Reaching for Yield in Decentralized Financial Markets*

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Abstract

Among the ecosystem of decentralized financial services, yield farming is a complex investment strategy with hidden downside risks providing opportunities for passively earning income. We characterize the risk and return characteristics of yield farming and show that yield farms dynamically compete for liquidity by offering high yields that are advertised as salient headline rates. Levering the full history of transactions available through blockchain data, we show that investors chase farms with high yields and that those farms with the highest headline rates record the most negative risk-adjusted returns. That underperformance is amplified by small investment stakes and investor mistakes. Overall, our evidence is consistent with salience theory that may underpin reaching for yield behavior. We exploit heterogeneity in shocks to the information set of yield farmers to show that improved information disclosure and reduction in product complexity reduces yield chasing and improves investor performance. Since yield farming is easily accessible to retail investors, our analysis has important implications for the regulation of decentralized finance.

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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, has grown exponentially to more than $200 billion over the past 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, one common type of decentralized financial service that is especially well-suited for the examination of investor behavior in the presence of product complexity. First, yield farms dynamically compete for liquidity provision through 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 by the average investor, 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 used 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 234 yield farms from PancakeSwap, a yield farm platform hosted on the Binance Smart Chain (BSC), between September 23, 2020 and August 1, 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 illustrate that gas fees that have to be paid for transactions on the blockchain are an order of magnitude larger for Ethereum.

There is a significant amount of heterogeneity in offered yields among the 234 farms in our sample. The average (median) offered yield is 77.15% (38.51%) 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 incentive 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 suggests that the average yield farmer invests in 1.81 farms and provides $6,959 of liquidity. Strikingly, we observe that smaller investment stakes are correlated with smaller staking ratios, suggesting that retail investors are more likely to lack financial sophistication. That conclusion is backed by survey evidence. According to a CoinGecko survey of 1,347 yield farmers, 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 empirical return performance of yield farming strategies and compare them to other benchmark strategies in cryptocurrency markets and the S&P500 index. We take the perspective of U.S. investor who needs to buy digital assets using the USD as a base currency and exchange all farm yields back to its local currency at the prevailing exchange rates. We find that yield farming strategies appear to generate attractive returns, with Sharpe ratios between 2 and 3. While such Sharpe ratios appear extraordinarily large, they are similar to those for investments into the S&P500 index, Bitcoin or Ethereum, and are partially explained by the extraordinary bull run in most asset markets during our sample period.

Yield farming also generates Sharpe ratios that are larger than those of simple buy-and-hold trading strategies in the underlying pairs of cryptocurrency tokens. It also generates superior performance to a strategy that considers liquidity mining without yield farming. Even though the joint investment activity is a strictly dominating strategy, not all investors appear to stake their liquidity tokens into yield farms. This is suggestive evidence of investor inertia and lack of investor sophistication.

While we uncover positive investment performance without the consideration of transaction costs, the performance becomes significantly weaker when we account for trading costs (a.k.a. gas fees) and price impact. While gas fees shift the return performance linearly downward for all yield farms, price impact is especially important for farms that advertise large headline yields. Using parameters such as average size of investment, rebalancing frequency, and degree of investor mistake obtained from the individual farmers' transaction data, we find that chasing high yield can result in negative risk-adjusted returns. This motivates our additional analysis on the relation between flows and performance in yield farms.

As a last step, we study the relation between yield farming flows and performance. We follow the mutual fund literature and define farm flows as the change in total value locked, after accounting for growth in liquidity associated with return performance. We scale flows by total value locked to make them comparable across yield farms. We find that farms with high headline yields attract more flows and that positive return performance predicts future flows. Moreover, we find that new flows are negatively correlated with future farm performance.

Overall, our evidence is consistent with evidence from other asset markets that reflects return chasing behavior, whereby flows chase positive past performance. Our findings also provide supportive evidence for patterns that are associated with reaching for yield. We consider these findings to be intriguing since they typically arise in a setting with financial intermediaries, while yield farming is implemented in a decentralized market without financial intermediaries.

A unique setting in PancakeSwap allows us to study the impact of information disclosure and reduction in complexity on reaching for yield behavior. Specifically, 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, thereby improving the overall investor performance. 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 leverage 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) and mutual fund markets (Choi and Kronlund, 2018).

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).

In a significant departure from previous work, we study complex financial products offered through smart contracts operating on a blockchain without centralized financial intermediaries who may drive the security design or benefit from sales. The advantage of our study is that we can 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 enables investors to earn passive income for liquidity provision to DeFi platforms. Intuitively, it is akin to a decentralized variant of securities lending with the distinctive feature that smart contracts operating on permissionless blockchains automatically execute transactions without involvement of financial intermediaries. We provide institutional details in Appendix A.

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, a popular automated market maker that ranks second in the league tables of decentralized exchanges offering cryptocurrency lending services. This figure illustrates that yield farming involves two sequential and independent investment decisions.

First, an investor can earn passive income by providing liquidity to a liquidity pool, as shown in Panel (a) of Figure 3. A liquidity provider stakes a pair of cryptocurrency tokens (in this example, BTH and ETH) in equal dollar amounts into a liquidity pool for trading BTC against ETH. Liquidity providers get compensated for their liquidity provision through trading fees collected from third party traders (i.e., liquidity demanders) who buy and sell BTC and ETH in the liquidity pool. The trading fees are paid in Binance Coin (BNB), the native currency of the Binance smart chain (BSC), and amount to 0.25% of a pool's trading volume. Of that amount, 0.17% is paid out to liquidity providers.

Second, the liquidity provision is certified by a liquidity token (i.e., the LP token), which can be staked into a yield farm specific to the BTC-ETH currency pair. In PancakeSwap, multiple liquidity pools are deployed to facilitate trading of cryptocurrency pairs and investors have to choose their preferred liquidity pool. Each pool is linked to a unique yield farm that offers additional passive income opportunities through the form of yields.

The passive income in the yield farm is earned in CAKE, the native governance token of PancakeSwap. In PancakeSwap, the CAKE token serves as the governance token for the Decentralized Autonomous Organization (DAO), where token holders can cast votes to influence the future development of the platform. They can decide to increase or decrease the offered yield. Yield farms, therefore, compete for liquidity by promising high returns.

Panel (b) of Figure 3 illustrates how governance tokens are issued, earned and distributed across yield farms. With each BSC block creation, PancakeSwap issues CAKE that is distributed to yield farmers as a compensation for the staking of their LP tokens. PancakeSwap uses a fraction of trading fees to buy back and burn (i.e., destroy) CAKE in order to minimize the currency's dilution.

The complicated chain of transactions described in Figure 3 implies that the returns to yield farming come from two components associated with liquidity mining and LP token staking. The total yield farming return between day t and $t+h$, $R_{t,t+h}$, is thus equal to:

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

where $R^{\ell}_{t,t+h}$ and $R^{f}_{t,t+h}$ define the returns from liquidity provision and the staking of LP tokens into a yield farm, respectively.

2.1 Liquidity Provision

To provide liquidity to a pool (e.g., the ETH/BNB pool), a liquidity provider needs to deposit ETH and BNB in equal amounts, taking into account their current market prices. For example, if the price of one ETH corresponds to 10 BNB, an investor would need to deposit 10 BNBs for each unit of ETH.

The pools' aggregate liquidity L_t is characterized by the aggregate token valuation, defined by the number of ETH and BNB tokens, α^A_t and α^B_t, and their prices, P^A_t and P^B_t, respectively:

$$L_t = \alpha^A_t \cdot P^A_t + \alpha^B_t \cdot P^B_t. \tag{2}$$

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:

$$\begin{aligned} R^{\ell}_{t,t+h} &= \frac{L_{t+h}}{L_t} + Trading\ Fee\ Return_{t,t+h} \\ &= \frac{\alpha^A_{t+h} \cdot P^A_{t+h} + \alpha^B_{t+h} \cdot P^B_{t+h}}{\alpha^A_t \cdot P^A_t + \alpha^B_t \cdot P^B_t} + Trading\ Fee\ Return_{t,t+h}. \end{aligned} \tag{3}$$

Intuitively, growth in the value of the liquidity pool is similar to a traditional price return. The key difference is that the number of shares α^i_t is neither constant nor based on the initial investment. Instead, it is time-varying and determined by the trading activity in the liquidity pool. This feature arises because of the constant-product technology hardwired into liquidity pools. See Lehar and Parlour (2021) for details.

In exchange for their liquidity provision, investors receive LP tokens to certify their partial ownership in the pool. While the fractional ownership stays constant over time, the pool's liquidity value may change when end users independently buy and sell ETH and BNB. The terms of trade for end users are such that the product of the quantities available in the pool is equal to a constant k:

$$k = \alpha_t^A \alpha_t^B = \alpha_{t+h}^A \alpha_{t+h}^B. \tag{4}$$

This implies that the fractional claim to the liquidity pool is constant over time. However, the number of units of ETH and BNB represented by this claim will change as a result of variation in the pool's composition arising from trading activity by end users. Thus, when a liquidity provider decides to redeem their liquidity tokens in exchange for ETH and BNB, the number of tokens they receive from redemption may differ from those initially deposited (i.e., $\alpha_{t+1}^i \neq \alpha_t^i$) despite the same fractional claim to the liquidity pool.

A second feature of the constant-product technology is that the products of price and quantity have to equalize across assets, that is, for all t:

$$\alpha_t^A P_t^A = \alpha_t^B P_t^B. \tag{5}$$

A consequence of the constant-product technology is that the returns to liquidity provision have two distinct components. Investors are exposed to capital gains/losses resulting from joint changes in the tokens' prices and in the pool's liquidity, since this leads to fluctuations in the composition of tokens that an investor can claim using the liquidity token. In addition, investors are exposed to impermanent losses, which depend on the relative returns of both ETH and BNB (i.e., changes in the ratio of token prices). To formalize our discussion, the return from liquidity growth can be expressed as:

$$\frac{L_{t+h}}{L_t} = \underbrace{\left(\frac{1}{2}R_{t,t+h}^A + \frac{1}{2}R_{t,t+h}^B\right)}_{\text{capital gain}} - \underbrace{\frac{1}{2}\left(\sqrt{R_{t,t+h}^A} - \sqrt{R_{t,t+h}^B}\right)^2}_{\text{impermanent loss}}, \tag{6}$$

where $R_{t,t+h}^A = P_{t+h}^A / P_t^A$ and $R_{t,t+h}^B = P_{t+h}^B / P_t^B$ denote the gross returns of tokens A and B, corresponding to ETH and BNB in our example. In Appendix B, we explicitly show how the above expression is obtained from the initial liquidity provision that starts with a nominal dollar investment.

Intuitively, the impermanent loss corresponds to the difference between the return from liquidity provision 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 difference in token returns. Importantly, they are strictly negative and expose investors to significant upside and downside risk analogous to a short volatility exposure (Aigner and Dhaliwal, 2021). See 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

$$Trading\ Fee\ Return_{t,t+h} = c \cdot \left((I_t/L_t)V_{t,t+h}\right)/I_t = c \cdot V_{t,t+h}/L_t. \tag{7}$$

2.2 Yield farming

A second passive source of income is generated by staking the liquidity tokens in yield farms which promise a yield y_t. That income is paid in terms of the platforms's governance token, which corresponds to Cake in the case of PancakeSwap.

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 to the farm with the creation of a new block; (d) the total liquidity staked to the farm L_t^{staked}; and (e) the price of Cake P_t^{Cake}.

Approximately 40 Cake tokens are created through blockchain validation corresponds for each three second period. Thus, assuming that 28,800 blocks are created each day, the annualized promised yield from staking liquidity tokens to a yield farm is given by:

$$y_t = \left(\frac{365 \times 28,800 \times 40 \times m_t}{M_t}\right)\left(\frac{P_t^{Cake}}{L_t^{staked}}\right). \tag{8}$$

Cake tokens may be allocated to other purposes than yield farming. Therefore, the aggregate multiplier does not have to correspond to the sum of all multipliers across yield farms on a platform like PancakeSwap, i.e., $M \neq \sum_k m^k$, where k corresponds to the number of farms. Note that we explicitly write out the price of the Cake reward for yield farming, P_t^{Cake}, because one of the token pair in the liquidity pools does not have to be Cake. Realized farm yield between t and $t+h$ is thus defined as

$$P_{t+h}^{Cake} \sum_{n=1}^{h} \left(\frac{y_{t+n-1}}{P_{t+n-1}^{Cake}}\right)\left(\frac{1}{365}\right). \tag{9}$$

2.3 Aggregation: Frictionless Benchmark

Aggregating across all components allows us to decompose the total ($h - period$) return to yield farming strategies into four components associated with token capital gains, impermanent losses, revenues from trading fees, and realized farm yields:

$$
\begin{aligned}
R_{t,t+h} \quad &= \quad \underbrace{\left(\frac{1}{2}R^A_{t,t+h} + \frac{1}{2}R^B_{t,t+h}\right)}_{\text{capital gain}} \underbrace{- \frac{1}{2}\left(\sqrt{R^A_{t,t+h}} - \sqrt{R^B_{t,t+h}}\right)^2}_{\text{impermanent loss}} \\
&+ \quad \underbrace{c \cdot V_{t,t+h}/L_t}_{\text{trading fee revenue}} \underbrace{+ P^{Cake}_{t+h} \sum_{n=1}^{h} \left(\frac{y_{t+n-1}}{P^{Cake}_{t+n-1}}\right)\left(\frac{1}{365}\right)}_{\text{realized farm yield}}. \qquad (10)
\end{aligned}
$$

2.4 Impact of trading frictions

In practice, yield farming involves a chain of transactions that, taken together, may involve sizable transaction costs. Table A.2 breaks down the chain of transactions for a hypothetical yield farming strategy. We provide additional details in Appendix B.2.

Harvesting yields at PancakeSwap involves a chain of 12 transactions (excluding step 1 and 14 in Table A.2 that are unrelated to the yield farmer's transactions). A full round-trip transaction involves three types of costs associated with gas fees, trading fees, and price impact. 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 have to pay gas fees for 10 of them. The average gas fee for a round-trip of yield farming in PancakeSwap is estimated to be \$3.28 in our sample period.

Gas fees are especially detrimental to smaller retail investors since the flat fee is more costly for small stake investments and frequent rebalancing. In addition, since the gas fee applies to each yield farm, it reduces the benefits of diversifying systematic risk across several yield farms. An initial \$1,000 investment will thus lose about 33 bps in a round-trip transaction due to gas fees alone, and 33 bps per week for weekly rebalancing. That consideration is important for retail investors who have a tendency to rebalance too frequently Odean (1999). A diversification strategy across 10 farms would incur a per period cost of 10×3.28 = \$32.8, which, for a \$1,000 investment, is more than the typical performance fee owed to a hedge fund, excluding any consideration for hurdle fees or water marks.

Gas fees thus encourage larger and more concentrated investments, which may not be appropriate for financially unsophisticated investors. In our analysis, we consider investment sizes of \$5,000, \$10,000, \$100,000 and \$1,000,000. This allows us to consider cases where gas fees do not wash out all potential yield farm returns.

Investors also incur trading fees. PancakeSwap charges a fee of 0.25% (proportional to trading volume) for each transaction. Since yield farmers need to buy and sell tokens in intermediate steps, they will lose at least an additional 0.50% of their initial investment for a round-trip transaction. See Appendix B.2 for more details.

The third transaction cost arises through price impact. To quantify price impact, we assume that yield farmers invest an amount I_t corresponding to a constant fraction f of the liquidity pool value L_t, i.e. $I_t = f \cdot L_t$. Equation (6) provides the return to liquidity provision without frictions. With price impact and ignoring trading fees, the return to liquidity provision is impacted as follows:

$$\lambda(f)\left[\left(\frac{1}{2}R^A_{t,t+h}+\frac{1}{2}R^B_{t,t+h}\right)-\frac{1}{2}\left(\sqrt{R^A_{t,t+h}}-\sqrt{R^B_{t,t+h}}\right)^2\right], \tag{11}$$

where $\lambda(f)$ is the price impact function. We illustrate in Panels (a) to (c) of Figure 4 how price impact relates to investment size. Considering both trading fees and price impact, the return to liquidity provision reduces to:

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

We emphasize another indirect channel through which yield farming performance is negatively affected. Equation (8) suggests a negative relation between the aggregate liquidity in a yield farm and the offered farm yield. We provide empirical support for that pattern 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

The non-negative earnings potential from yield farming suggests that staking LP tokens into the yield farm is always a dominating strategy. Thus, the optimal staking ratio k is equal to 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. Note that the selling of Cake tokens at redemption also requires a trading fee of 0.25%.

Given all trading frictions, we quantify the returns from yield farming with frictions as follows:

$$\begin{aligned}
R^{friction}_{t,t+h} \quad = \quad & (1-0.0050)\lambda(f)\left[\underbrace{\left(\frac{1}{2}R^A_{t,t+h}+\frac{1}{2}R^B_{t,t+h}\right)}_{\text{capital gain}}-\underbrace{\frac{1}{2}\left(\sqrt{R^A_{t,t+h}}-\sqrt{R^B_{t,t+h}}\right)^2}_{\text{impermanent loss}}\right] \\
+ \quad & \underbrace{c\cdot V_{t,t+h}/L_t}_{\text{trading fee revenue}} + \underbrace{(1-0.0025)\,k^*\left[P^{Cake}_{t+h}\sum_{n=1}^{h}\left(\frac{y_{t+n-1}}{P^{Cake}_{t+n-1}}\right)\left(\frac{1}{365}\right)\right]}_{\text{realized farm yield}} - \frac{Gas_{t,t+h}}{I_t}
\end{aligned} \tag{12}$$

2.6 Yield farm flows

In our analysis, we examine flows into yield farms. To measure net inflows of liquidity, we, therefore, follow the mutual fund literature (e.g., Sirri and Tufano, 1998; Coval and Stafford, 2007) and define the measure $flow_{t,t+h}$ over an h-period trading horizon

$$Flow_{t,t+h} = \frac{L_{t+h} - L_t \times R^*_{t,t+h}}{L_t}, \tag{13}$$

where $R^*_{t,t+h}$ corresponds to the yield farm return defined in Equation (12) 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 the realized farm yield term in our flow definition because it does not affect the size of next period's liquidity pool, unlike capital gains, impermanent losses and trading fees. The reason is that the farm yield is paid in Cake rather than using the base cryptocurrency of th liquidity pool or yield farm.

3 Building yield farm and yield farmer data

We assemble a novel data set on liquidity pools and yield farms listed at 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. We complement our data with cryptocurrency return factors as in Liu, Tsyvinski, and Wu (2019).

3.1 Farms and yields

We consider all contract addresses of liquidity pools with a corresponding yield farm stored in PancakeSwap's main staking contracts from their inception on September 23, 2020 to August 1, 2022. Given the addresses, we can reconstruct, from the blockchain, the time series of each farm's yield multiplier at the daily frequency. We consider only active farms with a non-zero yield multiplier.

To measure farm yields, we use information on the cryptocurrency shares provided to liquidity pools, α^i_t, using the tokens' balances in each pool. Given token prices, aggregate pool liquidity is computed as the total dollar value of a token pair, $L_t = P^A_t \alpha^A_t + P^B_t \alpha^B_t$. We further collect each pool's supply of liquidity tokens. The aggregate liquidity staked to a farm is then given by a pool's aggregate liquidity times the fraction of liquidity tokens that have been staked, $L^{staked}_t = (\#\text{ staked LP tokens}/\text{Aggregate }\#\text{ of LP tokens}) \cdot L_t$.

We impute farm yields using Equation (8). We verify their accuracy by collecting offered farm yields from PancakeSwap's homepage[1] at midnight Greenwich Meridian Time (GMT)

[1] https://pancakeswap.finance/farms

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.

Figure A.5 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 each liquidity pool (e.g., ETH–BNB), the price P_t^i of one token of the cryptocurrency pair, considered a token of interest (e.g., ETH), is typically expressed in terms of a numeraire token (e.g., BNB). We source daily prices P_t^i of the tokens of interest using the most recent end-of-day price in GMT.

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

We source gas fee data from a proprietary data provider specialized in blockchain data services covering Bitcoin, Ethereum, Binance Smart Chain, among others. Different functions executed by smart contracts incur different gas fees. To accurately impute the gas fees to the performance of yield farming strategies, we first identify the chain of transactions that incur gas fees (see Table A.2). We then compute the average daily gas fee in U.S. dollars for each transaction in the chain. Finally, we compute the round-trip cost of gas fees by summing the average gas fee across all corresponding transactions.

3.3 Yield farmers

We collect transaction data for all LP tokens from the transaction logs of BscScan[2], a freely-accessible utility for searching data on the BSC and reconstruct each wallet's token holdings. In the data, transactions in which a user deposits 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 underlying tokens are represented as a LP token transfers to the address of the LP token itself.

[2]https://bscscan.com/

We restrict our analysis to active accounts during our sample period. In addition, 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. Finally, we omit wallet addresses that have transacted LP tokens 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. For each transaction, we match the token prices and offered yield of the LP token to the nearest end-of-day price by block height difference. We also remove positions worth less than $1 at the beginning of the holding period.

To understand yield farming behavior, we compute, for each wallet, the number of invested farms (*No. Farms*) and liquidity pools (*No. Pools*). Second, 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 each 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, it is unlikely that yield farmers systematically use multiple wallets for yield farming since there are no monetary benefits and managing multiple wallets increases transaction and implementation costs for yield farming strategies. Relying on wallet clustering algorithms may help alleviate such concerns.

3.4 Cryptocurrrency 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.

In Appendix C, we describe our successful replication of Liu, Tsyvinski, and Wu (2019), suggesting that our cryptocurrency factors are reliably estimated.

3.5 The final sample

Our final sample contains 234 unique active yield farms during our sample period that starts with the inception of PancakeSwap on September 23, 2020 and ends on August 1, 2022. For our analysis, we work with 7,796,709 transactions initiated by 590,388 unique wallets.

Panel (a) of Figure 5 illustrates the number of active farms during our sample period (right axis). Since new farms may be listed and delisted, the cross-section of active farms varies over time. The total number of active farms on a given day increases quickly from inception of PancakeSwap to a peak of 160 farms in July 2021.

The left axis in Panel (a) of Figure 5 plots the the Total Value Locked (TVL) in all active farms, i.e., the aggregate amount of liquidity in yield farming. Yield farming at PancakeSwap has experienced extraordinary growth, with TVL surpassing \$7 billion in May 2021. Analogously to the boom and bust cycles experienced by Bitcoin and other cryptocurrency markets, 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 5, the consequential increase in liquidity provision coincides with the time when PancakeSwap became more prominently researched in Google (left axis). This is also the time when the number of active farmers jumped sharply (right axis). For that reason, we restrict our main analysis to start in March 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 Evidence on yield farms

We report in Table 1 a snap shot of yield farms on August 1, 2022. Each yield 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 (Table A), while yields range from 0.24% to 113.17% (Table B).

In Figure 6, we plot the time-variation in 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 in the interquartile range of the yield farm distribution. Such rich variation in yields across farms and across time provides an opportunity to better understand the drivers of cross sectional variation in the risk and return characteristics of yield farming strategies and the performance of liquidity provision.

Yields are salient to investors and marketed as headline rates that look attractive, especially in a low interest rate environment. In Appendix Table A.2, we provide an example of a yield farming user interface in PancakeSwap. The interface is engaging because it displays cartoons, rockets and emojis. The main information that is displayed relates to the offered yield (i.e., the annualized percentage return), the yield multiplier and the pool's liquidity.

On the other hand, it is difficult to find detailed information about the computation of the annualized percentage returns or the meaning of the yield multiplier. Moreover, it is difficult to find information on the decomposition of returns. There are hidden downside risks associated with impermanent losses and hidden costs related to the price impact of large trades, which the industry refers to as slippage.

Yield farming looks like a simple application, but is, in fact, a complex investment strategy, both in terms of payoffs and execution. The payoffs to yield farming depend on several underlyings, since trading fees are paid in the Binance base currency BNB, impermanent losses depend on the return correlation of a cryptocurrency pair, and farm yields are paid using the governance token of PancakeSwap, i.e., CAKE. Furthermore, the payoffs feature significant non-linearities, epitomizd 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 yields

In Equation 8, we describe the function for offered farm yields, which is driven by 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 token owners. However, Cake owners can actively decide on increasing or decreasing offered farm yields through a farm-specific multiplier $m_{i,t}$. The aggregate multiplier M_t sums across all farm multipliers and defines the amount of Cake tokens redistributed for staking. In Appendix Table A.6, we validate that all components are indeed strongly correlated with the level of offered farm yields and that they have the correct sign.

The ability to change the yield multiplier m equips Cake owners with centralized decision power on the amount of passive earnings potential, which goes against the spirit of the decentralized financial service. Thus, they can decide to increase the farm multiplier to increase the offered farm yield and, thereby, attract liquidity to a particular liquidity pool.

This gives us two interesting sources of variation that we can explore. First, we can 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}). Second, we can exploit variation to yield changes that are driven by shocks to other yield farms not associated with changes in yield multipliers m.

In Table 2, we isolate the impact of yield changes that comes 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.

In columns (1) and (2) of Table 2, we find that yields appear to be 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 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 features of the yield farming infrastructure at PancakeSwap enable us to infer information about the activities of its participants. In this subsection, we provide some evidence consistent with cross-sectional variation in sophistication across yield farmers.

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 strongly encouraged to switch their liquidity provision from version 1 to version 2, but had to trigger the switch themselves. The switch to the new version is considered to be a strictly dominant strategy, because migrating liquidity to the new version delivers higher rewards for staking the same tokens as in version 1, alongside lower transaction costs.

In Panel (a) of Figure 7, we show the outstanding assets that remain in the old version and that are not migrated. This shows that the migration of funds is sluggish, which could be a sign of investor attention or inertia. More 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 7 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.

Systematic evidence is available from staking ratios. Yield farming involves several independent transactions. Investors first need to provide liquidity to liquidity pools. The liquidity tokens that certify the liquidity provision then need to be independently staked to a yield farm. Combining both transactions is strictly dominating compared to liquidity provision alone, since earning Cake through farming is always superior to not earning Cake. However, we show in Figure 8 that the number of LP tokens staked in yield farms is significantly lower than the aggregate amount of LP tokens minted to certify liquidity provision.

We would expect the staking ratio to be equal to one at all times. However, the median ratio is below one most of the time. The 10th (25th) percentile of the distribution even drops to as low as 30% (85%). This is further evidence that supports the lack of investor sophistication in this market. However, we caveat this interpretation with the possibility of investors staking their LP tokens in third-party yield farm aggregators. While we currently do not have access to this information, we are in the process of collecting it.

In Panel A of Table 3, we show farmer-level statistics. The average yield farmer invests in 2.32 farms, has a holding period of 31.33 days, and has $28,837 worth of LP tokens.

However, the average staking ratio is only 0.8081. This suggests that a significant profit generated from farming is lost for investors who miss the farming opportunities, possibly due to the complex nature of trading strategies.

In Panel B of Table 3, we separate the farmers into quintiles based on their average *LP Balance*. Differences in average *LP Balance* are substantial across quintiles. For instance, the average *LP Balance* of the lowest quintile is only \$11.78, whereas that of the highest quintile is \$143,272. This indicates significant cross-sectional dispersion in investment sizes among PancakeSwap users. Thus, many yield farmers have small investment stakes.

We observe that *LP Balance* is positively correlated with the staking ratio, ranging from 0.6211 to 0.9197 between the lowest and highest LP balance 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 56.28% and 77.25% across quintiles, investors face non-trivial opportunity costs. Investors also have short staking times, with a holding period ranging between 8.7 and 67.93 days across quintiles.

Finally, we observe non-linear return performance across quintiles with the highest annualized return of 40.68% in quintile 3. This echoes our discussion in Section in Section 4.5.1, where we suggest that both large and small investment stakes could generate sub-optimal performance due to transaction costs and price impact.

Evidence from DappRadar[3] 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.

Survey evidence further supports the view that yield farmers may not be financially sophisticated. CoinGecko, a major cryptocurrency data provider, surveyed 1,347 cryptocurrency investors regarding yield farming in August 2020 (CoinGecko, 2020). Interestingly, a significant fraction of yield farmers seem to be overconfident and unsophisticated. According to the survey, 79% of yield farmers claim to understand the associated risks and rewards of yield farming to a reasonable extent. However, about 40% of yield farmers report that they could not read smart contracts to verify potential vulnerabilties or scams of the yield farms. In addition, 33% of yield farmers do not know the meaning of impermanent loss is, implying that they are taking risks that they do not understand.

4.4 Risks and returns of yield farming

In Table 4, we report the summary statistics of the return performance associated with yield farming strategies. In Panel A, we focus on annualized returns computed for a daily

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

trading horizon. The average (median) return to yield farming is -9.62% (47.26%) during our sample period. This is the average return across the 234 unique yield farms, which have a duration of about 201 days on average. Returns to yield farming are volatile with a standard deviation that is on average 116.84%. Yield farming generates a return performance that is negatively skewed (-0.5216), fat-tailed (10.2208) and weakly negatively serially correlated with a first-order autocorrelation coefficient of -0.0943.

In Panel B of Table 4, we provide the same statistics for a weekly trading horizon. the average yield farm has a duration of 28.8 weeks. The key differences at the weekly frequency are that yield farming performance has a weaker negative autocorrelation (AC1 coefficient of -0.0008), and is slightly less negatively skewed and less fat tailed.

We also provide information about the returns to liquidity provision that excludes the staking of liquidity tokens into yield farms (liquidity mining). The returns to liquidity mining alone are significantly lower with average (median) annualized returns of -105.20% and -112.32% (-43.18% and -47.24%) at the daily and weekly frequency, respectively.

Another useful comparison is the return performance of a simple buy-and-hold strategy that invests into the pair of cryptocurrency tokens associated with a pool. This comparison is useful because investors face a choice of directly investing into a pair of cryptocurrency tokens or stake them to a liquidity pool. At the daily (weekly) frequency, a buy-and-hold strategy earned on average -81.27% (-80.86%) on an annualized basis during our sample period. Thus, buy-and-hold strategies, on average, underperform comparable yield farming strategies, before considering the costs associated with each strategy.

In Table 5, we decompose yield farming returns into their four components: capital gains, impermanent losses, trading fees, and farm yields. We first focus on the full sample results at the daily frequency in Panel A. In Panel B of Table 5, we report the decomposed annualized return performance for weekly trading horizons. The patterns are broadly similar to those of daily trading horizons.

Farm yields contribute the most positively to yield farming performance, with an average daily log return of 95.38%. Capital gains are the largest negative contributor, with an annualized daily log return that is -81.27% on average.

We note that capital gains are significantly more volatile than farm yields, and that they have more extreme negative and positive outcomes. The annualized standard deviation is 116.52%, compared with 2.19% for farm yields, and the wider interquartile range for capital gains reflects the greater kurtosis of 10.29, compared to a a distribution that is much less fat-tailed for farm yields. The persistence of returns is also different across these two components. While capital gains exhibit weak negative serial correlations, farm yields are persistent with a first order autocorrelation coefficient of 0.8587.

The annualized daily impermanent loss is -33.73% on average. In addition, the distribution is negatively skewed and exhibits the largest excess kurtosis among all four components, a value of 58.68. This reflects investors' negative exposure to correlation risk, since impermanent losses are exponentially sensitive to the return divergence between the underlying pairs of cryptocurrency tokens.

The annualized daily trading fee is 9.74%, on average, making it the least important contributor to yield farming performance. Despite the lower volatility (standard deviation of 0.58%), trading fees can become important, as demonstrated by the positive skewness (3.7356) and kurtosis (28.9568).

In Figure 9, we report similar evidence for yield farms, sorted into quintiles by the magnitude of their average in-sample offered yield. This sorting exercise reveals a negative relationship between the headline yields and capital gains performance. See Appendix Table 5 for detailed statistics.

Panel (a) in Table 9 shows that the average realized farm yield increases monotonically across quintiles. In Panel (b), we illustrate capital gains. In farms with low headline yields (Quintile 1), capital gains are higher than the full sample average (−11.93% vs. −81.27%), while in farms with high headline yields, capital gains are far more negative, on average (−189.23%). Similarly, impermanent losses appear greatest in the highest quintiles of offered yields, as sohwn in Panel (c). On the other hand, in Panel (d) of Table 9, we show that trading fees appear roughly similar across all five quintiles.

This preliminary evidence at the farm level suggests that high yield farms' tokens generate the lowest returns and the largest impermanent loss. This calls for additional analysis, since high yields are salient to investors that appear to be unsophisticated, while risks are shrouded.

4.5 Yield farming performance

We assess the value-weighted performance of yield farming strategies in Table 6, using the pools' aggregate liquidity as weighting factors. We take the perspective of a U.S. investor who starts from an initial hypothetical $1 USD investment and ignore all transaction costs. We compute returns in excess of the three-month U.S. Treasury bill secondary market rate. We focus on the daily trading frequency in Panel A.

We find that, prior to transaction costs, yield farming was profitable during our sample period. The value-weighted index strategy delivered an annualized return of 30.67%. This is significantly better than the returns to a strategy that focuses only on liquidity mining (−4.47%), and superior to a buy-and-hold strategy in the same pairs of cryptocurrency tokens associated with the liquidity pools (−8.69%). All three strategies deliver negatively skewed performances, with a non-trivial amount of excess kurtosis.

To assess risk-return trade-offs, we standardize the return performance by the annualized standard deviations and compute Sharpe ratios for all investment strategies. These measures suggest risk-return trade-offs comparable to that of the S&P 500 (which had a Sharpe ratio of 0.370 in our sample period), with values ranging from 0.124 for buy-and-hold strategies to 0.434 for yield farming.

Although the Sharpe ratio of the yield farming index is somewhat superior to the S&P 500, and far superior to other benchmark investments such as Ethereum(0.103) and BNB (0.204), there are some caveats: It is important to note that, for reasons of simplicity and clarity, we do not account for autocorrelation in our annualization of return volatility. At a weekly measurement frequency, for instance, yield farming strategies have large and positive autocorrelation coefficients. Correcting for them will increase the annualized standard deviation, and thereby decrease our reported Sharpe ratios for yield farming strategies. Since these coefficients are much larger for yield-farming strategies at a weekly frequency compared to most our benchmarks, the overall effect of the correction will worsen the relative performance of yield farming strategies.

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 momentum factors can price the cross-section of cryptocurrency returns. Thus, we assess the risk-adjusted performance of yield farming performance relative to this three-factor+BNB cryptocurrency benchmark. We find that the alpha for yield farming investments is on average 22.08%. Because of the short and volatile sample period, this alpha is estimated with a t-statistic of only 1.61.

4.5.1 Accounting for frictions and investor mistakes

The evidence suggests that yield farming delivers attractive returns, with high risk adjusted returns and Sharpe ratios. We question whether these returns are realistically attainable, despite the positive bull run observed during our sample period. An important insight of our study is the careful examination of trading fees and the price impact implicit in staking cryptocurrency pairs to liquidity pools and in harvesting farm yields, in addition to the potential for users to miss out on staking their LP tokens in yield farms to earn yields.

In Table 7, we document the performance of yield farming strategies, accounting for gas fees, trading fees, price impact, and investor mistakes and compare these results to the frictionless benchmark. We assume a holding period of 10 days at the investor level, or that 1/10th of the investor population reblances their portfolio each day. This is between the mean and median holding periods across yield farmers. We choose an initial investment size of $5000, an amount between the mean and median values for the investor population. Finally, we simulate the staking ratio of the average investor by using the farm-level staking ratio on each day as the hypothetical strategy's staking ratio in that farm.

Despite the lower transaction costs recorded on BSC compared to Ethereum (see Figure 2), gas fees significantly lower the return performance. This is because the multiplicity of transactions that are needed for a round-trip transaction can accumulate to non-trivial amounts, especially with frequent rebalancing.

The impact of gas fees and trading costs is especially harmful for small size investments, since they are based on flat dollar amounts. When the investment size is too small, the fixed transaction costs reflect a large proportion of the investment so that they absorb a large fraction of the positive return performance. This incentivizes larger investment amounts to reduce the dollar cost basis. However, larger amounts may not be an option for unsophisticated retail investors, and we find that a large proportion of investors invest less than $1,000 in farms (see Section 4.3).

On the other hand, when the investment size is too large, there is too much capital relative to the liquidity provision ability of a pool. Thus, when swapping tokens, the slippage from illiquidity is too high. We previously discussed that larger investments endogenously lead to lower farm yields, thereby putting further downward pressure on the investment performance. Across the board, we notice that the risk-adjusted performance becomes negative, as suggested by the negative alphas, regardless of the investment size.

These observations bear implications for diversification. A portfolio of 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 illustrate our analysis from Table 7 in Figure 10. Both panels show that the average risk-adjsuted performande decreases for farms with the highest headline rates. 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) and consequentially 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).

More importantly, Panel (a) of Figure 10 shows that the investors who do not fully stake their LP tokens into yield farms perform significantly worse. This effect is especially pronounced for the farms with the highest headline rates. Since small investors are more likely to do mistakes (i.e., staking ratios below one), that evidence is concerning.

In Panel (b) of Figure 10, we compare yield farming without frictions to yield farming when we account for transactions and when we account for transaction costs and investor mistakes. Transaction costs unilaterally lower the risk-adjusted return performance across all yield quintiles. That adjusted is further amplified by investor mistakes. We showed before that transaction costs are most penalizing for small investment stakes, which are are also more prone to exhibit mistakes. Overall, this evidence motivates our next analysis o understand the relation between farm yields and investor flows.

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5 Reaching for yield in decentralized finance

Using detailed analysis on wallet transactions, we provide evidence that investors reach for yield. We show that flows chase yield farms with yield increases and the farms with strong inflows record weak subsequent returns.

To compute farm flows, we closely follow the mutual fund literature in using the time series variation in each pool's aggregate liquidity L_t and the per-period farm growth due to return performance $R_{t,t+h}$ (e.g., Sirri and Tufano, 1998; Coval and Stafford, 2007). See Section 2 for details. We aggregate flows at the daily frequency to obtain weekly flows. In Table 8, we report the results from a regression of farm flows on offered farm yield (y_t^j), lagged farm flows, and past performance of a yield farming strategy. Specifically, we regress

$$\begin{aligned} Flow^j_{t,t+7} = a &+ \beta_1 \Delta Offered\ Yield^j_{t-7,t} + \beta_2 Capital\ Gain^j_{t-7,t} + \beta_3 Impermanent\ Loss^j_{t-7,t} \\ &+ \beta_4 Trading\ Fee^j_{t-7,t} + \beta_5 Realized\ Yield^j_{t-7,t} + \gamma^\top X^j_t + FEs + \varepsilon^j_t, \end{aligned} \tag{14}$$

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

In column (1) of Table 8, we find a positive and statistically significant relation between $\Delta Offered\ Yield$ and $Flow$. This result is unchanged when we add lagged return performance in column (2), which by itself is insignificant.

In column (3), we add the four components of lagged return performance. We find 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. Besides their statistical significance at the 5% and 1% level, respectively, they are also economically significant. Based on the results in column (3), a one-standard-deviation increase in $\Delta Offered\ Yield$, *Trading Fee* and *Realized Yield* are associated with an increase of 4.3%, 8.0%, and 19.6% standard deviations of flows, respectively. This strongly suggests that farmers chase past fees and 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.

In columns (4) to (6) of Table 8, we replicate columns (1) to (3) by excluding observations of farms where the the farm's multiplier is adjusted through the PancakeSwap governance mechanism. This allows us to examine the rleation between changes in farm yields and investor flows when farm yields change in response to peer farms changing their headline rates. This further mitigates concerns that the positive cofficients of $\Delta Offered\ Yield$ and *Realized Yield* are endogeneously driven by the PancakeSwap governance team that manually increases yields in expectation of greater inflows. When the multiplier remains constant, more inflows into a farm can result in lower yields, potentially making the farm less attractive to yield farmers. In columns (4) to (6), we mitigate this reverse-causality concern, and find qualitatively similar results.

In Panel B of Table 8, we investigate the relation between lagged flows and future yield farming returns cumulated over the next 7, 14, 21, and 28 days. We find a weak negative relation between past flows and future returns on yield farming, suggesting that high past flows to a farm do not lead to superior performance going forward.

While the evidence at the farm level suggests that yield chasing behavior leads to underperformance, we next examine investor's entire trading history, thereby leveraging the richness of the blockchain data. We, therefore, construct investor characteristics. We compute the Annualized return as the average annualized return of a farmer's yield-farming investments and regress it on several key investor characteristics, namely the *Average Offered Farm Yield*, *Log (Holding Period (Day))*, *Number of Farms*, and *Average Size of Investment*.

In columns (1) and (2) of table 9, we use Start Date × End Date fixed-effects and Start Week × End Week fixed-effects, respectively, in order to better compare farmers who started and ended their investment activities at the same times. A notable observation is that *Average Offered Farm Yield* is negatively related to *Annualized return*. A 1% increase in *Average Offered Farm Yield* translates to a decrease of 0.34-0.40% in one's *Annualized return*. This result is consistent with the findings of Table 7 in suggesting that investors who chase high yields may significantly underperform.

5.1 The role of information disclosure

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). The vast majority of related research has emphasized the role of intermediaries as the source of the reaching-for-yield phenomenon and highlights the underperformance of yield-seeking strategies. A main advantage of the blockchain data is that it allows us to understand 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.3 provides a screenshot of YieldWatch Pro's user interface. Unlike

PancakeSwap's main user interface, which only provides information on a few farm-level characteristics like yield, size, and multiplier (See Appendix Figure A.2.), YieldWatch Pro provides a more user-friendly interface for individual farmers' yield farming portfolios. In addition to basic information on yield farm characteristics from PancakeSwap, YieldWatch Pro also provides information on farmers' historical capital gains (also called HODL value), impermanent losses, trading fee revenue, and realized yields for their yield farming positions. Notably, this information is only available to yield farmers who own YieldWatch.net's native utility token, 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 tokens 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 PancakeSwap farms out of 234 in our sample, which allows us to compare yield-chasing behavior in farms that are displayed in YieldWatch Pro, versus those that are not.

Panel B in Table 9 presents our main results. In column (1) and (2), we restrict our sample to WATCH token holders. In column (1), we regress individual investors' *Flow* into a farm over the next 7 days on the *Realized Yield* from their positions over the last 7 days, including farm, week, and farmer-level fixed-effects. We find a positive and statistically significant coefficient between past realized yields and future inflows. The magnitude of the coefficient is comparable to the coefficients for past *Realized Yield* in the farm-level regressions in Table 8. In column (2), we add *Displayed*×*Realized Yield* where *Displayed* is a dummy variable, equal to 1 if a farm is displayed in YieldWatch Pro and 0 otherwise. The coefficient for the interaction term is negative, and its magnitude is 45% of the coefficient for *Realized Yield*, suggesting that farmers who hold WATCH tokens show approximately 45% less yield-chasing tendencies in the farms featured by YieldWatch Pro, when compared to other non-featured farms.

In columns (3) and (4), we repeat this analysis for non-WATCH token holders. We find a comparable magnitude of coefficients for *Realized Yield*, while the coefficient of the interaction term is mildly negative and insignificant. This result suggests that non-WATCH token holders do not have different yield-chasing behavior in the farms that are covered by YieldWatch Pro, likely because non-WATCH token holders cannot access any information on YieldWatch Pro.

To formally test whether the diminished yield-chasing behavior is more significant for WATCH token holders compared to non-WATCH token holders, we run regressions on *Displayed*, *Realized Yield*, and *YieldWatch*, and their double and triple interaction terms, where *YieldWatch* is a dummy variable equal to 1 if a farmer holds WATCH tokens, and 0 otherwise. Our coefficient of interest is the coefficient of the triple interaction term. Column (6) shows that the coefficient is -0.8476 and statistically significant at the 1% level.

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, when investors are attracted by a few salient features of financial products, and that the increased availability of information for other less-salient features through third-party information services can reduce investor's reliance on these salient features in decision-making.

Our results have important policy implications. Even in the absence of regulation on information provision for investor protection, market-based alternatives - information provision by third-party information platforms - can help reduce the intensity of yield-chasing behavior and improve investment performance.

6 Conclusion

We provide the first characterization of yield farming, a novel decentralized financial service available to retail investors in the cryptocurrency ecosystem. Using a novel hand-collected dataset on 234 yield farms from PancakeSwap, the largest automated market-maker operating on the Binance Smart Chain, we assess yield farming's return performance and document its associated risks.

While yield farming appears to deliver positive investment performance during our sample period, comparable to other standard investment strategies, Sharpe ratios for yield-farming strategies are significantly reduced after accounting for transaction fees, price impacts, and investor mistakes in execution. With daily rebalancing, risk-adjusted returns become negative. Investors are also exposed to large impermanent losses, driven by diverging returns of underlying cryptocurrency pairs for yield farms.

We uncover a non-monotonic trade-off between investment size and return performance. Small trades are heavily penalized by high nominal transaction costs. Large trades are less penalized by excessive gas fees, but too much liquidity provision may lead to price impacts which hurt investors when trading, and amplifies return volatility. Under reasonable assumptions for investor characteristics, we find that chasing high yields can result in negative risk-adjusted returns.

Finally, by means of a unique setting available from a third-party information platform, we find consistent evidence that farmers' yield chasing becomes less pronounced once they are provided more detailed information on the performance of their portfolios. Even without formal enforcement on information provision, market-based alternatives, such as third-party information platforms, can help assuage yield-chasing behavior and improve investors' investment performance.

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Figure 1: Growing Popularity of Decentralized Finance

In this figure, we plot the total value locked (TVL, left axis) 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 is the number of DeFi platforms whose TVL is over $1 million. We obtain the related data from DeFiLlama (https://defillama.com/). The figure starts on January 1, 2020 and ends on August 1, 2022.

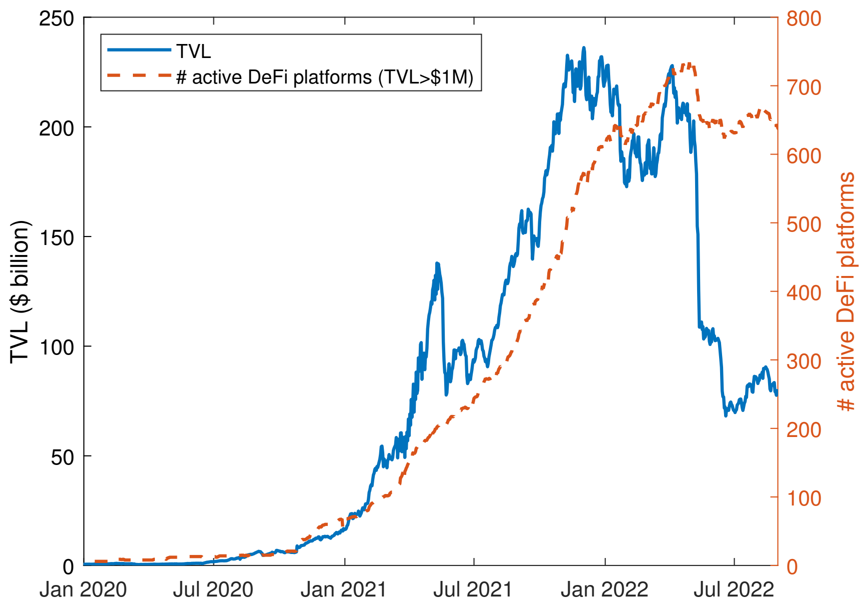


Figure 2: Average Gas Fee to Enter and Exit a Yield Farming Position

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).

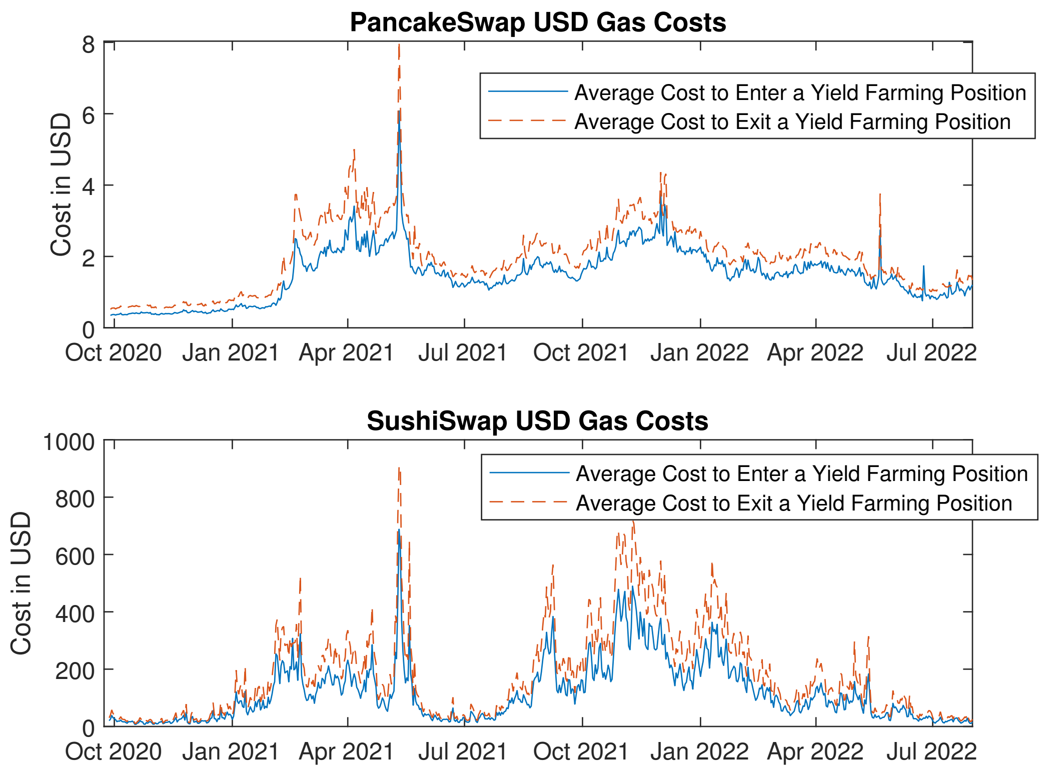
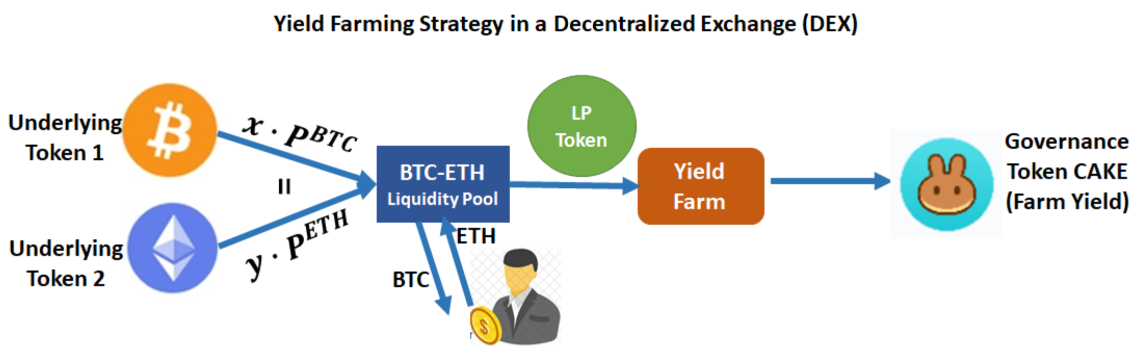


Figure 3: Heuristic Description of Yield Farming

Panel (a) in this figure provides a heuristic description of yield farming in PancakeSwap, which is built on the Binance Smart Chain (BSC). A liquidity provides stakes a pair of cryptocurrency tokens (in this example, BTH and ETH) in equal dollar amounts into a liquidity pool for trading BTC against ETH. Liquidity providers get compensated for their liquidity provision through trading fees colected from third party traders who buy and sell BTC and ETH in the liquidity pool. The trading fees are paid in Binance Coin (BNB). As a liquidity provider, an investor faces buy- and hold price risk from the price evoluton of BTC 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. The liquidity provision is certified ny a liquidity token (i.e., the LP token), which can be staked into a yield farm specific to the BTC-ETH currency pair. The passive income in the yield farm is earned in CAKE, the native governance token of PancakeSwap. Panel (b) illustrates how governance tokens are issued, earned and distributed across yield farms. PancakeSwap hosts a large cross-section of yield farms, each associated with a unique cryptocurrency pair. With each block creation on BSC, PancakeSwap issues Cake, of which part is distributed to yield farmers, and part is used to buy back and burn (ie.e., destroy) CAKE.

(a)



(b)

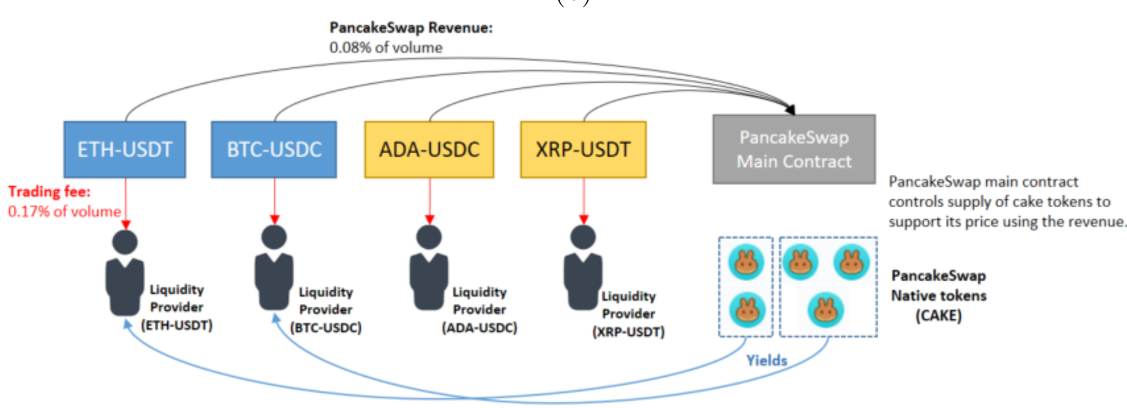
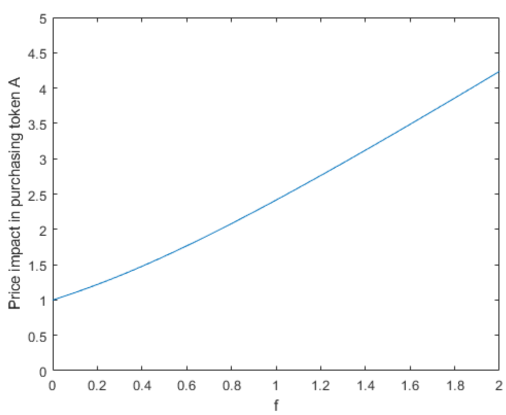


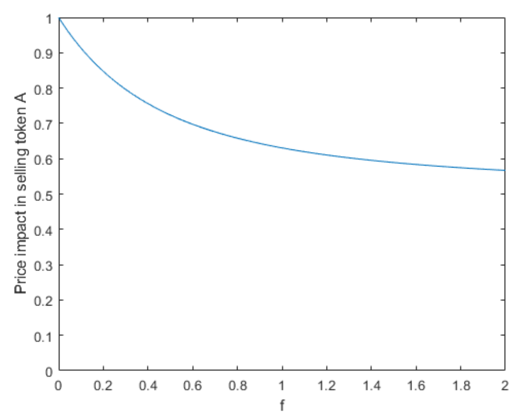
Figure 4: Model-Implied Price Impact due to Yield Farming

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)

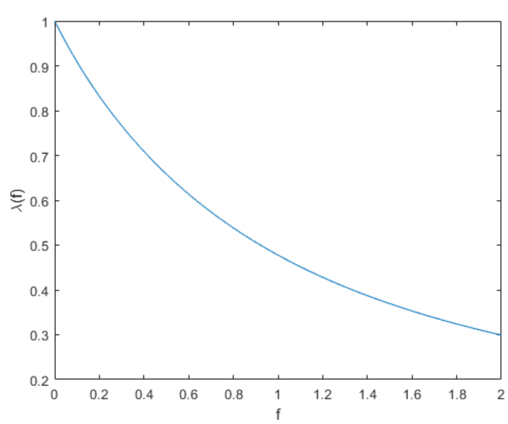


Figure 5: Yield Farm Activity

In Panel (a) of this figure, we plot the number of active farms and Total Value Locked (TVL) at a weekly frequency. In Panel (a), right axis, we provide the time series of active farms during our sample period. We define active farms as farms whose yield multipliers are larger than 0, implying that investors who stake LP tokens in these farms receive non-negative yields. In Panel (a), left axis, we plot TVL of active farms, or the amount of liquidity 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 blue line with dots (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 (beginning of yield farming at PancakeSwap) and end on August 1, 2022.

(a)

(b)

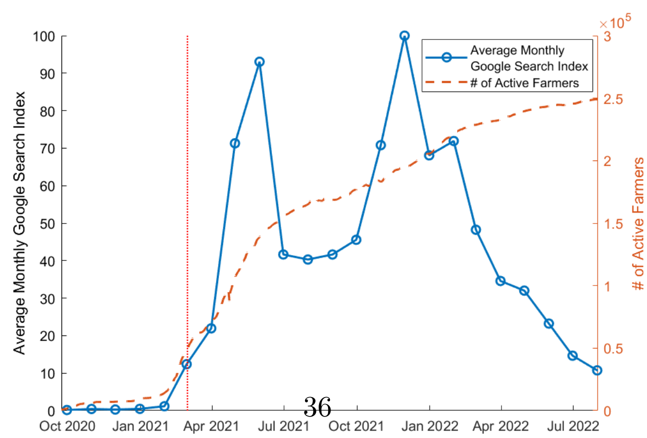


Figure 6: Offered Farm Yields

In this figure, we plot the annualized farm yields offered to yield farmers. In Panel (a), we provide the historical annualized offered farm yields between September 23, 2020 and August 1, 2022. In Panel (b), we re-scale the y-axis to focus on the period after October 2020. 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.

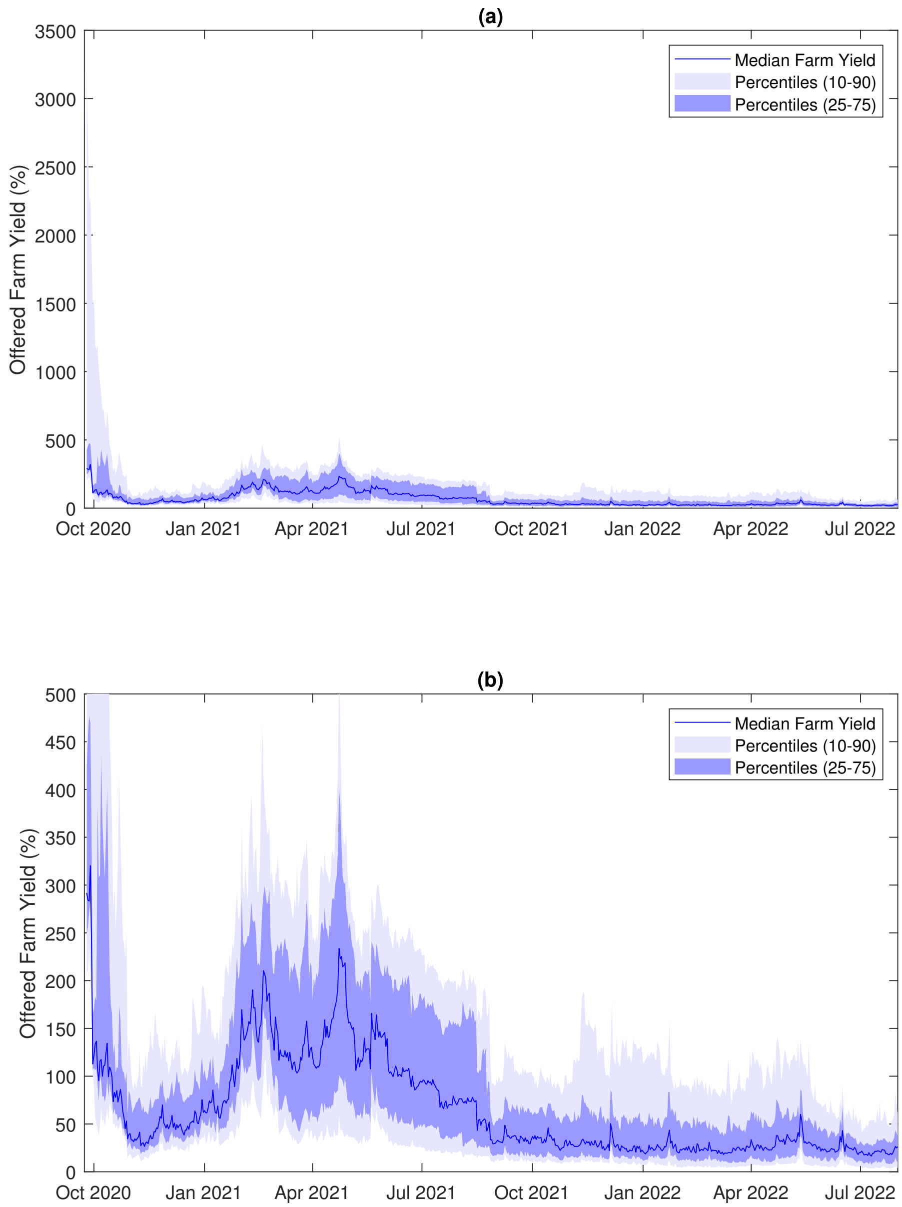


Figure 7: Migration of PancakeSwap Platforms

In this figure, we show the amount of remaining liquidity in obsolete platforms after two technical updates in the PancakeSwap platform. In Panel (a), we plot the total value locked in liquidity pools of yield farms at PancakeSwap v1 whose new counterpart yield farms are available in PancakeSwap v2. On April 24, 2021, farms corresponding to liquidity pools in PancakeSwap v1 stopped providing farm yields. Instead, PancakeSwap encouraged farmers to move to the corresponding counterpart farms available in PancakeSwap v2 so that the existing yield farmers could continue to earn farm yields. The blue line in Panel (a) is total value locked in the liquidity pools whose new counterpart yield farms are available in PancakeSwap v2. In Panel (b), we examine the remaining 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 yields. Pancakeswap advertised through Twitter and other means that users should unstake from the v1 contract and re-stake in the new v2 contract. However, many users failed to do so, even 100 days later.

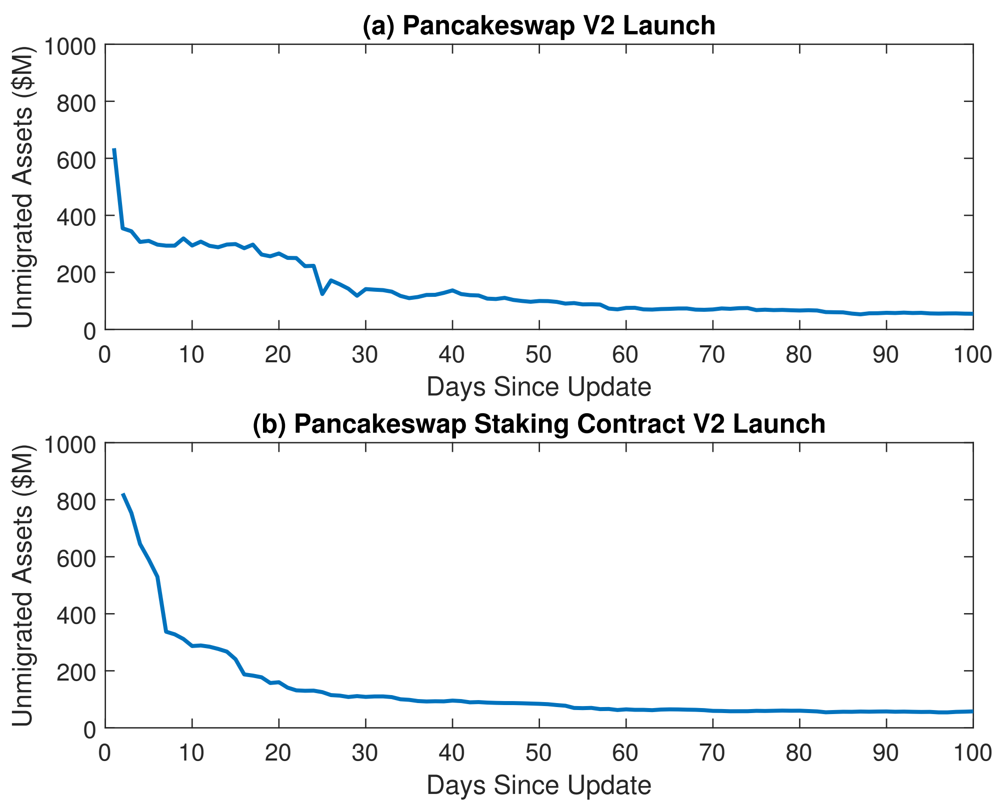


Figure 8: Staking Ratio of LP Tokens

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.

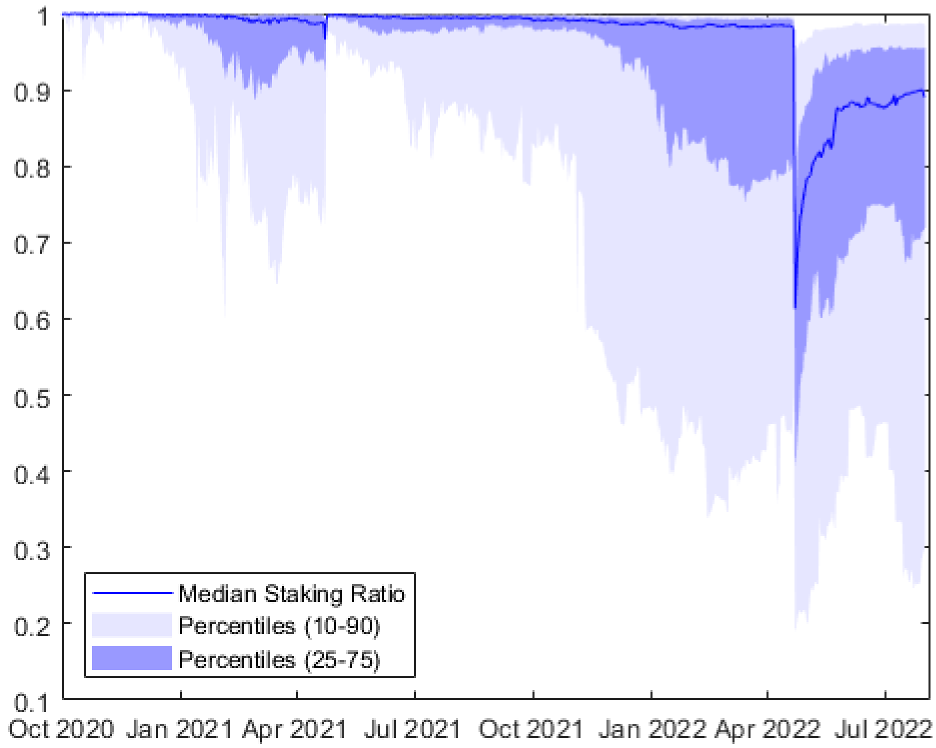


Figure 9: Yield Farming Return Decomposition

In this figure, we plot each component of returns in yield farming strategies. For each farm, we compute annualized logarithms of capital gain, impermanent loss, trading fee, and realized yield during its duration. Then, we take the average of each component across farms. In Panels A-D, the blue bars plot average capital gain, impermanent loss, trading fee, and realized yield, the red error bars plot their associated 95% confidence intervals.

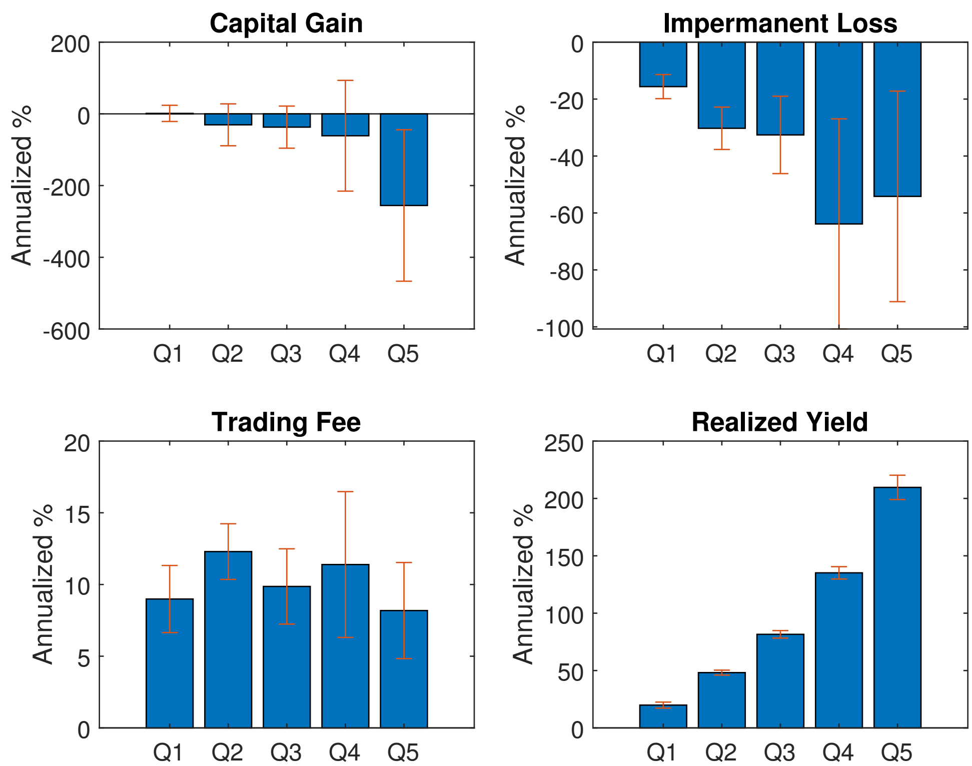
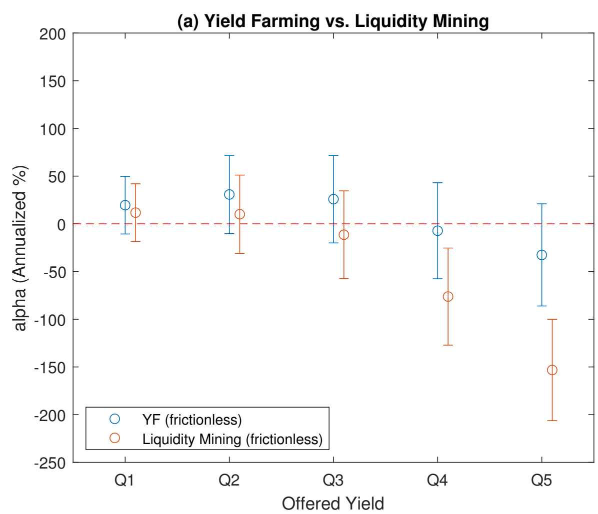


Figure 10: Risk-Adjusted Returns from Yield Farming

In this figure, we plot average risk-adjusted returns and their associated 95% confidence intervals of different trading strategies. In Panel A, we compare yield farming strategies and liquidity mining without considering any trading frictions. On each day, we sort farms into quintiles based on their offered yields. In each quintile, we form value-weighted portfolios by using size of the liquidity pools as weights. An 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). The blue (red) circle and the associated bar display alphas and their 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 considering frictions, yield farming strategies considering 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 B.2.



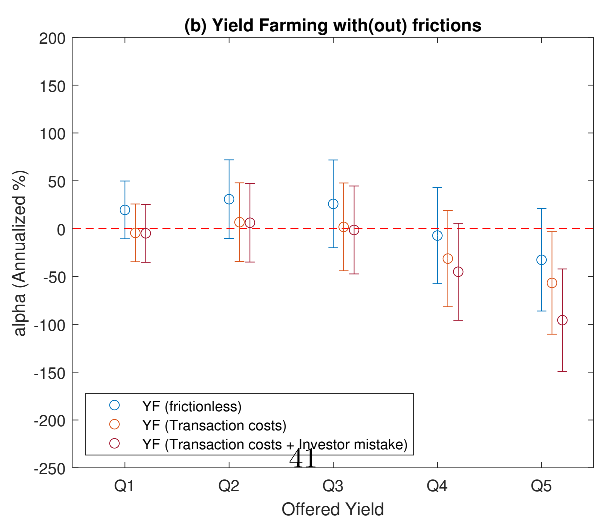


Table 1: Snap Shot of Yield Farms in PancakeSwap

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) at the end of our sample period, 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 Pairs**	**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 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*, and 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)
	$\Delta y^m_{i,t+1}$		$Delisting_{t+1}$	
$Capital\ Gain_{t-7,t}$	0.0041***	0.0021	0.0015	-0.0025
	(0.0010)	(0.0015)	(0.0021)	(0.0039)
$Impermanent\ Loss_{t-7,t}$	0.0063	0.0033	-0.0114	-0.0109
	(0.0048)	(0.0056)	(0.0096)	(0.0116)
$Trading\ Fee_{t-7,t}$	0.1624***	0.1151***	-0.1692***	-0.1304**
	(0.0304)	(0.0306)	(0.0584)	(0.0625)
$Realized\ Yield_{t-7,t}$	-0.1358***	-0.1477***	0.0148	-0.0511
	(0.0102)	(0.0197)	(0.0197)	(0.0347)
$log(Liquidity)$	0.0000	0.0001	-0.0014***	-0.0022***
	(0.0001)	(0.0001)	(0.0002)	(0.0003)
Day FE	No	Yes	No	Yes
N	52,046	52,046	52,323	52,323
adj. R^2	0.005	0.115	0.002	0.083

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. *Staked Balance* is the dollar value of LP tokens staked in farms. *LP Balance* is the dollar value of LP tokens. *Holding period* is the number of days during which a farmer keeps an investment in a farm. *Offered Farm Yield* is time-weighted average of the offered yield at the beginning of the holding period. *Annualized Return* is the time-weighted average of the annualized holding period returns for each user. *Avg. Staking Ratio* is the average of staking ratios of farms in which a farmer invested where staking ratio of a farm is average daily staking ratio during a farmer's holding period. In Panel B, we separate yield farmers into quintiles by *LP Balance*.

Panel A: Yield Farmers **Variables**	**Mean**	**SD**	**p25**	**Median**	**p75**	**OBS**
No. Farms	2.3197	3.5409	1.0000	1.0000	2.0000	590,388
LP Balance ($)	28,836.72	3,751,943.45	40.78	178.55	851.28	590,388
Holding Period (Days)	31.3257	70.6867	0.4280	2.4957	20.3800	590,388
Offered Farm Yield	0.7115	1.3563	0.1569	0.3851	0.7722	590,388
Annualized Return	0.2346	0.9031	-1.1641	0.0000	1.8017	590,388
Avg. Staking Ratio	0.8081	0.3654	0.9215	0.9987	0.9999	590,388

Panel B: Yield Farmers by LP Balance	**No. Farms**	**LP Balance($)**	**Holding Period(Days)**	**Offered Farm Yield**	**Annualized Return**	**Avg. Staking Ratio**	**OBS**
Quintile 1							
Mean	1.4689	11.78	67.9262	0.7627	0.1248	0.6211	118,078
S.D.	(1.1361)	(8.00)	(105.4467)	(1.5044)	(0.6702)	(0.4569)	
Quintile 2							
Mean	1.6705	59.98	38.4668	0.7725	0.3189	0.7787	118,077
S.D.	(1.5982)	(21.50)	(75.2511)	(1.3602)	(0.7602)	(0.3822)	
Quintile 3							
Mean	2.0191	186.22	25.4321	0.7529	0.4068	0.8360	118,078
S.D.	(2.3789)	(60.51)	(59.3924)	(1.3961)	(0.7816)	(0.3387)	
Quintile 4							
Mean	2.5714	653.01	16.1003	0.7061	0.2630	0.8851	118,077
S.D.	(3.4192)	(252.71)	(42.4468)	(1.3039)	(0.9999)	(0.2882)	
Quintile 5							
Mean	3.8687	143,272.16	8.7032	0.5628	0.0596	0.9197	118,078
S.D.	(6.1478)	(8,388,639.16)	(26.5200)	(1.1850)	(1.2004)	(0.2452)	

Table 4: Yield Farming Return Characteristics

In this table, we report summary statistics on the return characteristics from yield farming and alternative investment strategies. The sample period is March 1, 2021 to August 1, 2022. The sample includes 234 unique liquidity pools (as determined by their token pairs) associated with 234 unique yield farms. In Panel A, we report the cross-sectional average daily mean ($Mean$), median ($Median$), 25th ($p25$) and 75th ($p75$) percentiles of the log return distribution and the corresponding standard deviation (SD), skewness ($Skew$), kurtosis ($Kurt$), the first order autocorrelation coefficient ($AC1$), the number of time series ($\#TS$) and the average number of observations for each time series (OBS). In Panel B, we report the same information aggregated at a weekly frequency starting from March 1, 2021. All return-based statistics are annualized.

Panel A: Daily										
Variable	**Mean**	**SD**	**p25**	**Median**	**p75**	**Skew**	**Kurt**	**AC1**	**#TS**	**OBS**
Yield Farming Related Strategy										
Yield Farming	-0.0962	1.1684	-10.9802	0.4726	11.4755	-0.5216	10.2208	-0.0943	234	200.6652
Liquidity Mining	-1.0520	1.1684	-11.9521	-0.4318	10.5461	-0.5310	10.2380	-0.0948	234	200.6652
Buy and Hold (Capital Gain)	-0.8127	1.1652	-11.9026	-0.4677	10.6029	-0.1815	10.2866	-0.0944	234	200.6652
Benchmark Strategy										
Crypto Market Return	-0.4495	0.8605	-8.0559	1.7595	8.6008	-1.3082	11.0971	-0.0994	1	519
BTC	-0.4649	0.7351	-8.0881	-0.2191	7.2006	-0.2861	4.9756	-0.0457	1	519
ETH	0.1012	0.9786	-10.4473	0.7628	10.8729	-0.4325	6.7915	-0.0509	1	519
BNB	0.2126	1.0404	-9.0649	0.4567	10.8709	-0.7125	10.9266	-0.1214	1	519
S&P 500 Index	0.0679	0.1837	-1.4618	0.2103	1.8629	-0.4349	4.1438	0.0083	1	359
Panel B: Weekly										
Variable	**Mean**	**SD**	**p25**	**Median**	**p75**	**Skew**	**Kurt**	**AC1**	**#TS**	**OBS**
Yield Farming Related Strategy										
Yield Farming	-0.1326	1.1446	-4.2708	0.4254	4.9397	-0.4783	5.0868	-0.0008	234	28.8202
Liquidity Mining	-1.1232	0.4412	-5.3307	-0.4724	4.0377	-0.5259	5.1870	-0.0061	234	28.8202
Buy and Hold (Capital Gain)	-0.8086	1.1496	-5.0360	-0.3646	4.1746	-0.3621	5.4104	-0.0063	234	28.8202
Benchmark Strategy										
Crypto Market Return	-0.3905	0.8074	-3.8233	-0.1359	4.2456	-0.9450	4.5514	0.0194	1	75
BTC	-0.5402	0.7593	-2.7411	-0.3135	2.0144	-0.2828	4.4408	-0.0971	1	75
ETH	-0.0033	0.9908	-3.8160	-0.5561	4.5812	-0.5179	3.9912	-0.0013	1	75
BNB	0.1109	0.9714	-3.1797	0.2970	4.0572	-0.8557	6.7259	0.0640	1	75
S&P 500 Index	0.0535	0.1906	-0.3998	0.1664	0.9496	-1.1064	4.8914	-0.1347	1	75

Table 5: Yield Farming Return Decomposition

In this table, we decompose each return series into the contributions arising from (a) capital gains, (b) impermanent losses, (c) trading fees, and (d) farm yields. The sample period is March 1, 2021 to August 1, 2022. In Panel A, we report summary statistics on the return characteristics for each component. We report the cross-sectional average daily mean log return (Ret) median ($Median$), 25th ($p25$) and 75th ($p75$) percentiles of the log return distribution and the corresponding standard deviation (SD), skewness ($Skew$), kurtosis ($Kurt$), the first order autocorrelation coefficient ($AC1$), and the average number of observations for each time series (OBS). In Panel B, we report the same information aggregated at a weekly frequency starting from March 1, 2021. All return-based statistics are annualized.

Panel A: Daily **Component**	**Mean**	**SD**	**p25**	**Median**	**p75**	**Skew**	**Kurt**	**AC1**	**OBS**
Full Sample									
Capital Gains	-0.8127	1.1652	-11.9026	-0.4677	10.6029	-0.1815	10.2866	-0.0944	200.6652
Impermanent Loss	-0.3373	0.0681	-0.2212	-0.0548	-0.0127	-6.1250	58.6807	0.1093	200.6652
Trading Fees	0.0974	0.0068	0.0357	0.0605	0.1105	3.7356	28.9568	0.4469	200.6652
Farm Yields	0.9538	0.0219	0.6367	0.8983	1.2112	0.9027	4.5288	0.8587	200.6652

Panel B: Weekly **Component**	**Mean**	**SD**	**p25**	**Median**	**p75**	**Skew**	**Kurt**	**AC1**	**OBS**
Full Sample									
Capital Gains	-0.8086	1.1496	-5.0360	-0.3646	4.1746	-0.3621	5.4104	-0.0063	28.8202
Impermanent Loss	-0.3668	0.0954	-0.3604	-0.1431	-0.0778	-2.6289	12.0903	-0.0033	28.8202
Trading Fees	0.0973	0.0118	0.0477	0.0704	0.1179	1.5860	6.8195	0.3210	28.8202
Farm Yields	0.9525	0.0539	0.6608	0.9054	1.1973	0.7039	3.7337	0.6434	28.8202

Table 6: Returns from Yield Farming Portfolios

This table reports the summary statistics for 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 source from the Federal Reserve Bank of St.Louis. All returns are value-weighted using the pools' aggregate liquidity as weighting 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), and the t-statistic for alpha from the three-factor regressions. The sample period is March 1, 2021 to August 1, 2022. All return-based statistics are annualized. Because we report excess returns and alphas as annualized log returns, the mean return and alpha can be lower than -1, unlike arithmetic returns.

Panel A: Daily												
Strategy	**Mean**	**SD**	**p25**	**Median**	**p75**	**Skew**	**Kurt**	**AC1**	**SR**	**t-stat of α**	α	**OBS**
Yield Farming Related Strategy												
Yield Farming	0.3067	0.7064	-5.6704	0.6858	6.1957	-1.0922	17.8095	-0.1605	0.4342	1.6111	0.2202	519
Buy and Hold (Capital Gains)	0.0869	0.7027	-5.7026	0.5422	5.9119	-0.9835	16.6169	-0.1624	0.1237	0.0677	0.0092	519
Liquidity Mining	0.0447	0.7050	-5.8793	0.5777	5.9662	-1.1387	17.9089	-0.1636	0.0633	-0.2043	-0.0278	519
Benchmark Strategy												
Crypto Market Return	-0.4495	0.8605	-8.0559	1.7595	8.6008	-1.3082	11.0971	-0.0994	-0.5224	0.0000	0.0000	519
BTC	-0.4649	0.7351	-8.0881	-0.2191	7.2006	-0.2861	4.9756	-0.0457	-0.6325	-1.0884	-0.3392	519
ETH	0.1012	0.9786	-10.4473	0.7628	10.8729	-0.4325	6.7915	-0.0509	0.1034	0.7476	0.2671	519
BNB	0.2126	1.0404	-9.0649	0.4567	10.8709	-0.7125	10.9266	-0.1214	0.2043	-0.6233	0.0000	519
S&P 500 Index	0.0679	0.1837	-1.4618	0.2103	1.8629	-0.4349	4.1438	0.0083	0.3699	0.8557	0.1225	359
Panel B: Weekly												
Strategy	**Mean**	**SD**	**p25**	**Median**	**p75**	**Skew**	**Kurt**	**AC1**	**SR**	**t-stat of α**	α	**OBS**
Yield Farming Related Strategy												
Yield Farming	0.3633	0.6869	-1.8312	-0.0387	2.5816	-0.5243	7.5588	0.0228	0.5290	0.9696	0.1214	75
Buy and Hold (Capital Gains)	0.1049	0.6794	-2.0256	-0.2108	2.4261	-0.5084	7.4072	0.0140	0.1544	-1.0550	-0.1300	75
Liquidity Mining	0.0845	0.6818	-1.9947	-0.1665	2.4390	-0.6760	7.8435	0.0066	0.1240	-1.0673	-0.1331	75
Benchmark Strategy												
Crypto Market Return	-0.3905	0.8074	-3.8233	-0.1359	4.2456	-0.9450	4.5514	0.0194	-0.4836	-0.2025	0.0000	75
BTC	-0.5402	0.7593	-2.7411	-0.3135	2.0144	-0.2828	4.4408	-0.0971	-0.7115	-1.5334	-0.6103	75
ETH	-0.0033	0.9908	-3.8160	-0.5561	4.5812	-0.5179	3.9912	-0.0013	-0.0033	-0.1476	-0.0713	75
BNB	0.1109	0.9714	-3.1797	0.2970	4.0572	-0.8557	6.7259	0.0640	0.1142	0.0000	0.0000	75
S&P 500 Index	0.0535	0.1906	-0.3998	0.1664	0.9496	-1.1064	4.8914	-0.1347	0.2806	0.3154	0.0462	75

Table 7: 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 xxx. 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 weighting 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 August 1, 2022. All return-based statistics are annualized. Because we report excess returns and alphas as annualized log returns, the mean return and alpha can be lower than −1, unlike arithmetic returns.

Panel A: Daily							
Strategy	**Mean**	**SD**	**SR**	**IR**	α	**t-stat of α**	**OBS**
Yield Farming (Frictionless Benchmark)							
Quintile 1	0.1916	0.4846	0.3953	1.1017	0.1957	1.2691	519
Quintile 2	0.3734	0.8522	0.4381	1.2751	0.3078	1.4689	519
Quintile 3	0.2928	0.8836	0.3313	0.9584	0.2586	1.1041	519
Quintile 4	0.0616	0.9463	0.0651	-0.2443	-0.0723	-0.2815	519
Quintile 5	-0.2501	1.0094	-0.2477	-1.0366	-0.3259	-1.1942	519
Liquidity Mining							
Quintile 1	0.1088	0.4842	0.2247	0.6608	0.1173	0.7612	519
Quintile 2	0.1563	0.8514	0.1836	0.4177	0.1007	0.4812	519
Quintile 3	-0.0990	0.8825	-0.1122	-0.4224	-0.1140	-0.4866	519
Quintile 4	-0.6605	0.9457	-0.6985	-2.5496	-0.7621	-2.9370	519
Quintile 5	-1.5042	1.0049	-1.4968	-4.9051	-1.5320	-5.6506	519
Yield Farming with Frictions							
Quintile 1	-0.0496	0.4846	-0.1024	-0.2509	-0.0446	-0.2891	519
Quintile 2	0.1320	0.8522	0.1549	0.2793	0.0674	0.3217	519
Quintile 3	0.0513	0.8836	0.0580	0.0669	0.0181	0.0771	519
Quintile 4	-0.1801	0.9463	-0.1904	-1.0573	-0.3131	-1.2180	519
Quintile 5	-0.4926	1.0094	-0.4880	-1.8047	-0.5676	-2.0790	519
Yield Farming with Frictions & Investor Mistake							
Quintile 1	-0.0544	0.4846	-0.1123	-0.2744	-0.0487	-0.3161	519
Quintile 2	0.1258	0.8522	0.1476	0.2561	0.0618	0.2950	519
Quintile 3	0.0191	0.8840	0.0217	-0.0515	-0.0139	-0.0593	519
Quintile 4	-0.3244	0.9469	-0.3426	-1.5118	-0.4504	-1.7416	519
Quintile 5	-0.8999	1.0078	-0.8929	-3.0418	-0.9565	-3.5041	519

Panel B: Weekly							
Strategy	**Mean**	**SD**	**SR**	**IR**	α	t**-stat of** α	**OBS**
Yield Farming (Frictionless Benchmark)							
Quintile 1	0.2641	0.4788	0.5516	0.9030	0.1226	0.9761	75
Quintile 2	0.0544	0.8057	0.0676	-0.4533	-0.1066	-0.4900	75
Quintile 3	0.4169	0.9115	0.4574	0.7613	0.2086	0.8229	75
Quintile 4	-0.0434	0.8890	-0.0489	0.0125	0.0026	0.0135	75
Quintile 5	-0.0448	1.0668	-0.0420	-0.2301	-0.0796	-0.2487	75
Liquidity Mining							
Quintile 1	0.1715	0.4762	0.3601	0.3015	0.0413	0.3260	75
Quintile 2	-0.1857	0.8074	-0.2300	-1.3067	-0.3201	-1.4125	75
Quintile 3	0.0029	0.9171	0.0032	-0.5909	-0.1653	-0.6388	75
Quintile 4	-0.7880	0.8958	-0.8797	-3.0685	-0.6786	-3.3169	75
Quintile 5	-1.2809	1.0742	-1.1923	-3.6198	-1.2219	-3.9128	75
Yield Farming with Frictions							
Quintile 1	0.0206	0.4788	0.0431	-0.8807	-0.1197	-0.9520	75
Quintile 2	-0.1892	0.8058	-0.2347	-1.4796	-0.3490	-1.5993	75
Quintile 3	0.1732	0.9115	0.1900	-0.1236	-0.0339	-0.1337	75
Quintile 4	-0.2875	0.8889	-0.3234	-1.1668	-0.2403	-1.2612	75
Quintile 5	-0.2895	1.0669	-0.2714	-0.9332	-0.3231	-1.0088	75
Yield Farming with Frictions & Investor Mistake							
Quintile 1	0.0137	0.4783	0.0287	-0.9164	-0.1247	-0.9906	75
Quintile 2	-0.1955	0.8060	-0.2426	-1.5026	-0.3550	-1.6243	75
Quintile 3	0.1302	0.9191	0.1416	-0.2554	-0.0714	-0.2761	75
Quintile 4	-0.4230	0.8890	-0.4758	-1.7450	-0.3649	-1.8863	75
Quintile 5	-0.6789	1.0669	-0.6364	-1.9355	-0.6745	-2.0921	75

Table 8: Aggregate Farm Yields and Investor Flows

In this table, we report evidence on the relation between aggregate investor flows and farm yields. In Panel A, we regress future farm *Flow*, measured over the next 7 days (a week), on Δ*Offered Farm Yield*, past *Log 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* and *Log(Size of Liquidity Pool)*. All variables are defined in Section 2. *Log crypto MKT return* is the natural logarithm of the cryptocurrency market return, described in Section 3.4. The sample period is October 20, 2020 to August 1, 2022. In Panel B, we regress cumulative returns measured over 7, 14, 21, and 28 days on lagged *Flow* measured over a 7-day period. Standard errors are clustered at the farm level.*,**, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
			$Flow_{t,t+7}$			
$\Delta Offered\ Yield_{t-7,t}$	0.0380***	0.0382***	0.0360***	0.0236***	0.0220**	0.0201**
	(0.0093)	(0.0093)	(0.0093)	(0.0083)	(0.0085)	(0.0082)
$Return_{t-7,t}$		-0.0349			-0.0710***	
		(0.0244)			(0.0265)	
$Capital\ Gain_{t-7,t}$			-0.0462*			-0.0812***
			(0.0273)			(0.0291)
$Impermanent\ Loss_{t-7,t}$			0.0549			0.0438
			(0.0631)			(0.0630)
$Trading\ Fee_{t-7,t}$			3.6463**			4.0349**
			(1.5205)			(1.6348)
$Realized\ Yield_{t-7,t}$			2.6322***			2.6154***
			(0.5182)			(0.5317)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Full	Full	Full	$\Delta m = 0$	$\Delta m = 0$	$\Delta m = 0$
Farm FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
N	7,011	7,011	7,011	6,626	6,626	6,626
adj. R^2	0.150	0.150	0.161	0.162	0.163	0.174

Panel B	(1)	(2)	(3)	(4)
	$Return_{t,t+7}$	$Return_{t,t+14}$	$Return_{t,t+21}$	$Return_{t,t+28}$
$Flow_{t-7,t}$	-0.0132*	-0.0192**	-0.0220*	-0.0195
	(0.0068)	(0.0094)	(0.0113)	(0.0128)
Farm FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
N	7,015	6,680	6,356	6,051
adj. R^2	0.671	0.711	0.732	0.743

Table 9: Determinants of Yield Farmers' Return Performance

In Panel A of this table, we study the determinants of annualized returns of farmers. The dependent variable, *Annualized return*, is the time-weighted average annualized holding period return for each farmer. *Average Offered Farm Yield* is the time-weighted average of the log offered yield at the beginning of each holding period. *Log (Holding Period (Day))* is the average duration of a user's positions. *Number of Farms* is the number of unique farms that a user invests in. *Average Size of Investment* is the time-weighted average of the USD value at the beginning of a user's holding period. In Panel B, we investigate whether information disclosure in YieldWatch.net changes farmers' yield-chasing behaviors. $Flow_{t,t+7}$ is flow over the next 7 days. *YieldWatch* is a dummy variable equal to 1 if an investor holds YieldWatch tokens and 0 otherwise. *Displayed* is a dummy variable equal to 1 if a farm is displayed in YieldWatch.net and 0 otherwise. $Realized\ Yield_{t-7,t}$ is realized farm yield over the lagged 7 days. The sample period is from March 4, 2020, the date when YieldWatch Pro was introduced, to August 1, 2022. Standard errors are clustered at the first month when an investor participate in yield farming in Panel A and are double clustered at the investor and week level in Panel B.*,**, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A	(1)	(2)
	Annualized return	
Average Offered Farm Yield	-0.4026***	-0.3398***
	(0.1347)	(0.1164)
Log (Rebalancing Frequency (Day))	0.0872***	0.0442
	(0.0254)	(0.0549)
Number of Farms	-0.0804***	-0.0694**
	(0.0275)	(0.0247)
Average Size of Investment	0.0144	-0.0056
	(0.0230)	(0.0214)
Start Date X End Date FE	Yes	No
Start Week X End Week FE	No	Yes
N	544,550	583,909
adj. R^2	0.501	0.189

Panel B	(1)	(2)	(3)	(4)	(5)	(6)
			$Flow_{t,t+7}$			
$Realized\ Yield_{t-7,t}$	2.0416***	2.1117***	1.6876***	1.7179***	1.6956***	1.7244***
	(0.2500)	(0.2682)	(0.2275)	(0.2239)	(0.2268)	(0.2249)
$Displayed \times Realized\ Yield_{t-7,t}$		-0.9476**		-0.1990		-0.1909
		(0.4267)		(0.4912)		(0.4953)
$YieldWatch$						-0.0021
						(0.0042)
$YieldWatch \times Realized\ Yield_{t-7,t}$						0.0839
						(0.1072)
$Displayed \times Realized\ Yield_{t-7,t}$						0.0118***
						(0.0028)
$Displayed \times YieldWatch \times$ $Realized\ Yield_{t-7,t}$						-0.8476***
						(0.2640)
Sample	YW holders		non-YW holders		Full	
Farm FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Farmer FE	Yes	Yes	Yes	Yes	Yes	Yes
N	250,303	250,303	9,649,563	9,649,563	9,903,080	9,903,080
adj. R^2	0.293	0.293	0.237	0.237	0.237	0.238

A Institutional background

We first provide background information on decentralized finance, yield farming, the Binance Smart Chain, and PancakeSwap. We then discuss why PancakeSwap is especially useful for the study of 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[4], a public dashboard which provides data on DeFi, the total dollar value locked (TVL) in decentralized financial services is $205.76 billion as of October 11, 2021. This represents a dramatic increase from less than $1 billion in February 2020.

Yield farming is a way of earning income as compensation for providing liquidity to liquidity pools. Holders of cryptocurrency tokens earn rewards by locking tokens up in liquidity pools, which issue claims to the pledged tokens. These new claims, called 'LP tokens' or 'flip tokens', can be pledged to yield farms that promise yield enhancements. That additional passive income is paid to yield farming investors using the platform's governance token.

To an extent, yield farming is a decentralized variant of securities lending, although the chain of transactions is more complex. The main reason underlying its popularity is the critical need for platform owners to incentivize liquidity provision to ensure a platform's long-term success. In a decentralized exchange, a more liquid pool implies a smaller price impact per trade, which is desirable for traders. In a lending pool, a larger amount of liquidity in a pool may drive down the borrowing interest rate, which could attract larger groups of borrowers. Yield farming is a useful tool to encourage the injection of such liquidity.

Headline rates and promised investment rates in yield farms 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 6.

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

Yield farming strategies appear to be complex. The total return performance from yield farming has four components: the realized yield, capital gains from pairs of cryptocurrencies, fees from trading volume in liquidity pools and yield farms, and impermanent losses driven by the relative price change of cryptocurrency pairs locked in liquidity pools. Thus, the complexity of yield farming strategies 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. Transaction costs in PancakeSwap are significantly lower than in other popular decentralized exchanges like Uniswap. 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 recently taken by the U.S. Securities and Exchange Commission, who have become increasingly vocal about enhanced regulatory scrutiny of decentralized financial services. 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 allow for 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 excess 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 with the purpose of maintaining the high throughput of Binance Chain while still allowing for smart contracts within the ecosystem.

In the BSC ecosystem, Binance Coin (BNB) is used as the basic medium of exchange, similar to the role played by Ether (ETH) in the Ethereum network. End users pay their transaction fees in BNB and use BNB to trade cryptocurrencies on the many 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[5], BSC allows for a maximum of 300 transactions per second. 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 cheaper than those of Ethereum. As of September 5, 2021, the average transaction fee charged by BSC is $0.399, whereas the average transaction fee charged by Ethereum is $5.842. In fact, 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.[6]

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.[7] 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.

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

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

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

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. 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 0.25% of the trading volume, of which 0.17% is added to the liquidity pool associated with the corresponding cryptocurrency pair.

In addition to the income generated from trading fees, liquidity providers can earn additional passive 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. Farm yields are paid in PancakeSwap's governance token.

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. We study yield farming for both versions.

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

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

Numerous decentralized trading venues offer passive income opportunities through yield farming. Among many DeFi platforms, Uniswap and PancakeSwap consistently lead the league ranks in terms of their trading activity. The key difference between these two platforms is that Uniswap runs on the Ethereum blockchain, while PancakeSwap runs on the 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 passive income. However, liquidity providers cannot stake their LP tokens in farms in Uniswap to earn additional income through yield farming.

Second, PancakeSwap is one of the largest decentralized exchanges. In Table A.5, we report the daily trading volume for the ten largest decentralized exchanges as of October 9, 2021. The largest DEX is dYdX, which is specialized 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[8], PancakeSwap registered 435,130 active users on October 24, 2021, in contrast to 47,730 active users recorded for Uniswap. 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. This provides important variation to help understand the risk and return characteristics of yield farms. We study 219 unique yield farms created as of September 5, 2021.

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

B Appendix for Conceptual Framework

B.1 Capital gains and impermanent loss

In this section, we outline the procedure for deriving the main equations of Section 2 assuming that there are no trading frictions such as trading fees and gas fees. For expositional purposes, we consider the following scenario:

- Suppose a liquidity provider provides 1 BNB and 100 BUSD, a stablecoin pegged to U.S. dollar, to a liquidity pool.
- There is a total of 10 BNB and 1,000 BUSD in the pool after this liquidity provision. Therefore, the liquidity provider's share is 10%.
- After h days, the price of BNB becomes 200 BUSD.
- The liquidity provider withdraws his/her liquidity.

The constant product model imposes a condition that the product of two tokens should be constant. In this case, $k = \alpha_t^A \alpha_t^B = 10 \times 1,000 = 10,000$, where α^i is the number of cryptocurrency i in the liquidity pool. Let A and B be BNB and BUSD, repectively. Consider t as today and $t+h$ as h days after today. The value of A (BNB) in the pool should be identical to the value of B (BUSD) at any t, i.e. $P_t^A \alpha_t^A = P_t^B \alpha_t^B$ for all t. See Lemma 1 for more details.

Lemma 1) $P_t^A \alpha_t^A = P_t^B \alpha_t^B$ in a constant product model.

Proof) Under the constant product model, the product of the quantities of two cryptocurrencies should be constant, i.e. $\alpha_t^A \alpha_t^B = k$. This implies that $\frac{\partial \alpha_t^B}{\partial \alpha_t^A} = -\frac{\alpha_t^B}{\alpha_t^A}$. To purchase δ, a trader needs to pay $\delta \frac{\alpha_t^B}{\alpha_t^A}$., which means that $P_t^A \delta = P_t^B \delta \frac{\alpha_t^B}{\alpha_t^A} \rightarrow P_t^A \alpha_t^A = P_t^B \alpha_t^B$. $\square$

Since we have two equations: $P_t^A \alpha_t^A = P_t^B \alpha_t^B$ and $k = \alpha_t^A \alpha_t^B$, we can solve for both α_t^A and α_t^B:

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

Given that the rate of exchange for 1 BNB becomes 200 BUSD (which is equivalent to \$200, assuming that BUSD is perfectly pegged to the U.S. dollar) at time $t + h$:

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

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

The liquidity provider's share is 10%. If he/she withdraws their liquidity, he/she will get 0.707 BNB and 141.421 BUSD. This amounts to $0.707 \times 200 + 141.421 \times 1 = \$282.82$. 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 is $(282.82/300 - 1) \times 100 =$ -5.727%. To formalize this, we compute the following measure which is the ratio of investment outcomes at time $t + h$ in two scenarios minus 1. In this example, the liquidity provider's share is 10%. Let's assume that his/her share in general is ω.

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

Note that α^i in the denominator is the same as the number of shares the liquidity provider initially held, whereas α^i in the numerator is the number of shares after trading activities between t and $t+h$.

$$
\begin{aligned}
&\frac{\omega(P^A_{t+h}\alpha^A_{t+h} + P^B_{t+h}\alpha^B_{t+h})}{\omega(P^A_{t+h}\alpha^A_t + P^B_{t+h}\alpha^B_t)} - 1 \\
&= \frac{\left(\frac{P^A_{t+h}}{P^B_{t+h}}\right)\alpha^A_{t+h} + \alpha^B_{t+h}}{\left(\frac{P^A_{t+h}}{P^B_{t+h}}\right)\alpha^A_t + \alpha^B_t} - 1 \\
&= \frac{\left(\frac{P^A_{t+h}}{P^B_{t+h}}\right)\sqrt{k\left(\frac{P^B_{t+h}}{P^A_{t+h}}\right)} + \sqrt{k\left(\frac{P^A_{t+h}}{P^B_{t+h}}\right)}}{\left(\frac{P^A_{t+h}}{P^B_{t+h}}\right)\sqrt{k\left(\frac{P^B_t}{P^A_t}\right)} + \sqrt{k\left(\frac{P^A_t}{P^B_t}\right)}} - 1 \\
&= \frac{\left(\frac{P^A_{t+h}}{P^B_{t+h}}\right)\sqrt{\frac{P^B_{t+h}}{P^A_{t+h}}} + \sqrt{\frac{P^A_{t+h}}{P^B_{t+h}}}}{\left(\frac{P^A_{t+h}}{P^B_{t+h}}\right)\sqrt{\frac{P^B_t}{P^A_t}} + \sqrt{\frac{P^A_t}{P^B_t}}} - 1
\end{aligned}
$$

Denote the relative price of token A to token B at t by ρ_t $(=\frac{P^A_t}{P^B_t})$. Then, the above expression is reduced to

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

The above figure shows the relation between change of the relative price $(\frac{\rho_{t+h}}{\rho_t})$ and the impermanent loss, defined as the ratio of investment outcomes at time $t+h$ in the two scenarios, minus 1. If ρ changes and $\frac{\rho_{t+h}}{\rho_t}$ deviates from 1, the liquidity provider experiences a loss compared to a simple position of holding underlying tokens from t. It is straightforward to show that this loss, also called the impermanent loss, is non-positive: $\frac{2\sqrt{\frac{\rho_{t+h}}{\rho_t}}}{\frac{\rho_{t+h}}{\rho_t}+1} - 1 = -\frac{(\sqrt{\frac{\rho_{t+h}}{\rho_t}}-1)^2}{\frac{\rho_{t+h}}{\rho_t}+1}$.

However, the above approach is not directly applicable to our analysis because we analyze returns from liquidity provision, rather than comparing an investment outcome at $t+h$ with an investment outcome in a hypothetical situation at $t+h$. Therefore, our goal is to simplify the liquidity provider's gross return, expressed as follows:

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

We can decompose the above expression into two parts.

$$\begin{aligned}
&\frac{P^A_{t+h}\alpha^A_{t+h} + P^B_{t+h}\alpha^B_{t+h}}{P^A_t\alpha^A_t + P^B_t\alpha^B_t} \\
&= \left(\left(\frac{P^A_t\alpha^A_t}{P^A_t\alpha^A_t + P^B_t\alpha^B_t}\right) R^A_{t,t+h} + \left(\frac{P^B_t\alpha^B_t}{P^B_t\alpha^A_t + P^B_t\alpha^B_t}\right) R^B_{t,t+h}\right) \\
&+ \left(\frac{P^A_{t+h}\alpha^A_{t+h} + P^B_{t+h}\alpha^B_{t+h}}{P^A_t\alpha^A_t + P^B_t\alpha^B_t} - \left(\left(\frac{P^A_t\alpha^A_t}{P^A_t\alpha^A_t + P^B_t\alpha^B_t}\right) R^A_{t,t+h} + \left(\frac{P^B_t\alpha^B_t}{P^B_t\alpha^A_t + P^B_t\alpha^B_t}\right) R^B_{t,t+h}\right)\right)
\end{aligned}$$

We call the first term capital gains, which is a return that an investor can earn if he/she holds α^A_t and α^B_t shares of token A and B until time $t+h$ without providing liquidity to the pool. We define the second term as impermanent loss in our context, which is the difference between the return on liquidity provision and capital gains.

First, the capital gains are reduced to $\frac{1}{2}R^A_{t,t+h} + \frac{1}{2}R^B_{t,t+h}$ thanks to Lemma 1. Second, in order to simplify the impermanent loss, we use Lemma 1 again.

$$\begin{aligned}
&\frac{P^A_{t+h}\alpha^A_{t+h} + P^B_{t+h}\alpha^B_{t+h}}{P^A_t\alpha^A_t + P^B_t\alpha^B_t} - \left(\left(\frac{P^A_t\alpha^A_t}{P^A_t\alpha^A_t + P^B_t\alpha^B_t}\right) R^A_{t,t+h} + \left(\frac{P^B_t\alpha^B_t}{P^B_t\alpha^A_t + P^B_t\alpha^B_t}\right) R^B_{t,t+h}\right) \\
&= \frac{P^A_{t+h}\alpha^A_{t+h}}{P^A_t\alpha^A_t} - \left(\frac{1}{2}R^A_{t,t+h} + \frac{1}{2}R^B_{t,t+h}\right) \\
&= \frac{P^A_{t+h}\sqrt{k\left(\frac{P^B_{t+h}}{P^A_{t+h}}\right)}}{P^A_t\sqrt{k\left(\frac{P^B_t}{P^A_t}\right)}} - \left(\frac{1}{2}R^A_{t,t+h} + \frac{1}{2}R^B_{t,t+h}\right) \\
&= \sqrt{R^A_{t,t+h}R^B_{t,t+h}} - \left(\frac{1}{2}R^A_{t,t+h} + \frac{1}{2}R^B_{t,t+h}\right) \\
&= -\frac{1}{2}\left(\sqrt{R^A_{t,t+h}} - \sqrt{R^B_{t,t+h}}\right)^2
\end{aligned}$$

The impermanent loss defined in the context of return on liquidity provision is closely related to the impermanent loss defined as the ratio of investment outcomes at time $t+h$

in the two scenarios minus 1. It is straightforward to show that

$$-\frac{1}{2}\left(\sqrt{R^A_{t,t+h}}-\sqrt{R^B_{t,t+h}}\right)^2=\left(\frac{1}{2}R^A_{t,t+h}+\frac{1}{2}R^B_{t,t+h}\right)\left(\frac{2\sqrt{\frac{\rho_{t+h}}{\rho_t}}}{\frac{\rho_{t+h}}{\rho_t}+1}-1\right)$$

B.2 Trading frictions in yield farming

In this section, we explain trading frictions in yield farming and how they can affect the performance of a yield farming strategy. We investigate three different trading frictions: gas fees, trading fees, and price impact.

Gas fees

Table A.2 lists 14 steps for one round of the yield farming strategy. Out of the 14 steps, 10 require the farmer to pay gas fees. The gas fee is the transaction cost that BSC users need to pay whenever they execute transactions that require computational resources of the network. The gas fee is typically not proportional to the size of the transaction. We discuss in Section 3.2 about how we collect gas fee data in yield farming. We subtract the gas fee in each round of yield farming from invested capital to incorporate the effect of gas fee on the performance of yield farming.

Trading fees

Let c^*=0.0025 (0.25%) denote the fraction of trading volume that traders need to pay in trading fees at PancakeSwap. In Step 2, when a yield farmer buys token A, he/she pays a 0.25% trading fee. Because this trading fee does not apply to token B, the farmer pays effectively half of the trading fee $\frac{c*}{2}$ (=0.125%) of the additional liquidity that he/she provides. Moreover, the farmer has to pay an additional fee of 0.25%: when he/she converts the withdrawn token A to token B, he/she pays additional $\frac{c*}{2}$ fraction of trading fee. The farmer also needs to pay also $\frac{c*}{2}$ of trading fee in Step 3 and Step 13. Given that the yield farmer pays $\frac{c*}{2}$ our times, the yield farmer's gross return on capital gain and impermanent loss should be

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

In Step 10, the yield farmer also needs to pay trading fees when he/she sells CAKE tokens harvested from farming. For this, we multiply $(1-c^*)$ on the realized farm yield term in equation (12).

Price impact

Executing a yield farming strategy involves buying and selling token A. In Step 2, a yield farmer buys token A. 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 additional losses for the yield farmer. The size of the loss is proportional to the relative size of investment (I_t) to the size of the liquidity pool, i.e., $I_t = fL_t$. We go through each step in Table A.2 to investigate the price impacts involved in a yield farming strategy.

(1) Step 1: We start from a liquidity pool with two tokens A and B. It has α_t^A of token A and α_t^B of token B and the prices of token A and B are denoted as P_t^A and P_t^B.

(2) Step 2: An yield farmer buys Δ_t^A number of token A using a part of his/her fund, $I_t = fL_t$. What is important here is that the yield farmer must obtain tokens A and B proportionally to α_t^A/α_t^B. For this purpose, we divide his/her fund into xI_t and $(1-x)\,I_t$ to allocate towards token A and B, respectively. The yield farmer first converts $\$xI_t$ to token B in a liquid market for B. Then, the farmer will have $\frac{xI_t}{P_t^B}$ of token B on hand, which he/she will convert to token A by means of the liquidity pool. Due to the constant product model assumption,

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

If we solve this for Δ_t^A,

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

(3) Step 3: The yield farmer uses the rest of their 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.

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

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

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

Therefore,

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

If we solve for x,

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

There are two solutions, but only the above solution is positive.

(4) Step 4: Arbitrageurs correct the price by supplying Δ_t^A of token A and receiving Δ_t^B of token B in return, after which the liquidity pool becomes basically identical to the initial pool.

(5) Step 5: The yield farmer provides their liquidity to the pool and receives LP tokens. For simplicity of notation, let's 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 $\alpha_t^A\left(1+s(f)\right)$ and $\alpha_t^B\left(1+s(f)\right)$. 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:

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

$$= P_t^A\left(1+\left(f-1+\sqrt{f^2+1}\right)\right)$$

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

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

(7) Step 7: The yield farmer waits for h days. After the trading activities the shares of token A and B become $\alpha_{t+h}^{A}(1+s(f))$ and $\alpha_{t+h}^{B}(1+s(f))$.

(8) Step 8: The yield farmer receives (harvest) 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's withdrawing liquidity, the shares of token A and B in the pool become α_{t+h}^{A} and α_{t+h}^{B}.

(12) Step 12: The yield farmer sells his $\Delta_{t+h}^{A}=s(f)\alpha_{t+h}^{A}$ of token A and receives Δ_{t+h}^{B} of token B. Currently, there are α_{t+h}^{A} and $\alpha_{t+h}^{B}$of token A and token B in the pool. After the farmer's sending $\Delta_{t+h}^{A}=s(f)\alpha_{t+h}^{A}$ of token A, he/she receives Δ_{t+h}^{B} token B. Due to the constant product model,

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

$$\rightarrow \Delta_{t+h}^{B}=\frac{s(f)}{1+s(f)}\alpha_{t+h}^{B}$$

The farmer sends $s(f)\alpha_{t+h}^{A}$ of token A and in return $P_{t+h}^{B}\Delta_{t+h}^{B}$ worth of USD. This means that the effective price that the yield farmer receives when selling token A is

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

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

(13) Step 13: The yield farmer sells $\Delta_{t+h}^{B}+s(f)\alpha_{t+h}^{B}$ 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 and receiving Δ_{t+h}^{A} of token A. A new round of yield farming starts again.

Now we 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 $s(f)\alpha_t^{B}$ shares of token A and B at $\tilde{P}_t^{A}$ and P_t^{B}. After h days, the yield farmer withdraws $s(f)\alpha^A_{t+h}$ and $s(f)\alpha^B_{t+h}$ shares of token A and B and sell them at $\tilde{P}^A_{t+h}$ and P^B_{t+h}. Then, its gross return is expressed as

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

We simplify this as follows.

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

where

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

In sum, if we take into account of both price impact and trading fee, return will be

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

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

Figure 4 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 Accuracy of Constructed Cryptocurrency Factors

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. In Table A.4, we compare our parameter estimates to those obtained in Liu, Tsyvinski, and Wu (2019). The two are near-identical with only minor deviations, which may be from 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.4, 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.

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 logarithm of size of liquidity in the yield farm in units of \$1 million. The y-axis corresponds to the 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 logarithm of (1 + annualized offered farm yield) on the logarithm of the size of liquidity in the yield farm.

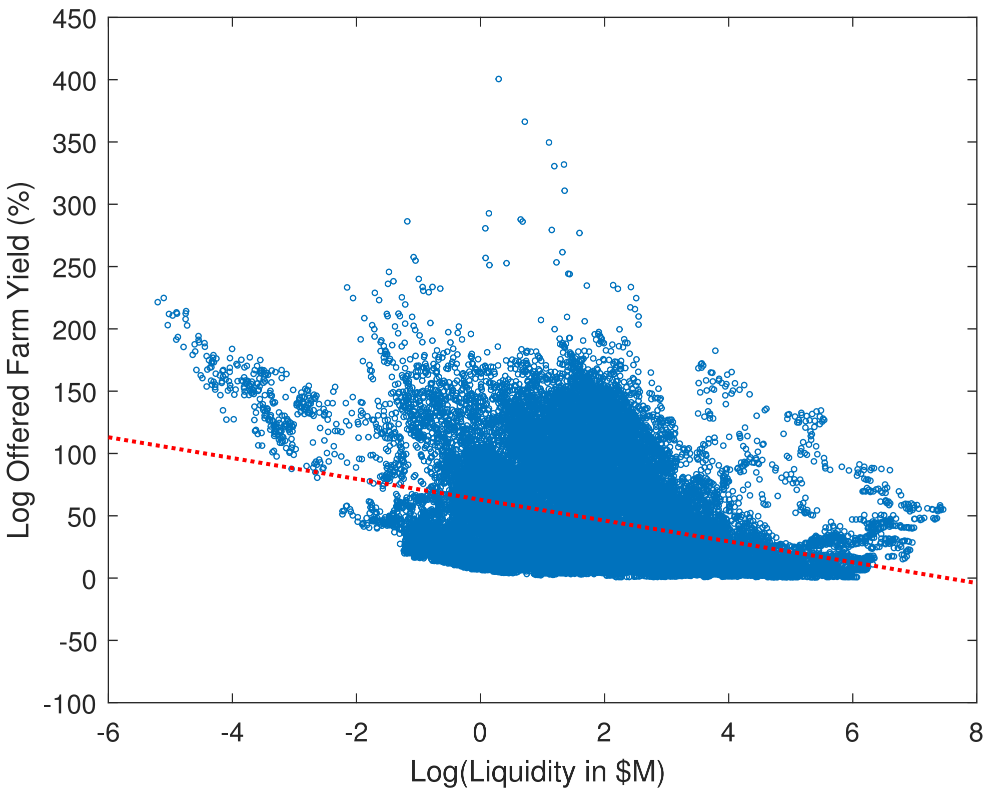


Figure A.2: UI of Yield Farms in PancakeSwap

In this figure, we provide a snapshot of the user-interface environment for yield farms in PancakeSwap.

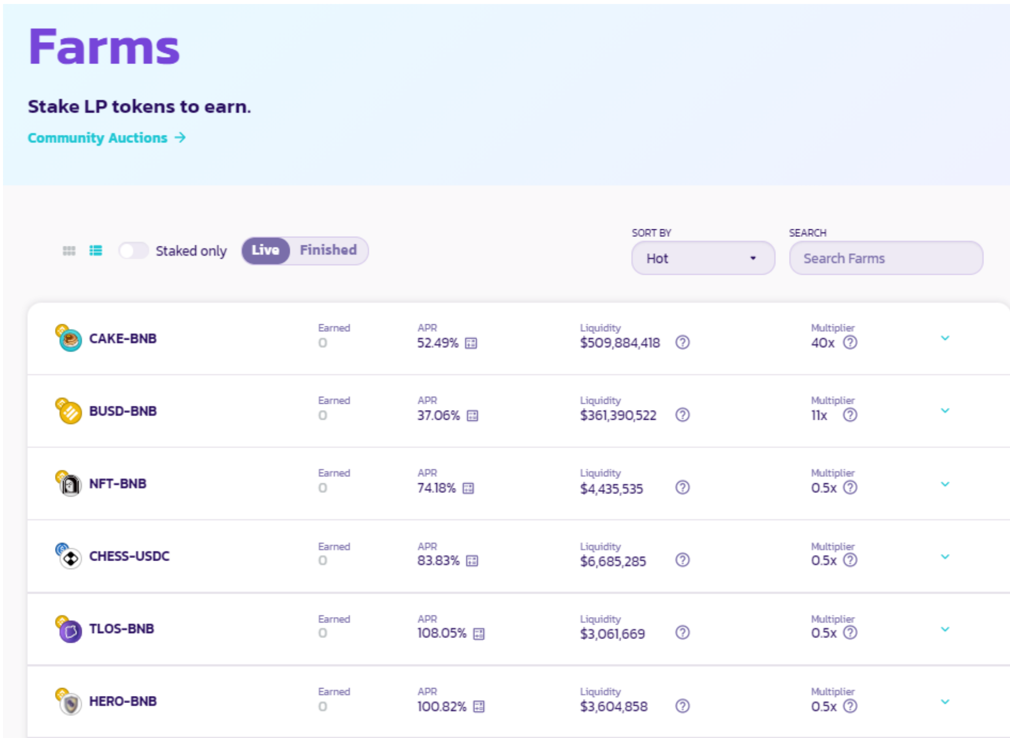


Figure A.3: UI of Yieldwatch

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

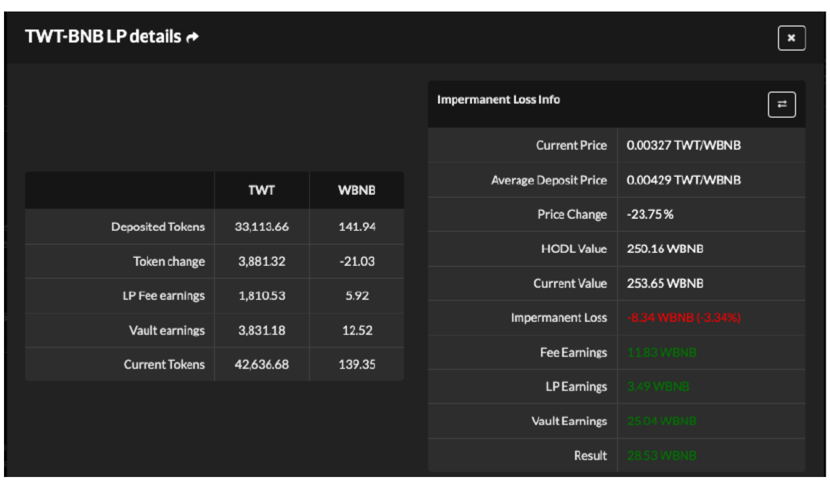


Figure A.4: Investment outcome from liquidity provision vs. Investment outcome from a buy-and-hold strategy

In this figure, we compare investment outcome from liquidity provision with investment outcome from a simple buy-and-hold strategy. A liquidity provider buys equal U.S. dollar amount of token A and token B of a liquidity pool at time t. y-axis is the ratio of investment outcome from a liquidity provision and investment outcome from a simple buy-and-hold strategy at time $t + h$ minus 1. x-axis is the growth of the ratio of prices of token A and token B between time t and $t + h$, i.e., $\frac{\rho_{t+h}}{\rho_t}$ where $\rho_t = \frac{P_t^A}{P_t^B}$

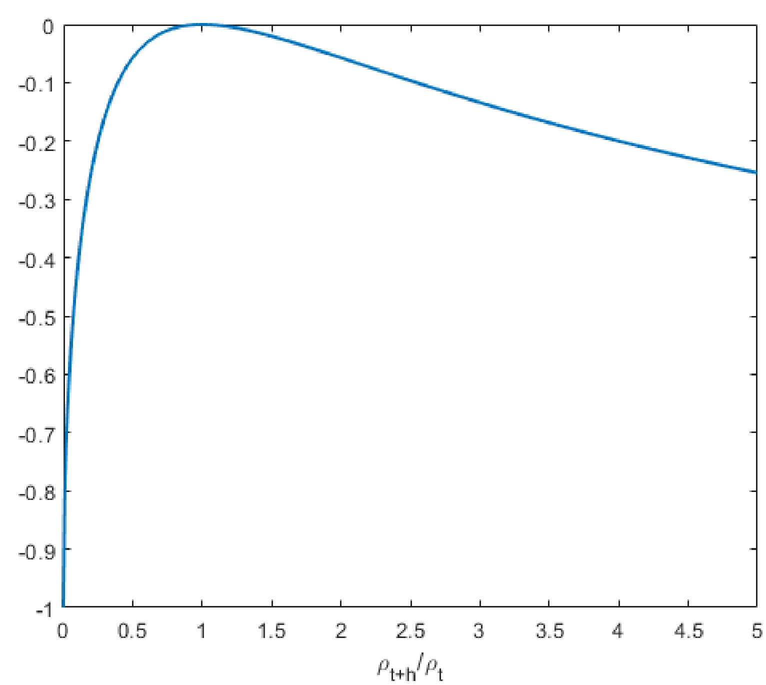


Figure A.5: Relation between Model-implied and Listed Offered Farm Yields

In this figure, we compare the offered farm yields calculated using Equation (8) on the y-axis to those listed on the 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 $\widehat{y}_t = 1.002 \times y_t - 0.001$.

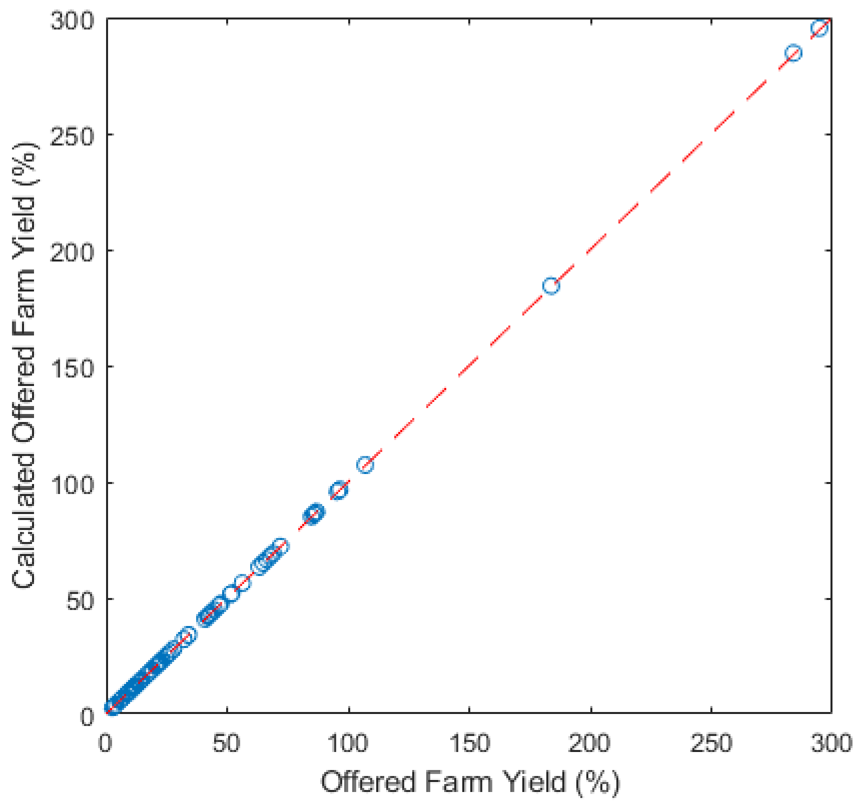


Table A.1: Literature on Decentralized Finance and Decentralized Exchanges

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: Summary Statistics of Coins used for Constructing Cryptocurrency Factors

In this table, we provide summary statistics of cryptocurrencies used for construction of cryptocurrency factors. Our sample period for cryptocurrency factors starts on December 28, 2013 and ends on September 5, 2021. 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.4: Comparison of Cryptocurrency Three-Factor Regressions

This table compares the regression results for portfolios sorted on one-week momentum by quintile. 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.

Panel A: Regressions from Liu, Tsyvinski, and Wu (2019)	**Quintile**				
	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.5: Top 10 Cryptocurrency Decentralized Exchanges

In this table, we report information regarding 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 spots 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.6: Determinants of Yields

In this table, we report the results from a projection of farm yields on their individual components. The farm yields are defined as $y_{i,t} = c \times (m_{i,t}/M_t)\left(P_t^{Cake}/L_{i,t}\right)$, 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 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.7: Yield Farming Return Decomposition

In this table, we decompose each return series into the contributions arising from (a) capital gains, (b) impermanent losses, (c) trading fees, and (d) farm yields. The sample period is March 1, 2021 to August 1, 2022. In Panel A, we report summary statistics on the return characteristics for each component. We report the cross-sectional average daily mean log return (Ret) median ($Median$), 25th ($p25$) and 75th ($p75$) percentiles of the log return distribution and the corresponding standard deviation (SD), skewness ($Skew$), kurtosis ($Kurt$), the first order autocorrelation coefficient ($AC1$), and the average number of observations for each time series (OBS). We also report the same information sorted by terciles in terms of average in-sample offered yield. In Panel B, we report the same information aggregated at a weekly frequency starting from March 1, 2021. All return-based statistics are annualized.

Panel A: Daily **Component**	**Mean**	**SD**	**p25**	**Median**	**p75**	**Skew**	**Kurt**	**AC1**	**OBS**
Full Sample									
Capital Gains	-0.8127	1.1652	-11.9026	-0.4677	10.6029	-0.1815	10.2866	-0.0944	200.6652
Impermanent Loss	-0.3373	0.0681	-0.2212	-0.0548	-0.0127	-6.1250	58.6807	0.1093	200.6652
Trading Fees	0.0974	0.0068	0.0357	0.0605	0.1105	3.7356	28.9568	0.4469	200.6652
Farm Yields	0.9538	0.0219	0.6367	0.8983	1.2112	0.9027	4.5288	0.8587	200.6652
Quintile 1									
Capital Gains	-0.1193	0.8418	-8.1881	0.4963	8.2028	-0.1842	14.8557	-0.1322	381.5870
Impermanent Loss	-0.1488	0.0414	-0.0918	-0.0257	-0.0051	-7.7476	95.0606	0.1572	381.5870
Trading Fees	0.0876	0.0056	0.0362	0.0575	0.1010	5.2043	48.8937	0.5001	381.5870
Farm Yields	0.1736	0.0069	0.0893	0.1195	0.2205	1.7970	7.1250	0.9276	381.5870
Quintile 2									
Capital Gains	-0.0365	1.1435	-10.5257	0.0147	10.2843	0.2934	12.6188	-0.0913	266.9130
Impermanent Loss	-0.2855	0.0638	-0.1709	-0.0486	-0.0099	-7.6081	84.6227	0.0970	266.9130
Trading Fees	0.1229	0.0104	0.0445	0.0735	0.1361	4.6174	44.6092	0.4781	266.9130
Farm Yields	0.4508	0.0157	0.2315	0.3714	0.5942	1.2208	5.1006	0.8932	266.9130
Quintile 3									
Capital Gains	-0.8460	1.0919	-11.2840	-0.5674	9.5490	-0.0281	8.5971	-0.0657	165.6087
Impermanent Loss	-0.3041	0.0853	-0.1831	-0.0504	-0.0095	-5.8237	51.3899	0.1249	165.6087
Trading Fees	0.0977	0.0065	0.0331	0.0597	0.1120	3.4331	22.5211	0.4780	165.6087
Farm Yields	0.7819	0.0247	0.3999	0.6468	1.0904	0.8725	4.0536	0.8809	165.6087
Quintile 4									
Capital Gains	-1.1694	1.3722	-13.9270	-1.3801	12.3961	-0.2775	7.6673	-0.1087	101.4565
Impermanent Loss	-0.5990	0.0947	-0.4183	-0.0817	-0.0239	-4.5939	29.5352	0.0992	101.4565
Trading Fees	0.1072	0.0079	0.0329	0.0607	0.1194	2.6393	13.6937	0.3824	101.4565
Farm Yields	1.3211	0.0315	0.8233	1.3059	1.7439	0.3849	3.1694	0.8333	101.4565
Quintile 5									
Capital Gains	-1.8923	1.3765	-15.5881	-0.9019	12.5823	-0.7112	7.6944	-0.0743	87.7609
Impermanent Loss	-0.3492	0.0550	-0.2419	-0.0677	-0.0152	-4.8515	32.7951	0.0683	87.7609
Trading Fees	0.0714	0.0038	0.0318	0.0511	0.0840	2.7560	14.6146	0.3953	87.7609
Farm Yields	2.0415	0.0308	1.6397	2.0481	2.4070	0.2386	3.1954	0.7586	87.7609

Panel B: Weekly **Component**	**Mean**	**SD**	**p25**	**Median**	**p75**	**Skew**	**Kurt**	**AC1**	**OBS**
Full Sample									
Capital Gains	-0.8086	1.1496	-5.0360	-0.3646	4.1746	-0.3621	5.4104	-0.0063	28.8202
Impermanent Loss	-0.3668	0.0954	-0.3604	-0.1431	-0.0778	-2.6289	12.0903	-0.0033	28.8202
Trading Fees	0.0973	0.0118	0.0477	0.0704	0.1179	1.5860	6.8195	0.3210	28.8202
Farm Yields	0.9525	0.0539	0.6608	0.9054	1.1973	0.7039	3.7337	0.6434	28.8202
Quintile 1									
Capital Gains	-0.1443	0.8107	-3.3747	0.0026	3.2803	-0.3171	7.9203	-0.0263	55.4565
Impermanent Loss	-0.1458	0.0518	-0.1206	-0.0313	-0.0086	-3.7015	20.2222	0.0813	55.4565
Trading Fees	0.0878	0.0101	0.0453	0.0661	0.1053	2.4262	11.4688	0.3719	55.4565
Farm Yields	0.1760	0.0186	0.0914	0.1223	0.2215	1.7292	6.7084	0.7592	55.4565
Quintile 2									
Capital Gains	-0.2899	1.0497	-4.3415	-0.1534	3.9020	-0.0296	6.1517	0.0215	37.7111
Impermanent Loss	-0.2738	0.1023	-0.2224	-0.0709	-0.0198	-3.5026	18.5633	0.0129	37.7111
Trading Fees	0.1233	0.0170	0.0576	0.0871	0.1514	1.9624	9.3362	0.3248	37.7111
Farm Yields	0.4576	0.0415	0.2483	0.3709	0.5982	1.0171	4.1799	0.7149	37.7111
Quintile 3									
Capital Gains	-0.9911	1.1259	-5.1219	-0.7413	3.7089	-0.3127	4.6290	-0.0445	23.0435
Impermanent Loss	-0.3430	0.1111	-0.3171	-0.0886	-0.0247	-2.4446	10.1387	-0.0322	23.0435
Trading Fees	0.0985	0.0122	0.0454	0.0691	0.1179	1.4390	5.5308	0.3826	23.0435
Farm Yields	0.7830	0.0610	0.4190	0.6797	1.0976	0.5386	2.5478	0.6915	23.0435
Quintile 4									
Capital Gains	-0.7900	1.3119	-5.4086	-0.2220	5.3325	-0.4818	4.2922	-0.0340	15.2000
Impermanent Loss	-0.6956	0.1326	-0.6864	-0.3574	-0.2887	-1.9327	6.5138	-0.0364	15.2000
Trading Fees	0.1060	0.0133	0.0480	0.0721	0.1323	1.0539	3.7237	0.2935	15.2000
Farm Yields	1.3327	0.0786	0.8764	1.3286	1.7185	0.2408	2.5570	0.5823	15.2000
Quintile 5									
Capital Gains	-1.8276	1.4496	-6.9334	-0.7090	4.6494	-0.6787	4.0038	0.0524	12.5870
Impermanent Loss	-0.3757	0.0792	-0.4553	-0.1674	-0.0470	-1.5236	4.7321	-0.0437	12.5870
Trading Fees	0.0710	0.0065	0.0423	0.0578	0.0827	1.0084	3.8122	0.2286	12.5870
Farm Yields	2.0132	0.0698	1.6687	2.0255	2.3507	-0.0321	2.6260	0.4637	12.5870