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Reaching for yield in decentralized financial markets

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Reaching for Yield in Decentralized Financial Markets[*]

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Abstract

Yield farms dynamically compete for liquidity by offering high yields, advertised as salient headline rates. Farming these yields involves complex investment strategies with hidden downside risks. Capitalizing on the full history of blockchain transactions data, we show that investors chase farms with high yields and that farms with the highest headline rates record the most negative risk-adjusted returns. We exploit heterogeneity in shocks to yield farmers' information set to show that improved information disclosure and reduction in product complexity reduces yield chasing and improves investor performance. Our evidence is consistent with salience theory that may underpin reaching for yield behavior.

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“Crypto ‘yield farmers’ chase high returns, but risk losing it all.”

Alexander Osipovich, Wall Street Journal

“We just don’t have enough investor protection in crypto [...], it’s more like the Wild West.”

Chair Gary Gensler, Securities and Exchange Commission

1 Introduction

Decentralized finance (DeFi) is a rapidly growing segment of the emerging cryptocurrency ecosystem (Harvey, Ramachandran, and Santoro, 2021; Makarov and Schoar, 2022; John, Kogan, and Saleh, 2022). Operating through applications built on blockchains and executed through smart contracts, DeFi intends to counteract the influence of traditional centralized financial intermediaries.

Figure 1 illustrates that total value locked (TVL) in DeFi, a measure of aggregate capital invested in decentralized financial applications, grew exponentially to more than $200 billion in less than 2 years. Despite the sharp drop associated with a general devaluation of digital currencies in the summer of 2022, Figure 1 shows that the number of active applications with TVL above $1 million has remained high, close to 700 DeFi platforms.

The rapid growth of DeFi has raised regulatory concerns. One concern originates from DeFi platforms competing for liquidity provision through offering extraordinarily high yields while exposing investors to significant downside risks (e.g., Oliver, 2021; Osipovich, 2021; Kruppa, 2022). Moreover, DeFi securities bear resemblance to complex structured retail products and are easily accessible to retail investors despite their product complexity. The Securities and Exchange Commission refers to certain investments as 'unregulated and complex strategies', with 'hidden risks to unsophisticated investors' (e.g., Gensler, 2021).

In this paper paper, we study yield farming, a decentralized financial service that is well-suited for examining investor behavior in the presence of product complexity. First, yield farms dynamically compete for liquidity provision by offering high yields to investors. These yields are salient and aggressively marketed as headline rates without disclosure of transaction costs, past performance, or potential downside risks. Second, yield farming is complex in both execution and payoffs, with hidden risks that are not well understood, according to survey evidence. Finally, we observe the entire history of transactions from blockchain data and can dynamically study investor behavior, including investment size, mistakes, and their response to changes in information disclosure and product complexity.

Our overall evidence is supportive of the key features of salience theory (Bordalo, Gennaioli, and Shleifer, 2012, 2016, 2013, 2022). Yield farms promise passive income at impressive headline rates and investors chase farms with high yields. High yield farms also appear to have shrouded risk attributes (Gabaix and Laibson, 2006), since those farms with the highest promised yields record the worst ex-post performance on a risk-adjusted basis. We find that this underperformance is amplified for small investment stakes and investor mistakes.

We first provide a conceptual framework for understanding the risk-return trade-offs of yield farming. Yield farming is a mechanism for passively earning income by supplying digital liquidity. While farming looks simple and accessible with salient high yields, it involves a long chain of interlinked transactions subject to complexity in both execution and payoffs.

To become yield farmers, investors first need to act as digital liquidity providers. That requires the provision of pairs of cryptocurrency tokens in equal dollar amounts to a liquidity pool. Investors can choose among a menu of liquidity pools, each one associated with a pair of cryptocurrency tokens. The liquidity provision is certified through a liquidity token that represents the fractional ownership to the aggregate liquidity in the pool.

Investors can increase their passive earnings by staking the liquidity token into a yield farm. Each liquidity pool is linked to a unique farm that promises a salient interest rate often exceeding several hundred percent. That yield, which is paid using the governance token of the yield farming platform, is a complex function of farm and aggregate market characteristics. Paradoxically, the owners of the governance tokens maintain centralized voting power to adjust the yield multiplier, which is one component of the yield function that can be influenced to dynamically compete for liquidity.

Yield farming performance can be decomposed into four components. First, the initial liquidity provision is rewarded through trading fees collected from third party investors buying and selling cryptocurrency tokens in a liquidity pool. Second, investors are exposed to the buy-and-hold price risk of the pledged tokens. Third, liquidity miners face significant downside risk through impermanent losses, which are defined through a loss function that non-linearly depends on the return correlation of the cryptocurrency pair. Fourth, yield farmers earn passive income in proportion to the aggregate liquidity locked in a yield farm.

Three types of transaction costs significantly alter yield farming performance. Each transaction requires the payment of a flat gas fee, implying that small investments are penalized by large overhead costs. Second, large investments relative to the existing liquidity result in significant price impact, especially at redemption. These observations suggest the existence of a trade-off that involves an optimal investment size. Finally, since it is strictly dominating to fully pledge the liquidity tokens into yield farms, staking ratios below one reduce investment performance and are a sign of investor mistakes.

In a second step, we provide new stylized facts on yield farms, investor behavior, and investment performance. Our analysis is based on a novel hand-collected data set of 262 yield farms from PancakeSwap, a yield farm platform hosted on the Binance Smart Chain (BSC), between March 1, 2021 and July 31, 2022. We focus on PancakeSwap because it is the largest yield farm ecosystem, with 435,130 active users on October 24, 2021, compared to 47,730 active users recorded on Uniswap. In addition, BSC features high trade execution speeds, lower congestion risks and lower trading fees than other comparable blockchains like

Ethereum, making it more easily accessible to retail investors. Figure 2 indeed illustrates that gas fees paid for blockchain transactions are an order of magnitude larger for Ethereum.

There is a significant amount of heterogeneity in offered yields among the 262 farms in our sample. The average (median) offered yield is 77.15% (77.60%) with a standard deviation of 135.63%. These yields are salient and advertised as headline rates in enticing ways that feature cartoons, rockets, or emojis. In contrast, information on past performance and impermanent losses is hidden and challenging to find. Investing into yield farms is complex both in payoff and complexity. There are three underlying assets, non-linearities, and a full round-trip cost can take up to 14 transactions.

Offered farm yields are driven by five components related to the issuance of the governance token of the yield farm platform CAKE, its price, which is common across all farms, each farm's liquidity, a farm multiplier, and the aggregate sum of multipliers across farms. Governance token owners may vote to increase or decrease farm multipliers, which can be used as an instrument to incentivize liquidity provision. We find that the component of yield changes associated with changes in the multiplier is positively related to past trading fees and negatively to past realized yields. In addition, we observe that farms are delisted in response to low liquidity and weak trading fee revenue.

The examination of transaction records on the blockchain suggests that many yield farmers are financially unsophisticated. First, we observe that many investors do not migrate their funds when PancakeSwap switched to a newer and more secure platform in April 2021, even though the new platform would mechanically provide superior return potential. We see similar patterns when PancakeSwap migrated its staking functionality to a new staking contract in April 2022. Second, in spite of an optimal yield farm staking ratio of one, we find that the median staking ratio is below one most of the time.

The farmer data further suggest that the average yield farmer invests about $7,732 in 2.64 farms. Strikingly, we observe that smaller investment stakes are correlated with smaller staking ratios, suggesting that retail investors are more likely to leave money on the table. Survey evidence of 1,347 yield farmers also suggests that many investors lack financial sophistication, since 79% of them claim to understand the associated risks and rewards of yield farming, while only 33% state that they understand impermanent loss.

We next assess the return performance of yield farming strategies. Without transaction costs, yield farming appears to be profitable on average, with Sharpe ratios that are similar (but higher) to those of investments into the S&P500 index or Ethereum. Sorting farms into quintiles based on the magnitude of the offered farm yield reveals that high yield farms systematically generate the lowest returns because they incur the greatest impermanent loss, which is the hidden downside risk that is poorly understood. We further show that farmers who invest in higher yielding farms underperform by an additional 22bps for every 100bps increase in offered yields. Our overall evidence suggests that farms with the highest headline rates exhibit the worst risk-adjusted performance.

High yield farms are also those where investor mistakes have the most severe consequences since more money is left on the table in the absence of yield farming using the LP tokens. Accounting for transaction costs such as gas fees, trading fees and price impact further reduces the return performance across all yield quintiles.

Third, we provide evidence that investors exhibit yield chasing behavior that can result in negative risk-adjusted returns. Specifically, we identify all cases where Pancake owners vote on changing the yield multiplier of one farm without significant changes to the multipliers of competing farms. In a difference-in-differences setting, we show that the differential increase (decrease) in aggregate farm flows in response to multiplier increases (decreases) is about 10%-19% (10%-12%), depending on the measurement of flows. A systematic analysis on the relation between fund flows and farm yields suggests that high headline yields predict positive net fund inflows, while flows are insensitive to impermanent losses.

At the farmer level, we document a positive propensity to buy riskier assets since we find that the average farmer provides about 1.45 percentage points more liquidity to a farm if it offers a 100bps larger yield. Because high yield farms exhibit the worst risk-adjusted returns, our evidence is consistent with reaching for yield behavior. We also find that experience, as measured by the number of investment farms and the farming duration, reduces the reaching-for-yield propensity by 30% to 64%.

As a last step, we capitalize on a unique setting in PancakeSwap to study the impact of information disclosure and complexity reduction on reaching for yield behavior. Yieldwatch, a third-party information platform summarizes statistics on investor performance, such as historical capital gains and impermanent losses of individual farmers, and discloses it conditional on the acquisition of Yieldwatch tokens. Using the comprehensive trading history of individual investors, including their acquisitions of Yieldwatch tokens, we show that the enhanced information disclosure and reduction in complexity alleviates the intensity of yield-chasing behavior by about 76%, thereby improving the overall investor performance.

We confirm these findings in a different setting using airdrops organized by APY.Vision, which provides similar functions than Yieldwatch, but randomizes the acquisition of tokens needed to access the information platform. That analysis is implemented on a different yield farming platform, SushiSwap, built on the Ethereum blockchain, and, therefore, supports external validity of our findings. Overall, this evidence has important implications for information disclosure and investor protection in markets for high-yielding financial securities.

Our work relates to theories on financial innovation and security design. One view is that financial securities can be tailored to complete the market and, therefore, improve risk sharing (Allen and Gale, 1994; Duffie and Huang, 1995). Another view is that when investors have salient preferences (Bordalo, Gennaioli, and Shleifer, 2012, 2013, 2022), financial intermediaries may compete by attracting consumers based on salient price attributes. An equilibrium outcome of salience bias may be that investors 'reach for yield' (Bordalo, Gennaioli, and Shleifer, 2016). If financial service providers also shroud risks (Gabaix and Laibson, 2006), then investors may suffer welfare losses (Inderst and Ottaviani, 2009, 2022).

We capitalize on the blockchain records to provide supporting evidence of salience bias in investor preferences. Using the investor-level transactions data across a cross-section of yield farms that compete for investor flows based on salient farm yields, we show that investors are attracted to farms with high salient yields although they turn out to be riskier ex-post. Thus, we document reaching for yield in decentralized financial markets even in the absence of financial intermediaries and related agency conflicts. Reaching for yield has been documented in the corporate bond (Becker and Ivashina, 2015; Chen and Choi, 2021), mutual fund (Choi and Kronlund, 2018), asset-backed securities (Efing, 2020), housing (Korevaar, 2023), and structured product markets Vokata (2023).

Yield farming is a complex and opaque investment strategy. Thus, we closely relate to the literature on complex structured finance. For example, Henderson and Pearson (2011) suggest that highly popular structured retail products (SRPs) deliver subpar performance for retail investors in spite of high promised returns. Supply-based theories explain the popularity of SRPs among retail investors by arguing that intermediaries exploit investors' lack of financial sophistication (e.g. Célérier and Vallée, 2017; Egan, 2019; Ghent, Torous, and Valkanov, 2019; Henderson, Pearson, and Wang, 2020). Shin (2021) advocates a demand-based explanation whereby investors extrapolate and aggressively chase past performance. For work on complex securities and structured products, see also Carlin (2009); Carlin and Manso (2011); Carlin, Kogan, and Lowery (2013); Griffin, Lowery, and Saretto (2014); Sato (2014); Amromin, Huang, Sialm, and Zhong (2018); Célérier, Liao, and Vallée (2022); Calvet, Célérier, Sodini, and Vallée (2022); Vokata (2021, 2023).

In a significant departure from prior work, we study complex financial products offered through smart contracts operating on a blockchain without centralized financial intermediaries who may drive security design to influence sales. The advantage of our study is that we observe the chain of all transactions at the farm and farmer level. This is in stark contrast to the existing literature on complex securities that bases its evidence on prices or transactions in primary markets. That feature of our data also enables us to understand investor mistakes (Campbell, 2006; Agarwal, Ben-David, and Vincent, 2017), how investors learn, and how information disclosure and reduction in complexity changes their behavior.

More broadly, our work is related to the emerging literature on decentralized finance.(e.g., Cong, Tang, Wang, and Zhao, 2022; Cong, Harvey, Rabetti, and Wu, 2022; Cong, He, and Tang, 2022) To our knowledge, this is the first empirical study of the risk and return characteristics of yield farming strategies using a hand-collected data set from PancakeSwap. Several studies investigate the properties of automated market makers (AMM) with the constant product model adopted by major decentralized exchanges (DEXs, Angeris, Kao, Chiang, Noyes, and Chitra, 2019; Aoyagi, 2021; Capponi and Jia, 2021; Han, Huang, and Zhong, 2021; Foley, O'Neill, and Putnins, 2022; Hasbrouck, Saleh, and Rivera, 2022), or focus on strategic trading and liquidity provision (Lehar and Parlour, 2021; Park, 2021). Appendix Table A.1 illustrates how we differ form these studies.

2 Conceptual framework

Yield farming allows investors to passively earn income for their liquidity provision to DeFi platforms. Intuitively, it is similar to securities lending with the distinctive feature that smart contracts, which operate on permissionless blockchains, automatically execute transactions without involvement of intermediaries. See Appendix A for institutional details.

In practice, yield farming is complex, both in execution and in payoffs. Figure 3 provides a heuristic illustration of the yield farming mechanism in PancakeSwap, the second largest decentralized exchange (DEX) offering cryptocurrency lending services. Figure 3 illustrates that yield farming involves two sequential and independent investment decisions.

First, an investor can passively earn income by providing liquidity to one or several among a large cross-section of liquidity pools. Each pool is defined by a pair of cryptocurrency tokens (USDT-ETH in our example). As liquidity providers, investors 'stake' (i.e., deposit) the pair of cryptocurrency tokens in equal dollar amounts to a liquidity pool. The liquidity provision is certified through the award of a liquidity token, also known as LP token.

Investors get compensated for their liquidity provision through trading fees, which are collected from third party traders who buy and sell USDT–ETH. The trading fees are paid in the pool's currency tokens, i.e., USDT vs. ETH, and amount to 0.25% of a pool's trading volume. Of that amount, 0.17% is paid out to liquidity providers, and 0.08% is paid as a reward to the PancakSwap main staking contract.

Second, investors can passively earn yield by staking the LP token to a yield farm that is exclusively linked to one liquidity pool (e.g., USDT–ETH). Farm yields are paid in a currency called CAKE, PancakeSwap's native governance token. In this Decentralized Autonomous Organization (DAO), CAKE token holders can influence the governance of the PancakeSwap ecosystem by casting votes on the future development of the platform or the reallocation of yields across farms. CAKE ownership also provides rights to participate in PancakeSwap lotteries and to access non-fungible token (NFT) lotteries.

CAKE tokens are continuously issued by PancakeSwap's main staking contract with each creation of a BSC block. The amount of CAKE tokens allocated to yield farms may vary across farms and over time, as determined by the votes of the aggregate CAKE ownership. PancakeSwap also uses a fraction of the revenue it receives from third party trading fees to continuously buy back and burn (i.e., destroy) CAKE to minimize the currency's dilution.

Based on the complicated chain of transactions described in Figure 3, the total return to yield farming between day t and $t+h$, $R_{t,t+h}$, comes from two sources associated with liquidity mining, $R^{\ell}_{t,t+h}$, and the staking of LP tokens to a yield farm, $R^{f}_{t,t+h}$. , such that:

$$R_{t,t+h} = R^{\ell}_{t,t+h} + R^{f}_{t,t+h}. \tag{1}$$

2.1 Liquidity provision

A liquidity provider must stake a pair (A, B) of cryptocurrency tokens (e.g., USDT and ETH) in equal dollar amounts. This implies that the absolute number (a_t, b_t) of tokens to be pledged is determined by market prices (P_t^A, P_t^B) through the relation $a_t \cdot P_t^A = b_t \cdot P_t^B$.

A pools' aggregate liquidity L_t is characterized by the value of the aggregate number of staked tokens $\alpha_t^A = \sum a_t$ and $\alpha_t^B = \sum b_t$, such that:

$$L_t = \alpha_t^A \cdot P_t^A + \alpha_t^B \cdot P_t^B. \tag{2}$$

Returns to liquidity provision are derived from two sources: growth in the value of the liquidity pool and fee revenue earned from third party trading activity in the pool, that is:

$$\begin{aligned} R^{\ell}_{t,t+h} &= \frac{L_{t+h}}{L_t} + Trading\ Fee\ Return_{t,t+h} \\ &= \frac{\alpha_{t+h}^A \cdot P_{t+h}^A + \alpha_{t+h}^B \cdot P_{t+h}^B}{\alpha_t^A \cdot P_t^A + \alpha_t^B \cdot P_t^B} + Trading\ Fee\ Return_{t,t+h}. \end{aligned} \tag{3}$$

Growth in the value of liquidity, L_{t+h}/L_t, is driven by fluctuations in market prices (P_t^A, P_t^B) and by fluctuations in the composition of tokens (α_t^A, α_t^B) in the pool. Both are pinned down mechanically by the constant-product automated market maker (AMM) technology hardwired into liquidity pools. See Lehar and Parlour (2021) for details.

The composition of a pool's liquidity changes because third party investors buy or sell tokens A and B, say USDT and ETH. The constant-product AMM technology defines the terms of trade by imposing that, at each point in time, the tokens' product must equal a constant k, i.e., $k = \alpha_t^A \alpha_t^B = \alpha_{t+h}^A \alpha_{t+h}^B$. In other words, the terms of trade are defined through an isoquant curve whose value is determined by aggregate liquidity provision.[1] The constant-product AMM technology also drives price fluctuations, since it imposes, for all t, that the products of price and quantity have to equalize across assets $\alpha_t^A P_t^A = \alpha_t^B P_t^B$.

Thus, liquidity providers are exposed to risks associated with joint changes in token prices and token composition. First, in exchange for their liquidity provision, investors receive LP tokens to certify their partial ownership in the pool. While the fractional ownership stays constant, the number of each token that can be claimed at redemption may change with the change in pool composition due to third party trading. Second, the change in token composition leads to mechanical price changes driven by the constant-product AMM.

In Appendix B, we explicitly show that the growth in liquidity value can be rewritten as a sum of two distinct components that are uniquely functions of prices:

$$\frac{L_{t+h}}{L_t} = \underbrace{\left(\frac{1}{2} R_{t,t+h}^A + \frac{1}{2} R_{t,t+h}^B\right)}_{\text{capital gain}} - \underbrace{\frac{1}{2}\left(\sqrt{R_{t,t+h}^A} - \sqrt{R_{t,t+h}^B}\right)^2}_{\text{impermanent loss}}, \tag{4}$$

[1] New liquidity provision or redemption can change k, and, therefore, the curvature of the isoquant curve.

where $R^A_{t,t+h} = P^A_{t+h}/P^A_t$ and $R^B_{t,t+h} = P^B_{t+h}/P^B_t$ denote the gross returns of tokens A and B, corresponding to USDT and ETH in our example.

The first term, which we call "capital gain," is the equally-weighted gross return from tokens A and B. The second term describes investors' risk exposure, referred to as impermanent loss. Intuitively, the impermanent loss corresponds to the difference between the return from liquidity provision L_{t+h}/L_t and the return from a buy-and-hold strategy (without pledging the cryptocurrency tokens to a liquidity pool). Impermanent losses depend non-linearly on the relative divergence in token returns. Importantly, they are strictly negative and expose investors to significant downside risk analogous to a short volatility exposure (Aigner and Dhaliwal, 2021). See Figure A.5 and Appendix B.1 for additional discussion.

The total return from liquidity provision may nonetheless exceed that of a simple buy-and-hold strategy due to the additional income generated from trading fees. As of August 14, 2021, PancakeSwap charges a trading cost equivalent to 25 basis points (bp) of trading volume. Part of that (17bp) is passed on to liquidity providers as a fraction c of total trading volume $V_{t,t+h}$ observed over two consecutive time periods t and $t+h$ and proportional to the initial fractional dollar investment I_t/L_t in the liquidity pool. Since the return from trading fees depends on the initial investment, the total fee return is characterized as

$$Trading\ Fee\ Return_{t,t+h} = c \cdot \left((I_t/L_t)V_{t,t+h}\right)/I_t = c \cdot V_{t,t+h}/L_t. \tag{5}$$

2.2 Yield farming

LP tokens may be staked to yield farms, which offer a farm yield y_t as a second source of passive income. That income is paid in CAKE, PancakeSwap's governance token.

The annualized yield is implicitly defined through a complicated function that depends on (a) the number of CAKE tokens created through the validation of a new block on the blockchain; (b) the total number of CAKE tokens redistributed for staking M_t; (c) a farm-specific multiplier m_t which defines the number of CAKE tokens allocated as reward for farming; (d) the total liquidity staked to the farm, L^{staked}_t; and (e) the price of CAKE, P^{CAKE}_t.

Approximately 40 CAKE tokens are created with each blockchain validation, which lasts about 3 seconds. This implies that 28,800 blocks are created per day. Given 365 days in a year, the annualized yield from farming is, therefore, given by:

$$y_t = c \times \left(\frac{m_t}{M_t}\right) \times \left(\frac{P^{CAKE}_t}{L^{staked}_t}\right), \tag{6}$$

where $c = 365 \times 28,800 \times 40$. Since CAKE tokens may be allocated to activities other than yield farming, the aggregate multiplier does not have to equal the sum of all yield farm multipliers, i.e., $M \neq \sum_k m^k$, where k corresponds to the number of farms. The realized farm yield between t and $t+h$ for a USD investor is thus defined as:

$$R^f_{t,t+h} = P^{CAKE}_{t+h} \sum_{n=1}^{h} \left(\frac{y_{t+n-1}}{P^{CAKE}_{t+n-1}} \right) \left(\frac{1}{365} \right). \tag{7}$$

2.3 Aggregation: Frictionless benchmark

The aggregate h-period return to yield farming is thus composed of four components associated with capital gains, impermanent losses, trading fees, and realized farm yields:

$$\begin{aligned} R_{t,t+h} &= \underbrace{\left(\frac{1}{2} R^A_{t,t+h} + \frac{1}{2} R^B_{t,t+h} \right)}_{\text{capital gain}} - \underbrace{\frac{1}{2} \left(\sqrt{R^A_{t,t+h}} - \sqrt{R^B_{t,t+h}} \right)^2}_{\text{impermanent loss}} + \underbrace{c \cdot V_{t,t+h}/L_t}_{\text{trading fee revenue}} \\ &+ \underbrace{P^{CAKE}_{t+h} \sum_{n=1}^{h} \left(\frac{y_{t+n-1}}{P^{CAKE}_{t+n-1}} \right) \left(\frac{1}{365} \right)}_{\text{realized farm yield}}. \end{aligned} \tag{8}$$

2.4 Impact of trading frictions

Table A.2, which breaks down the chain of transactions for a hypothetical yield farming strategy, shows that harvesting yields from PancakeSwap involves a chain of 12 transactions (excluding step 1 and 14 in Table A.2). A full round-trip transaction involves three types of costs associated with gas fees, trading fees, and price impact (see Appendix 4.5 for details). These costs may significantly lower the returns from yield farming.

Gas fees correspond to transaction costs associated with the use of BSC's computational resources for trade execution. Among the set of 12 transactions, yield farmers pay gas fees for 10 of them. The average round-trip gas fee is estimated to be \$3.45 in our sample period.

Since gas fees are flat overhead costs, they are more costly for small stake investments and frequent rebalancing. Thus, they are especially detrimental to smaller retail investors, who have a tendency to rebalance too frequently Odean (1999). Since gas fees multiply linearly with each additional yield farm, there is also less benefit from diversification across farms. As a result, gas fees encourage larger and more concentrated investments, which may not be optimal for financially unsophisticated investors.

For example, a \$1,000 investment would lose ≈35 bps in gas fees for a round-trip transaction, and 35 bps per week for weekly rebalancing. A diversification strategy across 10 farms would incur a per period cost of $10 \times 3.45 = \$34.5$, which, for a \$1,000 investment, is more than the typical hedge fund performance fee, not considering hurdle fees or water marks.

Besides gas fees, investors are charged a trading fee of 0.25% (proportional to trading volume) per transaction. Since one round-trip transaction includes the buying and selling of tokens at intermediate steps, yield farmers lose at least an additional 0.50% of their initial investment. The selling of CAKE tokens at redemption also requires a proportional trading fee of 0.25%. See Appendix 4.5 for more details.

The third transaction cost arises through price impact. We characterize a price impact function $\lambda(f)$, where f denotes the ratio of the investment amount I_t to the value of the liquidity L_t, i.e., $f = I_t/L_t$. Panels (a) to (c) of Figure A.6 illustrate how price impact is increasing in the size of an investment relative to a pool's liquidity. Considering both trading fees and price impact, the growth in liquidity value reduces to:

$$\frac{L_{t+h}}{L_t} = (1-0.0050)\lambda(f)\left[\left(\frac{1}{2}R^A_{t,t+h} + \frac{1}{2}R^B_{t,t+h}\right) - \frac{1}{2}\left(\sqrt{R^A_{t,t+h}} - \sqrt{R^B_{t,t+h}}\right)^2\right]. \tag{9}$$

We emphasize another indirect channel that negatively affects yield farming performance. Equation (6) highlights a negative relation between a yield farm's aggregate liquidity and the offered farm yield. We provide empirical support for that relation in Figure A.1. Since liquidity provision increases the size of a farm, it mechanically decreases the offered farm yield. Hence, too much liquidity provision can be a self-defeating strategy.

2.5 Investor mistakes and aggregation with frictions

Farm yields are strictly non-negative and yield farms are built on the same blockchain as liquidity pools. Thus, in the absence of lock-up periods, the staking of LP tokens is always a dominating strategy and the optimal staking ratio k^* should equal one. Because all transactions are observed on the blockchain, we can identify when investors do not reinvest their LP tokens into yield farms. We consider staking ratios below one to be a mistake.

Including all trading frictions, we quantify the returns to yield farming as follows:

$$\begin{aligned} R^{friction}_{t,t+h} &= (1-0.0050)\lambda(f)\left[\underbrace{\left(\frac{1}{2}R^A_{t,t+h} + \frac{1}{2}R^B_{t,t+h}\right)}_{\text{capital gain}} - \underbrace{\frac{1}{2}\left(\sqrt{R^A_{t,t+h}} - \sqrt{R^B_{t,t+h}}\right)^2}_{\text{impermanent loss}}\right] \\ &+ \underbrace{c \cdot V_{t,t+h}/L_t}_{\text{trading fee revenue}} + \underbrace{(1-0.0025)\,k^*\left[P^{CAKE}_{t+h}\sum_{n=1}^{h}\left(\frac{y_{t+n-1}}{P^{CAKE}_{t+n-1}}\right)\left(\frac{1}{365}\right)\right]}_{\text{realized farm yield}} - \frac{Gas_{t,t+h}}{I_t}. \end{aligned} \tag{10}$$

2.6 Yield farm flows

In our analysis, we examine two measures of yield farm flows. First, we follow the mutual fund literature (e.g., Sirri and Tufano, 1998; Coval and Stafford, 2007) and measure inflows net of price growth over an h-period trading horizon as:

$$Flow_{t,t+h} = \left(L_{t+h} - L_t \times R^*_{t,t+h}\right)/L_t, \tag{11}$$

where $R^*_{t,t+h}$ corresponds to the yield farm return defined in Equation (8) net of the realized farm yield, that is $R^*_{t,t+h} = \left(\frac{1}{2}R^A_{t,t+h} + \frac{1}{2}R^B_{t,t+h}\right) - \frac{1}{2}\left(\sqrt{R^A_{t,t+h}} - \sqrt{R^B_{t,t+h}}\right)^2 + c \cdot V_{t,t+h}/L_t$. We exclude realized farm yields in our flow definition because they don't affect the size of next period's liquidity pool, unlike capital gains, impermanent losses and trading fees. This is because farm yields are paid in CAKE rather than the liquidity pool tokens. Alternatively, we measure farm flows using the net token growth, i.e., $Flow_{t,t+h} = (\#LP\ tokens_{t+h}/\#LP\ tokens_t) - 1$.

3 Building yield farm and yield farmer data

We assemble a novel data set on liquidity pools and yield farms listed on PancakeSwap by tracing information on the Binance Smart Chain. Our data include the full history of prices, transactions, token shares, liquidity provision, and yield farm multipliers.

3.1 Farms and yields

We consider all contract addresses of liquidity pools with a corresponding yield farm stored in PancakeSwap's main staking contract from their inception on September 23, 2020 to July 31, 2022. With these addresses, we reconstruct, from the blockchain, the daily time series of farm yield multipliers. We consider only active farms with a non-zero yield multiplier.

Farm yields are a function of aggregate farm liquidity. We, therefore, source each pool's token balances α^i_t and prices P^i_t to compute aggregate pool liquidity given by $L_t = P^A_t\alpha^A_t + P^B_t\alpha^B_t$ (See Equation 2). Next, we collect each pool's supply of LP tokens and their staking ratios to compute aggregate farm liquidity defined as $L^{staked}_t = L_t \cdot (\#\ \text{staked LP tokens}/\text{Aggregate}\ \#\ \text{of LP tokens})$.

We impute farm yields using Equation (6). We verify their accuracy by collecting offered farm yields from PancakeSwap's homepage[2] at midnight Greenwich Meridian Time (GMT) on October 11, 2021. We manually verify that the multipliers collected from the main staking contract are identical to those advertised on PancakeSwap's web interface.

[2]https://PancakeSwap.finance/farms

Figure A.2 reports the relation between our imputed farm yields and those publicly listed by PancakeSwap. Nearly all observations are closely aligned with the 45-degree line. A linear projection of the imputed on the listed farm yields obtains a slope coefficient of 1.002 with an R^2 of 1.00. This strongly supports the validity of our data building procedure.

3.2 Prices, trades, and transaction costs

In a liquidity pool (e.g., ETH–BNB), one token of the cryptocurrency pair is considered a token of interest (e.g., ETH). Its price is typically expressed in terms of a numeraire token (e.g., BNB). We source daily end-of-day GMT prices, P_t^i, of the tokens of interest.

To find the prices of the numeraire token (BNB), we first use the native historical quote function on PancakeSwap. This pins down the historical exchange rate between BNB and Binance-Peg Tether (USDT), a stablecoin pegged to the US dollar. We then convert USDT to U.S. dollars using the USDT price from CoinMarketCap. This allows us to compute the U.S. dollar h-period trading volume $V_{t,t+h}$ as the daily sum of all trades.

We source gas fees from a proprietary data vendor specialized in blockchain data services covering BSC and other blockchains. Gas fees differ across functions executed by smart contracts. To accurately account for transaction costs in computing the performance of yield farming strategies, we first identify the transactions that incur gas fees (see Table A.2) and compute their average daily gas fee in U.S. dollars. Next, we compute the round-trip cost of gas fees by summing the average fee across all relevant transactions.

3.3 Yield farmers

We collect transaction data for all LP tokens from the transaction logs of BscScan[3], a freely-accessible analytics platform on BSC, and reconstruct each wallet's historical token holdings. Transactions that involve a user's deposit of cryptocurrency to a liquidity pool in exchange for LP tokens are represented as LP token transfer from the null address (0x000...000) to the user's wallet address. Transactions in which a user stakes/unstakes their LP tokens in a yield farm are captured as a token transfer to/from the active main staking contract. Redemptions of LP tokens at a liquidity pool in exchange for the underlying tokens are represented as a LP token transfers to the address of the LP token.

We restrict our analysis to active accounts during our sample period. We eliminate wallet addresses that are not associated with PancakeSwap smart contracts and accounts with more than 100,000 trades, since those wallets may camouflage yield aggregators or automated passive strategies. Relatedly, we remove positions worth less than $1 at the beginning of the holding period. In addition, we omit wallet addresses that have transacted LP tokens

[3]https://bscscan.com/

with third party smart contracts outside PancakeSwap, since the study of staking across multi-platform investment strategies is beyond the scope of our study. For accounts with a positive end-of-sample LP token balance, we assume that all open positions are closed out.

We merge each transaction with information on token prices and offered farm yield using the nearest end-of-day prices by block height difference. For each wallet, we also compute the number of invested farms (*No. Farms*) and liquidity pools (*No. Pools*). We define *Efficiency* at the wallet level as the duration of staking relative to the duration of liquidity provision (*Time Staked/Time in Liquidity Pool*), averaged across liquidity pools. Third, we define *Staked Balance* and *LP Balance* as the time-weighted average balance for staking and liquidity provision. For these calculations, we use the nearest end-of-day price from the beginning of each holding period and weight balances by the length of the holding period.

We define *Offered Farm Yield* at the yield farmer level as the time-weighted average offered yield at the beginning of each holding period. Finally, we calculate a farmer's *Average Daily Return* as the time-weighted average of their holding period log returns. We compute all return components as described in Section 2, making the simplifying assumption that offered yields are harvested daily without reinvestment.

Yield farmers may split their investments across multiple wallets. Hence, measures such as *No. Farms*, *Staked Balance*, and *LP Balance* could be underestimated. However, yield farmers are unlikely to systematically manage multiple wallets since there are no monetary benefits and transaction costs significantly increase. This bias is not central to our analysis, but wallet clustering algorithms could potentially alleviate related concerns.

3.4 The final sample

Our final sample contains 262 unique yield farms that were active between the inception of PancakeSwap on September 23, 2020 and July 31, 2022. We analyze 439,639 unique wallets which initiate 9,705,043 transactions. Appendix C provides a detailed account of our data cleaning and construction procedure.

Panel (a) of Figure 4 illustrates the number of active farms (right axis). The cross-section varies over time since new farms may be listed or delisted. The total number of active farms increases quickly from inception of PancakeSwap to a peak of 160 farms in July 2021.

The left axis in Panel (a) of Figure 4 plots Total Value Locked (TVL) in active farms, i.e., the aggregate amount of LP tokens staked to yield farms. Yield farming at PancakeSwap has experienced extraordinary growth, with TVL surpassing $7 billion in May 2021. Analogously to the boom-bust cycles experienced by Bitcoin and other cryptocurrencies, TVL dropped sharply following its peak and experienced renewed momentum.

Importantly, TVL stayed subdued until early 2021. As we show in Panel (b) of Figure 4, the consequential increase in liquidity provision coincides with PancakeSwap becoming more prominently researched in Google (left axis). Simultaneously, the number of active farmers jumped sharply (right axis). For that reason, we restrict our main analysis to start on March 1, 2021 to increase the stability of our estimations and avoid noisy inference.

4 Evidence

We first provide new stylized facts on yield farms and farmers. We then describe the trading behavior of yield farmers and examine the risk and return characteristics of yield farming.

4.1 Stylized facts about yield farms

Yield farms exhibit three important properties for our analysis of reaching for yield. First, they promise extraordinary high yields with cross-sectional heterogeneity in earnings potential. Second, promised yields are salient and conspicuously displayed has headline rates while information on risks and historical performance is hidden and difficult to find. Third, yield farms appear as simple and engaging platforms but involve a high degree of complexity.

We report in Table 1 a snap shot of yield farms on August 1, 2022. Each farm features a unique pair of cryptocurrency tokens. Panel A shows the ten largest farms in terms of TVL. The largest farm draws from \$187.20 million TVL staked in the USDT–BUSD pool. In Panel B, we show that the leading farm in terms of earnings potential offers an annualized yield of 113.17% for TVL of \$0.88 million staked in the TRIVIA–WBNB liquidity pool. Yield farms feature considerable cross-sectional heterogeneity in terms of liquidity and earnings potential. For example, the rankings in Table 1 show that TVL ranges from \$0.12 million to \$187.20 million (Panel A), while yields range from 0.24% to 113.17% (Panel B).

In Figure 5, we plot the time-variation of the median farm yield together with its cross-sectional distribution. The median farm yield is often higher than 100% and 77.6% in our sample, on average. In addition, there is significant variation in dispersion of farm yields, as is underscored by the fluctuations of the interquartile range of the yield farm distribution. Such rich variation in yields across farms and time together with transparency on blockchain transactions provides an opportunity for better understanding the motivation behind liquidity provision to yield farms and the performance of yield farming.

Yields are salient to investors and marketed as headline rates that look attractive, especially in a low interest rate environment. In Appendix Table A.3, we provide an example of PancakeSwap's user interface. The main information in the foreground relates to the offered yield (i.e., the annualized percentage return), the yield multiplier and the pool's liquidity.

In contrast, it is difficult to find information about the computation of annualized returns or the meaning of yield multipliers. Moreover, it is difficult to find information about the return decomposition. There are hidden downside risks associated with impermanent losses and hidden costs due to the price impact of large trades, also known as slippage.

The user interface of PancakeSwap is engaging because it displays cartoons, rockets and emojis. This gamification of an investment platform makes yield farming look like a simple application. It is, however, a complex investment strategy, both in terms of payoffs and execution. The payoffs to yield farming depend on three underlyings: the two cryptocurrencies in the liquidity pool and PancakeSwap's governance token CAKE, which is paid as a reward for yield farming. Furthermore, the payoffs feature significant non-linearities, epitomized by the impermanent loss function. Finally, a round trip in yield farming is complex to execute, since it involves a chain of up to 14 transactions (see Appendix Table A.2).

4.2 Determinants of farm yields

In Equation (6), we characterize the offered farm yield as a function of five components. Among these components, one is mechanically related to the continuous issuance of CAKE tokens (c), one depends on the aggregate price of CAKE (P_t^{CAKE}), and one depends on farm-specific liquidity ($L_{i,t}^{staked}$). These factors are outside the influence of CAKE owners. The farm-specific multiplier $m_{i,t}$ defines the allocation of CAKE tokens to a farm. The multiplier M_t sums across farm multipliers and defines the aggregate distribution of CAKE tokens. In Appendix Table A.4, we validate that all components are indeed strongly correlated with the level of offered farm yields and that they have the correct sign.

CAKE owners can vote on changing the farm-specific multiplier $m_{i,t}$ to increase or decrease the CAKE token allocation. Since increasing the farm multiplier increases the offered farm yield, CAKE owners can influence the reallocation of rewards across farms and attract liquidity to a liquidity pool of choice. Thus, the ability to change the yield multiplier $m_{i,t}$ equips CAKE owners with centralized decision power on the amount of passive earnings potential, which, in our opinion, goes against the spirit of decentralized financial services.

We want to examine the determinants of yield changes that are associated with decisions to change the yield multiplier, controlling for all common variation (e.g., M, L, P^{CAKE}). In Table 2, we, therefore, isolate the impact of yield changes that come from the active decision of farm governors (i.e., the owners of CAKE tokens). We examine the relation between the change in yield that is driven by platform governance ($\Delta y_{i,t+1}^{m} = y_{i,t} \times \frac{\Delta m_{i,t+1}}{m_{i,t}}$) and various components of the yield farming return performance over the previous seven days, i.e., capital gains, impermanent loss, trading fees, realized yields, farm liquidity.

Columns (1) and (2) of Table 2 suggest that yields are increased when past trading fees are high, and decreased when past realized yields are high. This result holds both with and without day fixed effects that absorb common movements across farm yields due to, for example, the price of CAKE.

In columns (3) and (4) of Table 2, we find that farms are more likely to be delisted when their liquidity or trading fee revenues are low. Overall, this evidence is consistent with the idea that offered farm yield is an instrument to make the strong farms stronger and the weak farms weaker. Thus, offering yields is a mechanism to enhance the long-term viability of the yield farm platform by channeling liquidity to a subset of farms.

4.3 Evidence on lack of investor sophistication

Several infrastructure developments of PancakeSwap enable us to examine trading behavior. First, PancakeSwap upgraded the technological and security features of its smart contract design on April 24, 2021, migrating from 'PancakeSwap v1' to a new version 'PancakeSwap v2'. Since then, liquidity pools and yield farms associated with a particular pair of cryptocurrency tokens have coexisted on both old and new platforms. Liquidity providers were encouraged to switch their liquidity provision from v1 to v2, but had to implement the switch themselves. The switch is strictly dominating, because migrating liquidity to the new version delivers higher staking rewards than in v1 alongside lower transaction costs.

In Panel (a) of Figure 6, we show the amount of outstanding assets in the old version of the platform. This figure shows that the migration of funds is sluggish, which could be a sign of investor inattention or inertia. Importantly, even after 100 days, a significant amount of liquidity remains in the liquidity pools associated with the old version.

A second update occurred on April 20, 2022, when PancakeSwap migrated its staking functionality to a new staking contract. Users were encouraged in advance, through Twitter and other channels, to migrate their assets. Migrating is again preferred because assets in the old staking contract would stop earning yields. Panel (b) of Figure 6 shows a similar pattern in that many users remain staked in the obsolete staking contract even 100 days after the migration, missing out on potential yield income in that period. This phenomenon is similarly a sign of investor inertia, inattention, or of their lack of sophistication.

More evidence on investor behavior comes from staking ratios, defined as the ratio of LP tokens staked in yield farms to the aggregate amount of LP tokens minted to certify liquidity provision. Remember that yield farmers sequentially provide liquidity to pools and then to farms. Implementing both transactions is strictly dominating liquidity provision alone, since earning CAKE through farming is always superior to leaving money on the table. Thus, we would expect the staking ratio to be equal to one at all times.

Figure 7 shows that the median staking ratio is below one most of the time. The 10th (25th) percentile of the distribution drops as low as 30% (85%). This evidence further suggests that some investors are financially unsophisticated. We caveat this interpretation because of the possibility that investors stake their LP tokens in third-party yield farm aggregators.

Table A.5 in the Appendix shows that staking ratios increase with experience. We regress the staking ratios on indicator variables that are one for the 3rd (4th, 5th, >5) farm investment and zero otherwise. The constant, which captures the baseline for the first two farms, indicates that the average staking ratio is 60.61%, based on the linear probability model in columns (1) to (3). The staking ratio significantly increases with every subsequent farm investment, suggesting that investors learn over time.

In Panel A of Table 3, we provide farmer-level statistics. The average yield farmer invests in 2.64 farms, has a holding period of 30.92 days, and has $7,732 invested. However, the average staking ratio is only 0.8081. This suggests that many farmers miss out on farming opportunities, possibly due to the complex nature of the trading strategy.

In Panel B of Table 3, we separate the farmers into quintiles based on their average *Investment Size*. There is significant cross-sectional dispersion in size among PancakeSwap users. For instance, the average investment in the lowest quintile is only $10.96, whereas that of the highest quintile is $37,736. Thus, many yield farmers have small investment stakes.

We observe that *Investment Size* is positively correlated with the staking ratio, ranging from 0.6211 to 0.9629 between the lowest and highest quintiles. This suggests that smaller yield farmers are more likely to leave money on the table. But even in the highest quintile do we see significant evidence of investor mistakes, given an average staking ratio that is far from one. Since the average farm yield ranges between 94.28% and 121.69% across quintiles, investors face non-trivial opportunity costs. Investors also have short staking times, with a holding period ranging between 9.8 and 61.31 days across quintiles.

Investment performance is non-linear across quintiles with the highest daily return of 20bps in quintile 4. This echoes our discussion in Section 2.4 that both large and small investments could generate sub-optimal performance due to transaction costs and price impact.

Evidence from DappRadar[4] indicates that PancakeSwap registered 435,130 active users on October 24, 2021, in contrast to 47,730 active users recorded for Uniswap. The trading volume in PancakeSwap was about $1.2 billion on that day, which implies that the average yield farmer in PancakeSwap traded $2,757. This suggests that many investors in PancakeSwap are small retail investors, consistent with our evidence in Table 3.

Survey evidence further supports the view that yield farmers may not be financially sophisticated. CoinGecko, a data provider, questioned 1,347 cryptocurrency investors about yield farming in August 2020 (CoinGecko, 2020). According to the survey, 79% of yield farmers claim to understand the risks and rewards of yield farming to a reasonable extent. However, about 40% of them report that they could not read smart contracts to verify potential yield vulnerabilities or scams. In addition, 33% of yield farmers are unfamiliar with the meaning of impermanent loss, implying that they take risks that they don't understand.

4.4 Yield farming performance without frictions

In Table 4, we assess the value-weighted performance of yield farming strategies using aggregate pool liquidity as weighing factor. We compute returns in excess of the 3-month U.S.

[4] DappRadar: https://dappradar.com/rankings

Treasury bill rate from the perspective of a U.S. investor and ignore transaction costs. Panel A (B) reports results at the daily (weekly) trading frequency with 518 (74) observations.

We find that, prior to transaction costs, yield farming is profitable during our sample period. The value-weighted index strategy delivers a daily return of 0.15%. This is about twice as large as the returns to a strategy that focuses only on liquidity mining (0.07%) or on a buy-and-hold strategy in the same pairs of cryptocurrency tokens associated with the liquidity pools (0.07%). All three strategies deliver negatively skewed performances, with a non-trivial amount of excess kurtosis, negative serial correlation, and exhibit a daily volatility of about 3.6%. Results for a weekly trading frequency are qualitatively similar.

In Figure 8, we report the performance for each the four components (capital gains, impermanent losses, trading fees, farm yields) after sorting yield farms into quintiles based on the magnitude of their average in-sample offered yield. Panel (a) shows that the average realized yield, which strongly correlates with the offered yield, increases monotonically across quintiles from about 2.5bps in Q1 to 40bps in Q5. Panel (b) of Figure 8 shows that trading fee revenue is smaller than other components and more similar across quintiles.

In Panel (c), we illustrate capital gains. While capital losses are largest for farms offering high yields, these are insignificantly estimated. In contrast, impermanent losses, which are significantly estimated, as shown by the 95% confidence bounds, are always negative and monotonically decreasing with the headline yields, as shown in Panel (d). Taken together, this evidence at the farm level suggests that high yield farms' tokens generate the lowest returns and the largest impermanent loss.

The evidence that farms with the highest headline yields perform worst ex-post raises concerns about retail investor protection for three reasons. First, yield farms compete for liquidity by offering high yields. Second, high yields are salient to investors who appear to be unsophisticated. Second, impermanent losses are shrouded, yet they significantly contribute to yield farming underperformance. Bordalo, Gennaioli, and Shleifer (2016) show that, in such an environment, reaching-for-yield behavior may be an equilibrium outcome.

To better assess the risk-return trade-offs, we standardize the return performance by the standard deviations and report in Table 4 Sharpe ratios for all investment strategies. These measures suggest risk-return trade-offs of yield farming that are comparable but higher to that of the S&P 500 (which has a daily Sharpe ratio of 0.03 in our sample period), with values ranging from 0.0209 for buy-and-hold strategies to 0.0405 for yield farming.[5] Thus, without accounting for frictions, yield farming appears to be profitable and to deliver superior performance to the S&P 500, according to Sharpe ratios.

We also report alphas estimated using the three-factor cryptocurrency return model of Liu, Tsyvinski, and Wu (2019), in addition to BNB, the native token of the BSC smart chain. Their framework suggests that a three-factor model with cryptocurrency market, size, and

[5]There are fewer observations for the S&P500 because DeFi markets are continuously open for trading.

momentum factors prices the cross-section of cryptocurrency returns. Thus, we assess the risk-adjusted yield farming performance relative to this three-factor+BNB cryptocurrency benchmark. We find that the daily yield farming alpha is, on average, 0.02%. Because of the short and volatile sample period, this alpha is estimated with a t-statistic of only 0.6822. The alphas of buy-and-hold investments and liquidity mining are negative, emphasizing that the positive yield farming performance is driven by farm yield and trading fee revenue.

4.5 Yield farming performance with frictions and investor mistakes

We next consider the impact of investor mistakes by comparing the performance of yield farming to that of liquidity mining. Panel (a) of Figure 9 shows that investors who do not fully stake their LP tokens into yield farms perform worse within each quintile. This effect is especially pronounced for the farms with the highest headline rates. Table 3 documents that smaller investors are more likely to do mistakes (i.e., staking ratios below one). Thus, they are more likely to leave money on the table and underperform. Detailed statistics are reported in Panel A of Appendix Table A.8.

We further assess the impact of trading frictions on yield farming performance, including gas fees, trading fees, and price impact. For that purpose, we assume a holding period of 10 days, or that 1/10th of the investors rebalance their portfolio each day. This lies within the mean and median holding periods across yield farmers (see Table 3). We choose an initial investment of \$5000, which is bounded by the mean and median investment amount in our sample. Finally, we approximate the staking ratio of the average investor using the average daily observed farm-level staking ratio.

Panel (b) of Figure 9 compares the yield farming performance with trading frictions and investor mistakes to that of the frictionless benchmark. Transaction costs unilaterally lower the risk-adjusted return performance across all yield quintiles. For example, the risk-adjusted return decreases by 7bps from 0.07% (-0.01%) to 0.00% (-0.08%) for Q1 (Q5). That downward adjustment is further amplified by investor mistakes such that, for Q5, the daily alpha decreases from -0.01% to -0.21% (see Table A.8). Figure A.8 and Panel B in Table A.8 provide qualitatively similar results at the weekly trading frequency, but the downward adjustments are larger in magnitude.

Figure A.9 illustrates robustness of our conclusions by showing similar results under alternative parameter assumptions for the trading frictions. In Panel (a), we first vary the rebalancing duration from 5 to 50 days. We report annualized alphas for a fair comparison across scenarios. Risk-adjusted returns decrease monotonically within each quintile. This is expected, since the multiplicity of transactions needed for a round-trip trade can accumulate to non-trivial amounts for gas and trading fees, especially with frequent rebalancing.

In Panel (b) of Figure A.9, we vary the investment size from \$100 to \$1million. Small size investments are impacted by gas fees, since these are based on flat dollar amounts. This incentivizes larger investment amounts to reduce the dollar cost per investment. However, larger amounts may not be an option for unsophisticated retail investors. Indeed, a large proportion of investors invests less than $1,000 (see Table 3). On the other hand, large investments relative to the size of the liquidity pool may suffer from price impact due to slippage. In addition, larger investments can endogenously lead to lower farm yields, thereby putting further downward pressure on the investment performance. Hence, we observe hump-shaped performance results within each quintile.

These observations bear implications for diversification and optimal portfolio allocation. A portfolio with fewer yield farms would save more on fixed transaction costs, but would be more exposed to illiquidity (slippage) when opening/closing positions, due to higher idiosyncratic risk. In contrast, holding a more diversified portfolio of farms would cost more but would lower potential losses from illiquidity (slippage) when opening/closing positions. We leave such analysis for further research.

In Table 5 we examine the role of trading frictions and investor mistakes at the farmer level. We regress the time-weighted average daily holding period return for each farmer on the average value-weighted offered farm yield and a set of explanatory variables related to transaction costs and mistakes. In columns (1) to (3), farmer-level returns without frictions are the dependent variable and there is little significance by any of the explanatory variables.

In contrast, in columns (4) to (6) of Table 5, which do account for frictions, all variables are significantly significant in explaining daily holding period returns. Investment size is non-linearly related to performance, as underscored by the positive and negative coefficients on investment size and its square. More frequent rebalancing is associated with higher gas and trading fees and lower performance, while higher staking ratios in yield farms lead to better performance since less money is left on the table. The average difference in daily return performance for a staking ratio of zero and one equals 1.84% to 1.95%. These results are robust to the inclusion of investment start and month fixed effects, which effectively allows for a comparison between investors over similar trading horizons.

Importantly, the coefficient on the average offered yield is negative and statistically significant at the 5% level. This suggests that farmers who invest in higher yielding farms underperform by an additional 22bps for every 100bps increase in offered yields. That evidence is consistent with our findings at the farm level (Figure 9) in that the farms with the highest headline rates exhibit the worst risk-adjusted performance. This important observation leads us to further assess the relation between flow and performance, since there is important evidence from other asset markets that suggest investors reach for yield (e.g., Becker and Ivashina, 2015; Choi and Kronlund, 2018; Chen and Choi, 2021; Bordalo, Gennaioli, and Shleifer, 2016; Vokata, 2023) and pursue investment strategies with large headline rates (e.g., Henderson and Pearson, 2011; Célérier and Vallée, 2017; Egan, 2019; Henderson, Pearson, and Wang, 2020; Shin, 2021).

5 Reaching for yield in decentralized financial markets

The PancakeSwap ecosystem hosts a large cross-section of yield farms that compete for liquidity by offering seemingly attractive investment opportunities while shrouding risks. The detailed account of all wallet transactions registered on the public blockchain provides a unique opportunity to examine whether and how such an environment encourages reaching-for-yield behavior (Bordalo, Gennaioli, and Shleifer, 2016).

We first examine whether aggregate fund flows to farms react to changes in farm yields. We follow the mutual fund literature and compute farm flows as a pool's aggregate liquidity growth net of price-driven growth (e.g., Sirri and Tufano, 1998; Coval and Stafford, 2007). As an alternative measure, we use the gross token growth. See Section 2 for details. We aggregate flows at the daily frequency to obtain weekly flows.

Equation (6) shows that yields are driven by many factors that are either farm-specific or common to all farms. We would like to isolate the variation associated with the farm multipliers $m_{i,t}$, since changes in multipliers are easily seen in PancakeSwap and are changed by votes of the platform owners. We also want to avoid capturing fund flows that are driven by multiplier changes to other farms and therefore restrict our analysis to changes in farm multipliers where the change in the aggregate multiplier M is small.

We identify 511 cases where $\Delta m_{i,t} \neq 0$ and $|dM_t/M_t| \leq 0.15$, among which 50 (461) cases are associated with an increase (decrease) in $m_{i,t}$. We then compare the change in flows to the treated farms with $\Delta m_{i,t} \neq 0$ to those to the non-treated farms with $\Delta m_{i,t} = 0$. Specifically, we plot the difference-in-differences coefficients β_k from a regression:

$$Flow_{t,t+7} = \alpha + \sum_{k=-7,k\neq-1}^{k=7} \beta_k I\{m=k\} \times Treatment_i + Event \times FarmFE + DayFE + \varepsilon_{i,t+m}.$$

Panels (a) and (c) ((b) and (d)) in Figure 10 show that there is a significant fund inflow (outflow) on the day that farm multipliers increase (decrease). The net inflow (token growth) for $\Delta m_{i,t} > 0$ is about 18%-19% (10%-13%) on average, which is economically meaningful.

Platform owners may increase farm multipliers in anticipation of future inflows. To mitigate that concern, we also examine the sensitivity of aggregate fund flows to yield changes that are associated with multiplier changes by peer farms, as reflected in the aggregate multiplier M_t. These shocks need to be large enough to have meaningful impact on M_t and, therefore, $y_{i,t}$. Thus, we identify 4 events where $\Delta m_{i,t} = 0$ with $|dM_t/M_t| > 0.15$. These 4 events are associated with increases in M_t. Since changes in M_t affect all farms simultaneously, we conduct a simple event study without control group. Appendix Figure A.10 confirms the finding that aggregate fund flows are sensitive to changes in yields.

In Table 6, we provide more direct evidence on reaching-for-yield behavior by testing whether future fund flows are related to high yield farms. Specifically, we regress farm flows on offered farm yield, lagged farm performance (*Return*) and the individual components related to capital gains, impermanent losses, trading fees and realized farm fields:

$$\begin{aligned} Flow^{j}_{t,t+7} = a &+ \beta_1 Offered\ Yield^{j}_{t-7,t} + \beta_2 Capital\ Gain^{j}_{t-7,t} + \beta_3 Impermanent\ Loss^{j}_{t-7,t} \\ &+ \beta_4 Trading\ Fee^{j}_{t-7,t} + \beta_5 Realized\ Yield^{j}_{t-7,t} + \gamma^{\top} X^{j}_{t} + FEs + \varepsilon^{j}_{t}, \end{aligned} \tag{12}$$

where j denotes the farm-level index. We include farm and week fixed-effects. The control vector X_t includes lagged flows, log size of the liquidity pools, and farm age.

In column (1) of Table 6, we find a positive and statistically significant relation between $Offered\ Yield$ and $Flow$. This result is unchanged when we add lagged return performance in column (2). Besides the statistical significance at the 1% level, the coefficient is also economically significant. A farm with a 100bps higher $Offered\ Yield$ is associated with a 5.4% greater increase in fund flows.

In column (3), we add the four components of lagged return performance and drop $Offered\ Yield$ due to its high collinearity with *Realized Yield*. We find a positive and strongly significant relation between farm flows and lagged trading fees and realized yields. Importantly, these measures are directly observable to investors in the PancakeSwap user interface. This strongly suggests that flows chase past fees and high yields.

The coefficient on *Impermanent Loss* is insignificant, which is consistent with the evidence that information on impermanent losses is challenging to find and difficult to understand, according to survey evidence. Overall, our results suggest that yield farmers chase farms offering higher, more salient yields, but do not seem to internalize past impermanent losses.

5.1 The role of learning in reaching-for-yield behavior

We next examine reaching-for-yield at the farmer level. Column (1) in Table 7 reports our baseline result for the relation between flows by investor i to farm j, $Flow^{i,j}_{t,t+7}$, and farm j's offered yield, $Offered\ Yield^{j}_{t-7,t}$. The positive and statistically significant coefficient of 0.0148 indicates a positive propensity of reaching-for-yield. The average farmer provides about 1.45 percentage points more liquidity to a farm if it offers a 100bps larger yield.

A significant literature has highlighted the underperformance of yield-seeking strategies (e.g., Henderson and Pearson, 2011; Becker and Ivashina, 2015; Bordalo, Gennaioli, and Shleifer, 2016; Célérier and Vallée, 2017; Choi and Kronlund, 2018). Similarly, we find that investor funds are more likely to be channeled to higher yielding farms, which systematically underperform due to greater capital and impermanent losses. The underperformance is especially pronounced for investors who leave money on the table due to their mistake of not staking the LP tokens to earn farm rewards. We are, therefore, interested in understanding whether experience and learning can contribute to mitigating reaching-for-yield behavior.

In columns (2) to (7) of Table 7, we ask whether proxies for learning and experience can reduce the reaching-for-yield propensity, defined as the regression coefficient between offered farm yields and future fund flows. Our three proxies for learning and experience are the amount of the investment (Size), the number of days elapsed since the first yield farm investment (Experience), and the number of farms to which an investor has provided liquidity (# Farms). For all three measures, we create indicator variables equal to one if the variable is above the 75th percentile of the variable's distribution and zero otherwise.

Columns (2) and (3) provide weak support for investment size playing a role in mitigating reaching-for-yield behavior. However, columns (4) to (7) show a significant reduction in the reaching-for-yield propensity based on the interaction terms between the offered farm yield and the experience proxies. The most conservative estimations in columns (5) and (7) include farm times week effects, allowing us to control for time-varying farm characteristics and compare high with low experience farmers within the same farms at different points in time. The magnitude of the coefficients in these estimations suggests that experience can mitigate the reaching-for-yield propensity by 30% to 64%, respectively.

5.2 The role of information disclosure in reaching-for-yield: Yieldwatch

High yield-seeking behavior has been observed in many other financial markets (Henderson and Pearson, 2011; Becker and Ivashina, 2015; Bordalo, Gennaioli, and Shleifer, 2016; Célérier and Vallée, 2017; Choi and Kronlund, 2018; Vokata, 2023). Much of that research emphasizes the role of complexity and risk shrouding in explaining reaching-for-yield behavior (e.g., Gabaix and Laibson, 2006; Célérier and Vallée, 2017). A main advantage of the blockchain data is that it allows us to directly test, using natural experiments, whether information disclosure and reduction in complexity can alleviate reaching-for-yield behavior.

In particular, we rely on the novel setting of Yieldwatch.net, a third-party information platform that selectively discloses information on past performance and return components in exchange for buying yield watch tokens. Launched on March 3, 2021, Yieldwatch Pro, Yieldwatch.net's main service, provides customized information on yield farming. Appendix Figure A.4 provides a screenshot of Yieldwatch Pro's user interface.

Unlike PancakeSwap's main user interface, which provides limited information on farm-level characteristics like yield, size, and multiplier (see Appendix Figure A.3.), Yieldwatch Pro provides a more user-friendly interface with richer information. In addition to information on farm characteristics, YieldWatch Pro breaks down farmers' historical capital gains (also called HODL value), impermanent losses, trading fee revenue, and realized yields for a particular yield farming position. Notably, this information is only available to yield farmers who own Yieldwatch.net's native utility token, called the WATCH token.

We leverage two unique features of YieldWatch Pro to reconstruct individual investors' information sets. First, through the complete transfer history of WATCH tokens available from Binance Smart Chain, we identify WATCH token holders and their balances on each day. We find that 38,441 out of 590,388 farmers held WATCH tokens in our sample period. Second, we find that YieldWatch Pro covers only 91 out of 234 PancakeSwap farms in our sample, which allows us to compare yield-chasing behavior in farms that are displayed in YieldWatch Pro, versus those that are not.

Column (1) of Table 8 provides the baseline result for the reaching-for-yield propensity based on the regression of individual investors' farm *Flows* on the one-week lagged farm-specific *Offered Yield*, accounting for farm, week, and farmer fixed-effects. In column (2), we restrict our sample to WATCH token holders and interact the offered yield with an indicator variable *Displayed* that is one if a farm is covered by Yieldwatch Pro and zero otherwise. The negative and statistically significant coefficient of -0.0346 in column (2) suggests that the access to more granular performance information and disclosure of hidden risks can fully offset the reaching-for-yield behavior. We do not find such results in column (3) for the sub-sample of non-WATCH token holders.

In column (4) of Table 8, we formally test whether the diminished yield-chasing behavior is more significant for WATCH token holders compared to non-WATCH token holders using a triple difference-in-differences test. We add the indicator variable *YieldWatch*, which equals one when a farmer acquires Yieldwatch tokens or provides liquidity to the WATCH-BNB pool, and zero otherwise. The coefficient of interest from the triple interaction is -0.0146 and statistically significant at the 1% level, indicating that WATCH token holders who are liquidity providers to farms covered by Yieldwatch.Pro experience a reduction in their reaching-for-yield propensity by about 76%.

Our results are robust to controlling for farm times week fixed effects in column (5), allowing us to compare the reaching-for-yield propensity among WATCH token holders and non-holders within farms covered by Yieldwatch.Pro at different points in time, while accounting for unobserved time-varying characteristics at the farm level. In column (6), we obtain qualitatively similar results when we control for investor controls (e.g., investment size). In column (7), we restrict the sample to farmers with investments above $10 to mitigate concerns that our results are driven by noise from tiny investments, and results are similar.

Another useful feature of the Yieldwatch Pro design is that it grants differential access to its information services depending on the amount of WATCH tokens acquired by a wallet. The threshold for the two tiers of information services is determined by the ratio of the value of WATCH token holdings to the aggregate liquidity provision to farms covered by Yieldwatch Pro. A ratio above 0.5% grants access to a granular performance breakdown and information about individual return components. A ratio below 0.5% grants limited access with basic information. For that reason, we further test whether the reduction in reaching-for-yield propensity differs for those investors with ratios above and below 0.5%.[6]

[6] The numerator of the ratio accounts for the dollar value of WATCH tokens held by the wallet, half of the LP token value issued by the WATCH-BNB pool, and the value of LP tokens staked in beefy finance, ApeSwap, Mdex, Acryptos, Hyperjump, Autofarm. Since we do not have information about the latter

In columns (8) and (9) of Table 8, we report the results. The coefficient on the triple interaction term is statisticaaly significant at the 1% level, and economically more meaningful when the WATCH token holdings ratio is above 0.5%. This finding provides further evidence that better risk disclosure decreases the salience of prices in a relative sense, and reduces the propensity to reach-for-yield.

Taken together, our evidence consistently shows that yield-chasing behavior becomes less pronounced once investors access more complete information on their yield farming portfolios, specifically more detailed information on the determinants of returns that tend to be hidden and are associated with downside risks (e.g., impermanent loss). This result is consistent with the hypothesis that investors chase yield because they are salient thinkers (Bordalo, Gennaioli, and Shleifer, 2016). We show that investor's reliance on salient features of financial products in their decision-making can be reduced by the increased availability of information of other less-salient features through third-party information services.

5.3 Randomizing the information acquisition through airdrops

One concern with our analysis is that more sophisticated investors are more likely to know about Yieldwatch.Pro and are more likely to acquire Yieldwatch tokens. In that case, our results could be explained by unobserved differences in financial sophistication rather than salience shocks introduced by a reduction in complexity and increased information about risks and historical investment performance.

While farmer fixed effects should absorb differences in sophistication across investors, we further address this concern by exploiting a natural experiment based on airdrops organized by APY Vision. Airdrops are events in which APY Vision provides a select group of users access to premium tracking services. APY Vision operates across multiple platforms and selects users randomly. PancakeSwap is not covered by APY Vision, which operates on Ethereum, a different blockchain, and we manually need to collect all the airdrop announcements through X (formerly Twitter). We, therefore, focus our data collection efforts on the SushiSwap platform. See Appendix C.5 for details.

Access to the APY.Vision information service is enabled through the ownership of NFT tokens. APY.Vision randomly allocates these NFT tokens to liquidity providers in eligible liquidity pools. In SushiSwap, all pools are eligible. During our sample period, we identify 21 airdrops, in which 57 unique wallets were randomly chosen to receive NFTs. We compare the reaching-for-yield propensity between the 57 investors with access to APY.Vision and 17,989 wallets without such access.

Table 9 reports results that are qualitatively similar to those obtained for the Yieldwatch experiment. First, the baseline magnitude of the coefficient, -0.0212 is reasonably close to

component, our measurement may be noisy. Specifically, we compute the Yieldwatch ratio, YW, as $YW = (\$WATCH \text{ Balance} + \text{WATCH-BNB } LP \times 0.5)/(\text{Balance of Displayed Farms})$.

that reported in Table 8, even though the data come from a different decentralized financial market operating on a different blockchain. This is reassuring and supports external validity of our findings. Second, the interaction term between offered yield and APY.Vision NFT token holder dummy variable is negative and statistically significant. This coefficient similarly suggests that a reduction in complexity and an increase in risk disclosure can significantly reduce investors' salience bias.

6 Conclusion

We provide the first characterization of yield farming, a decentralized financial service available to retail investors in the cryptocurrency ecosystem. Using a novel hand-collected dataset of all trade records in 262 yield farms listed on PancakeSwap, the largest automated market-maker operating on the Binance Smart Chain, we assess yield farming's return performance and document its associated risks.

Yield farms offer high yields that are saliently advertised as headline rates, while downside risks are hidden and not easily understood. Yield farming appears to be profitable, but risk-adjusted returns are significantly reduced after accounting for transaction fees, price impact, and investor mistakes. Investor flows are attracted to high yield farms but are insensitive to impermanent losses, a type of hidden downside risk. But, high yield farms systematically underperform due to large impermanent losses. Thus, we document reaching-for-yield behavior that results in negative risk-adjusted returns.

By means of two quasi-natural experiments designed by third-party information platforms, we study how information shocks that reduce complexity and increase risk disclosure affects yield-chasing behavior. We find consistent evidence that farmers' propensity to reach-for-yield becomes less pronounced once they are provided more detailed information on the performance of their portfolios. We also document evidence that investors' learning experience contributes to reducing heir yield-chasing behavior over time.

Our results have important policy implications. First, our evidence increases the role for better information disclosure, since it can mitigate investors' salience bias. Notably, the type of information matters, since our findings highlight the role of risk disclosure as opposed to price disclosure. In contrast, Frydman and Wang (2020) show that enhanced information about prices can increase the bias related to the disposition effect. Nonetheless, our results suggest that even without regulatory mandates on information provision, market-based alternatives, such as third-party information platforms, can help assuage yield-chasing behavior and improve investment performance. Second, our evidence on investor mistakes and learning emphasizes the importance of financial education, especially for retail investors. Third, mandatory reductions in product complexity and proactive notifications can help overcome investors' inattention or inertia and, therefore, improve their performance.

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Figure 1: Growing Popularity of Decentralized Finance

In this figure, we plot the total value locked (TVL, left axis), a measure of market capitalization, and the number of active platforms (right axis) in the market for decentralized finance. The solid blue line plots total value locked (TVL) in billions of dollars. The dashed red line illustrates the number of DeFi platforms whose TVL is over $1 million. We source these data from DeFiLlama (https://defillama.com/). The figure starts on January 1, 2020 and ends on July 31, 2022.

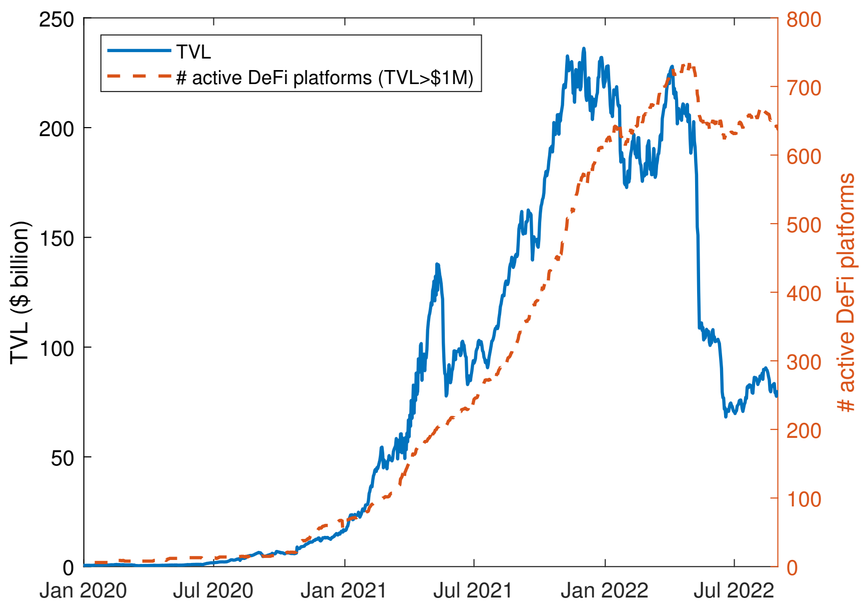
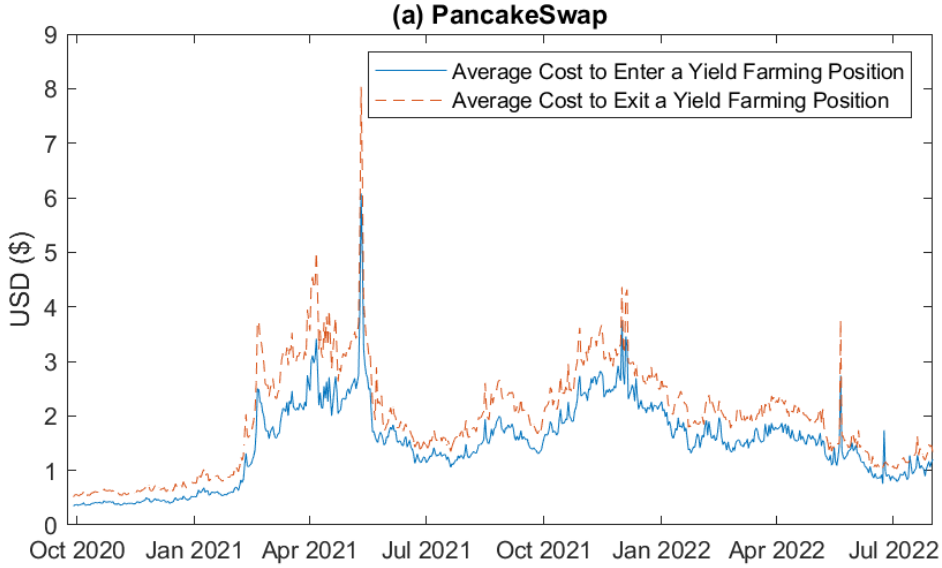


Figure 2: Average Gas Fee to Enter and Exit a Yield Farming Position

In this figure, we compute the average gas fee paid by users on PancakeSwap (Panel (a)) and SushiSwap (Panel (b)) to enter (exit) a yield farming position on each day since the inception of the respective platform. For one round of yield farming, the total gas fee paid is the entry fee on the portfolio formation day, plus the exit fee on the last day of the holding period. For PancakeSwap, the average cost to enter (exit) over all days is \$1.49 (\$1.96). For SushiSwap, the average cost to enter (exit) over all days is \$117.75 (\$178.10).

(a) PancakeSwap



(b) SushiSwap

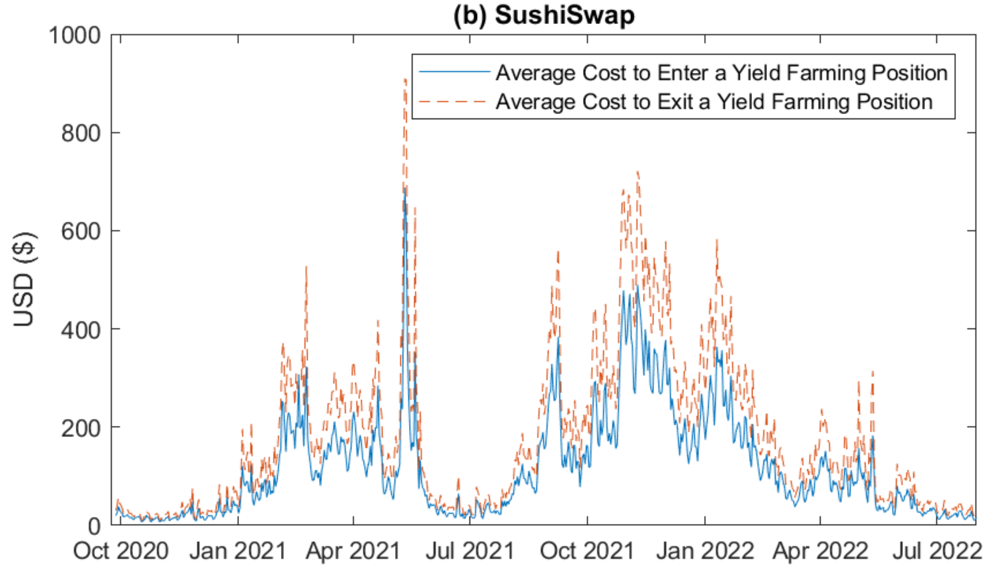


Figure 3: Heuristic Description of Yield Farming in PancakeSwap

This figure provides a heuristic description of yield farming in the decentralized exchange (DEX) PancakeSwap, which is built on the Binance Smart Chain (BSC). In PancakeSwap, investors face a menu of liquidity pools, each one being defined for a pair of cryptocurrencies. Our illustration showcases the USDT–ETH pool as an example. Investors can provide liquidity by "staking" a pair (a, b) of cryptocurrency tokens (in this example, USDT and ETH) in equal dollar amounts ($a \cdot P^{USDT} = b \cdot P^{ETH}$) into the liquidity pool, thereby making these tokens available for USDT–ETH trading by third-party investors. These must pay a trading fee for buying and selling USDT vs. ETH equal to 0.25% of trading volume. Of the 0.25% trading fee, 0.17% is paid to liquidity providers as compensation for their liquidity provision. The other 0.08% is passed on to the Treasury of PancakeSwap's main staking contract and partially used for burning (i.e., buy back and destroy) CAKE tokens, the native governance token of PancakeSwap. The main staking contract issues CAKE tokens on a continuous basis with each block creation in BSC. The trading fees are paid in the currency of the liquidity pool, i.e., USDT vs. ETH. As a liquidity provider, an investor faces buy-and-hold price risk from the price evolution of USDT and ETH as well as downside risk arising from the impermanent loss function, defined by the constant product trading rule of the automated market maker (AMM). The liquidity provision is certified by a liquidity token (i.e., the LP token), which can be staked into a USDT–ETH yield farm specific to the USDT-ETH currency pair. The passive income in the yield farm is earned in CAKE. The number of CAKE tokens distributed across yield farms depends on a farm multiplier that we describe in Section 2. This farm multiplier may change over time following a collective vote by all owners of CAKE tokens.

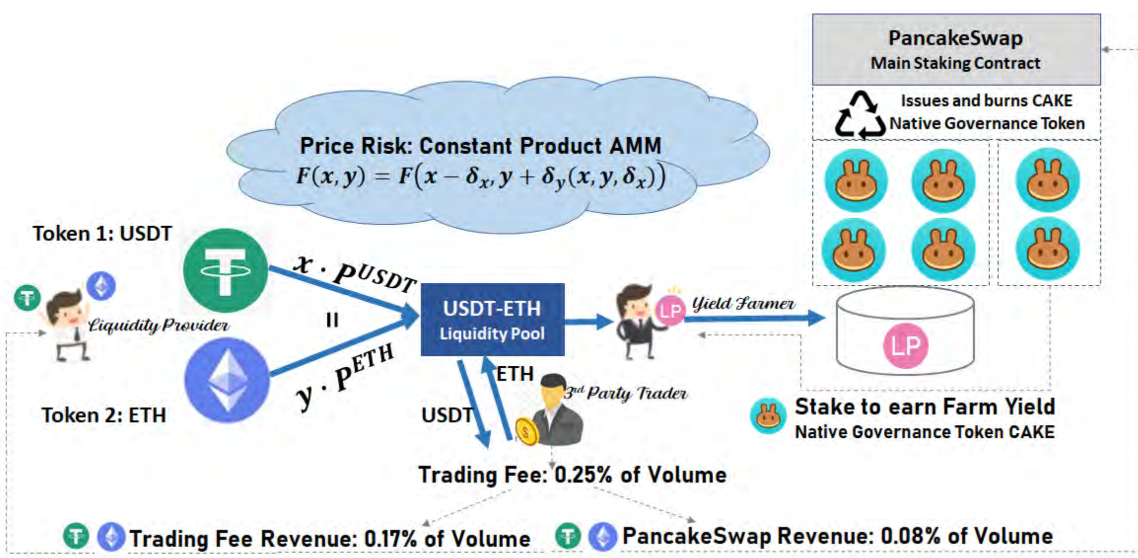
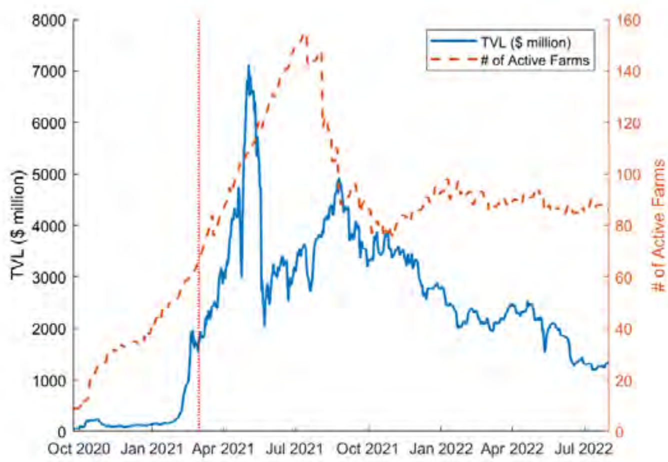


Figure 4: Yield Farm Activity

In Panel (a) of this figure, we plot the number of active farms and Total Value Locked (TVL) in $million at a weekly frequency during our sample period. On the right axis, we provide the time series of active farms. We define active farms as those whose yield multipliers are larger than 0, implying that investors who stake LP tokens in these farms receive non-negative yields. On the left axis, we plot TVL of active farms, or the amount of LP tokens deposited for yield farming. The vertical axis is in millions of USD. In Panel (b) of this figure, we illustrate the Google search intensity for the word, "PancakeSwap," and the number of active farmers in PancakeSwap. We download the Google search intensity for the word, "PancakeSwap," and calculate the monthly average search intensity. Then, we normalize it by the maximum monthly average search intensity so that the index is 100 at its maximum. The dotted blue line (left axis) plots the normalized monthly average of the search intensity. Google search data are available at https://trends.google.com/trends/explore?q=PancakeSwap. The solid red line (right axis) plots the number of active farmers, where an active farmer is defined to be an investor whose balance in yield farms is positive. The figures start on September 23, 2020 and end on July 31, 2022.

(a)



(b)

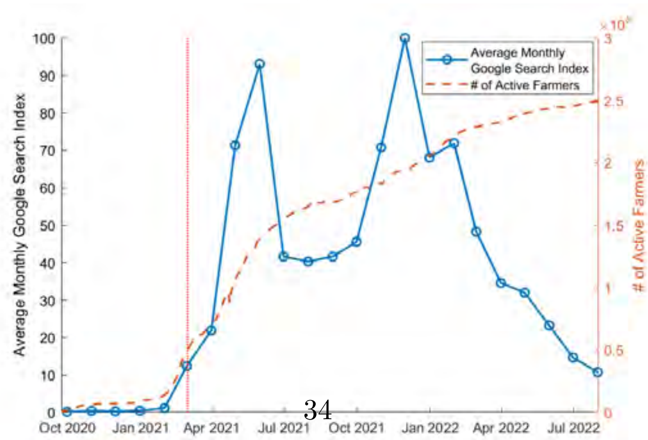


Figure 5: Offered Farm Yields

In this figure, we plot the annualized farm yields offered to yield farmers. We provide the historical annualized offered farm yields (in %) between March 1, 2021, and July 31, 2022. The solid blue line indicates the median annualized offered farm yield. Dark and light shaded areas represent the interquartile range, as well as the 10th and 90th percentiles of the yield farm distribution, respectively.

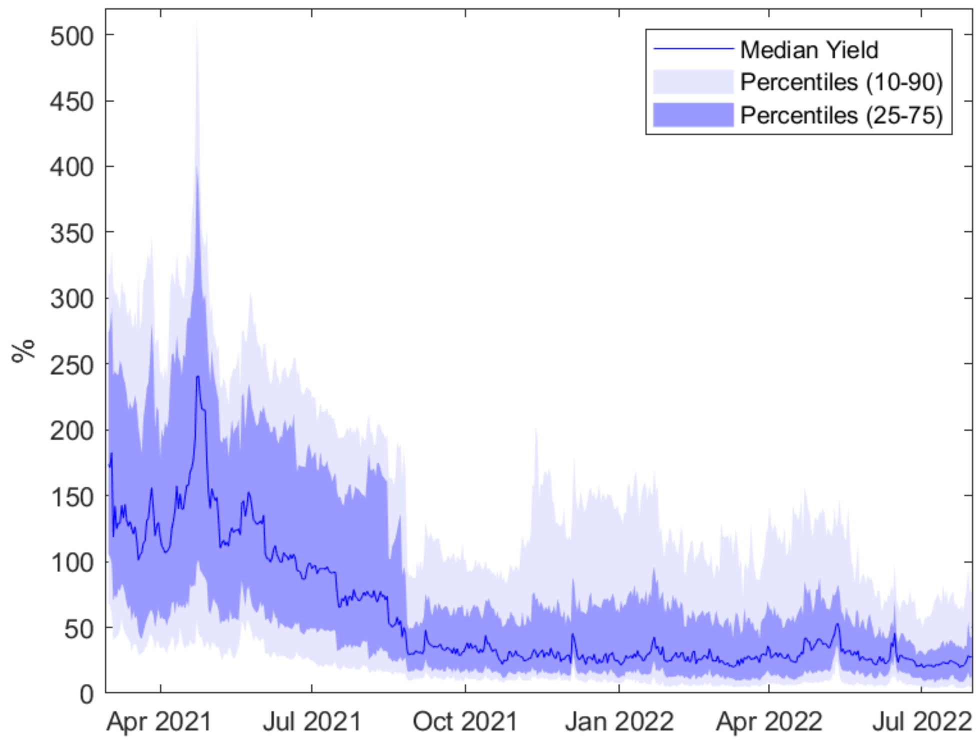


Figure 6: Migration of PancakeSwap Platforms

In this figure, we show the amount of outstanding liquidity in obsolete liquidity pools after two technical updates in the PancakeSwap platform. In Panel (a), we plot the total value locked in liquidity pools and their associated yield farms in PancakeSwap v1 with their equivalent counterpart yield farms available in PancakeSwap v2. On April 24, 2021, farms corresponding to liquidity pools in PancakeSwap v1 stopped providing farm yields. PancakeSwap encouraged farmers to move their liquidity to the corresponding counterpart farms available in PancakeSwap v2 so that the existing yield farmers could continue to earn farm yields. The solid blue line in Panel (a) indicates the total value locked of unmigrated assets that remained in the liquidity pools associated with PancakeSwap v1. In Panel (b), we examine the outstanding liquidity staked in the old PancakeSwap staking contract, following the contract's upgrade from v1 to v2 on April 20, 2022. Upon this migration, LP tokens staked in the old staking contract ceased to be eligible for earning yields. PancakeSwap advertised through Twitter and other means that users should unstake from the v1 contract and re-stake in the new v2 contract.

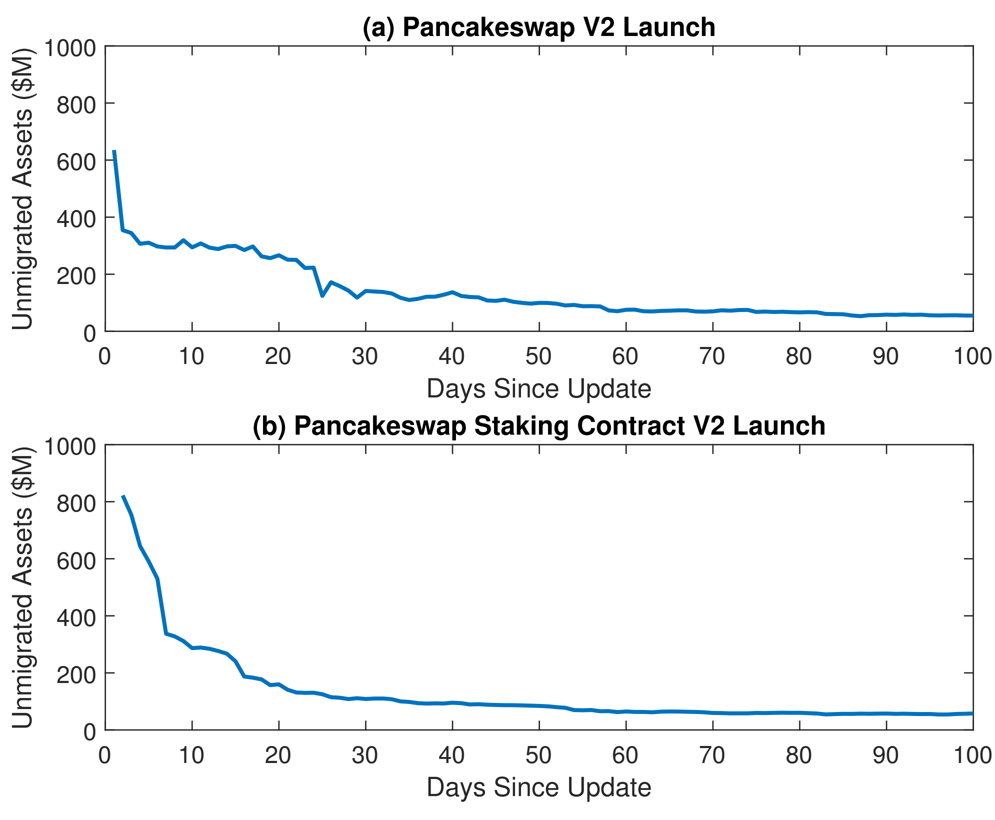


Figure 7: Staking Ratio of LP Tokens

In this figure, we plot the ratio of LP tokens staked in active yield farms listed in PancakeSwap, relative to the total number of LP tokens distributed as rewards for liquidity provision in the liquidity pools. Thus, the LP staking ratio is defined as the number of LP tokens of a liquidity pool staked in its corresponding farm, divided by the total number of outstanding LP tokens for the liquidity pool. The solid blue line indicates the median staking ratio. Dark and light shaded areas represent the interquartile range, as well as the 10th and 90th percentiles of the yield farm distribution, respectively.

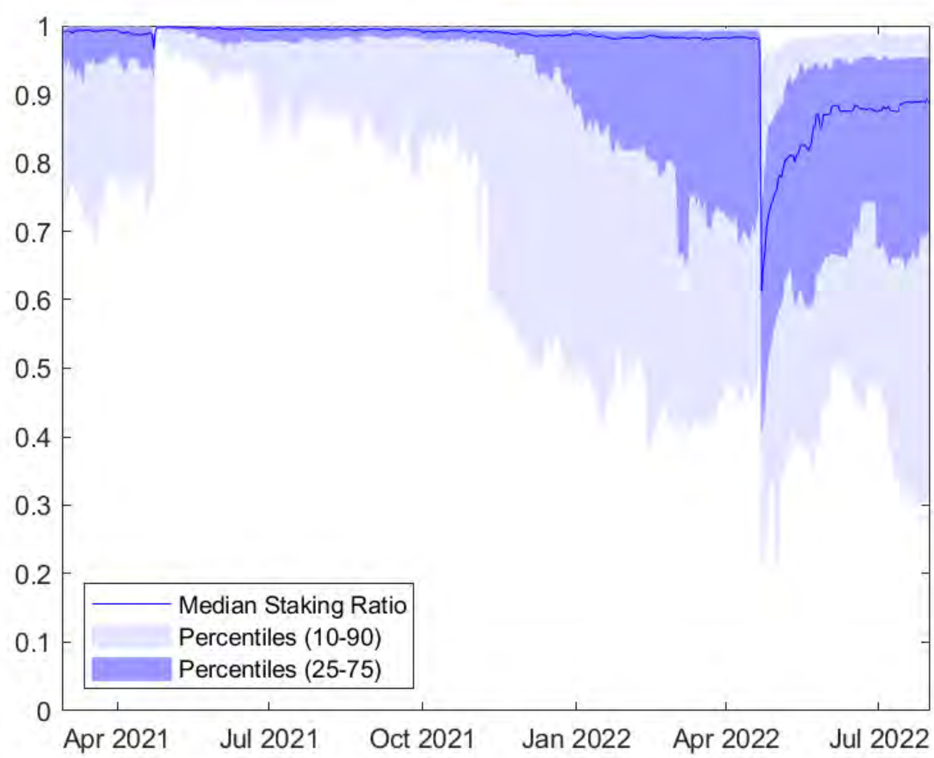


Figure 8: Yield Farming Return Decomposition

In this figure, we plot each component of daily value-weighted returns across yield farms after sorting the farms each week into quintiles based on the magnitude of their in-sample offered yield. For each farm, we compute the daily capital gain, impermanent loss, trading fee, and realized yield during its listing period. Then, we take the average of each component across farms using the size of each farm as weight. In Panels (a) to (d), the blue bars illustrate the average capital gain, impermanent loss, trading fee, and realized yield. The red error bars plot their associated 95% confidence intervals.

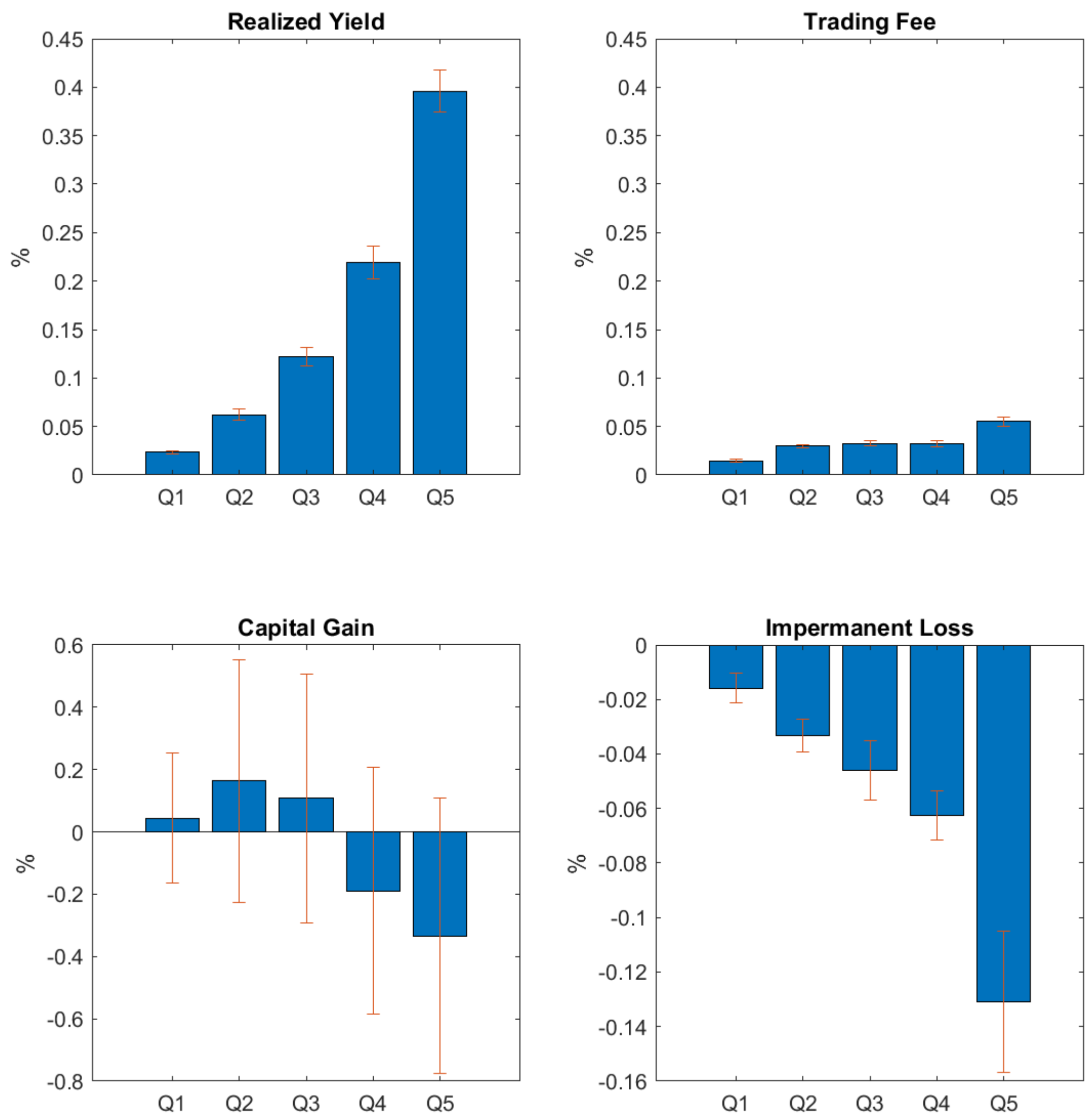


Figure 9: Risk-Adjusted Returns from Yield Farming

In this figure, we plot average risk-adjusted returns (i.e., alphas) and their associated 95% confidence intervals for different trading strategies. In Panel (a), we compare the performance of yield farming to that of liquidity mining without considering trading frictions. On each day, we sort farms into quintiles based on their in-sample offered farm yields. In each quintile, we form value-weighted portfolios by using size of the liquidity pools as weights. A yield farming strategy is a strategy in which investors not only earn trading fee revenue but also farm yields, whereas investors that restrict themselves to liquidity mining can only earn trading fee revenue. We estimate alphas from a three factor model based on the work of Liu, Tsyvinski, and Wu (2019) and also account for the performance of BNB. The blue (red) circle and the associated bar display alphas and their 95% confidence intervals for yield farming (liquidity mining) without considering frictions. In Panel (b), we follow a similar procedure but provide alphas for yield farming strategies without trading frictions, yield farming strategies with frictions including gas fees, trading fees, and price impact, and yield farming strategies considering not only the frictions but also investor mistakes.

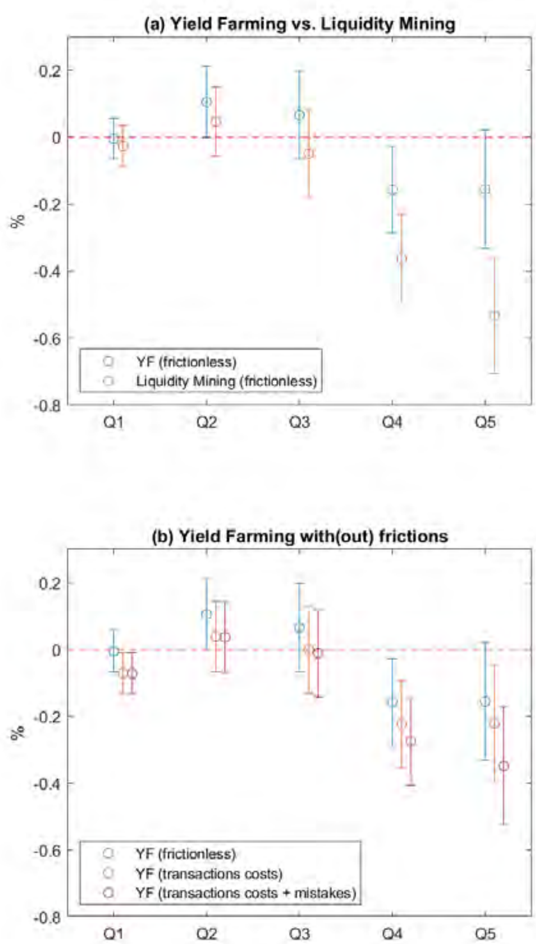
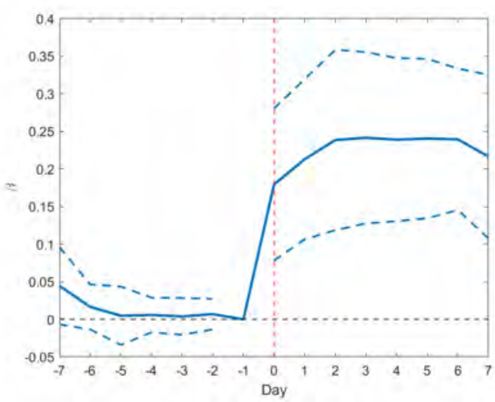


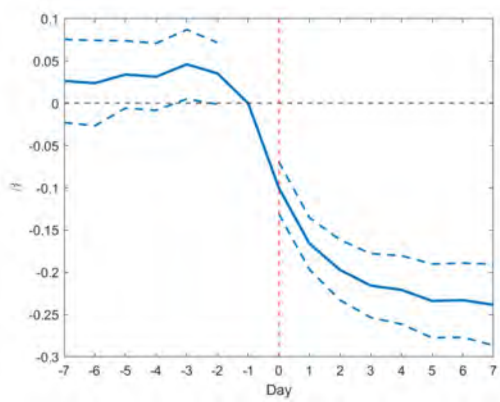
Figure 10: The Impact of Farm Multiplier Changes on Farm Flows

In this figure, we illustrate how changes in the CAKE allocation multipliers, $\Delta m_{i,t}$, affect flows to the farm. In Panels (a) and (b), we measure inflows net of any growth due to an increase in the market capitalization associated with an increase in prices as in Equation (11), such that $Flow_{t,t+h} = \left(L_{t+h} - L_t \times R^*_{t,t+h}\right)/L_t$, where $R^*_{t,t+h}$ corresponds to the yield farm return defined in Equation (8) and L_t denotes the aggregate value of a pool's liquidity. In Panels (c) and (d), we measure inflows as the net token growth, i.e., $Flow_{t,t+h} = (\#LP\ tokens_{t+h}/\#LP\ tokens_t) - 1$. We are interested in changes in flows that are driven by active decisions of a PancakeSwap platform owners while there are no significant changes to the multipliers of other farms, that is $\Delta m_{i,t} \neq 0$ with $|\frac{dM_t}{M_t}| \leq 0.15$. We identify such 511 cases, among which 50 cases are associated with an increase in $m_{i,t}$, and 461 cases are associated with a decrease in $m_{i,t}$. We then compare the change in flows to the treated farms relative to those to the non-treated farms. Specifically, we plot the difference-in-differences coefficients β_k from a regression $Flow_{t,t+7} = \alpha + \sum_{k=-7,k\neq -1}^{k=7} \beta_k I\{m = k\} \times Treatment_i + Event \times FarmFE + DayFE + \varepsilon_{i,t+m}$, where $Flow_{t,t+7}$ is defined as either $Flow_{t,t+7} = log(\frac{outstanding\ LP\ tokens_{i,t+m}}{outstanding\ LP\ tokens_{i,t}})$ or $Flow_{t,t+7} = log(\frac{size\ of\ pool_{i,t+m}}{size\ of\ pool_{i,t}})$. We cluster the standard errors at the farm and date levels. Panels (a) and (c) are event studies for $\Delta m_{i,t} > 0$ while Panels (b) and (d) are event studies for $\Delta m_{i,t} < 0$.

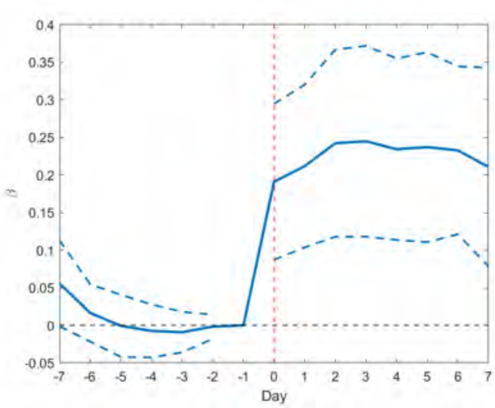
(a) $\Delta m_{i,t} > 0$



(b) $\Delta m_{i,t} < 0$



(c) $\Delta m_{i,t} > 0$



(d) $\Delta m_{i,t} < 0$

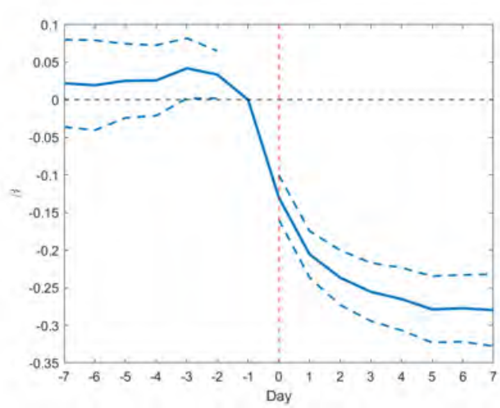


Table 1: Snap Shot of Yield Farms in PancakeSwap

In this table, we report information about the 10 largest farms in PancakeSwap in terms of total value locked (TVL, Panel A) or offered farm yield (Panel B) on August 1, 2022. For each farm, defined by a unique cryptocurrency pair, we provide information on the start date of a farm, the annualized offered farm yield (in %), and total value locked (TVL, in $ million). Panel A lists the 10 largest famrs in terms of TVL. Panel B lists the 10 largest farms in terms of offered farm yield.

Panel A: By TVL

Farm Rank	Cryptocurrency Pair	Start Date	TVL ($ million)	Offered Farm Yield (%)
1	USDT-BUSD	10/1/2020	$187.20M	1.29%
2	WBNB-BUSD	9/23/2020	$169.27M	5.67%
3	CAKE-WBNB	9/23/2020	$168.18M	20.92%
4	USDT-WBNB	10/13/2020	$158.66M	3.21%
5	USDC-BUSD	1/12/2021	$108.74M	0.80%
6	USDT-USDC	6/28/2021	$53.95M	1.69%
7	ETH-WBNB	10/6/2020	$53.06M	4.13%
8	BTCB-WBNB	10/6/2020	$45.01M	4.89%
9	BTCB-BUSD	4/29/2021	$43.62M	4.94%
10	TUSD-BUSD	5/31/2021	$36.54M	0.24%
...	...	...	...	...
86	GMI-WBNB	3/30/2022	$0.12M	70.37%

Panel B: By Offered Farm Yield

Farm Rank	Cryptocurrency Pair	Start Date	TVL ($ million)	Offered Farm Yield (%)
1	TRIVIA-WBNB	7/7/2022	$0.88M	113.17%
2	OLE-BUSD	7/8/2022	$1.26M	108.81%
3	XWG-USDC	11/5/2021	$0.68M	86.25%
4	RPG-BUSD	10/12/2021	$1,12M	81.46%
5	HIGH-BUSD	12/23/2021	$1,16M	73.52%
6	GMI-WBNB	3/30/2022	$0.12M	70.37%
7	FINA-BUSD	11/3/2021	$0.40M	68.70%
8	BCOIN-WBNB	1/12/2022	$0.24M	66.63%
9	CAKE-FROYO	3/25/2022	$0.74	56.19%
10	RACA-BUSD	1/28/2022	$5.78M	50.45%
...	...	...	...	...
86	TUSD-BUSD	5/31/2021	$36.54M	0.24%

Table 2: Determinants of Farm Yields driven by Platform Governance

In this table, we study the determinants of farm yield changes associated with active platform governance ($\Delta y^m_{i,t+1}$), i.e., the component of farm yield changes associated with changes in the farm yield multiplier m. This is computed as the product between the current yield level and the percentage change of the yield multiplier, i.e., $\Delta y^m_{i,t+1} = y_{i,t} \times \frac{\Delta m_{i,t+1}}{m_{i,t}}$. In columns (1) and (2), the dependent variable is the change in yield that is driven by platform governance. In columns (3) and (4), the dependent variable is $Delisting_{t+1}$, an indicator variable equal to one if a farm is delisted on the subsequent day and zero otherwise. Independent variables include *Capital Gain*, *Impermanent Loss*, *Trading Fee*, *Realized Yield* over the last 7 days, and *Log(Liquidity)*, which is the logarithm of the dollar value of aggregate liquidity in a pool. Standard errors are clustered at the farm level. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	$\Delta y^m_{i,t+1}$		Delisting_{t+1}	
Capital $\text{Gain}_{t-7,t}$	0.0067	0.0052	0.0050*	0.0036
	(0.0060)	(0.0065)	(0.0027)	(0.0027)
Impermanent $\text{Loss}_{t-7,t}$	0.0877	0.0866	-0.0031	-0.0040
	(0.0607)	(0.0611)	(0.0114)	(0.0111)
Trading $\text{Fee}_{t-7,t}$	0.3279***	0.3826***	-0.2011***	-0.1811***
	(0.1065)	(0.1057)	(0.0665)	(0.0650)
Realized $\text{Yield}_{t-7,t}$	-0.5957***	-0.6516***	0.0545	0.0181
	(0.0873)	(0.1019)	(0.0341)	(0.0406)
log(Liquidity_t)	-0.0009**	-0.0012**	-0.0019***	-0.0026***
	(0.0004)	(0.0005)	(0.0003)	(0.0003)
log(Farm Age_t)	-0.0024***	-0.0013	0.0003	0.0018***
	(0.0007)	(0.0008)	(0.0004)	(0.0004)
Day FE	No	Yes	No	Yes
N	48,350	48,350	48,628	48,628
adj. R^2	0.003	0.003	0.003	0.005

Table 3: Yield Farming Behavior

In this table, we report statistics that describe the behavior of yield farmers. The presented statistics are all farmer-level variables. In Panel A, we present aggregate summary statistics. *No. Farms* is the number of farms in which a yield farmer invests. *Investment Size* is the dollar value of LP tokens. *Holding Period (Days)* is the number of days during which a farmer keeps an investment in a farm. *Offered Yield* is the time-weighted average of the offered yield at the beginning of the holding period. *Daily Return* is the time-weighted average of the annualized holding period returns for each user. *Staking Ratio* is the average of the staking ratios of farms in which a farmer invested where the staking ratio of a farm is the average daily staking ratio during a farmer's holding period. In Panel B, we separate yield farmers into quintiles by *Investment Size*.

Panel A: Yield Farmers

Variable	**Average**	**Inv. Size Weighted Avg.**	**SD**	**p25**	**p50**	**p75**	**OBS**
No. Farms	2.6363	4.7687	3.9766	1.0000	1.0000	3.0000	439,639
Investment Size ($)	7,732.14		231,923.65	40.00	179.66	869.44	439,639
Holding Period (Days)	30.9191	7.7183	64.3387	0.7086	3.4648	24.7954	439,639
Offered Yield	1.1002	0.5976	1.0534	0.4013	0.6995	1.4569	439,639
Daily Return	0.0011	0.0011	0.0569	-0.0035	-0.0005	0.0049	439,639
Staking Ratio	0.8422	0.9745	0.3385	0.9790	0.9992	0.9999	439,639

Panel B: Yield Farmers by Investment Size

	No. Farms	**Investment Size($)**	**Holding Period(Days)**	**Offered Yield**	**Daily Return**	**Staking Ratio**	**OBS**
Quintile 1							
Average	1.7430	10.96	61.3089	0.9428	0.0000	0.6211	87,928
SD	(1.6136)	(7.9)	(92.4108)	(1.0317)	(0.0267)	(0.4580)	
Quintile 2							
Average	1.8986	59.08	39.3546	1.0461	0.0006	0.8144	87,928
SD	(2.0561)	(21.47)	(70.5432)	(1.0567)	(0.0481)	(0.3581)	
Quintile 3							
Average	2.3041	187.72	26.5402	1.1382	0.0011	0.8821	87,927
SD	(2.896)	(62.03)	(56.2208)	(1.0574)	(0.0286)	(0.292)	
Quintile 4							
Average	2.9168	665.36	17.5689	1.2169	0.0020	0.9306	87,928
SD	(3.8799)	(259.88)	(41.4067)	(1.0746)	(0.1083)	(0.2234)	
Quintile 5							
Average	4.3190	37,737.51	9.8229	1.1571	0.0018	0.9629	87,928
SD	(6.6658)	(517,512.29)	(25.8638)	(1.024)	(0.0246)	(0.1613)	

Table 4: Yield Farming Performance

This table reports the summary statistics for daily percentage excess returns from yield farming investment strategies. We take the perspective of a U.S. investor and report all information from the perspective of an initial USD investment. Excess returns are computed relative to the three-month U.S. Treasury bill secondary market rate sourced from the Federal Reserve Bank of St.Louis. All returns are value-weighted using the pools' aggregate liquidity as weighing factors. The column (OBS) reports the number of observations. We report the mean return ($Mean$), the standard deviation, 25th percentile, median, 75th percentile, skewness, and kurtosis of the yield farming strategies, as well as the serial correlation, the Sharpe ratio, the alpha from a three factor model based on the work of Liu, Tsyvinski, and Wu (2019) augmented with the return of BNB, the native token of BSC, and the t-statistic for alpha from the three-factor+BNB regressions. The sample period is March 1, 2021 to July 31, 2022.

Panel A: Daily												
Strategy	**Mean**	**SD**	**p25**	**Median**	**p75**	**Skew**	**Kurt**	**AC1**	**SR**	α	**t-stat of** α	**OBS**
Yield Farming Related Strategy												
Yield Farming	0.0015	0.0360	-0.0144	0.0023	0.0167	-0.3445	13.5692	-0.1638	0.0405	0.0002	0.6822	518
Buy and Hold (Capital Gains)	0.0007	0.0358	-0.0150	0.0018	0.0162	-0.2925	13.1318	-0.1681	0.0209	-0.0005	-1.5154	518
Liquidity Mining	0.0007	0.0358	-0.0148	0.0019	0.0162	-0.3959	13.5994	-0.1675	0.0197	-0.0005	-1.6229	518
Benchmark Strategy												
Crypto Market Return	-0.0002	0.0439	-0.0218	0.0049	0.0239	-0.7872	8.6170	-0.1026	-0.0052	0.0000	0.0000	518
BTC	-0.0005	0.0383	-0.0219	-0.0005	0.0200	-0.0654	4.7533	-0.0474	-0.0140	-0.0011	-1.2642	518
ETH	0.0016	0.0509	-0.0283	0.0023	0.0303	-0.0305	5.9682	-0.0522	0.0321	0.0009	0.9421	518
BNB	0.0021	0.0539	-0.0246	0.0013	0.0303	-0.0093	8.9147	-0.1232	0.0380	0.0000	0.0000	518
S&P 500 Index	0.0003	0.0116	-0.0059	NaN	0.0075	-0.3856	4.0643	-0.0157	0.0300	0.0004	0.7866	358
Panel B: Weekly												
Strategy	**Mean**	**SD**	**p25**	**Median**	**p75**	**Skew**	**Kurt**	**AC1**	**SR**	α	**t-stat of** α	**OBS**
Yield Farming Related Strategy												
Yield Farming	0.0105	0.0911	-0.0343	0.0076	0.0500	-0.4847	7.4880	0.1288	0.1147	0.0031	1.4936	74
Buy and Hold (Capital Gains)	0.0056	0.0904	-0.0380	0.0029	0.0470	-0.5332	7.6623	0.1158	0.0616	-0.0018	-0.8705	74
Liquidity Mining	0.0053	0.0898	-0.0372	0.0038	0.0473	-0.6369	7.8369	0.1099	0.0586	-0.0020	-0.9429	74
Benchmark Strategy												
Crypto Market Return	-0.0001	0.1110	-0.0764	0.0003	0.0800	-0.6809	4.6258	0.0948	-0.0005	0.0000	0.0000	74
BTC	-0.0047	0.0906	-0.0682	-0.0045	0.0479	-0.3788	2.9578	0.1803	-0.0516	-0.0022	-0.3390	74
ETH	0.0109	0.1298	-0.0771	-0.0032	0.0985	-0.1422	3.5841	0.1624	0.0840	0.0129	1.6482	74
BNB	0.0144	0.1402	-0.0636	0.0145	0.0829	-0.0877	6.3156	0.0606	0.1029	0.0000	0.0000	74
S&P 500 Index	0.0016	0.0239	-0.0131	0.0038	0.0155	0.1871	3.9293	-0.0739	0.0686	0.0026	1.0492	74

Table 5: Determinants of Yield Farmers' Return Performance

In this table, we study the determinants of the risk-adjusted return performance at the farmer level. The dependent variable, *Avg, Daily Ret. (w/o Frictions)*, is the time-weighted average daily holding period return for each farmer without considering trading frictions such as trading fees, gas fees, and price impact. *Avg. Daily Ret. (Frictions)* is the time-weighted average daily holding period return for each farmer considering the trading frictions. *Avg. Offered Yield* is the time-weighted average of the offered farm yield at the beginning of each holding period. *log(Avg. # of monthly Rebalancings)* is the average number of rebalancings in a month. *# of Farms* is the number of unique farms to which an investor provides liquidity. *Avg. Size of Investment* is the time-weighted average of the USD value at the beginning of an investor's holding period. *Avg. Staking Ratio* is the time-weighted average of the staking ratio of a farmer. We restrict our analysis to farmers whose investment duration is greater than or equal to one day. We include fixed effects for the entry month of the yield farming strategy (*Start Month*), the exit month of a yield farming investment (*End Month*), or the interaction of both. Standard errors are clustered at the first month when a farmer participated in yield farming. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Avg. Daily Ret. (w/o Frictions)			Avg. Daily Ret. (Frictions)		
Avg. Offered Yield	-0.0016**	-0.0018**	-0.0019**	-0.0029***	-0.0022**	-0.0022**
	(0.0007)	(0.0007)	(0.0007)	(0.0008)	(0.0008)	(0.0008)
# of Farms		-0.0000	-0.0001		0.0010***	0.0008***
		(0.0001)	(0.0001)		(0.0003)	(0.0002)
Avg. Size of Investment ($M)		-0.0109*	-0.0106*		0.1268***	0.1258***
		(0.0060)	(0.0058)		(0.0151)	(0.0143)
Avg. Size of Investment^2		0.0114	0.0105		-0.1479***	-0.1478***
		(0.0067)	(0.0066)		(0.0160)	(0.0153)
log(Avg. # of monthly Rebalancings)		0.0004	0.0006		-0.0056***	-0.0046***
		(0.0003)	(0.0003)		(0.0007)	(0.0006)
Avg. Staking Ratio		0.0017	0.0014		0.0195***	0.0184***
		(0.0015)	(0.0016)		(0.0021)	(0.0022)
Start Month	Yes	Yes	No	Yes	Yes	No
End Month	Yes	Yes	No	Yes	Yes	No
Start x End Month	No	No	Yes	No	No	Yes
N	439,639	439,639	439,639	439,639	439,639	439,639
adj. R^2	0.015	0.016	0.019	0.024	0.052	0.061

Table 6: Aggregate Farm Yields and Investor Flows

In this table, we report evidence on the relation between aggregate investor flows and offered farm yields. We regress future farm *Flow*, measured over the next 7 days (a week), on *Offered Farm Yield*, past *Return* on yield farming, *Capital Gain*, *Impermanent Loss*, *Trading Fee Revenue*, and *Realized Yield* over the last 7 days, including control variables consisting of *Past flow*, *Log(Size of Liquidity Pool)*, *Farm age*. The sample period is March 1, 2021 to July 31, 2022. Standard errors are clustered at the farm level. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
		$Flow_{t,t+7}$	
Offered Yield$_t$	0.0541***	0.0537***	
	(0.0098)	(0.0098)	
Return$_{t-7,t}$		0.0368**	
		(0.0149)	
Capital Gain$_{t-7,t}$			0.0196
			(0.0160)
Impermanent Loss$_{t-7,t}$			0.1055
			(0.2903)
Trading Fee$_{t-7,t}$			8.6621***
			(1.1559)
Realized Yield$_{t-7,t}$			2.2648***
			(0.4351)
Controls	Yes	Yes	Yes
Farm FE	Yes	Yes	Yes
Week FE	Yes	Yes	Yes
N	6538	6538	6538
adj. R^2	0.084	0.085	0.087

Table 7: The Role of Learning and Experience in Reaching-for-Yield

In this table, we examine reaching for yield through the relation between *Flow* at the farmer level, measured over the next 7 days (a week) and *Offered Yield*, i.e., the offered farm yield. We further examine the role of learning in explaining the relation between flows by farmers and Offered Yield using the size of yield farming portfolio, investor experience defined as the number of days invested in yield farming, and the number of invested farms. *High Size* is an indicator variable equal to one if an investor's dollar value of the yield farming portfolio is greater than the 75th percentile of the size distribution and zero otherwise. *High Experience (days)* is an indicator variable equal to one if an investor's number of days elapsed since the start of the yield farming investment is greater than the 75th percentile of the distribution and zero otherwise. *High # Farms* is an indicator variable equal to one if the number of farms to which an investor has provided liquidity is greater than the 75th percentile of the distribution and zero otherwise. Standard errors are double clustered at the investor and week level.*,**, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				$Flow_{t,t+7}$			
Offered Yield	0.0148**	0.0168***		0.0147**		0.0201***	
	(0.0068)	(0.0059)		(0.0069)		(0.0061)	
High Size		-0.0384***	-0.0380***				
		(0.0034)	(0.0030)				
Offered Yield× High Size		-0.0035	-0.0042*				
		(0.0033)	(0.0022)				
High Experience (days)				0.0140***	0.0114***		
				(0.0020)	(0.0013)		
Offered Yield× High Exp. (days)				-0.0066**	-0.0044***		
				(0.0029)	(0.0017)		
High # Farms						0.0147***	0.0173***
						(0.0037)	(0.0035)
Offered Yield× High # Farms						-0.0127***	-0.0128***
						(0.0034)	(0.0027)
Farmer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Farm FE	Yes	Yes	No	Yes	No	Yes	No
Week FE	Yes	Yes	No	Yes	No	Yes	No
Farm x Week FE	No	No	Yes	No	Yes	No	Yes
N	9,705,043	9,705,043	9,705,043	9,705,043	9,705,043	9,705,043	9,705,043
adj. R^2	0.281	0.282	0.315	0.281	0.314	0.281	0.314

Table 8: Yieldwatch Experiment: Information Display and Reaching-for-Yield

In this table, we investigate whether information on hidden risks and past performance displayed at YieldWatch.net impacts farmers' reaching-for-yield propensity. $Flow_{t,t+7}$ defines investors' farm flows over the subsequent 7 days. *Yieldwatch* is an indicator variable equal to one after an investor acquires the Yieldwatch token or provides lliquidity to the Watch-BNB liquidity pool, and zero before. *Displayed* is an indicator variable equal to one if a farm is covered by the YieldWatch.net initiative and 0 otherwise. *Offered Yield* is the offered farm yield of a farm. Investor controls include the natural logarithm of the dollar value of the yield farming portfolio of an investor and the natural logarithm of one plus the number of days since the starting date of the yield farming investment. Standard errors are double clustered at the investor and week level. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
					$Flow_{t,t+7}$				log(1+Inv.)	Withdrawal
Offered Yield	0.0148**	0.0339***	0.0182**	0.0193**						
	(0.0068)	(0.0109)	(0.0086)	(0.0084)						
Displayed x Offered Yield		-0.0346**	-0.0151	-0.0158						
		(0.0143)	(0.0103)	(0.0104)						
YieldWatch				-0.0182***	-0.0099*	-0.0151***	-0.0141**	-0.0135**	-0.1284***	0.0084
				(0.0069)	(0.0053)	(0.0053)	(0.0053)	(0.0052)	(0.0346)	(0.0051)
YieldWatch x Offered Yield				0.0003	-0.0043	0.0025	0.0024	0.0031	-0.0147	-0.0006
				(0.0042)	(0.0033)	(0.0034)	(0.0034)	(0.0032)	(0.0237)	(0.0033)
Displayed x YieldWatch				0.0162***	0.0107***	0.0098***	0.0097***	0.0082**	0.2364***	-0.0104***
				(0.0057)	(0.0034)	(0.0034)	(0.0035)	(0.0031)	(0.0362)	(0.0034)
Displayed x YieldWatch				-0.0146***	-0.0105***	-0.0076***	-0.0076***	-0.0074***	-0.1494***	0.0084***
x Offered Yield				(0.0036)	(0.0026)	(0.0025)	(0.0025)	(0.0024)	(0.0232)	(0.0025)
Farmer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Farm FE	Yes	Yes	Yes	Yes	No	No	No	No	No	No
Week FE	Yes	Yes	Yes	Yes	No	No	No	No	No	No
Farm x Week FE	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Investor Controls	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Sample	All	YW	non-YW	All	All	All	All	Size>$10	All	All
Def. of YieldWatch			YW+LP> $\$10^{-6}$				YW+LP> $0		YW+LP> $\$10^{-6}$	
N	9,705,043	592,897	9,109,178	9,705,043	9,705,043	9,705,043	9,705,043	7,844,242	9,680,642	9,705,043
adj. R-sq	0.281	0.300	0.281	0.281	0.314	0.321	0.321	0.325	0.734	0.336

Table 9: APY.Vision Airdrop Experiment: Information Display and Reaching for Yield

In this table, we investigate whether information on hidden risks and past performance displayedby APY.Vision impacts farmers' reaching-for-yield propensity. $Flow_{t,t+7}$ defines investors' farm flows over the subsequent 7 days. *APY.Vision NFT token* is an indicator variable equal to one if an investor holds the randomly allocated APY.Vision NFT token in the wallet and zero otherwise. *Offered Yield* is the offered farm yield. Investor controls include the natural logarithm of the dollar value of the yield farming portfolio of an investor and the natural logarithm of one plus the number of days since the starting date of the yield farming investment. Standard errors are double clustered at the investor and week level. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
		$Flow_{t,t+7}$		
Offered Yield	0.0212***	0.0217***		
	(0.0035)	(0.0035)		
Offered Yield × APY.Vision NFT token		-0.0534**	-0.0529***	-0.0392**
		(0.0211)	(0.0196)	(0.0191)
Farmer FE	Yes	Yes	Yes	Yes
Farm FE	Yes	Yes	No	No
Week FE	Yes	Yes	No	No
Farm x Week FE	No	No	Yes	Yes
Investor Control	No	No	No	Yes
N	427,486	427,486	427,433	427,433
adj. R^2	0.158	0.158	0.173	0.182

A Institutional background

We first provide institutional details on decentralized finance, yield farming, and Binance Smart Chain. We then discuss PancakeSwap and its benefits for studying yield farming.

A.1 Decentralized finance and cryptocurrency yield farming

Decentralized finance (DeFi) corresponds to an emerging ecosystem of protocols and financial applications built on blockchain technology with programmable capacities, such as Ethereum and Binance Smart Chain. Smart contracts on the blockchain execute all transactions automatically, without third-party intervention.

According to DeFi Llama[7], a public dashboard with data on DeFi, the total dollar value locked (TVL) in decentralized financial services, a measure of market capitalization, increased from less than $1 billion in February 2020 to a peak of $214.79 billion on December 27, 2021, and was measured at $72.79 billion on July 31, 2023 (sample end).

Yield farming is a financial service that offers compensation for liquidity provision in sequential steps. Holders of cryptocurrency tokens can deposit their tokens in liquidity pools, which issue and award 'LP tokens' (a.k.a. 'flip tokens') that certify the liquidity provision and represent a fractional claim on the pool's liquidity. These 'LP tokens' can be deposited in yield farms which promise farm yields as passive source of income, paid to yield farming investors in the governance token currency of the PancakeSwap platform, called CAKE.

Intuitively, yield farming is a decentralized variant of securities lending, although the chain of transactions is more complex. By offering yield enhancements for liquidity provisions, platform owners (i.e., the aggregate ownership of the native governance tokens) can incentivize liquidity provision. This impacts a platform's long-term success, since, in a decentralized exchange, a more liquid pool implies a smaller price impact per trade, which is desirable for traders. In a lending pool, greater pool liquidity may drive down borrowing costs, which can attract more borrowers. Since the platform owners can vote on the reallocation of yields across farms, they can also channel liquidity to the pools of their choice and encourage adoption of the corresponding tokens.

Headline rates for promised investment performance can be large. Annual yields north of 100% are commonly observed. There exists, however, significant cross-sectional heterogeneity in promised yields across the farms, as we show in Figure 5.

While yield farming is marketed as being simple through means of engaging platforms, cartoons, rockets, and emojis, both executing a yield farming investment and understanding

[7] https://defillama.com/home. See also Figure 1.

its payoffs is complex. The strategy involves a sequence of 12 transactions in three different underlyings. Return performance is highly non-linear and comes from 4 components: realized farm yield from staking LP tokens, capital gains from cryptocurrencies staked to liquidity pools, fees from trading by third-party investors in liquidity pools, and impermanent losses driven by relative price changes of the cryptocurrencies locked in liquidity pools. Thus, the complexity of yield farming resembles obfuscated investment strategies observed in complex structured derivative products (e.g. Henderson and Pearson, 2011; Célérier and Vallée, 2017; Egan, 2019; Henderson, Pearson, and Wang, 2020; Shin, 2021).

We focus our analysis on yield farms listed on PancakeSwap, a popular automated market maker that ranks second in the league tables of decentralized exchanges offering cryptocurrency lending services during our sample period. Transaction costs in PancakeSwap are significantly lower than in other popular decentralized exchanges like Uniswap (Figure 2). This lowers the barriers to entry for retail investors, who are active investors in yield farms.

The combination of low barriers to entry, a large number of service providers, and complex investment strategies promising high returns with significant downside risk raises concerns about the protection of retail investors in cryptocurrency markets. These concerns are underscored by the aggressive stance taken by the U.S. Securities and Exchange Commission, who have become increasingly vocal about enhanced regulatory scrutiny of decentralized financial services (e.g., Gensler, 2021). Our work is intended to inform this ongoing debate by means of assessing the risk and return characteristics of yield farming strategies.

A.2 Binance Smart Chain

Binance Chain was launched by Binance in April 2019. Its main goal is to facilitate faster decentralized trading. The largest and most well-known decentralized application on the Binance Chain is Binance DEX. Despite its success in DEX trading, Binance DEX embeds several limitations that limit its flexibility. For example, to guarantee high throughput, the application does not support smart contracts, which require significant computational resources. This can, therefore, easily congest the entire network.

Binance Smart Chain (BSC) is a public blockchain running in parallel to the Binance Chain. Distinctive features of BSC include smart contract functionality and compatibility with the Ethereum Virtual Machine (EVM). BSC was launched for the dual purpose of maintaining the high throughput of Binance Chain and allowing the integration of smart contracts.

In the BSC ecosystem, Binance Coin (BNB) is used as the basic medium of exchange, similar to Ether (ETH) in the Ethereum network. End users pay their transaction fees in BNB and use BNB to trade cryptocurrencies on decentralized exchanges deployed on BSC.

The primary advantages of BSC are its high throughput rate and low transaction fees. BSC updates its blocks approximately every 3 seconds, using a variant of the Proof-of-Stake consensus algorithm. More specifically, it employs Proof-of-Staked Authority (or PoSA), in which participants stake BNB to become validators of the blocks. As of September 5, 2021, the platform's 21 active validators play an important role in keeping the network running.

According to the CEO of Binance, Changpeng Zhao, BSC allows for a maximum of 300 transactions per second.[8] In contrast, Ethereum processes up to a maximum of 16 transactions per second. The current version of BSC is, thus, about 20 times faster than Ethereum.

BSC transaction fees are also lower than those of Ethereum. As of September 5, 2021, the average transaction fee charged by BSC is $0.399, whereas it is $5.842 for Ethereum. The difference in fees widens significantly when the Ethereum network becomes congested. For example, the average Ethereum transaction fee was $71.72 on May 19, 2021, whereas the maxium daily average transaction fee of BSC was $1.08 on May 11, 2021.[9]

These advantages make BSC one of the strongest competitors to Ethereum. As of October 9, 2021, total transactions on BSC have outpaced those on Ethereum, despite Ethereum preceding BSC by almost 4 years.[10] Binance Coin is currently the third largest cryptocurrency in terms of market capitalization, following Bitcoin and Ethereum.

Another important feature of the BSC is its EVM-compatibility. This implies that the chain can benefit from the rich universe of Ethereum tools and DApps. For example, project developers can easily transition their projects between Ethereum and BSC. The growth of PancakeSwap is in part spurred by the popularity of Uniswap, which is built on the Ethereum blockchain. This is because a significant part of Uniswap's source code was directly ported to BSC to build an initial version of PancakeSwap.

A.3 PancakeSwap

PancakeSwap is the largest decentralized exchange built on the Binance Smart Chain. Unlike traditional financial markets employing market-maker systems based on limit order books, PancakeSwap employs a new system called automated market maker (AMM), implemented through smart contracts. For details on the mechanism of AMMs and their pricing schedules, see, for example, Lehar and Parlour (2021).

In PancakeSwap, multiple liquidity pools are deployed to facilitate trading of pairs of cryptocurrencies. Investors deposit an equal dollar amount of two cryptocurrencies into a liquidity pool, and thereby become liquidity providers. In exchange for the liquidity provision, the liquidity provider receives LP tokens to certify their liquidity provision.

[8] https://twitter.com/cz_binance/status/1361596039698944000.

[9] https://ycharts.com/indicators/ethereum_average_transaction_fee and https://ycharts.com/indicators/binance_smart_chain_average_transaction_fee_es

[10] Ethereum launched on July 2015, whereas Binance Smart Chain launched on April 2019.

In return for their liquidity provision, liquidity providers receive a fixed proportion of trading volume registered in a pool. Third-party trades on PancakeSwap are charged a fee proportional to 0.20% and 0.25% of the trading volume in versions v1 and v2, respectively, of which 0.17% is added to the liquidity pool associated with the corresponding cryptocurrency pair. Despite the earnings potential, investors are also exposed to price risk associated with impermanent losses, which are driven by return divergence across a pool's tokens.

In addition to the income generated from trading fees, liquidity providers can passively earn income if the liquidity pool has a corresponding yield farm. Such income, called farm yield, is earned by staking the LP tokens to the corresponding yield farm in PancakeSwap's main staking contract. Farm yields are paid in PancakeSwap's governance token, called CAKE.

PancakeSwap migrated from version 1 (v1) to version 2 (v2) on April 24, 2021. This transition was implemented to enhance the platform's technological and security features. Both versions have co-existed since then. In April 2023, PancakeSwap announced another migration to version 3. We study yield farming for versions v1 and v2.

In PancakeSwap, the CAKE token serves as the governance token for the Decentralized Autonomous Organization (DAO). CAKE token holders can cast votes to influence the future development of the platform or to reallocate CAKE tokens across farms.

A.4 PancakeSwap as an ideal laboratory to study yield farming

Many decentralized trading venues offer passive income opportunities through yield farming. Among DeFi platforms, Uniswap and PancakeSwap consistently lead the league ranks in terms of trading activity in our sample period. The key difference between both platforms is that Uniswap (PancakeSwap) runs on the Ethereum blockchain (Binance Smart Chain).

Several features of PancakeSwap make it particularly appealing for the study of yield farming. First, and most importantly, Uniswap does not offer yield farms. Liquidity providers in Uniswap liquidity protocols receive a fixed fraction of trading volume as their reward. However, there are no farms in Uniswap to which liquidity providers can stake their LP tokens to earn additional income through yield farming.

Second, PancakeSwap is one of the largest decentralized exchanges. In Table A.3, we report the daily trading volume for the ten largest decentralized exchanges as of October 9, 2021. The largest DEX is dYdX, which specializes in derivatives trading. Augustin, Rubtsov, and Shin (2021) discuss the market for regulated and unregulated cryptocurrency derivatives.

The second largest DEX is PancakeSwap (v2) with a 24-hour trading volume of $1,185.34 on October 9, 2021. PancakeSwap (v2) is followed by Uniswap (v3), 1inch Liquidity Protocol, Uniswap (v2), and SushiSwap. The trading volume on PancakeSwap (v2) is comparable to the combined trading volumes of Uniswap (v3) and Uniswap (v2). While the rank tables vary over time, PancakeSwap is among the leading DEXs focused on spot trading.

Third, the low transaction cost and high transaction speed of Binance Smart Chain make PancakeSwap easily accessible to retail investors. As discussed in Section A.2, transaction costs of the Binance Smart Chain are an order of magnitude lower than those of Ethereum. Yet, the transaction speed of Binance Smart Chain is faster than that of Ethereum. According to DappRadar, PancakeSwap registered 435,130 active users on October 24, 2021, in contrast to 47,730 active users recorded for Uniswap.[11] The number of active users is highest for PancakeSwap among all decentralized applications built on all blockchains tracked by DappRadar. In light of the growing concern about the risks of complex yield farming strategies for retail investors, our study has policy implications for investor protection.

Fourth, PancakeSwap features a large cross-section of yield farms with heterogeneity in yield farming opportunities. This provides important variation to help understand the risk and return characteristics of yield farms. We study 262 unique yield farms that were active between the inception of PancakeSwap on September 23, 2020 and July 31, 2022.

[11] DappRadar: https://dappradar.com/rankings

B Derivation of conceptual framework

In this section, we provide supporting explanations for the conceptual framework and detailed steps in the derivation of Equations (8) and (10). In Section B.1, we ignore frictions, which we cover in Section B.2.

B.1 Capital gains and impermanent loss

To help build intuition, we explain all derivations using a specific example. We assume the existence of a liquidity pool with a cryptocurrency pair $(A, B) \equiv (BNB, BUSD)$. Thus, this liquidity pool covers the BNB-BUSD cryptocurrency token pair, where BUSD is a stablecoin pegged to USD. Assuming a BNB–BUSD exchange rate of 100, a liquidity provider deposits 1 BNB and 100 BUSD at time t to the liquidity pool. After the liquidity provision, the aggregate liquidity in the pool is 10 BNB and 1,000 BUSD, implying that the liquidity provider's fractional owenrship is 10%. After h days, at time $t + h$, the BNB price increases to 200 BUSD. The liquidity provider withdraws his/her liquidity.

The constant product model imposes that the product of the aggregate number of tokens in the pool is equal to constant K, i.e., $k = \alpha_t^A \cdot \alpha_t^B = 10 \times 1,000 = 10,000$, where α^i denotes the number of tokens of cryptocurrency i in the liquidity pool. Lemma B.1 shows that the valuation of token A (i.e., BNB) should be identical to the valuation of token B (i.e., BUSD) at any t, i.e., $\alpha_t^A \cdot P_t^A = \alpha_t^B \cdot P_t^B$ for all t.

Lemma 1. *In a constant product automated market maker, $\alpha_t^A \cdot P_t^A = \alpha_t^B \cdot P_t^B$ for all t.*

Proof. Under the constant product model, the product of the quantities of two cryptocurrencies should be constant, i.e. $\alpha_t^A \cdot \alpha_t^B = k$. This implies that $\frac{\partial \alpha_t^B}{\partial \alpha_t^A} = -\frac{\alpha_t^B}{\alpha_t^A}$. A third-party investor wanting to purchase δ units of A for the sale of asset B would need to sell a quantity B equivalent to $\delta \frac{\alpha_t^B}{\alpha_t^A}$. This implies that $\delta \cdot P_t^A = \delta \frac{\alpha_t^B}{\alpha_t^A} \cdot P_t^B \to P_t^A \alpha_t^A = P_t^B \alpha_t^B$. □

Since we have two equations including the aggregate number of tokens A and B, $\alpha_t^A \cdot P_t^A = \alpha_t^B \cdot P_t^B$ and $k = \alpha_t^A \cdot \alpha_t^B$, we can solve for the expressions of α_t^A and α_t^B, such that:

$$\alpha_t^A = \sqrt{k \left(\frac{P_t^B}{P_t^A} \right)}, \quad \alpha_t^B = \sqrt{k \left(\frac{P_t^A}{P_t^B} \right)}. \tag{B.1}$$

We numerically illustrate the impact of a transaction by a third-party investor on the pool's token composition at time $t + h$ using the example of an increase in the exchange rate of

BNB–BUSD from 100 to 200, which is equivalent to \$100 to \$200 if we assume that BUSD is perfectly pegged to USD:

$$\alpha^A_{t+h} = \sqrt{k\left(\frac{P^B_{t+h}}{P^A_{t+h}}\right)} = \sqrt{10,000 \times (\$1/\$200)} = \sqrt{50} = 7.07,$$

$$\alpha^B_{t+h} = \sqrt{k\left(\frac{P^A_{t+h}}{P^B_{t+h}}\right)} = \sqrt{10,000 \times (\$200/\$1)} = \sqrt{2,000,000} = 1414.21.$$

The liquidity provider's fractional pool ownership is 10%. Upon redemption, he/she will receive 10% of the pool's tokens, corresponding to 0.707 BNB and 141.421 BUSD. This amounts to $0.707 \times 200 + 141.421 \times 1 = \$282.82$.

Compare the redemption value to the counterfactual buy-and-hold strategy of the two tokens (1 BNB and 100 BUSD). In that case, the liquidity provider's portfolio would be worth $\$300 = 1 \times 200 + 100 \times 1$, more than the redemption value after liquidity provision. The difference is the impermanent loss, which arises due to divergence in price correlation of tokens A and B. In this case, the impermanent loss corresponds to a loss of $(282.82/300 - 1) \times 100 =$ -5.727%.

In the crypto community, the impermanent loss is often defined as the percentage of the ratio of investment outcomes at time $t+h$ in two scenarios: (1) providing liquidity to the pool at t or (2) directly holding the underlying assets. If the liquidity provider simply held the assets (1 BNB and 100 BUSD), he/she would now have $\$300 = 1 \times 200 + 100 \times 1$ worth of assets. In this case, the impermanent loss corresponds numerically to $(282.82/300 - 1) \times 100 = -5.727\%$.

We formalize the impermanent loss through the ratio of the portfolio value in the liquidity provision and buy-and-hold strategies minus one, using a generic ownership share ω:

$$\frac{\omega(P^A_{t+h}\alpha^A_{t+h} + P^B_{t+h}\alpha^B_{t+h})}{\omega(P^A_{t+h}\alpha^A_{t} + P^B_{t+h}\alpha^B_{t})} - 1. \tag{B.2}$$

We emphasize that α^i in the denominator corresponds to the number of tokens in the intial liquidity provision, whereas α^i in the numerator corresponds to the number of tokens after trading by third-party investors between t and $t+h$ has changed the token composition in the pool. We rewrite Equation (B.2) in terms of price ratios P^A/P^B and P^B/P^A using

Equation (B.1):

$$\frac{\omega(P^A_{t+h}\alpha^A_{t+h} + P^B_{t+h}\alpha^B_{t+h})}{\omega(P^A_{t+h}\alpha^A_t + P^B_{t+h}\alpha^B_t)} - 1 = \frac{\left(\frac{P^A_{t+h}}{P^B_{t+h}}\right)\alpha^A_{t+h} + \alpha^B_{t+h}}{\left(\frac{P^A_{t+h}}{P^B_{t+h}}\right)\alpha^A_t + \alpha^B_t} - 1$$

$$= \frac{\left(\frac{P^A_{t+h}}{P^B_{t+h}}\right)\sqrt{k\left(\frac{P^B_{t+h}}{P^A_{t+h}}\right)} + \sqrt{k\left(\frac{P^A_{t+h}}{P^B_{t+h}}\right)}}{\left(\frac{P^A_{t+h}}{P^B_{t+h}}\right)\sqrt{k\left(\frac{P^B_t}{P^A_t}\right)} + \sqrt{k\left(\frac{P^A_t}{P^B_t}\right)}} - 1 = \frac{\left(\frac{P^A_{t+h}}{P^B_{t+h}}\right)\sqrt{\frac{P^B_{t+h}}{P^A_{t+h}}} + \sqrt{\frac{P^A_{t+h}}{P^B_{t+h}}}}{\left(\frac{P^A_{t+h}}{P^B_{t+h}}\right)\sqrt{\frac{P^B_t}{P^A_t}} + \sqrt{\frac{P^A_t}{P^B_t}}} - 1.$$

We can simplify the above expression using the relative price ratio $\rho_t = \frac{P^A_t}{P^B_t}$:

$$\frac{\rho_{t+h}\sqrt{\frac{1}{\rho_{t+h}}} + \sqrt{\rho_{t+h}}}{\rho_{t+h}\sqrt{\frac{1}{\rho_t}} + \sqrt{\rho_t}} - 1 = \frac{2\sqrt{\rho_{t+h}}}{\rho_{t+h}\sqrt{\frac{1}{\rho_t}} + \sqrt{\rho_t}} - 1 = \frac{2\sqrt{\rho_{t+h}/\rho_t}}{\rho_{t+h}/\rho_t + 1} - 1.$$

The above expression illustrates the impermanent loss as a function of the relative price ratio between two tokens. This clearly emphasizes that, as long as prices are perfectly correlated, i.e., $\rho = 1$, there will be no impermanent loss. As soon as $\rho \neq 1$, there is a loss, since it is straightforward to show that the impermanent loss is strictly non-positive, i.e., $\frac{2\sqrt{\rho_{t+h}/\rho_t}}{\rho_{t+h}/\rho_t+1} - 1 = -\frac{(\sqrt{\rho_{t+h}/\rho_t}-1)^2}{\rho_{t+h}/\rho_t+1} < 0$. Figure A.5 illustrates numerically the non-linearity between the impermanent loss and ρ_{t+h}/ρ_t.

For our analysis, we simplify the liquidity provider's gross return defined as:

$$\frac{\omega(P^A_{t+h}\alpha^A_{t+h} + P^B_{t+h}\alpha^B_{t+h})}{\omega(P^A_t\alpha^A_t + P^B_t\alpha^B_t)},$$

by decomposing it into two independent parts:

$$\frac{\omega(P^A_{t+h}\alpha^A_{t+h} + P^B_{t+h}\alpha^B_{t+h})}{\omega(P^A_t\alpha^A_t + P^B_t\alpha^B_t)} = \underbrace{\left(\frac{P^A_t\alpha^A_t}{P^A_t\alpha^A_t + P^B_t\alpha^B_t}\right)R^A_{t,t+h} + \left(\frac{P^B_t\alpha^B_t}{P^B_t\alpha^A_t + P^B_t\alpha^B_t}\right)R^B_{t,t+h}}_{\textit{Capital Gains}}$$

$$+\underbrace{\frac{P^A_{t+h}\alpha^A_{t+h} + P^B_{t+h}\alpha^B_{t+h}}{P^A_t\alpha^A_t + P^B_t\alpha^B_t} - \left[\left(\frac{P^A_t\alpha^A_t}{P^A_t\alpha^A_t + P^B_t\alpha^B_t}\right)R^A_{t,t+h} + \left(\frac{P^B_t\alpha^B_t}{P^B_t\alpha^A_t + P^B_t\alpha^B_t}\right)R^B_{t,t+h}\right]}_{\textit{Impermanent Loss}},$$

where the gross returns to tokens A and B are defined as $R^A_{t,t+h} = \left(P^A_{t+h}\alpha^A_{t+h}\right)/\left(P^A_t\alpha^A_t\right)$ and $R^B_{t,t+h} = \left(P^B_{t+h}\alpha^B_{t+h}\right)/\left(P^B_t\alpha^B_t\right)$. The first term, which we call capital gains, reflects the counterfactual return from a buy-and-hold investment strategy without liquidity provision to the pool. The second term defines the impermanent loss and reflects the return difference between the liquidity provision and a buy-and-hold strategy.

Using Lemma B.1, we can rewrite the expression for capital gains as:

$$\left(\frac{P_t^A \alpha_t^A}{P_t^A \alpha_t^A + P_t^B \alpha_t^B}\right) R_{t,t+h}^A + \left(\frac{P_t^B \alpha_t^B}{P_t^B \alpha_t^A + P_t^B \alpha_t^B}\right) R_{t,t+h}^B = \frac{1}{2} R_{t,t+h}^A + \frac{1}{2} R_{t,t+h}^B.$$

Using Lemma B.1, we can also simplify the expression for the impermanent loss as:

$$\begin{aligned}
&\frac{P_{t+h}^A \alpha_{t+h}^A + P_{t+h}^B \alpha_{t+h}^B}{P_t^A \alpha_t^A + P_t^B \alpha_t^B} - \left[\left(\frac{P_t^A \alpha_t^A}{P_t^A \alpha_t^A + P_t^B \alpha_t^B}\right) R_{t,t+h}^A + \left(\frac{P_t^B \alpha_t^B}{P_t^B \alpha_t^A + P_t^B \alpha_t^B}\right) R_{t,t+h}^B\right] \\
&= \frac{P_{t+h}^A \alpha_{t+h}^A}{P_t^A \alpha_t^A} - \left(\frac{1}{2} R_{t,t+h}^A + \frac{1}{2} R_{t,t+h}^B\right) = \frac{P_{t+h}^A \sqrt{k\left(\frac{P_{t+h}^B}{P_{t+h}^A}\right)}}{P_t^A \sqrt{k\left(\frac{P_t^B}{P_t^A}\right)}} - \left(\frac{1}{2} R_{t,t+h}^A + \frac{1}{2} R_{t,t+h}^B\right) \\
&= \sqrt{R_{t,t+h}^A R_{t,t+h}^B} - \left(\frac{1}{2} R_{t,t+h}^A + \frac{1}{2} R_{t,t+h}^B\right) = -\frac{1}{2}\left(\sqrt{R_{t,t+h}^A} - \sqrt{R_{t,t+h}^B}\right)^2.
\end{aligned}$$

It is straightforward to show that the impermanent loss defined in the context of return on liquidity provision is closely related to the percentage impermanent loss:

$$-\frac{1}{2}\left(\sqrt{R_{t,t+h}^A} - \sqrt{R_{t,t+h}^B}\right)^2 = \left(\frac{1}{2} R_{t,t+h}^A + \frac{1}{2} R_{t,t+h}^B\right)\left(\frac{2\sqrt{\rho_{t+h}/\rho_t}}{\rho_{t+h}/\rho_t + 1} - 1\right).$$

B.2 Trading frictions in yield farming

We examine three types of trading frictions: gas fees, trading fees, and price impact.

Gas fees

Table A.2 lists the 14 steps involved in one round trip yield farming strategy. Among the 14 steps, 10 require the farmers to pay gas fees. Gas fees are the transaction costs imposed on BSC users for using the computational resources of the network. Gas fees are flat overhead costs and are not proportional to the size of the transaction. We source gas fees from Bitquery, a data provider specialized in blockchain services. To compute the returns to yield farming with frictions, we subtract the aggregate gas fee for each round trip investment from the initially invested capital.

Trading fees

Let c^*=0.0025 (0.25%) denote the trading fee cost paid by third-party investors as a proportion of trading volume. In step 2 of Table A.2, the purchase of token A requires the payment of a 0.25% trading fee. Because this trading fee applies to half the investment amount dedicated to token A, the farmer effectively pays half the trading fee $\frac{c*}{2}$ (=0.125%). Moreover, the farmer pays an additional $\frac{c*}{2}$ fee when he/she converts the withdrawn token A to token B. Similar arguments apply in steps 3 and 13 enumerated in Table A.2. A yield farmer would thus pay $\frac{c*}{2}$ four times, implying that a farmer's gross return on capital gain and impermanent loss should be adjusted by $(1 - 2c^*)$.

In step 10 of Table A.2, the yield farmer also pays trading fees when he/she sells CAKE tokens harvested from yield farming. Thus, we further multiply the realized farm yield term in Equation (8) with $(1 - c^*)$.

Price impact

Executing a yield farming strategy involves buying and selling token A, as we illustrate in step 2 of Table A.2. As a result of price impact, the yield farmer will buy token A at a price above the current market price. Symmetrically, the yield farmer will sell token A at a price below the current market price. Such adverse price impacts will result in losses for the yield farmer. The size of the loss is proportional to the relative contribution of the investment (I_t) to the size of the liquidity pool, i.e., $I_t = f \cdot L_t$. We go through each step in Table A.2 to examine the price impacts involved in a yield farming strategy.

(1) Step 1: The liquidity pool has two tokens A and B. The aggregate number of tokens are given by α_t^A and α_t^B and their prices are denoted by P_t^A and P_t^B.

(2) Step 2: A yield farmer must provide tokens A and B in equal amounts. Thus, he/she must acquire tokens A and B proportionally to α_t^A/α_t^B. For this purpose, we divide his/her investment into $x \cdot I_t$ and $(1 - x) \cdot I_t$ to allocate towards tokens A and B, respectively. The yield farmer first converts $\$x \cdot I_t$ to acquire token B in a liquid market for B. Then, the farmer will own $x \cdot \frac{I_t}{P_t^B}$ of token B, which he/she will use to buy Δ_t^A units of token A by means of the liquidity pool. Due to the constant product model technology, we have that:

$$\left(\alpha_t^A - \Delta_t^A\right)\left(\alpha_t^B + \frac{xI_t}{P_t^B}\right) = \alpha_t^A \alpha_t^B$$

Solving for Δ_t^A yields:

$$\Delta_t^A = \frac{\left(\frac{xI_t}{P_t^B}\right)\alpha_t^A}{\alpha_t^B + \frac{xI_t}{P_t^B}} = \frac{xI_t\alpha_t^A}{P_t^B\alpha_t^B + xI_t} = \frac{xI_t\alpha_t^A}{\frac{1}{2}L_t + xI_t} = \frac{xf\alpha_t^A}{\frac{1}{2} + xf}.$$

(3) Step 3: The yield farmer uses the remaining funds, $\$(1 - x)\,I_t$, to buy token B in a liquid market for B. Then, he/she will get Δ_t^B of token B, where Δ_t^B is expressed as follows.

$$\Delta_t^B = \frac{(1-x)\, I_t}{P_t^B} = \frac{(1-x)\, f L_t}{P_t^B}.$$

Finally, we solve for x that satisfies: $\frac{\Delta_t^A}{\Delta_t^B} = \frac{\alpha_t^A}{\alpha_t^B}$.

$$\frac{\Delta_t^A}{\Delta_t^B} = \frac{\frac{xf\alpha_t^A}{\frac{1}{2}+xf}}{\frac{(1-x)fL_t}{P_t^B}} = \frac{\frac{xf\alpha_t^A}{\frac{1}{2}+xf}}{\frac{(1-x)f\left(2P_t^B\alpha_t^B\right)}{P_t^B}} = \left(\frac{x}{1-x}\right) \left(\frac{1}{1+2xf}\right) \frac{\alpha_t^A}{\alpha_t^B},$$

implying that:

$$\left(\frac{x}{1-x}\right) \left(\frac{1}{1+2xf}\right) = 1,$$

with two solutions for x, with the relevant positive solution given by:

$$x = \frac{f-1+\sqrt{f^2+1}}{2f}.$$

(4) Step 4: Arbitrageurs correct the price by supplying Δ_t^A of token A in reurn for Δ_t^B of token B. This restores the liquidity pool to its initial state.

(5) Step 5: The yield farmer receives LP tokens to certify the liquidity provision. Define $s(f)$ the ratio of the yield farmer's share to the current share in the liquidity pool before the yield farmer provides the liquidity.

$$s(f) = \frac{\Delta_t^A}{\alpha_t^A} = \frac{\frac{xI_t\alpha_t^A}{\frac{1}{2}L_t+xI_t}}{\alpha_t^A} = \frac{xfL_t}{\frac{1}{2}L_t + xfL_t} = \frac{f \times \left(\frac{f-1+\sqrt{f^2+1}}{2f}\right)}{\frac{1}{2} + f \times \frac{f-1+\sqrt{f^2+1}}{2f}} = \frac{f-1+\sqrt{f^2+1}}{f+\sqrt{f^2+1}}.$$

After the liquidity provision by the yield farmer, the shares of token A and B become $\alpha_t^A\,(1+s(f))$ and $\alpha_t^B\,(1+s(f))$. Now, we measure the price impact when the yield farmer buys Δ_t^A of token A. The farmer uses $\$xI_t$ to buy Δ_t^A of token A. This means that the effective price paid by the farmer is:

$$\tilde{P}_t^A = \frac{xI_t}{\Delta_t^A} = \frac{xfL_t}{\frac{xf\alpha_t^A}{\frac{1}{2}+xf}} = \frac{xf\left(2P_t^A\alpha_t^A\right)}{\frac{xf\alpha_t^A}{\frac{1}{2}+xf}} = 2P_t^A\left(\frac{1}{2}+xf\right) = P_t^A\,(1+2fx) = P_t^A\left[1+\left(f-1+\sqrt{f^2+1}\right)\right]$$

Since $f-1+\sqrt{f^2+1} > 0$, we have that $\tilde{P}_t^A > P_t^A$.

(6) Step 6: The yield farmer stakes the LP tokens to a farm.

(7) Step 7: The yield farmer waits for h days. After trading by third-party investor, the aggregate number of tokens A and B in the pool change and become $\alpha_{t+h}^{A}\left(1+s(f)\right)$ and $\alpha_{t+h}^{B}\left(1+s(f)\right)$.

(8) Step 8: The yield farmer receives (harvests) realized farm yields in CAKE tokens.

(9) Step 9: The yield farmer withdraws his/her LP tokens from the farm.

(10) Step 10: The yield farmer sells CAKE tokens.

(11) Step 11: The yield farmer withdraws his/her liquidity from the liquidity pool by sending the LP tokens to the pool. After the farmer has withdrawn liquidity, the shares of token A and B in the pool change to α_{t+h}^{A} and α_{t+h}^{B}.

(12) Step 12: The yield farmer sells his/her $\Delta_{t+h}^{A}=s(f)\alpha_{t+h}^{A}$ of token A and receives Δ_{t+h}^{B} of token B. At this stage, there are α_{t+h}^{A} and $\alpha_{t+h}^{B}$of token A and token B in the pool. After the farmer has sent $\Delta_{t+h}^{A}=s(f)\alpha_{t+h}^{A}$ of token A, he/she receives Δ_{t+h}^{B} units of token B. Due to the constant product model, we have that:

$$\left(\alpha_{t+h}^{A}+s(f)\alpha_{t+h}^{A}\right)\left(\alpha_{t+h}^{B}-\Delta_{t+h}^{B}\right)=\alpha_{t+h}^{A}\alpha_{t+h}^{B}\rightarrow\Delta_{t+h}^{B}=\frac{s(f)}{1+s(f)}\alpha_{t+h}^{B}.$$

The farmer sends $s(f)\alpha_{t+h}^{A}$ units of token A in return for $P_{t+h}^{B}\Delta_{t+h}^{B}$ worth of USD. Thus, the effective price faced by the yield farmer when selling token A is equal to:

$$\tilde{P}_{t+h}^{A}=\frac{P_{t+h}^{B}\Delta_{t+h}^{B}}{s(f)\alpha_{t+h}^{A}}=\frac{\frac{s(f)}{1+s(f)}\alpha_{t+h}^{B}P_{t+h}^{B}}{s(f)\alpha_{t+h}^{A}}=\frac{\frac{s(f)}{1+s(f)}\alpha_{t+h}^{A}P_{t+h}^{A}}{s(f)\alpha_{t+h}^{A}}=\left(\frac{1}{1+s(f)}\right)P_{t+h}^{A}<P_{t+h}^{A}.$$

This illustrates that the yield farmer sells at a lower price than P_{t+h}^{A}.

(13) Step 13: The yield farmer sells $\Delta_{t+h}^{B}+s(f)\alpha_{t+h}^{B}$ units of token B in a liquid market for token B.

(14) Step 14: An arbitrageur corrects the price by supplying Δ_{t+h}^{B} of token B in reurn for Δ_{t+h}^{A} units of token A. A new round of yield farming starts.

Our goal is to compute the return of this yield farming strategy considering the price impact. First, the yield farmer uses his/her fund $I_t=fL_t=\tilde{P}_t^{A}\left(s(f)\alpha_t^{A}\right)+P_t^{B}(s(f)\alpha_t^{B})$ to buy $s(f)\alpha_t^{A}$ and $s(f)\alpha_t^{B}$ units of token A and B at $\tilde{P}_t^{A}$ and P_t^{B}. After h days, the yield farmer withdraws $s(f)\alpha_{t+h}^{A}$ and $s(f)\alpha_{t+h}^{B}$ units of token A and B and sells them at $\tilde{P}_{t+h}^{A}$ and P_{t+h}^{B}. In this case, the gross return can be expressed as:

$$\frac{\tilde{P}_{t+h}^{A}\left(s(f)\alpha_{t+h}^{A}\right)+P_{t+h}^{B}(s(f)\alpha_{t+h}^{B})}{\tilde{P}_t^{A}\left(s(f)\alpha_t^{A}\right)+P_t^{B}(s(f)\alpha_t^{B})}=\frac{\tilde{P}_{t+h}^{A}\alpha_{t+h}^{A}+P_{t+h}^{B}\alpha_{t+h}^{B}}{\tilde{P}_t^{A}\alpha_t^{A}+P_t^{B}\alpha_t^{B}}.$$

We simplify this expression as follows:

$$\frac{\tilde{P}^A_{t+h}\alpha^A_{t+h} + P^B_{t+h}\alpha^B_{t+h}}{\tilde{P}^A_t\alpha^A_t + P^B_t\alpha^B_t} = \frac{\left(\frac{1}{1+s(f)}\right) P^A_{t+h}\alpha^A_{t+h} + P^B_{t+h}\alpha^B_{t+h}}{P^A_t\left(1+\left(f-1+\sqrt{f^2+1}\right)\right)\alpha^A_t + P^B_t\alpha^B_t}$$

$$=\frac{\left(\frac{1}{1+s(f)}+1\right) P^A_{t+h}\alpha^A_{t+h}}{\left(1+\left(f-1+\sqrt{f^2+1}\right)+1\right) P^A_t\alpha^A_t} = \frac{\frac{1}{1+s(f)}+1}{f+1+\sqrt{f^2+1}}\left(\frac{P^A_{t+h}\alpha^A_{t+h}}{P^A_t\alpha^A_t}\right)$$

$$=\lambda(f)\left(\frac{P^A_{t+h}\alpha^A_{t+h} + P^B_{t+h}\alpha^B_{t+h}}{P^A_t\alpha^A_t + P^B_t\alpha^B_t}\right) = \lambda(f)\left(\left(\frac{1}{2}R^A_{t+h}+\frac{1}{2}R^B_{t+h}\right) - \frac{1}{2}\left(\sqrt{R^A_{t+h}}-\sqrt{R^B_{t+h}}\right)^2\right),$$

where

$$\lambda(f) = \frac{\frac{1}{1+s(f)}+1}{f+1+\sqrt{f^2+1}} = \frac{\frac{1}{1+\frac{f-1+\sqrt{f^2+1}}{f+\sqrt{f^2+1}}}+1}{f+1+\sqrt{f^2+1}} = \frac{3f+3\sqrt{f^2+1}-1}{\left(2f+2\sqrt{f^2+1}-1\right)\left(f+1+\sqrt{f^2+1}\right)}.$$

Accounting for both price impact and trading fees, the gross return is adjusted as follows:

$$(1-2c^*)\lambda(f)\left(\left(\frac{1}{2}R^A_{t+h}+\frac{1}{2}R^B_{t+h}\right) - \frac{1}{2}\left(\sqrt{R^A_{t+h}}-\sqrt{R^B_{t+h}}\right)^2\right),$$

where $(1-2c^*)\lambda(f) < 1$.

Figure A.6 illustrates the price impact in buying and selling token A and $\lambda(f)$, which summarizes the overall effect of price impacts on the performance of yield farming. Panel A shows the relation between f and $\frac{\tilde{P}^A_t}{P^A_t}$. $\frac{\tilde{P}^A_t}{P^A_t}$ is greater than or equal to 1 and increasing in f, which implies that the yield farmer pays higher prices than the current market price when they purchase token A, which is attenuated as the size of his/her investment increases. Panel B shows the relationship between f and $\frac{\tilde{P}^A_{t+h}}{P^A_{t+h}}$. This is less than or equal to 1 and decreasing in f, which means that the yield farmer sells token A at a larger discount as the size of investment increase. Finally, Panel C plots $\lambda(f)$ with respect to f. $\lambda(f)$ is less than or equal to 1, decreasing in f, and its effect is substantial when f is large. For example, if the yield farmer's investment is very small such that f is close 0, $\lambda(f) = 1$ and therefore, there is no effect. However, if the yield farmer invests as much as the size of the pool ($f = 1$), he/she will lose more than 50% of their gross return.

C Data appendix

We describe the technical construction of all data sets related to farms (C.1), prices (C.2), token transfers (C.3), Yieldwatch (C.4), and cryptocurrency factors (C.6).

We source all information from public blockchains. Interactions with the blockchain are facilitated by the Web3 application programming interface (API) together with a blockchain archive node service. Archive nodes provide the record of all blocks since inception of the blockchain, unlike full nodes, which tend to store only more recent blockchain data. The Web3 API operates as a middleman between the user and the archive node, allowing for a simple object-oriented programming interface. Our technical documentation primarily reflects the perspective of a Python Web3 interface, although most of its functionality should be comparable to Web3 interfaces based on other programming languages.

To clarify the time convention, note that blockchain time is measured by the 'height' of a block, a unique identifier which represents the order of a particular block relative to the inception of the blockchain. The history of all mined blocks is freely accessible through an archive node or a block explorer service. A given block height can be passed onto an archive node as an optional argument in an API to 'restrict' observable data to everything in that block and before. This enables the reproduction of the historical conditions of the blockchain corresponding to a specific point in time. For our analysis, we use the height of the last block mined on each day in coordinated universal time (UTC+0) to index an observation on a particular date for all following sections. As an example, the last Binance Smart Chain block height in our sample is 20045095, a block that was mined on July 31, 2022 at 11:59:58 PM UTC, and used to extract observations for July 31, 2022.

C.1 Accessing farm data

We extract farm data in two steps: first, we identify each day the set of addressable smart contracts corresponding to yield farms on a given platform and calculate, for each farm, the quantities of interest in the set.

We find the set of contracts on each day by interacting with the active version of the main staking contract through the $poolInfo(q)$ function, where q is a non-negative integer. This returns information about the q-th liquidity pool added to the main staking contract: first, the blockchain address of the pool, and second, the weight corresponding to the current share of minted tokens that this pool receives ('allocPoint'). The total amount of pools stored in this way is given by the $poolLength()$ function at each day, and it is straightforward to iterate over them until all information has been collected.

For each farm, we then make several direct calls to its smart contract to extract further information: $token0()$ and $token1()$ return the addresses of the two tokens traded by the pool, while $getReserves()$ returns the balances of the two tokens. To stake tokens, users must transfer LP tokens to the main staking contract, so we simply call $balanceOf(mainStakingContract)$ to get the amount of staked tokens, and $totalSupply()$ to get the total outstanding amount of LP tokens. For these steps, it is critical to account for variable decimal precision across different tokens, which we can identify by calling the $decimals()$ function for each token and then explicitly adjust for.

C.2 Prices and trades

To identify prices for each token, we use the $getAmountsOut(N, [B, Token])$ function from the main router of the platform. The main router for a decentralized exchange is the smart contract responsible for quoting swap rates, and $getAmountsOut(N, [B, Token])$ is a request for a quote where N units of token B are exchanged for quoted units of $Token$, absent considerations of fees or price impact. For our purpose, we take the wrapped version of the native token for a block chain (e.g. WBNB for BSC) as B, and 0.01 as N.

Our choice of B is motivated by the fact that the native token is the most liquid token on its smart chain, N is chosen such that there is no loss of exchange rate precision from trading overly small amounts[12], nor is the size big enough to distort the liquidity of any pool. This function allows us to compute exchange rates on the decentralized exchange. Finally, we determine the exchange rate between B and $USDT$ and source a centralized quote for $USDT$ against USD. This allows us to get the exchanges of all tokens versus USD.

To determine trading volume for each pool, we pass the pool address and date range to Bitquery, a third-party data provider which calculates the total amounts of the two tokens traded through a given smart contract for a given date range. We merge this information with the main dataset. Once all of these items are compiled, it is then straightforward to calculate the total return and its individual components according to our formulae in the main text: the offered yield, the offered total yield, and the staking ratio.

C.3 Token transfer data

We construct token transfer data using the event logs emitted by smart contracts when they update their internally stored variables. We utilize the *eth.getLogs*() function to collect these logs. Each log has the following fields: the block height of record, the smart contract/token which performs the update, an id corresponding to the particular event that has occurred (the 1st 'topic'), additional key information (subsequent 'topics'), and additional general information (log 'data').

Events for which LP tokens are transferred always follow the same event id, which allows us to restrict our attention to the set of events corresponding to this particular id and emitted by the LP tokens within our sample. For such events, the second topic in an event log is the address of the token sender, and the third topic is the recipient. The amount transferred is contained in the log data, in hexadecimal.

We validate a subset of the reconstructed token transfer data against the displayed token transfer records on the bscscan website (https://bscscan.com/), and find a perfect match. These data form the backbone of our user-level analysis.

[12]If N is less than 1e-06 USDT, the quote is zero because it is less than the token's decimal precision.

C.4 Yieldwatch coverage

To determine the coverage of a farm by Yieldwatch, we follow three steps: (i) we identify an account with an active position in the liquidity pool associated with the farm; (ii) we track the account using Yieldwatch to see its displayed positions; (iii) we filter for the name of the farm of interest to verify if it is among the positions.

We perform the first step by looking for wallets which have had a net token inflow at the time of the procedure. Since negative LP token holdings are impossible, wallets with net inflows must hold positive token balances at the time of observation, making them eligible for tracking on Yieldwatch.

In practice, there are too many eligible wallets that fit this criterion, making and it challenging to track all of them. Fortunately, the restriction of a zero lower bound for LP token balances implies reduces our task to checking for wallets with a net positive token inflow within a smaller time window. Using real-time information from bscscan, we collect the 10 most recent wallets to have received LP tokens and record their addresses.

For the second and third steps, we use Selenium to automate a web crawler which interacts with the Yieldwatch interface. This package allows the code to automatically open up the Yieldwatch website, select the PancakeSwap platform to track, and paste in the wallet address of interest for tracking, in order to access the 'preview' tracking page. We do this as soon as the wallet addresses are collected to minimize the risk of positions being closed between the collection of wallet addresses and our tracking requests. We then search for the symbols of the token pair corresponding to the farm of interest on the interface, to determine if it is displayed on the interface. This procedure is repeated for each of the 10 wallets that we have identified. If at least one wallet's tracking page shows information consistent with the farm, we consider the farm to be covered by Yieldwatch.

While it is technically possible that all ten active wallets close their positions between the first and subsequent steps, it is exceedingly unlikely. The entire procedure takes only a few seconds to execute, well below the holding time of the average user. It is also possible that some farms, which were supported in the past, are no longer supported. Due to the opacity of Yieldwatch's internal processes, previously-supported farms are not possible to identify. We executed this task from Oct 14 to 17, 2022, and found that Yieldwatch covers 91 out of the 262 PancakeSwap farms in our sample.

C.5 APY Vision Giveaways

In our sample period, APY Vision organized several airdrops. Airdrops (or give-away) are events in which APY Vision gives a select group of users access to premium tracking services. APY Vision operates across multiple platforms and selects users randomly to provide their services. We identify 21 airdrops through their announcements on X (formerly Twitter) between December 2020 and May 2022.

Upon selection, a recipient is granted a unique NFT belonging to a collection of NFTs. Each collection is unique to a specific give-away. Using NFT tracking websites Rarible and Opensea, we first match each give-away to the corresponding collections minted by the APY Vision minting address, and then collect information on the address of the recipient manually. Through this methodology, we collected 585 winning addresses across the 21 give-aways. There are many cases where the totsl amount allocated to winning addresses was below the advertised amount for a particular give-away, which corresponds to NFTs that were minted by the official account, but never distributed. These cases are dropped.

C.6 Cryptocurrency Factors

Liu, Tsyvinski, and Wu (2019) document that a three-factor model using the cryptocurrency equivalents of the market, size and momentum factors are useful for explaining the cross section of expected cryptocurrency returns. We replicate these factors using their approach.

We obtain the cross-section of daily closing prices for cryptocurrencies from Coinmarketcap's historical API endpoint. We then compute volume-weighted average prices across all markets for which Coinmarketcap has data. Our risk-free rate is from the St. Louis Fed's one-month constant maturity Treasury rate.

We exclude from our sample coins without trading volume, coins with less than $1 million in market capitalization at the time of portfolio formation, and coins without price data for the following day. To control for potential outliers, we winsorize the market capitalization at the 1st and 99th percentiles during portfolio formulation.

For all three factors, we form portfolios at the end of the prior day and consider a one-day holding period. All returns are measured in U.S. dollars. The daily excess cryptocurrency market return is constructed as a value-weighted portfolio of all coins with data on the portfolio formation day (prior to applying the filters) minus the risk-free rate.

The excess cryptocurrency size factor is computed using the return from a long-short trading strategy that takes a long (short) position in the value-weighted portfolio of coins ranked in the bottom (top) quintile of market capitalizations on the portfolio formation day. For the cryptocurrency momentum factor, we exclude coins for which the three-week price history is unavailable. The momentum factor is then constructed from a long-short strategy with a long (short) position in the value-weighted portfolio of coins ranked in the top (bottom) quintile of coins with positive three-week momentum on the portfolio formation day.

As a test of the accuracy of our methodology, we replicate the three-factor regressions from Table 11 in Liu, Tsyvinski, and Wu (2019) for portfolios sorted on one-week momentum by quintile, a set of implementable trading strategies not used in the construction of the three factors. Table A.7 provides summary statistics on the coins used for the construction of cryptocurrency factors. In Table A.6, we compare our parameter estimates to those obtained in Liu, Tsyvinski, and Wu (2019). The two are nearly identical with only minor deviations, which may be due to small variations in the sample period used and/or changes in the markets for which Coinmarketcap tracks price data.

In addition, it is worth noting that the estimates for alpha obtained in Liu, Tsyvinski, and Wu (2019) are reported in weekly frequency, whereas our measures of alpha have been annualized. For instance, a weekly alpha of 0.025, as is the case for the fourth quintile of one-week momentum in Table A.6, translates into a yearly alpha of 2.611 when annualized. Therefore, the magnitudes of our estimates of alpha for yield-farming strategies are reasonably comparable to strategies analyzed in Table 11 of Liu, Tsyvinski, and Wu (2019), in which three-factor weekly alphas exceed 0.02 (or an annualized alpha of 1.80) for many price- and momentum-based strategies.

C.7 Data Cleaning: Farm Data

After the initial data construction, we identify 304 unique yield farms. We restrict our analysis to the sample period March 1, 2021 to July 31, 2022. This reduces our sample to 299 farms with 281 unique cryptocurrencies and 61,023 observations. We exclude 6 farms where UST was one of the tokens in the LP pool (UST-MCOIN, 'UST-MIR', 'UST-mAMZN', 'UST-mGOOGL', 'UST-mNFLX', and 'UST-mTSLA'), since we could not obtain a reliable estimate of the token price for the complete sample, owing to the events of the Terra-Luna collapse. We further exclude two farms, 'PNT-PBTC' and 'QSD-KUN', for which our data provider does not have any trading volume information. We exclude farms that have less than two weeks' worth of data in our sample. These farms most likely correspond to 'Farm Auctions' - promotional partnerships where a liquidity pool receives yield for a week to generate interest and trading activity. These filters reduce our sample to 262 unique farms that cover 247 unique cryptocurrencies and 59,051 daily observations at the farm level.

C.8 Data Cleaning: Farmer Data

We collect all wallet addresses with transactions in the 262 unique farms in our sample. After removing two common burn (null) addresses that do not represent investors, we have 1,190,623 unique wallet addresses (wallets) which have provided liquidity to 529 unique smart contracts (i.e., liquidity pools), corresponding to 2,687,061 unique wallet-liquidity pool pairings (wallet pools) and 62,352,957 observed historical states of wallet pools (total positions).

In a second step, we exclude wallets which trade at an implausibly high frequency, with over 10,000 positions held through our sample period. This reduces our sample to 1,190,442 wallets in 529 liquidity pools and 2,682,603 wallet pools, and 23,944,735 total positions.

Third, we exclude wallets with a smart contract interface, since their positions are not directly managed by investors. This lowers our sample to 1,172,762 wallets in 529 liquidity pools and 2,647,640 wallet pools, and 18,618,936 total positions.

Finally, we exclude wallet-pools in which the wallet transferred LP tokens to a third party, as these represent multi-platform strategies outside the scope of this paper. This leads to a final sample of lowers our sample to 641,477 wallets in 529 liquidity pools and 1,442,486 wallet pools, and 7,838,261 total positions.

Figure A.1: Liquidity and Offered Farm Yield

In this figure, we show the relation between a yield farm's offered yield and its aggregate liquidity. The x-axis corresponds to the natural logarithm of the dollar value of liquidity in the yield farm in units of \$1 million. The y-axis corresponds to the natural logarithm of one plus the annualized offered farm yield measured in decimal units. (For example, 50% of the annualized farm yield is 0.5 in decimal units.) The blue dots are observations measured at a daily frequency. The red dashed line plots the best linear fit obtained by regressing the natural logarithm of (1 + annualized offered farm yield) on the natural logarithm of the dollar value of liquidity in the yield farm.

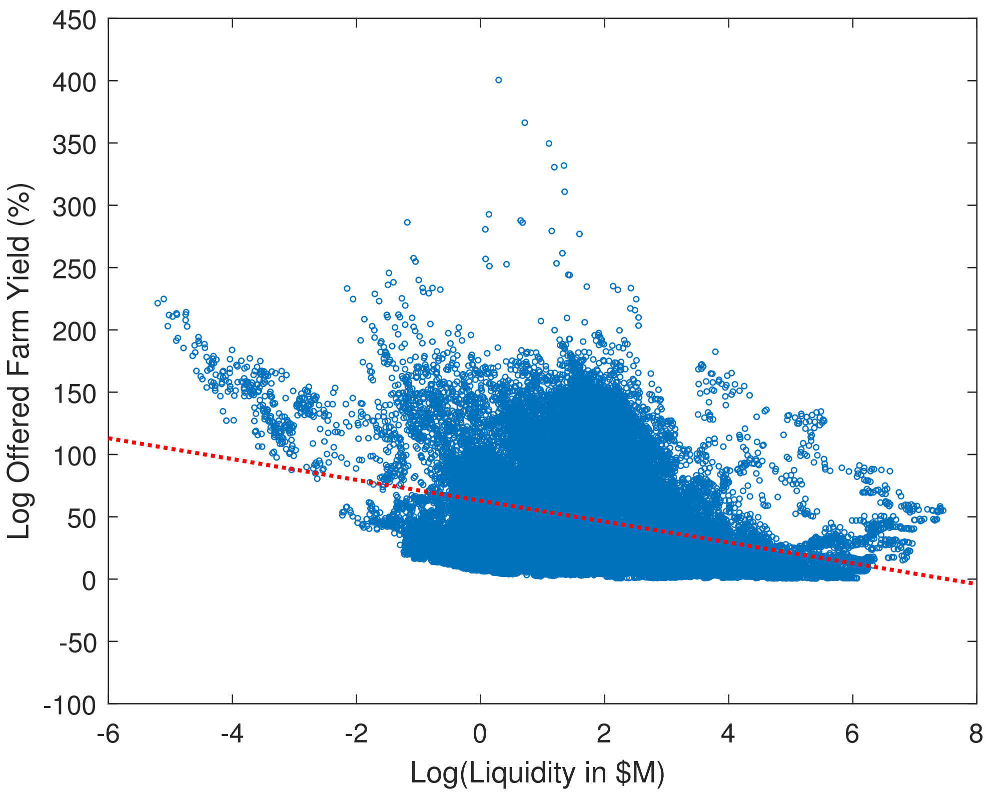


Figure A.2: Relation between Model-implied and Listed Offered Farm Yields

In this figure, we compare the offered farm yields calculated using Equation (6) on the y-axis to those listed on PancakeSwap's homepage on the x-axis (https://PancakeSwap.finance/farms). The listed farm yields are manually collected from PancakeSwap's web page at midnight Greenwich Meridian Time (GMT) on October 11, 2021. All values are reported in percentage points. The blue circles represent all observations and the red dashed line connects (0%,0%) and (300%,300%), i.e., a 45-degree line. A linear regression where we regress the calculated on the listed farm yields obtains an R^2 of 1.00 and an estimated regression line given by $\widehat{y}_t = 1.002 \times y_t - 0.001$.

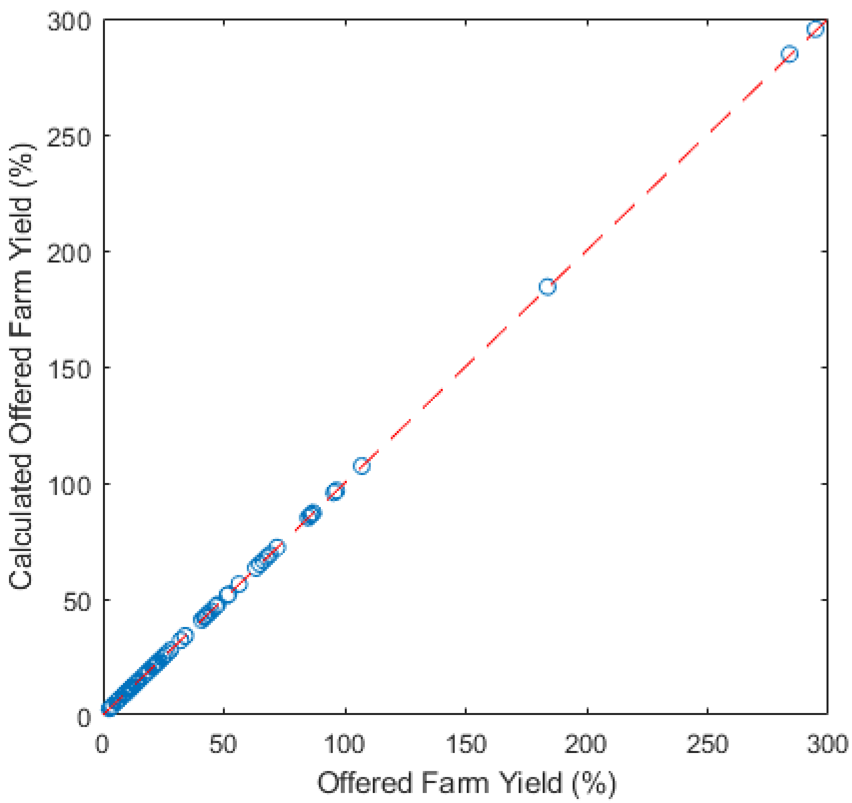


Figure A.3: User Interface of Yield Farms in PancakeSwap

In this figure, we provide a snapshot of the user-interface environment for yield farms in PancakeSwap. For a current snapshot, see https://PancakeSwap.finance/farms.

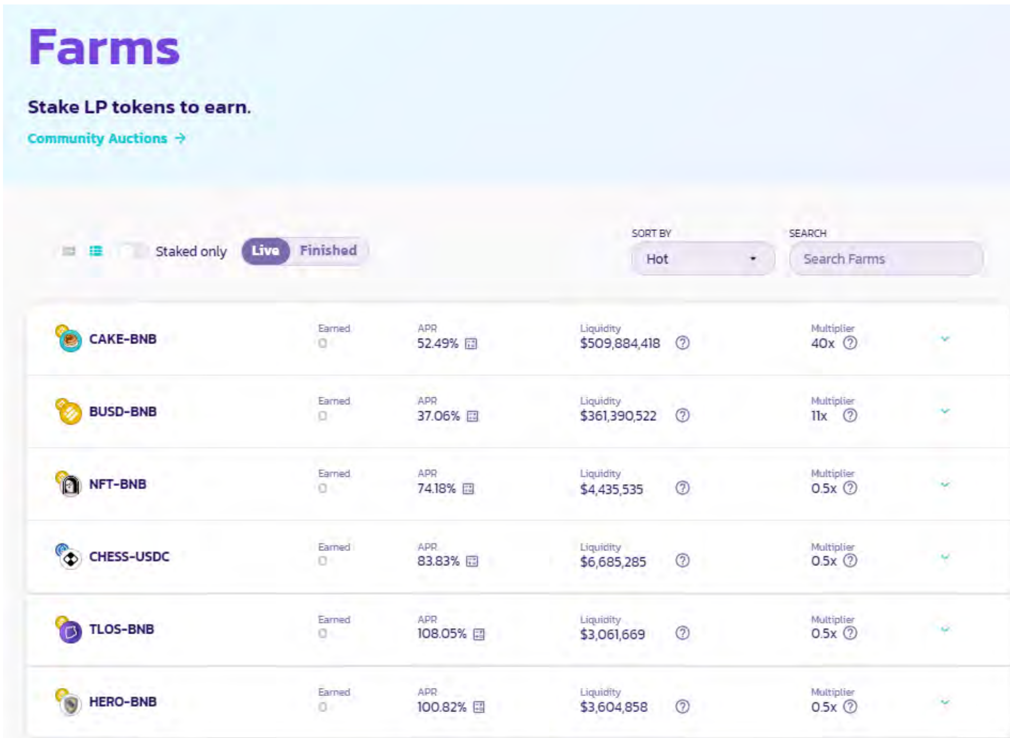


Figure A.4: UI of Yieldwatch

In this figure, we provide a snapshot of user-interface environment of Yieldwatch, a 3rd-party information platform.

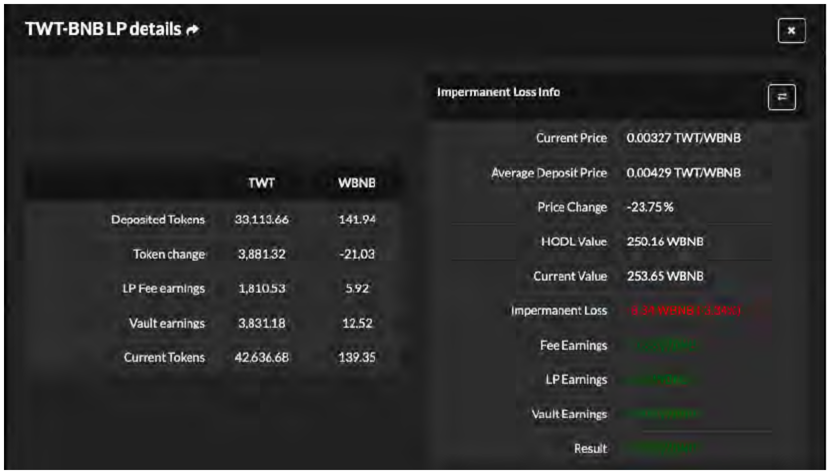


Figure A.5: The Impact of Price Divergence on Impermanent Loss

In this figure, we illustrate the impact of price divergence on impermanent loss, defined as the ratio of the portfolio value in the liquidity provision and buy-and-hold strategies minus one (see Equation (B.2)). The y-axis indicates the impermanent loss (in %). The x-axis provides, for a representative pair of tokens A and B used for liquidity provision, a measure of price divergence over an h-period horizon defined as ρ_{t+h}/ρ_t, where $\rho_t = P_t^A/P_t^B$.

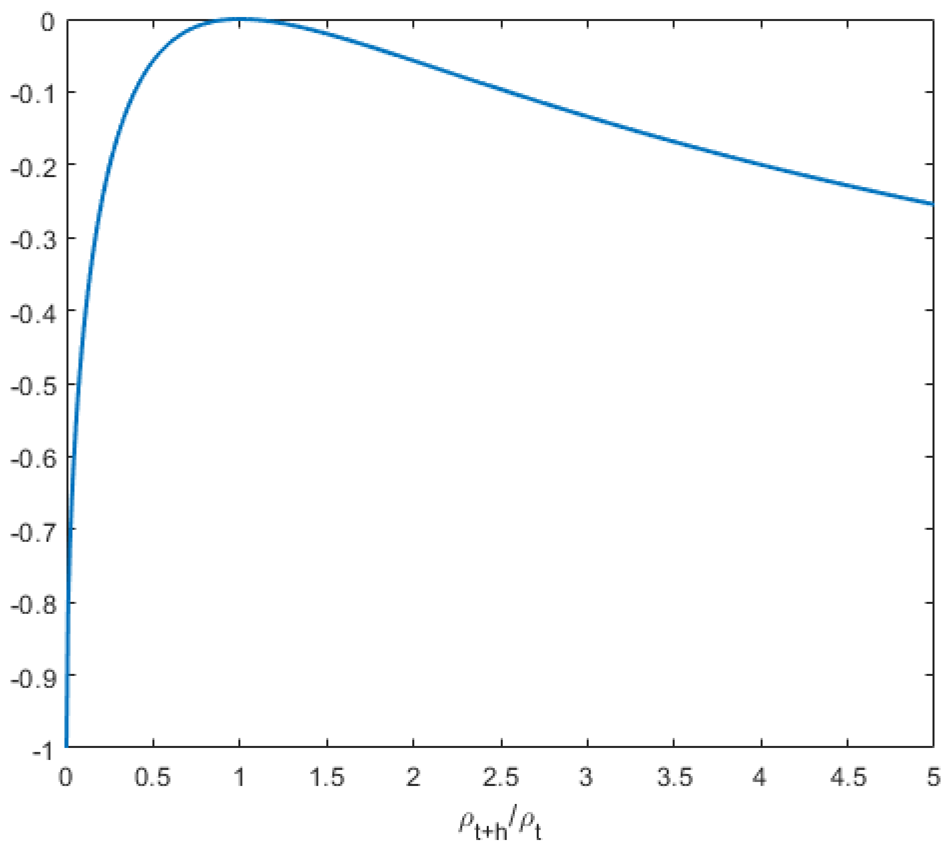
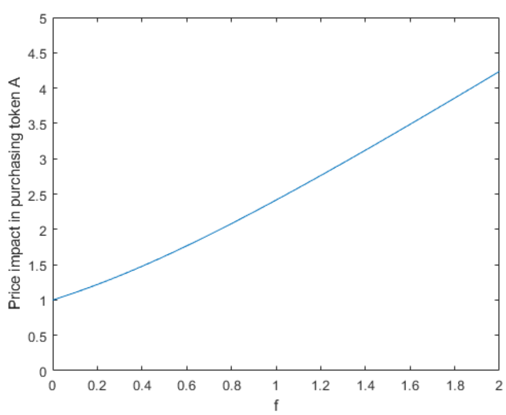


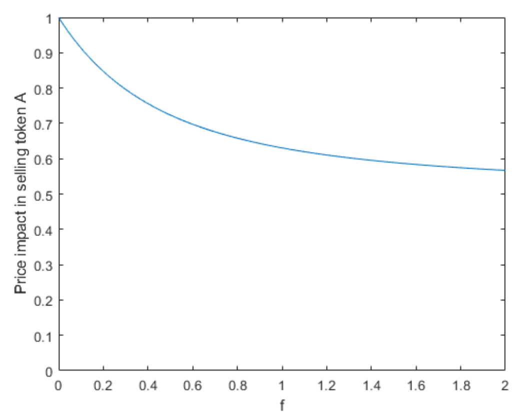
Figure A.6: Model-Implied Price Impact due to Yield Farming

In this figure, we illustrate how the size of investment in yield farming creates price impact, which affects returns from yield farming. The parameter f defines the relative ratio of the size of the investment to the size of the liquidity pool, i.e. investment/size of liquidity pool (I_t/L_t). Consider two cryptocurrencies A and B in a liquidity pool with token B being the numeraire token such as BNB or BUSD. Panel (a) shows the relation between f and the price impact on token A when purchasing token A for providing liquidity (together with token B) to a pool. The y-axis plots the multiple to the current price of token A in U.S. dollars. A value of 2 implies that a yield farmer would have to pay twice the current market price of token A to acquire it for liquidity provision. Panel (b) plots the relation between f and the price impact on token A when selling it after liquidity withdrawal from the pool. Panel (c) plots the impact of investment size on gross returns from capital gain and impermanent loss. For example, $\lambda(f) = 0.5$ implies that the gross return of capital gain and impermanent loss is halved by the price impact.

(a)



(b)



(c)

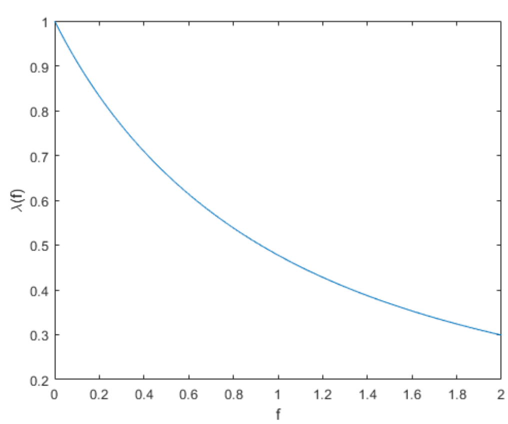


Figure A.7: Yield Farming Return Decomposition - Weekly Frequency

In this figure, we plot each component of weekly value-weighted returns across yield farms after sorting the farms each week into quintiles based on the magnitude of their in-sample offered yield. For each farm, we compute the weekly capital gain, impermanent loss, trading fee, and realized yield during its listing period. Then, we take the average of each component across farms using the size of each farm as weight. In Panels (a) to (d), the blue bars illustrate the average capital gain, impermanent loss, trading fee, and realized yield. The red error bars plot their associated 95% confidence intervals.

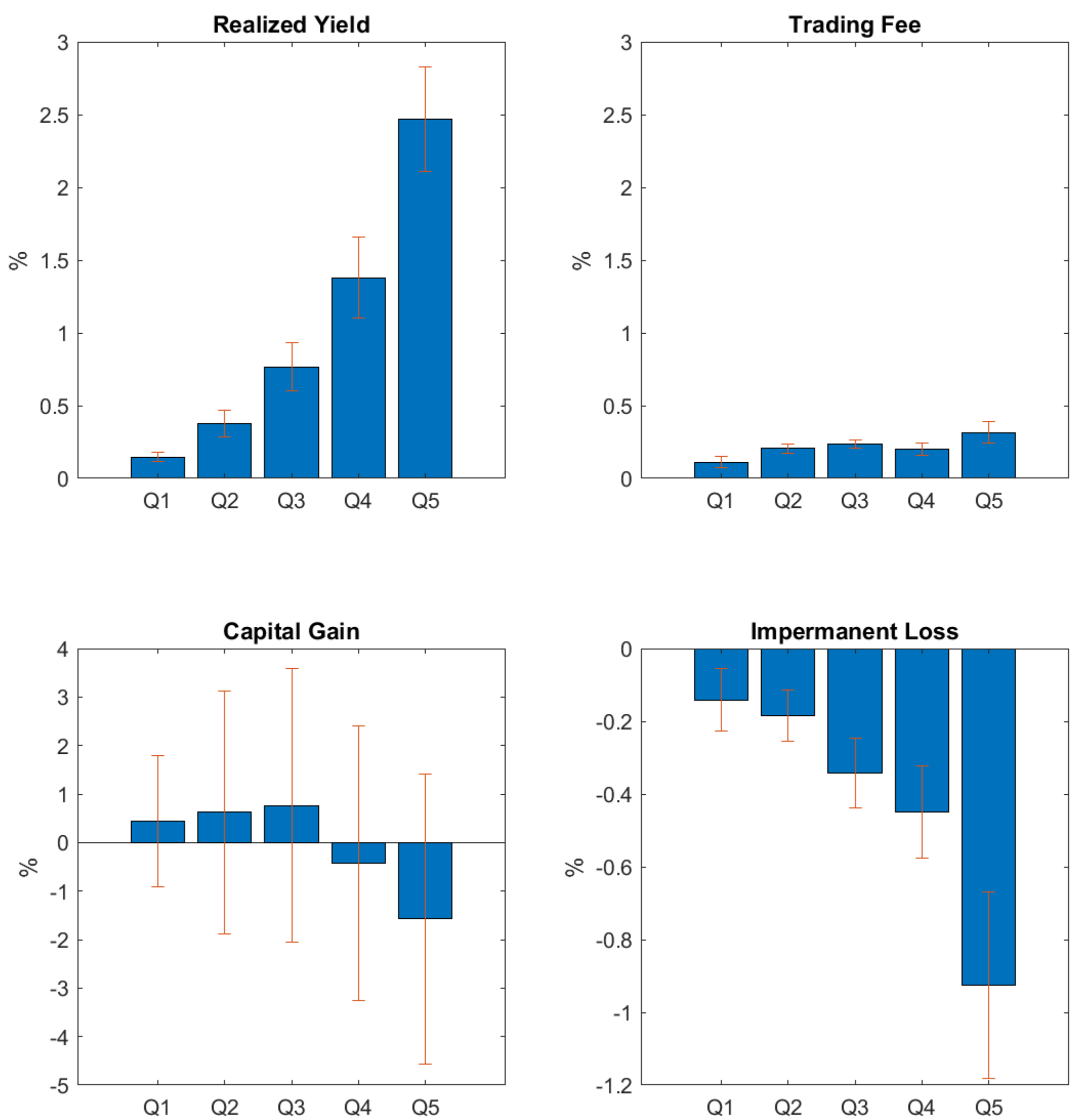


Figure A.8: Risk-Adjusted Returns from Yield Farming - Weekly Frequency

In this figure, we plot average risk-adjusted returns (i.e., alphas) and their associated 95% confidence intervals for different trading strategies at the weekly trading frequency. In Panel (a), we compare the performance of yield farming to that of liquidity mining without considering trading frictions. On each day, we sort farms into quintiles based on their in-sample offered farm yields. In each quintile, we form value-weighted portfolios by using size of the liquidity pools as weights. A yield farming strategy is a strategy in which investors not only earn trading fee revenue but also farm yields, whereas investors that restrict themselves to liquidity mining can only earn trading fee revenue. We estimate alphas from a three factor model based on the work of Liu, Tsyvinski, and Wu (2019) and also account for the performance of BNB. The blue (red) circle and the associated bar display alphas and their 95% confidence intervals for yield farming (liquidity mining) without considering frictions. In Panel (b), we follow a similar procedure but provide alphas for yield farming strategies without trading frictions, yield farming strategies with frictions including gas fees, trading fees, and price impact, and yield farming strategies considering not only the frictions but also investor mistakes. We describe detailed trading strategies in Section 4.5.

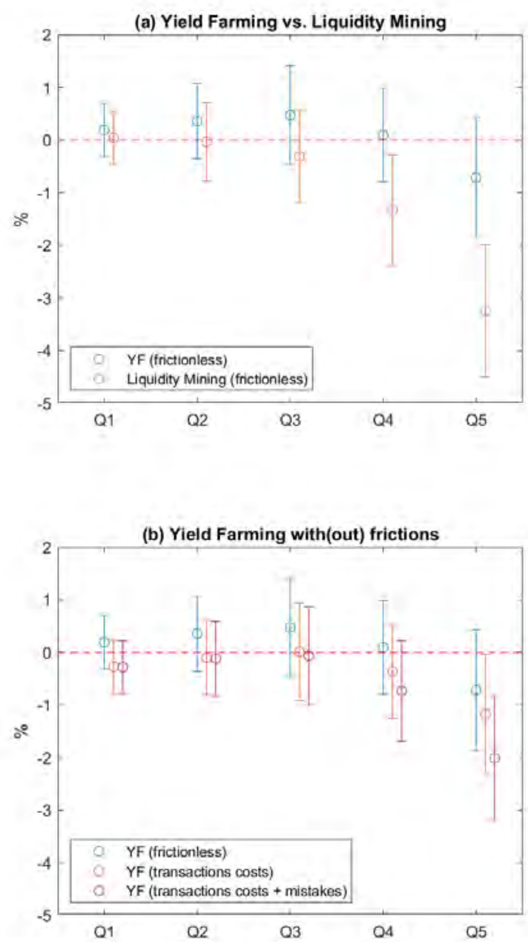


Figure A.9: Risk-Adjusted Returns from Yield Farming - Robustness

In this figure, we plot average risk-adjusted returns (i.e., alphas) and their associated 95% confidence intervals for different trading strategies, varying certain parameter choices. The starting set of parameters include an investment size of $5,000, investment duration (i.e., time to rebalance) of 10 days, and diversification across two farms. In Panel (a), we change the duration, keeping all other parameters fixed. In Panel (b), we change the investment size keeping all other parameters fixed. We estimate alphas from a three-factor model based on the work of Liu, Tsyvinski, and Wu (2019) and also account for the performance of BNB. We account for frictions including gas fees, trading fees, price impact, and investor mistakes.

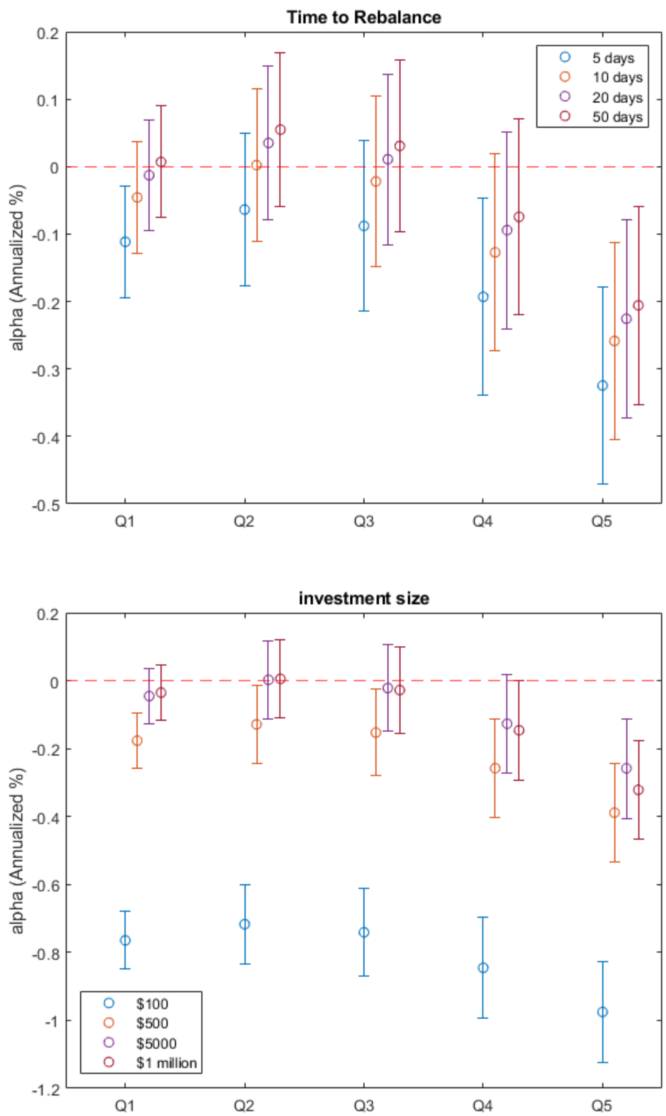


Figure A.10: The Impact of Aggregate Farm Multiplier Changes on Flows

In this figure, we illustrate how changes in the aggregate CAKE allocation multiplier, ΔM_t, affect flows to farms. In Panel (a), we measure inflows net of any growth due to an increase in the market capitalization associated with an increase in prices as in Equation (11), such that $Flow_{t,t+h} = \left(L_{t+h} - L_t \times R^*_{t,t+h}\right)/L_t$, where $R^*_{t,t+h}$ corresponds to the yield farm return defined in Equation (8) and L_t denotes the aggregate value of a pool's liquidity. In Panel (b), we measure inflows as the net token growth, i.e., $Flow_{t,t+h} = (\#LP\ tokens_{t+h}/\#LP\ tokens_t) - 1$. We are interested in changes in flows that are driven by shocks to the the multipliers of other farms, i.e., $\Delta m_{j,t} \mid j \neq i$. These shocks need to be large enough to have meaningful impact on M_t and, therefore, $y_{i,t}$. We identify 4 events where $\Delta m_{i,t} = 0$ with $|dM_t/M_t| > 0.15$. These 4 events are associated with increases in M_t. We then plot the average change in flows around the event dates, using a simple event study analysis. Specifically, we plot the coefficients β_k from a regression $Flow_{t,t+7} = \alpha + \sum_{k=-7,k\neq -1}^{k=7} \beta_k I\{m = k\} + Event \times FarmFE + \varepsilon_{i,t+m}$, where $Flow_{t,t+7}$ is defined as either $Flow_{t,t+7} = log(\frac{outstanding\ LP\ tokens_{i,t+m}}{outstanding\ LP\ tokens_{i,t}})$ or $Flow_{t,t+7} = log(\frac{size\ of\ pool_{i,t+m}}{size\ of\ pool_{i,t}})$. We cluster the standard errors at the farm and date levels.

(a) (b)

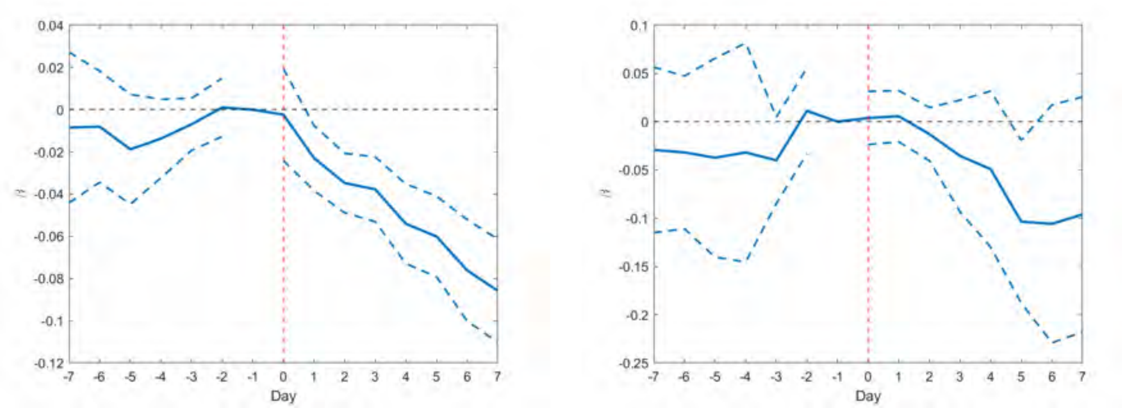


Table A.1: Literature on Decentralized Finance and Decentralized Exchanges

This table summarizes a selection of key academic studies that focus on decentralized exchanges (DEXs) within the emerging ecosystem of decentralized finance. We indicate whether the study is primarily of empirical or theoretical nature, and list the decentralized platforms studied in each paper: Uniswap, SushiSwap, PancakeSwap. We also emphasize whether the study focuses on liquidity mining/provision and market making, strategic trading and hedging or yield farming.

	Theory vs. Empirical		**DEX**			**Activity**		
Study	**Theory**	**Empirical**	**Uniswap**	**SushiSwap**	**PancakeSwap**	**Liquidity Provision/ Market Making**	**Strategic Trading/ Hedging**	**Yield Farming**
Angeris, Kao, Chiang, Noyes, and Chitra (2019)	✓		✓			✓		
Aoyagi (2021)	✓		✓			✓		
Aoyagi and Ito (2021)	✓		✓			✓	✓	
Neuder, Rao, Moroz, and Parkes (2021)	✓		✓			✓	✓	
Park (2021)	✓		✓			✓	✓	
Lehar and Parlour (2021)	✓	✓	✓			✓	✓	
Han, Huang, and Zhong (2021)		✓	✓				✓	
Capponi and Jia (2021)	✓	✓	✓	✓			✓	
Foley, O'Neill, and Putnins (2022)	✓	✓	✓	✓		✓	✓	
This study		✓			✓	✓		✓

Table A.2: Chain of Transactions for Yield Farming Strategies

In this table, we itemize the individual transactions in a yield farming strategy. We explain how each step of the yield farming strategy can change the number of tokens in a liquidity pool and we describe three different types of transaction costs: gas fees, trading fees, and price impact. We refer to a hypothetical pair of cryptocurrency tokens A and B in a liquidity pool (LP) A/B.

Step	**Timing**	**Event**	**# Tokens A in LP for A/B**	**# Tokens B in LP for A/B**	**Trading Frictions**		
					Gas Fee	**Trading Fee**	**Price Impact**
1	t	Yield farming starts.	α_t^A	α_t^B			
2	t	The yield farmer buys Δ_t^A units of token A using a part of his/her fund, $I_t = fL_t$, using Δ_t^B units of token B. This generates a temporary price change from price impact.	$\alpha_t^A - \Delta_t^A$	$\alpha_t^B + \Delta_t^B$	✓	✓	✓
3	t	The yield farmer buys token B in a liquid pool for B using the rest of his/her fund.	$\alpha_t^A - \Delta_t^A$	$\alpha_t^B + \Delta_t^B$	✓	✓	
4	t	Arbitrageurs correct the price by supplying Δ_t^A of token A and receiving Δ_t^B of token B.	α_t^A	α_t^B			
5	t	The yield farmer provides liquidity to the pool and receives LP tokens. Denote the fraction of his/her tokens to the tokens in the current pool by $s(f)$.	$(1+s(f))\alpha_t^A$	$(1+s(f))\alpha_t^B$	✓		
6	t	The yield farmer stakes the LP tokens in a farm.	$(1+s(f))\alpha_t^A$	$(1+s(f))\alpha_t^B$	✓		
7	$t+h$	h days elapse.	$(1+s(f))\alpha_{t+h}^A$	$(1+s(f))\alpha_{t+h}^B$			
8	$t+h$	The yield farmer receives (harvests) realized farm yields in CAKE tokens.	$(1+s(f))\alpha_{t+h}^A$	$(1+s(f))\alpha_{t+h}^B$	✓		
9	$t+h$	The yield farmer withdraws his/her LP tokens.	$(1+s(f))\alpha_{t+h}^A$	$(1+s(f))\alpha_{t+h}^B$	✓		
10	$t+h$	The yield farmer sells their CAKE tokens.	$(1+s(f))\alpha_{t+h}^A$	$(1+s(f))\alpha_{t+h}^B$	✓	✓	
11	$t+h$	The yield farmer redeems their LP tokens at the liqudity pool and receives his/her shares of token A and B.	α_{t+h}^A	α_{t+h}^B	✓		
12	$t+h$	The yield farmer sells his/her $\Delta_{t+h}^A = s(f)\alpha_{t+h}^A$ of token A using the same pool. This generates a temporary price change from price impact. They receive Δ_{t+h}^B of token B in exchange from the liquidity pool.	$\alpha_{t+h}^A + \Delta_{t+h}^A$	$\alpha_{t+h}^B - \Delta_{t+h}^B$	✓	✓	✓
13	$t+h$	The yield farmer sell his/her $(\Delta_{t+h}^B + s(f)\alpha_{t+h}^B)$ of token B in a liquid pool for B.	$\alpha_{t+h}^A + \Delta_{t+h}^A$	$\alpha_{t+h}^B - \Delta_{t+h}^B$	✓	✓	
14	$t+h$	Arbitrageurs correct the price by supplying Δ_{t+h}^B of token B and receiving Δ_{t+h}^A of token A. A new round of yield farming starts again.	α_{t+h}^A	α_{t+h}^B			

Table A.3: Top 10 Cryptocurrency Decentralized Exchanges

In this table, we report information about the 10 largest cryptocurrency decentralized exchanges in terms of daily trading volume as of October 9, 2021. For each exchange, we provide information on the daily trading volume (in $ million), the market share (in %), the number of markets at the exchange, the exchange type (swap, aggregator, order book, ...), whether spot assets or derivatives are traded on a DEX, and the month/year in which the exchange was launched. Source: https://coinmarketcap.com/rankings/exchanges/dex/.

Rank	**DEX**	**Daily Volume ($ million)**	**Mkt Share (%)**	**# Markets**	**Type**	**Spot /Derivatives**	**Launch Date**
1	dYdX	$1,756.41	25.05%	13	Orderbook	Derivatives	Apr 2019
2	PancakeSwap (V2)	$1,185.34	16.90%	1667	Swap	Spot	Apr 2021
3	Uniswap (V3)	$789.82	11.26%	627	Swap	Spot	May 2021
4	1inch Liquidity Protocol	$515.69	7.35%	26	Swap	Spot	Dec 2020
5	Uniswap (V2)	$287.57	4.10%	1556	Swap	Spot	Nov 2018
6	Sushiswap	$278.78	3.98%	387	Swap	Spot	Sep 2020
7	Honeyswap	$220.18	3.14%	66	Swap	Spot	Jul 2020
8	MDEX	$206.81	2.95%	140	Swap	Spot	Jan 2021
9	QuickSwap	$96.52	1.38%	330	Swap	Spot	Oct 2020
10	Raydium	$93.89	1.34%	112	Swap	Spot	Feb 2021

Table A.4: Determinants of Farm Yields

In this table, we report the results from a projection of farm yields on their individual components. The farm yields are defined as $y_{i,t} = c \times (m_{i,t}/M_t) \times \left(P_t^{CAKE}/L_{i,t}\right)$, where $c = 28800 \times 365 \times 40$. The components are the farm yield multiplier $m_{i,t}$, the amount of CAKE tokens redistributed for staking M_t, aggregate staked liquidity $L_{i,t}^{staked}$, and the price of the CAKE governance token P_t^{CAKE}. We report the adjusted R^2 and the number of observations. Standard errors are corrected for heteroscedasticity.

		(1)	(2)	(3)	(4)	(5)
		Offered Farm Yield				
Farm multiplier	$m_{i,t}$	-0.0011				0.0403***
		(0.0035)				(0.0141)
CAKE tokens redistributed for staking	M_t		-0.0003***			-0.0003***
			(0.0000)			(0.0000)
Staked Liquidity	$L_{i,t}^{staked}$			-0.0015**		-0.0032***
				(0.0007)		(0.0008)
Price of governance token	P_t^{CAKE}				0.0249***	0.0334***
					(0.0027)	(0.0025)
	N	53088	53088	53088	53088	53088
	adj. R^2	0.000	0.044	0.027	0.073	0.207

Table A.5: Determinants of Staking Ratios

In this table, we regress the staking ratio on a constant and indicator variables that take the value one if the staking ratio corresponds to the third farm (*3rd farm dummy*) to which the farmer provides liquidity and zero otherwise. Other indicator variables are defined similarly for the 4th (*4th farm dummy*), 5th (*5th farm dummy*), and more than five farms (*> 5th farm dummy*). The staking ratio is defined as the ratio of LP tokens staked in yield farms to the aggregate amount of LP tokens minted to certify liquidity provision. In columns (1) to (3), we deploy a linear probability model. In columns (4) to (6), we deploy a logistic regression model. Standard errors are clustered at the farmer level. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Staking Ratio (0 or 1)					
3rd farm dummy	0.1735***	0.0867***	0.0682***	0.8289***	0.9372***	1.0034***
	(0.0102)	(0.0106)	(0.0079)	(0.0363)	(0.0769)	(0.1390)
4th farm dummy	0.2076***	0.0964***	0.0765***	1.0381***	1.1242***	1.1645***
	(0.0152)	(0.0121)	(0.0088)	(0.0666)	(0.0980)	(0.1571)
5th farm dummy	0.2322***	0.1082***	0.0783***	1.2079***	1.3628***	1.1514***
	(0.0148)	(0.0134)	(0.0118)	(0.0636)	(0.1150)	(0.2460)
>5th farm dummy	0.2467***	0.1075***	0.0840***	1.3182***	1.3722***	1.1882***
	(0.0153)	(0.0156)	(0.0165)	(0.0707)	(0.1436)	(0.3719)
Sample	All	All	inv. > $1000	All	All	inv. > $1000
Model		LPM			Logit	
Control	No	Yes	Yes	No	Yes	Yes
Week FE	No	Yes	Yes	No	Yes	Yes
Farm FE	No	Yes	Yes	No	Yes	Yes
unique farmers	438,449	438,449	165,514	438,449	438,449	165,514
N	10,473,902	10,390,840	2,021,994	10,473,902	10,390,840	2,021,994
adj. R-sq	0.049	0.534	0.686			
pseudo R-sq				0.042	0.489	0.645

Table A.6: Comparison of Cryptocurrency Three-Factor Regressions

This table compares our regression results for portfolios sorted on one-week momentum by quintile to those reported in Liu, Tsyvinski, and Wu (2019). The sample period used in Liu, Tsyvinski, and Wu (2019) is from the beginning of 2014 to the end of 2018, which we interpret to be from the first week in 2014 to the 52nd (last) week of 2018 as the period for our replication.

Panel A: Regressions from			**Quintile**		
Liu, Tsyvinski, and Wu (2019)	**1**	**2**	**3**	**4**	**5**
α	-0.015	-0.010	-0.003	0.025	-0.012
$t(\alpha)$	*-1.970*	*-1.525*	*-0.657*	*1.470*	*-1.080*
β_{CMKT}	1.041	1.029	0.958	1.093	0.924
β_{CSMB}	0.124	0.014	0.204	0.072	0.297
β_{CMOM}	-0.164	-0.125	-0.071	0.072	0.424
R^2	0.531	0.606	0.687	0.198	0.435

Panel B: Replicated Regressions			**Quintile**		
	1	**2**	**3**	**4**	**5**
α	-0.019	-0.015	-0.004	0.031	-0.013
$t(\alpha)$	*-2.640*	*-2.362*	*-0.718*	*1.562*	*-1.230*
β_{CMKT}	0.994	0.957	0.873	1.119	0.996
β_{CSMB}	0.019	0.030	0.150	-0.034	0.081
β_{CMOM}	-0.148	-0.056	-0.045	-0.040	0.325
R^2	0.578	0.635	0.699	0.190	0.503

Table A.7: Summary Statistics of Coins used for Constructing Cryptocurrency Factors

In this table, we provide summary statistics of cryptocurrencies used for the construction of cryptocurrency factors as in Liu, Tsyvinski, and Wu (2019). Our sample period for cryptocurrency factors starts on December 28, 2013 and ends on July 31, 2022. The unit for market capitalization and daily trading volume in this table is $ million.

Year	**# Coins**	**Market Capitalization**		**Daily Trading Volume**	
		Mean	**Median**	**Mean**	**Median**
2013	26	409.8	7.3	2.01	0.05
2014	100	260.1	4.1	1.21	0.03
2015	79	136.9	2.8	1.13	0.10
2016	157	171.5	3.5	1.76	0.02
2017	675	427.9	9.9	17.89	0.13
2018	1,250	415.8	10.9	23.64	0.15
2019	1,175	227.8	6.0	68.67	0.18
2020	1,520	301.0	6.8	121.25	0.29
2021	2,291	724.8	13.9	146.86	0.53

Table A.8: Impact of Trading Frictions on Returns from Yield Farming Portfolios

This table reports the summary statistics for percentage excess returns from yield farming investment strategies, accounting for gas fee, trading fee, price impact, and investor mistakes. We take the perspective of a U.S. investor and report all information from the perspective of an initial USD investment. We provide detailed description of parameters that we choose to compute returns on each strategy in Section 4.5.1. On each day, we sort farms based on their offered yields and make 5 quintiles in each quintile to form value-weighted portfolios by using size of liquidity pool as weights. An yield farming strategy is a strategy in which investors not only earn trading fee revenue but also farm yields whereas in liquidity mining, investors can only earn trading fee revenue. *Yield Farming (Frictionless Benchmark)* (*Liquidity Mining*) refers to yield faring strategies (liquidity mining strategies) assuming no frictions (gas fee, trading fee, and price impact) and investors' unstaking. *Yield Farming with Frictions* refers to yield farming strategies considering gas fee, trading fee, and price impact that adversely affect returns. *Yield Farming with Frictions & Investor Mistake* not only considers the frictions but also investors' unstaking. In Panel A (B), we provide trading strategies for which we rebalance the portfolios every day (week). Excess returns are computed relative to the three-month U.S. Treasury bill secondary market rate sourced from the Federal Reserve Bank of St.Louis. All returns are value-weighted using the pools' aggregate liquidity as weighing factors. The column (OBS) reports the number of observations. We report the mean return ($Mean$), the standard deviation, skewness, and kurtosis of the yield farming strategies. We also report the Sharpe ratio (SR), information ratio (IR), the alpha from a three factor model based on the work of Liu, Tsyvinski, and Wu (2019), and the t-statistic for alpha from the three-factor regressions. The sample period is March 1, 2021 to July 31, 2022. All return-based statistics are not annualized.

Panel A: Daily							
Strategy	**Mean**	**SD**	**SR**	**IR**	α	**t-stat of α**	**OBS**
Yield Farming (Frictionless Benchmark)							
Quantile 1	0.0007	0.0242	0.0276	-0.0066	0.0000	-0.1489	518
Quantile 2	0.0022	0.0451	0.0492	0.0763	0.0011	1.9541	518
Quantile 3	0.0022	0.0465	0.0464	0.0442	0.0007	0.9833	518
Quantile 4	0.0000	0.0463	-0.0002	-0.1120	-0.0016	-2.3707	518
Quantile 5	-0.0001	0.0513	-0.0027	-0.0858	-0.0015	-1.7218	518
Liquidity Mining							
Quantile 1	0.0004	0.0242	0.0179	-0.0372	-0.0003	-0.8421	518
Quantile 2	0.0016	0.0450	0.0355	0.0339	0.0005	0.8812	518
Quantile 3	0.0009	0.0463	0.0203	-0.0326	-0.0005	-0.7265	518
Quantile 4	-0.0022	0.0460	-0.0478	-0.2550	-0.0036	-5.3006	518
Quantile 5	-0.0041	0.0509	-0.0806	-0.2947	-0.0053	-6.0304	518
Yield Farming with Frictions							
Quantile 1	0.0000	0.0242	0.0003	-0.0989	-0.0007	-2.2406	518
Quantile 2	0.0016	0.0451	0.0345	0.0285	0.0004	0.7309	518
Quantile 3	0.0015	0.0465	0.0321	0.0002	0.0000	0.0035	518
Quantile 4	-0.0007	0.0462	-0.0145	-0.1591	-0.0022	-3.3681	518
Quantile 5	-0.0008	0.0512	-0.0157	-0.1225	-0.0022	-2.4564	518
Yield Farming with Frictions & Investor Mistakes							
Quantile 1	0.0000	0.0242	-0.0002	-0.1004	-0.0007	-2.2746	518
Quantile 2	0.0015	0.0451	0.0342	0.0275	0.0004	0.7046	518
Quantile 3	0.0014	0.0465	0.0296	-0.0074	-0.0001	-0.1644	518
Quantile 4	-0.0012	0.0462	-0.0264	-0.1945	-0.0027	-4.1073	518
Quantile 5	-0.0021	0.0512	-0.0417	-0.1925	-0.0035	-3.8731	518

Panel B: Weekly							
Strategy	**Mean**	**SD**	**SR**	**IR**	α	t**-stat of** α	**OBS**
Yield Farming (Frictionless Benchmark)							
Quantile 1	0.0056	0.0584	0.0955	0.0933	0.0019	0.7312	74
Quantile 2	0.0104	0.1089	0.0954	0.1206	0.0036	0.9790	74
Quantile 3	0.0145	0.1240	0.1172	0.1026	0.0047	0.9853	74
Quantile 4	0.0077	0.1236	0.0621	0.0275	0.0009	0.2076	74
Quantile 5	0.0036	0.1333	0.0273	-0.1396	-0.0072	-1.2262	74
Liquidity Mining							
Quantile 1	0.0041	0.0582	0.0699	0.0201	0.0004	0.1591	74
Quantile 2	0.0065	0.1082	0.0599	-0.0114	-0.0003	-0.0892	74
Quantile 3	0.0065	0.1224	0.0534	-0.0686	-0.0031	-0.6837	74
Quantile 4	-0.0067	0.1224	-0.0550	-0.3513	-0.0133	-2.4858	74
Quantile 5	-0.0219	0.1304	-0.1678	-0.6232	-0.0324	-5.0570	74
Yield Farming with Frictions							
Quantile 1	0.0009	0.0581	0.0162	-0.1326	-0.0027	-1.0377	74
Quantile 2	0.0057	0.1084	0.0529	-0.0349	-0.0010	-0.2839	74
Quantile 3	0.0099	0.1234	0.0798	0.0023	0.0001	0.0221	74
Quantile 4	0.0030	0.1230	0.0245	-0.1065	-0.0037	-0.8038	74
Quantile 5	-0.0010	0.1326	-0.0076	-0.2301	-0.0117	-2.0172	74
Yield Farming with Frictions & Investor Mistakes							
Quantile 1	0.0008	0.0581	0.0144	-0.1381	-0.0028	-1.0796	74
Quantile 2	0.0056	0.1083	0.0517	-0.0401	-0.0012	-0.3266	74
Quantile 3	0.0091	0.1237	0.0739	-0.0141	-0.0006	-0.1356	74
Quantile 4	-0.0007	0.1238	-0.0056	-0.2016	-0.0073	-1.5074	74
Quantile 5	-0.0095	0.1319	-0.0723	-0.3937	-0.0201	-3.3361	74