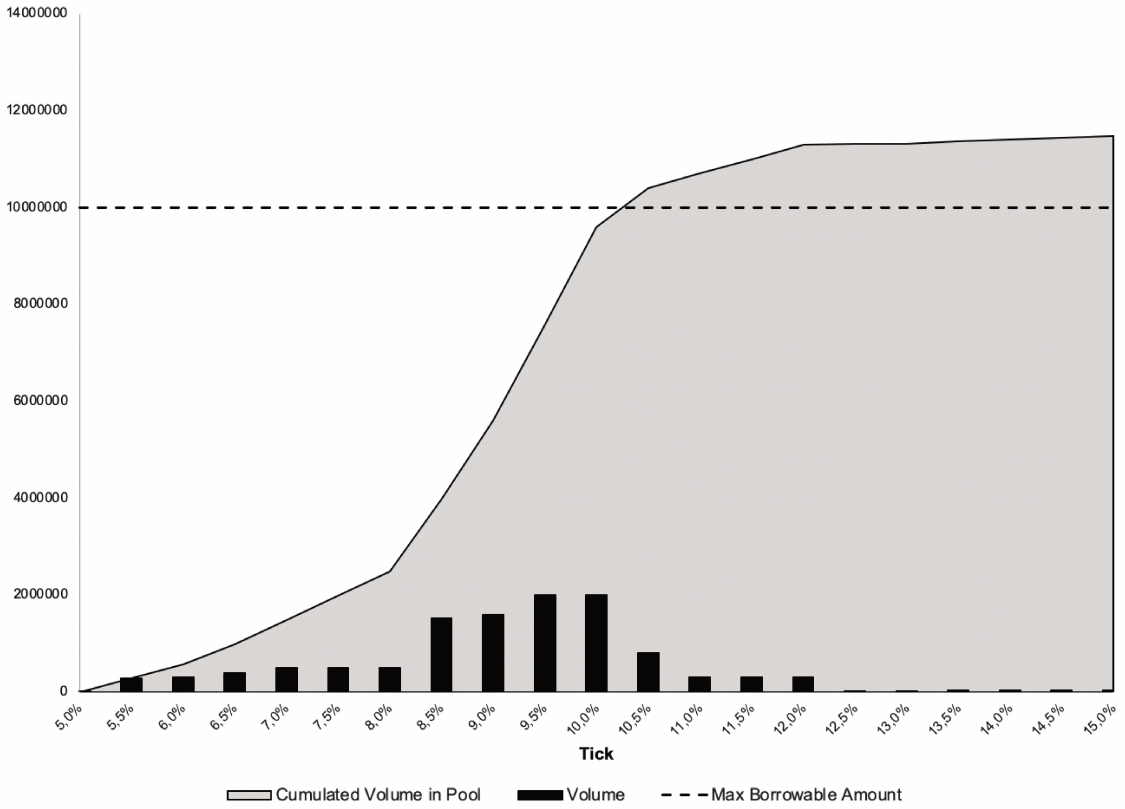

FIGURE 2.1 – Borrower's lending pool represented as an order book. Each tick corresponds to a specific interest rate and amount of available liquidity, and together they form the supply curve lenders offer to borrowers.

The integration of auctions and ticks in decentralized lending frameworks offers several advantages over traditional DeFi models like Aave. Auctions facilitate market-driven rate discovery by leveraging competitive bidding [Klemperer, 1999 ; Milgrom, 1981] , ensuring rates reflect true market values and enhancing transparency and fairness [Krishna, 2002 ; Myerson, 1981]. The use of ticks allows for granular rate adjustments, dynamically aligning lending rates with market conditions [Ausubel, 2004 ; McAfee, 1987] and incentivizing information disclosure. This approach can lower transaction costs [Rothkopf, 1990] by streamlining the lending process. Academic literature supports these benefits, highlighting the efficiency and effectiveness of auction mechanisms in promoting accurate rate determination and market stability.

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

3.3 Book Building Phase

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

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

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

TABLE 2.1 – Order book representation of a lending pool. Each row shows a bid with its interest rate r_i, available deposit d_i, the implied bond price p_i for a zero-coupon bond of face value 100 maturing at T, and the corresponding number of bond units that can be bought with the available deposit.

where :

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

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

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

3.4 Loan Origination Phase

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

Lenders are provided with their chosen lending rate, resembling a form of discriminatory auction where the winning participants pay their bid prices [Klemperer, 1999]. It is essential to emphasize that, given the on-chain nature of bids, the auction is not sealed but open, fostering transparency and accessibility. The borrowing rate is simply the lowest volume-weighed rate that corresponds to the amount borrowed. It is derived from the ticks and is the result of the amount available in each tick. The borrowing rate is fixed and does not change during the life period of the loan.

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

Monostori [Monostori, 2014] suggests that the choice of auction format can significantly impact the behavior of bidders and the functioning of the primary market. Monostori's findings indicate that uniform-price auctions tend to attract a larger number of bidders and enhance the role of the primary market compared to discriminatory-price auctions [Engelbrecht-Wiggans, 2006]. However, a deeper analysis of discriminatory-price auctions

reveals potential advantages, such as ensuring continuity of financing, reducing volatility on the primary market, and preventing collusion. This is supported by Morales-Camargo et al [Morales-Camargo, 2013], who argue in favor of discriminatory auctions, contrary to the conclusions drawn by proponents of uniform-price auctions. Furthermore, Goldreich [Goldreich, 2007] highlights the susceptibility of uniform-price auctions to overbidding, as participants attempt to signal the secondary market, indicating potential drawbacks of this format. Additionally, Myers et al. [Myers, 2021] emphasize the increased risk of collusion in uniform auctions, particularly in repeated settings, due to the payoff irrelevance of infra-marginal bids. It is crucial to acknowledge that the advantages of each auction format may vary based on specific market conditions and the objectives of the issuer. This is in line with the study by Beierlein and Katô [Beierlein, 2003], which highlights the trade-offs between auction formats, indicating that uniform-price auctions achieve lower award concentration and higher average revenues but experience higher revenue variance compared to discriminatory-price auctions. Therefore, Monostori's article concludes that the choice between auction formats should be carefully considered based on the specific context and desired outcomes. Hence, the decision to prefer discriminatory matching over uniform for practical reasons does not contradict observed choices in Monostori's article [Monostori, 2014].

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

contributes to the overall effectiveness of the smart contract implementation.

3.5 Loan Life Period

Depending on the type of loan, borrowers are required to make principal and interest payments either before or at maturity. Throughout the loan duration, lenders with unused funds in the pool can withdraw their remaining amount at any time. This allows for the withdrawal of pre-maturity interest payments and installment payments. Once the final payment is made, all liquidity providers can freely withdraw their funds from the lending pool.

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

4 Modeling the Rate Discovery

4.1 Rate Discovery Game Framework

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

Our game model comprises the following components :

1. **Players :** One borrower, N lenders.
2. **Action Sets :**

— $A_{\text{lender}} = \{$*does not deposit, deposits any amount between 1 and K at a rate in the range* r_1 *to* r_n*, updates rate of an existing position*$\}$

— $A_{\text{borrower}} = \{$*borrows K, does not borrow*$\}$

3. **Choice Nodes :** Lenders are free to deposit and/or update their rate until the end of the book-building phase. The borrower cannot perform any action before the end of that phase.
4. **Terminal Nodes :** At the end of the book-building phase, the borrower can either borrow or not borrow.

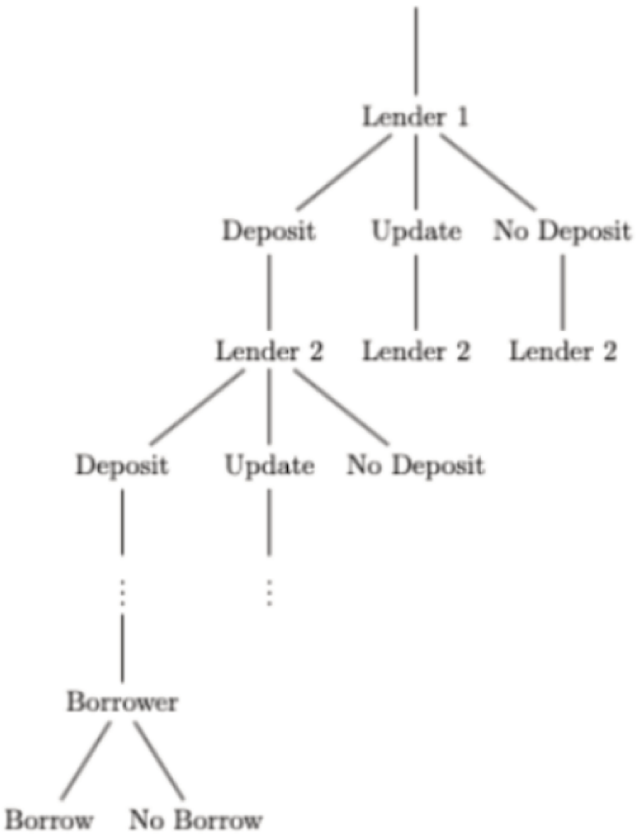

FIGURE 2.2 – Game tree of the rate discovery mechanism. Lenders move sequentially and, at each stage, can either deposit funds, update their previous rate, or choose not to deposit. After all lenders make their decisions, the borrower chooses whether to borrow or not based on the resulting order book.

We make the following assumptions :

— We consider a borrower who has placed a significant amount as collateral and is a repeat borrower, thus being cautious about reputation risk. This implies that the

borrower will not default maliciously and that there is no incentive for them to borrow regardless of the borrowing rate.

— The borrower expects to make a certain return on investment (ROI) on the borrowed amount, and any additional cost from borrowing is priced into the ROI. The ROI corresponds to the borrower's reserve rate, which is the maximum rate that they are willing to accept for each unit. If the reserve rate is too low, there may not be enough lenders willing to bid at or below that rate, and the auction will not generate any revenue. If the reserve rate is too high, the borrower may not get the maximum revenue possible.

— The ROI is known by the lenders, or the borrower discloses a maximum rate at which they'd be willing to borrow, which is representative of the ROI. The assumption that borrowers' reserve rates (ROI) are known to lenders may be supported through verifiable disclosures. In practice, this could be enabled by cryptographic tools such as zero-knowledge proofs, DAO-approved financial statements, or decentralized credit scoring protocols. These mechanisms would allow borrowers to demonstrate expected returns without compromising decentralization or privacy.

— We assume heterogeneous beliefs among lenders. Each lender k associates a default probability $p_{d,k}$ to the borrower which remains constant throughout the game. The assumption of heterogeneous beliefs among bidders is well-supported by the literature. Ockenfels & Roth [Ockenfels, 2006] discuss the incidence of multiple bidding and its relation to late bidding, indicating that bidders may have varying beliefs about the auctioned item, leading to diverse bidding behaviors. Li & Zheng [Li, 2009] develop an empirical model of entry and bidding controlling for unobserved auction heterogeneity, highlighting the presence of diverse beliefs among bidders in auction settings. Krasnokutskaya [Krasnokutskaya, 2011] and Decarolis [Decarolis, 2018] emphasize the importance of considering unobserved auction heterogeneity and the impact of asymmetric information, which can be indicative of heterogeneous beliefs among bidders. Moreover, Crosetto et al. [Crosetto, 2020] provide evidence that individual belief reports can be rationalized by subjective beliefs that differ from the objective truth, further supporting the presence of diverse beliefs among bidders in auction scenarios.

— We define as RR the recovery rate, the estimated percent of the loan that will still be repaid to creditors in the event of default or bankruptcy.

— We set the risk free rate to zero without loss of generality.

— As borrowing time is known and lenders have the ability to update their rate, we assume that lenders choose their lending rate with the knowledge of all the choices made by others. This implies that we are considering a finite perfect information game, and at least one pure strategy Nash equilibrium exists.

4.2 Objective Definition

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

— Convergence : We aim to understand the mechanism that links the borrowing rate to the borrower's default probability that is assessed by the market

— Speed of Convergence : Literature has shown that in centralized lending processes, banks can fail to discriminate between risky and non-risky borrowers [Stiglitz, 1981 ; Bester, 1985]. In decentralized lending, borrowers are compelled to provide their own information since there is no third party to furnish it. In the early 1980s, particularly in works by Milgrom [Milgrom, 1981] and in collaboration with Weber [Milgrom, 1982], significant advancements were made in auction theory. This research explored scenarios involving both private and common values, within reasonably straightforward mathematical conditions governing bidder information and value distribution. Milgrom's comprehensive analysis shed light on instances where sellers could potentially increase their revenues by sharing expert appraisals, like authenticity certificates or inspection protocols, with prospective bidders [Klemperer, 2004]. We will try to assess whether our rate discovery model can serve as an incentive for borrowers to provide more information, thus enabling their borrowing rate to converge more rapidly.

We proceed to assess our model equilibrium and evaluate whether it corresponds to len-

ders depositing in a tick that represents their true valuation of the borrower's default probability.

5 Multi-Unit Game under Perfect and Complete Information

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

5.1 Game Description

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

5.2 Utility Functions

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

5.2.1 Lenders

For lender k, who deposits m at tick r_i, the lender's utility function *conditional on the borrower borrowing* (event B) is

$$u_k(m, r_i \mid B) = m\Big[(1 - p_{d,k})\, r_i - p_{d,k}\,(1 - RR)\Big]\mathbf{1}_{\{CD_{r_i} \leq K\}},$$

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

5.2.2 Borrower

For the borrower, who borrows a total amount K, the utility function is defined as

$$u_{\text{borrower}}(K \mid B) = K\Big(ROI - \sum_i \delta_i \, r_i\Big),$$

where ROI denotes the expected return on investment, and the allocation vector $\boldsymbol{\delta} = (\delta_1, \delta_2, \ldots, \delta_n)$ solves

$$\boldsymbol{\delta} = \arg \min_{\substack{0 \le \delta_i \le d_i \\ \sum_i \delta_i = K}} \sum_i \delta_i \, r_i.$$

5.3 Equilibrium

Let $r_{borrowing}$ be the rate that corresponds to the one that would have been achieved if the borrower were to borrow K in the current state. We observe that in the case where the total value in the pool is lower than K, it is a strictly dominant strategy for all lenders to deposit at the rate that corresponds to the borrower's ROI as it maximizes their utility function. However, if the total value in the pool exceeds K, the lenders are incentivized to deposit at a lower rate. If a certain percentage of the lenders are willing to lower their rate, in that case, they will lower their rate as low as they need in order to guarantee matching. We can derive an analogy between our model and the model described by Ausubel [Ausubel, 2004] who proposes an ascending-bid auction for multiple objects. Nonetheless, in our model, the bids (both the lending rate and the deposit amount) are updated not because the auctioneer raises the price but because bidders might want to lower their bidding rate to ensure matching. In the Ausubel auction, sincere bidding is an ex-post equilibrium [Masuda, 2022] meaning that it is in the best interest of each bidder to submit sincere bids and accurately reveal their valuations for the items they want. In hindsight, after the auction concludes, no bidder could have achieved a better outcome by submitting

dishonest or manipulative bids. The auction's design encourages truthful bidding, making it a strategy-proof mechanism. In our model, lenders will only be inclined to lend at their 'true value rate' r^* if their true value rate is below ROI and $CD_{r^*+\text{rate spacing}} > K$. Overall, this requirement for lenders to deposit at their true value implies that the pool's total value must significantly exceed the amount to be borrowed, which leads to challenges in terms of capital efficiency.

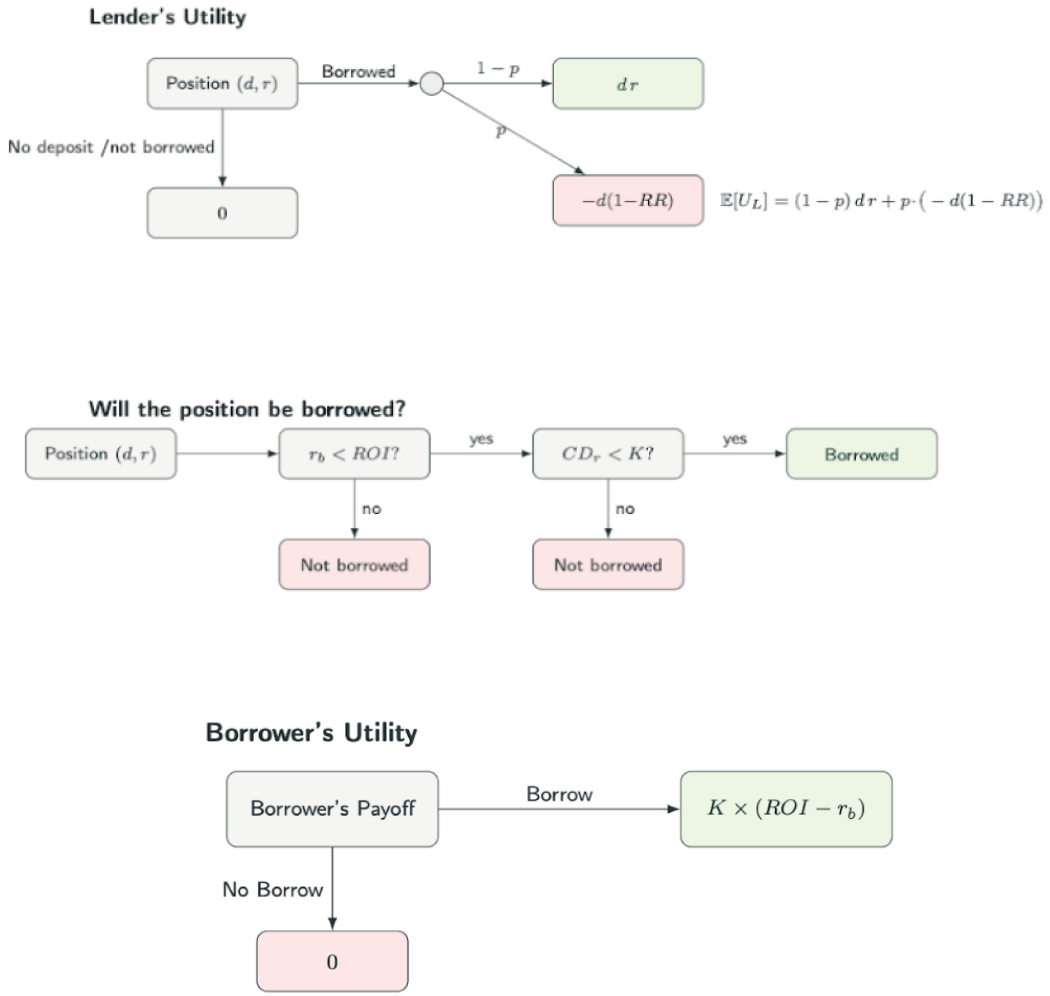

FIGURE 2.3 – Utility functions used in the game. The first panel shows the lender's utility as a function of the interest rate and allocated amount. The second panel shows the borrower's utility depending on the total borrowed amount and the implied borrowing cost.

5.4 Numerical Illustration

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

We use the following parameters :

— Order book range from 2% to 18%, rate spacing of 0.5%
— Target loan amount : 100,000
— Declared reserve rate 15% : the borrower declares that they will only be willing to borrow if their borrowing rate is lower or equal to 15%.
— Recovery rate 30%
— Lenders deposit sequentially in the pool. They choose their rate in order to maximize their utility function based on the status of the pool at deposit time.
— They can only deposit once in the pool but can update their rate later. One deposit corresponds to one time stamp.
— Lenders can freely update their rate based on the other lenders' bids until the end of the auction. Their decision is also driven by their utility function.
— For simplicity, the amount deposited by each lender is the same and does not change throughout the duration of the book building phase. It differs for Borrower A and Borrower B as explained below.

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

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

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

To account for increased risk aversion for Borrower B and lower uncertainty for Borrower A, we model differently the lenders' bidding behavior. Esö & Szentes [Eső, 2007] argue that in auctions, information plays a crucial role in attracting bidders. They discuss how the level of information affects bidder participation and the optimal strategy for the seller in disclosing information. From their research, we can derive that an auction with more information on the valued item will attract more bidders compared to an auction with less information. Cohen & Einav [Cohen, 2007] conducted research on risk preferences by analyzing deductible choices in insurance. Although their study focuses on insurance deductibles, it provides insights into risk aversion and decision-making under uncertainty. In their benchmark model, they assume that individuals have full information about their risk exposure and level of risk aversion. This assumption implies that individuals with more information are better equipped to assess their risk profile accurately. Therefore, a risk-averse agent with more information on the Borrower would be more likely to choose a lower lending rate. Hinz & Spann (2008) [Hinz, 2008] find that the amount and dispersion of information significantly impact bidding behavior. They demonstrate that more information and greater dispersion of information lead to more competitive bidding behavior. Additionally, they highlight the importance of betweenness centrality in the social network context, indicating that individuals who are well-connected and have access to diverse information sources are more likely to exhibit competitive bidding behavior.

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

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

5.5 Analysis

TABLE 2.2 – Simulated evolution of borrowing conditions in a DeFi lending pool for two different borrowers. At different time steps, the table reports the total value locked (TVL) available to each borrower, the average borrowing rate they face, and the standard deviation of that rate as a proxy for rate volatility. Higher TVL corresponds to deeper liquidity, which generally leads to lower borrowing rates.

(a) Borrower A

Time	TVL	Avg rate (%)	Std (%)
20	$100,000	15.00	0.00
40	$200,000	11.22	0.05
100	$500,000	9.75	0.06

(b) Borrower B

Time	TVL	Avg rate (%)	Std (%)
20	$60,000	15.00	0.00
40	$120,000	14.07	0.05
100	$300,000	9.82	0.06

5.5.1 Convergence

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

5.5.2 Speed of Convergence

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

5.5.3 Gas Consideration

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

5.5.4 Gas and Capital Efficiency

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

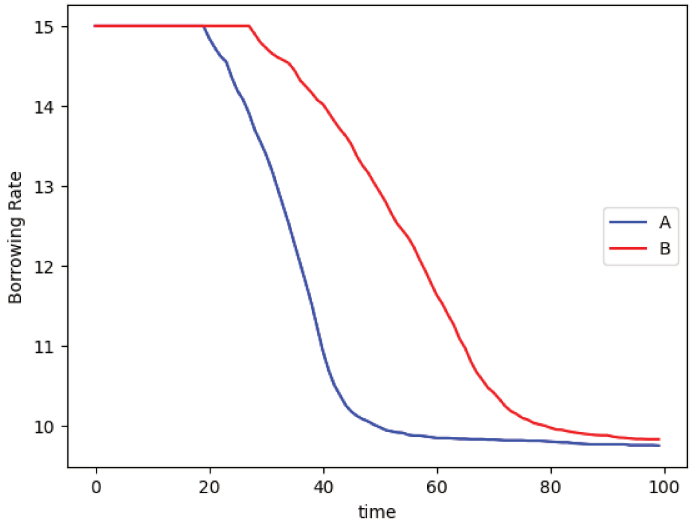

FIGURE 2.4 – Evolution of the theoretical borrowing rate over time for Borrower A and Borrower B. The curves reflect how the rate adjusts based on the liquidity available in the pool and the borrowers' demand.

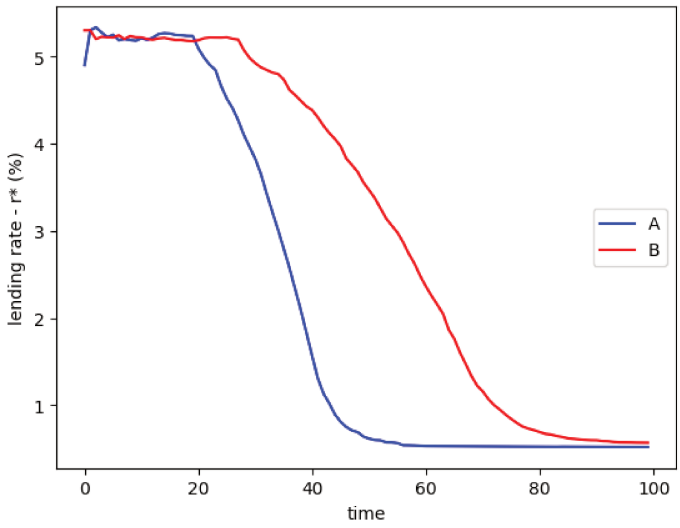

FIGURE 2.5 – Lending rate over time compared to the reference rate r^*. The plot shows how the pool rate converges towards or diverges from r^* depending on borrowing activity and available liquidity.

6 Multi-Unit Game under Perfect and Incomplete Information

6.1 Game Description

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

— Type 1 : probability q_1, high liquidity needs : they will borrow K_1

— Type 2 : probability q_2, medium : they will borrow K_2

— Type 3 : probability q_3, low : they will borrow K_3

with $K_1 > K_2 > K_3$ and $q_1 + q_2 + q_3 = 1$.

We also make the following assumptions :

— The lenders are unaware of the borrower's type.

— All lenders associate the same probability q to each opportunity leading to r^*, the lowest rate at which the lender would be willing to lend to maintain a positive utility function.

— The reserve price / ROI on each business opportunity remains constant

6.2 Utility Functions

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

6.2.1 Lenders

For lender k, who deposits m at tick r_i, the lender's utility function *conditional on the borrower borrowing* (event B) is

$$u_k(m, r_i \mid B) = m\Big[(1-p_{\text{default}})\, r_i + p_{d,k}\,(1-RR)\Big]\Big(q_1\,\mathbf{1}_{\{CD_{r_i}\le K_1\}} + q_2\,\mathbf{1}_{\{CD_{r_i}\le K_2\}} + q_3\,\mathbf{1}_{\{CD_{r_i}\le K_3\}}\Big).$$

6.2.2 Borrower

For a borrower taking a total loan amount M, the utility function is

$$u_{\text{borrower}}(M \mid B) = \frac{1}{M}\sum_i \delta_i\, r_i,$$

where the allocation vector $\boldsymbol{\delta} = (\delta_1, \delta_2, \ldots, \delta_k)$ solves

$$\boldsymbol{\delta} = \arg \min_{\substack{0\le\delta_i\le d_i \\ \sum_i \delta_i = M}} \sum_i \delta_i\, r_i.$$

6.3 Numerical Illustration

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

— Order book range from 2% to 20%, rate spacing of 0.5%

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

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

6.4 Analysis

6.4.1 Convergence and Speed of Convergence

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

TABLE 2.3 – Total value locked (TVL), average borrowing rate, and rate volatility over time for Borrower A and Borrower B in the simulated lending pool. Higher TVL corresponds to lower borrowing rates as liquidity increases.

(a) Borrower A

Time	TVL	Avg rate (%)	Std (%)
10	$50,000	14.34	0.00
20	$100,000	11.34	0.00
40	$200,000	9.55	0.05
100	$500,000	9.05	0.06

(b) Borrower B

Time	TVL	Avg rate (%)	Std (%)
10	$30,000	14.44	0.00
20	$60,000	12.95	0.00
40	$120,000	9.76	0.05
100	$300,000	9.15	0.06

their borrowing rate and reach their true borrowing rate at a faster pace ie. with a lower amount of TVL.

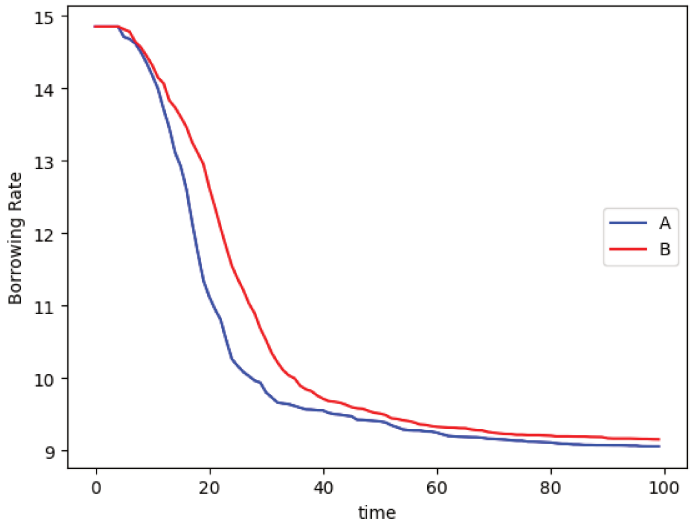

FIGURE 2.6 – Simulated borrowing rate over time for Borrower A and Borrower B under the Bayesian updating mechanism. The rate adjusts as lenders update their beliefs about borrower risk based on previous borrowing activity and available liquidity in the pool.

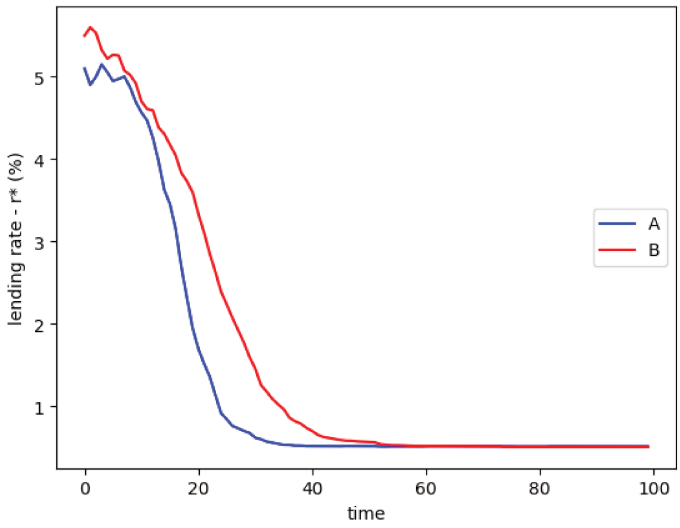

FIGURE 2.7 – Lending rate over time compared to the reference rate r^* under Bayesian learning. The figure shows how lending rates converge or diverge from r^* as lenders update their expectations based on pool utilization and past repayment outcomes.

6.4.2 Comparison with Previous Model

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

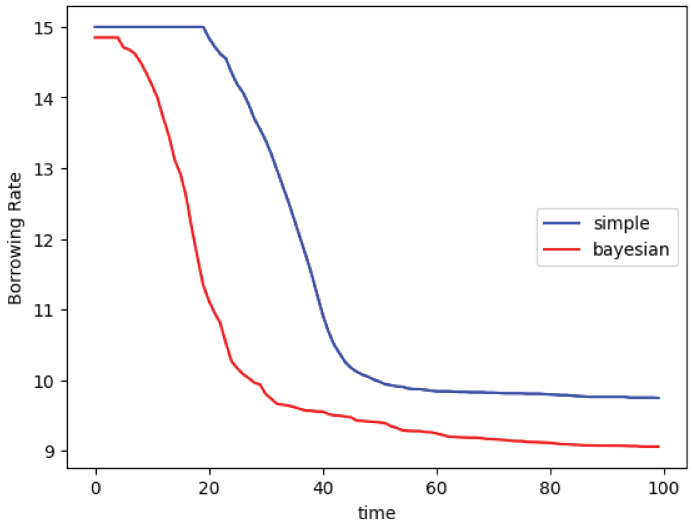

FIGURE 2.8 – Borrowing rate over time for Borrower A in the Bayesian setting. The rate adjusts as lenders update their beliefs based on observed borrowing behaviour and liquidity available in the pool.

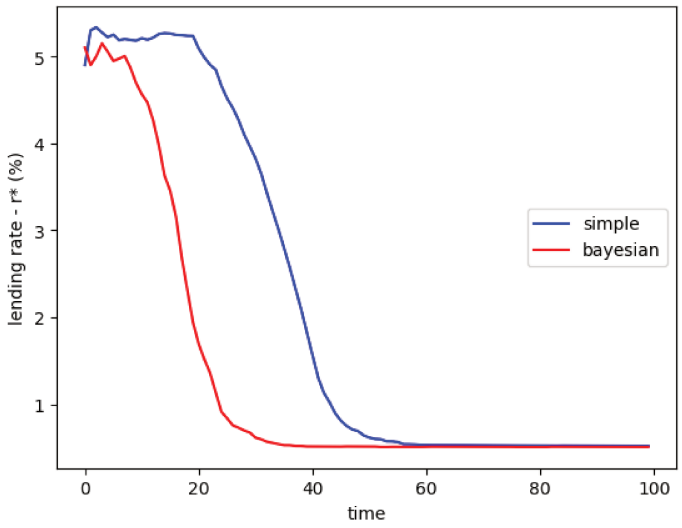

FIGURE 2.9 – Lending rate faced by Borrower A over time compared to the reference rate r^*. The rate reflects lenders' Bayesian belief updates and pool utilization levels.

7 Model Representation Limitations

7.1 Borrower's Creditworthiness

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

However, this assumption becomes more tenuous when applied to "traditional" borrowers, such as individuals or conventional businesses. These entities may not operate on blockchain platforms and thus do not benefit from the same level of automated transparency. For example, a small business seeking a loan in a DeFi platform might not have its finan-

cial records or operational data readily accessible on a blockchain, making it challenging for lenders to assess creditworthiness with the same degree of confidence as they would with a DAO.

Stiglitz and Weiss [Stiglitz, 1981] argue that when there is imperfect information, lenders may not be willing to lend to all borrowers who are willing to pay the market interest rate. Stiglitz and Weiss suggest that governments can address credit rationing by providing more information about borrowers' creditworthiness, either directly or through institutions such as credit bureaus. This can help lenders make more informed lending decisions and reduce the need for credit rationing. In decentralized finance, this can be replicated by creating data room accessible to all potential lenders where the borrowers could freely disclose all their financial documents. A limitation would be to verify the validity of the documents and ensure that everything has been shared.

7.2 Unknown Borrowed Amount

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

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

bidding process.

7.3 Market Frictions.

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

7.4 Lenders' Interactions

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

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

The impact of lenders' interactions on credit markets has been widely studied in the finance literature. Martin and Ventura [Martín, 2012] shows how banks' decisions to lend to each other can lead to systemic risk and banking crises. In the context of decentralized lending, lenders' interactions may also play a significant role in determining the efficiency and stability of the lending market.

One way to address the issue of lenders' interactions is to introduce mechanisms that encourage lenders to share information and collaborate. For example, lenders could be

incentivized to share their expertise or data about borrowers, or to form coalitions that jointly assess borrowers' creditworthiness. Such mechanisms could lead to a more efficient allocation of credit and reduce the risk of cascading defaults. However, implementing such mechanisms would require overcoming coordination and free-riding problems, as well as ensuring that lenders do not collude to manipulate the lending market.

8 Conclusion

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

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

Chapitre 3

What drives DeFi Token Prices ?

Objectives

This chapter studies how economic and behavioural factors explain returns of DeFi protocol tokens. It uses weekly data for 43 major tokens from 2019 to 2025. The analysis combines market variables, trading activity, and on-chain measures such as Total Value Locked with proxies for lottery preference, recency bias, salience, and anchoring. A two-way fixed effects panel with BIC-based selection and Fama MacBeth regressions is applied. Results show that anchoring, recency bias, trading volume growth, and TVL dynamics are systematically related to returns. The findings indicate that DeFi token prices reflect both behavioural distortions and protocol usage.

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1 Introduction

This article focuses on the pricing dynamics of tokens issued by decentralised finance (DeFi) protocols. DeFi tokens are tied to decentralised protocols such as lending markets, decentralised exchanges, or liquid staking platforms. Their value often depends on protocol usage, user activity, and token economics.

Despite rapid growth and adoption, crypto market display high volatility and weak links to traditional risk factors. Crypto markets are widely viewed as informationally inefficient, influenced by speculative cycles and attention-driven trading rather than by fundamental valuation. Participation remains dominated by young retail investors whose decisions are often guided by sentiment and social coordination rather than systematic analysis. These features create a trading environment where collective attention, market narratives, and behavioural biases play an important role in price formation.

Research on DeFi token valuation remains limited. Most empirical studies focus on Bitcoin, Ethereum, or large-cap assets, with little attention to how protocol activity interacts with DeFi token returns. [Shahzad, 2024] show that behavioural indicators such as maximum past return, cumulative return, short-term reversal, and anchoring are systematically related to token returns ; however, their analysis adopts a broad scope across token types, without specifically isolating DeFi tokens. This chapter extends that line of research by focusing specifically on DeFi protocol tokens, where market prices can respond both to on-chain fundamentals and to behavioural interpretations of that activity.

The analysis explores how market, liquidity, and behavioural factors jointly explain variation in DeFi token returns. It combines standard indicators such as past returns, market capitalisation, and trading volume with behavioural dimensions such as lottery preference, recency bias, investor attention, and anchoring, following the framework of [Shahzad, 2024]. This framework is extended to incorporate DeFi-specific indicators derived from TVL, including measures of growth, momentum, divergence, and anchoring. If TVL reflects real economic activity and cash flow potential, then unexpected changes in TVL should correspond to price adjustments as investors update beliefs about protocol perfor-

mance.

By combining behavioural and on-chain perspectives, this chapter offers a clearer understanding of price formation in DeFi markets. This chapter contributes to the literature on the behavioural foundations of digital asset pricing and show how market psychology and protocol usage jointly shape valuations in decentralised finance.

2 Related Literature

Empirical evidence shows that cryptocurrency markets exhibit persistent inefficiencies driven by behavioural dynamics. Investor biases such as herding, lottery preferences, and asymmetric reactions to news challenge classical asset pricing assumptions. Despite rapid growth and adoption, crypto assets remain marked by speculative cycles and excess volatility [Shiller, 2017 ; Li, 2021]. Traditional risk factors explain little of this variation [Borri, 2019 ; Liu, 2021], revealing recurring anomalies such as momentum, reversals, and boom–bust patterns.

Herding behaviour intensifies during periods of stress and volatility [Kumar, 2020 ; Mandaci, 2022]. Around March 2020, this pattern shifted as institutional investors entered the market, marking a structural break in behaviour [Liu, 2023]. [Gherghina, 2024] show that herding, once typical of downturns, later appeared more strongly during bull markets. Analyses based on user-level data further illustrate heterogeneous trading styles : [Aspembitova, 2021] classify blockchain investors into optimists, pessimists, and momentum traders, and find that Ethereum users are more long-term oriented than Bitcoin investors. Lottery-type payoff preferences, characterised by extreme upside potential and frequent small losses, are also present in crypto assets [Yadav, 2024], echoing patterns observed in equity markets.

Attention and sentiment, rather than risk premia alone, account for much of the observed price variation. [Shahzad, 2024] find that retail and speculative traders dominate crypto markets and that their decisions reflect social narratives and coordination. Theoretical

models linking overconfidence and self-attribution [Daniel, 1998], salience-based expectations [Bordalo, 2013], lottery preferences [Bali, 2011], and anchoring [Kaustia, 2008] provide economic foundations for these patterns. Behavioural indicators such as momentum, attention, and anchoring often explain returns more effectively than traditional risk-based factors [Liu, 2021 ; Ballis, 2022].

Asymmetric reactions to news and feedback loops reinforce these inefficiencies. Prices tend to overreact more strongly to negative events [Malkina, 2020], and momentum effects remain powerful despite limited reversals [Yang, 2018]. The efficient-market hypothesis therefore only partially describes crypto price dynamics. Models that include noise traders, attention cycles, and bounded rationality better capture the evidence [Urquhart, 2016 ; Bariviera, 2017 ; Bouri, 2019 ; Shrotryia, 2021].

Within this broader context, decentralised finance introduces additional layers of economic and behavioural complexity. DeFi protocols operate on blockchain infrastructures but issue tokens that represent claims on specific applications, such as lending, trading, or liquidity provision, rather than on the base network itself. The value of these tokens depends on the activity generated within the protocol and on the incentive or governance rights granted to token holders. At the base layer, network value derives from consensus and incentive mechanisms that align participants' behaviour [Biais, 2019]. Total Value Locked (TVL) serves as a key measure of engagement and liquidity depth, often used as a proxy for adoption and potential fee generation.

Despite extensive research on major cryptocurrencies, DeFi protocol tokens, which embed functional utility and link directly to on-chain metrics such as TVL, remain underexplored. Few papers explicitly connect behavioural pricing with protocol-specific fundamentals. [Shahzad, 2024] apply a behavioural anomaly decomposition to a wide range of crypto assets and show that return variation can be explained by behavioural variables such as maximum past return (MAX), cumulative return (CRO), short-term reversal (ST), and anchoring (ANC). Their framework, however, takes a broad approach that encompasses all types of tokens, without specifically distinguishing DeFi tokens from other protocol categories.

This study extends that research by applying the behavioural decomposition approach specifically to DeFi protocol tokens, a class directly tied to protocol usage and on-chain fundamentals such as TVL. It also introduces behavioural proxies derived from TVL dynamics, including TVL momentum, surprise, anchoring, and divergence measures that capture investor reactions to changes in protocol activity. Combining traditional behavioural anomalies (MAX, CRO, ANC, ST) with DeFi-specific indicators allows an assessment of how market sentiment and on-chain fundamentals jointly shape DeFi token returns.

3 Data

3.1 Sample Selection and Scope

This study analyses the pricing dynamics and return characteristics of tokens issued by decentralised finance (DeFi) protocols. The sample includes protocols ranked among the top 50 by Total Value Locked (TVL), according to DeFiLlama at the time of data collection. This selection ensures coverage of protocols with active user participation and substantial on-chain activity. Only protocols that have issued a native, tradable token are retained. The final dataset contains 43 unique tokens observed between 2019 and 2025.

3.2 Data Sources

Two main data sources are used :

— **DeFiLlama** : provides protocol-level variables such as TVL and its evolution over time.

— **CoinGecko** : provides token-level market data including prices, trading volume, and market capitalisation.

All variables are sampled at a **weekly frequency** using end-of-week observations. Weekly aggregation mitigates noise from intraday volatility and extreme short-term price swings.

3.3 Winsorisation Methodology

Extreme observations in decentralised finance (DeFi) data often arise from early protocol activity, reporting errors, or temporary liquidity spikes. To limit the influence of such outliers while retaining all observations, each variable was winsorised within protocol at the 1st and 99th percentiles. For tokens with short histories or limited variation, the bounds were relaxed to the 5th and 95th percentiles to ensure stable quantile estimation. This procedure was applied to market capitalisation, total value locked (TVL), trading volume, and weekly returns. Winsorisation was performed at the token level rather than globally so that the distribution of each series remained comparable across protocols with different scales.

3.4 Descriptive Statistics (Weekly Data)

All results and descriptive statistics are computed from the winsorised sample. Table 3.1 reports summary statistics for weekly returns, TVL, market capitalisation and trading volume.

TABLE 3.1 – Descriptive Statistics (Weekly Data)

Statistic	**Return (decimal)**	**TVL (USD)**	**Market Cap (USD)**	**Volume (USD)**
Count	7,744	7,744	7,744	7,744
Mean	0.0056	2,174,688,000	599,893,900	433,701,500
Std	0.1710	4,312,829,000	1,372,427,000	916,600,200
Min	-0.5420	33,750	25,041	19
25%	-0.0938	56,132,310	68,123,490	27,040,270
Median	-0.0103	452,692,600	216,378,800	125,082,700
75%	0.0799	2,131,075,000	517,655,300	428,943,900
Max	1.3532	37,756,990,000	18,641,630,000	10,974,380,000

Notes : This table reports descriptive statistics for weekly observations of market capitalisation, total value locked (TVL), trading volume, and returns for 43 DeFi protocol tokens between 2019 and 2025. All monetary values are in USD and winsorised within protocol at the 1st and 99th percentiles (relaxed to 5th–95th where necessary). Returns are computed as weekly percentage price changes expressed in decimal form (e.g., 0.01 = 1%). The statistics are based on the same cleaned sample used in the empirical analysis.

The sample includes 43 DeFi protocol tokens observed weekly between 2019 and 2025. Market capitalisation, total value locked (TVL), and trading volume are measured in US dollars, and returns are weekly percentage price changes expressed in decimal form. The dataset covers protocols that are currently among the top 50 by TVL. Several were launched during the sample period, allowing their early expansion phases to be captured, while others were already established when the sample begins. Average market capitalisation is approximately 600 million USD, average TVL is about 2.2 billion USD, and average weekly trading volume is around 430 million USD. The distributions are right-skewed, with some protocols reaching market capitalisations above 18 billion USD and TVLs near 38 billion USD. Weekly returns are centred close to zero with a standard deviation of 0.17, indicating the high volatility characteristic of DeFi markets.

3.5 Token Level Correlation Matrice

Table 3.2 reports pairwise Pearson correlations between weekly returns, total value locked (TVL), market capitalisation, and trading volume. The correlations between returns and the other variables are close to zero, indicating that short-term price changes have little association with protocol size or trading activity. In contrast, market capitalisation, TVL, and trading volume display moderate to strong correlations, reflecting the common scale patterns among larger protocols. The correlation of 0.69 between market capitalisation and trading volume suggests that tokens with greater valuation typically experience higher trading activity. Overall, the correlation structure indicates that weekly DeFi token returns are largely independent of static measures of protocol size or aggregate liquidity.

Table 3.2 – Correlation Matrix (Weekly Data)

	Return	**TVL**	**Market Cap**	**Volume**
Return	1.0000	0.0119	0.0370	0.0732
TVL		1.0000	0.4191	0.4029
Market Cap			1.0000	0.6949
Volume				1.0000

Notes : This table reports Pearson correlation coefficients between weekly returns, total value locked (TVL), market capitalisation, and trading volume for 43 DeFi protocol tokens over the period 2019–2025. TVL, market capitalisation, and volume are measured in USD. For regressions, these ratios are used in logarithmic form Returns are computed as weekly percentage price changes expressed in decimal form (e.g., 0.01 = 1%).

3.6 Distribution of Weekly Returns

Weekly returns display clear deviations from normality. Figure 3.1 shows the histogram of weekly returns alongside a normal density fitted with the same mean and standard deviation.

— Skewness : 1.2421 (right-skewed distribution)

— Excess kurtosis : 4.7723 (fat tails)

— Jarque–Bera statistic = 9327.27, $p < 0.001 \Rightarrow$ reject normality

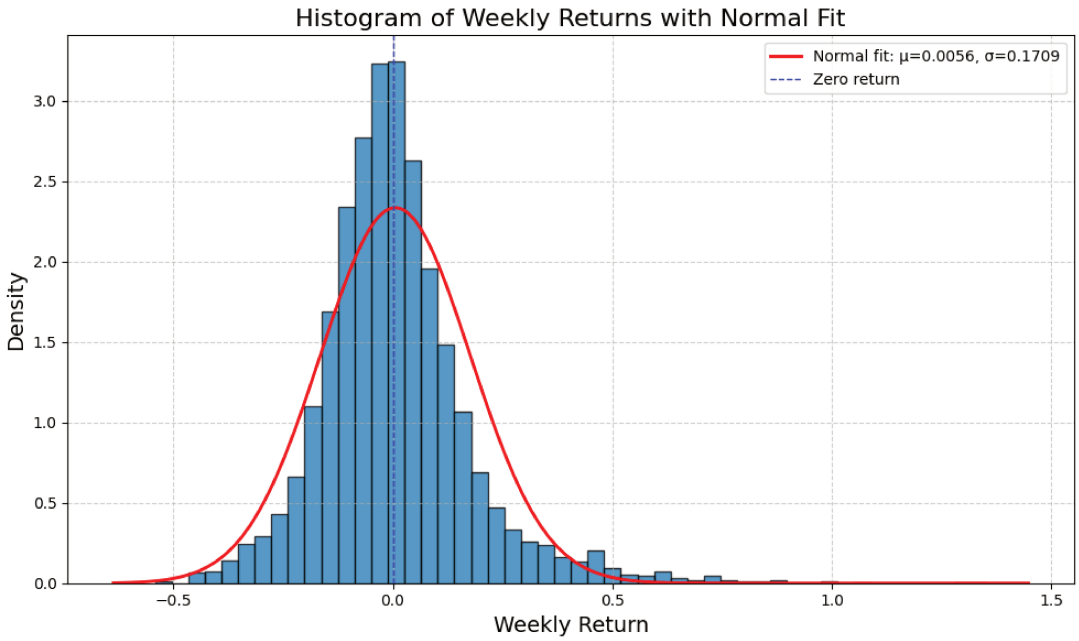

FIGURE 3.1 – Histogram of weekly token returns with a fitted normal distribution. The bars show the empirical distribution of returns, while the smooth curve represents the corresponding normal density using the sample mean and standard deviation. This allows a visual comparison between actual return behavior and the normal assumption often used in financial models.

4 Feature Construction

This section outlines the construction of weekly variables used to explain return variation in DeFi tokens. Features are grouped into : (i) log-scaled token and protocol level variables, (ii) market and liquidity variables, (iii) behavioral indicators based on token prices, and (iv) TVL-based behavioral extensions. All features are lagged appropriately to avoid look-ahead bias.

4.1 Log-Scaling

To improve comparability across protocols, the following variables are log-transformed :

$$\text{TVL}_{i,t} = \log(\text{TVL}_{i,t}), \quad \text{MarketCap}_{i,t} = \log(\text{MarketCap}_{i,t}), \quad \text{Volume}_{i,t} = \log(\text{Volume}_{i,t})$$

4.2 Market and Liquidity Variables

We construct the following market-based and protocol-activity variables :

— **Momentum :** A 1-week lagged price momentum measure captures short-term return persistence without introducing look-ahead bias :

$$Momentum_{1w,lag,t} = \frac{P_{t-1}}{P_{t-2}} - 1.$$

— **Growth :** To measure protocol adoption and trading intensity, we compute 12-week log growth rates in total value locked (TVL) and trading volume :

$$\Delta_{12} \log(\text{TVL})_t = \log(\text{TVL}_t) - \log(\text{TVL}_{t-11}),$$
$$\Delta_{12} \log(\text{Volume})_t = \log(\text{Volume}_t) - \log(\text{Volume}_{t-11}).$$

These log differences represent continuously compounded growth rates.

— **Volatility :** Time-varying risk is captured using a lagged 52-week rolling standard deviation of weekly returns :

$$Vol_{52w,lag,t} = std(r_{t-1}, r_{t-2}, \ldots, r_{t-52}),$$

where lagging avoids the use of contemporaneous information.

— **Relative Valuation :** To capture differences in valuation and liquidity across protocols, we compute two key ratios based on aggregate quantities. The first is the

market capitalisation to total value locked ratio :

$$\frac{\text{MarketCap}_t}{\text{TVL}_t},$$

which proxies for the market valuation per dollar of assets locked in the protocol. The second is the trading volume to market capitalisation ratio :

$$\frac{\text{Volume}_t}{\text{MarketCap}_t},$$

which reflects trading activity relative to token size and serves as a liquidity measure. For regression analysis, we use their logarithmic forms,

$$\log(\text{MarketCap}_t) - \log(\text{TVL}_t) \quad \text{and} \quad \log(\text{Volume}_t) - \log(\text{MarketCap}_t),$$

to reduce skewness and ensure comparability across protocols with heterogeneous scales.

TABLE 3.3 – Descriptive Statistics — Market and Liquidity Features (Weekly)

Statistic	Momentum_{1w}	TVL Growth_{12w}	$\text{Volume Growth}_{12w}$	Volatility_{52w}	MC/TVL	Volume/MC
Mean	0.0085	0.0013	-0.0073	0.1610	28.2255	0.9039
Std	0.2114	0.7192	1.1102	0.0680	236.1114	1.1489
Min	-0.9614	-6.0749	-8.4433	0.0584	0.0005	0.0003
25%	-0.0933	-0.2769	-0.6697	0.1217	0.1501	0.2464
Median	-0.0102	-0.0261	-0.0910	0.1469	0.4015	0.5772
75%	0.0797	0.2437	0.5890	0.1852	1.1864	1.1470
Max	8.7690	8.8839	6.6530	1.2452	6764.8768	24.8872

Notes : This table reports summary statistics for weekly market and liquidity-related variables for 43 DeFi protocol tokens between 2019 and 2025. Momentum is the one-week lagged return. TVL and Volume growth are 12-week percentage changes computed from level values. Volatility corresponds to the 52-week rolling standard deviation of weekly returns. The ratios MC/TVL and Volume/MC represent, respectively, protocol valuation relative to locked assets and trading activity relative to market capitalisation. For regressions, these ratios are used in logarithmic form to reduce skewness and ensure comparability. All variables are winsorised at the 1st and 99th percentiles within protocol.

Table 3.3 presents summary statistics for weekly market and liquidity variables. Momentum and volatility are centred near zero, with volatility averaging around 0.16, consistent

with the high variability of DeFi token returns. The 12-week growth rates in TVL and trading volume display wide dispersion, reflecting heterogeneous adoption patterns across protocols. The median MC/TVL ratio is approximately 0.4, indicating that market capitalisations are generally below the value of assets locked, while the median Volume/MC ratio is around 0.6, suggesting moderate trading intensity relative to market size. Overall, these figures highlight the diversity and volatility characteristic of DeFi markets.

4.3 Price-Based Behavioral Features

To complement previous indicators, we include a set of behavioral features, motivated by findings in behavioral finance and recent research on cryptocurrency markets [Liu, 2023]. There are both theoretical and empirical reasons to consider behavioral factors in this context. Decades of research in behavioral finance show that investors often deviate from rational expectations, especially in settings characterised by uncertainty, limited information, and non-standard assets [Shiller, 2017 ; Barberis, 1998]. These conditions are typical of decentralised finance, where retail investors dominate participation, disclosure is limited, and valuation benchmarks are less well defined [Bouri, 2019]. As a result, sentiment, heuristics, and collective behaviour can have a significant impact on token prices.

We follow the four bias proxies introduced by [Shahzad, 2024], adapting them to the context of DeFi tokens. These variables aim to capture systematic deviations from rational investor behaviour that may influence DeFi token prices. All behavioral indicators are computed using rolling or exponentially weighted windows and are lagged to prevent look-ahead bias.These four behavioral biases are well-documented in the literature and particularly relevant to the dynamics of digital asset markets. First, **lottery preference** captures investors' tendency to overreact to extreme past gains and overpay for assets with positively skewed payoffs, expecting such outcomes to repeat [Bali, 2011]. Second, **recency bias** reflects the overweighting of recent price movements when forming expectations, which can lead to short-term momentum or reversal effects [Barberis, 1998 ; Daniel, 1998]. Third, **salience** captures the idea that large price swings attract disproportionate

investor attention, influencing demand even when such movements are not justified by fundamentals [Bordalo, 2013 ; Barber, 2007]. Finally, **anchoring** measures the extent to which investors rely on recent peak prices as reference points, potentially overreacting when current prices deviate significantly from those benchmarks [Kaustia, 2008]. Focusing on these four biases represents a balance between theoretical relevance, empirical feasibility, and data availability. Together, they capture both cognitive (recency bias, anchoring) and attention-related (lottery preference, salience) aspects of investor behaviour. Other biases, such as loss aversion or ambiguity aversion, may also play a role, but incorporating them is beyond the scope of this analysis given the challenges of measuring them at high frequency.

We now translate these behavioral ideas into measurable variables using market data. **The variables are expressed at time t, but they are lagged appropriately in regressions to avoid look-ahead bias.** The following proxies correspond to the four biases described above and will be used in the empirical analysis :

— **Lottery Preference (MAX) :** Investors tend to overreact to extreme recent gains, which may attract attention and cause temporary overvaluation. To capture this effect, we construct a 12-weeks lottery preference proxy, **MAX** :

$$MAX_{i,t} = \max_{t-12 \leq k \leq t-1} R_{i,k}$$

where $R_{i,k}$ denotes the weekly return of token i at week k. The maximum is computed over the past 12 weeks.

— **Recency Bias (CRO) :** To capture the tendency of investors to overweight recent returns, we compute cumulative returns over past weeks using an exponentially weighted moving average of lagged returns, with a half-life of 4 weeks. Formally, for token i :

$$CRO_{i,t} = \sum_{k=1}^{\infty} w_k R_{i,t-k}, \qquad w_k = (1-\alpha)^{k-1}\alpha, \qquad \alpha = 1 - 2^{-\frac{1}{4}} \approx 0.159$$

— **Salience (ST) :** To account for potential salience effects, we introduce a short-term

indicator, **ST**, which measures the relative price swing over the past 12 weeks :

$$ST_{i,t} = \frac{\max\limits_{t-11\leq k\leq t} P_{i,k} - \min\limits_{t-11\leq k\leq t} P_{i,k}}{\min\limits_{t-11\leq k\leq t} P_{i,k}}$$

where $P_{i,k}$ is the price of token i at week k.

— **Anchoring (ANC) :** Finally, to capture whether investors anchor to recent peak prices and overreact when prices fall below this reference point, we define a one-year anchoring factor, **ANC** :

$$ANC_{i,t} = \frac{P_{i,t}}{\max\limits_{t-51\leq k\leq t} P_{i,k}}$$

where $P_{i,t}$ is the current price and the denominator is the highest price in the past year. A value close to 1 indicates that the token is trading close to its recent peak.

Table 3.4 – Descriptive Statistics — Price-Based Behavioral Features (Weekly Data)

Statistic	MAX_lag	ANC	CRO_lag	ST
Mean	0.3389	0.4718	0.0096	1.3737
Std	0.3839	0.2602	0.0753	6.5820
Min	-0.3922	0.0043	-0.3922	0.0000
25%	0.1532	0.2664	-0.0252	0.5196
Median	0.2506	0.4463	0.0001	0.7765
75%	0.4248	0.6537	0.0316	1.2837
Max	8.7690	1.0000	1.8883	233.7967

Notes : This table reports descriptive statistics for weekly price-based behavioral indicators across 43 DeFi protocol tokens from 2019 to 2025. MAX_{lag} is the maximum weekly return over the preceding 12 weeks. ANC measures anchoring as the current price relative to its 52-week high. CRO_{lag} captures recency bias using an exponentially weighted moving average of past returns with a four-week half-life. ST measures salience as the 12-week high–low price range relative to the recent low. All indicators are lagged by one week to prevent look-ahead bias and winsorised at the 1st and 99th percentiles within protocol.

Table 3.4 summarises weekly price-based behavioural indicators. MAX_{lag} has a median of 0.25, indicating that the typical token experienced a 25% peak weekly return within the prior 12 weeks ; the right tail is long, with values up to 8.77. ANC has a median of 0.45 and an upper quartile of 0.65, showing that prices are often below their 52-week highs.

CRO_{lag} is centred near zero with a narrow interquartile range, consistent with limited persistence in recent average returns. ST has a median of 0.78 but a wide dispersion, reflecting occasional large high–low ranges over 12 weeks. Overall, the indicators exhibit skewed distributions with occasional extreme values, consistent with episodic surges in volatility and attention.

4.4 TVL-Based Behavioral Features

To extend the analysis with protocol-specific sentiment measures, we construct a set of TVL-based behavioral features. Specifically, we compute the same behavioral indicators as above, but replace price with Total Value Locked (TVL) as the underlying variable, expressed in logarithmic terms for consistency and robustness.

The choice of TVL is motivated by its importance as an indicator of user activity and capital allocation in DeFi protocols. Unlike token price, which reflects market expectations, TVL captures the actual movement of assets into a protocol and thus provides a direct measure of participation [Harvey, 2020 ; Schär, 2021]. Because decisions to deposit, withdraw, or reallocate funds are often influenced by behavioral factors, TVL-based indicators offer a complementary view of sentiment. They help assess whether behavioral patterns appear not only in market prices but also in user allocation decisions.

— MAX_{TVL} captures the lottery preference effect by measuring the maximum weekly TVL return over the past 12 weeks, reflecting investor attraction to protocols experiencing extreme past growth.

— ANC_{TVL} proxies for anchoring bias by comparing the current TVL level to its 52-week historical maximum, quantifying how far a protocol's usage has declined from its perceived peak.

— CRO_{TVL} models recency bias via an exponentially weighted moving average of TVL returns (with a 4-week half-life), placing greater emphasis on recent activity trends.

— ST_{TVL} captures salience effects through the relative gap between recent high and low TVL levels, defined as the 12-week rolling range scaled by the recent low. This

feature reflects heightened investor attention in response to large and salient changes in protocol usage.

5 Empirical Methodology

5.1 Baseline Panel Specification

We examine weekly cross-sectional return variation using a two-way fixed effects panel model. For token i in week t,

$$r_{i,t} = \alpha_i + \gamma_t + \beta^\top X_{i,t-1} + \varepsilon_{i,t}, \tag{3.1}$$

where $r_{i,t}$ denotes the weekly log return, $X_{i,t-1}$ is a vector of lagged explanatory variables, and $\varepsilon_{i,t}$ is the idiosyncratic error term.

The model includes both protocol fixed effects (α_i) and time fixed effects (γ_t). The protocol effects control for unobserved, time-invariant characteristics of each protocol such as governance design, fee structure, or risk profile. The time effects capture market-wide shocks that simultaneously affect all tokens in a given week. Standard errors are clustered by protocol to allow for correlation of residuals within the same entity over time.

5.2 Predictor Set and BIC Selection

The set of candidate predictors includes market- and liquidity-related variables as well as behavioral indicators. [1] Model selection is based on a stepwise forward–backward procedure guided by the Bayesian Information Criterion (BIC). The procedure begins by estimating all single-variable models to identify the best initial specification. In each iteration, variables are sequentially added or removed depending on whether they reduce the

1. Full list : `tvl_log`, `market_cap_log`, `volume_log`, `momentum_1w_lag1`, `tvl_growth_12w`, `volume_growth_12w`, `vol_12w_lag1`, `log_mc_to_tvl`, `log_volume_to_mc`, `MAX_TVL`, `ANC_TVL`, `CRO_TVL`, `ST_TVL`, `MAX_lag`, `ANC`, `CRO_lag`, and `ST`.

BIC value. The algorithm terminates when no single addition or removal yields further improvement.

The BIC criterion balances model fit and parsimony by penalizing unnecessary complexity. For a model with k parameters and n observations, it is defined as

$$\text{BIC} = -2\log(\hat{L}) + k\log(n),$$

where $\hat{L}$ is the maximized likelihood of the model. The first term rewards better fit (higher likelihood), while the second term penalizes overfitting by increasing with the number of estimated parameters. Compared to the Akaike Information Criterion (AIC), the BIC imposes a stronger penalty for model complexity, favouring more parsimonious specifications. In the present context, this ensures that the selected regression includes only variables that contribute meaningfully to explaining cross-sectional return variation, while avoiding redundant or collinear predictors.

To ensure valid inference, all explanatory variables were tested for stationarity using Augmented Dickey–Fuller (ADF) tests. Results confirm that all series are stationary at the 5% significance level. Consequently, no additional transformations or differencing were required.

5.3 Baseline Results : Two-Way Fixed Effects (BIC-Selected Set)

The Bayesian Information Criterion (BIC) stepwise procedure selects a parsimonious set of eight explanatory variables that account for approximately 10% of the within-entity variation in weekly DeFi token returns.

TABLE 3.5 – BIC-Selected Panel Regression (Two-Way FE, Clustered by Entity)

Variable	Coefficient	Std. Err.
volume_growth_12w	0.0286***	(0.0054)
momentum_1w_lag1	0.0670***	(0.0244)
ANC	0.3357***	(0.0748)
CRO_lag	-1.7348***	(0.3865)
MAX_lag	0.1032**	(0.0452)
CRO_TVL	0.2933**	(0.1236)
MAX_TVL	-0.0246*	(0.0138)
ANC_TVL	-0.0465**	(0.0205)
Observations		5,603
Entities		38
Time periods		285
R^2 (Within)		0.099
Effects		Entity and Time Fixed Effects
SEs		Clustered by protocol

TABLE 3.6 – This table reports estimates from a two-way fixed effects panel regression of weekly token returns for 38 DeFi protocols between 2019 and 2025. Independent variables are selected via a stepwise Bayesian Information Criterion (BIC) procedure that iteratively adds or removes predictors to minimize model complexity while preserving explanatory power. The selected variables include anchoring (ANC), recency bias (CRO_lag), 12-week volume growth, lottery preference (MAX_lag), short-term momentum, and corresponding TVL-based behavioral indicators (CRO_TVL, ANC_TVL, MAX_TVL). All predictors are lagged to mitigate look-ahead bias. Protocol and time fixed effects control for, respectively, token-specific heterogeneity and market-wide conditions. Standard errors are clustered at the protocol level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Liquidity activity, measured by 12-week *volume growth*, is positively related to returns. Higher trading activity usually reflects greater participation and lower transaction costs, consistent with the idea that liquidity enhances market efficiency [Amihud, 1986 ; Pástor, 2001]. It can also signal stronger investor interest and a healthier market.

Short-term *momentum* has a positive sign, meaning that recent price changes often continue for a short period before reversing. This is typical of markets where information

spreads slowly and investors follow visible trends [Jegadeesh, 1993].

The *anchoring* variable (ANC) is positive and significant. Tokens that trade near their previous highs tend to keep performing better, suggesting that investors use past peaks as reference points when judging value. This reflects reference dependence and the tendency to hold on to recent winners [Kaustia, 2008 ; Barberis, 2009].

The *recency bias* variable (CRO_lag) has a large negative coefficient. This means that when tokens have performed well for several weeks, they often show reversals. Investors seem to give too much weight to recent outcomes and adjust later when expectations prove too optimistic [Barberis, 1998 ; Daniel, 1998].

The *lottery preference* proxy (MAX_lag) is positive. Tokens that recently had extreme gains tend to attract extra demand, as some investors seek assets with small chances of very high payoffs. This behaviour is well documented in traditional markets [Bali, 2011 ; Kumar, 2009].

Among the TVL-based variables, CRO_TVL is positive and significant. Protocols that recently attracted more locked capital generally have higher returns. Investors may see rising TVL as a sign of adoption and confidence in the protocol [Cong, 2019 ; Harvey, 2020].

The coefficient on MAX_TVL is negative. When TVL grows very fast over a short period, returns tend to fall later. These sharp increases are often linked to temporary incentives or attention waves that fade once rewards decline. This mean-reverting pattern is consistent with salience and attention effects [Bordalo, 2013 ; Barber, 2007] and with temporary capital flows in DeFi [Schär, 2021 ; Harvey, 2020]. Many DeFi protocols rely on token emissions to attract deposits, temporarily boosting TVL during incentive periods. When rewards are distributed or yield programs taper off, participants often withdraw or sell accumulated tokens, leading to short-term price pressure. This mechanism complements the behavioural interpretation of overreaction, as both dilution and strategic profit-taking contribute to weaker returns once saturation is reached.

Finally, ANC_TVL is also negative. When a protocol's TVL approaches its previous

maximum, returns decrease. Investors may anchor on past participation levels and become less responsive to further increases [Kaustia, 2008]. A similar adjustment may occur as liquidity incentives unwind near these peaks, contributing to the observed decline in returns around saturation points.

Overall, these results show that DeFi token returns depend on both market activity and investor behaviour. Trading volume and TVL capture how active and engaged users are, while behavioural factors such as anchoring, recency, and lottery preference reveal how investors interpret recent trends and past peaks.

To assess potential multicollinearity among the selected regressors, Variance Inflation Factors (VIFs) were computed (see Appendix 4). All VIF values are below the conventional threshold of 10, indicating that collinearity is not a material concern. The moderate values for ANC and ANC_TVL reflect their conceptual proximity rather than statistical redundancy. To further assess multicollinearity, pairwise correlations among the selected regressors are reported in Appendix 4. The correlations are moderate overall, with the strongest associations observed between ANC and ANC_TVL ($\rho = 0.57$).

6 Robustness Checks

This section evaluates whether the baseline findings are robust to alternative model specifications, changes in sample composition, and the treatment of extreme observations. We compare the baseline two-way fixed effects panel regression to a Fama–MacBeth [Fama, 1973] cross-sectional approach. Next, we test whether results differ across subsamples of tokens by protocol scale (high vs. low TVL) or by size (large vs. small market capitalisation). Finally, we winsorise extreme returns at the 5th and 95th percentiles to ensure results are not driven by outliers.

6.1 Fama-MacBeth

6.1.1 Baseline (two–way fixed effects).

For reference, the baseline model controls for protocol and time heterogeneity :

$$r_{i,t} = \alpha_i + \gamma_t + \beta^\top X_{i,t-1} + \varepsilon_{i,t}, \tag{3.2}$$

where $r_{i,t}$ is the weekly return of token i in week t, α_i are protocol effects, γ_t are time effects, and $X_{i,t-1}$ is the vector of lagged covariates. Estimation uses clustered standard errors at the protocol level.

6.1.2 Fama–MacBeth cross-sectional regressions.

Cross-sectional regressions are estimated using the Fama–MacBeth [Fama, 1973] two-step procedure, which averages factor loadings across time to obtain standard errors robust to cross-sectional dependence. The complementary cross-sectional approach runs, for each week t, the regression

$$r_{i,t} = a_t + b_t^\top X_{i,t-1} + u_{i,t} \qquad (i = 1, \ldots, N_t), \tag{3.3}$$

and then averages the weekly slope estimates :

$$\bar{b} = \frac{1}{T}\sum_{t=1}^{T} b_t, \qquad \widehat{\mathrm{Var}}(\bar{b}) = \frac{1}{T}\sum_{t=1}^{T}(b_t - \bar{b})(b_t - \bar{b})^\top \tag{3.4}$$

The Fama-MacBeth approach mitigates biases from time-series dependence by estimating separate cross-sectional regressions for each period and averaging their coefficients. Standard errors are based on the variability of these weekly slopes over time, providing inference that reflects how stable the relationships are across different market conditions.

To clarify how the different estimators isolate time-series and cross-sectional variation, Appendix 5 presents a simple numerical example with two tokens observed over three

weeks.

TABLE 3.7 – Comparison of Panel and Cross-Sectional Specifications

	(1) Two-Way FE	(2) Fama–MacBeth
ANC	0.336*** (4.49)	0.164*** (4.59)
CRO_lag	-1.735*** (-4.49)	-1.080*** (-4.70)
volume_growth_12w	0.029*** (5.27)	0.038*** (5.85)
MAX_lag	0.103** (2.28)	0.005 (0.16)
momentum_1w_lag1	0.067*** (2.74)	0.050 (1.06)
CRO_TVL	0.293** (2.37)	0.583*** (5.39)
MAX_TVL	-0.025* (-1.79)	-0.045* (-1.78)
ANC_TVL	-0.047** (-2.27)	-0.072*** (-4.49)
Entity FE	Yes	No
Time FE	Yes	No
Observations	5,603	5,603
R-squared (Within)	0.099	0.099

Notes : This table compares coefficient estimates across two specifications using weekly returns for 38 DeFi tokens from 2019 to 2025. Column (1) reports results from a two-way fixed effects (entity and time) panel regression. Column (2) presents Fama–MacBeth estimates based on weekly cross-sectional regressions averaged over time, with Newey–West corrections for temporal dependence. All variables are lagged to mitigate look-ahead bias. t-statistics are reported in parentheses. Standard errors are clustered by entity in Column (1) and use Fama–MacBeth/Newey–West correction in Column (2). Significance levels : * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The Fama–MacBeth results in Table 3.7 show that most patterns found in the panel model also hold when returns are averaged across time. Anchoring (ANC) and recency bias (CRO_lag) remain strongly related to returns, while liquidity growth (volume_growth_12w) and the TVL-based measures (CRO_TVL and ANC_TVL) also keep their significance. In contrast, the effects of short-term momentum and lottery preference (MAX) are weaker, which suggests that these factors mostly act over short horizons rather than across tokens.

The differences between the two methods have a clear economic meaning. The Fama–MacBeth approach compares tokens with each other in each week, while the panel model focuses on changes over time within each token. The persistence of anchoring and recency bias across tokens means these behaviours are not just temporary reactions. Instead, they describe how investors in DeFi often value tokens based on recent highs and short-term trends [Barberis, 1998 ; Daniel, 1998 ; Kaustia, 2008].

Momentum and lottery-type effects are weaker in this setting because they capture time-series dynamics rather than stable cross-sectional differences. Momentum reflects slow information adjustment and temporary herding [Jegadeesh, 1993], while lottery preference tends to appear during speculative phases with high retail activity [Bali, 2011 ; Kumar, 2009]. When averaging across tokens, these temporary effects cancel out.

Liquidity growth and TVL-based measures remain significant in both models. This shows that market activity and user engagement are key features of DeFi valuation. Protocols that attract more users or capital inflows are consistently priced higher, which is in line with network-effect explanations [Cong, 2019 ; Harvey, 2020]. Overall, both behavioural and liquidity-related factors seem to shape token pricing in a durable way.

6.2 Subsample Analysis by Protocol Scale

To test whether the main relationships differ across protocol size, the sample is divided into two groups based on the median Total Value Locked (TVL). The large-scale group includes protocols above the median TVL, while the small-scale group includes those below it. Separate two-way fixed effects regressions are then estimated for each group. Results are reported in Table 3.8.

Table 3.8 – Return Variation Across Low- and High-TVL Tokens

	(1) Low TVL	(2) High TVL
ANC	0.412*** (4.40)	0.229*** (8.04)
CRO_lag	-2.027*** (-4.88)	-1.425*** (-13.06)
volume_growth_12w	0.032*** (4.76)	0.047*** (9.28)
MAX_lag	0.130** (2.73)	-0.003 (-0.19)
momentum_1w_lag1	0.054 (1.37)	0.068** (2.34)
CRO_TVL	0.348*** (3.21)	1.235*** (6.47)
MAX_TVL	-0.024 (-1.59)	-0.061*** (-3.89)
ANC_TVL	-0.069** (-2.49)	-0.113*** (-3.78)
Entity FE	Yes	Yes
Time FE	Yes	Yes
Observations	3,630	3,607
R-squared (Within)	0.092	0.216

Notes : This table reports results from two-way fixed effects regressions estimated separately for tokens with below-median TVL (Column 1) and above-median TVL (Column 2). The dependent variable is weekly token return. All explanatory variables are lagged to prevent look-ahead bias. Entity fixed effects account for time-invariant protocol characteristics, while time fixed effects control for common market shocks. t-statistics are reported in parentheses. Standard errors are clustered by protocol. Significance levels : * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The results show that most behavioural and liquidity variables are stronger for smaller protocols. Volume growth, anchoring (ANC), recency bias (CRO_lag), and lottery preference (MAX_lag) have larger coefficients in the low-TVL group. This suggests that investor behaviour and sentiment play a bigger role when protocols are less established and less liquid. Smaller tokens are often traded by retail investors and are more sensitive to shifts in attention and speculation.

For larger protocols, the coefficients are smaller and less significant. High-TVL projects tend to have more stable participation, professional investors, and lower price sensitivity to short-term sentiment. Their valuations may rely more on fundamentals and network usage than on behavioural effects.

The positive and significant coefficients on *CRO_TVL* in both groups indicate that recent growth in locked capital supports returns across the board. Investors seem to view TVL expansion as a signal of success, regardless of protocol size [Cong, 2019 ; Harvey, 2020]. However, the slightly higher magnitude for smaller protocols suggests that inflows have a

stronger marginal effect when the base of users and capital is limited.

The negative coefficients on ANC_TVL and MAX_TVL confirm that returns tend to slow after periods of exceptional growth in protocol usage. This likely reflects temporary incentives or saturation in user activity, especially for smaller protocols where short-term campaigns can cause sharp but unsustainable surges [Schär, 2021 ; Harvey, 2020].

Overall, this subsample analysis indicates that DeFi token pricing is more behaviourally driven among smaller protocols and relatively more fundamental for larger ones. The importance of investor sentiment and liquidity conditions decreases as protocols mature and achieve greater depth.

6.3 Subsample Analysis by Market Capitalisation

This subsection examines whether the main relationships depend on token market capitalisation. The sample is divided at the median market capitalisation each week, creating two groups : large-cap and small-cap tokens. Two-way fixed effects regressions are estimated separately for each group. Results are reported in Table 3.9.

Table 3.9 – Return Analysis : Small vs. Large Market Capitalisation Tokens

	(1) Small Cap	(2) Large Cap
ANC	0.417*** (4.45)	0.264*** (7.91)
CRO_lag	-1.932*** (-4.41)	-1.481*** (-9.98)
volume_growth_12w	0.027*** (3.66)	0.058*** (14.26)
MAX_lag	0.112** (2.12)	-0.020 (-0.81)
momentum_1w_lag1	0.054 (1.28)	0.061** (1.99)
CRO_TVL	0.389*** (3.04)	0.971*** (6.27)
MAX_TVL	-0.029 (-1.58)	-0.030 (-1.58)
ANC_TVL	-0.083*** (-2.89)	-0.105*** (-4.27)
Entity FE	Yes	Yes
Time FE	Yes	Yes
Observations	3,588	3,649
R-squared (Within)	0.096	0.203

Notes : This table reports two-way fixed effects regressions estimated separately for tokens with below-median (Column 1) and above-median (Column 2) market capitalisation. The dependent variable is weekly token return. All explanatory variables are lagged to avoid look-ahead bias. Entity fixed effects capture time-invariant protocol characteristics, and time fixed effects absorb common market-wide shocks. Standard errors are clustered at the protocol level, and t-statistics are reported in parentheses. Significance levels : * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The results show a similar pattern to the TVL-based split. Behavioural and liquidity effects are generally stronger for small-cap tokens. Volume growth, anchoring, recency bias, and lottery preference all have higher coefficients for small caps. These tokens are often less liquid and have smaller investor bases, making their prices more sensitive to shifts in sentiment and trading activity.

In contrast, the same variables have weaker effects for large-cap tokens. Established projects tend to attract more sophisticated investors and experience smaller relative changes in liquidity or user participation. Their prices are therefore less affected by short-term behavioural dynamics and more influenced by longer-term fundamentals.

The positive and significant coefficient on CRO_TVL across both groups indicates that recent increases in TVL are associated with higher returns. Investors interpret rising locked value as evidence of growing usage or trust in the protocol [Cong, 2019 ; Harvey, 2020]. The effect is stronger for small-cap tokens, where new inflows represent a larger proportional change in activity.

The negative coefficients on *MAX_TVL* and *ANC_TVL* confirm that periods of extreme or peak TVL growth tend to be followed by weaker returns. These results suggest that when activity reaches abnormally high levels, expectations become difficult to sustain, leading to later corrections. This is consistent with the idea of attention-driven overreaction and mean reversion [Bordalo, 2013 ; Barber, 2007 ; Schär, 2021 ; Harvey, 2020].

Overall, the findings indicate that small-cap DeFi tokens are more exposed to behavioural forces and market sentiment, while large-cap tokens show more stable dynamics linked to their established user base and liquidity depth.

6.4 Winsorization of Extreme Returns

To test whether the main findings are driven by extreme weekly returns, the analysis is repeated after winsorizing the dependent variable at the 5th and 95th percentiles. This reduces the influence of outliers that may result from short-term dislocations, low liquidity, or token-specific events such as hacks or protocol exploits. Table 3.10 compares the baseline and winsorised regressions.

TABLE 3.10 – Baseline vs. Winsorised Returns (5th–95th Percentile)

	(1) Baseline FE	(2) Winsorised FE
ANC	0.336*** (4.49)	0.189*** (11.82)
CRO_lag	-1.735*** (-4.49)	-0.838*** (-10.88)
volume_growth_12w	0.029*** (5.27)	0.023*** (8.90)
MAX_lag	0.103** (2.28)	0.042*** (3.09)
momentum_1w_lag1	0.067*** (2.74)	0.013 (1.02)
CRO_TVL	0.293** (2.37)	0.235*** (4.29)
MAX_TVL	-0.025* (-1.79)	-0.014*** (-3.36)
ANC_TVL	-0.047** (-2.27)	-0.041*** (-3.59)
Entity FE	Yes	Yes
Time FE	Yes	Yes
Observations	5,603	7,237
R^2 (Within)	0.099	0.140

Notes : Column (1) reports the two-way fixed effects regression using the BIC-selected feature set on the cleaned sample (5,603 observations, 38 entities, 285 weeks). Column (2) repeats the specification with the dependent variable winsorised at the 5th and 95th percentiles (7,237 observations, 41 entities, 326 weeks). All regressors are lagged one week. Standard errors are clustered by protocol ; t-statistics in parentheses. Significance levels : * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The winsorized results are very similar to the baseline estimates, and all key coefficients keep their sign and significance. This confirms that the main findings are not driven by a few extreme observations but reflect broader patterns in the data.

The stability of the results has a clear economic meaning. In the DeFi market, extreme returns often come from short-lived shocks such as sudden liquidations, contract vulnerabilities, or one-off incentive campaigns. The persistence of the main relationships after removing these outliers suggests that the identified behavioural and liquidity effects are structural rather than episodic.

Liquidity growth remains positively related to returns, which shows that market activity continues to be an important driver even when extreme weeks are excluded [Amihud, 1986 ; Pástor, 2001]. Anchoring and recency bias also remain strong, confirming that investor reference points and short-term memory play a systematic role in DeFi pricing [Kaustia, 2008 ; Barberis, 1998]. Similarly, the negative coefficients on MAX_TVL and ANC_TVL continue to indicate that extreme inflows or near-peak participation often precede corrections, consistent with salience-based overreaction and short-term attention cycles [Bordalo, 2013 ; Barber, 2007 ; Schär, 2021 ; Harvey, 2020].

Overall, winsorization strengthens the interpretation that these behavioural and liquidity variables capture persistent features of DeFi token valuation rather than noise from a few extreme weeks.

7 Conclusion

This chapter studied the economic and behavioural drivers of DeFi token returns using a panel of major protocols. The analysis combined market-based variables, on-chain indicators of user participation, and behavioural measures derived from price and activity patterns. A two-way fixed effects model and complementary Fama–MacBeth regressions were used to capture both time-series and cross-sectional relationships. Several robustness checks and subsample analyses confirmed the consistency of the results.

The findings reveal that investor behaviour and market activity jointly explain a meaningful share of DeFi token price variation. Anchoring and recency bias remain significant across all models, showing that investors often value tokens relative to recent highs and short-term trends. These effects persist after controlling for time and protocol heterogeneity, indicating that they are structural features of DeFi markets rather than temporary reactions. Liquidity growth also plays a central role : higher trading activity is associated with stronger returns, consistent with classic liquidity-based asset pricing [Amihud, 1986 ; Pástor, 2001].

On-chain engagement, measured through Total Value Locked (TVL), provides an additional economic dimension. Rising TVL and recent inflows are linked to higher returns, suggesting that investors treat user participation as a sign of protocol success. Conversely, extreme or peak levels of TVL predict slower returns, consistent with overreaction and fading attention once participation saturates [Bordalo, 2013 ; Barber, 2007 ; Schär, 2021 ; Harvey, 2020]. These patterns persist even after controlling for extreme returns, confirming that they reflect broader market mechanisms.

Subsample analyses show that behavioural and liquidity effects are more pronounced among smaller and lower-cap protocols. In these markets, participation is thinner, information diffuses more slowly, and investor sentiment has greater influence. Larger protocols show more stable patterns, suggesting that market depth and professional participation mitigate behavioural distortions. Together, these results portray DeFi markets as a hybrid environment, partly shaped by fundamentals related to liquidity and usage, and partly by behavioural biases that influence short-term price formation.

What makes this study distinct is its integration of behavioural finance with blockchain-based economic data. By combining traditional asset-pricing insights with observable measures of protocol activity, the analysis provides an empirical link between investor behaviour and on-chain fundamentals. This dual perspective helps explain how market sentiment and user engagement coexist as drivers of token valuation. The chapter therefore contributes to the growing literature on decentralised finance by showing that DeFi tokens are not priced purely on speculation or purely on fundamentals, but through an interaction

between investor psychology and real network usage.

These findings have important implications for both researchers and market participants. For DeFi developers and protocol designers, understanding which structural or behavioral signals consistently drive token returns can inform better tokenomics design and incentive structures. For investors, especially in retail or DAO-governed contexts, incorporating behavioral signals such as anchoring or salience may enhance return forecasts beyond traditional metrics. Finally, regulators and market monitors may use these behavioral distortions as early indicators of speculative excess or liquidity stress, helping to improve market resilience.

Future research may explore causal mechanisms, multi-chain behaviour, or apply higher-frequency data at the pool level to refine the behavioral interpretation of DeFi return dynamics.

Overall, the results suggest that as DeFi markets evolve and liquidity deepens, behavioural effects may gradually weaken, giving way to valuations driven more by participation and protocol revenue. For now, however, behavioural dynamics remain a defining feature of DeFi pricing, reflecting a market still in transition between experimentation and maturity.

Conclusion

Decentralised finance (DeFi) has emerged as a rapidly evolving segment of the financial system, enabling lending, trading, and credit formation without traditional intermediaries. While DeFi expands financial access, its openness, reliance on code, and incentive-driven structures also introduce new forms of volatility, coordination risk, and uncertainty in pricing and user behaviour. This thesis explored these challenges through three complementary essays on protocol design, interest rate formation, and token pricing.

Before addressing these essays, an extended introductory chapter examined DeFi as a technological and institutional environment. It traced the evolution from blockchain-based payments to programmable smart contracts, described the main financial primitives, and analysed how composability, transparency, and permissionless access reshape intermediation. It also highlighted structural risks, including smart contract failures, oracle dependence, governance concentration, and the re-centralisation introduced by real-world asset tokenisation. This chapter provided the conceptual context for the rest of the thesis, clarifying how lending, rate formation, and token valuation operate once embedded in code.

The first essay developed the architecture of a decentralised credit protocol. By formalising a lending mechanism without conventional on-chain over-collateralisation and analysing liquidity provision and credit assessment, it showed how core banking functions can be recreated in a permissionless environment. Using the Atlendis protocol as a case study, the essay documented how borrower-specific pools, automated rate mechanisms, and off-chain underwriting can be combined to support unsecured or partially secured lending.

It emphasised the constraints imposed by blockchain infrastructure, such as transaction costs, state management, and execution limits, and explained how these constraints shape feasible design choices. In doing so, it connected protocol engineering with the economics of intermediation and established the analytical basis for the subsequent essay on rate discovery.

The second essay examined interest rate formation in DeFi. Modelling lending pools as discriminatory auctions with tick-based supply schedules, it showed how decentralised protocols can produce transparent and algorithmic price discovery without central coordination. The model characterised the equilibrium rate as the outcome of strategic interactions between heterogeneous lenders and a borrower under both complete and incomplete information. It analysed how liquidity depth, information frictions, tick size, and participation costs affect convergence, borrowing conditions, and efficiency. It also discussed how simple design choices can either support robust price discovery or amplify strategic behaviour and instability. Empirical observations from the Atlendis protocol further revealed that the assumption of fully rational participants in DeFi markets was overly optimistic, as lender and borrower behaviour often deviated from theoretical predictions. This evidence motivated the shift in the third essay toward examining behavioural biases and investor psychology as key determinants of market outcomes.

The third essay investigated the economic and behavioural drivers of DeFi token returns using a panel of major DeFi protocol tokens. It combined market and liquidity variables, on-chain indicators of user participation, and price- and TVL-based behavioural measures within a two-way fixed effects framework and complementary Fama–MacBeth regressions. The results show that investor behaviour and trading activity explain an important share of return variation : anchoring and recency bias are consistently significant, and higher trading volume growth is associated with higher returns. On-chain engagement, captured through Total Value Locked (TVL), also matters. Rising TVL and recent inflows tend to coincide with stronger returns, while extreme or near-peak TVL levels coincide weaker subsequent returns. This pattern is consistent with investors rewarding participation growth but overreacting around saturation points. These reversals often reflect the unwinding of liquidity incentive programs, where high token emissions or reward distributions

lead to temporary inflows followed by dilution or profit-taking once rewards are realised. Subsample and robustness analyses confirm that these effects are stronger for smaller protocols and thinner markets, where sentiment and attention play a larger role. Overall, the essay portrays DeFi token pricing as hybrid, shaped jointly by metrics related to usage and liquidity and by persistent behavioural biases, rather than being purely speculative or entirely metric-driven.

Taken together, the three essays demonstrate that DeFi markets are shaped by both technical design choices and behavioural dynamics. They show how decentralised credit can be structured, how interest rates can emerge without a central authority, and how token prices reflect the interaction of protocol usage, liquidity conditions, and investor biases. This highlights both the opportunities and limits of decentralisation : code can automate financial mechanisms, but market outcomes remain influenced by expectations, narratives, and coordination.

Overall, the thesis shows that DeFi operates at the intersection of engineering, economics, and psychology. It provides a new laboratory for studying financial mechanisms in a transparent, programmable environment where behaviour, incentives, and design interact directly. Decentralisation changes the technical and governance infrastructure of finance, but not its basic goals of credit allocation and risk sharing. Market outcomes depend not only on how protocols are designed but also on how participants interpret information, manage uncertainty, and respond to incentives.

This research contributes to debates on financial intermediation, market design, and asset pricing in decentralised settings. It also offers practical insights for protocol designer, and token issuers by clarifying how design parameters, such as pool structure, rate mechanisms, disclosure rules, and incentive schemes, shape lending conditions and secondary market behaviour.

Several limitations remain. Protocols evolve quickly, data quality is uneven across sources, and many behavioural mechanisms are inferred from proxies rather than directly observed actions. These constraints limit causal interpretation but point to clear extensions. As DeFi matures, future research should test whether revenue-sharing mechanisms, clearer

governance rights, and more stable regulatory frameworks strengthen the link between token prices and market data. Future work could also link these dynamics to the design and timing of liquidity mining programs, clarifying how incentive cycles influence market depth, volatility, and capital allocation. The growth of real-world asset tokenisation and regulated DeFi also raises new questions on legal enforceability, credit risk, and systemic interdependence between on-chain and off-chain markets, which offer promising directions for subsequent work.

In conclusion, this thesis shows that DeFi is neither fully efficient nor purely algorithmic. It is a financial system where code, incentives, and human behaviour coexist. Understanding this interplay is essential for assessing current protocols and for designing more robust decentralised financial infrastructures. Whether DeFi becomes a durable component of the global financial architecture will depend on its capacity to align programmable mechanisms with transparent governance, credible claims on underlying activity, resilience against speculative pressures, and an appropriate regulatory framework. This transformation is already underway. As protocol design advances, regulation adapts, and institutional participation deepens, DeFi is moving from experimentation toward a more stable and integrated form of finance.

Appendix

1 Nonstandard Repayment Procedure

Credit markets inevitably face instances of delinquency or partial default. In conventional finance, these are managed through restructuring, renegotiation, or liquidation, often involving complex intermediation. The protocol introduces a simplified governance-driven procedure to handle such cases.

In special circumstances, for instance, missed repayment schedules under the Master Loan Agreement, pools may be placed by the governance under a nonstandard repayment process, where governance decides on appropriate adjustments. The borrower and the lender no longer interact with the lending pool itself, but with a nonstandard repayment module instead. The lending pool ceases to exist after that. The nonstandard repayment module enables the following actions.

Borrowing Side

The borrower can perform four actions :

Table 4.11 – Borrower Actions and Repayment Outcomes

Borrower Action	**When**	**Repaid Amount**	**Uncovered Amount**
Default	Before or after maturity date	None	Yes
Partial Default	Before or after maturity date	Partial	No
Repay	After maturity date	Full	No
Early Repay	Before maturity date	Full minus interests accrued up to the early repayment date	No

Governance

The governance can declare the pool as defaulted. This can be done past maturity date in the absence of repayment or pre-maturity after the opening of insolvency proceedings against the borrower, for instance, as defined in the Master Loan Agreement.

Lending Side

Lenders with borrowed positions can send their position to the nonstandard repayment module. In exchange, they will receive their portion of the repaid amount (if existing) and if required an NFT displaying the amount of "bad debt" that corresponds to the uncovered amount (amount due - partially repaid amount). The NFT is not transferable. One of the specificities of the nonstandard repayment module is the withdrawal mechanisms to enable a different withdrawal method tailored to the situation.

Although less flexible than traditional negotiation, this framework illustrates how default resolution can be operationalized in a transparent, rule-based system.

2 Tokens List

TABLE 4.12 – Token History (in Years)

Token	Years	Token	Years
spark	0.0055	lido-dao	4.4682
babylon	0.2081	1inch	4.4983
morpho	0.5941	frax-share	4.5092
eigenlayer	0.7310	truefi	4.5886
sky	0.7474	venus	4.7173
kamino	1.1526	aave	4.7255
jito-governance-token	1.5496	dodo	4.7337
radiant-capital	2.9158	pancakeswap-token	4.7365
euler	3.0034	uniswap	4.7693
hop-protocol	3.0418	perpetual-protocol	4.7912
velodrome-finance	3.0637	harvest-finance	4.8104
notional-finance	3.6085	sushi	4.8241
gmx	3.7782	curve-dao-token	4.8624
dydx	3.7947	yearn-finance	4.9363
centrifuge	3.8467	balancer	5.0048
joe	3.8768	compound-governance-token	5.0240
instadapp	4.0246	just	5.1307
convex-finance	4.1068	ankr	6.3025
maple	4.1533	rocket-pool	6.7488
pendle	4.1588	maker	7.5127
liquity	4.2218		
alchemix	4.3231		
raydium	4.3395		
idle	4.3860		

3 Features Set Correlation Matrices

To assess linear dependence between features and returns, we report correlation matrices for (i) market/liquidity features, (ii) price-based behavioral features, and (iii) TVL-based behavioral extensions. All variables are computed at a weekly frequency and lagged where

appropriate.

3.1 Market and Liquidity Features

TABLE 4.13 – Correlation Matrix — Market and Liquidity Features (Weekly Data)

	Return	Momentum_{1w}	TVL Growth_{12w}	$\text{Volume Growth}_{12w}$	Volatility_{52w}	log(MC/TVL)	log(Volume/MC)
Return	1.0000	0.8862	0.0762	0.1996	-0.0002	0.0382	0.0350
Momentum_{1w}		1.0000	0.0731	0.1693	0.1144	0.0286	0.0207
TVL Growth_{12w}			1.0000	0.1891	-0.0031	-0.1318	-0.0680
$\text{Volume Growth}_{12w}$				1.0000	-0.0777	0.1077	0.2708
Volatility_{52w}					1.0000	-0.0729	-0.0892
log(MC/TVL)						1.0000	0.0389
log(Volume/MC)							1.0000

Notes : This table reports Pearson correlation coefficients between weekly return, momentum, 12-week growth rates in total value locked (TVL) and trading volume, 52-week return volatility, and two log-ratio measures : log(MC/TVL) and log(Volume/MC). The sample includes 43 DeFi protocol tokens observed between 2019 and 2025. All variables are winsorised within protocol at the 1st and 99th percentiles. Ratios are expressed in logarithmic form to reduce skewness and ensure comparability across protocols.

Table 4.13 shows correlations among market and liquidity variables. Weekly returns are highly correlated with one-week momentum (0.89), reflecting short-term continuation effects typical of high-frequency trading in DeFi markets. Correlations between returns and other variables such as TVL or volume growth remain low, suggesting that short-term price changes are weakly linked to fundamentals. Volume growth and volatility display moderate positive association (around 0.17), consistent with periods of heightened trading activity. Logarithmic ratios show limited correlation with other variables, indicating that valuation and liquidity structure vary independently from short-term market dynamics.

3.2 Price-Based Behavioral Features

TABLE 4.14 – Correlation Matrix — Price-Based Behavioral Features (Weekly Data)

	Return	**MAX_lag**	**ANC**	**CRO_lag**	**ST**
Return	1.000	-0.0168	0.2225	-0.0058	0.0003
MAX_lag		1.000	0.0854	0.5701	0.0966
ANC			1.000	0.4552	-0.0637
CRO_lag				1.000	0.0003
ST					1.000

Notes : This table presents Pearson correlation coefficients between weekly returns and price-based behavioral indicators for 43 DeFi protocol tokens over the period 2019–2025. MAX_{lag} is the maximum return over the preceding 12 weeks. ANC is the anchoring ratio, computed as the current price divided by the past 52-week maximum. CRO_{lag} is an exponentially weighted moving average of past returns (half-life = 4 weeks), reflecting recency bias. ST captures salience, defined as the 12-week high–low price range relative to the recent low. All behavioral variables are lagged by one week to prevent look-ahead bias and winsorised within protocol at the 1st and 99th percentiles.

Among behavioural variables, anchoring (ANC) shows the strongest positive correlation with returns (0.22), while MAX_{lag}, CRO_{lag}, and ST display near-zero associations. This suggests that short-term price movements are more related to relative price positioning than to momentum-driven or salience effects. The behavioural indicators are only weakly correlated with each other, indicating that they capture different facets of investor behaviour.

3.3 TVL-Based Behavioral Features

TABLE 4.15 – Correlation Matrix — TVL-Based Behavioral Extensions

	Return	MAX_TVL	ANC_TVL	CRO_TVL	ST_TVL
Return	1.000	0.0231	0.0811	0.1368	0.0285
MAX_TVL		1.000	-0.0006	0.4015	0.8104
ANC_TVL			1.000	0.5513	-0.1242
CRO_TVL				1.000	0.1925
ST_TVL					1.000

This table reports Pearson correlation coefficients between weekly token returns and behavioral indicators constructed using total value locked (TVL) instead of price, for 41 DeFi tokens over 2019–2025. MAX_{TVL} denotes the maximum TVL return over the past 12 weeks. ANC_{TVL} is the ratio of current TVL to its past 52-week maximum. CRO_{TVL} is an exponentially weighted moving average of past TVL returns (half-life = 4 weeks). ST_{TVL} measures TVL salience as the 12-week high–low range scaled by the recent low. All TVL-based indicators are lagged by one period to mitigate look-ahead bias. Correlations indicate that anchoring (`ANC_TVL`) and recency (`CRO_TVL`) are moderately related, while salience (`ST_TVL`) is strongly correlated with extreme TVL movements (`MAX_TVL`).

4 Variance Inflation Factors and Correlation Matrix for BIC-Selected Regressors

Table 4.16 – Variance Inflation Factors for BIC-Selected Regressors

Variable	VIF	Interpretation
ANC	7.08	Moderate collinearity (with ANC_TVL)
CRO_lag	3.45	Acceptable
volume_growth_12w	1.37	Low
MAX_lag	3.03	Acceptable
momentum_1w_lag1	1.47	Low
CRO_TVL	1.67	Low
MAX_TVL	1.53	Low
ANC_TVL	7.92	Moderate collinearity (with ANC)

Notes : The table reports Variance Inflation Factors (VIFs) computed from the final BIC-selected regression. All values are below the conventional threshold of 10, suggesting that multicollinearity is not a material concern. The moderate VIFs for ANC and ANC_TVL reflect conceptual overlap between price- and TVL-based anchoring measures rather than statistical redundancy.

Table 4.17 – Correlation Matrix of BIC-Selected Regressors

	ANC	CRO_lag	volume_growth_12w	MAX_lag	momentum_1w_lag1	CRO_TVL	MAX_TVL	ANC_TVL
ANC	1.000	0.455	0.377	0.085	0.189	0.361	0.033	0.570
CRO_lag		1.000	0.474	0.570	0.538	0.346	0.084	0.254
volume_growth_12w			1.000	0.179	0.177	0.167	0.046	0.151
MAX_lag				1.000	0.222	0.165	0.128	0.108
momentum_1w_lag1					1.000	0.146	0.029	0.087
CRO_TVL						1.000	0.402	0.551
MAX_TVL							1.000	-0.001
ANC_TVL								1.000

Notes : The table reports pairwise correlations among regressors included in the BIC-selected specification. Correlations are generally moderate, with the strongest values observed between `ANC` and `ANC_TVL`, and between `CRO_lag` and `MAX_lag`.

5 Illustrative Example : Comparing Estimators

To clarify how different regression estimators isolate variation, consider two tokens (A and B) observed for three weeks :

Week	Token	Volume	Return (%)
1	A	10	5
1	B	20	8
2	A	15	4
2	B	30	6
3	A	20	3
3	B	35	5

Here, both tokens become more liquid (volume increases), while returns decline over time (a maturity effect). Yet in any given week, the token with higher volume earns a higher return (a liquidity premium). This small setup lets us see how each estimator captures a different relationship.

5.0.0.1 (1) Two-way fixed effects (entity and time).

$$R_{i,t} = \alpha_i + \gamma_t + \beta \, \text{Volume}_{i,t} + \varepsilon_{i,t}.$$

This removes token-specific averages and week-specific shocks. The coefficient β measures whether, within the same week and token, unusually high volume is associated with higher returns. In this example, after removing both token and week means, token B tends to have relatively higher residual volume and return so β is slightly positive.

5.0.0.2 (2) Fama–MacBeth (cross-sectional, week by week).

For each week t :

$$R_{i,t} = a_t + b_t \,\text{Volume}_{i,t} + u_{i,t}, \qquad \bar{b} = \frac{1}{T}\sum_t b_t.$$

Each week shows higher-volume tokens having higher returns ($b_t > 0$ in all weeks), giving $\bar{b} > 0$. This captures a cross-sectional effect : at a point in time, more liquid tokens outperform their peers.

The Fama-MacBeth regression captures cross-sectional return relationships at each point in time, while the two-way fixed effects specification accounts for both token-specific heterogeneity and market-wide conditions. Comparing these estimators helps distinguish whether the documented patterns arise from common market cycles, individual protocol dynamics, or stable differences across tokens.

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RÉSUMÉ

Cette thèse explore les fondements économiques et comportementaux de la finance décentralisée (DeFi), un champ en pleine expansion où les fonctions de prêt, d'emprunt et de fixation des taux d'intérêt sont assurées par des contrats intelligents plutôt que par des institutions financières. À travers trois essais complémentaires, ce travail analyse la conception des protocoles de crédit décentralisés, la formation des taux d'intérêt dans des marchés automatisés et les déterminants fondamentaux et comportementaux de la valorisation des tokens DeFi.

Le premier essai examine l'architecture du protocole Atlendis, qui permet des prêts non ou partiellement collatéralisés grâce à l'articulation entre souscription off-chain et exécution on-chain. Le deuxième propose un modèle théorique de découverte de taux basé sur une approche de jeu multi-unités, identifiant les conditions d'efficience et les frictions propres aux marchés décentralisés. Le troisième évalue empiriquement les facteurs économiques et comportementaux influençant les rendements des tokens, révélant le rôle central du sentiment des investisseurs et de la liquidité on-chain dans la dynamique des prix.

En combinant ingénierie financière, modélisation théorique et analyse empirique, cette recherche met en lumière les mécanismes par lesquels la DeFi redéfinit l'intermédiation, la formation des prix et la gouvernance financière dans un environnement transparent et programmable.

MOTS CLÉS

Finance décentralisée, blockchain, crédit, taux d'intérêt, contrats intelligents, intermédiation financière, comportement des investisseurs, tokens DeFi, économie numérique, marchés financiers décentralisés.

ABSTRACT

This dissertation investigates the economic and behavioral foundations of decentralized finance (DeFi) where lending, borrowing, and rate discovery are executed by smart contracts rather than traditional financial institutions. Through three complementary essays, it analyzes the design of decentralized credit protocols, the formation of interest rates in decentralized markets, and the fundamental and behavioral drivers of DeFi token valuation.

The first essay examines the Atlendis protocol, which enables non- or partially-collateralized lending by combining off-chain underwriting with on-chain execution. The second develops a theoretical model of decentralized rate discovery based on a multi-unit game framework, identifying the conditions for efficiency and the frictions specific to these markets. The third provides an empirical analysis of DeFi token returns, showing that investor sentiment, liquidity dynamics, and behavioral factors play a significant role in price formation alongside economic fundamentals.

By bridging financial engineering, theoretical modeling, and empirical research, this thesis sheds light on how DeFi reshapes intermediation, price formation, and governance in a transparent, programmable financial environment.

KEYWORDS

Decentralized finance, blockchain, lending, interest rates, smart contracts, financial intermediation, investor behavior, DeFi tokens, digital economy, decentralized markets.