PEER REVIEWED RESEARCH

OPEN ACCESS
ISSN Online: 2516-3957
ISSN Print: 2516-3949
https://doi.org/10.31585/jbba-6-1-(5)2023

DeFi Lending Platform Liquidity Risk: The Example of Folks Finance

Matthias Hafner,[1, 2] Romain de Luze,[2] Nicolas Greber,[2] Juan Beccuti,[2, 3] Benedetto Biondi,[4] Gidon Katten,[4] Michelangelo Riccobene,[4] Alberto Arrigoni[4]
[1] University of Zurich, Switzerland
[2] Center for Cryptoeconomics and Swiss Economics, Switzerland
[3] University of Bern, Switzerland, and Informal Systems, Canada
[4] Folks Finance

Correspondence: matthias.hafner@swiss-economics.ch
Received: 03 January 2023 **Accepted**: 03 March 2023 **Published**: 02 April 2023

Abstract
Decentralised finance (DeFi) lending platforms may experience liquidity risk, which occurs when users are unable to withdraw their assets. Researchers and practitioners have found that the concentration of deposits among a small group of users is one of the main drivers of liquidity risk. Typically, lending platforms experience high concentration at the beginning of their operations. As a result, they face a significant liquidity risk that has not been investigated so far. This article closes this gap by investigating liquidity risk from the perspective of a new lending platform, describing the use case of Folks Finance. First, we describe the liquidity risk the lending protocol faces using platform economics. Second, we theoretically assess the efficacy of different liquidity risk measurements. Third, we investigate how a reward mechanism can reduce liquidity risk. We show that the liquidity risk is more pronounced for a new lending platform than for an incumbent protocol. In addition, we find that the Herfindahl–Hirschman index (HHI) outperforms other liquidity risk measurements. Finally, we show that if rewards are sufficient but not too large, a programme that incentivises depositors to lock their assets can reduce liquidity risk and increase liquidity bootstrapping. Several conclusions are drawn from the case study: First, new lending platforms should be particularly cautious regarding liquidity risk. Second, lending protocols should use HHI instead of other concentration measurements when calibrating their parameters. Third, rewards can be used to bootstrap liquidity and incentivise liquidity holdings but should not be overused.

Keywords: *DeFi, Lending Platform, Liquidity Pools, Platform Economics, Liquidity Risk*

JEL Classifications: *C63, D47, G10, L10*

1. Introduction

In the last years, decentralised finance (DeFi) has experienced rapid growth, attaining a peak of total value locked (TVL), which refers to the overall value of crypto assets deposited in DeFi, of about $50 billion in December 2022 [1]. Among the different types of DeFi projects, lending protocols account for a big share of DeFi's TVL. A lending protocol is a type of financial service that allows individuals and organisations to lend and borrow funds from each other without the need for a traditional financial institution, such as a bank, to facilitate the transaction.

Such protocols, and more broadly DeFi, present a range of new opportunities and can mitigate some traditional risks. This is not necessarily the case for liquidity risk. Liquidity risk can affect the ability of users to access and trade their assets. This article investigates liquidity risk for a new lending platform in the DeFi ecosystem and aims to provide insights and strategies that can help to mitigate potential vulnerabilities and challenges faced by DeFi platforms.

There exists a large literature on market liquidity and liquidity risk in the context of traditional finance. In general, liquidity refers to the ease with which an individual or entity can exchange their wealth for goods, services, or other assets [2, 3]. Multiple definitions for liquidity risk exist, but in this article we stick to the definition related to banks, where it refers to the possibility that an entity is unable to service its liabilities as they come due without incurring unacceptable losses (e.g., [3, 4, 5]). Liquidity risk depends on various factors, such as the volatility and the concentration of the assets held in custody [6]. Researchers investigated the impact of it on the economy and market prices (e.g., [7, 8]). The literature shows that liquidity risk can lead to, among other things, financial crises, which can damage financial stability, disrupt the allocation of resources, and ultimately destabilise the real economy [3]. Given the significant negative impacts that can result, understanding, measuring, and effectively managing liquidity risk is of critical importance.

In a DeFi lending protocol, users can lend and borrow assets directly from one another without the need for a traditional financial intermediary, such as a bank. In this system, liquidity risk refers to the risk that a protocol will not have enough assets available to support basic operations, including the ability of a depositor to exit the protocol [9]. This risk can arise if, for example, there is a large outflow of assets from the platform, leading to a lack of available liquidity for depositors to use to withdraw their own assets.

The literature on liquidity risk in the context of DeFi is sparse. Gudgeon et al. [10] provide a theoretical overview of interest rate mechanisms of different lending protocols and empirically assess their interest rates at different points in time. They found that deposits are often very concentrated which presents a significant liquidity risk. Sun et al. [11] investigate liquidity risks focusing on Aave, a popular lending protocol. They analyse the behaviour of a small group of users who are both borrowers and depositors. Those users can have complex and potentially amplifying effects on the platform's liquidity risks, which may be transmitted to other liquidity providers in the market.

Empirical evidence suggests that liquidity concentration tends to be high in the initial stages of lending platforms (see also section 3.2). This presents a significant risk for these platforms that has not been investigated so far. This article closes this gap by investigating liquidity risk from the perspective of a new lending platform and proposes a solution to mitigate it.

We investigate liquidity risk by presenting the use case Folks Finance, a DeFi lending platform on the Algorand blockchain. We do this in two parts. First, we describe Folks Finance as a lending protocol and the associated liquidity risk using platform economics. In line with the literature, we find that concentration is a major driver of liquidity risk. Second, we discuss the practical implementation of a reward system to mitigate liquidity risk. More specifically, we theoretically assess the efficacy of different liquidity risk measurements and investigate how a reward mechanism for locking the assets for a fixed period can reduce liquidity risk. We find that the Herfindahl–Hirschman index (HHI) outperforms other liquidity risk measurements. Finally, we show that a programme that incentives depositors to lock their assets can reduce liquidity risk and increase liquidity bootstrapping.

The article is structured as follows. In section 2, an overview of the relevant components of Folks Finance is presented. In section 3, we describe how DeFi lending platforms work from an economic point of view and describe the risks they face. In section 4, we analyse different possibilities of measuring concentration of liquidity in a pool. In section 5, we present a solution to mitigate liquidity risk. In section 6, we conclude.

2. Lending Platform Model: The Example of Folks Finance

Lending platforms are DeFi platforms that allow individuals to lend and borrow money from each other without the need for a traditional intermediary such as a bank. In this section, we show how participants on a lending platform interact by presenting the use case of Folks Finance, a lending protocol in the Algorand ecosystem.

Lending platforms typically have two main participant types: borrowers and depositors (also called lenders). Borrowers are individuals or organisations who take loans and increase or repay existing loans. For any loan, the borrowers must provide collateral. Depositors are individuals or organisations who provide assets or withdraw them. As explained later, in Folks Finance depositors can additionally lock their assets. The platform acts as a facilitator, connecting borrowers and depositors and managing the loan process. Depending on the complexity of a platform, more participants can interact. That is the case of Folks Finance.

Figure 1 illustrates the various users of Folks Finance and how they interact with each other.

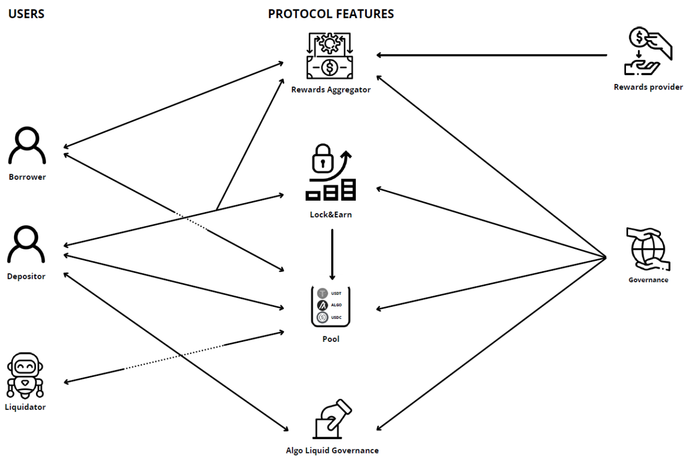

Figure 1. Interactions between Folks Finance's users

Besides borrowers and depositors, the other actors involved on Folks Finance are liquidators, reward providers, and governance. Liquidators buy the collateral and liquidate positions when the borrow balance value falls below an under-collateralisation threshold. Reward providers are entities that provide rewards for Lock & Earn. Governance may execute parameter updates and other related actions.

The different operations and participants are described in more detail in Folks Finance's official documentation [12].

3. Lending Platform Economics and Associated Risks

Folks Finance and other lending protocols are multi-sided platforms, acting as intermediaries between interdependent groups (in particular, lenders and borrowers). To understand the challenges that new lending platforms face, it is necessary to understand their economic models. In this section, we introduce the platform economics of lending platforms and discuss the liquidity risks that they face.

3.1 Platform Economics of Lending Protocols

There is a wide range of markets where users benefit from choices made by other users. Such users differ in needs or interests (e.g., buyers and sellers, borrowers and depositors).

Platforms are intermediaries that make the interaction between such heterogeneous users possible [13].

A platform business model has a key economic characteristic. The distinct groups expose themselves to so-called cross-network effects. The effects are positive if the platform becomes more attractive/valuable for one group when the other user group grows and negative in the opposite case. The main challenge for a platform with cross-network effects is to bring all user groups on board. Notably, the platform must determine its pricing strategy, which is crucial for influencing various groups to join. This usually results in platforms charging different prices to user groups [13, 14].

As discussed in the previous section, lending platforms facilitate the interactions between depositors and borrowers of crypto assets. Borrowers and depositors exert positive cross-network effects on each other. Depositors exert positive cross-network effects on borrowers since a larger pool size increases the likelihood that a borrower can borrow the type and amount of asset they choose. Borrowers have a positive effect on depositors because an increasing amount borrowed from the pool raises the efficiency of the deposited assets. Under reasonable protocol designs, increased efficiency results in higher returns for depositors.

Lending protocols use a dynamic pricing strategy to control cross-network effects. To optimally match demand from borrowers and depositors, platforms adjust interest rates algorithmically to attract participants from the two groups using the following principles: (1) If the total assets deposits are high, but only a small amount is borrowed, the interest rate is reduced to attract borrowers. (2) If the total amount of loans is high compared to the deposits in the pool, the interest rate is high. In practice, lending platforms set the interest rate i based on the so-called utilisation ratio U, which describes how much of the available assets in a pool (deposited amount) are borrowed:

$$U = \frac{Borrowing\ Amount}{Deposit\ Amount}$$

Lending platforms set the interest rate using a positive transformation of this utilisation ratio:

$$i = f(U)$$

An example of such a function is presented in Figure 2.

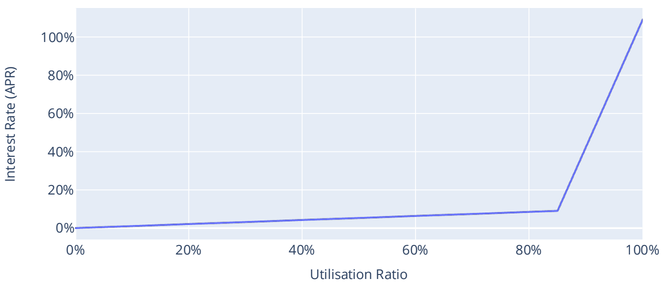

Figure 2. Folks Finance's USDC interest rate as a function of the utilisation ratio

Figure 2 presents the interest rate of USDC on Folks Finance as a function of the utilisation ratio at the time of writing. The blue line represents borrowers' interest rate (y-axis), which increases with the utilisation ratio (x-axis). The interest rate function balances demand from borrowers and depositors. If groups are unbalanced, the protocol will dynamically adjust the interest rate. Assume, for example, a utilisation ratio of 10%, meaning that only 10% of the deposited USDC is borrowed. Then the function will set an interest rate of 1% (see Figure 2). The low interest rate will attract borrowers (low cost of borrowing) and deter depositors (low reward for lending assets) and thus result in a more balanced state.

Note that in Figure 2 the slope of the interest rate curve becomes sharply steeper above a certain threshold (utilisation ratio 85%). This kink is used to manage liquidity risk, which we discuss in more detail in the next section.

3.2 Liquidity Risk

The utilisation ratio – the percentage of available assets borrowed at any given time – is a key factor determining a lending protocol's success. Lending protocols aim to maintain a utilisation ratio that is close to but below 100% to maximise profits and minimise risk (cf. the kink in Figure 2). The main reason for targeting a utilisation ratio below 100% is to manage liquidity risk. If all assets were borrowed (utilisation ratio 100%), depositors would not be able to withdraw their assets. Such a situation represents an undesired liquidity shortage.

The optimal target for the utilisation ratio depends on the probability of a liquidity shortage: For a given asset or market condition, the higher the liquidity risk, the lower the target ratio to mitigate the risk. To find the optimal target ratio, it is therefore necessary to analyse the conditions under which liquidity risk is high.

One of the significant liquidity risk drivers in DeFi is the concentration of deposited amounts. Concentration is high if only a few depositors make up most of the protocol's assets. In a concentrated protocol state, a large depositor withdrawing assets is likely to cause liquidity issues because a relatively larger amount of the pool is now in the hands of the borrowers and not freely available for withdrawals. In contrast, pools with many small depositors are less likely to cause liquidity issues because the withdrawal of assets by any one depositor has less impact on the overall market (see also section 4.2). In other words, liquidity shortage is less likely in these pools because the risk is spread out among many different depositors rather than being concentrated in a few large ones.

Incumbent lending protocols such as Aave have proven that the problem can be solved using specific utilisation ratio targets lower than 100%. However, the problem is more pronounced at the launch of a new protocol, when only a few lenders and borrowers are participating on the platform. In this case, the concentration is usually higher. For example, Figure 3 shows the deposit shares of the top 50 USDC depositors on Aave at the time when the platform was first deployed on the Ethereum network.

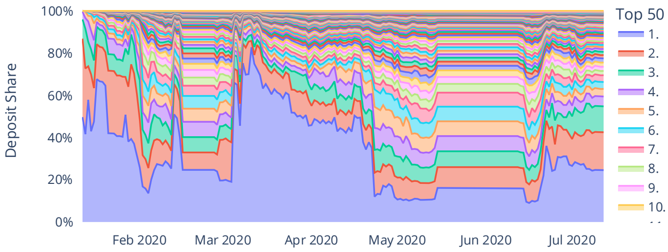

Figure 3. Deposit shares of the top 50 USDC depositors on Aave between January and June 2020 (relative to each other) [15]

Note: Deposit shares and rank (top 50) are calculated using the 50 largest depositors at specific points in time. This means that the largest depositor on a given day may be a different user than the largest depositor on another day.

Figure 3 clearly illustrates that the percentage of the largest depositors and, thus, concentration decreases over time. In the first few months of a new lending protocol, governors may, therefore, need to set a lower target ratio to compensate for the increased liquidity risk.

However, setting a low target ratio has major downsides. Low interest rates may not be attractive to depositors, who may prefer to deposit their funds on other platforms that offer higher rates. Setting a lower utilisation target ratio will make the platform less efficient than incumbent platforms. With such a strategy, in combination with network effect, it is difficult for a new lending platform to reach a critical size, and thus it is at risk of failing.

To mitigate the problem, Folks Finance proposed a reward mechanism to incentivise depositors to lock up their assets initially, thus reducing the risk of withdrawals at a critical time. This strategy allows for setting competitive interest rates without increasing liquidity risk. To implement the solution, however, several practical challenges must be solved. First, there is a need to determine how to measure concentration. Second, a reward system must be designed that incentivises users to lock assets without negatively impacting the incentive design around the utilisation ratio.

4. Risk Measurements

As explained in the previous section, liquidity concentration relates to liquidity risk. But what is the best way to measure concentration? Several existing economic indices can be considered to quantify the risk in liquidity pools on a lending platform: the concentration ratio, the HHI, and the Gini index. The concentration ratio and HHI are commonly used to measure the market concentration in whole industries [16]. The HHI can additionally be used to measure the distribution of wealth between households [17]. The Gini index can be used to measure concentration as well as inequality on blockchains [6, 18].

4.1 Measuring Concentration

Concentration Ratio. The concentration ratio is used to measure market concentration in industries. Because it is a straightforward representation of the size of major actors in an industry, the concentration ratio is an obvious choice to represent the size of significant actors in liquidity pools. To calculate the index, the liquidity shares for the m largest depositors are added together,

$$CR_m = \sum_{i=1}^{m} s_i$$

with $s_1 \geq s_2 \geq \cdots \geq s_n$,

for a total of n depositors. For example, CR_4 denotes the combined liquidity share of the four largest depositors. This results in an index between 0 and 1. The higher the index, the more liquidity the largest m depositors hold.

Herfindahl–Hirschman index. Instead of including only the largest depositors in the pool, the HHI considers the whole distribution. The HHI is calculated by squaring each depositor's market share and adding these squared values together,

$$HHI = \sum_{i=1}^{n} s_i^2$$

with $s_1 \geq s_2 \geq \cdots \geq s_n$ and n depositors.

The resulting index again ranges from 0 to 1, with a higher value indicating a more concentrated liquidity pool.

Gini index. The Gini index measures concentration and economic inequality by comparing the distribution of wealth among members in a pool. It too ranges from 0 to 1, with 0 indicating perfect equality (everyone has the same amount) and 1 indicating perfect inequality (one person has everything and the rest nothing). A higher Gini index indicates a greater degree of inequality in the distribution of wealth or income. The formula is as follows:

$$G = \frac{2\sum_{i=1}^{n} i \times s_{n+1-i}}{n\sum_{i=1}^{n} s_i} - \frac{n+1}{n}$$

with $s_1 \geq s_2 \geq \cdots \geq s_n$.

4.2 Efficacy of the Indices

We turn now to examining the suitability of the CR, HHI, and Gini index for assessing liquidity risk on a lending platform. To do so, it is necessary to consider their ability to adequately reflect the risk associated with the distribution of deposit shares and the number of deposits.

Liquidity risk relates to the probability of a significant withdrawal from the liquidity pool. The CR cannot capture the liquidity risk of an entire distribution because it does not account for variations between depositors – it simply reflects the *combined* share of the largest depositors.

To illustrate, consider a market where the concentration ratio of the five largest liquidity holders is 50%, i.e., $CR_5 = 0.5$. It is unclear whether one liquidity holder is providing 40% of the pool and the remaining four holders are providing the remaining 10%, or all five holders are providing 10% of the pool. The liquidity risk associated with these two scenarios is quite different, yet the CR would be the same in both cases. Therefore, we conclude that CR is not suited for liquidity risk assessment and focus on the other two measurements that consider details of the contribution.

Concerning the number of depositors, the HHI outperforms the Gini index. As stated, liquidity risk is related to the ability to withdraw a certain share from the liquidity pool. It is therefore crucial to know if the liquidity pool consists of a few large or many small deposits. In other words, the number of deposits matters. While the HHI takes into account the number of deposits, the Gini index does not. To illustrate, assume all deposits are the same size. If there are N liquidity holders with identical shares, the HHI is $1/N$. As the number of users increases, this index converges to 0, the minimum value. On the other hand, if a single holder provides 100% of the pool, the HHI is 1, the maximum. Thus, the HHI reflects liquidity risk adequately. The exact opposite holds for the Gini index, however. If deposit size does not vary, the Gini index remains the same independent of the number of deposits. Furthermore, additional depositors with very small deposits can have a large impact on the index, whereas this is not the case with the HHI.

Given these considerations, in what follows we use HHI as the preferred measure of liquidity risk.

5. Risk Mitigation with Lock & Earn Using HHI

To protect liquidity pools – especially at their early stages – against risks stemming from high market concentration, Folks Finance has developed a scheme called "Lock & Earn".

5.1 Lock & Earn

To ensure the constant and wide availability of funds in the protocol, Folks Finance differentiates ordinary depositors from those who participate in Lock & Earn (L&E), considering the latter as long-term depositors by tying up their liquidity for a fixed term. This mechanism differentiates them from ordinary depositors, who can withdraw their assets at any time. This system has been specifically designed to create a pillow pool of assets that will allow low-cost loans to launch a new pool and increase the security of redeemable assets.

L&E participants agree to keep the liquidity inside the protocol for a long time to stabilise it. In return, they receive folks-reward tokens. This incentive increases their annual percentage rate relative to ordinary depositors.

The value of the incentive is set by Folk Finance governors. Considering the liquidity needs of the different pools, the incentives can be updated and adjusted based on governance choices.

5.2 The Impact of L&E and Reward Calibration

It can be shown analytically that L&E increases liquidity bootstrapping and reduces liquidity risk. Assume we have a liquidity pool that has not yet introduced L&E. The depositors earn an interest rate $i_d(U)$ which depends on the utilisation ratio U. The outside option for the depositors is $r > 0$, i.e., the return they could get elsewhere. Because depositors value their ability to withdraw assets at any moment (as renouncing liquidity entails a risk), the total reward for L&E needs to be higher, i.e., $i_l > i_d$.

Proposition: The introduction of L&E always helps bootstrapping more liquidity.

Proof:
We consider a mass of potential depositors with different valuations of the outside option r and the value of being liquid in the next period ϕ, distributed according to the continuous function $f(r, \phi)$. Assume that an equilibrium exists for the utilisation ratio U^* and corresponding equilibrium depositor and borrower interest rates i_d^* and i_b^*. Without L&E, only depositors with $i_d^* > r$ make deposits. The introduction of L&E leads to two changes:

1. *Some potential depositors with $i_d^* < r$ and $i_l > r + \phi$ who did not participate before deposit with L&E.*
2. *All depositors with $i_l - i_d^* > \phi$ and $i_l - r - \phi > 0$ now deposit with L&E instead of normally.*

The resulting total deposits (deposits + L&E) are larger than before if $i_l > i_d$. The change in the number of total depositors affects the utilisation ratio and, in turn, the interest rates, which deviate from the equilibrium. There are two cases to consider:

1. *If only the borrowers react to the change in interest rates, they borrow additional assets until the interest rates return to their previous levels.*
2. *If only the depositors react to the change in interest rates, some will reduce their deposits in favour of making L&E deposits, while others will decrease their deposits in favour of not participating. This gradual return to the equilibrium leads to the same total amount of deposits as before, but with a fraction now participating in the L&E programme.*

Any combination of borrower and depositor reactions will result in a scenario between these two extremes, with total deposits being slightly larger than before.

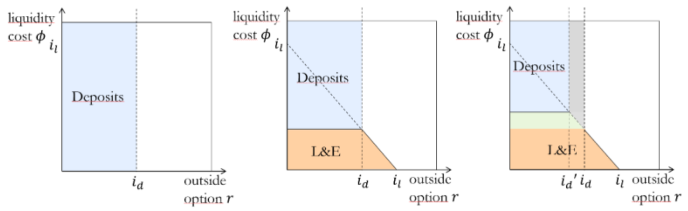

Figure 4. Illustration of the proof

Figure 4 illustrates the proof using the distribution $f(r, \phi) = U(r) \times U(\phi)$. Without L&E, only normal deposits are made by depositors with an interest rate higher than their outside option (left). If L&E is introduced, new potential depositors are gained, and a fraction of existing depositors with low liquidity costs also switch to L&E (middle). After the change in the utilisation ratio, the depositors' interest rates also change. Depending on whether borrowers or depositors react more to this change, the grey area consists of depositors or non-depositors, and the green area consists of depositors or L&E depositors (right).

As the total number of deposits (including L&E) increases, the relative size of each individual depositor (who is not participating in the L&E programme) in the pool decreases. This results in a lower concentration of the pool, which reduces liquidity risk. Figure 4 shows that boosting liquidity through the L&E programme comes at the cost of losing some normal depositors. The size of L&E (and thus the difference between i_l and i_d^*) is a trade-off between safety and cost. If the rewards are sufficient but not too large, the L&E programme can increase liquidity and reduce liquidity risk at a low cost. This raises the question: How to determine optimal L&E level?

5.3 Computation of Optimal L&E Level

L&E is expensive for a lending platform. Therefore, finding a suitable trade-off between the protocol's security and expenses is essential. To determine the safety of a liquidity pool, it must be calculated how much liquidity is at risk. This is strongly dependent on the concentration in the liquidity pool. The higher the concentration, the more the platform's safety is exposed to individual liquidity providers.

In the first step, we assume that a certain fraction, α, of the liquidity pool is at risk of being withdrawn in a short period of time. This value will be determined later using HHI discussed in section 5.4. We also assume that a total value of D (in USDC) has been deposited in the pool by depositors and a total of B (in USDC) has been borrowed. Therefore, the initial utilisation ratio is $U = B/D$. If a fraction α of the pool is withdrawn, the utilisation ratio will immediately become $U = B/(1-\alpha)D$.

The minimum amount of L&E the lending platform provides for long-term deposits can now be calculated. Depending on the risk aversion of the lending platform, the governance sets a maximum utilisation ratio, $U_{max} > 0$. The higher U_{max} is set, the less risk-averse the platform is and the lower the cost it incurs on interest payments for L&E. L&E (referred to as L for short) is now determined by

$$\frac{B}{(1-\alpha)D + L} \leq U_{max}.$$

This formula calculates the amount of additional L&E that is required to ensure that the utilisation rate does not exceed U_{max}. Solving for L yields

$$L \geq \frac{B}{U_{max}} - (1-\alpha)D,$$

where α is the fraction of deposits at risk and U_{max} is the exogenously set maximum utilisation ratio. This allows us to calculate the minimum amount

$$L = \frac{B}{U_{max}} - (1-\alpha)D,$$

that will ensure that the utilisation rate, U, is less than or equal to U_{max}. If the interest rate payments for L&E i_l are high enough, the full amount L can be brought into the pool (see the graphic illustration in Figure 4).

If the amount of L&E in the pool has already been determined, a different formula is used. In this case, the formula uses total deposits, which includes the existing L&E and normal deposits, instead of just deposits D. The purpose of this formula is to calculate the remaining amount of L&E needed rather than determining the overall required amount of L&E.

5.4 Implementation of L&E at Folks Finance

Folks Finance introduced L&E to mitigate liquidity risk and for liquidity bootstrapping. To balance the trade-off between safety and cost, an index based on s_1 and HHI was chosen for the calculation of liquidity at risk α. Specifically, Folks Finance has taken the size of the largest depositor (s_1) and multiplied it by a scalar which represents the remaining concentration,

$$\alpha = s_1 \times f(HHI)$$

with $$f(HHI) = f(x) = \begin{cases} 1, HHI < 0.15, \\ 1.25, 0.15 \leq HHI < 0.25, \\ 1.5, HHI \geq 0.25. \end{cases}$$

The choice of α for the liquidity at risk index is based on a balance between security and cost savings. It considers the effect of the largest depositor's withdrawing assets quickly on the concentration of the remaining depositors. The resulting formula for L&E is

$$L_{Folks} = \max\left(\frac{B}{U_{max}} - \left(1 - s_1 \times f(HHI)\right)D, 0\right).$$

5.5 Numerical Example

For this example, we used data from three deposit distributions on USDC on Aave in early 2020. The data for this example was downloaded from Flipside on 21 February 2022 [16]. We calculated s_1, the HHI, and the relative amount of L&E compared to deposits ($\Delta L = L/D$) for three different expected utilisation ratios ($U = B/D$) at three different timestamps. The maximum utilisation ratio used for this calculation is $U_{max} = 0.99$. The resulting L&E ratios for the three days and scenarios are shown in Table 1.

Table 1. Calculation of L&E level

	HHI	s_1	$\Delta L\|_{U=0.65}$	$\Delta L\|_{U=0.75}$	$\Delta L\|_{U=0.85}$
1.2.2020	0.16	26%	0	8%	18%
1.4.2020	0.22	44%	21%	31%	41%
1.6.2020	0.06	15%	0	0	1%

Table 2 shows the utilisation ratios with and without the introduction of L&E on the platform, assuming that the largest depositor withdraws their fund immediately on that day.

Table 2. Resulting utilisation ratio if the largest depositor withdraws his assets.

Utilisation ratio if s_1 withdraws	U for $\Delta L\|_{U=0.65}$		U for $\Delta L\|_{U=0.75}$		U for $\Delta L\|_{U=0.85}$	
	L&E	No L&E	L&E	No L&E	L&E	No L&E
1.2.2020	0.87	0.87	0.91	1.01	0.92	1.14
1.4.2020	0.85	1.17	0.86	1.35	0.87	1.53
1.6.2020	0.76	0.76	0.88	0.88	0.99	1.00

Note: The table shows the scenario with and without L&E.

With the liquidity risk mitigation introduced, the utilisation ratio is less likely to reach critical levels and does not reach 100% if the largest depositor withdraws, assuming the L&E depositors did not deposit before.

6. Conclusion

This article investigates the liquidity risk faced by new DeFi lending platforms, using the example of Folks Finance. It is found that liquidity risk is particularly pronounced for new lending platforms and can be effectively measured using the HHI. The article also shows that a reward mechanism, when properly implemented, can reduce liquidity risk and increase liquidity bootstrapping for a new lending platform. The findings suggest that new DeFi lending platforms (a) should be cautious about liquidity risk, (b) should consider using HHI for risk measurement, and (c) should consider implementing a reward programme to incentivise liquidity holdings.

Competing Interests:
All authors are affiliated with the use case presented in this manuscript.

Ethical Approval:
Not applicable.

Author's Contribution:
MH coordinated the manuscript, drafted sections on economics and liquidity risk, and edited all sections. RD conducted analysis on liquidity risk, conducted and drafted the literature review, and edited various sections. NG drafted the sections on risk measurements and risk mitigation with L&E using HHI. JS provided input on platform economics. BB, GK, MR, and AA provided inputs on the L&E mechanism and drafted the section on lending platforms.

Funding:
This research was self-funded by the Center for Cryptoeconomics and Folks Finance.

Acknowledgements:
Not applicable.

References:

[1] DefiLlama 2022. Accessed on: December 23, 2022. [Online]. Available: https://www.defillama.com

[2] A. Crockett, "Market liquidity and financial stability", Financial Stability Review, vol. 11, pp.13–17, February 2008. Accessed on: December 29, 2022. [Online]. Available: https://ideas.repec.org/a/bfr/fisrev/2008113.html

[3] K. Nikolaou, "Liquidity (risk) concepts: definitions and interactions", European Central Bank Working Paper Series 1008, February 2009. Accessed on: December 29, 2022. [Online]. Available: http://dx.doi.org/10.2139/ssrn.1333568

[4] BIS: Bank for International Settlement BIS Basel Committee on Banking Supervision, "Principles for Sound Liquidity Risk Management and Supervision", Bank Asset and Liability Management, pp. 143–146, September 2018. Available: https://doi.org/10.1002/9781119444497.app1

[5] IMF: International Monetary Fund IMF, "Global Financial Stability Report 2008", April 2008. ISBN 9781589067202. Available: https://doi.org/10.5089/9781589067202.082

[6] CEBS: Committee of European Banking Supervisors, "Guidelines on the management of concentration risk under the supervisory review process (GL31)", European Banking Authority, 2010. Accessed on: December 20, 2022. [Online]. Available: https://www.eba.europa.eu/regulation-and-policy/supervisory-review/guidelines-on-the-management-of-concentration-risk-under-the-supervisory-review-process

[7] V. V. Acharya and L. H. Pedersen, "Asset pricing with liquidity risk", Journal of Financial Economics, vol. 77, no. 2, pp. 375-410, August 2005. Available: https://doi.org/10.1016/j.jfineco.2004.06.007

[8] L. Pástor and R. F. Stambaugh, "Liquidity Risk and Expected Stock Returns", Journal of Political Economy, vol. 111, no. 3, pp. 642-685, 2003. Available: http://dx.doi.org/10.1086/374184

[9] Aave 2022: Aave documentation. Accessed on: December 23, 2022. [Online]. Available: https://docs.aave.com/risk/liquidity-risk/introduction

[10] L. Gudgeon, S. M. Werner, D. Perez, and W. J. Knottenbelt. "DeFi Protocols for Loanable Funds: Interest Rates, Liquidity and Market Efficiency", ACM Conference on Advances in Financial Technologies, pp 92-112, 2020. Available: https://doi.org/10.1145/3419614.3423254

[11] X. Sun, C. Stasinakis, and G. Sermpinis. "Liquidity Risks in Lending Protocols: Evidence from Aave Protocol", SSRN, October 2022. Accessed on: December 23, 2022. [Online]. Available: https://dx.doi.org/10.2139/ssrn.3985105

[12] Folks Finance Docs 2022. Accessed on: June 17, 2022. [Online]. Available: https://docs.folks.finance/

[13] P. Belleflamme and M. Peitz, "The Economics of Platforms", Cambridge University Press, 2021.

[14] J.-C. Rochet and J. Tirole, "Platform Competition in Two-Sided Markets", Journal of the European Economics Association, vol. 1, no. 4, pp. 990-1029, June 2003. Available: https://doi.org/10.1162/154247603322493212

[15] M. Armstrong, "Competition in Two-Sided Markets." The RAND Journal of Economics, vol. 37, no. 3, pp. 668–91, Autumn 2006. Available: https://doi.org/10.1111/j.1756-2171.2006.tb00037.x

[16] Flipside. Accessed on: February 21, 2022. [Online]. Available: https://flipsidecrypto.xyz/

[17] P. Belleflamme and M. Peitz. Industrial Organization: Markets and Strategies. Cambridge University Press, 2010. ISBN 9780521862998. Available: https://books.google.ch/books?id=nmUcldoQ

[18] S. A. Rhoades. "The Herfindahl-Hirschman Index", Federal Reserve Bulletin, vol. 79, no. 3, pp. 188-189, March 1993. Accessed on: December 10, 2022. [Online]. Available: https://fraser.stlouisfed.org/files/docs/publications/FRB/pages/1990-1994/33101_1990-1994.pdf

