Token Incentives and Platform Competition: A Tale of Two Swaps

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Abstract

Platforms compete intensively to attract users. Monetary subsidies are commonly used to incentivize users' adoption but such subsidies are expensive. In this paper, we study impacts of token incentives, an alternative incentive approach, in the competition of two decentralized exchange platforms. Decentralized exchanges enable the exchange between a pair of crypto tokens through a liquidity pool, among many liquidity pools on a decentralized exchange platform. The platform depends on liquidity providers to supply liquidity that facilitates transactions from the demand side, which makes the amount of liquidity supply the key to platform success. In our context, the entrant platform, Sushiswap, launched token incentives to attract liquidity providers from the incumbent, Uniswap, who then also retaliated with its own token incentives. Our empirical analysis of the two platforms shows that Uniswap's own token incentives attract more liquidity to the platform. Surprisingly, we find that the token incentives from the competitor, Sushiswap, also bring more liquidity to the incumbent. Regarding potential mechanisms, we find that increased liquidity of Uniswap mainly comes from the increased number of liquidity providers. The token incentives from the competitor Sushiswap may have brought more new liquidity providers to Uniswap. Meanwhile, the incentives from Sushiswap may also impose a competition effect that decreases the amount of liquidity per provider on Uniswap, as existing providers shift liquidity to Sushiswap to harvest the rewards from both platforms. The analysis of heterogeneous effects reveals that high-volatile pools benefit less from the competitor's token incentives relative to more-stable pools. Our results provide important insights and practical guidelines on the design of token incentives in platform competition.

Keywords: Token Incentives, Platform Competition, Decentralized Exchanges, Liquidity Supply, Network Effects, Information Diffusion

1. Introduction

Two-sided platforms have been penetrating into various industries, from digital applications (e.g., Apple and Google's App stores), to physical products (e.g., Amazon, eBay), and to service-oriented goods (e.g., Uber, Airbnb, TaskRabbit) (Cullen and Farronato, 2021). Acting as intermediaries between two groups of participants, these platforms provide venues for buyers and sellers to meet and transact, and the efficiency generated by two-sided platforms can also be amplified by the increased size of markets (i.e., network effects). However, platform growth is never easy (Caillaud and Jullien, 2003; Hagiu and Spulber, 2013; Dou and Wu, 2021). To jump-start the network effects and assist platform growth, monetary incentives are commonly used to subsidize one side of the platform[1] (Rochet and Tirole, 2003, 2006; Eisenmann et al., 2006). Platforms sometimes may have to adopt incentives to protect their market position in competition. Such incentives are expensive. For example, Uber offers drivers a cash bonus upon finishing a certain number of rides within a week in some cities,[2] and spent $250 million in drivers' incentives in 2021 alone to lure drivers away from its competitor Lyft.[3]

Relying on users' expectation of future platform success, token incentives could be a helpful and less expensive alternative to foster platform growth and fight against competition. In the crypto space, many crypto projects are two-sided platforms and token airdrops are not uncommon (Cong et al., 2021). Prior literature (Catalini and Gans, 2018; Li and Mann, 2018; Bakos and Halaburda, 2019) shows that tokens could encourage early platform adoption, as early adopters can enjoy the benefits of token appreciation from future platform growth, but the effectiveness and mechanism of

[1] We use subsidies and incentives interchangeably in this paper.
[2] Through the Power Driver Plus program. Source: https://therideshareguy.com/power-driver-plus-strategy-guide/
[3] Based on Uber's full-year financial report of 2021, the earnings from rideshare service was $ 575 million in 2021, and thus $ 250 million of drivers' incentives was about 43.5% of their entire earnings from rideshare service.
source: https://www.uber.com/newsroom/getting-drivers-back-on-the-road/;
https://investor.uber.com/news-events/news/press-release-details/2022/Uber-Announces-Results-for-Fourth-Quarter-and-Full-Year-2021/

token incentives in platform competition haven't gained much attention. Going beyond the crypto space, when we talk about platform competition, we generally assume a static market setup and the gain of one platform often comes as the cost of the other platform. While in an emerging market (e.g., crypto space), it might not be the case, but the research studying the incentives and platform competition under the possibility of market expansion still remains rare in the literature.

In this paper, we examine token incentives and platform competition in the context of decentralized exchanges[4], and analyze two major decentralized exchange platforms Uniswap and Sushiswap. Uniswap is the largest decentralized exchange and the fourth-largest cryptocurrency exchange overall by daily trading volume[5], and Sushiwap is an entrant. Decentralized exchanges enable the exchange between two tokens through a liquidity pool, among many liquidity pools on a decentralized exchange platform. Traders are on the demand side of a liquidity pool, and they pay trading fees to swap one token for another. Liquidity providers are on the supply side, depositing the corresponding pair of tokens into the pool. Liquidity providers gain trading fees as a reward for providing liquidity, but they may also face the risks of losing values if the token price changes dramatically (i.e., impermanent loss[6]). Since more liquidity in a pool means lower slippage[7] and a better experience for traders, it is important to attract more liquidity to assist the growth of decentralized exchanges.

[4] A brief explanation of how decentralized exchanges work is included in Appendix A.1.1. For more detailed information, see Aoyagi (2020) and Capponi and Jia (2021)for reference.

[5] The daily trading volume of Uniswap is about 1.5 trillion dollars, similar to the only publicly traded centralized exchange Coinbase. Source: https://www.coingecko.com/en/exchanges; https://www.bloomberg.com/news/articles/2020-10-16/defi-boom-makes-uniswap-most-sought-after-crypto-exchange #xj4y7vzkg

[6] Liquidity deposited into a decentralized exchange platform is exposed to the impermanent loss. This loss typically occurs when token prices fluctuate and cause the ratio of token values uneven. This loss is calculated by comparing the value of the tokens deposited in the liquidity pool versus the value of holding them. A simple numeric example of impermanent loss is included in Appendix A.1.2.

[7] In a financial context, slippage refers to the difference between the expected price of a trade compared with the actual price when the trade is executed. In the decentralized exchanges, since the exchange price is determined by the amount ratio of two tokens, when the size of a single trade is very large relative to the size of the liquidity pool it may have a large impact on the executed price. If the pool has a large volume of liquidity supply, it will have a higher tolerance of the large single trades, and traders could suffer less from the financial loss caused by slippage.

As an entrant and a forked version of Uniswap, it was challenging for Sushiswap to capture liquidity and compete with Uniswap during the initial period. Sushiswap launched its token SUSHI and related SUSHI token incentives where liquidity providers will be rewarded SUSHI tokens if they deposit tokens to Sushiswap pools[8]. Uniswap retaliated by launching its own token UNI and UNI incentives shortly afterwards. We can expect that the token incentives from its own platform would be beneficial for the focal platform. For example, the SUSHI token incentives helped Sushiswap acquire $840 million of values of deposited tokens in two weeks[9]. This was a massive success, because Uniswap only had $185 million of liquidity before the launch of Sushiswap[10]. However, the impact of token incentives from a competitor on the focal platform is not clear. There could be two theorized effects of negative competition and positive spillovers. On the one hand, token incentives could, to some extent, compensate for the risks of providing liquidity, so it may make providing liquidity on the competitor platform more attractive. Some users might migrate from the focal platform to its competitor, so the competitor's token incentives could have a negative *competition effect* on the focal platform. On the other hand, the competitor's token incentives may make more users aware of decentralized exchanges, and further have a positive *spillover effect* on the focal platform. During the battle between Uniswap and Sushiswap, we surprisingly see that overall the spillover effect dominates. Both platforms grew and gained more liquidity even with head-to-head competition of token incentives.

In this study, we seek to answer the following research questions about the impacts of UNI and SUSHI token incentives: (1) What are the impacts of token incentives (from its own platform and from a competing platform) on liquidity supply of the focal platform? (2) What is a potential

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[8] Initial period of SUSHI token incentives was a vampire attack against Uniswap, because liquidity providers need to transfer liquidity from Uniswap to Sushiswap to be qualified to get SUSHI token rewards. The rewards during vampire attack were more than the later period when liquidity providers could gain SUSHI token rewards as long as depositing tokens to Sushiswap, regardless the source of liquidity.

[9] https://www.yahoo.com/video/defi-deep-dive-sushiswap-disciple-093000530.html

[10] https://www.gemini.com/cryptopedia/sushiswap-uniswap-vampire-attack

mechanism of token incentive on liquidity supply? (3) How does token price volatility moderate the impacts of token incentives? (4) Are the impacts of token incentives the same for the incumbent and the entrant? To answer these research questions, we extract liquidity and trading transactions from the Ethereum blockchain, and construct a pool-day level panel data on each selected active pool on Uniswap and Sushiswap from August 2020 to November 2020. A coarsened exact matching method is used to make the incentivized pools and control pools comparable. Pool fixed effect models and a relative time model are utilized to analyze the impacts of token incentives.

Our empirical analysis verifies that token incentives that rely on users' expectation of future platform success are an effective incentive approach in platform growth and competition. The results first explain the impacts of token incentives on liquidity supply in detail from three aspects. (1) Token incentives indeed attract more liquidity to its own platform, and token incentives from a competing platform may have positive spillovers on the liquidity supply of the focal platform. (2) Token prices of the incentives could intensify such positive impacts on the pairs incentivized by the focal platform or its competitor. (3) Network effects exist in impacts of token incentives and decentralized exchanges, and liquidity supply is the main contributor to platform growth.

Second, our results shed light on the mechanism of token incentives. The positive effects from the focal platform on its liquidity supply are from both acquiring more liquidity providers and more liquidity per holder. In addition, the positive spillover of competitor's token incentives is mainly from attracting more providers to the platform, which may be driven by information diffusion and increased awareness from the competitor's incentives programs as well as the positive impacts of Sushiswap's vampire attack. However, the competitor's token incentives may impose a negative competition effect on the cumulative liquidity per holder, as existing providers who adopted the platform earlier may shift to the competitor platform to take advantage of both token incentives.

Third, our results also reveal the heterogeneous effects of token incentives on different pools. The pools with more-stable tokens whose prices do not change much benefit more from the positive spillover of the competitor's token incentives. On the contrary, the pools with tokens whose prices are highly volatile benefit less, or may even face a negative competition effect from the competitor on liquidity supply, if the token pairs are only incentivized by the competitor platform. This is mainly because token incentives could partially compensate providers for the risks of losing values when token prices are highly volatile, and the only availability of the competitor's incentives makes the decision of providing liquidity on the competitor platform more attractive. Lastly, our Sushiswap analysis reveals that the impacts of a competitor's token incentives on an entrant platform is not the same as that on an incumbent platform. The Sushiswap token pairs with both UNI and SUSHI incentives do not have a significant change on their liquidity supply during the period of UNI token incentives, but they obtain a significant increase from the closure of UNI token incentives.

This paper makes several theoretical contributions to platform competition and cryptoeconomics. First, prior literature on platform competition is mostly theoretical in nature, and our paper provides valuable empirical evidence. Because it is almost impossible to get detailed data across different platforms, the existing empirical research mainly studies from platform level or examines only one platform. By using the individual-level transaction data from the Ethereum blockchain, we are able to analyze different markets on both incumbent and entrant platforms. Second, the conventional wisdom tells us that platform competition is near a zero-sum game and research on incentives and platform competition typically only consider a static market, but our results demonstrate that there could be positive spillovers of a competing program by increasing public awareness and attracting more users to the whole industry and the incentives could induce market expansion, especially in an emerging one. Third, we complement the nascent field of cryptoeconomics by introducing token incentives into not only platform adoption, but also platform competition. We also deep dive into the potential mechanism and heterogeneous effects of token incentives.

Our study also provides several useful implications for designing a token incentive program. First, when a competitor launches token incentives, it would be beneficial for the focal platform to launch it too. If it is a mature industry where existing users are dominant or acquiring new users is challenging, the platform must retaliate. Furthermore, the platform should consider offering incentives for the pools whose token prices are highly volatile, since these pools are more likely to suffer from the competitor's attack.

The rest of the paper is organized as follows. Section 2 reviews relevant literature. Section 3 describes how we construct the sample and variables with a brief introduction of Uniswap, Sushiswap and their token incentives programs. We also demonstrate model-free evidence in Section 3 to show possible positive effects of token incentives on liquidity supply. We explain our identification strategies and methods in Section 4, and Section 5 presents our results of Uniswap and Sushiswap analysis. The concluding remarks are in Section 6. Lastly, we provide additional robustness checks to support our main findings in the Appendix.

2. Literature

2.1 Platform Competition

Our paper contributes to platform competition from the perspectives of incentive design, network effects, and dynamics of competition. First, our paper is related to the literature of subsidies and incentives in platform competition. Literature has recognized that subsidies are common pricing controls (Eisenmann et al., 2006; Rochet and Tirole, 2006) and a platform may achieve the maximum profit by subsidizing one side (e.g., Rochet and Tirole, 2003; Eisenmann et al., 2006; Bolt and Tieman, 2008). Prior studies working on the conditions where such subsidization could be effective (Rochet & Tirole, 2003; Parker & Van Alstyne, 2005; Eisenmann et al., 2006; Bakos & Halaburda, 2020) have shown that subsidizing the quality- and price- sensitive side or the side with higher externalities could be beneficial for the focal platform when the subsidies enhance the potential connections between the two sides. However, these studies assume the market size is static. Dou and Wu (2021) model market expansion in the platform competition but via a non-pricing control piggybacking strategy and examine how the strategy interacts with subsidies. Our research contributes to the literature by explicitly considering and providing empirical evidence to the case where subsidies and incentives could induce market expansion. It presents a new perspective for analytical research to derive the optimal incentives scheme. We also investigate the potential mechanism and heterogeneous effects of incentives on market expansion.

In addition, there is rich literature about modeling platform competition with network effects (e.g., Katz and Shapiro, 1985; Parker and Van Alstyne, 2005; Cabral, 2011; Dou et al., 2013). Prior literature well studies the impacts of network effects on platform strategies. It shows that network effects could magnify the effects of subsidies (Jullien, 2011), restrain the entrant and protect the market position of incumbent platforms (Niculescu et al., 2018). It is important for practitioners to understand the size of network effects and identify the main driver of the platform growth (Cullen and Farronato, 2021), so they could prioritize the scarce resources on the side with higher network effects to achieve a faster growth rate. Our paper offers valuable empirical observations to the growing but limited empirical research on network effects (Shankar and Bayus, 2003; Rysman, 2004; Wilbur, 2008; Chu and Manchanda, 2016). We verify that the network effects exist on decentralized exchanges and liquidity supply is the main contributor to the growth of the platforms. Our results have the new insights to the literature that even under network effects, both incumbent and entrant platforms could grow with token incentives, and we also identify the impact paths of token incentives on the liquidity demand.

Lastly, Jullien and Sand-Zantman (2021) summarize and discuss whether platform competition leads to monopolization. Incumbent platforms have an incumbency advantage (Biglaiser and Crémer, 2020), but an entrant could still survive or even replace the dominant when considering network effects and incentives (Eisenmann et al., 2011). Prior literature on dynamics of platform competition is mostly theoretical in nature, and tends to consider the benefit gained by one platform in the competition is often at the cost of the other platform. The existing literature about cross-platform spillover effects primarily study the spillovers of consumer's demands across different platforms when the same products are introduced sequentially (Krijestorac et al., 2020). Our research focuses on the nature of head-to-head competition among platforms, and highlights the possible spillovers of the entrant's attack on the incumbent, which remains rare in the existing literature. Cao et al. (2021) find similar positive spillovers of an entrant on an incumbent in the context of bike-sharing platforms, and we further contribute to the literature by empirically analyze different markets on both incumbent and entrant platforms as we use the individual-level transaction data from the Ethereum blockchain and we are able to observe an individual's behavior across different platforms.

2.2 Cryptoeconomics

This paper also contributes to the emerging field of cryptoeconomics. One of the nascent literature is to study roles of cryptographic tokens in platform settings. Some research discusses the coordinating role of platform-specific digital tokens in platform adoption (Catalini and Gans, 2018; Li and Mann, 2018; Bakos and Halaburda, 2019; Cong et al., 2021). Tokens could encourage early adoption of productive platforms, since early adopters could enjoy the future benefits from token price appreciation and platform growth. Building beyond these analytical works, we introduce the role of token incentives to platform competition and provide empirical findings on the information-diffusion role of token incentives.

The context of our paper is also connected to blockchain-based decentralized finance (DeFi), a growing topic in cryptoeconomics. Harvey et al. (2021) provide a comprehensive survey on the topic of DeFi. Our work is specific to decentralized exchange, a key component of decentralized finance. In the literature of decentralized exchange, a few papers compare between the decentralized changes with traditional centralized exchanges (e.g., CoinBase and Binance). Lehar and Parlour (2021) study expected payoff of liquidity provision and derive the conditions where decentralized exchanges will dominate the traditional cryptocurrency exchanges. Aoyagi and Ito (2021) evaluate the impacts of coexistence of decentralized and centralized exchanges on asset prices and traders' behavior. Barbon and Ranaldo (2021)compare liquidity and price efficiency between two types of exchanges. There are also some researchers analyzing different designs within the decentralized exchanges. For example, Capponi and Jia (2021)examine market microstructure and the adoption of decentralized exchanges. Our paper contributes to this growing field by evaluating the dynamics between two decentralized exchange platforms from the perspective of platforms.

3. Research Context and Data

3.1 Uniswap and Sushiswap

To study the impacts of token incentives on liquidity supply, we analyze two competing decentralized exchange platforms, Uniswap and Sushiswap. On these platforms, liquidity providers are in the supply side, depositing tokens and receiving trading fees as a reward of providing liquidity; and traders are in the demand side, paying trading fees to swap one token for another one. One liquidity pool can be seen as a market for exchanging a specific pair of tokens on a platform, and there are many liquidity pools on a platform.

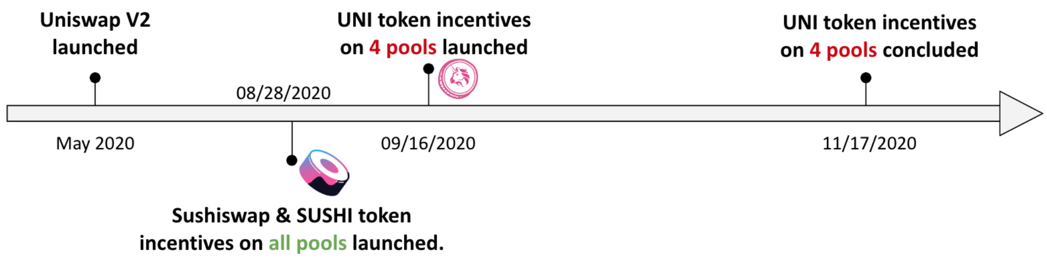

Figure 1. Timeline with Important Start and End Dates of Uniswap and Sushiswap

Figure 1 shows the launch dates of two platforms and their token incentives. Uniswap V2 was launched in May 2020, and Sushiswap came out in late August 2020. Sushiswap is a forked platform of Uniswap V2, so their features are almost identical, except for one difference that Sushiswap launched its governance token SUSHI and SUSHI token incentives together with its platform but Uniswap didn't have them initially. During the initial period (August. 28th 2020 - September 9th 2020), SUSHI token incentives was a vampire attack that directly went against Uniswap. Liquidity providers need to transfer liquidity from Uniswap to Sushiswap to get the SUSHI tokens and the amount of rewards during vampire attack periods was more than the periods after September 9th. Uniswap also launched its governance token UNI and UNI token incentives shortly after Sushiswap's debut.

UNI and SUSHI tokens are governance tokens, and users can use these governance tokens to create and vote on governance proposals for the platforms. The prices of UNI and SUSHI tokens rely on users' expectation of future platform growth. Even though the issuance of governance tokens is not backed by any assets, UNI and SUSHI tokens are tradable and can be exchanged for cash. Token incentives aim to attract more liquidity to the platforms by rewarding liquidity providers with UNI or SUSHI tokens if they deposit tokens to the incentivized pools on the platforms. Since more funds in a liquidity pool means lower slippage and a better experience for traders, enlarging the supply side could further benefit the platform by capturing more trading volume from the demand side.

3.2 Sample Construction and Variables

Transaction-level data from the Ethereum blockchain is our primary data set. We extract liquidity and trading transactions on Uniswap and Sushiswap from the data set to construct the sample. Liquidity transactions are our main interest of transactions, containing the information of transaction date, a liquidity provider's identifier, identifier of a liquidity pool, the amount of liquidity that a provider deposited or withdrawn (deposited amount is positive, and withdrawn amount is negative). Trading transactions with the information of trading paths and trading amount will be used to calculate the trading volume of a liquidity pool.

August 1st 2020 to November 30th 2020 are set as our study period, because it covers all important start and end dates, and it is also not so long that may capture other important events which could influence the liquidity supply. In addition, the number of liquidity transactions for each pool appears to be a long-tail distribution. For example, many liquidity pools on Uniswap had only 1-2 liquidity transactions within half a year. To reduce the noise from inactive pools, we only consider active pools which account for 90%[11] of cumulative liquidity transactions when sorting descendingly and considering two platforms together. The minimum number of liquidity transactions in these selected pools is 103 in the four months combined. If the amount of cumulative liquidity in a pool is zero and no new liquidity is deposited in the following periods, the pool will be marked as a closure. Furthermore, individual-level liquidity and trading transactions are

[11] We test 95% and 85% coverage for robustness checks, and the results shown in Table A.4 in the Appendix A.3 are consistent.

aggregated to pool-day level. Since pools were created on a platform at different times, we construct an unbalanced daily panel for all the selected pools.

The secondary data set we use in the analysis is the historical token price obtained via CoinGecko APIs. The historical token price is the aggregate daily price from different exchange platforms. This data set helps us to get UNI and SUSHI token prices and calculate the dollar value of daily trading volume for each selected pool.

Table 1 provides variable definitions and descriptive statistics on the Uniswap full sample.[12] It contains 995 Uniswap pools with 73,488 observations. The impacts of token incentives are our main interests. In Uniswap analysis, they are represented by two dummy variables, $SUSHI\text{-}Incentive_{it}$ and $UNI\text{-}Incentive_{it}$. $SUSHI\text{-}Incentive_{it} = 1$ means that the token pair of Uniswap pool *i* has a corresponding pool on Sushiswap and has SUSHI incentives at time *t*, and $UNI\text{-}Incentive_{it} = 1$ means that Uniswap pool *i* has UNI token incentives at time *t*. $SUSHI\text{-}Incentive_{it}$ shows the impact of token incentives from a competing platform, and $UNI\text{-}Incentive_{it}$ reveals the effect from its own platform. Besides the dummy variables, we also use two continuous variables, the prices of SUSHI and UNI token (denoted by $SUSHI\text{-}Price_t$ and $UNI\text{-}Price_t$), to capture the time variant impacts of token incentives by incorporating users' expectation of the platform's future growth.

Table 1. Descriptive Statistics on the Uniswap Full Sample

Variable	Description	Mean	Std. Dev	Min	Max
$SUSHI\text{-}Incentive_{it}$	Whether the token pair of pool *i* has a corresponding pool on Sushiswap (and has SUSHI incentives) at time *t*	0.040	0.196	0	1
$UNI\text{-}Incentive_{it}$	Whether pool *i* has UNI incentives at time *t*	0.003	0.058	0	1
$SUSHI\text{-}Price_t$	*SUSHI* token price at time *t-1*	1.124	1.014	0	8.839
$UNI\text{-}Price_t$	*UNI* token price at time *t-1*	2.805	1.464	0	7.098
$Liquidity_{it}$	Log-amount of cumulative liquidity for pool *i* at time *t*	8.445	3.115	0	21.746

[12] The descriptive statistics of the Sushiswap sample are included in Table A.2 in the Appendix A.2.

$TradeVolume_{it}$	Log-value of trading volume in US dollar for pool *i* at time *t*	5.479	5.546	0	29.912
$Liquidity\text{-}lag_{it}$	Log-amount of cumulative liquidity for pool *i* at time *t-1*	8.445	3.116	0	21.746
$TradeVolume\text{-}lag_{it}$	Log-value of trading volume in US dollar for pool *i* at time *t-1*	5.494	5.549	0	29.912
$Holder_{it}$	Log-number of liquidity providers who hold liquidity of pool *i* at time *t*	3.555	1.329	0	8.993
$LiquidityPerHolder_{it}$	Log-amount of cumulative liquidity per holder on pool *i* at time *t*	5.076	2.567	0	15.924
$UNI{+}SUSHIPools_{i}$	Whether the token pair *i* is one of the 4 UNI incentivized pools	0.007	0.081	0	1
$SUSHIOnlyPools_{i}$	Whether pool *i* is one of the pools with SUSHI incentives only	0.061	0.239	0	1
$High\text{-}Volatile_{i}$	Whether pool *i* is a high-volatile pool	0.039	0.193	0	1
$w/o\text{-}Price_{it}$	Whether as least one token in pool *i* does not have price information at time *t*	0.384	0.486	0	1
Age_{it}	Log-number of weeks since the start of pool *i*	2.082	0.658	0.693	3.401
$Age2_{it}$	Square value of Age_{it}	4.768	2.692	0.480	11.568
$Week_{t}$	Week of 2020 for time *t*	42.081	4.311	31	48

Note:
1. subscript *i* stands for pool *i*, and *t* stands for day *t*.
2. Uniswap pools = 995, observations = 73,488.
3. To reduce the skewness of the data, the transformation of natural logarithm is applied to numeric variables (except for $SUSHI\text{-}Price_t$, $UNI\text{-}Price_t$, and $Age2_{it}$). For a variable x, we transform it to $\log(x + 1)$ according to Wooldridge (2010).

After explaining the variables characterizing token incentives, we move to another important aspect of our research: liquidity supply. We choose to use the log-amount of cumulative liquidity[13] denoted by $Liquidity_{it}$ to quantify the liquidity supply, instead of using daily liquidity change, because cumulative amount of liquidity is a more direct measurement of how large the supply side is, and we

[13] To be more specific, $Liquidity_{it}$ is defined as the log-amount of cumulative LP tokens in pool *i* at time *t*. The amount of LP tokens is proportional to the amount of deposited tokens in a pool, so it could represent the liquidity supply. Since the amount of deposited tokens are not always available for some transactions and the amount of LP tokens can be revealed in all transactions, we choose to use the amount of LP tokens to characterize the liquidity supply. In the calculator of $Liquidity_{it}$, we scale up the values of cumulative LP tokens based on the number of decimals of each token pair to reduce the magnitude difference of LP tokens. More detailed information about LP tokens and scaling is discussed in Appendices A.1.1 and A.1.3. Since the same scaling is applied to a pool in all time periods, it does not impact our main findings. We rerun the analysis on the $Liquidity_{it}$ without scaling in Tables A.8 and A.9 in the Appendix A.3, and the results are robust.

are less interested in how fast the liquidity supply changes which is captured by the variable of daily liquidity changes. $TradeVolume_{it}$ is the log-value of trading volume in US dollars and measures the demand size of Uniswap. $Liquidity\text{-}lag_{it}$ and $TradeVolume\text{-}lag_{it}$ are the corresponding 1-day lag terms, and will be used in the analysis of the network effects of the token incentives. Since the prices of some tokens are unavailable on CoinGecko, we are not able to calculate the specific dollar value of trading volume in these pools. In this case, we replace the dollar value of trading volume by zeros and introduce a dummy variable $w/o\text{-}Price_{it}$ to capture the average value of these pools. Additionally, another two important numeric variables in our data are $Holder_{it}$ and $LiquidityPerHolder_{it}$. $Holder_{it}$ is defined as the log-number of liquidity providers who hold liquidity in pool i at time t. $LiquidityPerHolder_{it}$ = log($Liquidity_{it}/Holder_{it}$ + 1), meaning the log-amount of cumulative liquidity per holder for pool i at time t. These two variables could help us reveal the underlying mechanism of token incentives on the liquidity supply.

Furthermore, we construct three variables, $UNI{+}SUSHIPools_i$, $SUSHIOnlyPools_i$, and $High\text{-}Volatile_i$ to analyze the heterogeneous effects of token incentives. $UNI{+}SUSHIPools_i$ is a dummy variable identifying whether a token pair is one of the 4 UNI incentivized pools. As all the Uniswap incentivized pools are also available and incentivized on Sushiswap, we call these 4 pools *UNI+SUSHIPools*. $SUSHIOnlyPools_i$ is also a dummy variable showing whether a Uniswap pool is one of the pools with SUSHI incentives only. In addition, $High\text{-}Volatile_i$ is a dummy variable to represent whether it is a highly volatile pool in the 49 pools with SUSHI incentives. Price volatility is defined by variance of token prices across different periods. Since 48 out of 49 pools have ETH as one of the tokens and they face the same price fluctuation from ETH, the price of non-ETH token is used to calculate the volatility[14]. If price volatility of a pool is greater than or equal to the median value, the pool will be labeled as high-volatile pool. Otherwise, it is a more-stable pool. Lastly, we

[14]The other pool without ETH has a stablecoin cryptocurrency in its token pair, and we use the non-stablecoin to calculate the price volatility.

also include weekly time fixed effects ($Week_t$), and linear and quadratic terms of pool log-age (Age_{it} and $Age2_{it}$), which control for the time trend of platform growth and the potential effects of pool life cycle on the liquidity supply.

Within the 995 token pairs on Uniswap, 4 of them are incentivized on both Uniswap and Sushiswap. There are 45 pools whose token pairs only have SUSHI token incentives, and the rest 946 token pairs don't have any token incentives on either platform. There might be a concern that the pools with token incentives are fundamentally different from the ones without incentives, so we adopt a coarsened exact matching method (CEM) to make the pools more comparable[15]. The detailed procedures of CEM that we use are explained in Section 4.1. In the end, there are 28 pools with SUSHI incentives (including 3 pools with both SUSHI and UNI incentives) and 117 matched pools without any token incentives in the CEM-generated sample.

[15] We run analysis in the full sample for robustness checks and receive consistent results as shown in Tables A.5 to A.7 in the Appendix A.3.

3.3 Model-Free Evidence

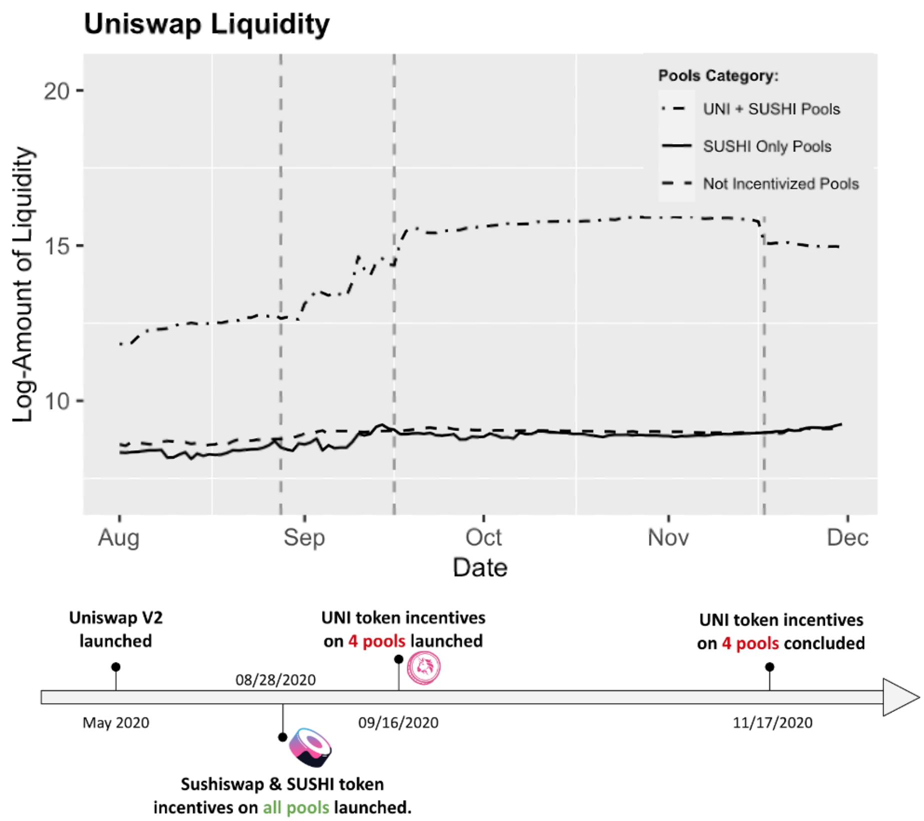

Figure 2. Model-Free Evidence of Impacts of Token Incentives on Uniswap Liquidity Supply

Figure 2 is generated from the Uniswap CEM sample and plots the average log-amount of cumulative liquidity on the 3 types of Uniswap pools along with the important dates. The dot dashed line is for UNI + SUSHI Pools which have both UNI and SUSHI incentives. The solid line is for the pools with SUSHI token incentives only, and the dashed line is for the pools without any token incentives. It is the model-free evidence of the impacts of token incentives on Uniswap liquidity supply, and we would like to highlight a few interesting observations from the figure:

- From 08/28/2020 to 09/16/2020 is the period when only SUSHI tokens incentives were available. The liquidity supply on UNI + SUSHI pools and SUSHI only pools was higher during this period than the level before 08/28/2020.

- When Uniswap launched UNI token incentives on 09/16/2020, there was a big jump in the amount of Uniswap liquidity supply for UNI + SUSHI pools and a consistent increasing trend afterwards.
- When UNI token incentives concluded on 11/17/2020, there was a noticeable decrease in Uniswap liquidity supply of UNI + SUSHI pools.
- Not incentivized pools' average liquidity supply is stable with a steady increasing trend over time. It shows that not incentivized pools are good control pools.

It seems that token incentives from its own platform and competing platform have both positive effects on the focal platform based on the model-free evidence, and we will use our sample to further examine it in Section 5.

4. Identification Strategies and Methods

4.1 Coarsened Exact Matching Method

We utilize a coarsened exact matching method (CEM) to ensure that the incentivized pools and control pools are more comparable. CEM is to "coarsen" each important observable characteristic based on researchers' self-defined cutoff points and then perform exact matching on the coarsened data. CEM provides a great alternative for the exact matching method (EM), because it is often difficult to find an exact match if most of the matched variables are numeric. In addition, CEM has several advantages over propensity score matching (PSM) which is also a widely-adopted matching method. CEM is a nonparametric approach without assumptions about data generation process, and it is easier to understand and could achieve higher balance (Iacus et al., 2012). This CEM matching method has been commonly used in the literature (e.g., Overby & Forman, 2015).

To perform CEM, we first filter out the pools which were created before Sushiswap and its SUSHI token incentives were launched. This is because these selected pools have pre-SUSHI periods for matching. We get 32 incentivized pools (including 4 pools with both UNI and SUSHI incentives) and 220 potential non-incentivized pools for matching. Next, we calculate the mean and variance of liquidity supply ($Liquidity_{it}$) and demand ($TradeVolume_{it}$) over pre-SUSHI periods for each selected pool. We "coarsen" each variable into 5 bins. In the end, 28 pools with SUSHI incentives (including 3 pools with both SUSHI and UNI incentives) are matched to 117 pools without any token incentives in the CEM-generated sample.[16]

4.3 Main Regression Specification

The following two major differences between UNI and SUSHI token incentives provide us with the opportunity to identify the effects of token incentives. Taking Uniswap as the focal platform, the variation in Uniswap pools and the observations before the incentives help us to identify the impact of UNI incentives. Because only some Uniswap pools have corresponding pools on Sushiswap, we can identify the impact of SUSHI incentives.

- **Different coverage of pools:** SUSHI token incentives are applied to all Sushiswap pools, while UNI token incentives are only available for 4 liquidity pools on Uniswap. They are the pools associated with token pairs ETH-DAI, ETH-USDT, ETH-USDC, and ETH-WBTC[17].

[16] Table A.3 in the Appendix A.2 reports the 4 important observable characteristics between the pools with token incentives and the matched control pools without any incentives. The comparison means t-tests show that there is not any significant difference between two groups of pools before token incentives.

[17] ETH is the native token that facilitates operations on the Ethereum blockchain. DAI, USDT, and USDC are stablecoin cryptocurrencies with exchange rates of $1 US dollar. WBTC represents BTC (Bitcoin) on the Ethereum network.

- **Different duration of incentives:** UNI token incentives were a limited-time program. It started in September 2020, and concluded in November 2020[18], but SUSHI token incentives are an all-time available program.

Our main empirical model is a Difference-in-Differences (DiD) regression. By isolating the effects of SUSHI incentives and UNI incentives, we assume that two incentive programs do not spillover to other not incentivized token pairs. This assumption is reasonable, because Figure 2 shows that the dashed line for non-incentivized pools is flat with a steady growing trend throughout all periods, and the launch of UNI incentives does not lead to a significant surge on the solid line for SUSHI only pools. For liquidity pool *i* at time *t*, the impacts of token incentives on liquidity supply are specified as:

$$Y_{it} = \beta_1 \times SUSHI\text{-}Incentive_{it} + \beta_2 \times UNI\text{-}Incentive_{it} + Age_{it} + Age2_{it} + Week_t + v_i + \varepsilon_{it} \qquad (1)$$

where $SUSHI\text{-}Incentive_{it} = 1$ if pool *i* has SUSHI incentives at time *t*, $UNI\text{-}Incentive_{it} = 1$ if pool *i* has UNI incentives at time *t*; Age_{it} and $Age2_{it}$ control for potential effects of pool life cycle on the liquidity supply; $Week_t$ denotes week fixed effects; v_i denotes pool fixed effects; ε_{it} is the idiosyncratic error term. Our main interest dependent variable Y_{it} is the log-amount of cumulative liquidity of pool *i* at time *t* ($Liquidity_{it}$).

4.4 A Relative Time Model

An important assumption of DiD model is that the pools with token incentives should have a common pre-trend as the pools without token incentives. We estimate a relative time model to test this assumption. Besides, the relative time model could help us better understand the dynamic

[18] The start and end dates of UNI incentives were announced at the same time when UNI token incentives were launched.

aspects of the liquidity supply after incentives launch. For liquidity pool i at time t, the relative time model is specified as:

$$Y_{it} = \sum_{k} \gamma_k \times D_{it} + Age_{it} + Age2_{it} + Week_t + v_i + \varepsilon_{it} \tag{2}$$

where γ_k is the coefficient of the interaction term over relative time for the pools with token incentives. Since estimation in a relative-day model might be too noisy, we focus on the relative-week time model. k ranges from [-3, 13], and $k = 0$ denotes week 35 of 2020, the launch week of SUSHI incentives. The dummy variable $D_{it} = 1$ if $t = k$ and pool i is a pool with token incentives, zero otherwise.

5. Results

The results of the impacts of token incentives in the context of decentralized exchanges are presented in this section. We first examine the incumbent platform Uniswap, and study the impacts of UNI token incentives (from the focal platform) and SUSHI token incentives (from the competitor platform) on liquidity supply of Uniswap. Following that, we deep dive into the mechanism of token incentives on liquidity supply. Furthermore, we analyze the heterogeneous effects of token incentives and check how token price volatility moderates the impacts. Lastly, the analysis of the entrant platform Sushiswap is also included.

5.1 Incumbent: Uniswap and Token Incentives

5.1.1 Impacts of Token Incentives on Liquidity Supply

Table 2[19] reports the parameter estimates for the impacts of token incentives on Uniswap liquidity supply. The dependent variable is the log-amount of cumulative liquidity in a pool

[19] Subscripts are omitted for brevity in the discussion of Section 5.

(*Liquidity*$_{it}$). As explained in Section 3, 28 Uniswap pools have corresponding pools on Sushiswap, so these pools on Uniswap are exposed to the impacts of SUSHI token incentives. The *positive* and significant coefficient of *SUSHI-Incentive* in Column (1) indicates that there is a *positive spillover* of a competitor's token incentives on Uniswap liquidity supply. Since 3 of the 28 pools are also incentivized on Uniswap, we add the variable *UNI-Incentive* to get a more accurate estimate of the impact magnitude in Column (2). The coefficients of *SUSHI-Incentive* and *UNI-Incentive* are both positive and significant, and it confirms that the token incentives from a competitor and its own could both attract more liquidity to the focal platform. The pools with SUSHI incentives on average acquire 35.93%[20] more liquidity than those without SUSHI incentives. The liquidity supply of the UNI incentivized pools is increased by several times compared with control pools.

Table 2. Parameter Estimates for Impacts of Token Incentives on Uniswap Liquidity Supply

	Dependent variable:			
	Uniswap Analysis			
	Liquidity$_{it}$			
	(1)	(2)	(3)	(4)
SUSHI-Incentive	0.418***	0.307***		
	(0.037)	(0.037)		
UNI-Incentive		1.845***		
		(0.089)		
SUSHI-Price			0.010	0.008
			(0.008)	(0.008)
UNI-Price				-0.002
				(0.012)
SUSHI-Price:SUSHI-Incentive			0.055***	0.072***
			(0.015)	(0.015)
UNI-Price:UNI-Incentive				0.490***
				(0.024)
Age	1.806***	1.809***	1.772***	1.845***
	(0.173)	(0.171)	(0.174)	(0.172)
Age2	-1.026***	-1.004***	-1.026***	-1.036***
	(0.069)	(0.068)	(0.070)	(0.069)
Week Dummies	Yes	Yes	Yes	Yes
Pool Fixed Effects	Yes	Yes	Yes	Yes
Observations	17,087	17,087	17,087	17,087
Note:				*p<0.1; **p<0.05; ***p<0.01

[20] $e^{0.307}$-1 = 35.93%

To validate the common pre-trend assumption and capture how the impacts of token incentives change over time, we estimate the relative time model specified in Equation (2) and plot the coefficients with 95% confidence intervals in Figure 3. Panel (a) on the left side with dots is for UNI + SUSHI pools relative to control pools, and Panel (b) on the right side with squares is for SUSHI only Pools relative to control pools. The three vertical dashed lines are week 0 for the launch of SUSHI incentives, week 3 for the launch of UNI incentives, and week 12 for the conclusion of UNI incentives. 95% confidence intervals before week 0 contain zeros in both panels, which verifies that the assumption of common pre-trend. The 95% confidence intervals for week 1, 2, 12, and 13 in Panel (a) are positive and significantly different from zeros, showing SUSHI incentives have positive spillovers on UNI + SUSHI pools. The discrete increase and decrease in week 3 and 12 reveal the positive effects of token incentives from Uniswap itself. Panel (b) demonstrates that SUSHI only pools enjoy significant positive spillovers from SUSHI incentives over time as the confidence intervals do not contain zeros since week 2. This plot supplements our findings in Columns (1) and (2) of Table 2.

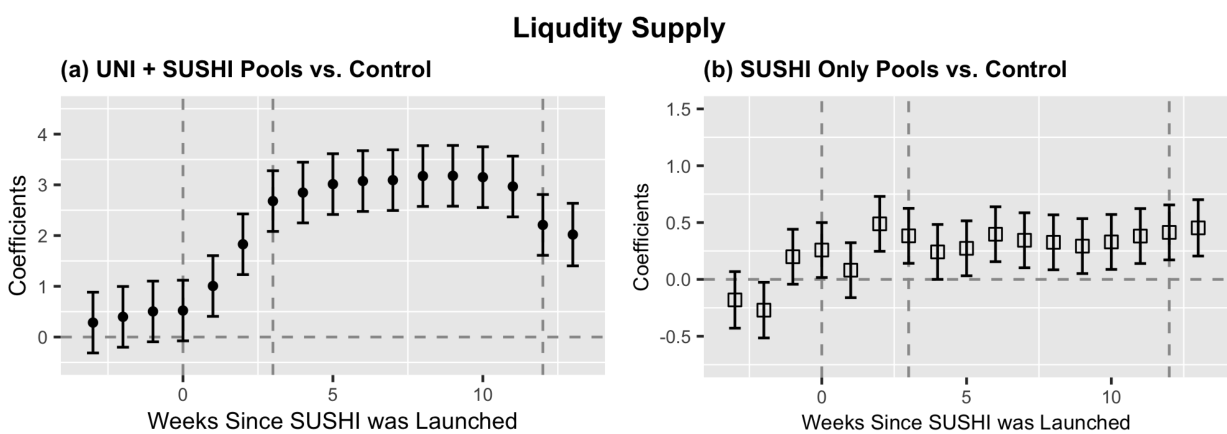

Figure 3. Plot of Coefficients and 95% Confidence Intervals in Relative Time Models

Besides, we also examine the impacts of SUSHI and UNI prices on the Uniswap liquidity supply. UNI and SUSHI prices represent users' expectation of the future platform growth, and they reveal time variant effects of token incentives. In Column (3) of Table 2, the insignificant coefficient of *SUSHI-Price* shows that the value of SUSHI price does not have an overall impact on all Uniswap pools, but when we only focus on the pools with SUSHI token incentives, the estimate of *UNI-Incentive: SUSHI-Price* tells that $1 increase in SUSHI price at the previous period could on average lead to 5.65%[21] increase in current liquidity supply on Uniswap. We also include UNI token price related variables in Column (4). The result reveals that $ 1 increase in UNI price at the previous period does not have a significant impact on the whole platform but could drive 63.23%[22] increase for the UNI incentivized pools at the current period.

Table 3. Parameter Estimates for Token Incentives on Network Effects

	Dependent variable:	
	Uniswap Analysis	
	$Liquidity_{it}$	$TradeVolume_{it}$
	(1)	(2)
SUSHI-Incentive	0.169***	0.722***
	(0.035)	(0.063)
UNI-Incentive	1.743***	-0.330**
	(0.083)	(0.154)
TradeVolume-lag	0.154***	
	(0.004)	
Liquidity-lag		0.496***
		(0.013)
w/o-Price	-0.013	-7.664***
	(0.058)	(0.090)
Age	0.864***	1.532***
	(0.171)	(0.312)
Age2	-0.645***	-1.035***
	(0.067)	(0.123)
Week Dummies	Yes	Yes
Pool Fixed Effects	Yes	Yes
Observations	16,942	16,942
Note:	*p<0.1; **p<0.05; ***p<0.01	

Moreover, we present the parameter estimates for the impacts of token incentives on the network effects in Table 3. The dependent variables are the log-amount of cumulative liquidity in a

[21] $e^{0.055}$-1 = 5.65%
[22] $e^{0.490}$-1 = 63.23%

pool in Column (1) and the log-value of trading volume in US dollar in Column (2), representing the supply and demand sides of Uniswap respectively. The positive and significant coefficient of *TradeVolume-lag* in Column (1) shows that higher trading volume at the previous period could attract more liquidity at the current period, since more trading volume indicates more trading fees income for liquidity providers. More specifically, on average 1% increase in demand side yields 0.154% increase in supply side. Similarly, the result in Column (2) shows that more liquidity at the previous period could attract more trading volume at the current period, since more liquidity supply means lower slippage and a better experience for traders. 1% increase in supply side could convert into 0.496% increase in demand. By comparing the size of network effects on both sides, we can confirm the idea that the liquidity supply of Uniswap is the major driver of the platform's overall growth. In addition, the estimates of *SUSHI-Incentive* and *UNI-Incentive* in Column (1) are similar to the results in Table 2. As *UNI-Incentive* has a large impact on *Liquidity-lag* shown in Table 2, *UNI-Incentive* and *Liquidity-lag* are highly correlated and the impact of UNI token incentives has been captured by *Liquidity-lag*, a negative coefficient is observed for *UNI-Incentive* in Column (2). It shows that the impacts of UNI incentives on Uniswap liquidity demand only go through the network effect of the supply side. By comparison, the positive and significant coefficient of *SUSHI-Incentive* indicates that the SUSHI token incentives could have a direct positive spillover on the liquidity demand.

Lastly, we include pool age, week dummies, and pool fixed effects to account for potential effects of life cycle, time trend of platform growth, and pool-level heterogeneity. The results show that the estimates of pool log-age and its quadratic term are consistent in Table 2 and Table 3. Pool log-age has a significant positive coefficient, and the quadratic term of pool log-age has a significant negative coefficient. Overall, we can expect that the liquidity supply has a natural decreasing trend as pool age increases.

5.1.2 Mechanism of Token Incentives on Liquidity Supply

We have shown that the token incentives from Uniswap itself and from its competitor Sushiswap both have positive effects on the liquidity supply of Uniswap. In this section, we seek to explain its underlying mechanism of the impacts. There are two possible paths. Token incentives might attract more providers to join the platform. Or the increased liquidity supply might be from more liquidity deposited by each provider. To unveil the potential mechanism, two new dependent variables, log-number of liquidity providers ($Holder_{it}$) and log-amount of cumulative liquidity per holder ($LiquidityPerHolder_{it}$) are analyzed in this section.

Table 4. Parameter Estimates for Mechanism of Token Incentives on Uniswap Liquidity Supply

	Dependent variable:	
	Uniswap Analysis	
	$Holder_{it}$	$LiquidityPerHolder_{it}$
	(1)	(2)
SUSHI-Incentive	0.681***	-0.268***
	(0.020)	(0.026)
UNI-Incentive	1.165***	0.657***
	(0.050)	(0.064)
Age	1.784***	0.051
	(0.095)	(0.123)
Age2	-0.667***	-0.347***
	(0.038)	(0.049)
Week Dummies	Yes	Yes
Pool Fixed Effects	Yes	Yes
Observations	17,087	17,087
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 4 reports the parameter estimates using a similar regression setup as Column (2) in Table 2. In Column (1), the coefficients of *SUSHI-Incentive* and *UNI-Incentive* are both positive and significant. It shows that on average the liquidity providers attracted to the Uniswap token pairs with SUSHI incentives are near doubled[23] compared to the pairs without SUSHI incentives. In addition, the number of liquidity providers at the 4 incentivized pools have more than tripled relative to the

[23] $e^{0.681}$-1 = 97.59%

pools without UNI incentives. As we explain in Section 3.1, the initial period of SUSHI token incentives was a vampire attack against Uniswap. During the vampire attack, liquidity providers who would like to get SUSHI incentives need to have liquidity on Uniswap first and then migrate the liquidity from Uniswap to Sushiswap. The purpose of the Sushiswap vampire attack is to quickly drain the Uniswap liquidity, but it could potentially bring more liquidity providers to Uniswap. Another possible explanation for the increased number of liquidity providers is information diffusion and awareness increase from the launch of SUSHI incentives.

In terms of the impact on cumulative liquidity per holder, Column (2) shows that UNI token incentives also acquire more cumulative liquidity per holder to the UNI incentivized pools, but the significant negative coefficient of *SUSHI-Incentive* reveals that SUSHI incentives impose a negative competition effect on the amount of cumulative liquidity per holder. The decrease is about 23.51%[24] relative to the control pools who do not have token incentives. There are also two possibilities driving the competition effect on $LiquidityPerHolder_{it}$. (1) New liquidity providers join Uniswap with less liquidity. (2) Some existing liquidity providers take advantage of both UNI and SUSHI token incentives, so they migrate somee liquidity to SUSHI or even leave Uniswap.

To further examine the mechanism, we run subsample analysis on existing, vampire-period, and new liquidity providers. Existing providers are the ones who joined Uniswap before the launch of SUSHI incentives. Vampire-period providers are the group of users who adopted Uniswap during the vampire attack of SUSHI token incentives (August 28th 2020 - September 9th 2020), and new providers are the rest individuals who started to provide liquidity on Uniswap after Sushiswap's vampire attack. The analysis of new liquidity providers could isolate the mechanism of information diffusion because the vampire attack had ended when they joined Uniswap, and also verify whether the decreased amount of liquidity per holder is from new providers. Vampire-period providers'

[24] $e^{-0.268}$-1 = $-$23.51%

adoption of Uniswap is more likely driven by the Sushiswap vampire attack than other two groups. We could use this analysis to check whether the vampire attack had any positive spillovers on Uniswap adoption. Although we cannot disentangle the information diffusion and vampire attack in the analysis of existing providers, the analysis could assist the understanding of the negative competition on the amount of liquidity per holder.

Table 5. Parameter Estimates for Subsample Analysis on Existing and New Providers

	Dependent variable:								
	Uniswap Analysis								
	Liquidity$_{it}$			*Holder$_{it}$*			*LiquidityPerHolder$_{it}$*		
	(1) Existing	(2) Vampire	(3) New	(4) Existing	(5) Vampire	(6) New	(7) Existing	(8) Vampire	(9) New
SUSHI-Incentive	-0.093***	0.441***	0.501***	0.348***	0.371***	0.205***	-0.359***	-0.014	0.304***
	(0.033)	(0.084)	(0.107)	(0.015)	(0.024)	(0.043)	(0.025)	(0.071)	(0.080)
UNI-Incentive	0.828***	1.057***	0.975***	0.553***	0.681***	0.899***	0.250***	0.397***	0.130
	(0.077)	(0.135)	(0.160)	(0.035)	(0.038)	(0.064)	(0.060)	(0.114)	(0.120)
Age	0.674***	0.500	-3.625***	1.098***	1.007***	-1.709***	-0.408***	-0.570	-0.638
	(0.148)	(0.623)	(1.387)	(0.067)	(0.176)	(0.551)	(0.114)	(0.524)	(1.040)
Age2	-0.450***	-0.389*	0.433	-0.379***	-0.465***	0.045	-0.072	0.122	0.028
	(0.059)	(0.209)	(0.420)	(0.027)	(0.059)	(0.167)	(0.046)	(0.176)	(0.315)
Week Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pool Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,023	11,808	10,624	17,023	11,808	10,624	17,023	11,808	10,624
Note:									*p<0.1; **p<0.05; ***p<0.01

The results of the subsample analysis are presented in Table 5. It shows that UNI token incentives have positive effects for existing, vampire-period, and new providers on the three main dependent variables, consistent with the main results in Tables 3 and 5. However, the impacts of SUSHI token incentives are different for the three groups of liquidity providers. New providers on average provide more liquidity (in Column (3)), and the pools with SUSHI incentives attract more new providers (in Column (6)) with more cumulative liquidity per provider (in Column (9)), compared with the new providers in the control pools. The results for vampire-period providers are similar, except for SUSHI incentive not having a significant impact on *LiquidityPerHolder$_{it}$*. When we look into the magnitude of SUSHI incentives on these two groups, new providers have a higher percentage increase on the overall liquidity supply (*Liquidity*$_{it}$) which could be explained by the information diffusion, and vampire-period providers contribute more to the increase of Uniswap adoption (*Holder*$_{it}$) which may be mainly from the positive spillovers of vampire attack. On the contrary, although SUSHI incentives also attract more existing adopters to re-enter or stay in the pools (in Column (4)), the overall cumulative liquidity deposited by existing providers in the pools with SUSHI incentives is decreased (in Column (1)) as the cumulative liquidity per holder is decreased (in Column (7)). In a nutshell, we can conclude that the spillover from SUSHI incentives is mainly from attracting more providers to Uniswap pools, driven by both the positive impacts of vampire attack and information diffusion. The negative competition effect of SUSHI token incentives on the cumulative liquidity per holder is largely driven by existing providers shifting from Uniswap to Sushiswap to enjoy the token incentives from both platforms.

5.1.3 Heterogeneous Effects of Token Incentives on Liquidity Supply

Pools may face different impacts of token incentives on liquidity supply, so we look into the heterogeneous effects of SUSHI token incentives in this section. The heterogeneous effects of UNI incentives are skipped, because only 3 UNI incentivized pools are available in the CEM sample and there is not enough variation within the 3 pools. We first separate the pools with both UNI and SUSHI incentives from other pools with SUSHI incentives only, and then we examine how price volatility moderates the impacts. Since providers might face higher risk of impermanent loss in the pools whose prices are highly volatile, the availability of token incentives could compensate for some risks and makes the choice of Sushiswap more attractive when UNI incentives are not enabled. We can expect the positive spillover of SUSHI token incentives on these pools might be smaller than those pools whose prices are more stable, or even it might turn out to be a competition effect from SUSHI incentives on Uniswap high volatile pools.

Table 6. Parameter Estimates for Heterogeneous Effects on Pools with High Price Volatility

	Dependent variable:					
	Uniswap Analysis					
	$Liquidity_{it}$		$Holder_{it}$		$LiquidityPerHolder_{it}$	
	(1)	(2)	(3)	(4)	(5)	(6)
SUSHI-Incentive:UNI+SUSHIPools	1.179***	1.187***	1.135***	1.136***	0.101	0.104
	(0.126)	(0.126)	(0.070)	(0.070)	(0.091)	(0.091)
SUSHI-Incentive:SUSHIOnlyPools	0.238***	0.557***	0.645***	0.684***	-0.298***	-0.185***
	(0.038)	(0.056)	(0.021)	(0.031)	(0.027)	(0.040)
SUSHI-Incentive:SUSHIOnlyPools: High-Volatile		-0.559***		-0.068*		-0.197***
		(0.072)		(0.040)		(0.052)
UNI-Incentive	1.451***	1.450***	0.960***	0.960***	0.490***	0.490***
	(0.105)	(0.104)	(0.058)	(0.058)	(0.075)	(0.075)
Age	1.800***	1.831***	1.779***	1.782***	0.047	0.058
	(0.171)	(0.170)	(0.095)	(0.095)	(0.123)	(0.123)
Age2	-0.994***	-0.999***	-0.662***	-0.662***	-0.342***	-0.344***
	(0.068)	(0.068)	(0.038)	(0.038)	(0.049)	(0.049)
Week Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Pool Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,087	17,087	17,087	17,087	17,087	17,087
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 6 reports the parameter estimates for the heterogeneous effects of SUSHI token incentives. By interpreting the interaction term *SUSHI-Incentive: UNI+SUSHIPools*, we find that SUSHI incentives have stronger spillover effects on the liquidity supply of UNI incentivized pools, acquiring more liquidity providers and not having a significant change on liquidity per holder. In addition, the coefficients of *SUSHI-Incentive: SUSHIOnlyPools* in Columns (1), (3), and (5) show the overall effects for the pools with SUSHI incentives only, and the magnitudes are similar to the main results in Tables 3 and 5. After *High-Volatile* indicating whether the token price of a pool is highly volatile is introduced in Columns (2), (4), and (6), the interpretation of *SUSHI-Incentive: SUSHIOnlyPools* becomes the estimates of SUSHI token incentives on the SUSHI-only incentivized pools whose token price is more stable, and the three-way interaction coefficients with *High-Volatile* reveal the the impacts of SUSHI incentives for high-volatile pools relative to the more-stable pools.

The results show that compared with more-stable pools, the pools with high-volatile tokens benefit much less from the SUSHI incentives in terms of overall liquidity supply and liquidity per holder, but the difference for the number of liquidity providers is only marginally significant under the significant level of 0.1.

5.2 Entrant: Sushiswap and Token Incentives

The impacts of token incentives on the *incumbent* platform Uniswap have been studied so far, and we now would like to further examine whether the impacts would be different for the *entrant* platform Sushiswap. As SUSHI incentives are applied to all pools since the launch of the platform, we are not able to identify the impacts of SUSHI incentives on its own platform, so we focus on the impacts of token incentives from a major competitor (UNI token incentives) on the liquidity supply of the entrant platform Sushiswap in this section.

Table 7. Descriptive Statistics of Two Key Variables in Sushiswap Analysis

Variable	Description	Mean	Std. Dev	Min	Max
$UNI4Pools_i$	Whether token pair i is one of the 4 incentivized pairs on Uniswap	0.099	0.299	0	1
$Period_t$	$Period_t$ = *beforeUNI*, if t in [08/01/2020, 09/16/2020]; $Period_t$ = *duringUNI*, if t in [09/17/2020, 11/16/2020]; $Period_t$ = *afterUNI*, if t in [11/17/2020, 11/30/2020]	2.124	0.531	1	3

Note:
1. subscript i stands for pool i, and t stands for day t.
2. Sushiswap pools = 54, observations = 3,577.

We construct $UNI4Pools_i$ and $Period_t$ for Sushiswap analysis. $UNI4Pools_i$ is a dummy variable showing whether the token pair of Sushiswap pool i is one of the 4 incentivized pairs on Uniswap. We also split the study period into 3 periods, represented by $Period_t$. $Period_t$ = *beforeUNI* is the period before the launch of UNI incentives (from 08/01/2020 to 09/16/2020), and $Period_t$ = *duringUNI* is the period when UNI incentives were available (from 09/17/2020 to 11/16/2020), and $Period_t$ =

afterUNI is the period after UNI incentives concluded (from 11/17/2020 to 11/30/2020). The definition and descriptive statistics of these two variables are shown in Table 7.

Table 8. Parameter Estimates for Impacts of Token Incentives on Sushiswap

	Dependent variable:		
	Sushiswap Analysis		
	$Liquidity_{it}$	$Holder_{it}$	$LiquidityPerHolder_{it}$
	(1)	(2)	(3)
UNI4Pools:duringUNI	0.021	0.027	0.034
	(0.221)	(0.101)	(0.141)
UNI4Pools:afterUNI	2.221^{***}	1.184^{***}	0.831^{***}
	(0.278)	(0.128)	(0.178)
Age	19.112^{***}	7.683^{***}	10.105^{***}
	(0.675)	(0.310)	(0.432)
Age2	-12.480^{***}	-4.603^{***}	-6.950^{***}
	(0.464)	(0.213)	(0.297)
Week Dummies	Yes	Yes	Yes
Pool Fixed Effects	Yes	Yes	Yes
Observations	3,577	3,577	3,577
Note:			*p<0.1; **p<0.05; ***p<0.01

The interaction terms between *Uni4Pools* and *Period* are our main interest, because they explain how the liquidity supply of the 4 Sushiswap pools changed when the UNI incentives for these token pairs were on and off. The results are in Table 8. *UNI4Pools: beforeUNI* and other 50 pools are set as a baseline, so the other two interaction terms are the relative change compared with the baseline. The insignificant coefficient of *UNI4Pools: duringUNI* in Column (1) shows that UNI token incentives don't have any significant effect on the liquidity supply of the 4 pairs on Sushiswap. This is an interesting result, because it demonstrates that the effects of token incentives are not symmetric for incumbent and entrant platforms and also entrant platforms do not necessarily get hurt when facing competition from incumbent. Log-number of holders (in Column (2)) and log-amount of cumulative liquidity per holder (in Column (3)) of the 4 pools don't have a significant change in *duringUNI* period either.

Furthermore, UNI token incentives were concluded in *afterUNI* period, but SUSHI incentives were still available during that period. The significant positive coefficients of *UNI4Pools:afterUNI* reveal that these 4 Sushiswap pools benefit from the closure of UNI token incentives: more deposited liquidity, more liquidity providers, and more cumulative liquidity per holder. This might be driven by the fact some liquidity providers found Uniswap less attractive when UNI incentives ended, and then they switched to Sushiswap to continue harvesting token rewards. This result highlights, from a competitive perspective, the importance of having an all-time available incentives program for an entrant platform.

5.3 Robustness Checks

We conduct robustness checks to test some key assumptions in sample construction and the detailed results can be found in Appendix A.3. First, we ensure that the results are robust to how we select active pools. Active pools are the pools which account for 90% of cumulative liquidity transactions when sorting descendingly and considering Uniswap and Sushiswap together. In the robust check, we change the coverage to 85% and 95% of cumulative liquidity transactions, and the results are shown in Table A.4. When it is under 85% coverage, the sample contains 593 Uniswap pools and 39 Sushiswap pools with 52,319 observations. The minimum number of liquidity transactions in the selected pools with 85% coverage is 215. When it is under 95% coverage, the sample contains 2,309 Uniswap pools and 80 Sushiswap pools with 174,737 observations, and the minimum number of liquidity transactions becomes 20. These basic descriptive statistics also demonstrate that the distribution of the number of liquidity transactions is heavily skewed, especially in Uniswap. The results in Table A.4 are consistent with the main results.

Second, we use the CEM-generated sample to conduct analysis, and we rerun the analysis on the full Uniswap sample as a robustness check. The descriptive statistics of the Uniswap full sample is in Table A.4, and the key results are shown on Tables A.5 to A.7. We can see that the estimates of *SUSHI-Incentive* in this robustness check are generally smaller than the ones in the main results. This could be because there are 17 Uniswap token pairs with SUSHI incentives in the full sample but not in the CEM-generated sample as they were created after the week of 35 when SUSHI incentives were launched and these pools might be smaller with less liquidity supply.

Lastly, we scale up $Liquidity_{it}$ based on the number of digits of each token pair to reduce the impacts of small values in the main analysis. Since the same scaling is applied to a pool in all time periods and log-value and individual fixed effects are used in the analysis, the scaling should not impact our main findings. We conduct the robustness check on non-scaled $Liquidity_{it}$ to double check on it, and the results are presented in Tables A.8 and A.9. The coefficients of *SUSHI-Incentive* and *UNI-Incentive* are consistent with our main results. The impacts of scaling are captured by the control variables.

6. Conclusion

In this study, we analyze the impacts of token incentives on liquidity supply in the context of decentralized exchange platforms and deep dive into the potential mechanism and heterogeneous effects. Our empirical results first verify token incentives indeed attract more liquidity to its own platform. In addition, although the competitor's token incentives could impose a negative competition effect on the focal platform, their *positive* spillover effects on liquidity supply dominate. Our results also show the network effects exist in the decentralized exchanges and liquidity supply is a main driver of the platform growth. Second, the analyses of mechanism and heterogeneous effects reveal that these positive spillovers are mainly from the increased number of liquidity providers joining the platform, which may be driven by information diffusion and even the direct vampire attack from the competitor's incentives programs. Pools with more-stable tokens whose prices do not change much benefit more from the positive spillovers. On the contrary, the negative competition effect from competitor's token incentives is reflected on the cumulative liquidity per holder on the focal platform, as some existing providers who adopted the platform earlier may migrate to the competitor platform to take advantage of both token incentives. Pools with tokens whose prices are highly volatile may suffer more from the negative competition effect. Third, by comparing Sushiswap analysis with Uniswap analysis, we can conclude that the positive effects from a competitor's token incentives on an entrant and an incumbent platform are not symmetric, but the incumbent platform's incentives do not necessarily impose negative impacts on the entrant. Lastly, our results are robust to various assumption checks.

Our findings bring several theoretical contributions and managerial implications. We extend the scope of cryptoeconomics by introducing token incentives in the context of decentralized exchanges to the literature of platform competition. In addition, our analysis provides detailed empirical examination on two competing platforms and complement the literature by revealing that token incentives might be favorable in the prosperity of a whole industry, since when the incumbent platform benefits from its incentives, the entrant platform's performance is not necessarily to be hurt. Moreover, platform managers may find our results useful, because it presents that token incentives relying on users' expectation of future platform success, could be an effective and less expensive incentive alternative in platform growth and competition, and our study offers practical guidelines on token incentives design from the perspectives of user structure, pool characteristics, and duration of incentives. We hope our paper could inspire more future research on the possible positive spillovers in the platform competition to assist the understanding of market expansion and platform competition.

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Appendix

A.1 Detailed Explanation for Key Concepts

A.1.1 How Decentralized Exchanges Work

Decentralized exchanges enable the exchange between a pair of tokens through a liquidity pool, and the exchange rates between two tokens are determined through a predefined function of the supply of tokens in the pool. This is fundamentally different from centralized exchanges (e.g., Binance and Coinbase) which match between buy orders and sell orders. The price on centralized exchanges is the price of the most recent trade.

The pricing function implemented by Uniswap V2 and Sushiswap is the "constant product function". Consider a liquidity pool associated with token A and token B. The constant product function means the amount of token A times the amount of token B is a constant *K*. When a liquidity transaction happens, the liquidity supply in the pool is changed, so *K* will be changed, but if it is a trading transaction, the liquidity supply does not change and *K* keeps the same. We use two numeric examples to demonstrate how liquidity and trading transactions work in Uniswap V2.

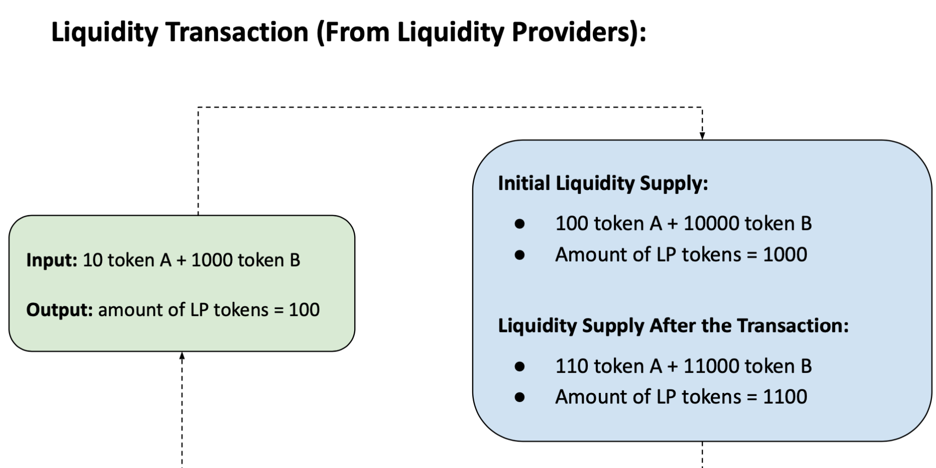

Figure A.1. An Illustrative Example for Liquidity Transactions on Uniswap

Figure A.1 is an illustrative example for liquidity transactions on Uniswap. Assume the initial liquidity supply is 100 token A and 10,000 token B in the liquidity pool. Since the value of token A is always equal to the value of token B, the current exchange rate between token A and token B is 100 : 1. Whenever liquidity is deposited into a pool, unique tokens known as LP tokens are minted and sent to the liquidity providers as a receipt of depositing liquidity. The amount of LP tokens a liquidity provider receives is proportional to the amount of liquidity the liquidity provider deposits into the liquidity pool. If it is a new liquidity pool, the amount of LP tokens the liquidity provider will receive is equal to sqrt($x \times y$), where x and y is the amount of token A and token B deposited. Suppose a liquidity provider deposits an equal value of both tokens, 10 token A and 1000 token B. It is 10% share of the liquidity and the amount of LP tokens the liquidity provider receives is 100. The liquidity supply becomes 110 token A and 11,000 token B in the liquidity pool.

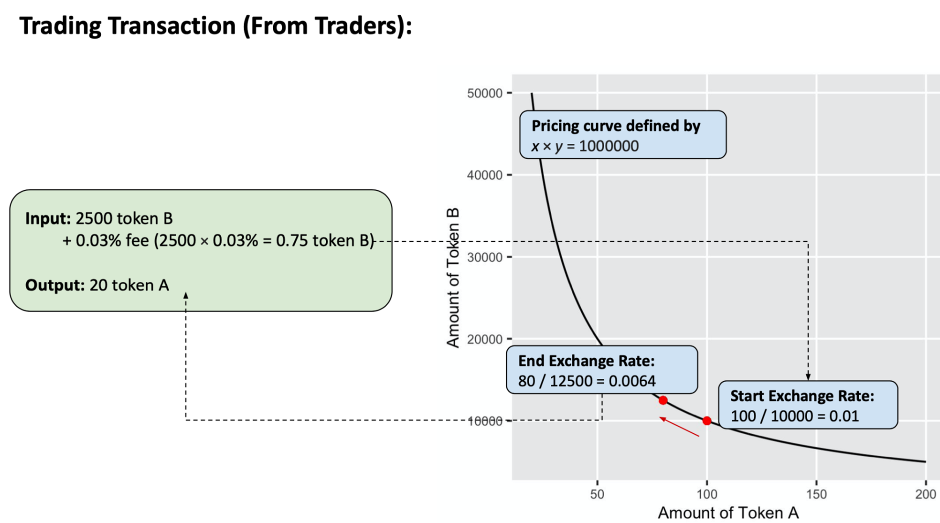

Figure A.2. An Illustrative Example for Trading Transactions on Uniswap

Figure A.2 is an illustrative example for trading transactions on Uniswap. Assume currently there are 100 token A and 10,000 token B in the liquidity pool. The question is how many token B should be put into the pool if a trader would like to get 20 token A. Since the pricing curve is defined by $x \times y = 1000000$ and the trading transaction does not change the constant, we will get

$(100 - 20) \times (10000 + y) = 1000000$. $y = 2500$, so the trader needs to deposit 2500 token B to get 20 token A. To facilitate the trading transaction, the trader needs to pay 0.03% of the amount of input token, 0.75 token B as trading fees. The 0.03% fee is added to the pool as new liquidity. The fee is distributed proportionally to all liquidity providers in the pool upon completion of the trading transaction.

A.1.2 How to Calculate Impermanent Loss

We provide a numeric example of impermanent loss in this appendix. Suppose the current exchange rate between token A and token B is 1:100 in the Uniswap liquidity pool associated with these two tokens. Without loss of generality, we assume 1 token B = \$1, so 1 token A = \$100. Let's say we deposit an equal value of both tokens, 1 token A and 100 token B to the liquidity pool. The dollar amount of the deposit is \$200 because token A and token B are both worth \$100 each. Assume currently there are 100 token A and 10,000 token B in the Uniswap liquidity pool, so we hold 1% share in the liquidity pool and we can redeem 1% share of liquidity in the future.

If the exchange rate of 1 token A is changed to \$200 now and 1 token B is still \$ 1, we set the number of token A as x and the number of token B as y. Based on the condition of equal value of both tokens in the pool and Constant Product Market Makers explained in Appendix A.1.1, we could get that the liquidity pool would have changed to 70.7 token A and 14142.1 token B by solving the following two equations.

$$200 \times x = y$$

$$100 \times 10000 = x \times y$$

Since we have a 1% share of the liquidity, we can withdraw 0.707 token A and 141.4 token B, which equals \$282.8. However, if we simply held the 1 token A and 100 token B instead of depositing them into the liquidity pool, we would have \$300. The difference between \$300 and

$282.8, $17.2 is the amount of impermanent loss. Figure A.3[25] demonstrates the impermanent loss at different price ratios.

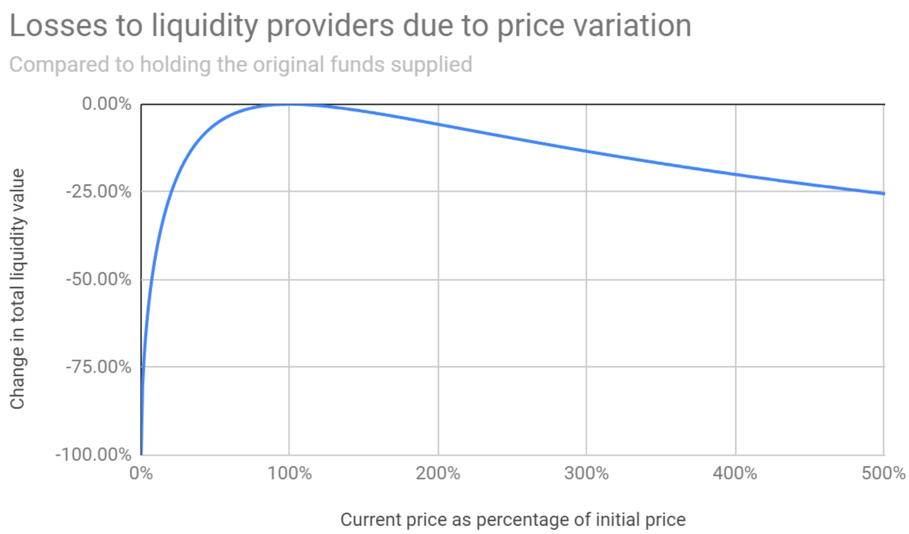

Figure A.3. Plot of Changes in Total Liquidity Value at Different Price Ratios

A.1.3 Why We Scale up $Liquidity_{it}$

We describe the concept of LP tokens and discuss how to calculate the amount of LP tokens in a new liquidity pool and in an existing pool in Appendix A.1.1, and in this appendix, we would like to explain why and how we scale up the cumulative LP tokens to construct the variable $Liquidity_{it}$.

Before we answer this question, let's take a look at the decimals of tokens first. Since Soldity, the programming language library that is commonly used in Ethereum blockchain (e.g., Uniswap) does not support decimals, it is common to multiply by a large number before storing a number on the blockchain. A common large number is 10^{18}, and we say that the decimal of the token is 18. The decimals could be different across tokens, and the decimal is specified when the token was created. For example, ETH has 18 decimals, but WBTC has only 8 decimals.

[25] https://pintail.medium.com/uniswap-a-good-deal-for-liquidity-providers-104c0b6816f2

When we talk about the "amount" of tokens, it refers to the number after multiplying the large number, so we implicitly assume the decimals are 0 for token A and token B in the previous examples. When decimals are 0, we get the amount of initial LP tokens is 1000 as calculated in Appendix 4.1.1. If we set the decimal of token A as 18, then the amount of LP tokens will be 10^{12}. It is much larger than the original amount, even though they refer to the same dollar value. The decimals of all LP tokens are 18, so to get the actual unit of LP tokens we need to divide the amount of LP tokens by 10^{18}. In this case, if the decimal for a token is very small, the unit of LP tokens will be very small too. In our earlier example, if the decimal of token A is 0, there are 10^{-15} ($= 10^3/10^{18}$) LP tokens, while if the decimals of token A is 18, the unit of LP tokens will be 10^{-6} ($= 10^{12}/10^{18}$). To reduce the magnitude difference of LP tokens caused by the decimals, we divide the amount of LP tokens by 10 to the power of the average of the decimals of two tokens, instead of 10^{18}. Continued with the example and assuming the decimal of token B is 0, if the decimal for token A is 0, the unit of LP tokens is 10^3 ($= 10^3/10^{(0+0)/2}$). If the decimal of token A is 18, the unit of LP tokens is 10^3 ($= 10^{12}/10^{(0+18)/2}$). The following table summarizes the example, and it shows that the scaling could help to reduce the large magnitude difference caused by the token decimals, especially for the case where the pools have similar dollar values.

Table A.1. A Numeric Example Comparing the "Unit" of LP Tokens Before and After Scaling

	Amount of LP Tokens	**"Unit" of LP Tokens (Before the Scaling)**	**"Unit" of LP Tokens (After the Scaling)**
Token A decimal = 0	sqrt($100 \times 10^0 \times 10{,}000 \times 10^0$) = 10^3	$10^3 / 10^{18} = 10^{-15}$	$10^3 / 10^{(0+0)/2} = 10^3$
Token A decimal = 18	sqrt($100 \times 10^{18} \times 10{,}000 \times 10^0$) = 10^{12}	$10^{12} / 10^{18} = 10^{-6}$	$10^{12} / 10^{(18+0)/2} = 10^3$

Note: we assume that in this example 100 token A and 10,000 token B are deposited to a new liquidity pool. The decimal of token B is 0.

A.2 Additional Descriptive Statistics

Table A.2. Descriptive Statistics on the Sushiswap Sample

Variable	Description	Mean	Std. Dev	Min	Max
$Liquidity_{it}$	Log-amount of cumulative liquidity for pool i at time t	9.022	3.893	0	17.051
$Holder_{it}$	Log-number of liquidity providers who hold liquidity of pool i at time t	4.022	1.746	0	8.440
$LiquidityPerHolder_{it}$	Log-amount of cumulative liquidity per holder on pool i at time t	5.185	2.544	0	13.855
Age_{it}	Log-number of weeks since the start of pool i	1.864	0.544	0.693	2.708
$Age2_{it}$	Square of Age	3.771	1.901	0.480	7.334
$Week_t$	Week of 2020 for time t	42.993	3.524	35	48

Note:
1. subscript i stands for pool i, and t stands for day t.
2. Sushiswap pools = 54, observations = 3,577.
3. To reduce the skewness of the data, the transformation of natural logarithm is applied to numeric variables (except for Age_{it}). For a variable x, we transform it to $\log(x + 1)$ according to Wooldridge (2010).

Table A.3. Characteristics of the Pools in the Uniswap CEM Sample

	Pools with Incentives			Pools without Incentives			*t*-test	
	Mean	SD	N	Mean	SD	N	Diff.	*p*-value
$Liquidity_{it}$ Mean	8.766	2.632	28	8.551	2.529	117	0.215	0.689
$Liquidity_{it}$ Variance	0.334	0.407	28	0.395	0.558	117	-0.061	0.587
$TradeVolume_{it}$ Mean	11.058	5.075	28	10.292	4.847	117	0.766	0.458
$TradeVolume_{it}$ Variance	0.873	0.788	28	0.849	0.822	117	0.024	0.889

A.3 Additional Results in Robustness Checks

Table A.4. Robustness Checks for Different Selection of Active Pools

	Dependent variable:					
	Uniswap Robust Analysis: Active Pools					
	85% Coverage			95% Coverage		
	$Liquidity_{it}$	$Holder_{it}$	$LiquidityPerHolder_{it}$	$Liquidity_{it}$	$Holder_{it}$	$LiquidityPerHolder_{it}$
	(1)	(2)	(3)	(4)	(5)	(6)
SUSHI-Incentive	0.517***	0.531***	-0.068**	0.373***	0.637***	-0.212***
	(0.047)	(0.028)	(0.031)	(0.033)	(0.015)	(0.025)
UNI-Incentive	2.156***	1.260***	0.864***	2.224***	1.360***	0.814***
	(0.091)	(0.054)	(0.060)	(0.092)	(0.041)	(0.071)
Age	3.813***	2.579***	0.990***	2.034***	1.268***	0.622***
	(0.085)	(0.050)	(0.056)	(0.048)	(0.021)	(0.036)
Age2	-1.621***	-1.048***	-0.497***	-1.013***	-0.570***	-0.391***
	(0.041)	(0.024)	(0.027)	(0.023)	(0.010)	(0.018)
Week Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Pool Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	44,835	44,835	44,835	155,969	155,969	155,969
Note:						*p<0.1; **p<0.05; ***p<0.01

Table A.5. Parameter Estimates for Impacts of Token Incentives on Uniswap Liquidity Supply (Full Sample)

	Dependent variable:			
	Uniswap Robust Analysis: Full Sample			
	$Liquidity_{it}$			
	(1)	(2)	(3)	(4)
SUSHI-Incentive	0.316***	0.141***		
	(0.038)	(0.039)		
UNI-Incentive		2.293***		
		(0.093)		
SUSHI-Price			-0.003	-0.004
			(0.007)	(0.007)
UNI-Price				0.017**
				(0.007)
SUSHI-Incentive:SUSHI-Price			0.047***	0.057***
			(0.016)	(0.016)
UNI-Incentive:UNI-Price				0.588***
				(0.025)
Age	3.218***	3.207***	3.227***	3.233***
	(0.069)	(0.069)	(0.069)	(0.069)
Age2	-1.457***	-1.446***	-1.468***	-1.466***
	(0.033)	(0.033)	(0.033)	(0.033)
Week Dummies	Yes	Yes	Yes	Yes
Pool Fixed Effects	Yes	Yes	Yes	Yes
Observations	73,488	73,488	73,488	73,488
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A.6. Parameter Estimates for Impacts of Token Incentives on Network Effects (Full Sample)

	Dependent variable:	
	Uniswap Robust Analysis: Full Sample	
	$Liquidity_{it}$	$TradeVolume_{it}$
	(1)	(2)
SUSHI-Incentive	0.116***	0.208***
	(0.035)	(0.070)
UNI-Incentive	2.133***	-0.219
	(0.084)	(0.169)
TradeVolume-lag	0.139***	
	(0.002)	
Liquidity-lag		0.549***
		(0.007)
w/o-Price	0.591***	-8.196***
	(0.027)	(0.046)
Age	1.551***	0.472***
	(0.067)	(0.136)
Age2	-0.743***	-0.712***
	(0.032)	(0.064)
Week Dummies	Yes	Yes
Pool Fixed Effects	Yes	Yes
Observations	72,493	72,493
Note:		*p<0.1; **p<0.05; ***p<0.01

Table A.7. Parameter Estimates for Mechanism of Token Incentives on Uniswap Liquidity Supply (Full Sample)

	Dependent variable:	
	Uniswap Robust Analysis: Full Sample	
	$Holder_{it}$	$LiquidityPerHolder_{it}$
	(1)	(2)
SUSHI-Incentive	0.439***	-0.242***
	(0.021)	(0.026)
UNI-Incentive	1.311***	0.917***
	(0.051)	(0.064)
Age	2.032***	0.980***
	(0.038)	(0.047)
Age2	-0.836***	-0.553***
	(0.018)	(0.023)
Week Dummies	Yes	Yes
Pool Fixed Effects	Yes	Yes
Observations	73,488	73,488
Note:		*p<0.1; **p<0.05; ***p<0.01

Table A.8. Parameter Estimates for Impacts of Token Incentives on Uniswap Liquidity Supply (Without Scaling)

	Dependent variable:			
	Uniswap Robust Analysis: Without Scaling			
	$Liquidity_{it}$			
	(1)	(2)	(3)	(4)
SUSHI-Incentive	0.536***	0.463***		
	(0.029)	(0.029)		
UNI-Incentive		1.221***		
		(0.070)		
SUSHI-Price			-0.003	-0.004
			(0.006)	(0.006)
UNI-Price				0.001
				(0.009)
SUSHI-Price:SUSHI-Incentive			0.084***	0.096***
			(0.012)	(0.012)
UNI-Price:UNI-Incentive				0.350***
				(0.019)
Age	0.552***	0.554***	0.518***	0.570***
	(0.134)	(0.133)	(0.136)	(0.134)
Age2	-0.537***	-0.523***	-0.543***	-0.549***
	(0.054)	(0.053)	(0.054)	(0.054)
Week Dummies	Yes	Yes	Yes	Yes
Pool Fixed Effects	Yes	Yes	Yes	Yes
Observations	17,087	17,087	17,087	17,087
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A.9. Parameter Estimates for Impacts of Token Incentives on Network Effects (Without Scaling)

	Dependent variable:	
	Uniswap Robust Analysis: Without Scaling	
	$Liquidity_{it}$	$TradeVolume_{it}$
	(1)	(2)
SUSHI-Incentive	0.382***	0.662***
	(0.028)	(0.064)
UNI-Incentive	1.166***	0.023
	(0.067)	(0.156)
TradeVolume-lag	0.091***	
	(0.003)	
Liquidity-lag		0.461***
		(0.017)
w/o-Price	0.227***	-8.074***
	(0.047)	(0.090)
Age	-0.025	2.050***
	(0.137)	(0.317)
Age2	-0.293***	-1.269***
	(0.054)	(0.125)
Week Dummies	Yes	Yes
Pool Fixed Effects	Yes	Yes
Observations	16,942	16,942
Note:		*p<0.1; **p<0.05; ***p<0.01