How Does Relaxing Capital Constraints Affect Market Liquidity?

Evidence from Flash Loans

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Abstract

We study how sudden expansions in capital constraint affect market liquidity. Exploiting the token-level introduction of flash-loan eligibility as a natural experiment, we show that treated pools experience a persistent increase in depth and total value locked without deterioration in slippage or volatility. Trading activity rises and becomes more concentrated, while liquidity provision becomes more dispersed and dynamic. To understand the mechanism, we show that flash loans reshape market liquidity through two forces: by relaxing short-term funding constraints for arbitrageurs and by strengthening price discovery.

Keywords: Market Liquidity; Funding Liquidity; Capital Constraints; Limits to Arbitrage; Price Discovery; Decentralized Finance (DeFi); Automated Market Makers; Flash Loans.

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1 Introduction

Financial markets increasingly rely on the smooth flow of capital across traders, intermediaries, and platforms, yet surprisingly little is known about how sudden expansions in financing capacity reshape market liquidity. Episodes such as the 2008 margin spiral, the 2020 COVID liquidity crunch, and periodic stress in Treasury markets reveal how quickly liquidity can evaporate when capital becomes constrained. But policymakers face a fundamental ambiguity: does easing financing conditions stabilize markets by empowering arbitrageurs and broadening participation, or does it destabilize them by strengthening the hand of informed traders at the expense of passive liquidity providers?

Theoretical work provides conflicting predictions. Models of limits to arbitrage emphasize that trading activity is constrained by funding capacity. When financing frictions bind, mispricing can persist and liquidity may thin. Relaxing these constraints should enable arbitrageurs to scale positions, reduce price deviations, and deepen markets (Gromb & Vayanos, 2002, 2010, 2018; Shleifer & Vishny, 1997). Similarly, Brunnermeier and Pedersen (2008) point out the link between funding conditions and market liquidity that easier financing dampens liquidity spirals and improves market functioning. On the other hand, microstructure theory highlights that expanding funding capacity may disproportionately benefit informed or technologically sophisticated traders. Greater access to capital allows such traders to exploit information more aggressively, potentially increasing adverse selection faced by passive liquidity suppliers (Glosten & Milgrom, 1985; Kyle, 1985). If liquidity providers anticipate higher information risk, they may widen spreads or withdraw capital. Broader theories of leverage cycles further suggest that easier funding can amplify risk-taking and systemic fragility rather than stabilize markets (Geanakoplos, 2010).

Despite its importance for regulation and market design, credible empirical evidence on this question is scarce. Traditional financial markets rarely offer clean experiments in capital access: margin regulations change infrequently, credit conditions evolve gradually, and institutions differ in balance sheet capacity. Flash loans provide an unusually sharp counterexample. Their design, uncollateralized borrowing with instant, atomic settlement, removes credit risk by construction and allows traders to deploy large capital amounts at effectively zero cost. This creates what is arguably one of the clearest, most exogenous shocks to financing frictions in any modern market.

Moreover, because eligibility is determined at the asset level rather than the trader level, flash loans allow us to observe how specific assets respond to a sudden change in arbitrage and funding technologies.

Economically, the introduction of flash loans could push markets in opposite directions. On one hand, previously constrained arbitrageurs can suddenly execute large trades across venues, equalizing prices and attracting liquidity providers who benefit from higher volumes. On the other hand, sophisticated traders may use the new leverage to extract rents from passive liquidity providers, raising inventory risk and discouraging depth. Whether liquidity ultimately improves or degrades depends on which of these forces dominates, and importantly how non-incumbent participants (new LPs, smaller arbitrageurs, part-time traders) respond to the change in funding technology.

To address this question, we exploit the sharply timed, token-level rollout of flash-loan eligibility on Aave in January 2020 as a natural experiment. We find that treated pools experience a pronounced and persistent expansion in market liquidity and activity. Executable depth and total value locked (TVL) increase discretely relative to matched control pools following eligibility. Quantitatively, treated pools can absorb about 5 more ETH before the price moves by 0.5%, while TVL increases by roughly $0.8 million per pool. Event-time estimates show that these quantity effects emerge immediately after the launch and remain elevated for several months. By contrast, traditional measures of market quality do not deteriorate. Slippage and price volatility display no sustained increase, and average treatment effects on these dimensions are statistically indistinguishable from zero. The data therefore indicate a clear deepening of liquidity without a corresponding decline in execution quality or price stability.

A natural concern in our empirical strategy is that flash-loan eligibility was not randomly assigned. Aave's initial token list may have reflected assets that were already more prominent or on stronger performance trajectories. To mitigate this selection concern, we refine our sample in two steps to construct a more balanced comparison group, bringing treated and control pools closer in economic relevance and market prominence. First, we restrict attention to utility tokens whose value is primarily driven by endogenous protocol usage rather than exogenous pegs or mechanical anchors, thereby ensuring comparability across treated and control assets. Second, we construct the control group from high-volume, non-treated utility tokens that were already active prior to

the event, rather than from a broad universe of small or illiquid pools. The test of pre-treatment dynamics exhibit parallel trends prior to flash loan adoption. Although treated pools have higher liquidity levels in the pre-period, the difference-in-differences design relies on relative changes rather than levels, and the absence of differential pre-trends supports the identifying assumption.

Another identification concern is that flash loans were introduced alongside the broader Aave lending protocol. The observed liquidity effects could therefore reflect the arrival of a new lending venue, since it could expand collateralized borrowing opportunities and bring greater integration across DeFi markets. To address this possibility, we implement a placebo test around the implementation of a competing lending protocol, Compound, which expanded lending functionality without introducing flash loans. Re-estimating our specifications around the Compound launch yields no comparable liquidity effects. This absence of parallel responses suggests that the documented changes are not driven by the general introduction of lending infrastructure, but are specific to the flash-loan technology that relaxes transaction-level funding constraints.

We further show that this liquidity expansion is accompanied by a systematic reconfiguration of both trading demand and liquidity supply. On the demand side, treated pools experience significant increases in daily trading volume and swap counts. At the same time, trading activity becomes more concentrated. The largest traders account for a greater share of volume, and a larger fraction of total trading is executed through large transactions. The rise in order flow therefore reflects not a broad influx of small participants, but a shift toward larger and more concentrated trading activity.

On the liquidity supply side, the response moves in the opposite direction. Treated pools attract new liquidity providers at a higher rate, liquidity adjustments become more frequent, and liquidity provision becomes less concentrated across addresses. Incumbent LPs expand positions system-wide rather than retreating from treated pools, and cross-pool mobility increases in both directions, indicating greater capital dynamism rather than zero-sum reallocation. Despite these structural changes, the average economic return to liquidity provision does not increase. Fee revenue rises with higher trading intensity, but impermanent loss rises by a comparable magnitude, leaving net profitability statistically unchanged. Markets therefore become deeper and more active without delivering higher average returns to liquidity suppliers.

We then examine the mechanisms through which flash loans reshape market quality, and our

evidence suggests two opposing but complementary channels. First, by relaxing transaction-level funding constraints, they strengthen corrective arbitrage and support deeper markets. This is consistent with the limits-to-arbitrage theory: when funding constraints bind, arbitrageurs cannot scale positions sufficiently, allowing mispricing to persist (Gromb & Vayanos, 2002, 2010; Shleifer & Vishny, 1997). Flash loans directly relax this friction by making capital elastically available within a transaction. Using transaction-level price gaps between Uniswap v1 and Bancor v1, we find that flash-loan-financed trades are more likely to be corrective precisely when cross-venue mispricing is larger. This indicates that flash loans matter most when arbitrage opportunities are large and capital-intensive.

Second, flash loans also raise adverse selection risk for liquidity providers by increasing the informational content of order flow and strengthening price discovery. Transactions associated with flash loans predict persistent same-direction future returns over horizons of up to 48 hours, both in Uniswap and in Bancor as an external reference market. This makes it difficult to attribute the results to purely mechanical within-pool price pressure. Instead, the evidence suggests that flash loans enable sophisticated traders to act more aggressively on information and mispricing, with flash-loan-linked trades followed by roughly 0.75% to 1% more same-direction price movement than comparable non-flash-loan trades. This helps reconcile our demand- and supply-side results: markets become deeper and more active, yet liquidity providers face a different risk-return trade-off rather than a simple increase in profitability.

The implications of our findings extend well beyond cryptocurrency markets. Flash loans are simply the most extreme manifestation of an increasingly common phenomenon: the ability of algorithmic traders to access large amounts of capital within milliseconds. In equities, this takes the form of intraday credit lines; in foreign exchange, of internalized netting; in commodities, of leveraged roll strategies; and in fixed income, of repo funding available on demand. Understanding how instantaneous capital access affects liquidity providers, market depth, and arbitrage activity speaks to the structure of modern markets writ large. Our setting allows these mechanisms to be observed clearly, offering insight into how future financial technologies might influence market stability.

This paper contributes to the literature in three ways. First, the paper contributes to the literature on the interaction between funding conditions and market liquidity. Brunnermeier and

Pedersen (2008) develop a framework in which funding liquidity and market liquidity are mutually reinforcing: shocks to trader capital raise margins, reduce market liquidity, and can trigger destabilizing liquidity spirals. Subsequent empirical work shows that funding constraints shape the behavior of arbitrage spreads and liquidity provision across markets. Siriwardane et al. (2023) documents that arbitrage spreads across equity, fixed income, and foreign exchange markets are largely uncorrelated, suggesting that funding frictions are segmented and tied to intermediary-specific balance sheet constraints rather than a single aggregate capital factor.

We provide complementary causal evidence from a setting in which short-term financing frictions are technologically relaxed at the transaction level. We show that such an expansion deepens market liquidity. These findings refine the funding-liquidity nexus: easing capital constraints can reshape liquidity supply and trading structure even when informational efficiency remains largely unchanged.

Second, the paper contributes to the growing literature on decentralized finance and cryptocurrency market microstructure (Aiello et al., 2023; Chemla et al., 2025; Di Maggio, 2025; Griffin & Shams, 2020; J. Liu et al., 2023; Y. Liu & Tsyvinski, 2021; Makarov & Schoar, 2020, 2022). A central strand of this literature studies how automated market makers (AMMs) shape price discovery and strategic trading (Angeris et al., 2021; Aspris et al., 2021; Cao et al., 2023; Capponi & Jia, 2021). Several papers analyze the economics of liquidity provision in AMMs. Hasbrouck et al. (2023) model concentrated liquidity as economically equivalent to a covered call strategy, implying that equilibrium liquidity declines when volatility—and therefore option time value—is high. Lehar and Parlour (2021) show that AMMs can sustain stable equilibrium liquidity and closely track centralized exchange prices. Lehar et al. (2023) identify fixed transaction costs as a key friction generating economies of scale in liquidity provision. Other work examines informed trading and fee dynamics, including how priority fees signal private information (Capponi & Jia, 2023), how just-in-time liquidity can cream-skim passive providers (Capponi et al., 2024), and how asymmetric information shapes equilibrium liquidity supply (Aoyagi, 2020; Fan et al., 2023). Additional studies quantify liquidity provider profitability and adverse selection costs (Aigner & Dhaliwal, 2021; Canidio & Fritsch, 2023; Milionis et al., 2023) and analyze price discovery in AMMs (Hansson, 2024).

Third, the paper contributes to the emerging literature on flash loans and their role in decentralized markets. Existing work has primarily studied flash loans as a technological building block

for multi-leg attacks, protocol exploits, and complex trading strategies (Gan et al., 2023; Qin et al., 2021; Xia et al., 2023). Related work by Mandin (2025) documents their rapid growth and institutional adoption across EVM-compatible blockchains. We shift the focus from security risks and descriptive usage patterns to their equilibrium market effects. In particular, we show that flash loans affect market liquidity through two key channels: they relax short-term funding constraints for arbitrageurs, and they strengthen price discovery by making order flow more informative. The paper connects a distinctly DeFi innovation to central questions in financial economics about funding constraints, information, and market liquidity.

The remainder of the paper proceeds as follows. Section 2 introduces the institutional background, describing the mechanics of the Uniswap V1 automated market maker and the introduction of flash loans. Section 3 outlines the data, construction of liquidity measures, and empirical strategy. Section 4 presents the main difference-in-differences results on the causal impact of flash-loan eligibility on market liquidity. Section 5 decomposes these effects into liquidity demand and supply responses. Section 6 investigates the underlying mechanisms. Section 7 concludes.

2 Automated Market Makers and Flash Loan

This section provides essential institutional background on the two key financial primitives at the center of this study: Automated Market Makers (AMMs), specifically Uniswap V1, and flash loans.

2.1 Automated Market Makers

Automated Market Makers (AMMs) represent a significant innovation in the architecture of financial markets, particularly within the decentralized finance (DeFi) ecosystem. Unlike traditional exchanges that facilitate trading through order books by matching explicit buy and sell orders, AMMs employ liquidity pools and algorithmic pricing mechanisms.

AMMs operate with several core features. At the heart of an AMM are liquidity pools, which are smart contracts holding reserves of two or more distinct cryptocurrency tokens, against which users can directly trade. Pricing within these pools is determined algorithmically by a pre-defined mathematical formula based on the relative quantities of the tokens in reserve. Liquidity for these pools is supplied by users known as liquidity providers (LPs). These LPs deposit assets into the pools and, in return, earn a pro-rata share of the trading fees generated from swaps within that pool. AMMs operate on public blockchains, enabling decentralized and permissionless access—anyone can provide liquidity or trade without approval from a central intermediary, typically in a non-custodial manner that allows users to retain control over their private keys.

Uniswap, launched in November 2018, stands as one of the earliest and most influential decentralized exchanges to successfully implement and popularize the AMM model on the Ethereum blockchain. The version of the protocol relevant to this study is Uniswap V1. Each of its liquidity pools contains a unique ERC20 token and Ether (ETH). Consequently, trading between two different ERC20 tokens involves two liquidity pools. The pricing is defined by the CPMM formula $X \cdot Y = K$, where X and Y represent the quantities of two tokens in a pool, and K is a constant value (ignoring fees, which typically accrue to the pool, thereby increasing K over time).

The first key operation is the swap, which allows traders to exchange one token for another. When a trader wants to sell token X and buy token Y, he or she swaps tokens by sending the input asset ΔX_{in} to the pool. After a 0.3% fee is deducted (creating ΔX_{trade}), the contract calculates

the output amount ΔY_{out} such that $(X_0 + \Delta X_{\text{trade}})(Y_0 - \Delta Y_{\text{out}}) = K$, and transfers ΔY_{out} back to the trader's account. This mechanism allows traders to execute a swap immediately, 24/7, and without a need to place an order and wait for a counterparty to fill it. The trader's cost includes two main components: the flat fee at 0.3% and the price slippage. Slippage is the price impact of the trade itself, as the execution price moves along the $X \cdot Y = K$ curve. This cost is non-linear and is inversely related to the pool's market depth: a large trade in a thin pool will incur significant slippage, resulting in a poor execution price. In addition, since Uniswap V1 pairs each pool with ETH, trading between two different ERC20 tokens (e.g., Token A for Token B) requires two sequential swaps: first, Token A for ETH, and then ETH for Token B. Consequently, this process incurs 0.6% in fees plus slippage from two different pools. This limitation was later addressed in Uniswap V2 by introducing direct ERC20-to-ERC20 pools.

On the other hand, the market liquidity is supplied by liquidity providers (LPs). LPs can choose to deposit or withdraw tokens into or from the liquidity pools, known as liquidity provision and liquidity removal, respectively. The act of liquidity provision involves a user depositing both assets (the ERC20 token and ETH) in a proportion that matches the pool's existing reserve ratio, thereby not altering the current price. In return for this capital, the LP receives newly minted LP tokens, which are themselves ERC20 tokens that represent a pro-rata share of the pool's total assets. Conversely, liquidity removal occurs when an LP "burns" their LP tokens to withdraw their proportional share of both assets from the pool.

The major revenue for LPs is the transaction fees generated by the traders during swaps. This fee is not paid out to LPs directly; instead, it is automatically reinvested in the liquidity pool, increasing the constant K and proportionally benefiting all LPs by growing their share of the pool's assets and increasing the value of their LP tokens. High trading volume, therefore, directly translates into higher returns for all LPs in the pool. Conversely, the primary risk LPs face is impermanent loss (IL). This loss arises when the relative price of the two assets in the pool diverges from the price at which the LP initially deposited them. Because the AMM's formula effectively forces the LP to be a passive rebalancer—selling the asset that is appreciating and buying the one that is depreciating—their share of the pool's value can underperform a simple strategy of holding the original assets in a wallet. Impermanent loss is the direct AMM analogue to adverse selection (Glosten & Milgrom, 1985). LPs are passive, uninformed liquidity providers. When the "true" market price

of a token changes on an external, more informed venue (such as a centralized exchange or other AMMs), informed arbitrageurs will immediately trade *against* the Uniswap pool at its now-stale price. This arbitrage trade is profitable for the arbitrageur but directly costly for the LP, who is left holding more of the depreciating asset and less of the appreciating one. This is the "toxic order flow" (Kyle, 1985) that the "information" view warns against. While this loss is "impermanent" as long as the capital remains in the pool (as prices could theoretically revert), it becomes a realized loss at the moment the LP withdraws their liquidity.

2.2 Flash Loans: Capital-on-Demand

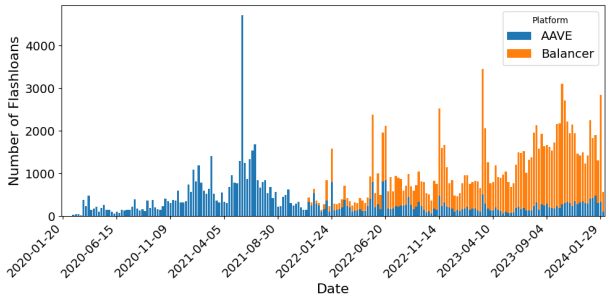
A flash loan is a novel financial primitive unique to decentralized finance (DeFi). While the concept was first proposed by Marble in 2018, it was not until Aave's launch in January 2020 that flash loans became a practically viable and widely adopted financial tool, providing the clean, exogenous shock to capital access central to our study. A flash loan enables users to borrow substantial amounts of cryptocurrency instantly without posting any collateral.

The mechanism's innovation lies in its enforcement through atomic transactions. A borrower must request the loan, execute a series of operations, and repay the principal plus a small fee, all within the confines of a single blockchain transaction. If the borrower fails to repay the loan in full by the end of the transaction, the entire sequence of operations is automatically reverted. This atomicity—the "all-or-nothing" nature of the transaction—is what fundamentally enables uncollateralized lending. It effectively eliminates all credit risk for the lender, as the funds are either repaid instantly or are treated as if they never left the lending pool.

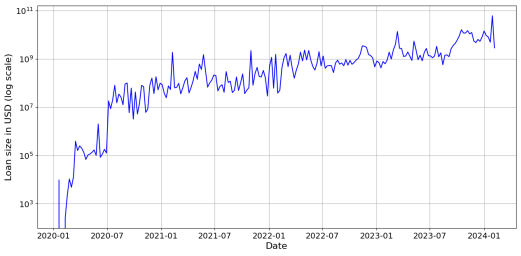
This mechanism has profound implications for market participants, as it radically alters financing frictions. Unlike traditional finance or even other DeFi lending protocols, flash loans are not issued based on a borrower's credit profile, supporting documents, or collateral. Instead, the loan is granted based purely on the borrower's ability to execute a profitable strategy within the transaction itself, as defined by the smart contract they deploy. This effectively removes capital constraints for any trader capable of codifying a profitable strategy, such as cross-venue arbitrage or the complex rebalancing of collateralized debt positions. A trader is no longer limited by their own capital but only by the profitability of their strategy and the total liquidity available in the lending pool.

While our causal analysis focuses on the initial introduction in early 2020, the subsequent growth of this primitive underscores its economic significance. Our dataset, comprising over 168,000 successful flash loan transactions from January 2020 to January 2024 across major platforms, including Aave and Balancer, reveals the market's scale. As shown in Figure 1a, weekly transactions grew exponentially from their inception, later accelerating as new platforms such as Balancer (which offers zero-fee flash loans) entered to compete with Aave. The economic scale, shown in Figure 1b, is staggering. Aggregate weekly volume exploded from near-zero to over $100 million in the first year and has consistently facilitated tens of billions of dollars in weekly activity in subsequent years, with an average loan size of approximately $1.8 million. This confirms flash loans are not a niche product but a major financial primitive facilitating a massive flow of capital-on-demand.

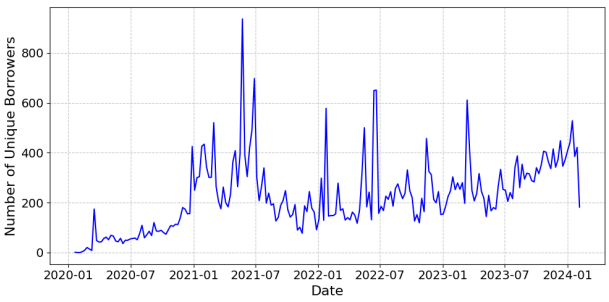
This growth in activity is mirrored by an expanding user base, as shown in Figure 1c. The number of unique wallet addresses executing flash loans grew in concert with transaction volume, indicating a growing community of participants. However, despite this "permissionless" access, Figure 1d reveals that usage is highly concentrated. In our sample of approximately 20,000 unique wallet addresses, the top 200 borrowers (1% of users) account for nearly 60% of all transactions.



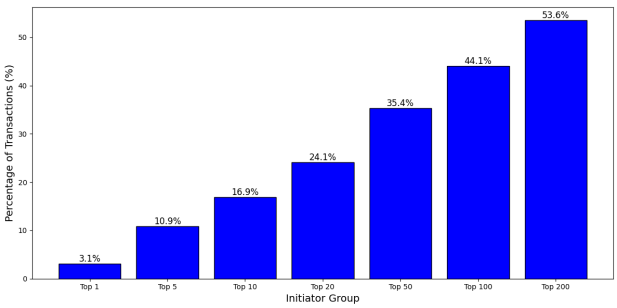
(a) Weekly Transactions per Platform



(b) Weekly Aggregate Loan Size (USD)



(c) Weekly Unique Borrowers



(d) Transactions by Top Groups

Figure 1: Flash Loan Market Dynamics.

2.3 How are Flash Loans Used?

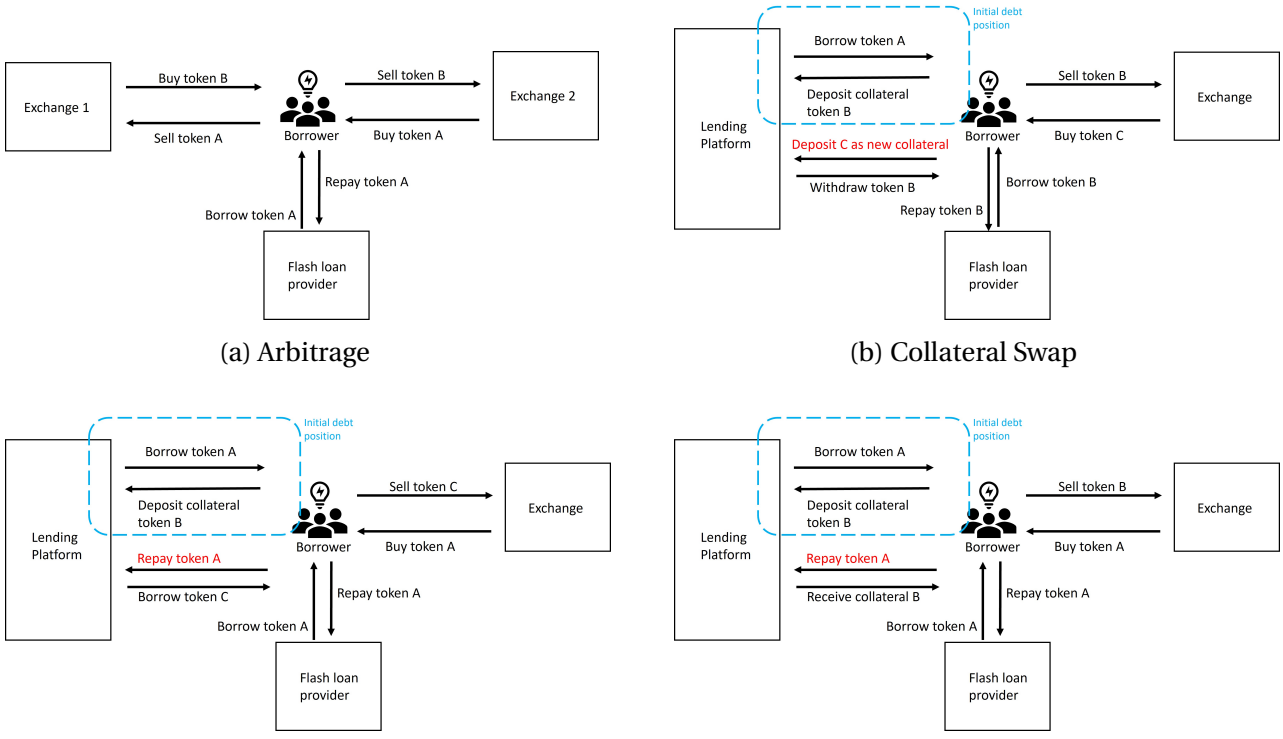
A common narrative around flash loans emphasises a handful of high-profile attacks and protocol exploits, portraying them primarily as instruments of manipulation. This view is largely grounded in anecdotal case studies rather than in systematic, large-sample evidence. To provide a more comprehensive picture, we combine manual inspection and programmatic classification to identify the economic purpose of every flash-loan transaction in our sample.

We group transactions into four economically meaningful categories: *Arbitrage*, *Debt Restructuring*, *Attack*, and *Testing*, together with a residual *Other* category. The classification is based on the sequence and structure of smart-contract calls within each atomic transaction.

Panel (a) of Figure 2 illustrates a typical *Arbitrage* transaction. The contract borrows an asset via a flash loan, executes a cycle of trades across two or more decentralised-exchange liquidity pools to exploit price discrepancies, and repays the loan from the resulting profits. Panels (b)–(d) show the main forms of *Debt Restructuring* activity. These transactions interact with lending protocols such as Aave and Compound and are used to manage collateralised debt positions (CDPs) without upfront capital. A *collateral swap* (panel b) changes the posted collateral asset, a *debt swap* (panel c) changes the borrowed asset, and a *self-liquidation* (panel d) repays a loan to avoid external liquidation penalties. In all three cases, the flash loan finances a temporary unwind and re-establishment of the position within a single atomic transaction.

We group transactions into four economically meaningful categories: *Arbitrage*, *Debt Restructuring*, *Attack*, and *Testing*, together with a residual *Other* category. The classification is based on the sequence and structure of smart-contract calls within each atomic transaction. Panel a of Figure 3 shows *Arbitrage* transactions follow a characteristic pattern: the contract borrows an asset via a flash loan, executes a cycle of trades across two or more decentralised-exchange liquidity pools to exploit price discrepancies, and repays the loan from the resulting profits. *Debt Restructuring* transactions interact with lending protocols such as Aave and Compound and are used to manage collateralised debt positions (CDPs) without upfront capital. These include collateral swaps (changing the posted collateral asset), debt swaps (changing the borrowed asset), and self-liquidations (repaying a loan to avoid external liquidation penalties).

Attack and *Testing* transactions are defined more conservatively and are not the main focus of the analysis. Identifying malicious intent ex ante is inherently difficult, so we classify attacks



(a) Arbitrage

(b) Collateral Swap

(c) Debt Swap

(d) Self Liquidation

Figure 2: Major Flash Loan Use Cases

using a structural proxy: a transaction is labelled as an *Attack* if its internal transaction graph exhibits extreme complexity, as measured by the topology and density of on-chain call relationships. *Testing* transactions are flash loans that are borrowed and repaid immediately with no additional operations. The remaining transactions, for which the economic purpose cannot be confidently inferred, are allocated to the residual *Other* category. For the empirical results that follow, the primary objects of interest are arbitrage and debt-restructuring flash loans; the formal classification algorithm and robustness checks are described in Appendix B.

Figure 3 summarises the resulting distribution across categories. The evidence is starkly at odds with the conjecture that flash loans are predominantly malicious. Debt Restructuring is the single largest category, accounting for 48.6% of all flash-loan transactions. Arbitrage is the second-largest at 31.8%. Together, these two economically productive uses—arbitrage and balance-sheet management—represent 80.4% of all flash-loan activity in our sample. Transactions classified as Attacks make up only 2.4%. The residual categories are *Other* (16.8%), capturing unclassified or mixed-purpose activity, and *Testing* (0.4%), consisting of transactions that initiate and repay a flash loan without performing additional operations.

The time-series patterns in Figure 4 further illuminate how these productive uses evolve over

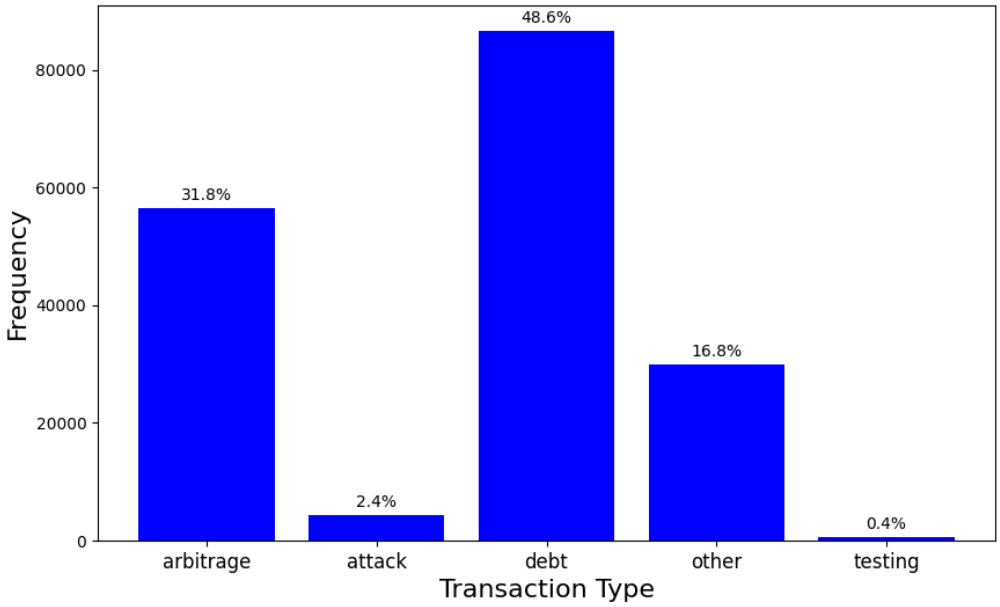


Figure 3: Distribution of Flash Loan Transaction Types

the sample. Before 2022, flash loans are used predominantly for debt restructuring, with considerable volatility and a pronounced peak around mid-2021. Following the introduction of Balancer's zero-fee flash loans, arbitrage activity increases noticeably, while the number of debt restructurings remains relatively stable. Arbitrage use exhibits a clear upward trend, accelerating in 2023. Both arbitrage and debt-restructuring activity are volatile over time and occasionally spike together, particularly during 2022, but the relative importance of arbitrage clearly rises in the later part of the sample. This pattern indicates a gradual shift in the dominant productive application of flash loans—from balance-sheet management towards cross-venue price alignment and liquidity reallocation via arbitrage.

Overall, this anatomy shows that flash loans relax capital constraints across heterogeneous strategies, including legitimate and economically meaningful activities: managing leveraged positions and arbitraging price discrepancies across venues. Malicious attacks are quantitatively rare in the aggregate data.

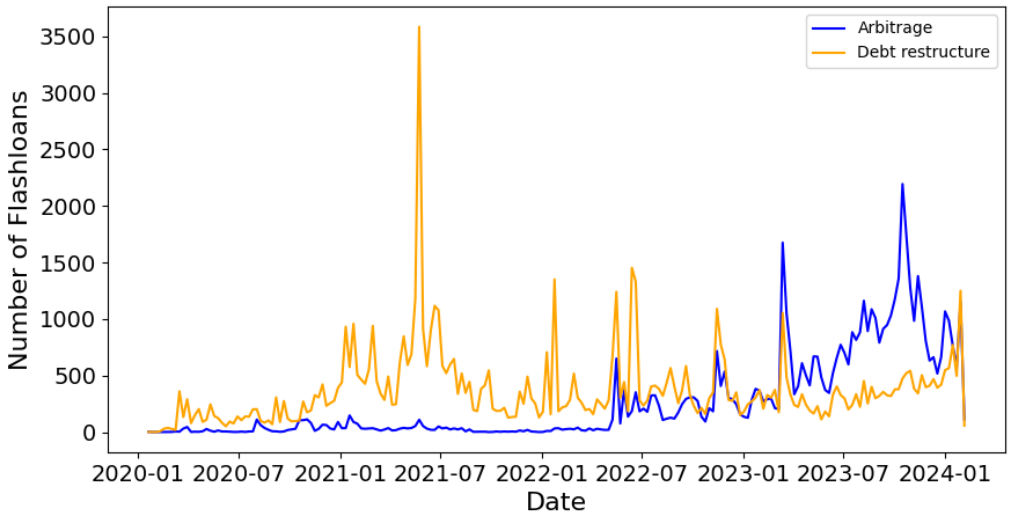


Figure 4: Weekly Number of Arbitrages and Debt Restructurings Over Time

3 Data and Methodology

3.1 Data

Our empirical analysis relies on a granular, transaction-level dataset constructed from the Ethereum blockchain. We extract all historical events associated with the Uniswap V1 smart contracts. This provides a complete record for each liquidity pool, including its address, the addresses of its paired tokens, and the pool's inception timestamp. For each pool, we collect every swap, liquidity provision, and liquidity removal transactions from its creation. Each transaction includes a block number, timestamp, the amount of tokens transferred, and the user's wallet address.

From this event-level data, we reconstruct the state of each Uniswap V1 liquidity pool on a block-by-block basis. This process allows us to calculate the exact reserves of the ERC20 token and ETH in each pool at a high frequency. This granular data is then aggregated into a daily panel for our main analysis.

The main sample window for our DiD analysis runs from May 1, 2019, to June 30, 2020. This window is chosen to isolate the treatment effect. It provides a substantial pre-treatment period for identification and, crucially, ends just before the launch of Uniswap V2 began attracting substantial liquidity and ahead of the subsequent "DeFi Summer," either of which would fundamentally alter market structure and confound our estimates.

Finally, we supplement our on-chain data with daily USD price data for all tokens and ETH from CoinGecko, a comprehensive cryptocurrency data aggregator. This is used to value our liquidity measures and to construct control variables for our regression models.

3.2 Liquidity Measures

We analyze four primary outcome variables to measure market liquidity from both quantity and quality perspectives, aggregated at the pool-day level for pool i on day t. We consistently define X as the reserve of the ERC20 token and Y as the reserve of ETH.

Market depth (D_{it}) refers to the amount of an asset that can be traded without causing a significant price change. It is defined as the quantity of the ERC20 token, ΔX, that can be purchased from the pool (using ETH) such that the marginal spot price changes by a pre-specified impact

factor s. For a constant product AMM ($X \cdot Y = K$), the depth D_{it} is calculated as:

$$D_{it} = X_{it}\left(\frac{1}{\sqrt{1-s}} - 1\right) \tag{1}$$

where X_{it} represents the reserve of the ERC20 token in pool i on day t, and s is the price impact threshold, set at 0.5%. A higher D_{it} indicates a deeper market capable of absorbing larger orders.

Total value locked (TVL_{it}) represents the total USD value of the assets in the pool. It is a standard measure of market size (quantity) and is calculated as:

$$TVL_{it} = (P^{\text{USD}}_{\text{Token},t} \times X_{it}) + (P^{\text{USD}}_{\text{ETH},t} \times Y_{it}) \tag{2}$$

where X_{it} and Y_{it} are the reserves of the ERC20 token and ETH, respectively, and P^{USD} is the USD price of the corresponding asset at time t.

Slippage (S_{it}) is a key measure of market quality, capturing the price difference between the expected spot price and the actual execution price. For a single trade, it is:

$$S = \frac{|P_{\text{exec}} - P_{\text{spot}}|}{P_{\text{spot}}} \tag{3}$$

where P_{spot} is the ratio of reserves before the trade, and P_{exec} is the effective price at which the trade is executed. Our daily measure, S_{it}, is the trade-weighted average of this slippage calculation for all swaps in pool i on day t. Lower slippage indicates higher market quality.

Volatility (V_{it}) measures the intra-day price risk and dispersion within the pool. It is constructed as the daily standard deviation of transaction-level log returns (changes in the pool's marginal price) for each pool. Higher volatility indicates greater price instability.

3.3 Empirical Strategy

To estimate the causal impact of flash-loan eligibility on market liquidity, we employ a Difference-in-Differences (DiD) research design. This strategy compares the change in liquidity outcomes for a treated group of pools to a control group of non-eligible pools, before and after the treatment event.

The treatment event is the launch of the Aave protocol on January 8, 2020, which introduced

flash loans for a specific set of ERC20 tokens. This initial list comprised prominent "blue-chip" assets. The Uniswap V1 pools for these non-ETH tokens constitute our initial treated group.

A primary endogeneity concern is that this initial list of tokens was not random. These assets were already favored by investors and thus might have been on a different performance trajectory irrespective of the treatment. To mitigate this selection bias, we implement a two-step refinement to construct our final sample.

First, we restrict our entire sample (both potential treated and potential control pools) to utility tokens, whose primary purpose is to provide access or usage rights within a protocol. This sharpens our identification by excluding assets like stablecoins or wrapped tokens that have exogenous pegs or different value drivers. This restriction yields a more comparable set of assets whose performance is endogenously driven by factors like protocol adoption, and thus is harder to predict ex ante.

Second, from the set of non-treated utility tokens, we construct our control group by selecting the top pools with the highest pre-treatment volume. This ensures our control group consists of similarly prominent utility tokens that were not selected by Aave, rather than a broad set of small, illiquid, and incomparable assets. To ensure a balanced panel, our final sample includes only pools that were created prior to our event time. This refinement creates a plausible control group for satisfying the parallel trends assumption.

Finally, our final sample consists of 8 treated utility tokens (MKR, LINK, BAT, REP, KNCL, ZRX, LEND, MANA) and 40 control utility tokens, the detailed token list is presented in Appendix A.

Our DiD model is specified as a two-way fixed effects panel regression that includes time-varying, token-specific controls:

$$Y_{it} = \gamma_i + \delta_t + \beta(\text{Treat}_i \times \text{Post}_t) + \mathbf{X}_{it} + \epsilon_{it} \tag{4}$$

where Y_{it} is one of the four liquidity measures for pool i on day t. γ_i are pool fixed effects, which control for all time-invariant differences between pools, such as the underlying token's project quality. δ_t are date fixed effects, which control for all common time-varying shocks, such as overall crypto market sentiment.

Treat_i is an indicator equal to 1 if pool i contains the treated tokens and 0 for the control ones. Post_t is an indicator equal to 1 for all dates on or after January 8, 2020, and 0 otherwise. $\mathbf{X}_{it}$ is a

vector of time-varying controls, including the token's total daily trading volume across all markets (not just Uniswap) and the log return of the token's daily USD price. These controls absorb token-specific shocks to demand or valuation that might be correlated with liquidity, further isolating the effect of flash-loan eligibility.

The coefficient of interest is β, which captures the average differential change in the liquidity outcome for the treated group in the post-treatment period, relative to the control group. Standard errors are clustered at both the pool and time level to account for correlations.

4 Market Effects of Capital Constraint Relaxation

Table 1 reports the core difference-in-differences (DiD) results using two quantity measures—Depth and TVL (USD)—and two quality measures—Slippage and Volatility. The coefficient of primary interest is the Interaction term, which captures the post-introduction differential in the outcome for treated pools relative to contemporaneous changes in control pools, with pool and time fixed effects and standard errors clustered by pool and time.

The interaction terms are positive and statistically significant for both quantity outcomes. Following flash-loan introduction, treated pools exhibit approximately 5 additional ETH of executable depth at the 0.5% price-impact threshold relative to controls, and an average increase of roughly $0.8 million in TVL. These effects remain stable in sign, magnitude, and significance after including token-specific time-varying controls (aggregate volume and returns), indicating that the results are not driven by concurrent shifts in trading intensity or broad market conditions. Substantively, the estimates point to a discrete expansion in available liquidity, deeper pools and greater capital commitment, over and above changes observed in comparable control pools. The depth and TVL findings are mutually reinforcing: in AMM pools, local price impact is inversely related to reserves, so an increase in TVL mechanically raises executable depth around the prevailing price. This suggests that treated pools became far more resilient and capable of absorbing large trades.

By contrast, the interaction coefficients for slippage and volatility are statistically indistinguishable from zero across specifications, indicating that treated and control pools experienced similar changes in execution costs and short horizon price dispersion. Economically, slippage proxies the marginal cost of immediacy, that is, the price impact a trade faces given pool curvature and available reserves, while volatility summarizes transitory return variability induced by order flow and information arrival. These findings are consistent with intuition for automated market makers: both slippage and short run volatility are largely mechanical outcomes of the constant product pricing formula and the distribution of reserves. Thus, when the pricing formula is held fixed, changes in quality should be modest as capital scales up. In this light, the treatment appears to operate primarily through quantity, namely an expansion of reserves that deepens pools, rather than through alterations to pricing mechanics. As a back of the envelope diagnostic, the stability of these quality metrics supports the robustness of the specification and reduces concerns that the

estimated quantity effects reflect shifts in execution quality or unmodeled price dynamics.

	Depth	Depth	TVL (USD)	TVL (USD)	Slippage	Slippage	volatility	volatility
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Interaction	4.230**	5.124**	0.772**	0.808**	29.716	43.812	0.000	-0.001
	(1.887)	(2.217)	(0.356)	(0.355)	(47.340)	(66.858)	(0.002)	(0.003)
Token Agg Volume (million)		0.000		-0.000		0.009		0.000
		(0.000)		(0.000)		(0.024)		(0.000)
Token Agg Return (log)		-0.385*		0.017		-63.291		0.027*
		(0.201)		(0.039)		(84.481)		(0.016)
Pool FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.033	0.089	0.045	0.056	0.031	0.043	0.032	0.044
N	15041	10701	11721	10701	15041	10701	14196	10249

Note: *p<0.1; **p<0.05; ***p<0.01
Clustered standard errors by pool and time.

Table 1: Effect of flash loan introduction on market liquidity with fixed effects

To validate our DiD design and explore the dynamic nature of the treatment effect, we implement an event-time DID in weekly time, plotted in Figures 5 and 6. Each observation is assigned to a week relative to the flash-loan introduction, with negative values for pre-event weeks and nonnegative values thereafter. For each outcome, we estimate a panel regression with pool fixed effects and a full set of week indicators interacted with the treatment status. The resulting weekly treatment effects are then normalized to the week immediately before the event. Therefore every plotted points shows the difference between treated and control pools in that week compared with the pre-event baseline. These normalized coefficients with 95 percent confidence bands are shown in the figures. The vertical line marks the event week, and the horizontal line at zero marks the normalized baseline.

This estimate serves two purposes. First, it offers a visual assessment of the parallel-trends assumption. For three outcomes—Depth, TVL, and Volatility—the pre-treatment coefficients (May 2019 to December 2019) are tightly clustered and statistically indistinguishable from zero, consistent with comparable trajectories for treated and control pools before flash-loan introduction. The slippage series is noisier in the pre-period and shows occasional week-to-week deviations. This does not undermine the design for two reasons. Slippage is inherently volatile at weekly frequency because it reflects episodic order flow and transient network conditions, which generate high-variance but mean-reverting fluctuations rather than a directional drift. Moreover, the event-time coefficients are normalized to the week immediately prior to treatment and there is no persistent or monotonic pre-trend, so identification relies on a stable baseline rather than exact equality in

every pre-event week.

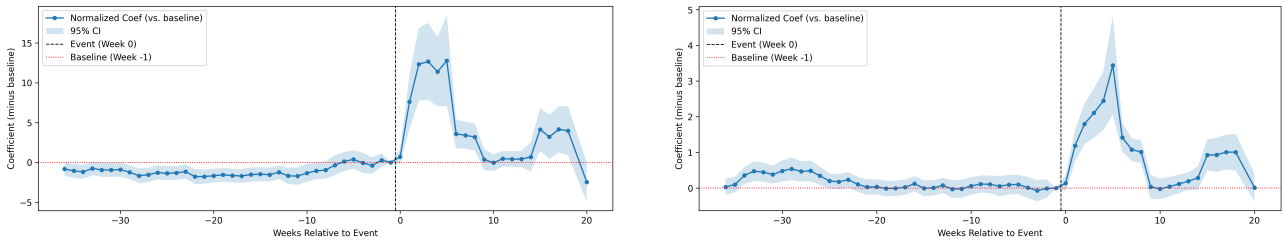
Second, the estimates reveal the timing and persistence of the effects and place the average DiD coefficients in Table 1 in context. As shown in Figure 5, the quantity responses are sharp and immediate. In the first post treatment week, both Depth and TVL begin a large and statistically significant increase. The effects persist for several months before gradually declining toward the end of the sample. This tapering might be consistent with several economic forces. First, as inventories are better managed, the initial gains attract capital until marginal fee revenues compress, at which point additional liquidity yields smaller incremental benefits. Second, portfolio rebalancing by liquidity providers can lead to partial outflows as opportunities normalize, especially if risk compensation falls or impermanent loss risk rises. Third, market wide conditions evolve over the sample, and a return toward a new steady state is plausible once the main frictions alleviated by flash loans have been reduced. Together, these mechanisms suggest that the treatment produces a durable increase in baseline liquidity, followed by convergence toward a long run equilibrium where the marginal contribution of additional capital is lower.

Figure 6 reconciles these quantity gains with the modest average movements in quality measures. The slippage series is noisy and short-lived: occasional positive and significant weeks contribute to a small positive average in Table 1, but these episodes are not sustained and are often offset by negative or insignificant weeks. The volatility series is even more stable. Coefficients remain close to zero throughout the post period except for a single pronounced spike in mid-March 2020, coinciding with the widely documented “Black Thursday” market stress episode due to Covid pandemic. This suggests that the small positive average effect on volatility is not indicative of a structural change in price stability but is largely driven by that transitory, market-wide shock.

Taken together, the event time evidence sharpens the message from the main regression table. The introduction of flash loans is followed by a swift and durable expansion in market quantity, both depth and TVL. This pattern is consistent with an easing of balance sheet frictions that allows capital to be mobilized quickly and deployed where liquidity is scarce, thereby supporting more effective risk sharing and tighter cross venue alignment. At the same time, the dynamic profiles make clear that the modest average movements in slippage and volatility from Table 1 do not represent a lasting erosion of market quality. The upward blips are sporadic and short lived, in line

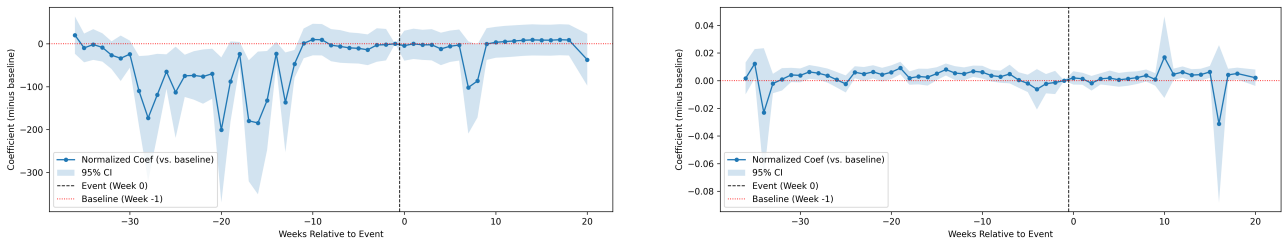
with occasional episodes of selection risk rather than a sustained increase in execution costs.

This mix of outcomes is more supportive of the first hypothesis. On net, flash loans function as a mechanism that relaxes capital constraints and increases available liquidity. We do observe episodic disturbances consistent with informed trading, but these episodes are short lived and do not cumulate into a sustained deterioration in execution quality or price stability. Thus, while transient costs cannot be ruled out, the aggregate evidence over the sample points to a positive liquidity effect with limited and nonpersistent quality impacts.



(a) Depth (b) TVL

Figure 5: Dynamic effects for market quantity



(a) Slippage (b) Volatility

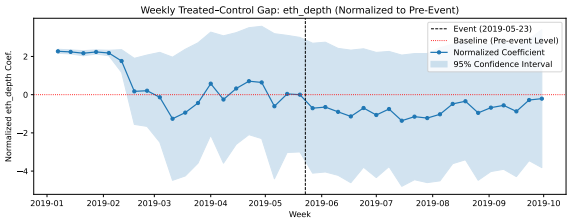
Figure 6: Dynamic effects for market quality

A remaining identification concern is that flash loans were introduced alongside the broader Aave lending protocol. The observed liquidity expansion could therefore reflect the arrival of a new lending venue, greater collateralized borrowing capacity, or increased integration across DeFi markets, rather than the flash-loan feature itself. If so, similar liquidity effects should be observable around the introduction or expansion of other lending protocols that did not implement flash loans.

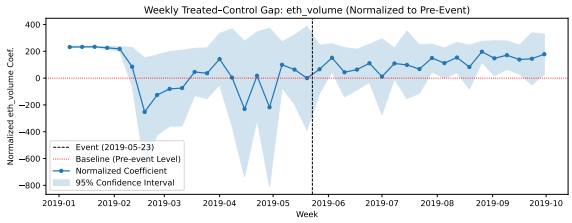
To address this concern, we conduct a placebo test around the introduction of Compound, a competing lending protocol that expanded collateralized borrowing functionality but did not introduce flash-loan-style transaction-level funding. We replicate our event-time difference-in-differences framework using the Compound implementation date as the placebo event and re-estimate the same set of outcomes: Depth, TVL, Slippage, and Volatility.

Figure 7 presents the corresponding dynamic treatment effects. In contrast to the sharp and persistent liquidity expansion observed around flash-loan adoption, we find no comparable patterns around the Compound event. Pre-trends remain flat, and post-event coefficients for Depth and TVL are small and statistically indistinguishable from zero. Similarly, there is no systematic movement in Slippage or Volatility. The absence of discrete quantity responses suggests that the liquidity expansion documented earlier is not driven by the general arrival of lending infrastructure or improved collateralized borrowing opportunities.

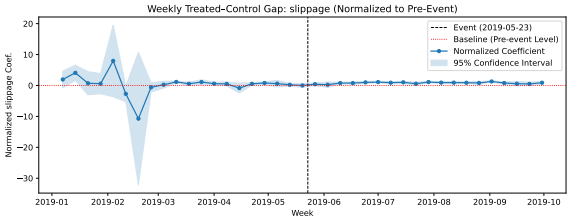
This placebo evidence strengthens the causal interpretation of our baseline results. While the introduction of a lending protocol may enhance ecosystem connectivity, only flash loans relax capital constraints at the transaction level by allowing instantaneous, uncollateralized borrowing that must be repaid within a single block. The lack of similar liquidity effects around Compound indicates that the observed expansion in market depth is specific to the technological relaxation of short-term funding constraints rather than to broader DeFi growth or contemporaneous platform innovation.



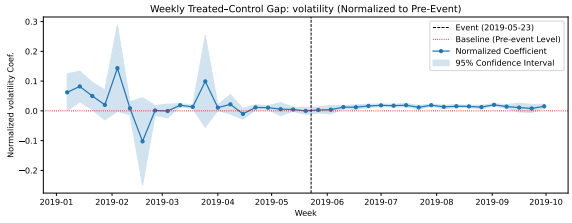
(a) Depth



(b) TVL



(c) Slippage



(d) Volatility

Figure 7: Dynamic effects around the introduction of Compound

5 Liquidity Demand and Supply Responses

5.1 The Demand-Side Trigger

To better understand the channels behind the aggregate liquidity effects, we first examine the demand side of liquidity provision.

5.1.1 Trading activity

Table 2 reports difference-in-differences estimates for two indicators of trading intensity: daily trading volume (in ETH) and the number of swaps. Across all specifications, the interaction term is positive and statistically significant. Treated pools experience an increase of approximately 0.25 thousand ETH in daily trading volume and about 60 additional swaps per day relative to control pools. These results are robust to the inclusion of token-level controls for aggregate trading volume and token returns, suggesting that the increase is not driven by broader market conditions or contemporaneous token-specific shocks. Instead, flash-loan eligibility coincides with a meaningful expansion in trading activity.

This increase in order flow represents a direct demand-side channel through which liquidity can deepen. Higher volume raises fee revenue and can attract additional liquidity supply. However, aggregate trading intensity does not reveal whether participation becomes more dispersed or more concentrated. To examine this, we turn to measures of trader concentration and trade size distribution.

5.1.2 Market concentration

Table 3 examines whether the composition of trading activity changes following flash-loan adoption. Columns (1)–(3) report trader-level concentration measures. For each pool and day, we aggregate ETH trading volume at the trader level and compute each trader's market share as the ratio of their volume to total pool-day volume. Traders are ranked by their volume contribution. We can see that flash loan adoption is associated with a statistically significant increase in Top-1 trader's share in treated pools than control pools. The coefficient for Top-5 trader share is positive though not significant. Column (3) reports the Herfindahl–Hirschman Index (HHI), computed as the sum of squared trader-level volume shares across all traders within the pool-day. The

	Volume (ETH)	Volume (ETH)	Num Swap	Num Swap
	(1)	(2)	(3)	(4)
Interaction	0.210**	0.250**	63.428***	58.593***
	(0.099)	(0.104)	(19.227)	(19.870)
Token Agg Volume (million)		-0.000***		-0.001
		(nan)		(0.004)
Token Agg Return (log)		0.208***		105.098***
		(0.040)		(22.228)
Pool FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Adj R^2	0.026	0.031	0.005	0.024
N	15041	10701	15041	10701

Note: *p<0.1; **p<0.05; ***p<0.01
Clustered standard errors by pool and time.

Table 2: Trading activity

regression estimation suggests that trading activity becomes more concentrated among the largest participants once pools become flash-loan eligible.

Columns (4)–(6) turn to trade-size concentration. Here, we rank individual swaps within each pool-day by input size (in ETH), and we compute the empirical distribution of trade sizes and define large trades relative to that day's distribution, including top quartile (above 75th percentile), top decile (above 90th percentile) and top 5 percentile. These percentile thresholds are recomputed separately for each pool-day, so the measures capture relative size within the contemporaneous trading environment rather than absolute ETH cutoffs. Across all three thresholds, the interaction term is positive and highly significant, which means that a larger fraction of total volume is executed through large trades in treated pools after flash-loan adoption relative to controls.

Both the trader-based concentration measures (Columns 1–3) and the trade-size measures (Columns 4–6) point in the same direction. The expansion in aggregate trading activity documented earlier does not primarily reflect dispersion across many small participants. Instead, once we account for overall volume growth, trading becomes more concentrated and more skewed toward large transactions.

This demand-side shift suggests that flash-loan eligibility amplifies the role of large and sophisticated traders in generating order flow, rather than broadening participation across a wider base of small entrants. In the next subsection, we examine how liquidity suppliers respond to this

reconfiguration of trading demand.

	Top-1 Trader Share	Top-5 Trader Share	HHI	Large Trade Share (Top Quartile)	Large Trade Share (Top Decile)	Large Trade Share (Top 5%)
	(1)	(2)	(3)	(4)	(5)	(6)
Treated × Post	0.127***	0.039	0.138***	0.089***	0.115***	0.127***
	(0.034)	(0.024)	(0.035)	(0.019)	(0.026)	(0.028)
Log Volume	-0.095***	-0.063***	-0.105***	-0.051***	-0.071***	-0.081***
	(0.006)	(0.004)	(0.007)	(0.005)	(0.006)	(0.007)
Pool FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.312	0.446	0.341	0.158	0.210	0.247
N	15230	15230	15230	15230	15230	15230

Note: *p<0.1; **p<0.05; ***p<0.01
Clustered standard errors by pool and time.

Table 3: Market concentration

5.2 The Supply-Side Response

We now turn to the supply side to examine how liquidity providers (LPs) responded to the introduction of flash loans.

5.2.1 Entry and Dispersion of Liquidity Supply

We begin by studying entry and the cross-sectional distribution of liquidity provision. Table 4 shows that flash-loan eligibility is associated with a significant increase in the number of new LPs joining treated pools relative to controls. This pattern indicates that the liquidity expansion documented earlier is accompanied by broader participation, not solely larger positions by a fixed set of incumbents.

Consistent with entry, Table 5 examines whether liquidity provision becomes more or less concentrated among a few large liquidity adjustments. Columns (1)–(3) report concentration measures constructed from liquidity events aggregated at the pool-week level. The interaction term is negative for all three metrics and statistically significant for the Top-5 and Top-10 shares, indicating that liquidity adjustments in treated pools become less dominated by the largest events relative to the control group. Column (4) reports the number of unique LP initiators and shows a statistically significant increase. Taken together, these results suggest that liquidity supply becomes more dispersed across addresses and less concentrated in a small set of large liquidity moves.

This dispersion contrasts with the demand-side evidence that trading activity becomes more concentrated among sophisticated traders. In other words, flash-loan eligibility is associated with more concentrated *demand* but more dispersed *supply*: treated pools attract additional LPs and

	Num New LP	Num New LP
	(1)	(2)
Interaction	3.607*	3.848*
	(1.959)	(2.024)
Token Agg Return (log)		8.674
		(6.146)
Token Agg Volume (million)		0.000***
		(nan)
Pool FE	Yes	Yes
Time FE	Yes	Yes
R^2	0.024	0.046
N	1342	1192

Note: *p<0.1; **p<0.05; ***p<0.01
Clustered standard errors by pool and time.

Table 4: Number of New Liquidity Providers

exhibit broader participation in liquidity events even as trading becomes increasingly driven by large or strategic participants.

	Top-1 Event Share	Top-5 Event Share	Top-10 Event Share	Unique Initiators
	(1)	(2)	(3)	(4)
Treated × Post	-0.070	-0.107***	-0.060**	15.383***
	(0.055)	(0.040)	(0.029)	(5.335)
Pool FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
R^2	0.004	0.046	0.036	0.135
N	1598	1598	1598	1598

Note: *p<0.1; **p<0.05; ***p<0.01
Clustered standard errors by pool and time.

Table 5: LP market concentration

5.2.2 Liquidity Adjustments and Capital Mobility

We next examine whether LPs become more active in managing positions. Table 6 reports difference-in-differences estimates for liquidity additions and removals at daily frequency. Across specifications, the interaction term is positive and statistically significant, implying that treated pools experience more frequent liquidity adjustments after flash-loan adoption. The estimates indicate economically meaningful increases in both adds and removes relative to controls, and

the results are robust to including additional controls.

More frequent adjustments are consistent with a setting in which LP capital is more responsive to changing conditions. Higher trading intensity, evolving price dynamics, and increased competition for fee revenue can all increase the value of monitoring and re-optimizing LP exposure. The increase in both additions and removals suggests that liquidity provision becomes more dynamic rather than simply expanding in a one-directional manner.

	Num Add Liquidity	Num Add Liquidity	Num Remove Liquidity	Num Remove Liquidity
	(1)	(2)	(3)	(4)
Interaction	1.976**	1.958**	1.236***	1.321**
	(0.771)	(0.937)	(0.464)	(0.558)
Token Agg Volume (million)		0.000		-0.000
		(0.000)		(0.000)
Token Agg Return (log)		0.166		0.077
		(0.149)		(0.133)
Pool FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Adj R^2	0.034	0.074	0.031	0.069
N	15041	10701	15041	10701

Note: *p<0.1; **p<0.05; ***p<0.01
Clustered standard errors by pool and time.

Table 6: LP activity change

5.2.3 Spillovers Across Treated and Control Pools

Greater entry and more frequent rebalancing raise the question of whether treated pools expand at the expense of control pools, or whether liquidity provision expands more broadly. Table 7 compares pre- versus post-event balances for incumbent LPs—addresses that provided liquidity before flash loans were introduced—separately for flash-loanable pools and other pools. Average incumbent balances increase in both groups, and the differences are statistically significant. This pattern is difficult to reconcile with a purely zero-sum reallocation from control to treated pools; instead, incumbents appear to expand positions system-wide over the sample window.

Group	N	Avg Pre-FL Balance	Avg Post-FL Balance	T-statistic	P-value
Flash-Loanable Pools	804	154.06	194.10	2.288**	0.0224
Other Pools	310	891.26	1,273.48	2.004**	0.0459

Table 7: Incumbent LP Position T-Test Table

Figure 8 provides complementary evidence on cross-pool mobility. Panel A counts LP "movements," defined as instances in which the same address exits one pool type and enters the other within a short window. Movements increase in both directions in the post period, indicating higher overall mobility rather than one-way migration into treated pools. Panel B reports net LP entries (mint minus burn events) by pool type and period, showing that treated pools experience a clear increase in net inflows after the event. Control pools also exhibit positive inflows, though the magnitudes differ.

Overall, the spillover evidence supports an interpretation in which flash-loan adoption coincides with greater LP dynamism and increased capital mobility across pool types, while treated pools experience net gains without clear evidence of systematic displacement from control pools.

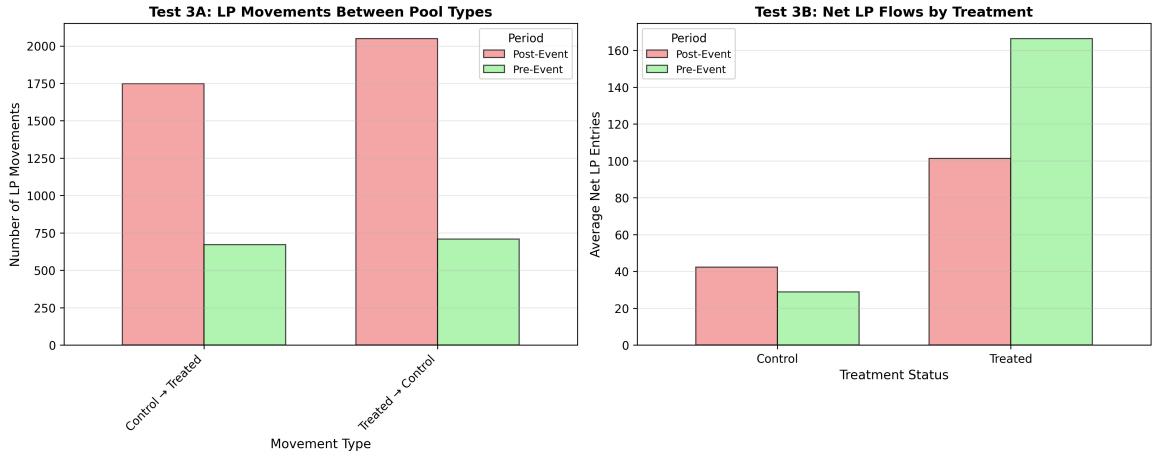


Figure 8: Incumbent LP Change Analysis

5.2.4 Compensation and Risk Exposure

Finally, we assess whether this reorganization improves the average economic return to liquidity provision. We measure LP performance through fee income, impermanent loss, and net profit. Fee income is mechanically tied to trading activity in Uniswap v1: pools charge a 0.3% fee on swaps, and total daily fee revenue follows directly from swap flow. Impermanent loss captures the relative underperformance of an AMM position compared to a buy-and-hold portfolio in the same tokens, reflecting the cost of providing liquidity when relative prices move. Net profit is defined as fee income minus impermanent loss.

Table 8 shows that flash-loan adoption substantially increases fee revenue, consistent with the demand-side rise in trading activity. However, impermanent loss increases by even more, and net

profit is slightly negative and statistically indistinguishable from zero. Thus, while treated pools generate more fees, they also expose LPs to higher adverse-selection and rebalancing costs, leaving average net returns broadly unchanged.

	Fee (ETH)	Fee (ETH)	Impermanent Loss (ETH)	Impermanent Loss (ETH)	Profit (ETH)	Profit (ETH)
	(1)	(2)	(3)	(4)	(5)	(6)
Interaction	197.887**	197.685**	272.983***	272.911***	-75.096	-75.226
	(90.807)	(90.753)	(93.336)	(93.301)	(85.389)	(85.464)
Token Agg Volume (million)		0.007		-0.019		0.026
		(0.009)		(0.015)		(0.021)
Token Agg Return (log)		-25.073*		-54.528**		29.455
		(13.123)		(25.505)		(28.985)
Pool FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.269	0.269	0.034	0.034	0.050	0.051
N	10698	10697	10698	10697	10698	10697

Note: *p<0.1; **p<0.05; ***p<0.01
Clustered standard errors by pool and time.

Table 8: Liquidity provider net profitability

6 Mechanisms

6.1 Limits to Arbitrage

A central mechanism through which flash loans can affect market quality is by relaxing short-horizon funding constraints for arbitrageurs. If some cross-venue mispricing opportunities are too capital intensive to exploit with traders' own balance sheets, then access to flash loans should matter most precisely when the available price discrepancy is large. In that case, flash-loan-funded trades should be more likely to move prices in the direction of correcting the pre-existing deviation.

To test this idea, we construct a transaction-level measure of cross-market mispricing by comparing prices for the same token pair across Uniswap v1 and Bancor v1. Bancor v1 serves as a natural reference market in this setting. During our sample period, it was one of the largest automated market makers alongside Uniswap v1, operating under a similar on-chain liquidity pool structure. Because prices are determined independently within each pool, they can temporarily diverge, creating arbitrage opportunities. At the same time, both platforms rely on arbitrage to keep prices aligned across venues, making arbitrage a central force behind price efficiency in decentralized markets (Angeris & Chitra, 2020; Lehar & Parlour, 2023; Milionis et al., 2025).

We restrict attention to token pairs that are traded on both platforms and construct a measure that captures the real-time deviations faced by arbitrageurs. For each swap i occurring at block b, we compute the pre-trade price gap as

$$e_i^{pre} = \log(P_i^{uni}) - \log(P_i^{bancor}), \tag{5}$$

where P_i^{uni} is the realized price of the Uniswap trade, and P_i^{bancor} is the most recent Bancor transaction price observed at or before block b for the same token. Both prices are converted in ETH. As a result, the cross-venue price gap e_i^{pre} captures the instantaneous cross-venue price discrepancy faced by traders at the time of execution, and can be interpreted as the ex ante arbitrage opportunity available at the moment of the trade.

Finally, we examine whether flash-loan-financed trades are more likely to be used to correct mispricing gaps when the absolute pre-trade price gap across venues is larger. We estimate the

following transaction-level specification:

$$\text{IsCorrective}_i = \beta_1 \left(FL_i \times |e_i^{pre}| \right) + \beta_2 FL_i + \beta_3 |e_i^{pre}| + \text{FEs} + \epsilon_i, \tag{6}$$

where IsCorrective_i is an indicator equal to one if transaction i moves the relative price in the direction of reducing the pre-trade cross-exchange deviation, and FL_i indicates whether the trade is financed with a flash loan. All specifications are estimated at the transaction level and include progressively richer sets of fixed effects.

Table 9 reports the results. The coefficient on the interaction term, $FL_i \times |e_i^{pre}|$, is positive and highly statistically significant across all specifications. This implies that flash-loan-funded trades become more likely to be corrective exactly when the ex-ante arbitrage opportunity is larger. Economically, the result indicates that flash loans are especially valuable in states where more capital is required to exploit the available mispricing.

The direct effect of flash-loan usage, β_2, is negative or close to zero once the interaction is included, while the coefficient on $|e_i^{pre}|$ by itself is not consistently positive across specifications. We do not place much weight on these lower-order terms in isolation, since the key object of interest is the interaction: the extent to which the corrective role of flash loans varies with the size of the arbitrage opportunity. The robust positive interaction shows that flash loans are disproportionately used for trades that lean against larger deviations rather than merely accompanying mechanically more corrective trading environments.

Overall, these findings support a limits-to-arbitrage interpretation. In models such as Gromb and Vayanos (2010), arbitrage activity is constrained by traders' capital and funding frictions, which prevent them from fully eliminating mispricing, especially when deviations are large or require substantial balance sheet capacity. As a result, price discrepancies can persist even in the presence of rational arbitrageurs. In our setting, flash loans effectively relax these short-horizon funding constraints, enabling traders to deploy capital elastically at the transaction level. When price discrepancies are small, traders can often correct them using internal capital alone. When discrepancies become larger, however, exploiting them requires taking on larger positions and deploying more capital within a short horizon. Flash loans relax this transaction-level financing constraint, allowing arbitrageurs to scale up and execute trades that push prices back toward parity.

Consistent with this view, we find that flash-loan-financed trades are disproportionately used

in states with larger mispricing, where traditional arbitrage would be most constrained. By lowering the effective cost of capital for arbitrage, flash loans allow traders to act more aggressively on these opportunities, helping restore price parity. This provides a micro-founded channel through which relaxing funding constraints can improve price efficiency, complementing the theoretical predictions in the limits-to-arbitrage literature.

	Dependent variable: Is Corrective			
	(1)	(2)	(3)	(4)
FL × $\lvert e^{pre} \rvert$	0.538***	0.428***	0.531***	0.570***
	(0.049)	(0.062)	(0.073)	(0.043)
FL	-0.080***	-0.044*	-0.078***	-0.028
	(0.013)	(0.023)	(0.029)	(0.025)
$\lvert e^{pre} \rvert$	-0.340***	-0.265***	-0.182**	1.152*
	(0.012)	(0.044)	(0.090)	(0.627)
Pool FE	✓		✓	
Time FE		✓	✓	
Pool × Time FE				✓
R^2	0.003	0.001	0.000	0.003
N	211159	211159	211159	211159
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 9: Flash loans and corrective trading

6.2 Price Discovery

In addition to relaxing capital constraints, flash loans may also affect market quality by strengthening price discovery. If flash-loan users are better able to identify and act on mispricing, their trades should contain more information about subsequent price movements. In that case, trades associated with flash loan transactions should be followed by price changes in the same direction as the initiating trade.

To test this channel, we examine whether Uniswap swaps that are part of flash loan transactions predict future returns at horizons of up to 48 hours. The regression is estimated at the

transaction level. In the spirit of local projections, for each swap i and horizon h, we estimate

$$y_{i,h} = \beta_h FL_i + \gamma_1 |e_i^{pre}| + \gamma_2 \ln(\text{Size}_i) + \text{FE} + \epsilon_{i,h}, \tag{7}$$

where the dependent variable is the signed forward log return,

$$y_{i,h} = s_i \cdot \left(\log P_{t_i+h} - \log P_{t_i}\right). \tag{8}$$

Here, $s_i \in \{+1, -1\}$ denotes trade direction. By construction, a positive value of $y_{i,h}$ means that the price subsequently moves in the direction of the trade. The indicator FL_i equals one if the Uniswap swap is part of a flash loan transaction. The coefficient of interest, β_h, therefore captures the additional same-direction price movement over the next h hours following a flash-loan-linked swap, relative to a non-flash-loan swap of the same direction, conditional on the pre-trade dislocation and trade size. The regression also includes pool and hour fixed effects, which absorb time-invariant pool characteristics and market-wide shocks common to all pools within a given hour.

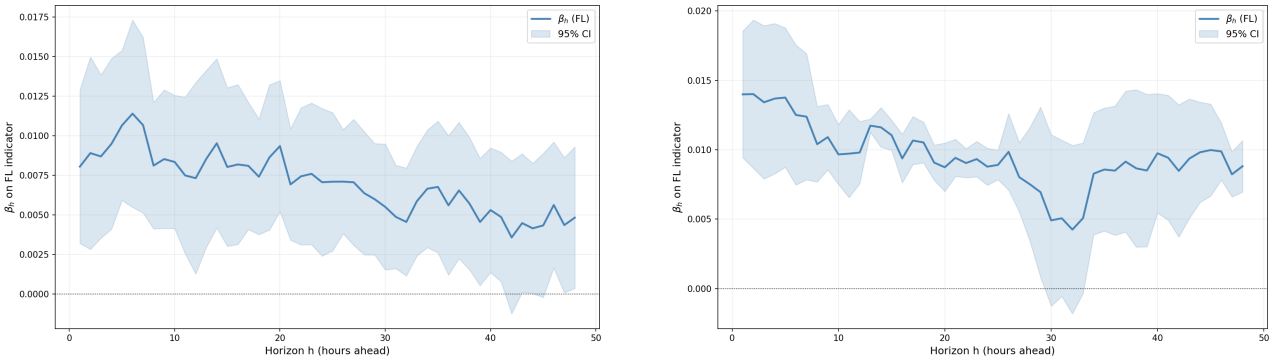
This specification is interpreted as a test of post-trade continuation. In particular, it captures whether prices continue to move in the direction of the trade over subsequent hours. This is precisely the relevant object for a price discovery interpretation: if β_h is positive only at short horizons and then decays to zero, flash-loan trades mainly generate temporary price pressure; if β_h remains positive at longer horizons, then flash-loan trades are associated with more persistent, informationally relevant price movements.

Figure 9 reports the estimated path of β_h. We begin with Panel (a), which uses Uniswap prices. The coefficients are positive throughout the horizon and remain economically meaningful out to 48 hours, fluctuating around roughly 0.0075. In return terms, this corresponds to about 0.75% more same-direction price movement following flash-loan-linked swaps relative to comparable non-flash-loan swaps. The persistence of this pattern suggests that these trades contain information about subsequent price movements, rather than merely generating temporary liquidity effects that quickly reverse.

A natural concern is that the Uniswap result may still reflect mechanical dynamics within the originating pool. To address this concern, Panel (b) repeats the exercise using Bancor prices as the

outcome. If the Uniswap pattern were driven purely by within-pool mechanics, the predictive content should weaken substantially when future returns are measured in Bancor instead. Instead, we again find a positive and persistent response, with coefficients of similar magnitude and, if anything, slightly larger, around 0.01, corresponding to about 1% more same-direction price movement over much of the horizon. This indicates that flash-loan-financed Uniswap swaps predict subsequent price movements not only in the originating venue, but in the broader market as well.

The evidence points to a price discovery channel. Flash-loan-financed swaps are followed by persistent same-direction returns in Uniswap itself, and this predictive content also appears in an external reference market. Although flash-loan-financed transactions represent only a small fraction of overall trading activity, their estimated effects are economically meaningful and highly persistent. This suggests that a relatively small subset of trades carries disproportionate informational content in the price discovery process. The pattern is difficult to reconcile with purely transitory price pressure. Instead, it is more consistent with flash loans enabling sophisticated traders to act more aggressively on information, thereby accelerating the incorporation of information into prices. This interpretation also helps reconcile the findings in Section 5.2, where liquidity providers earn higher fees but are also exposed to greater adverse selection risk. The price discovery channel therefore complements the limits-to-arbitrage mechanism and helps explain why flash loans can simultaneously improve market efficiency while altering the risk-return trade-off faced by liquidity suppliers.



(a) Uniswap (b) Bacor

Figure 9: Dynamic effects for market quantity

7 Conclusion

This paper studies how a sharp expansion in short-term financing capacity affects market liquidity. Exploiting the token-level rollout of flash-loan eligibility as a natural experiment, we show that relaxing transaction-level funding constraints leads to a persistent deepening of liquidity. Executable depth and total value locked rise, trading activity increases, and liquidity provision becomes more dispersed and more dynamic. At the same time, average liquidity provider profitability remains broadly unchanged, as higher fee income is offset by greater exposure to adverse selection.

We show that these effects operate through two complementary channels. First, flash loans relax short-horizon funding constraints for arbitrageurs. Flash-loan-financed trades are more likely to correct cross-venue mispricing precisely when price gaps are larger, indicating that access to elastic capital matters most when arbitrage opportunities are more capital intensive. Second, flash loans strengthen price discovery. Swaps associated with flash loan transactions are followed by more persistent same-direction future price movements, both in Uniswap and in an external reference market, suggesting that flash loans also make order flow more informative. Together, these findings imply that flash loans improve market functioning not simply by increasing trading activity, but by reshaping the balance between corrective arbitrage and informed trading.

These results have broader implications beyond decentralized finance. Modern markets increasingly rely on technologies and institutions that expand short-term access to capital, including intraday credit, repo funding, and algorithmic leverage. Our evidence suggests that easing financing constraints can deepen liquidity and support market participation, but it can also intensify price discovery and raise the information sensitivity of liquidity provision. The central implication is that financing innovations do not merely increase the quantity of capital in markets; they also change how that capital is deployed, how prices adjust, and how risks are shared across market participants. Understanding these equilibrium effects is essential for evaluating new financial technologies and their implications for market stability.

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8 Appendix A: Token List

Token Symbol	Protocol	Category	Pool Creation	Num Txns
MKR	MakerDAO	Lending	2018-11-02	135610
BAT	Basic Attention Token	Advertising	2018-11-07	71004
SNX	Synthetix	Derivatives	2019-08-09	80774
REP	Augur	Prediction Market	2018-11-02	45914
KNCL	Kyber Network	DEX Aggregator	2018-11-02	40829
ZRX	0x Protocol	DEX Infrastructure	2018-11-02	32455
MANA	Decentraland	Metaverse	2018-11-02	15175
LEND	Aave	Lending	2019-03-14	19657
LINK	Chainlink	Oracle	2018-11-02	77639

Table 10: List of Treated Tokens

Token Symbol	Protocol	Category	Pool Creation	Num Txns
HEX	HEX	Staking	2019-12-04	127965
CNCC	Centric Cash	Payments	2019-12-17	69893
UBT	Unibright	Enterprise Blockchain	2019-09-23	65434
PNK	Kleros	Dispute Resolution	2018-11-08	37863
NMR	Numerai	Hedge Fund	2018-11-10	34626
SLP	Smooth Love Potion	Gaming	2019-12-24	21472
ANT	Aragon	DAO Framework	2018-11-11	20014
REN	Ren Protocol	Interoperability	2018-11-11	18941
ANJ	Aragon Court	Dispute Resolution	2020-01-07	18725
XIO	XIO Network	Launchpad	2019-11-01	18255
RLC	iExec RLC	Decentralized Cloud	2019-01-07	17223
LPT	Livepeer	Video Streaming	2018-11-13	16384
DATA	Streamr	Data Marketplace	2019-01-06	16372
RPL	Rocket Pool	Liquid Staking	2019-01-06	16269
BAND	Band Protocol	Oracle	2019-10-06	15932
LRC	Loopring	DEX	2019-05-23	15305
JRT	Jarvis Network	Synthetics	2019-12-30	14146
AMPL	Ampleforth	Algorithmic Stablecoin	2019-07-03	13763
CSAI	Compound Dai	Lending	2019-05-09	13565
TKN	Monolith (TokenCard)	Crypto Card	2018-12-08	12875
SNT	Status	Social Network	2018-11-02	12460
DIP	Etherisc	Decentralized Insurance	2019-04-19	11898
BNT	Bancor	DEX	2019-02-06	11864
NEXO	Nexo	Lending	2018-11-05	11219
SOCKS	Unisocks	DEX	2019-05-08	10855
CEL	Celsius Network	Lending	2019-04-15	10294
ENJ	Enjin Coin	Gaming	2019-02-22	9983
MLN	Enzyme (formerly Melon)	Asset Management	2019-02-21	9469
GEN	Aragon	DAO Framework	2019-02-17	9325
LOOM	Loom Network	Gaming	2018-11-02	9127
CDAI	Compound Dai	Lending	2019-11-25	8966
GNO	Gnosis	Prediction Market	2018-11-02	8782
FUN	FunFair	Gaming	2018-11-07	8653
SPANK	SpankChain	Adult Entertainment	2018-11-02	8275
RDN	Raiden Network	Payments	2019-01-30	8221
BLT	Bloom	Credit Scoring	2019-02-26	7347
RCN	Ripio Credit Network	Lending	2018-12-12	7332
OXT	Orchid	VPN/Privacy	2019-12-10	7283
TMV	Inverse Finance	Lending	2019-12-05	7143
HOT	Holo	Distributed Hosting	2019-01-26	6925

Table 11: List of Control Tokens

9 Appendix B: Classification of Flash Loans

In this section, we discuss methodologies for classifying flash loan transactions according to their intended purpose, focusing primarily on arbitrage and debt restructuring activities. We exclude graphs that are too simple, with fewer than three nodes indicating testing purposes, or too complex, with more than 16 nodes and 35 edges indicating market attacks. Thus, our analysis centers on the middle range of the distribution, focusing on rational use cases of flash loans.

The key difference between arbitrage and debt restructure lies in the source of funding. Arbitrage relies solely on the flash loan as the source of capital, while debt restructuring involves external sources of capital. Specifically, in arbitrage, the process starts with flash loan borrowing, followed by buying and selling in different marketplaces, and concludes with repaying the flash loan. The profits generated are transferred out to wallet addresses, and fees may be paid to third parties for services. This process forms a complete path with no additional inflow of tokens. In contrast, debt restructuring involves spontaneous inflows of tokens other than the token borrowed from the flash loan provider. As illustrated in Figure (2), debt restructuring transactions involve multiple token transfers to and from the lending protocol. However, these transfers are not merely between the same addresses, rather, they involve various liquidity pools within the DeFi lender. Consequently, the asset swapped out is transferred from a pool address to the flash loan contract. Notably, this address records no incoming transfers and remains unconnected to the main network. Furthermore, blockchain-based collateralized lending may also incorporate the exchange of platform-specific wrapped tokens. For example, in Aave, aTokens are minted and burnt as assets are deposited into or withdrawn from the platform, serving as a method of bookkeeping. In the dataset, these transactions are recorded as transfers to and from a null address [1]. This action also forms an isolated node, which interacts solely with the flash loan smart contract node, but does not establish any other connections.

To distinguish between arbitrage and debt restructuring, we propose a novel method based on the transfer graph. For each transfer graph $G(V,E)$, we test whether a Hamiltonian path exists that incorporates all nodes. In graph theory, a Hamiltonian path is a path that visits each node exactly once (Trudeau, 2013). In a rooted directed graph, such a path must begin at the root and traverse each vertex exactly once, following the direction of the edges (Chartrand & Zhang, 2012).

[1] 0x0000000000000000000000000000000000000000

We find the longest Hamiltonian path that starts from the flash loan lender node, using a dynamic programming algorithm (Held & Karp, 1965). This path connects the main body of the graph, including any destination nodes receiving tokens from the main body, but excluding nodes transferring to the main body. According to the definition of arbitrage, there must be a Hamiltonian path connecting all nodes in the graph. If there are nodes outside this path, the transaction is dropped out of the arbitrage set.

We further enhance the accuracy of the classification based on the functions listed in the event logs other than the transfer function. When a smart contract interacts with a lending protocol to adjust collateralized debt positions, it is more likely to execute functions related to borrowing, such as Borrow or Repay. Arbitrage transactions typically do not contain these functions. Additionally, transactions involving prominent lending protocols such as Maker or Compound are indicative of debt restructuring activities. We classify a transaction as potential debt if it includes at least one function containing keywords such as 'borrow', 'interest', 'collateral', 'repay', or 'repaid', and if it includes at least one node associated with Maker or Compound.

Finally, we classify a transaction as arbitrage if it has all nodes on the Hamiltonian path and does not belong to the potential debt list. A transaction is classified as debt restructure if it has at least one node outside the Hamiltonian path and belongs to the potential debt list. Transactions not fitting these criteria are left unclassified. These typically include transactions with nodes not on the Hamiltonian path but not identified as potential debt, possibly representing less common use cases. One example is that flash loans can be used to bundle complex transactions into a single contract and execute them in one go, thereby reducing fees. Some flash loans have a zero borrowing amount, which may indicate the existence of this type of transaction.

Manual analysis

To demonstrate the performance of our classification methods, we randomly select 100 flash loans and manually analyze the associated graphs to classify them into different categories. We cross-check our classifications with graphs provided by professional data providers such as EigenPhi [2] and Bloxy [3] to ensure accuracy and reliability. In our sample, we identify 30 transactions as arbitrages and 45 as debt restructurings. To validate our methodology, we compare these manual

[2] eigenphi.io
[3] bloxy.info/api_methods

classifications with the results from our algorithm. Our findings reveal that the algorithm correctly classifies 67% of the arbitrages and 93% of the debt restructurings. These results highlight the algorithm's robustness, particularly in identifying debt restructuring transactions, which often involve more complex interactions and external capital inflows. In arbitrage transactions, inaccuracies often stem from transactions with atypical patterns or involving minor external capital inflows that our initial parameters do not account for. For debt restructurings, the few misclassifications are typically due to the presence of unusual token flows or interactions with less commonly used DeFi protocols.

Overall, our method demonstrates a high degree of accuracy, particularly for debt restructuring transactions, showcasing its potential for widespread application in analyzing and classifying flash loan transactions. Future improvements include refining the algorithm to better account for edge cases and incorporating additional data sources to enhance classification precision.