Phantom Liquidity in Decentralized Lending[*]

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June 11, 2024

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Abstract

As two-sided platforms, decentralized finance (DeFi) applications face a key challenge: they need to attract participants on both market sides to function. Most DeFi-platforms rely on an innovative bootstrapping approach called "liquidity mining", which involves participation rewards with protocol tokens to both market sides. We assess the efficacy of liquidity mining on the largest DeFi lending protocols Aave and Compound. Our findings indicate that while liquidity mining attracts deposits and borrowers, its discontinuation prompts withdrawals. Using account-level data, we identify a peculiar strategy that shapes the overall effect: a small subset of users deposits and simultaneously re-borrows tokens to capture rewards on both market sides, creating substantial "phantom" liquidity, a phenomenon similar to wash trading. These strategies account for 18% of deposits and 31% of loans, with peaks above 80%. Additionally, up to 25% of total deposits constitute phantom liquidity. We show that on balance such opportunistic behavior does not impose negative externalities but rather contributes positively to overall welfare.

Keywords: Decentralized Finance, Blockchain, Lending Platforms, Yield Aggregators, Yield Farming, Alternative Finance

JEL Codes: G23, G28

[*]We would like to thank the conference participants of the 2024 SNB-CIF Conference, 2023 Tokenomics, 2023 Cardiff Fintech Conference, 2023 ABFC Conference, and 2023 Shanghai-Edinburgh-UCL Fintech Conference for their valuable comments and discussions. The authors have no financial or proprietary interests in any material discussed in this article. Andreas gratefully acknowledges financial support from SSHRC (grant number 435-2017-0647), the Global Risk Institute, and the Canadian Securities Institute Research Foundation.

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The fundamental premise of Decentralized Finance (DeFi) platforms is to eliminate intermediaries and directly connect producers and consumers of financial services. However, this approach introduces a notable obstacle: peer-to-peer trading requires willing participants, options and futures necessitate contractual counterparts, and borrowing is contingent upon available lenders. DeFi platforms, facing constrained capital and fierce competition, grapple with a critical question: how can they attract both liquidity suppliers and demanders?

This paper examines the incentive strategies of two leading DeFi lending platforms, Compound and Aave. In contrast to cash incentives prevalent in traditional intermediated platforms, DeFi protocols primarily rely on protocol-native tokens that grant their holders a variety of rights. We analyze the unique challenges, DeFi-specific solutions, and blockchain-related peculiarities intrinsic to these innovative models. An common behavior that we observe in the context of these "liquidity mining programs" is that a group of market participants deposits and immediately borrows back the same crypto-asset; these deposits are therefore never accessible to the broader market — instead, they are "phantom liquidity."

We tackle four key empirical questions: first, do liquidity mining programs attract liquidity? Second, is the generated liquidity of a long- or short-term nature? Third, does the reward distribution to both consumers *and* producers lead to phantom liquidity? And fourth, most importantly, if phantom liquidity exists, does it benefit or harm other users?

Traditional platforms are organized by an intermediary that either funds incentives directly or sets fees that incentivize one market side at the expense of the other. For instance, in card-based payment systems, card issuers act as intermediaries. To thrive, issuers require both merchant acceptance and consumer adoption. Merchants are captive and accommodate to their consumers' payment preferences, allowing card issuers to incentivize users with perks such as cashback (financed by merchant fees). Uber provides another example of the challenges in platform adoption: as drivers need to allocate time and passengers need to request rides, Uber often provides discounts to both sides that they pay "out-of-pocket."

DeFi platforms are different. First, by cutting out the intermediary that earns the spread between user payments and producer income, there is no one left to directly subsidize or redistribute benefits from the captive to the non-captive market side. Second, the customary distinction between producers and consumers blurs as individuals can and often do fulfill both roles within a protocol. Third, there is an external effect in DeFi: individual users often outsource the capital allocation to algorithmic asset managers, called "yield aggregators." While frictions and limited attention decelerate capital movements in traditional deposit markets, automated yield aggregators swiftly distribute capital to the platforms with the best risk-adjusted returns, as we document here. Overall, these institutional differences create new, unexplored challenges for DeFi protocols in bootstrapping their marketplaces.

Most DeFi applications approach the bootstrapping problem by distributing protocol-native tokens to both market sides on their platform. These tokens comprise several functions, such as voting rights in periodic decisions about platform parameters, and they can also be considered implicit claims on future revenues generated by the protocol.[1] Ideally, these tokens promote a self-reinforcing cycle of growth: early adopters benefit from the protocol's success as effective incentives lead to higher fee income, raising the tokens' value as claims on that revenue. Known as liquidity mining, such incentive programs are a central strategy of many protocols to attract capital and activity.

The DeFi ecosystem spans thousands of applications across multiple blockchains, and many have offered incentive schemes. Our study focuses on lending and borrowing markets, as these are the largest category within DeFi, accounting for about 40% of total deposits.

Token-based incentives in two-sided markets with externalities are considerably more complex than cash-based schemes. We thus split our investigation: First, we study the impact of liquidity mining on deposits, loans and related volume parameters at the protocol level. Second, we utilize account-level data to identify and quantify behavior motivated solely by these incentives, and then evaluate its impact on other protocol users.

A key insight of our study arises from opportunistic users who act as both borrowers and lenders of the same asset. Specifically, depositors may benefit from borrowing back a

[1]Most protocols build "rainy day" or "reserve" pools out of fee payments, resembling the protocol's equity. Token holders vote on the reserve specifics and, in principle, could allocate these funds to themselves.

portion of their funds to simultaneously earn both lending and borrowing incentives. The amount they borrow is never genuinely accessible to other users within the protocol which is why we dub it as "phantom liquidity." Moreover, as the interest rate level is dynamically tied to demand, phantom liquidity alters interest payments for others users. This situation is analogous to an Uber driver who profitably drives themselves around as a passenger (phantom supply/demand), but whose activities inflate the prices for users interested in the service (price externality). In the context of financial applications it resembles wash trading except that, arguably, phantom liquidity is transparent and not driven by nefarious motives such as price or behavior manipulation.

Our data covers the Ethereum implementations of Aave and Compound, the two largest lending protocols on the leading smart contract platform. We examine all activities from their respective launches in 2019 and 2020 until early 2023. Combined, these platforms represent 85% of historical deposits in Ethereum-based lending markets. Both Aave and Compound have implemented various incentive programs and adjusted numerous parameters, providing us with multiple events to study behavioral changes. Across both platforms, there were 39 distinct tokens available for borrowing, and for these we identify a total of 135 platform-token incentive changes that occur on 12 different dates.

We examine ±two-week event windows around the introduction/adjustments of incentive programs based on a token-day-protocol panel constructed directly from blockchain transactions. The results for our first two questions are clear: First, the introduction or increase of rewards prompts users to deposit more and borrow larger amounts. We further note an mild expansion of platform activity through a rise in the ratio of loans to deposits, called "utilization," which leads to an increase in lending and borrowing interest rates. Second, the liquidity is not sticky: Reductions or terminations in incentives lead to fund outflows, decreased borrowing, and a lower utilization. The latter effect implies that borrowers pay (and lenders receive) less interest. This finding is somewhat concerning for platforms, as they cannot provide incentives indefinitely, and ideally, platform activity should be robust enough to sustain activities when incentives are phased out.

Our main focus is to understand the incentive dynamics at the account level. Suspecting that automated fund management plays a major role in DeFi, we collect data from the account addresses of the top 10 yield aggregator services and match them with accounts that interact with the two lending protocols. We observe that many yield aggregators systematically deposit assets into a lending pool and borrow them back immediately. One explanation for this behavior is that they establish a leveraged position. However, we find that it is particularly prevalent for stablecoins. Building a leveraged stablecoin (aka cash) position makes little economic sense, except that it enables users to collect liquidity incentives on both deposits and borrowings. Yield aggregators are not the only addresses using a deposit-and-borrow-back strategy: we identify all accounts employing such stablecoin-to-stablecoin strategies and, along with recognized yield aggregators, classify them as "yield-seekers."

Yield-seeking strategies dominate DeFi lending protocols. On average, yield-seekers contribute 18% of deposits and 31% of loans with peak rates of above 80%. Their activities concentrate in a few accounts: in February 2023, Compound's top ten yield-seeking addresses hold 98% of yield-seekers' funds, representing 43% and 23% of the protocol's loans and deposits, respectively. Across platforms, 85% of liquidity rewards are allocated to stablecoin pools to which yield-seekers directed 92% of their funds. We can then answer our third question: weighted by investment, yield-seekers re-borrowed 69% of their deposits, thereby creating phantom liquidity equal to 25% of the pool's total liquidity. Our findings generally show that deposits ("total value locked (TVL)"), which is often touted as a success metric by DeFi lending platforms, needs to be absorbed with a grain of salt.

Unlike "sticky" bank deposits, algorithmic strategies swiftly reallocate funds when incentives change. For instance, when Aave launched its incentive program in April 2021, yield-seekers increased deposits from \$39M to \$1.22B within ten days, elevating their protocol share from 0.2% to 30%. Aave's incentive reductions prompted an immediate 18% decline in deposits and a 19% decline in borrowing by yield-seekers. We present further evidence on the impact of liquidity incentives on yield-seeker exposure through several regression analyses using an event-study design, comparing the treatment to its main competitor.

This leads us to our final question: do lending markets benefit or suffer from the engagement of yield-seekers? Their strategy of lending and promptly borrowing funds back modifies lending conditions for *all* users; thus, their presence creates an externality. Collateral constraints in the lending design mandate that yield-seekers cannot borrow back their entire deposits. Hence, they always generate a liquidity surplus even if they absorb most of the deposits they provide. However, yield-seekers also escalate the borrowing demand, which raises borrowing costs. The net effect, as we show formally, is theoretically not obvious and depends on the relative contributions of total deposits to loans. Consequently, whether liquidity mining is overall harmful or beneficial in practice requires empirical investigation.

To empirically quantify the effect, we exploit the granularity of blockchain data to compute borrowing and lending rates in a hypothetical scenario where yield-seekers would be absent. We find that yield-seekers lower the utilization rate by 3.7 and 2 percentage points on Compound and Aave, respectively, leading to reduced borrowing and lending rates. Based on these hypothetical rates, we calculate the cash value of the interest that other users would have paid or received in the counterfactual scenario. In dollar terms, depositors lost $602M in interest, but borrowers saved $649M in interest payments compared to the counterfactual scenario. Therefore, the answer to our fourth question is that for our observation period, yield-seekers created a net positive externality of $47M, corresponding to about 7% of the total cash value of the liquidity incentives paid out in the programs.

Our research, though focused on two platforms, provides broader insights into the incentive mechanism of DeFi: We show that while liquidity mining programs effectively attract activity, much of it is phantom, arising from users capitalizing on rewards from both sides of the market. Any platform that subsidizes both market sides faces this challenge, especially when yield-seeking algorithms start to structurally exploit rewards. In our sample, the genuine liquidity generated was sufficient to create a positive externality. However, our theory shows that the direction of this externality can vary. Finally, we document that liquidity mining markedly distorts platform activities and parameters, implying that empirical studies in DeFi should control for such programs in their data.

Related Literature. This article contributes to three streams of literature.

First, we contribute to the growing literature exploring the mechanisms and economic implications of decentralized finance. Harvey et al. (2021), John et al. (2023), and Makarov and Schoar (2022) provide overviews and feature various elements of DeFi. One strand of literature focuses on decentralized trading markets (e.g., Capponi & Jia, 2021; Lehar & Parlour, 2023; Park, 2023). Decentralized exchanges and credit markets often compete for the same liquidity. In addition, various applications in the DeFi ecosystem complement services by interacting with trading and lending protocols.

Another strand of literature studies the performance and architecture of yield aggregators and decentralized asset managers (e.g., Augustin et al., 2022; Cousaert et al., 2022). Yield aggregators often build leveraged positions using lending protocols. As we show in this paper, a yield-seeking strategy can also target the lending platforms' incentives and affect key market variables such as interest rates and consequently market outcomes.

Several contributions delve into decentralized lending markets. Rivera et al. (2023) propose an equilibrium interest rate model revealing a welfare loss in DeFi protocols due to inelastic rates at full utilization, leading to inefficient capital allocation. They propose a step-wise rising function that sharply increases near full utilization. Chaudhary et al. (2023) examine interest rate determinants, suggesting a weak link between rates and future premiums on the underlying cryptocurrencies. They argue that lending markets predominantly serve to assemble speculative positions. Carre and Gabriel (2023) develop welfare-maximizing pricing rules of DeFi lending platforms operating in Proof-of-Stake blockchains. Cornelli et al. (2023) study why individuals use Aave and argue that depositors seek an investment return while borrowers speculate and seek participation in platform governance. As we show, liquidity mining renders borrowers' and lenders' motives to be two sides of the same coin, at least for yield-seekers. Heimbach and Huang (2023) examine leverage in Aave and Compound, finding that users do not fully exploit their leverage potential. Chiu et al. (2022), Lehar and Parlour (2022), and Qin et al. (2021) address the inherent robustness of the lending and liquidation process. While we do not feature liquidations in this paper, the liquidity extent in a pool influences risks related to borrowing/lending. Yield seekers' stablecoin-to-stablecoin activities resemble wash trading, as identified by Cong et al. (2023) on centralized crypto exchanges, albeit wash-lending arguably has no manipulative intent.

Liquidity mining programs are interesting beyond the narrow lens of finance and lending protocols. A lending protocol essentially resembles a decentralized two-sided platform that needs to attract producers and consumers to its market. The input (capital) for the produced good (liquidity) is scarce, prompting the platform to provide a native token linked to its success (transaction volume) as a production and usage incentive. Liquidity provision involves a positive externality and generates network effects. Attracting a critical mass of participants poses a major challenge, which has been studied in various industries (e.g., Cabral (2011), Evans and Schmalensee (2010), and Rysman (2009)). In this context, liquidity mining has emerged as an instrument with distinctive advantages for competing platforms. Moreover, several papers study externalities in markets facilitated by digital platform firms (e.g., Kamepalli et al., 2019; Liu et al., 2021; Reisinger et al., 2009).

Finally, there is a significant literature that studies the general role of tokens in platform finance; Canidio et al. (2021) and Li and Mann (2021) provide overviews. Recent contributions that study the financing of blockchain-native projects, taking into account specific features such as platform building are Chod et al. (2022), Gan et al. (2021), Catalini and Gans (2018), Shakhnov and Zaccaria (2021), Lee and Parlour (2022) (for crowdfunding), Malinova and Park (2023), Gryglewicz et al. (2021), and Goldstein et al. (2022). While we do not test questions regarding specific optimal token design, we offer novel empirical insights into the application of tokens as an incentive tool and the consequences for the platforms.

1 Fundamentals of DeFi Lending

Overview. Decentralized lending uses a number of concepts and terms that may not be familiar to most readers. We provide a detailed description in the Appendix; in this section we highlight the main components that are relevant for our analysis of liquidity mining.

Decentralized lending encompasses two primary application types: liquidity pool-based and minting protocols. Our focus is on liquidity pool-based applications because these, in contrast to minting protocols (such as Maker), rely on third-party liquidity.

In pool-based lending platforms (henceforth: LPs), depositors contribute crypto-assets to a non-custodial liquidity pool on the public blockchain, which earn them passive interest income when somebody borrows from the pool. Deposits (and loans) can include multiple assets. Interest income accounting is tied to the transferable token that depositors receive in return for their pool contribution.

Borrowing and the Role of Collateral. Because blockchain interactions are by design pseudo-anonymous, there is no credit as such. Instead, borrowers must provide collateral that exceeds the value of the loan.[2] If the collateral value falls below a certain threshold, any third party can repay the loan and trigger the liquidation of the collateral.

Procedurally, prospective borrowers initiate the lending process by depositing funds into a lending pool. Borrowing becomes available once they designate a portion of their deposit as collateral. The protocol assigns a collateral factor via the governance process to each asset that is accepted as collateral. This factor determines the maximum outstanding debt relative to the collateral. For instance, a collateral factor of 0.8 allows a depositor to borrow up to 80 cents for every dollar of collateral.

Borrowers receive the borrowed asset into their wallet from the general pool, and the protocol continually tracks their loan balance and interest. Loan repayment is facilitated by submitting the total amount borrowed plus interest to the lending pool.

Determination of Interest Rates Interest accrues per block, and the interest rate for all loans adjusts continuously. For a given liquidity pool, rates are determined programmatically based on the *utilization rate*, defined as the ratio of outstanding debt to supplied deposits.

[2] An exception are so-called "flash loans," which are riskless by design. Flash loans, as offered on Aave, necessitate borrowing and repayment execution within a single block, eliminating any counterparty and liquidity risks (see, e.g., Lehar & Parlour, 2022). We do not feature flash loans in our analysis.

Let B_{it} denote the amount borrowed and D_{it} the supplied deposits in liquidity pool i at day t. The key input for the determination of borrowing and lending rates is the *utilization rate*, defined as the ratio of open borrowings to deposits

$$U_{it} = \frac{B_{it}}{D_{it}}. \tag{1}$$

The interest rates are deterministic, increasing functions of the prevailing utilization rate and can be backed out for any block from the available data. We delegate a detailed description of the interest rate determination to Subsection 8.4 in the Appendix.

Each user interaction with a pool changes the utilization rate. In our subsequent analysis, we identify users that deposit and also borrow from the same pool at the same time. Since loans must be over-collateralized, one might suspect that such a trader would nevertheless reduce utilization because they must borrow less than what they contribute. The details, however, are more subtle. We show the following Lemma.

Lemma *A pool user who borrows and lends in the same pool increases pool utilization if their relative contribution to borrowing exceeds their relative contribution to deposits.*

Proof. Ignoring time subscript t and pool subscript i, suppose user a deposits D_a and borrows B_a. The subsequent utilization U is:

$$U = \frac{B + B_a}{D + D_a} \iff U = \frac{B}{D}\left(\frac{1 + \frac{B_a}{B}}{1 + \frac{D_a}{D}}\right). \tag{2}$$

It follows that a pool user increases pool utilization if and only if their relative contribution to borrowing exceeds their relative contribution to deposits, $\frac{B_a}{B} > \frac{D_a}{D}$. ■

The utilization shift hinges on the user's relative contributions to both borrowing and deposits: A new position decreases (amplifies) utilization if the relative borrowing proportion requested is less (more) than the relative deposit provided. It is therefore an empirical question whether a user's platform engagement increases or decreases utilization.

2 Liquidity Mining and User Behavior

2.1 Liquidity Mining

Attracting ample liquidity is essential for the loan mechanics of LPs and benefits users for several reasons. Liquid pools are less susceptible to illiquidity risks, enabling frictionless lending even in peak demand periods. Moreover, large individual loans or deposit withdrawals are less disruptive, akin to a highly liquid traditional bank. Thus, high liquidity typically guarantees lower and less volatile lending rates with protocols often advertising their aggregate TVL, knowing that users gravitate towards the most liquid pools.

Capital is scarce and the growth of DeFi has sparked fierce competition among protocols for liquidity. In traditional finance, banks usually compete for funding by providing higher deposit or reduced borrowing rates. As banks serve as intermediaries for both loans and deposits, such incentives are typically financed by the institution's profits with the bank accepting a smaller spread between rates.

A decentralized platform neither intermediates nor captures the spread, making it challenging to apply a similar mechanism. To address this problem, most platforms implement *liquidity mining programs* that incentivize liquidity provision by rewarding users with platform-specific tokens, which may posses several features. Most commonly, the token allows its owner to vote on platform policies and parameters, such as the properties of the interest rate function, use of the reserve, and even fee payments to token holders.

In the typical liquidity mining process, a LP generates a fixed quantity of new native tokens and distributes them to protocol users over a fixed time horizon. Details of the schemes differ, but in most cases, users receive rewards on a block-by-block basis for as long as they keep their positions (deposits and/or loans) open.

There are different models for obtaining these tokens: one is to update the wallet balance of depositors and/or borrowers. Another is to require that users deposit (or "stake") the receipt token in a smart contract that accounts for the rewards over time. Using platform tokens is often touted as a mechanism to align the interests of token holders with those of the platform and, in particular, to entice them to keep their funds in the protocol even after rewards run out due to their "skin in the game." However, as is well-known from contract theory, such incentives may not work well if the claims are trade-able (i.e., no skin in the game) or if the user is a minor player; see Bakos and Halaburda (2019). Whether these tokens serve their intended purpose is one of the empirical questions that we address here.

2.2 Yield Aggregators and Yield Farming

Yield Farming is the process of allocating capital to the DeFi protocols that provide the largest rewards — a fundamental attribute of capitalism. Although users can deploy their assets themselves in any way they choose, in practice, the process of "farming" is usually facilitated by delegating the task to decentralized asset managers known as *yield aggregators*; Yearn Finance is a prominent example.

These tools are usually computer algorithms that organize and execute the strategic allocation of agents' assets to the protocols that provide the highest rewards based on a pre-specified set of features. A yield-aggregation service collects users' funds in smart-contract-based pools, which are then invested by the protocol according to a predefined yield-generating strategy. Investment strategies can range from simple re-balancing to capturing liquidity mining rewards to complex sequences involving leveraged (sometimes referred to as "spiral") borrowing-lending.

Yield aggregators are decentralized organizations: strategies submitted by contributors are reviewed by the community and eventually approved through a decentralized voting process. Once the strategy script is formalized in a smart contract, users can allocate funds and the protocol executes the strategy autonomously (Cousaert et al., 2022).

2.3 Compound's and Aave's Liquidity Mining Programs

Aave's and Compound's liquidity mining programs were initiated by the community and were triggered by the votes of the respective tokenholders of Decentralized Autonomous Organizations (DAOs). Both protocols ran liquidity mining programs with several adjustments during our observation period from May 2019 to February 2023.

Compound launched its governance token COMP in June 2020 and used it in an extensive liquidity mining program. At its initiation, the program deposited 4.23M COMP tokens in a reserve contract to be allocated over four years. Subsequently, the contract started distributing 0.5 tokens per Ethereum block, which was gradually reduced to currently 0.17 COMP/block. Rewards are split among qualifying pools, and within most pools, 50% of the tokens are distributed to borrowers and lenders, respectively. For instance, in February 2023, the protocol distributed $\approx$ 1300 COMP per day, corresponding to USD 71,500. Which pools qualify is determined based on the community votes of the COMP holders.

Compound publishes its incentive allocation scheme and votes relating to it on its governance website. Prior to a vote on December 26, 2020, liquidity incentives were allocated proportionally to the interest accrued in a respective pool (see CIP 7). Subsequently, the incentive distribution was linked to a fixed ratio — subject to modification through community voting. Most rewards go to stablecoin pools: in early 2023, about 97% of COMP tokens. To date, Compound has changed the pool distribution 12 times, and its liquidity mining program is active at the time of writing.

The AAVE protocol token was established in September 2020 through a migration from the LEND token — the protocol's original native coin in its first launch under the name "ETHLend" (see AIP 1). Aave allocated 3M of the total 16M AAVE tokens to an ecosystem reserve for future protocol development. The protocol's liquidity mining program, similar to Compound, was financed with these tokens. This program started on April 26, 2021.

Initially, the Aave liquidity mining program distributed 2200 stkAAVE per day from the ecosystem reserve in proportion to the borrowing activity in supported pools.[3] A fixed distribution scheme was established on August 24, 2021, with roughly 85% of coins allocated to stablecoin pools thereafter. There were three reductions as decided by the community on August 24, 2021, November 22, 2021, and February 21, 2022. Additionally, the pool

[3]stkAAVE is a staked version of the AAVE token with a vesting period of 7 days upon withdrawal.

distribution was adjusted five times. The program concluded on May 21, 2022. On its last active day, 1078 AAVE tokens were shared among protocol users, representing a value of USD $\approx$ 97,000. Overall, 680,282 AAVE tokens were distributed over the program's lifespan.

Table 1 provides the programs' most important dates and parameter adjustments. Tokens of Compound and Aave include no explicit rights on revenue but through governance votes users have the implicit ability to determine the use of the reserve pools.

Overall, including the start and end, Aave adjusted rewards five times, and Compound four times. The adjustments, however, do not always involve an across-the-board-reduction. Rather, rewards for specific pools are sometimes increased, decreased, newly established, or entirely eliminated. Our analysis focuses on identifying significant structural shifts in reward schemes per protocol and coin, defining a shift as a change exceeding $\pm 10\%$ that lasts, on average, for two weeks.

During the first two weeks after its launch, Compound adjusted its program several times affecting various pools between June 15, 2020 and July 3, 2020. These changes would not lend themselves to sufficiently long event windows, and we therefore do not study these separately. Rather, we assess the start of Compound's liquidity mining program by studying the 14 days prior to June 15 and the 14 days after July 3, 2020.

Furthermore, we drop three tokens from consideration. First, we ignore changes to the pools involving the lending protocols' native tokens AAVE and COMP. Second, we exclude the AMPL token, which exhibits negligible deposits and token rewards but highly volatile utilization rates. As a result, this token's interest rates fluctuate between 0 and several hundred percent numerous times, creating its own (dis-)incentive scheme.

In summary, we identify 135 protocol-token changes to rewards, which lead to 12 distinct 28-day event intervals.

2.4 Yield-Seekers' Behavior

From their respective launches until February 2023, Compound and Aave disbursed total rewards of USD 445M and USD 193M. Unsurprisingly, some users systematically "farm" these rewards using (or mimicking) automated yield aggregation strategies. A key objective of our investigation is to comprehend the impact of these activities. We exploit a peculiar pattern in the behavior of some users to identify these strategies in the data.

Specifically, there is a type of user that deposits and promptly borrows back the same token. For volatile tokens, such behaviour can create a leveraged position. However, we observe that this phenomenon is most prevalent in stablecoins, where users deposit and borrow digital USD. It is difficult to see an economic rationale in depositing and borrowing the same stablecoin: there is no price appreciation to speculate on, users pay more interest for borrowing than they receive on their collateral, and because the position must be over-collateralized, they have less disposable income. We thus argue that this observation is driven by the desire to receive liquidity rewards for lending *and* borrowing. This view is not merely our opinion — some yield aggregators directly advertise this strategy with attractive historical returns (e.g., Yearn Dai). Henceforth, we refer to the accounts that exclusively hold stablecoin-to-stablecoin positions as *yield-seekers*.

To illustrate our argumentation, consider the borrowing and lending activities on Compound during the liquidity mining program. On February 1, 2023, a total of 8,957 addresses collectively borrowed USD 721M, utilizing collateral worth USD 1.17B. Of these borrowings, 96.3% were made in the three stablecoins USDC, DAI, and USDT. A small subset of borrower accounts (7%) exclusively borrowed *and* deposited the same stablecoin. This small fraction of addresses accounted for 44% of the total loan volume. The top 10 addresses within the subset covered 97% of the borrowed amount. In our view, liquidity rewards drive the stable-to-stable borrowing. These rewards distort the economics of borrowing and lending, as they overcompensate for the interest rate spread. Yield-seekers capitalize on these incentives and — as 97% of rewards are granted to stablecoin pools — allocate funds accordingly.

A large-scale example for a yield-seeking strategy is the Yearn DAI vault. In February 2023, its smart-contract held USD 54M in funds and deployed this capital to repeatedly deposit and borrow stablecoins. This created the largest single position on Compound, accounting for 15.5% (or USD 111M) of borrowing volume. More generally, seven out of the top ten loan positions in our data belong to yield-seekers holding stablecoin pairs.

Since yield-seekers are a driving force behind Compound's TVL, their behaviour may significantly affect the protocol: their deposits add liquidity, their borrowing extracts it. Whether the net impact is positive is an empirical question that we address in Section 6.

3 Data and Summary Statistics

3.1 Data

We examine the two largest lending protocols, Compound and Aave V2, on the Ethereum network, the largest smart contract blockchain by total value.[4] Since their inception on May 07, 2019, and December 01, 2020, the smart contracts of these protocols have collectively managed a time-weighted average of USD 14.9B in deposits and USD 5.64B in loans. Although these numbers are significant, the protocols would rank outside of the top 100 U.S. banks, many of which are small, by total deposits.[5] Within the Ethereum-based lending markets, Aave V2 and Compound represent 85% of the historical TVL.

The Ethereum blockchain records all transactions transparently so that we can observe every call to the smart contract functions of the lending protocols. We construct three data panels for our analysis from these records. The first is based on scraped raw transaction data and includes user addresses, timestamps, and token prices for our sample protocols Compound and Aave since they went live until February 1, 2023. This data stems directly

[4]Ethereum's market value accounts for 69% of total market capitalization of smart contract networks at the time of writing; see https://coinmarketcap.com/view/smart-contracts/. Ethereum is also the most attractive network for lending protocol deployment: Out of the 70 listed blockchains on DeFi-Llama, 48.5% of the TVL in lending protocols is derived from Ethereum-based protocols.

[5]See the Dec 2022 data from the FDIC.

from the Ethereum blockchain and we scraped it using The Graph.[6]

During our sample period, Aave and Compound hosted pools for 37 and 19 tokens, respectively, encompassing a total of 39 distinct tokens. Table 7 lists all tokens. In broad terms, there are two categories of token pools: USD-linked stablecoins and volatile assets. Stablecoins are digital representations of the US dollar and can be classified into three distinct types: the fiat-backed coins USDT, USDC, USDP, TUSD issued by Tether, Circle, Paxos, and TrueUSD; the crypto-backed coins DAI and FEI; and the algorithmic stablecoin UST from Terra. The second group of assets are volatile tokens, including well-known cryptocurrencies, such as ETH and Bitcoin. Additionally, this category includes tokens from major DeFi protocols, such as UniSwap's UNI token. As described above, we omit the AAVE and COMP tokens from our sample as well as the token AMPL.

The dataset covers all 3.4M interactions with the relevant pools of the protocols. We aggregate this data to the daily level based on Universal Standard Time by account, pool, and protocol. This step requires us to aggregate deposits, borrowings, repayments, withdrawals, and liquidations and to calculate the interest incurred. As a result, we can compute the inflows, outflows and balances for each account per day. In the process, we identify 474,274 unique addresses; 17,237 of these are active on both platforms.

Our second key dataset is the hand-collected historical information on the liquidity mining rewards for the two platforms. We collect information on liquidity mining programs from a review of all 322 governance decisions (154 for Compound and 168 for Aave), related forum discussions, and on-chain data.[7] From this information, we obtain the start, change, and end dates, the reward allocation structure per protocol and pool, and the depositor-to-borrower distribution weight of all liquidity mining programs since the protocols went live. This data allows us to reconstruct the comprehensive time series of token and USD-denominated rewards on Aave and Compound.

The third dataset concerns yield aggregation services. We collect the blockchain address

[6]See https://thegraph.com/explorer for the indexed protocols, methodology, and documentation.

[7]See https://app.aave.com/governance/ and https://compound.finance/governance for the documentation of governance proposals, the related forum posts, and vote distributions.

information for ten yield aggregator services.[8] As of February 2023, this sample constitutes 95% of the total volume of Ethereum-based aggregators, according to DeFi-Llama.[9] Our dataset covers 4,138 Ethereum addresses associated with the yield aggregator protocols. We obtained the data by retrieving vault and strategy addresses from the protocols' respective websites and from a smart contract search on Etherscan. Of these 4,138 addresses, we identify the 177 addresses that accessed Aave V2 and Compound during our sample period.

Finally, we compile data for several time series and cross-sectional control variables from public sources: we gather USD prices and circulating supply data for each sample token from Coinmarketcap.[10] This data allows us to compute a normalized variable for TVL: pool deposits as a fraction of total outstanding coins. For wrapped coins, such as WBTC, we employ the circulating supply of the underlying native crypto-asset. Due to the unavailability of reliable circulating supply data for DAI, KNC, RENFIL, STETH, UST, and XSUSHI, we exclude them when analyzing changes in the share of deposits to circulating supply. Moreover, we calculate daily returns for the largest crypto-asset, BTC, as a time series control. We collect the daily number of processed blocks and the average Ethereum transaction fee per day from Etherscan and BitInfocharts.[11] To measure volatility in the crypto market, we use COTI's Crypto Volatility Index (CVI), which tracks the 30-day implied volatility of Bitcoin and Ethereum-based options backed by prices from the Deribit exchange.[12]

3.2 Identifying Yield-Seekers

We are interested in yield aggregators in general and we are also particularly interested in accounts that deposit and borrow the same stablecoin at the same time; we dub the latter "stable-to-stable" users. We identify the smart contract addresses for yield aggregators (sometimes referred as "vaults") as outlined above. Many of these yield-aggregators are

[8]These are: Yearn Finance, Beefy Finance, Flamincome, Badger DAO, Idle Finance, Vesper, Origin Dollar, Chicken Bond, Harvest Finance, and Sommelier.

[9]See https://defillama.com/protocols/yield%20aggregator/Ethereum

[10]See https://coinmarketcap.com/api/ for the API documentation.

[11]See https://etherscan.io/chart/blocks and https://bitinfocharts.com/ethereum-transactionfees.html.

[12]The documentation and calculation process is described on https://docs.cvi.finance/cvi-index/cvi-index.

stable-to-stable user, but there are others: We identify all "stable-to-stable" users directly from our data as addresses that exclusively deposit and borrow stablecoin pairs in DAI, USDC, or USDT. For the purposes of our analysis, we qualify an account as a *yield-seeker* if it is either a stable-to-stable user or a yield aggregator.

3.3 Summary Statistics

Protocols and Pools. Figure 1 depicts historical statistics on deposits, borrowings, interest rates, and fees at the protocol level for Compound and Aave. The total combined deposits and borrowed amounts peak at USD 39.6B and 17.6B in mid-September 2021.

The subsequent decline is driven by both a drop in activity and by a decline in token values. Stablecoin pools, such as DAI, saw an 80-90% decrease in token balances across protocols. USD balances for the volatile assets decreased mostly because of the price declines; some pools' token balances even increased. Fees from interest payments and penalties from liquidations are closely correlated with deposit/borrow levels. The cumulative historical fee revenues on Aave and Compound until February 2023 amounted to USD 556.8M and USD 460.3M, respectively. The largest pools are Aave's ETH pool with peak deposits of up to $9.3B, and Aave's USDC pool with a borrowing volume of to $5.8B. We note, however, that ETH pools received only a small amount of the total liquidity mining rewards.

Utilization Rates of our sample pools are 30% for Aave and 24% for Compound, on average. Stablecoin pools exhibit higher utilization rates in comparison to volatile tokens, with borrowing primarily occurring in stablecoin assets. Furthermore, while there are various stablecoins (see Table 7), activity concentrates predominantly in USDC, DAI, and USDT. These three coins account for 92.5% and 82% of the cumulative historical borrowing volume on Compound and Aave, respectively. Table 2 presents descriptive statistics on the volumes and collateralization ratios of the lending pools in our sample.

Interest Rates are a function of utilization levels. The cross-sectional, TVL-weighted average deposit rates on Aave and Compound platforms for the sample horizon are 1.5% and 1.8%. The average borrow rates are 5.6% and 5.8%. Notably, smaller pools exhibit high rates during periods of surging utilization. As an illustration, on December 31st, 2020, the CRV pool in the Aave protocol contained yokens worth USD 5.7M. Due to a sudden surge in utilization, both deposit and borrowing rates escalated to 306.1% and 306.4%, respectively. However, such extreme rates are confined to small pools and rarely persist for more than a day. We carefully examined our data and can confirm that such surges did not arise during the event windows of our analysis.

In the absence of arbitrage, borrowing rates on one protocol must exceed lending rates on the other. Borrowing and lending rates for the same tokens across protocols therefore co-move. No arbitrage holds almost always, except for a brief episode from September 9 to 12, 2022, when the weighted deposit rates on Aave exceeded the borrowing rates on Compound by an average of 1.8 percentage points.[13]

Structure of the Subsequent Analysis. We split our empirical analysis into three parts.

First, in Section 4 we present evidence from a series of panel regression models at the pool-protocol-day level from Aave and Compound. We study the aggregate impact of the starts, adjustments, ends, as well as all increases and decrease events for liquidity mining programs on deposits, borrowings, utilization, and token flows.

Second, in Section 5 we study account-level and in particular yield-seekers' behavior, based on a panel analysis at the at the pool-protocol-day-accounttype level.

Third, Section 6 presents our analysis of externalities created by yield-seekers.

[13]Comparing average monthly rates on Aave and Compound with the three-month LIBOR shows that lending rates in decentralized credit markets are uncorrelated with interest rates in traditional finance.

4 Empirical Analysis and Results at the Pool Level

Our first analysis comprises four types of events: the start of the program, reductions and increases of incentives, and the end of incentives. As rewards adjustment occur at different times for different tokens *within* a protocol, we study four-week, non-overlapping panel event windows (± 14 days). We perform analyses for (1) each event individually and (2) pooled starts and increases, as well as decreases and ends. We note that Aave V2 did not exist at the time when Compound introduced its liquidity mining program.

We consider five variables of interest: (1) The logarithm of dollar-deposits or total value locked in the pool; (2) the logarithm of the total USD amounts borrowed; (3) the deposits as a fraction of the circulating supply of the respective token; (4) the utilization rate (the ratio of borrowed to deposited tokens); and (5) the daily netflows, measured as the difference of the logarithm of the inflow and the logarithms of the outflows in USD. To ensure comparability across events and considering the significant growth and decline of the DeFi ecosystem between 2020 to 2023, we normalize our variables of interest to the beginning of each event window by subtracting a benchmark value from all observations. As the benchmark, we use the value of the day before the event window (-15 days).

We need to consider the economic mechanisms that may lead to changes in our variables of interest. We rely on first principles. All DeFi protocols require liquidity: automated market makers, derivatives exchanges, and even proof-of-stake protocols only work if some users make their capital available. Constrained liquidity providers shift funds to the most attractive protocol. Since protocols are aware of the competitive environment, we hypothesize that they set up a program that is attractive and therefore the start of a liquidity mining program should lead to inflows. Since protocols also incentivize lending, we hypothesize that there should also be an increase in borrowings.

Liquidity mining programs aim to either "prime the pump" to initiate activity, or they may be simply an attempt to keep up with competitors. One way or another, these programs subsidize activity and thus their premise is to be temporary. In an ideal world for the platforms, demand becomes self-sustaining and liquidity incentives are no longer necessary. In other words, when incentives decrease or are removed, the platform should outperform the alternatives to prevent outflows. Since a no-change is not testable, we test for the opposite.

Hypothesis 1 (Level Changes) *The introduction of incentives leads to level inflows of funds and increased borrowing (H1a), reductions and terminations lead to outflows and decreases in borrowing (H1b).*

Predicting changes in rates is more complex because they reflect alterations in the derivative, not the levels. We test as follows

Hypothesis 2 (Rates of Flows) *The introduction of incentives increases the rate of inflows of funds (H2a), reductions and terminations depress the rate of inflows (H2b).*

Finally, as argued in Section 1, the impact of liquidity mining on utilization is indeterminate: ceteris paribus, new deposits lower utilization and thus borrowing rates, making borrowing more attractive. Token rewards however, also distort borrowing costs. The resulting net effect is an empirical question (H3).

Hypothesis 3 (Utilization) *We predict that utilization is unchanged (H3).*

In an ideal world, to ascertain the causal effect of changes in mining programs, we would require a DeFi protocol that meets the exclusion restrictions and serves as a benchmark in a difference-in-differences analysis. However, liquidity can go to any protocol and all protocols compete. Thus, the introduction of liquidity rewards for one protocol influences all others. It is conceptually plausible that the effects of one network should go in the opposite direction of a competitor. For example, if the treated protocol experiences an inflow, competitors should experience an outflow of funds. The same argument can even be applied to different, conceptually fungible tokens (e.g., USDT vs. TUSD)

Our estimation technique, strictly an event study, compares the treatment per affected token-protocol relative to all protocol-token combinations that experience no reward change.

Note that the number of observations for, e.g., a pooled decrease/end event is not the sum of the decrease and end events because of overlapping controls. Our approach is similar to the DiD designs with staggered adoption of treatments as established by Borusyak et al. (2023).

Each panel contains the coin-protocol combinations that saw a start/increase/decrease/end, respectively, over the relevant event window as well as token-protocol combinations that saw no change at all during the event window. Overall, we identify 135 protocol-token changes to rewards, which lead to 12 distinct 28-day event intervals. The variable of interest is the treatment effect for the events as well as the pooled rewards up (start/increase) and down (decrease/end) events. Formally, for each of the variables of interest, we estimate

$$\begin{aligned} DV_{jit} = \beta_0 + \beta_1 \cdot \textit{LM change}_{jt} \times \textit{treated}_{jt} \quad &+ \beta_2 \cdot \textit{LM change}_{jt} + \beta_3 \cdot \textit{treated}_{jt} \\ &+ \textit{time series controls}_t + \epsilon_{jit}, \end{aligned} \tag{3}$$

for pool i and protocol j at time t; DV_{jit} are the log of the normalized dollar-deposits and dollar-borrowings, the fraction of deposits of coins outstanding, the utilization, and the log-netflows; $\textit{LM start}_{jt}$ is a dummy equal to 1 for the 14 days following an liquidity mining change in protocol j; $\textit{treated}_{jt}$ is a dummy equal to 1 for the 28 day event window around a protocol's change date; time-series controls are the log of Ethereum gas fees in USD, the volatility index CVI, and the daily bitcoin return. Inference for all regressions is based on time-clustered standard errors, using token fixed effects.[14] The main variable of interest is β_1, the treatment effect, computed over the six different specifications.

Results. Figure 3 plots the variables of interest averaged over all pools for the treated and untreated protocols for the 28-day event window for reward-up (start and increase) and reward-down (decrease and end) pooled panels. The plots on the left are for up-events, the plots on the right are for down-events; depicting deposits, loans, deposits as a fraction of coins outstanding, utilization, and netflows. The figure suggests that a reward up is

[14] In untabulated regressions we also include protocol fixed effects as well as no fixed effects at all; the conclusions are quantitatively and qualitatively the same.

associated with a significant increase in deposits and loans, and a moderate relative increase in utilization. The effects for down-events are more muted with a relative decline in loans, deposits, and utilization. Net flows show little change for either series.

The estimation results for the four week event window are presented in Table 3. We focus on the pooled by up/down description. The regression analysis confirms the visual inspection of the data, indicating that the introduction of the liquidity mining program resulted in a significant increase in deposits, loans, and utilization, albeit the latter at low statistical significance. Conversely, a reduction in incentives is associated with a decrease in deposits, loans, and utilization. There is no indication of a change in net flows.

5 Empirical Analysis and Results at the Account Level

5.1 Yield-Seekers and Liquidity

In Section 3.2, we introduced three account subgroups: yield aggregators, stable-to-stable accounts (holding positions exclusively in the same stablecoin), and others. In our analysis, we combine yield aggregators and stable-to-stable accounts to form the group of *yield-seekers*.

Figure 5 plots the time series detailing the deposit/borrowing contributions of these groups to each protocol. Panels A and B display absolute values while panels C and D show percentages. Overall, yield-seekers make up a sizable proportion at the protocol level. During periods with active liquidity rewards, yield-seekers are responsible for a time-weighted average of 19% of deposits and 29% of borrowings on Compound. These shares peak on June 24, 2021, reaching 44% and 69% for deposits and borrowings, respectively. Similarly, on Aave, yield-seekers account for 17% of deposits and 33% of borrowings on average, with peaks of 32% and 57% observed on May 24, 2021. On average, yield-seekers contribute to Compound and Aave deposits of USD 1.8B and USD 2.5B, as well as loans of USD 1.2B and USD 1.9B, respectively. Since loans are immediately absorbed from the provided liquidity, yield-seekers borrowings correspond to the amount of "phantom" liquidity in the protocols.

Their engagement outside of periods with liquidity rewards is negligible, with average deposit shares of only 3% on Compound and 1% on Aave.

At the pool level, yield-seekers direct most of their investments to stablecoin pools, with 87% on Compound and 96% on Aave. They account for extensive fractions of activity in these pools: On Compound, yield-seekers contribute on average 45% and 41% of total stablecoin deposits, and take out 43% and 41% of loans in the largest stablecoin pools, DAI and USDC, respectively. Meanwhile, on Aave, yield-seekers account for 60% and 31% of all deposits and 61% and 33% of all loans in the DAI and USDC pools, respectively.

Yield-seekers commonly supply to and borrow from the same pool to receive both incentives. In the Compound protocol, yield-seekers borrow and lend simultaneously in 5 out of the 7 pools that have rewards. The TVL-weighted ratio of loans to deposits in all pools where yield-seekers actively borrow is 62%. On Aave, yield-seekers borrow from 6 of the 8 with-reward pools and their weighted loan-to-deposit ratio is 74%.[15] When examining stablecoin pools during periods with active rewards, we find that 22% and 29% of total deposits on average are attributable to phantom liquidity on Compound and Aave, respectively. The highest observed values are 64% and 62%, respectively, both occurring in the DAI pool.

We find a strong positive correlation between yield-seekers engagement and the amount of liquidity mining rewards allocated per pool (Pearson's $\rho_{Comp} = 0.98$ and $\rho_{Aave} = 0.91$). Post January 2021, Compound primarily allocated rewards to stablecoin pools and we observe a contemporaneous increase in users establishing stable-to-stable positions. Looking at the subset of yield aggregator contracts, the proportion of stablecoins steadily increased from January 2021, nearing 100% by February 2023. On Aave, the reward percentage distributed in stablecoin pools increased to ≈80% from November 22, 2021. Subsequently, we observe a similar reaction from aggregator services (see panel A of Figure 6).

Yield aggregators executed 22,187 transactions from 113 distinct addresses on Compound, and 4,062 transactions from 64 addresses on Aave. Figure 6 shows that interactions are linked to the USD rewards and TVL of the reward program. Yield aggregators exhibit high activity

[15]We exclude pools with yield-seekers average investment volume below 0.1%, as described below.

on both platforms: The median yield aggregator address conducted 35 on Compound and 21 on Aave over the sample period. For comparison, the median user conducts only 1 transaction on Compound and 2 transactions on Aave. Transaction count and volume of yield aggregators are concentrated, with the top 10 addresses accounting for 66% and 58% of transactions, and 65% and 83% of the flow volume on Aave and Compound, respectively.

5.2 Yield-seekers' Engagement with Liquidity Mining

Table 4 summarizes yield-seekers' activities within the ±14-day windows surrounding rewards adjustments, with separate sections for reward-up and reward-down events.

Note that the different observation periods affect the levels: most reward-up events took place early in the sample when DeFi markets were still in their infancy, whereas down-event occurred when markets where more developed, with larger aggregate deposits.

Notwithstanding the different periods, the summary statistics yield a few important observations: First, yield seekers mostly engage in stablecoin pools; although our identification of these types of actors is somewhat biased towards stablecoins, we note that yield seekers include all yield aggregators, not just those depositing stablecoins.

Second, it is immediately visible from the data that yield-seekers considerably boost the liquidity pools in absolute terms and in relative contributions. Additionally, they play a significant role in influencing borrowing and lending volumes. On Aave, for example, during decrease events in the middle of the sample period, yield-seekers account for 74% of deposits and they borrow back 57% of all deposits (and 77% of their own deposits).

Third, when rewards are reduced, yield seekers remove their funds rapidly and at scale: they remove 21% of their deposits and 23% of their borrowings from Compound and 18% and 19% from Aave, respectively. Notably, (which is not apparent from this specification), yield-seekers had already curtailed their deposits by almost 85% by the time Aave closed its liquidity mining program.

Additionally, we perform a formal regression analysis for the pre/post period to control for external factors and coin-specific covariates. Since yield seekers are predominantly active we focus our analysis on stablecoins only.[16] The analysis employs the same specifications as in (3), except that we partition the data into observations for yield-seekers and everyone else, and thus interact the treatment effect variable with a yield seeker indicator. Our variable of interest is the treatment effect for yield-seekers.

Table 5 exhibits the regression results for the ±14 day event window. We discuss here the pooled reward up/down findings. The estimates confirm our observations from the summary statistics: yield-seekers significantly increase their deposits and borrowing at the extensive and intensive margin, i.e., both in terms of the absolute levels, and their fractions of deposits and borrowing. They further significantly decrease their deposits and borrowing when incentives are lowered. The findings on borrowings following increases in funds are sometimes conflicting. Here, we cannot exclude that despite the higher incentives, increases in utilization triggered by other traders make borrowing less attractive.

Looking at reward termination events only (the fourth row), we observe that dollar deposits and borrowings display no significant effect. However, it is important to note that the estimated coefficient gauges the relative impact on yield-seekers. As evident from the summary statistics, they decrease their activities, but the magnitude of the reduction appears to align with the withdrawals of other participants. Namely, almost all of the yield-seekers' deposits and borrowings consists of USDC tokens (67% and 68%, respectively), and they reduced their USDC holdings by \$180M and \$130M, respectively, on average post-termination. The DAI token, the second most popular token among yield-seekers (representing 25% and 26% for deposits and loans, respectively), saw inflows of \$55M and \$21M.

In summary, the statistics clearly illustrate the crucial role that yield-seekers play in stablecoin activities and their sensitivity to changes in liquidity mining incentives.

[16] In untabulated regressions, we performed the analysis from Section 4 for stablecoins only. Our findings are robust for this subset.

6 The Yield-Seeker Externality

The results indicate that when rewards increase or are introduced, utilization in the affected pools rises, and when rewards decrease or disappear, utilization declines. Higher utilization implies higher interest payments. The variable utilization is an increasing function of borrowing and a decreasing function of deposits. Therefore, the findings suggest that incentive programs attract a disproportionate amount of borrowing activity.

Our account-level analysis reveals that yield-seekers, engaging in both depositing and borrowing, exhibit a abrupt reaction to incentive changes. The heightened utilization translates directly into increased borrowing and lending rates, with a stronger impact on borrowing rates due to the reserve pool wedge. In essence, the data suggest that an increase in incentives leads to higher borrowing costs, and our regression results imply that yield-seekers and their "phantom liquidity" may be the driving force behind this phenomenon. Therefore, yield seekers and their phantom liquidity appear to impose a negative externality on other users.

In this section, our objective is to offer a conclusive assessment of their impact. By equation (2), the utilization shift from a position is conditional on the relative share of borrowings to deposits. Thus, yield-seekers may increase or decrease the utilization. Consider two anecdotal examples:

- On February 1, 2021, yield-seekers held 61% of deposits and 50% of borrowings in Compound's DAI pool. If we would exclude their deposits and borrowings from the pool, all else equal, utilization would be 16 percentage points *higher*.
- Conversely, on February 1, 2023, yield-seekers accounted for 72% of borrowings and 51% of deposits. If yield-seekers were not present, utilization would be 21 percentage points *lower*.

We gauge the net effect of yield-seekers by computing the total dollar transfers from borrowers to lenders resulting from their presence. A larger transfer induced by yield-seekers is interpreted as a negative externality to the ecosystem.

A key advantage of our collected data is that we can almost directly quantify this externality.[17] Using knowledge of yield-seekers' aggregate positions, we compute the counterfactual utilization and APY rates for each pool that would pertain in their absence.[18] We then derive the hypothetical interest rates for each pool where yield-seekers allocated more than 0.1% of total investments[19] and compute the total payments and receipts of interest. We note the caveat that this counterfactual approach is ceteris paribus and cannot capture general equilibrium effects, i.e., we do not know how the other borrowers and lenders would have acted had yield-seekers not been there.

Figure 7 presents the transfers between borrowers and lenders with and without the funds supplied and borrowed by yield-seekers. Panels (A) and (B) show the TVL-weighted borrowing and deposit rates and the difference between the subgroups; these rates are based the utilization rate and in Panel (C), we display the 20-day moving average utilization rate across pools. Table 6 provides pool-level statistics.

Our results demonstrate that yield-seekers strongly affect the borrowing and deposit rates. The average utilization spread between the two scenarios amounts to 3.8 percentage points on Compound and 2 percentage points on Aave. Specifically, on Compound, deposit and lending rates are 1.5 percentage points and 1.7 percentage points *lower* because of the presence of yield-seekers. Meanwhile, on Aave the deposit and lending rates are on average spreads 2 and 2.4 percentage points *lower*.[20]

Their impact is particularly pronounced in the biggest pools, DAI and USDC, consistent with their significant presence in these markets (see Table 6 for details). Therefore, in terms of the rates, depositors get paid less and borrowers pay less, but the benefit for borrowers is

[17] As is common practice in empirical work, we compute daily aggregate account balances and daily interest rates. We note, however, that the protocols compound interest rates per block, and that discrepancy can lead to minor account balance differences. In our data, these differences are smaller than 0.5% of the total.

[18] Removing yield-seekers' funds in the counterfactual scenario may sometimes result in hypothetical utilization rates above 100%. Since pool-based utilization has a natural maximum, we cap U at 1.

[19] Pools with negligible yield-seeker exposure on Compound are AAVE, BAT, COMP, FEI, REP, SUSHI, TUSD, UNI, YFI, and ZRX. On Aave, this set includes 1INCH, AAVE, AMPL, BAL, BAT, CRV, CVX, ENJ, ENS, GUSD, KNC, MANA, MKR, PAX, REN, SNX, UNI, XSUSHI, and ZRX.

[20] Stable borrow rates, offered on Aave, are on average 3.6 percentage points lower due to the presence of yield-seekers.

larger than the loss for lenders.

To quantify the cumulative dollar transfers over the sample, we compute the cash value of the yield-seeker presence. The two panels D in Figure 7 illustrate the results. Red lines represent the hypothetical, additional deposit interest that lenders would have earned, while blue lines indicate additional borrowing interest borrowers would have paid in the absence of yield-seekers. Compound depositors received USD 214M less in interest, but borrowers paid USD 223M less in borrowing interest. For Aave, these amounts are USD −388M for lenders and USD +425M for borrowers, respectively.

To conclude, although yield-seekers borrow back a substantial portion of their deposits and thereby create phantom liquidity, they still generate a surplus of liquidity that benefits the market as a whole: other users saved about USD 46.2M net interest across both protocols.

7 Summary and Conclusion

Decentralized finance is a genuinely clever idea with a simple workflow: at the core are decentralized applications, pieces of code that have been registered on a public blockchain and that are operated by the network, or, rather, the community of validators. These apps run (almost) autonomously, based on a transparent set of rules. A decentralized application can be accessed in two ways: one is by direct function calls to the blockchain smart contract. The other, more consumer-friendly approach is via a website. Notably, there is no exclusivity — anyone can create a new website to access the same or multiple functions, and multiple parties can collaborate or jointly use the network and all its applications.

If decentralized finance has a future, however, it is critical to understand the specific economic challenges for platforms that are intrinsic to blockchains. Our paper provides important, novel insights into these challenges for a core application: decentralized lending.

There are two distinct features of the defi eco-system that make it economically and not just functionally different from traditional finance. First, decentralized lending applications are two-sided, intermediary-less, and undercapitalized platforms that need to bootstrap their market by attracting both borrowers and lenders. Second, they operate in an environment where automated algorithms act as de-facto intermediaries by collecting capital and then moving it swiftly to exploit at scale any incentives offered.

We make three important observations: first, platform incentives work, but they do not create stickiness, in part because automated intermediaries move to greener pastures. Second, liquidity mining rewards incentivize automated intermediaries to create phantom liquidity. It is a phenomenon similar to wash trading, where the automated intermediary deposits funds and borrows most of them back immediately, creating the illusion of liquidity that is never accessible to the general public. Third, it is theoretically possible that this behavior creates a negative externality by creating inefficient wealth transfers between borrowers and lenders. However, we show that this is not the case, that is, phantom liquidity is ultimately welfare-improving for the protocol users, at the rate of about 7% of the total distributed liquidity incentives of USD 638M.

A question for future work that requires a theoretical analysis is whether phantom liquidity is an unintended (albeit welcome) consequence or a deliberate design feature of two-sided platform incentives, and whether it may emerge naturally over time as yield-seeking token holders steer incentives via DAO votes to attract phantom liquidity.

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Appendix

8 Additional Institutional Details

8.1 Overview

This appendix reviews the institutional details of lending protocols that do not feature prominently in our analysis. The last subsection features and example of a loan, with borrowing and lending rates, and a liquidation.

8.2 Detailed Token Accounting

LPs use pool-specific synthetic, tradable tokens to track user balances and interest, created when users deposit cryptocurrencies and burned upon withdrawal. There are two main token accounting systems. The first continuously updates the wallet balance of synthetic token holders. This type of accounting system is used, for instance, by Aave. Specifically, a user who supplies Q_0 units of an A-token to the Aave pool obtains Q_0 aA-token. While the user holds the token, the balance updates continuously. To withdraw her deposit with any accrued interest after holding the token for T blocks, the user sends her Q_T aA-tokens to the contract, where

$$Q_T = Q_0 \prod_{t=1}^{T} (1 + r_t), \tag{4}$$

with time t measured in blocks and r_t as the interest allocated per block t. The returned aA-tokens are "burned" by the contract, meaning that they are sent to an address that is not controlled by a private key.

The second type of interest accounting system provides users with a fixed number of synthetic tokens that represent fractional ownership of the pool at the time of the deposit. When they withdraw, their claim will have grown by the interest paid. Specifically, suppose a user deposits q_0 units of the A-token into a pool that contains Q_0 of A-tokens and assume there are Q_0^c units of the cA-tokens outstanding at the time of the deposit. Then the user obtains a number q^c tokens such that

$$\frac{q^c}{Q_0^c + q^c} = \frac{q_0}{Q_0 + q_0}. \tag{5}$$

We define $z_t = \frac{Q_t}{Q_t^c}$ as the exchange rate of A to cA-tokens. Over time, interest accrues on the lend-out portion of the liquidity pool, with the result that the pool contains $Q_T > Q_t$ of the A token after time T, all else equal. When withdrawing their funds, users send q^c tokens to the contract and receive $q_T > q_0$ of the A-token at exchange rate $z_t > z_0$, where $q_T = Q^c \times z_T$; see Leshner and Hayes (2018).

8.3 Borrowing, Collateral, and Liquidations

Since all blockchain activities are based on pseudo-anonmymous addresses and since users can create arbitrarily many representations, reputation effects or institutional sanction mechanisms known from traditional lending have no bite in the blockchain world. To prevent moral hazard problems, all loans in the DeFi protocols that we consider are over-collateralizated. Each permissible asset $i \in I$ is associated with a collateral factor $CF_i \in [0,1]$.[21] This factor determines a user's *borrowing capacity*: a prospective borrower $a \in A$ who has made deposits $D_{a1}, \ldots, D_{aI}$ in assets $i \in I$, has borrowing capacity BC_a defined as

$$\mathrm{BC}_a = \sum_{i=1}^{I} D_{ai} \times CF_{ai}. \tag{6}$$

Value fluctuations of the token underlying the collateral/loan may lead to a situation where a position approaches under-collateralization. LPs include a process known as a liquidation event to maintain the system's stability and security. A position qualifies for liquidation once the collateral value falls below a minimum threshold relative to the outstanding debt. Specifically, in terms of the numeraire, liquidation becomes eligible when the collateral multiplied by the asset's liquidation threshold $LT_i \in [0,1]$ declines below the outstanding debt. The liquidation threshold corresponds to the percentage at which a position is defined as undercollateralized. Akin to the collateral factor, the LT reflects liquidity and volatility risks associated with the underlying asset and can be interpreted as a risk buffer. For instance, the Aave protocol specifies $LT_{BTC} = 0.75$, resulting in a minimum over-collateralization of BTC-secured lending of 133%. More formally, the liquidation risk of agent a with outstanding debt ($\sum_{i=1}^{I} D_{ai} > 0$) at time t is given by the the health factor $HF_{at} \in \mathbb{R}_+$:

$$HF_{at} = \frac{\sum_{i=1}^{I} D_{ait} \times LT_{it}}{\sum_{i=1}^{I} B_{ait}} \tag{7}$$

The health factor summarizes the risk exposure of a position: If the value of the col-

[21] In the Aave protocol, the collateral factor is applied to the loan-to-value ratio (LTV).

lateral remains high relative to the borrowed funds ($HF_a > 1$), the health factor will be high, indicating that the position is secure. In contrast, positions with inadequate collateral coverage ($HF_a < 1$) can be liquidated by any agent (referred to as liquidators) willing to invoke the smart-contract function and perform the liquidation. Note that an insufficient HF_a can result from both decreasing collateral value or increasing debt value. In the liquidation process, the liquidator settles the outstanding debt (including interest) and seizes the collateral at a discounted rate.

The collateral share C_i^l the liquidator is allowed to seize against payment of defaulted debt is equal to $C_i^l = D_i^l \times (1 + LB_i)$, where D_i^l corresponds to the debt repaid by the liquidator and LB_i to the liquidation bonus (or penalty from the borrower's perspective) of 5-15%. The liquidation bonus is intended as an incentive for agents to act as liquidators and keep the system healthy.[22] As documented by Qin et al. (2021) and Lehar and Parlour (2022), specialized bots (i.e., automated scripts) primarily perform liquidations. While the fixed-spread liquidation model provides a deterministic and transparent financial incentive, liquidators must account for transaction fees on the Ethereum network when calculating liquidation profits. Bots typically execute atomic liquidation scripts to limit risks, including a flash loan for the amount repaid upon liquidation and a currency swap on a decentralized exchange to adjust the seized collateral.

8.4 Detailed Interest Rate Determination

Interest rates in decentralized lending pools are a linear function of utilization U — the ratio of outstanding loans to provided deposits. When pool i approaches full utilization, $U_i \to 1$, liquidity risks arise because deposits can no longer be withdrawn seamlessly. The two-stage linear interest function is designed to mitigate these risks; see (AAVE, 2020). For low values of U_i, the slope is relatively small, but it increases sharply when utilization exceeds the

[22] Some LPs limit the proportion of debt that can be repaid in a single liquidation event to a maximum percentage share determined by the close factor. For instance, the close factor on Aave is set to 50%.

pool-specific optimal threshold U_i^*. Formally, the **borrow** interest rate R_{it}^b is defined as:

$$R_{it}^b = \begin{cases} R_{i0} + \frac{U_{it}}{U_i^*} R_{i1} & \text{if } U_{it} \leq U_i^* \\ R_{i0} + R_{i1} + \frac{U_{it} - U_i^*}{1 - U_i^*} R_{i2}, & \text{if } U_{it} > U_i^*, \end{cases} \tag{8}$$

where R_0 denotes the base interest for $U_{it} = 0$ (typically 0), R_{i1} the (modest) interest increase per unit of relative utilization below the pool's optimal utilization, and R_{i2} the (sharp) increase when U_{it} exceeds the target and liquidity risks become urgent (50-300%).

Some LPs offer debt at stable borrow rates R_{it}^s, allowing agents to predict interest payments. Stables rates are higher than variable rates R_{it}^v, and their availability is limited by certain constraints. Aave, for example, deterministically increases the stable rate when both pool utilization exceeds $U_{it} > 95\%$ and the weighted average borrow rate across all pools $\bar{R}^b$ is below 25%, $\bar{R}_t^b < 25\%$. Conversely, the stable rate of an open position R_i^s in asset i declines if the rate surpasses the current stable rate of new debt by 20%, i.e, $R_i^s > R_{it}^s \times 1.2$.

The **deposit** rates R_{it}^d follow from (8): interest payments from borrowers are channeled to depositors with a deduction allocated to the pool's reserve. The reserve is an important feature of lending pools to provide users with additional insurance against default. As discussed by Qin et al. (2021), technical issues, high market volatility, and other frictions may prevent an under-collateralized position from being liquidated, thereby leaving the pool under-capitalized. The reserve acts as a backstop by accumulating funds over time by retaining a fraction of interest payments. Eventually, depositors receive all borrower interest payments R_{it}^{bsv} net of payment to the pool's reserve, determined by the reserve factor RF_i (typically 5-20% of the interest payment). Let V_{it} and S_{it} denote the fractions of variable and stable borrowers in i; the deposit interest R_{it}^d is

$$R_{it}^d = \begin{cases} U_{it}(V_{it}R_{it}^{bv} + S_{it}R_{it}^{bs})(1 - RF_i) & \text{if stable debt is offered,} \\ U_{it}R_{it}^b(1 - RF_i) & \text{otherwise.} \end{cases} \tag{9}$$

8.5 An Example from the Ethereum Blockchain

This example is based on ETH address "0x1514c5928534db6bcd97458515afc715c3a5b554". On April 17, 2021, the user deposited ETH 0.6=USD 1421, into the Aave V2 ETH lending pool. Eleven days later, on April 28, the user borrowed USDC 1000 from the Aave USDC pool, using her provided deposit as collateral. The key statistics are as follows:

- The pool's total liquidity was USDC 1.73B and its outstanding debt USDC 1.58B implying a utilization rate of $U_{USDC} = 89.8\%$.
- The pool's target utilization is $U^*_{USDC} = 90\%$.
- The interest slope before the breakpoint U^* is $R_{USDC,1} = 4\%$, implying a variable borrowing rate of $R^d_{USDC} = 3.99\%$ for the user.
- The liquidation threshold for this asset was 82.5%.
- Therefore, the user's position had a health factor of 1.35.

Between April 28 and late July, the ETH price dropped by more than 30%, causing the user's health factor to drop below 1 on July 22. The following happened

- A liquidator repaid USDC 761.1 of the loan and seized ETH 0.42 collateral, earning a liquidation bonus of 5% or USD 38.05 before fees.
- The user then repaid the outstanding debt of USDC 252.19, collected the remaining collateral of ETH 0.17, including ETH 0.00015 interest, and withdrew all funds from the Aave protocol.

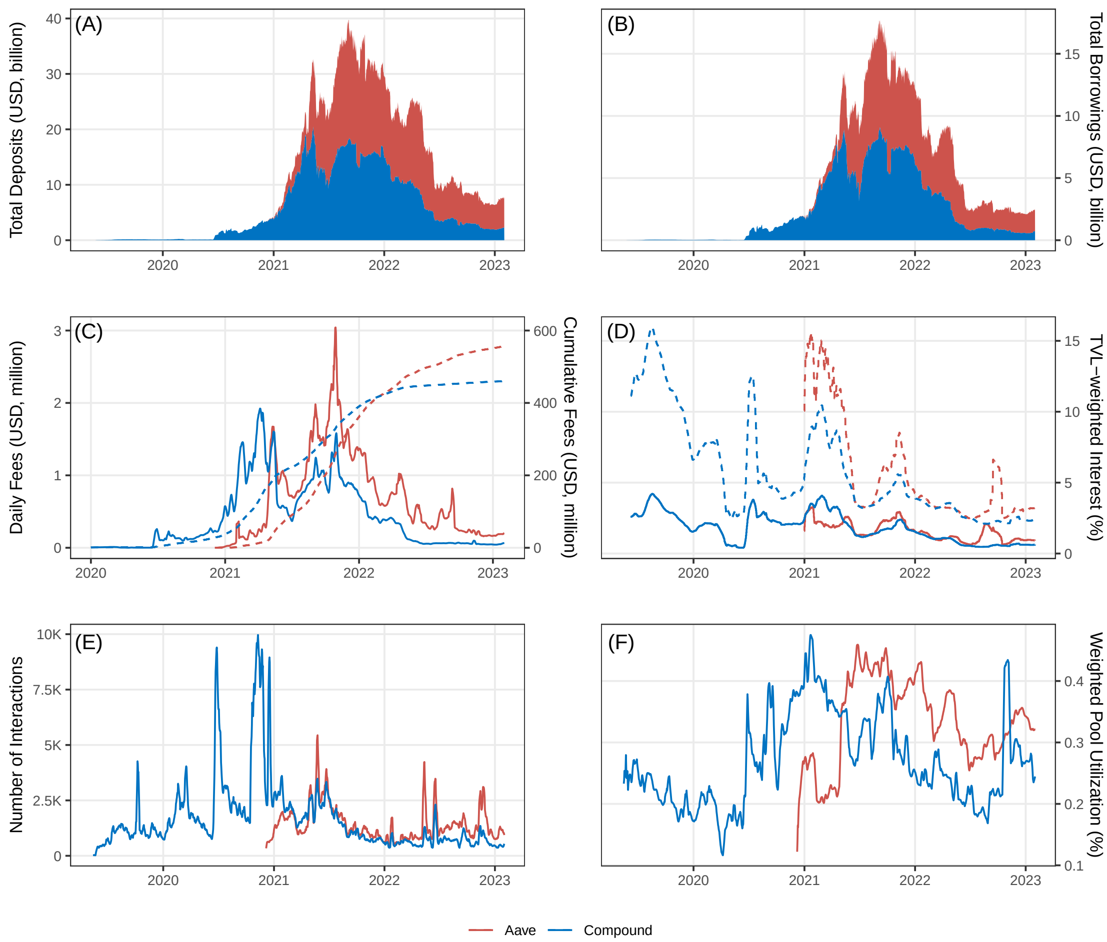


Figure 1
Evolution of Aave and Compound (May 2019 to February 2023)

This figure shows the daily trajectory of important protocol parameters: Panel A and B show the total deposits and borrows. Panel C highlights daily fees from interest and liquidation penalties (solid line, left-axis), and the cumulative historical fee revenue generated by the protocols (dashed line, right-axis). Panel D reflects the TVL-weighted deposit (solid) and borrow rate (dashed), denoted as the 30-day moving average. Fee data is obtained from https://tokenterminal.com/docs/api/.

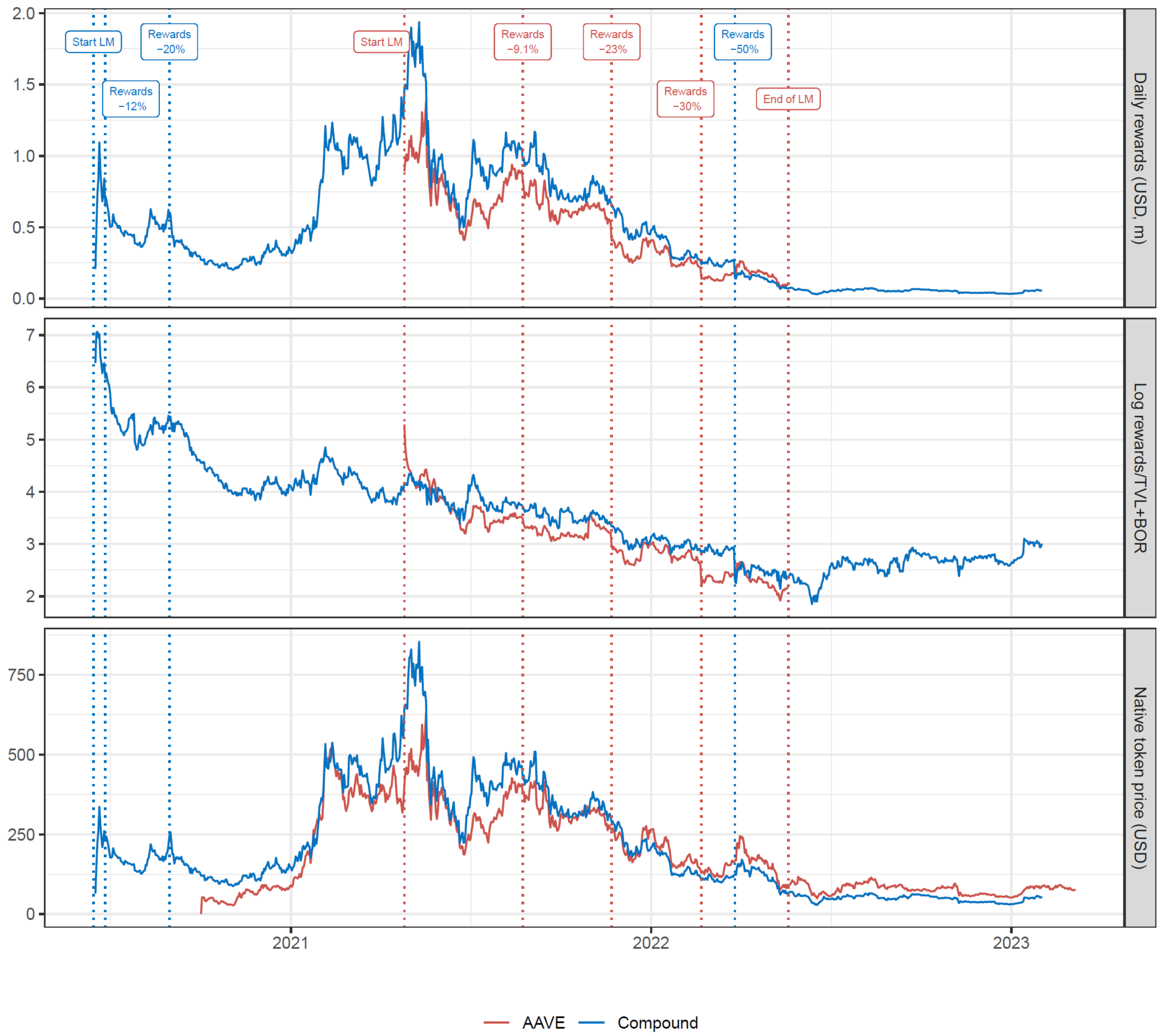


Figure 2
Liquidity Mining Rewards on
Compound and AAVE (June 2020 to February 2023)

This graph plots the evolution of liquidity rewards distributed on Compound and Aave. The upper panel shows the daily USD rewards calculated by multiplying the number of distributed tokens per protocol with the respective USD native coin price (lower panel). USD rewards relative to the total number of deposits and loans, which serve as an indicator of competitiveness for rewards, are shown in the middle panel. Dashed vertical lines indicate adjustments in the number of reward tokens allocated per day.

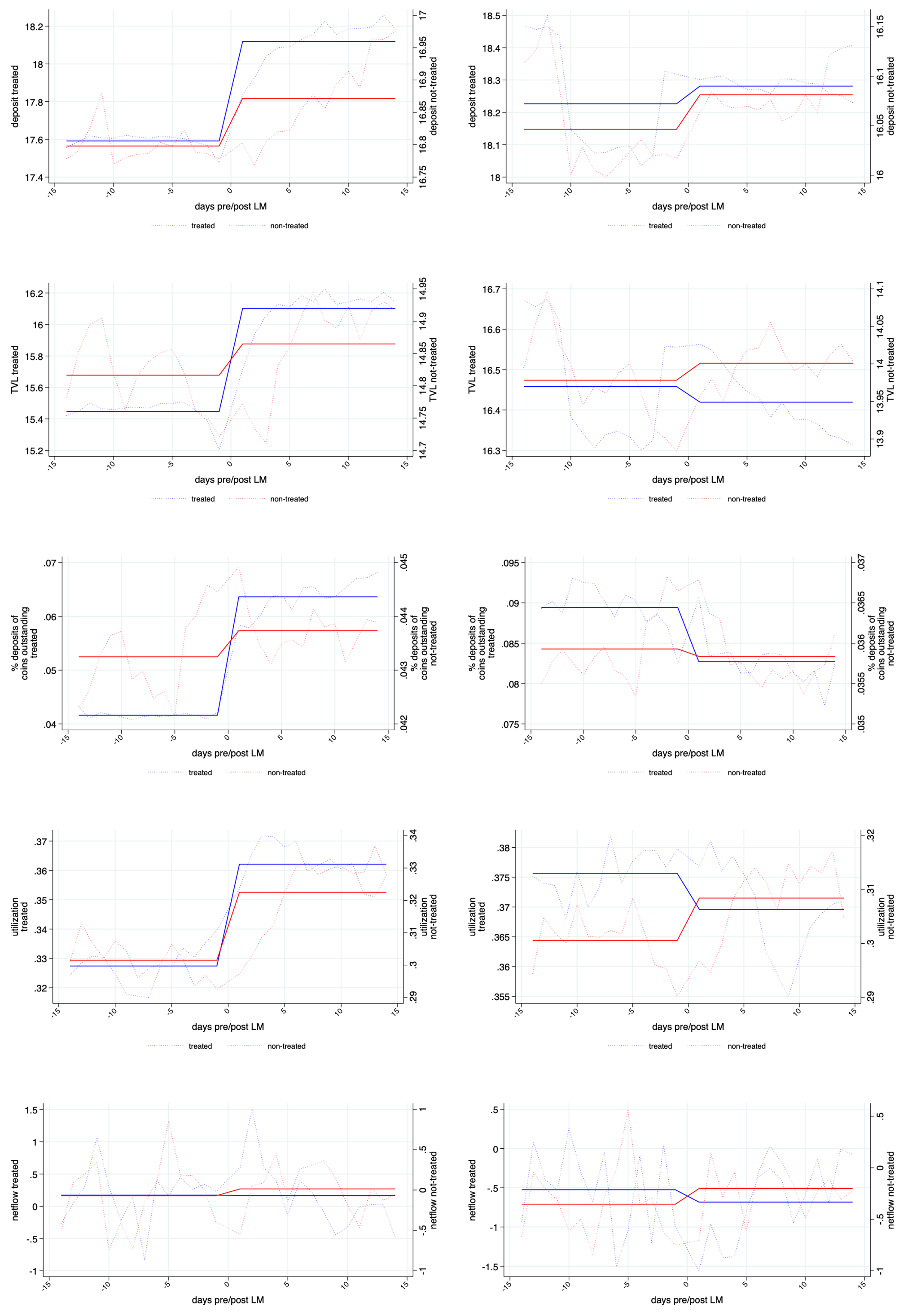


Figure 3
Effect of Liquidity Mining Programs

This plot illustrates the changes in essential variables throughout the beginning, reduction, and termination phases of liquidity mining programs on Compound and Aave. All observations are standardized and centered for a period of ± 14 days around each event. The left column depicts increases in rewards (starts and improved rewards); the right column depict reductions or ends of rewards. The first and second rows represent the extensive margin (the dollar amounts of deposits and loans), the third row captures the fraction of marketcap of a token that's been deposited in a protocol, the fourth row displays the utilization rate, and the last row shows the net token flows (inflows minus outflows).

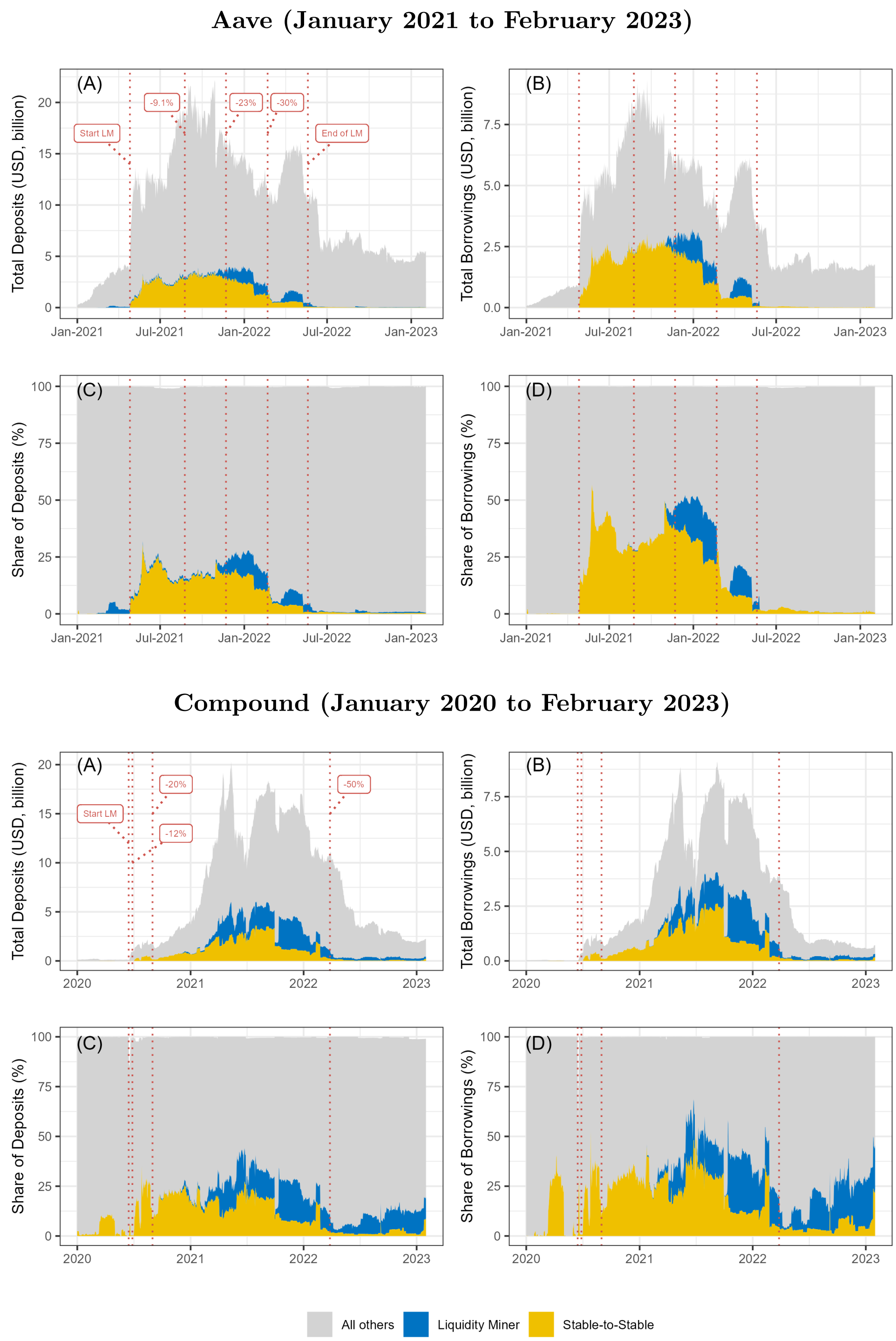
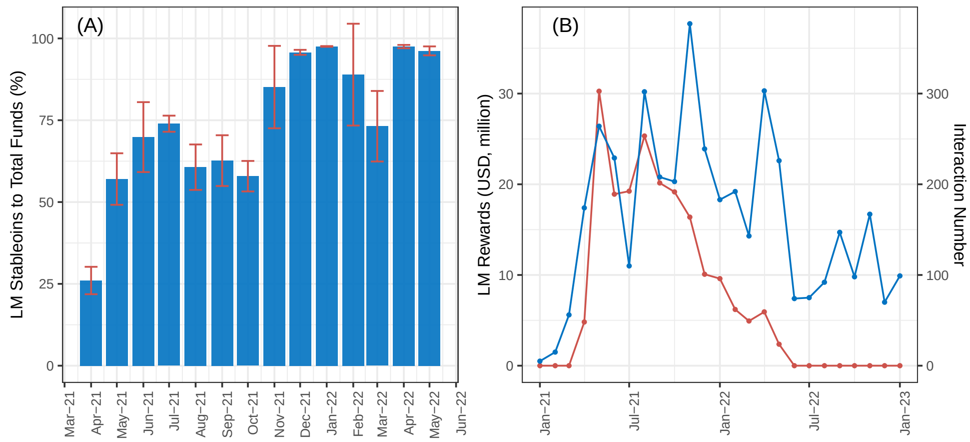


Figure 5
Activity of Yield-Seekers

This plot illustrates the total deposits and loans (panels A and B) and the percentage of total pool TVL and loans (panels C and D) contributed by liquidity miners and stable-to-stable addresses on Aave and Compound. Red-dotted lines indicate adjustments of the liquidity rewards. The data is aggregated from daily user balances and includes 113 and 64 addresses associated with yield aggregation services on Compound and Aave, respectively, as well as all observed stable-to-stable addresses.

Aave (March 2021 to February 2023)



Compound (June 2020 to February 2023)

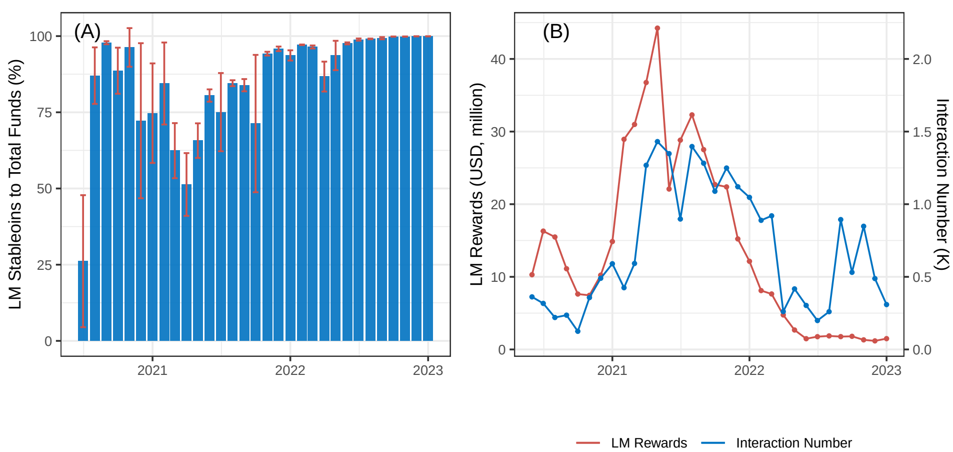
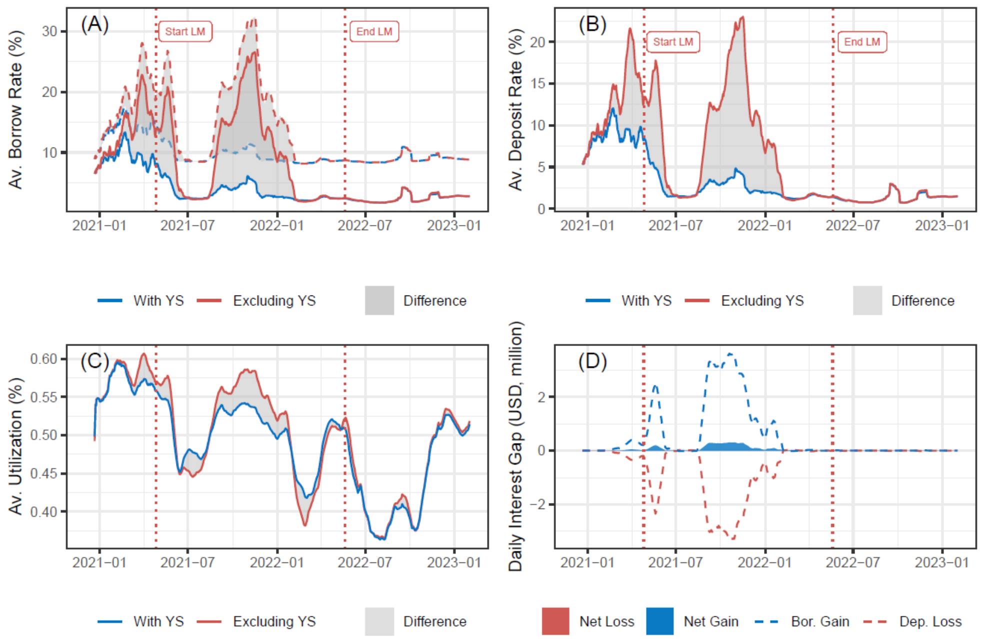


Figure 6
Stablecoins Share of Yield Aggregator Funds (Panel A).
LM Rewards and Number of Yield Aggregator Interactions (Panel B)

Panel A illustrates the monthly mean proportion and standard deviation of stablecoins (including USDC, DAI, and USDT) in the total investment of yield aggregator services. Panel B displays the yearly USD rewards allocated in the liquidity incentive program on the left-axis, and the number of protocol interactions of yield aggregators on the right-axis. Protocol interactions refer to deposits, borrows, repays and withdrawals.

Aave (January 2021 to February 2023)



Compound (May 2020 to February 2023)

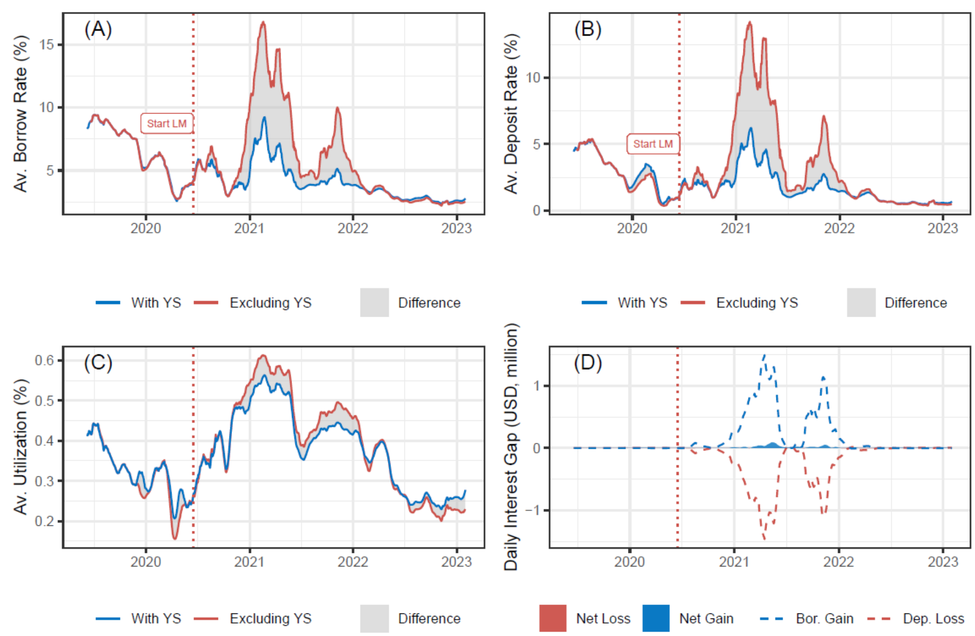


Figure 7
Effect of Yield-Seekers on Utilization and Lending Rates

Panels A and B highlight the TVL-weighted average borrow and deposit rates, both with and without yield-seeking accounts, as defined in Subsection 2.4. Counterfactual rates are calculated by excluding the deposit and borrow balances of yield-seekers. Stable rates on Aave are depicted as dashed lines. Panel C presents the utilization rate for both scenarios. Panel D depicts the USD value of interest saved/lost by other users, resulting from the influence of yield-seekers on interest rates. All figures are standardized using the 20-day rolling mean. The red-dotted line indicate the commence and end of liquidity mining programs.

Table 1

Coverage of Liquidity Mining Programs and important Modifications.

This table shows the essential start, adjustment, and end dates of liquidity incentive programs implemented on Compound and Aave, together with the volume of payouts. The data are based on the evaluation of 322 governance decisions (154 for Compound and 168 for Aave). The "Proposal" row contains the link to the corresponding community vote. Within the protocols, several smaller modifications of inter- and intra-pool distributions were made, which we capture in our data; however, for the sake of brevity, they are not included in this table.

Date	Protocol	Program	Amount/day (in native token)	Proposal
June 15, 2020	COMP	Start of the LM (4 years)	3250 COMP	CIP 7
June 27, 2020	COMP	Adjustment of LM (-12%)	2880 COMP	CIP 10
August 31, 2020	COMP	Adjustment of LM (-20%)	2140 COMP	CIP 21
April 26,2021	AAVE V2	Start LM	2200 stkAAVE	AIP 11
August 24, 2021	AAVE V2	Adjustment of LM (-9%)	2000 stkAAVE	AIP 28
November 22, 2021	AAVE V2	Adjustment of LM (-23%)	1540 stkAAVE	AIP 47
February 21, 2022	AAVE V2	Adjustment of LM (-30%)	1078 stkAAVE	AIP 60
March 27, 2022	COMP	Adjustment of LM (-50%)	1163 COMP	CIP 92
May 20, 2022	AAVE V2	End of LM	-	-

Table 2
Pool-level Summary Statistics on Daily Data for Aave and Compound.

This table provides summary statistics on daily values for 38 and 19 lending pools on Aave and Compound, respectively. The observation period spans from May 2019 to February 2023 for Compound, and December 2020 to February 2023 for Aave. USDC is the largest pool in both protocols regarding deposits and borrowings. Note that we removed the minimum values from this table, since they are zero for all variables and groups.

	Aave					
Statistic	Mean	Median	St. Dev.	Pctl(25)	Pctl(75)	Max
Deposits (USD, M)	305.3	16.9	842.5	5.3	115.5	9,316.9
Borrows (USD, M)	108.6	2.2	447.1	0.3	15.9	5,832.4
Deposit Rate (%)	4.8	0.5	39.3	0.04	2.1	677.7
Borrow Rate (%)	7.5	2.3	44.8	0.7	3.8	753.0
Utilization (%)	30.2	18.6	29.8	3.7	53.2	100.0
Liquidation threshold (%)	50.9	65.0	32.3	0.0	75.0	90.0
Share circulating supply (%)	5.7	1.9	9.2	0.5	5.7	97.5

	Compound					
Statistic	Mean	Median	St. Dev.	Pctl(25)	Pctl(75)	Max
Deposits (USD, M)	438.7	36.7	984.6	1.9	262.4	6,417.2
Borrows (USD, M)	182.8	2.8	580.4	0.1	36.6	4,233.7
Deposit Rate (%)	1.2	0.3	2.3	0.04	1.4	70.2
Borrow Rate (%)	4.8	3.7	3.6	2.6	5.7	94.8
Utilization (%)	23.8	10.8	26.8	3.8	39.1	100.0
Liquidation threshold (%)	50.8	65.0	30.4	35.0	75.0	85.5
Share circulating supply (%)	5.1	0.8	11.4	0.1	6.8	99.9

Table 3
Regression Table for the Impact of Liquidity Mining Programs

This presents our results on the impact of the introduction and changes to liquidity mining program on five key variables: the log of the dollar equivalent of deposited assets; the log of the dollar equivalent of borrowed assets; the fraction of the token's market capitalization that has been deposited in the lending pool; the utilization rate measured as the ratio of borrowed to deposited capital; and the net flows measured as the difference in the logs of daily inflows and outflows in USD. All dependent variables are normalized to the day before the event window. The data is an unbalanced panel by day, token, and protocol for the 14 days before and after a change to the liquidity mining protocol. There were a total of 135 changes in liquidity pools on 12 separate days. Each column represents a panel regression on the subset of the sample including protocol-tokens combinations that experience a fee change and those that experienced no change. An observation is "affected" if the change happened for the date-coin observation for the respective protocol. We use the following times series controls: the log of the token's price, the token's market capitalization, the crypto volatility index CVI, the return for the crypto-currency ETH, and the logarithm of the daily average Ethereum gas fee. The underlying regressions include token fixed effects, and standard errors are clustered by calendar date. *, **, *** indicate significance at the 10%, 5%, and 1% levels; the table shows the standard errors.

	Panel A: log(USD deposits)					
start	1.25***					
	(0.22)					
increase		0.01				
		(0.08)				
decrease			-0.04			
			(0.12)			
end				-0.19**		
				(0.08)		
rewards up					0.74***	
					(0.17)	
rewards down						-0.14*
						(0.07)
Observations	4,618	3,208	5,888	4,630	6,717	7,624
R-squared	0.425	0.683	0.246	0.339	0.328	0.169

	Panel B: log(USD borrows)					
start	1.22***					
	(0.25)					
increase		0.26***				
		(0.07)				
decrease			-0.09			
			(0.12)			
end				-0.28***		
				(0.09)		
rewards up					0.84***	
					(0.18)	
rewards down						-0.21***
						(0.07)
Observations	4,618	3,208	5,888	4,630	6,717	7,624
R-squared	0.453	0.429	0.257	0.299	0.322	0.166

Table 3
Regression Table for the Impact of Liquidity Mining Programs (cont'd)

This table is identical to Table 3 except that it presents our regressions for a 14 days before/after change to the liquidity mining protocol event windows.

	Panel C: % deposits of total marketcap					
start	0.03***					
	(0.00)					
increase		0.01***				
		(0.00)				
decrease			-0.00			
			(0.00)			
end				-0.01***		
				(0.00)		
rewards up					0.02***	
					(0.00)	
rewards down						-0.01***
						(0.00)
Observations	3,962	2,848	5,029	3,997	5,858	6,541
R-squared	0.190	0.174	0.109	0.284	0.141	0.116

	Panel D: utilization					
start	0.02*					
	(0.01)					
increase		0.00				
		(0.02)				
decrease			-0.01**			
			(0.01)			
end				-0.03***		
				(0.01)		
rewards up					0.02*	
					(0.01)	
rewards down						-0.02***
						(0.01)
Observations	4,596	3,163	5,795	4,540	6,672	7,513
R-squared	0.268	0.171	0.223	0.280	0.173	0.169

	Panel E: log(netflows)					
start	0.13					
	(0.31)					
increase		-0.13				
		(0.37)				
decrease			-0.67*			
			(0.36)			
end				0.18		
				(0.42)		
rewards up					-0.07	
					(0.26)	
rewards down						-0.33
						(0.28)
Observations	4,623	3,208	5,891	4,630	6,722	7,627
R-squared	0.117	0.187	0.067	0.115	0.110	0.055

Table 4
Summary Statistics for Deposits and Borrowing of Yield-Seekers

This table summarizes the deposits and borrowing of yield-seeking accounts. A yield-seeking account is defined as either the address of a yield aggregator vault or as an address that simultaneously borrows and lends in stablecoins. The data is based on the Aave and Compound protocol; the time horizon is ±14 days from the starting day of the liquidity mining program/reductions in mining incentives. Stablescoins are DAI and FEI (crypto-collateral backed), USDT, USDC, USDP (fiat-backed, issued by Tether, Circle and Paxos respectively), and TUSD (the ultimately collapsed algorithmic stablecoin from Terra). The largest volatile assets are ETH and BTC. We note that most start and increase events happen early in the sample when the market was at its infancy whereas reduction events occurred later in the sample when the market had grown substantially.

	Rewards up (start or increase)				Rewards down (decrease or end)			
	deposit		borrow		deposit		borrow	
	before	after	before	after	before	after	before	after
*Panel A: Stablecoins on **Compound***								
in million USD	2.5	249.8	0.6	180.8	1,514.1	1,189.0	1,027.8	796.1
%TVL	3.1	37.1	0.8	26.8	55.6	47.4	37.7	31.7
%of borrowing			1.0	37.2			51.9	41.3
%own funds borrowed			25.3	72.4			67.9	67.0
*Panel B: Volatile Assets on **Compound***								
in million USD	6.9	6.5	0.7	0.6	15.8	12.1	2.8	0.5
%TVL	1.5	1.3	0.2	0.1	1.1	0.8	0.2	0.0
%of borrowing			3.6	1.4			4.6	0.8
%own funds borrowed			10.0	10.0			17.6	4.1
*Panel C: Stablecoins on **Aave***								
in million USD	541.0	984.8	400.0	731.1	4,143.7	3,401.0	3,197.6	2,603.1
%TVL	55.7	56.6	41.2	42.0	73.9	64.5	57.1	49.4
%of borrowing			50.8	49.3			72.9	64.8
%own funds borrowed			73.9	74.2			77.2	76.5
*Panel D: Volatile Assets on **Aave***								
in million USD	65.0	51.9	13.1	8.5	47.9	44.6	0.9	1.7
%TVL	4.7	3.7	1.0	0.6	3.0	3.4	0.1	0.1
%of borrowing			17.6	12.0			0.8	2.0
%own funds borrowed			20.2	16.4			1.9	3.8

Table 5
Regression Table for the Impact of Liquidity Mining Programs on Yield-Seeker Activity

This table presents the regression results analyzing the effect of the introduction and modifications to liquidity mining programs on yield-seekers' activities. We define yield-seekers as per the criteria detailed in Subsection 3.2. Dependent variables in the analysis comprise the log-USD deposits and log-USD borrowings, the fraction of the total TVL that yield-seekers deposit, the fraction of the total TVL that yield-seekers borrow back, and the fraction of total borrowings that pertain to yield seekers. All dependent variables are normalized to the beginning of the event window. The data set exclusively focuses on the stablecoin pools, partitioning funds provided by yield-seekers and others as indicated by the yield-seeker dummy variable. The definitions for incentive changes and the cross-sectional control variables specifications align with those in (3). For better readability, the table only represents only the treatment effect and omits all estimates for the other dummy and control variables. The underlying regressions include token fixed effects where indicated, and standard errors are clustered by date. *, **, *** indicate significance at the 10%, 5%, and 1% levels.

	Panel A: log(USD deposits)						Panel B: log(USD borrows)					
start	5.15***						6.79***					
	(0.33)						(0.32)					
increase		0.59***						-2.12***				
		(0.21)						(0.37)				
decrease			-0.61***						-0.06			
			(0.10)						(0.14)			
end				-0.19						0.11		
				(0.12)						(0.17)		
rewards up					3.48***						3.40***	
					(0.41)						(0.64)	
rewards down						-0.48***						-0.07
						(0.10)						(0.11)
Observations	2,898	1,942	4,054	2,842	4,168	4,950	2,898	1,942	4,054	2,842	4,168	4,950
R-squared	0.303	0.246	0.159	0.292	0.206	0.082	0.269	0.220	0.089	0.225	0.129	0.068

	Panel C: % deposits of TVL						Panel D: % of TVL borrowed					
start	0.16***						0.14***					
	(0.01)						(0.01)					
increase		0.01						-0.05***				
		(0.01)						(0.01)				
decrease			-0.15***						-0.09***			
			(0.02)						(0.02)			
end				-0.12***						-0.05**		
				(0.02)						(0.02)		
rewards up					0.11***						0.07***	
					(0.01)						(0.01)	
rewards down						-0.15***						-0.08***
						(0.02)						(0.02)
Observations	2,898	1,902	4,014	2,842	4,128	4,910	2,898	1,902	4,014	2,842	4,128	4,910
R-squared	0.161	0.103	0.145	0.170	0.112	0.127	0.142	0.091	0.053	0.069	0.094	0.047

Table 5
(Continued from previous page)

	Panel E: % of total borrow					
start	0.54***					
	(0.06)					
increase		-0.05***				
		(0.01)				
decrease			-0.16***			
			(0.02)			
end				-0.18***		
				(0.02)		
rewards up					0.33***	
					(0.05)	
rewards down						-0.17***
						(0.02)
Observations	2,896	1,840	3,948	2,840	4,064	4,844
R-squared	0.074	0.150	0.140	0.198	0.050	0.109

Table 6
Daily Average Balances of Yield-Seekers and Impact on Market Parameters.

This table presents metrics on the positions of yield-seeking accounts by pool and their impact on market parameters. Data is based on 177 yield-seeking accounts and the aggregated balances from 3.4 million protocol interactions between June 15, 2020 and February 1, 2023 on Compound and Aave. The shortcut "YS" refers to the sum of yield-seeking accounts, defined as either the address of a yield aggregator vault or an address that simultaneously lends and borrows the same stablecoin. Total investment and total borrows relate yield-seekers' volume in a given pool to the average total across all pools of YS-accounts. The spread variables in the table describe the percentage change ($\Delta\%$) from the observed market value to the counterfactual value excluding the volumes of YS. The deposit loss metric encompasses the USD amount of deposit interest that regular users would have earned if yield-seekers were not active in the market. Likewise, the borrowing gain metric reflects the interest saved by users. The net gain/loss represents the residual between the two figures.

	Compound							Aave							
	USDC	DAI	ETH	WBTC	LINK	USDT	Total	USDC	DAI	USDT	WBTC	UNI	WETH	YFI	Total
Av.YS investment (USD, M)	766.3	669.5	66.7	61.6	17.9	16.8	1598.8	714.3	498.8	27.0	25.1	9.2	3.3	2.6	1281.6
% of total pool TVL	45.2	41.1	3.7	7.1	37.3	3.9	23	30.9	59.4	3.9	2.4	23.9	0.1	7.1	17.2
% of YS total investment	47.9	41.9	4.2	3.9	1.1	1.1	100	55.7	38.9	2.1	2.0	0.7	0.3	0.2	100
Av.YS borrowing (USD, M)	540.7	452.8	1.3	4.5	0.3	1.7	1001.3	558.6	376.0	14.6	1.1	0.0	0.0	1.6	953
% of total pool borrowing	42.8	41.3	1.5	8.2	4.9	0.6	16.6	32.6	61.1	2.7	2.0	0.0	0.0	31.2	17.8
% of YS total borrowing	54.0	45.2	0.1	0.4	0.0	0.2	100	58.6	39.4	1.5	0.1	0.0	0.0	0.2	100
% YS loans to deposit	70.6	67.6	2.0	7.2	1.6	10.3	26.6	78.2	75.4	54.0	4.5	0.0	0.0	62.5	44.9
% Utilization spread	6.3	6.4	0.1	0.5	6.0	3.1	3.7	2.9	5.4	1.4	0.1	0.1	0.0	0.1	1.4
% Deposit interest spread	2.6	4.4	0.0	0.0	0.7	1.3	1.5	7.4	6.9	1.3	0.0	0.0	0.0	0.0	2.1
% Var. Borrow interest spread	3.0	4.3	0.0	0.1	1.5	1.4	1.7	8.3	8.3	1.5	0.0	0.0	0.0	0.0	2.4
% St. Borrow interest spread	-	-	-	-	-	-	-	8.3	8.2	1.5	0.0	-	0.0	-	3.6
Cum. deposit loss (USD, M)	-80.4	-119.6	-0.1	0.8	-0.3	-14.4	-214	-306.0	-56.1	-26.3	0.0	0.0	-0.1	0.0	-388.7
Cum. borrow gain (USD, M)	87.7	121.4	0.0	-0.2	0.2	14.1	223.2	335.6	61.2	28.6	0.0	0.0	0.1	0.0	425.7
Cum. net gain/loss (USD, M)	7.3	1.9	-0.1	0.6	-0.1	-0.3	9.3	29.6	5.0	2.3	0.0	0.0	0.0	0.0	36.9

Table 7
List of Token Pools offered on Aave and Compound

This table lists the lending pools operated by Aave and Compound. Percentage values show the positions as of February 2023. "Frozen" or "deprecated" pools are either temporarily or permanently unavailable. "UTI", "STA", and "CRY" refer to utility (often governance) tokens, stablecoins, and cryptocurrencies.

Aave

	Pool Name	Symbol	Obs. N. (days)	% of TVL	% of borrowing	Type	Category
1	1INCH Token	1INCH	187	0.10	0.00	Volatile	UTI
2	Aave Token (omitted from sample)	AAVE	793	2.60	0.00	Volatile	UTI
3	Ampleforth (omitted from sample)	AMPL	558	0.20	0.00	Volatile	STA
4	Balancer (frozen)	BAL	730	0.00	0.00	Volatile	UTI
5	Basic Attention Token (frozen)	BAT	793	0.10	0.00	Volatile	UTI
6	Binance USD (frozen)	BUSD	793	0.50	0.80	Volatile	STA
7	Curve DAO Token	CRV	767	1.50	2.00	Volatile	UTI
8	Convex Token (frozen)	CVX	234	0.00	0.00	Volatile	UTI
9	Dai Stablecoin	DAI	793	2.60	2.90	Stable	STA
10	DefiPulse Index (frozen)	DPI	530	0.10	0.00	Volatile	UTI
11	Enjin Coin (frozen)	ENJ	793	0.00	0.00	Volatile	UTI
12	Ethereum Name Service	ENS	332	0.00	0.00	Volatile	UTI
13	Fei USD (frozen)	FEI	500	0.00	0.00	Stable	STA
14	Frax	FRAX	509	0.30	0.70	Stable	STA
15	Gemini dollar	GUSD	761	0.00	0.10	Stable	STA
16	Kyber Network Crystal (frozen)	KNC	793	0.00	0.00	Volatile	UTI
17	ChainLink Token	LINK	793	1.80	0.80	Volatile	UTI
18	LUSD Stablecoin	LUSD	157	0.00	0.00	Stable	STA
19	Decentraland MANA (frozen)	MANA	793	0.10	0.00	Volatile	UTI
20	Maker	MKR	793	0.40	0.00	Volatile	UTI
21	Rai Reflex Index (frozen)	RAI	593	0.00	0.00	Volatile	UTI
22	Republic Token (frozen)	REN	793	0.00	0.00	Volatile	UTI
23	renFIL (frozen)	RENFIL	649	0.00	0.00	Volatile	UTI
24	Synthetix Network Token	SNX	793	0.10	0.30	Volatile	UTI
25	Liquid staked Ether 2.0	STETH	340	27.20	0.00	Volatile	CRY
26	Synth sUSD	SUSD	793	0.00	0.00	Stable	STA
27	TrueUSD	TUSD	793	0.20	0.20	Stable	STA
28	Uniswap	UNI	794	0.30	0.10	Volatile	UTI
29	USD Coin	USDC	793	17.80	26.80	Stable	STA
30	Pax USD	USDP	557	0.00	0.00	Stable	STA
31	Tether USD	USDT	794	7.30	17.00	Stable	STA
32	UST (Wormhole) (frozen)	UST	397	0.00	0.00	Stable	STA
33	Wrapped BTC	WBTC	794	12.50	5.90	Volatile	CRY
34	Wrapped Ether	WETH	794	23.40	43.10	Volatile	CRY
35	SushiBar (frozen)	XSUSHI	718	0.20	0.00	Volatile	UTI
36	yearn.finance (frozen)	YFI	794	0.10	0.10	Volatile	UTI
37	0x Token (frozen)	ZRX	794	0.20	0.00	Volatile	UTI

Compound

	Pool Name	Symbol	Obs.N. (daily)	% of TVL	% of borrowing	Type	Category
1	Aave Token (omitted from sample)	AAVE	547	0.10	0.10	Volatile	UTI
2	Basic Attention Token	BAT	1366	1.30	0.00	Volatile	UTI
3	Collateral (omitted from sample)	COMP	838	1.10	0.10	Volatile	UTI
4	Dai	DAI	1162	21.80	32.80	Stable	STA
5	Single DAI (deprecated)	DAI	1366	0.10	0.00	Stable	STA
6	Ether	ETH	1366	20.40	3.60	Volatile	CRY
7	Fei USD (deprecated)	FEI	357	0.00	0.00	Stable	STA
8	ChainLink Token	LINK	621	0.20	0.00	Volatile	UTI
9	Augur (deprecated)	REP	1366	0.00	0.00	Volatile	UTI
10	Sushi Token	SUSHI	547	0.10	0.10	Volatile	UTI
11	TrueUSD	TUSD	622	0.40	0.90	Stable	STA
12	Uniswap	UNI	852	1.10	0.40	Volatile	UTI
13	USD Coin	USDC	1366	28.30	41.10	Stable	STA
14	Pax Dollar	USDP	409	0.00	0.00	Stable	STA
15	USDT	USDT	1007	11.30	19.70	Stable	STA
16	Wrapped BTC	WBTC	685	13.50	1.10	Volatile	CRY
17	Wrapped BTC (deprecated)	WBTC	1297	0.10	0.00	Volatile	CRY
18	yearn.finance	YFI	547	0.00	0.00	Volatile	UTI
19	0x	ZRX	1366	0.10	0.00	Volatile	UTI