Illiquidity risks in Lending Protocols (LPs):

Evidence from Aave Protocol

Xiaotong Sun

University of Glasgow

Abstract

Decentralized Finance (DeFi) can replicate most financial activities in traditional financial markets. Among various DeFi, Lending Protocols (LPs) resemble banks, allowing users to borrow and lend tokens. By analysing Aave protocol, we investigate illiquidity risks of stablecoins. Furthermore, some users play dual roles, i.e., borrowers and depositors, and these users perform differently from others. The potential illiquidity risks caused by such users are measured. Though higher illiquidity risks will affect the growth of LPs, the potential risks caused by selected users have complex influence.

Keywords: illiquidity, lending protocol, stablecoin, decentralized finance, blockchain

1.Introduction

Benefiting from blockchain infrastructure, *Decentralized Finance (DeFi)* has experienced rapid growth. Simply, DeFi applications are blockchain-based financial systems, and DeFi has advantages brought by blockchain, e.g., openness and transparency. Since 2017, various DeFi has been developed, and it can replicate most activities in traditional finance. *Lending Protocols (LPs)* are a crucial component of DeFi, which resemble banks in DeFi ecosystem (Harvey et al., 2021). But in LPs, there is no third party, e.g., central banks. The trustless intermediaries are smart contracts, which are written in programming languages. In other words, all parameters of borrowing and lending are programmatic in LPs.

In LPs, an intractable problem is Illiquidity risks. In a LP, users can borrow and lend their on-chain assets, and funds are pooled. So, a depositor can lend to several borrowers and vice versa. For a LP, illiquidity means that the total demand is more than the total supply. Currently, main depositors contribute to most liquidity in LPs (Gudgeon et al., 2020), and a small group of borrowers account for most loans (Saengchote, 2021). Therefore, if main depositors successive withdraw their deposits, illiquidity problems will occur, causing market panic. Besides, borrowers that do not repay their loan can cause illiquidity problems as well.

Illiquidity risks are first discussed in banking literature. Previously, models of illiquidity risks are developed (Bryant, 1980; Diamond and Dybvig, 1983; Rochet and Vives, 2004; Goldstein and Pauzner, 2005), and the ability of banks to survive is studied (Morris and Shin, 2004; Goldstein and Pauzner, 2005). In LPs, illiquidity risks are also investigated. By establishing formal models of LPs, illiquidity risks are possible in some cases, e.g., a large price drop (Gudgeon et al., 2020). Currently, most research about LPs is theoretical discussion, e.g., economic models of fundamental settings and incentive mechanisms. But the empirical evidence of illiquidity risks has not been investigated.

In this paper, we first establish measurements of illiquidity risks in LPs. Beside borrow and deposit events, we also consider liquidation in LPs. To provide empirical evidence, we use Aave protocol as a case study. By analysing events in Aave, we detect that some users have dual roles, i.e., borrowers and depositors, and they perform differently when price and volatility vary. So, these users may result in illiquidity risks in some cases, and we establish measurements of potential illiquidity risks caused by these users. Then, we investigate the drivers of illiquidity risks and potential risks caused by dual-role users. Finally, the effects of both illiquidity risks and potential risks caused by selected users are examined.

In Aave, most transactions are about several mainstream tokens. In this paper, we focus on three *stablecoins*, namely *Dai (DAI)*, *USD Coin (USDC)* and *Tether (USDT)*. For DAI, volatility is a driver of illiquidity risks. Price and volatility of stablecoins will influence the potential risks caused by users with dual roles as well. On the other hand, illiquidity risks have influence on LPs. Higher illiquidity risks can lower the adoption of LPs. For example, total value locked and borrowing volume in Aave protocol will decrease when illiquidity risks are lower. Higher illiquidity risks will affect loans in Aave as well. For example, the loan-to-value ratios of stablecoins will decrease with higher risks caused by users with dual roles. The results imply that the suspicious activities may have positive influence on Aave as well. Besides, the value of Aave ownership will be affected. However, the effects of potential risks caused by dual-role users are complex. For example, when potential risks caused by these users are higher, market cap and revenue of Aave will increase. The value of Aave ownership will be higher as well. Finally, we consider Twitter sentiment. Illiquidity risks may lead to more discussion, but DeFi users may not detect potential risks caused by some certain users and their activities.

The remainder of our paper is organized as follows. We introduce lending protocols in Chapter 2. Chapter 3 defines the measurements of illiquidity risks in lending protocols, and empirical results are presented in Chapter 4. Conclusion and discussion are given in Chapter 5.

2. Lending protocol

2.1 Ethereum and Decentralized Finance (DeFi)

Over time, many public blockchain have emerged. In this paper, we focus on *Ethereum*, which is a programmable blockchain. The programmable character allows agents to write and execute *smart contracts* on Ethereum. Smart contracts are written in programming languages (Wood, 2014), e.g., *Solidity*. Smart contracts resemble a set of rules for interactions and functions on blockchain. Benefiting from smart contracts, Ethereum users can execute complicated activities.

Based on a standard interface, *tokens* can be implemented by executing smart contracts. In Ethereum, tokens usually adhere to standardized *ERC-20 tokens* and *ERC-721 tokens*. ERC-20 interface defines fungible tokens, while ERC-721 interface is regulation for non-fungible tokens (Fröwis, Fuchs and Böhme, 2019). The pivotal difference is that fungible tokens have the interchangeable property, while non-fungible tokens are irreplaceable (Vogelsteller and Buterin, 2015). In Ethereum, the underlying token is *Ether (ETH)*.

To participate in activities on Ethereum, an entity needs to control *accounts*, i.e., *addresses*. The accounts can be divided into three categories, i.e., *external owned accounts (EOA)*, *smart contract owned accounts (COA)* and *token owned accounts (TOA)* (Chen, Cong and Xiao, 2020). Simply, EOAs are controlled by humans, while COAs and TOAs are controlled by token contracts and other smart contracts, respectively. For each account, their address is fixed, and the address is the identity of the account in Ethereum.

Decentralized Finance (DeFi) protocols are blockchain-based financial systems. Based on a series of smart contracts, DeFi can replicate most financial activities in traditional financial markets. According to the provided financial services, DeFi protocols can fall into five main categories, namely *Lending Protocols (LPs)*, *Assets*, *Decentralized Exchanges (DEXes)*, *Derivatives* and *Payments*. Currently, most DeFi protocols are established on Ethereum.

2.2 Lending protocols (LPs)

Lending protocols (LPs) resemble banks in cryptocurrency markets, allowing their users to borrow and lend on-chain assets (Bartoletti, Chiang and Lluch-Lafuente, 2021). Different from banks, funds are pooled in LPs. It is to say, a lender may lend to several borrowers and vice versa. Another pivotal difference is that borrowing and saving in LPs are programmatic. For more details, we refer readers to overviews of LPs, such like Gudgeon et al. (2020).

Figure 1 illustrate the basic activities in LPs, i.e., borrowing and lending. For each token, there will be a pool, and users can deposit or borrow the tokens. For depositors (or lenders), they will receive an amount of *claim* after transferring tokens to a LP. The claim is a token minted by a LP, and it is a proof of deposits. For depositors, the amount of claim received will correspond to the amount of deposits. The claim will be redeemable for a value of the same token type of the original deposit. So, when depositors want to *withdraw* their deposits, they need to transfer claim to LPs.

For borrowers, they can initial loans from a LP. Usually, overcollateralization is required (Bartoletti, Chiang and Lluch-Lafuente, 2021), meaning that the value of debt is lower than the value of collateral. Collateral can be tokens supported by LPs and will be locked in the loan duration. Once borrowers cannot *repay* their loans, or debt is undercollateralized, *liquidators* can (partly) repay the loans to acquire a discount amount of collateral (See Figure 2). In LPs, the process is called *liquidation* (Kao et al, 2020). The liquidation thresholds vary between asset markets across different protocols (Gudgeon et al., 2020).

[Figure 1 here]

[Figure 2 here]

In LPs, there is no third party, e.g., central banks. The trustless intermediaries are smart contracts (Perez et al., 2021). All the parameters, e.g., interest rate, are programmatically determined. Usually, LPs provide with higher saving interest rates (Klages-Mundt et al., 2020). Models of interest rates in LPs are introduced by Gudgeon et al. (2020). Besides, smart contracts also format economic incentive mechanisms in LPs (Bartoletti, Chiang and Lluch-Lafuente, 2021). For example, depositors can earn interests according to interest rate models in smart contracts.

LPs introduce *flash loans*, i.e., a loan borrowed and repaid within an atomic transaction group. The atomic transaction group will not be executed if the flash loan cannot be repaid within it. Therefore, flash loans do not have debt default risks. Besides, flash loans do not require collateral, and loan size is not limited (Qin et al., 2021). Though flash loans enable non-collateral borrowing, the new functionality also causes problems. Without requirement of assets, malicious users can more easily launch attacks and other vicious operations using flash loans. For example, flash loans can be used in governance attacks (Gudgeon et al., 2020), and the attackers can take full control of a DeFi protocol. Wang et al. (2021) and Qin et al. (2021) present more malicious activities deriving from flash loans.

2.3 Risks in lending protocols

Beside attacks with flash loans, illiquidity is an intractable problem in LPs. For a user, their account is liquidatable if the value of debt exceeds borrowing capacity. In this case, liquidators will repay a part of their debt and get corresponding amount of collateral at a discount. For a token in LPs, liquidity means that the total supply is more than the total demand. Theoretically, LPs can be undercollateralized in certain ranges of some parameters (Gudgeon et al., 2020). Practically, when funds in LPs are not sufficient, illiquidity problems will occur. In this case, withdraw and borrow events will fall, causing market panic (Alethio, 2019). Such problems can be implemented by successive withdrawals. So, depositors with large deposits in LPs can launch such attacks. Though potential illiquidity risks are discussed, no empirical studies measure the probability of illiquidity.

3. Measurements of illiquidity risks

In this section, we will introduce measurements of illiquidity risks. For each token, we first calculate the risks in a LP and then the potential risks caused by certain users. For stablecoins, we establish a coefficient to measure potential risks caused by its reserves.

3.1 Illiquidity risks in a lending protocol

For token α, the total supply and demand on date d can be defined as

$$total\ supply_d = \sum_{t=1}^{d} deposit_t - withdraw_t \ (1)$$

and

$$total\ demand_d = \sum_{t=1}^{d} borrow_t - repay_t \ (2)$$

where $deposit_t$ is the amount of token α in deposit events on date t, $withdraw_t$ is the amount of token α in withdraw events on date t, $borrow_t$ is the amount of token α in borrow events on date t, and $repay_t$ is the amount of token α in repay events on date t.

Then, liquidity of token α on date d is

$$liquidity_d = total\ supply_d - total\ demand_d (3)$$

Here, illiquidity risks of token α on date d can be measured by

$$illiquidity_d = -\arctan(liquidity_d) + \frac{\Pi}{2} \quad (4)$$

where $illiquidity_d \in (0, \Pi)$. When $liquidity_d$ is lower, $illiquidity_d$ is higher.

3.2 Illiquidity risks caused by certain users

For token α, the liquidity provided by user i on date d is

$$supply_{i,d} = \sum_{t=1}^{d} deposit_{i,t} - withdraw_{i,t} \quad (5)$$

and the amount of token α borrowed by user i on date d is

$$demand_{i,d} = \sum_{t=1}^{d} borrow_{i,t} - repay_{i,t} \quad (6)$$

Hence, the total amount of token α controlled by user i on date d is

$$balance_{i,d} = supply_{i,d} + demand_{i,d} \quad (7)$$

Assuming there are n users that can cause potential illiquidity risks, their total balance of token α on date d is

$$balance_d = \sum_{i=1}^{n} balance_{i,d} \quad (8)$$

The illiquidity risks caused by certain n users on date d are

$$user_d = \arctan(balance_d) + \frac{\Pi}{2} \quad (9)$$

where $user_d \in (0, \Pi)$. When $balance_d$ is higher, the potential illiquidity risks caused by users are higher.

So, on date d, the proportion of risks caused by n users to illiquidity risks in LP can be defined as

$$illiquidity\_share_d = \frac{user_d}{illiquidity_d} \quad (10)$$

where $illiquidity_{t,i}$ is illiquidity risks caused by user i on date t. When the measurement is higher, illiquidity might occur when these certain depositors withdraw their token. As these users may not repay their loans of token α, borrow events can aggravate illiquidity risks.

3.3 Illiquidity risks combing with liquidation

In LPs, users can gain some amount of token α by liquidating others' collateral. If certain users try to liquidate as much collateral as possible, the original owners of collateral may suffer from risks, causing failure of the pool.

The total amount of token α liquidated by certain n users on date d is

$$liquidation_d = \sum_{i=1}^{n} \sum_{t=1}^{d} liquidation_{i,t} \, (11)$$

where $liquidation_{i,t}$ is the amount of token α liquidated by user i on date t.

Therefore, the illiquidity risks combing with liquidation can be measured by

$$risk\_share_d = \frac{user_d + \arctan\,(liquidation_d) + \frac{\Pi}{2}}{illiquidity_d} \, (12)$$

3.4 Risk coefficient of stablecoins

For stablecoins, its risks highly depend on the value of reserves. For stablecoin α, excess of reserves over liability on date d are

$$excess_d = total\ reserve_d - price_d \times amount_d (13)$$

where $total\ reserve_d$ is the value of total reserves, $price_d$ is price of stablecoin α, and $amount_d$ is the outstanding number of stablecoin α on date d.

Then, the risks caused by reserves can be measured by

$$reserve_d = -\arctan(excess_d) + \frac{\Pi}{2} (14)$$

When excess of reserves over liability is higher, the risks caused by reserves are lower.

Hence, for stablecoin α, the risks in a lending pool can be defined as

$$risk_d = illiquidity_d \times reserve_d (15)$$

4. Empirical results

In this section, we first introduce data resources, and descriptive statistics of datasets are presented. In the datasets, we detect that some users are borrowers and depositors at the same time, and these users with dual roles have different behaviours from behaviour of Aave users. After filtering Aave users with dual roles, we establish measurements of illiquidity risks for stablecoins. Then the drivers of such risks are investigated. Here, we mainly consider financial statistics, e.g., price and volatility, of selected tokens. Finally, we investigate the effects of illiquidity risks.

4.1 Data resources

In this paper, we use *Aave* protocol as a case study. Aave is a leading lending protocol in DeFi ecosystem, and it has experienced rapid growth since 2021. As of Dec 2021, the Total Value Locked (TVL) in Aave is more than 10 billion US dollars. Currently, Aave protocol has updated to *Aave v2*, and *LendingPool*[1] contract is the main contract of the protocol (Aave, 2021). Transaction history in *LendingPool* of Aave v2 can be accessed on *Etherscan.io*, and we query all transactions from December 1, 2020 to December 15, 2021. The datasets can capture the growth of Aave protocol. *Tokenterminal.com* provides key metrics of Aave protocol, and *IntoTheBlock.com* presents stablecoin statistics.

4.2 Descriptive statistics of datasets

Table 1 and 2 presents descriptive statistics of datasets in Aave. In deposit and borrow events, three stablecoins, i.e., DAI, USDC and USDT account for a significant proportion. More introduction to stablecoins is given in Table 3.

[Table 1 here]

[Table 2 here]

[Table 3 here]

By examining events on Aave, we find that some users have dual roles, i.e., borrowers and depositors. In Table 4, we give some examples of such users. For users with dual roles, we calculate the amount of tokens traded in borrow and deposit events. For all users in Aave, the amount of token traded in borrow and deposit events is calculated as well. For each token, we investigate the correlation between the token's financial statistics and the amount of deposits and loans, respectively. Table 5 shows the correlation between token statistics and the amount traded by dual-role users. Similarly, Table 6 shows a correlation matrix between token statistics and traded tokens in Aave. Comparing to Aave pool, the users with dual roles may make different decisions in certain cases, and their decision, e.g., collective and successive withdraw events, will probably lead to illiquidity risks. Therefore, we will use the datasets for users to calculate measurements of risks in LPs.

[Table 4 here]

[Table 5 here]

[Table 6 here]

4.3 Measurements of illiquidity risks

For each stablecoin, we first establish measurements of illiquidity risks according to equations (4), then measurements of risks caused by dual-role users are defined as equations (10) and (12). Table 7 presents the descriptive statistics.

[Table 7 here]

4.3 The drivers of illiquidity risks

For each token, we investigate the relationship between financial statistics and the risk measurements. The financial statistics include token price, daily return, and volatility (from 2-day volatility to 7-day volatility). Besides, we also consider total supply of stablecoins, the number of stablecoin users, and borrow rates on Aave. Table 8 presents the results. For DAI, higher volatility can result in higher illiquidity risks in Aave, while USDC and USDT are not sensitive to financial statistics. For DAI, its illiquidity risks caused by users of dual roles will increase when volatility is higher, while illiquidity risks of USDC caused by selected users will decrease when volatility is higher. Besides, USDT price is a driver of illiquidity risks caused by users of dual roles. With more total supply and total users, illiquidity risks will decrease, but risks caused by selected users will be higher. Besides, when borrowing rates are lower, risks caused by selected users will be higher. The findings imply that some users may tend to control as much stablecoins as possible when the cost is low.

Overall, illiquidity risks of stablecoins may not be driven by volatility. But for potential illiquidity risks caused by certain users, price and volatility might be crucial. The total supply and borrowing rates are also important drivers of risks caused by users with dual roles.

[Table 8 here]

4.4 The effects of illiquidity risks

In this section, the effects of illiquidity risks are examined. We mainly consider four categories of factors, i.e., factors of Aave protocol, factors of loans in Aave, statistics of Aave ownership, and Twitter sentiment of stablecoins. The definition of factors is given in Table 9.

[Table 9 here]

4.4.1 Effects on Aave protocol

Illiquidity risks may have direct influence on status of Aave protocol. The factors of Aave lending pool can falinclude fully diluted market cap, circulating market cap, total revenue, supply-side revenue, protocol revenue, P/S ratio, P/E ratio, total value locked in Aave protocol, and borrowing volume daily.

Table 10 presents the effects of stablecoins. For activities on Aave, higher illiquidity risks will decrease market cap, revenue, total value locked in Aave and borrowing volume, while P/S and P/E ratio will increase. For activities of users with dual roles, potential risks caused by them will lead to higher market cap, revenue, total value locked in Aave, and borrowing volume. But potential risks caused by these users will lead to lower P/S and P/E ratio. Overall, illiquidity risks will do harm to the growth of LPs. But when users with dual roles can cause higher potential risks, their activities may have positive influence on LPs.

[Table 10 here]

4.4.2 Effects on loans in Aave

The illiquidity risks might have direct effects on loans in Aave. Here, we consider the number of active borrowers and depositors, the borrowing volume (in USD), loan-to-value (LTV) ratio, daily value of total deposits, daily value of total outstanding loans, and excessed deposits (i.e., the deposits minus the outstanding loans). Table 11 reports the results.

Higher illiquidity risks will decrease the number of active borrowers and depositors in Aave, and the borrowing volume of stablecoins will decrease as well. As for the potential risks caused by users with dual roles, the risks can be a driver of active borrowers. The loan-to-value ratios of stablecoins will decrease with higher risks caused by certain users. The results imply that the potential risks can promote borrowing events and lower the risks of loans in Aave. On the other hand, the value of total deposits and loans will decrease, implying that the growth of Aave will be affected by these probably malicious users.

[Table 11 here]

4.4.3 Effect on ownership of Aave protocol

Aave protocol issues their own governance token, i.e., AAVE. Theoretically, governance token for a DeFi protocol resembles stocks for corporations. AAVE holders are owners of Aave protocol. They can participate in governance process and gain a part of fee generated. Therefore, we consider AAVE price, value of distributed AAVE, and trading volume of AAVE. Besides, the number of AAVE holders may be important. So, we collect the number of AAVE holders and new AAVE holders daily.

Table 11 presents the effects of illiquidity risks of stablecoins. Higher illiquidity risks of DAI and USDC will decrease AAVE price, token incentive, trading volume and the number of total AAVE holders. For USDT, its illiquidity risks will lead to lower price and token incentives of AAVE. The number of total AAVE holders will decrease as well. As for potential risks caused by users with dual roles, when these users account for more risks, AAVE price, token incentives and the number of AAVE holders will increase. But AAVE trading volume and the number of new AAVE holders will decrease. For dual-role users in DAI activities, their potential risks will lead to higher token incentives and more AAVE holders. But trading volume and the number of new AAVE holders will decrease.

To summarize, when illiquidity risks are higher in Aave, the value of Aave ownership will decrease, and people are less willing to hold AAVE, as the token represents ownership of Aave protocol. But when users with dual roles can cause more potential risks, the value of Aave ownership will increase.

[Table 12 here]

4.4.4 Effects on Twitter sentiment of stablecoins

As some certain users initiate stablecoin transactions with potential risks, their activities might cause attention of other DeFi users. Here, we consider Twitter sentiment of stablecoins. For each stablecoin, we consider the number of Tweets with positive, neutral, and negative connotation.

Table 13 presents the results. For DAI and USDC, more negative Tweets will be posted with higher potential risks caused by users with dual roles. It implies that the DeFi community might realize the risky activities executed by certain users. On the other hand, for USDC and USDT, more positive discussion on Twitter can be observed when higher potential risks are caused by users with dual roles. Therefore, the relationship between Twitter sentiment and potential risks in Aave is not clear, implying that DeFi users may not detect potential risks caused by malicious users.

[Table 13 here]

4.4.5 DAI-specific risk measurement

As we have daily value of DAI's collateral, we establish a risk measurement of DAI using equations (13) - (15). Table 14 gives descriptive statistics of DAI-specific risk measurement. This measurement combines illiquidity risk of DAI in Aave with its underlying collateral.

[Table 14 here]

Table 15 presents the drivers of DAI-specific risks. When 6-day and 7-day volatility of DAI is higher, DAI-specific risks will increase. More DAI users will lead to lower DAI-specific risks. But the risks might not be correlated with DAI price and daily return. Then, we investigate the effects of DAI-specific risks. In Table 16, higher DAI-specific risks will lead to lower market cap, revenue, and total value locked. But P/E and P/S ratio will be higher. DAI-specific risks are related to loan-specific factors in Aave as well (in Table 17). When DAI-specific risks are higher, there will be fewer active borrowers and depositors, and the borrow volume will decrease as well. Table 18 presents the effects of DAI-specific risks on Aave ownership. Higher DAI-specific risks will lower AAVE price, token incentives, trading volume and the number of total AAVE holders will decrease. Besides, for effects of DAI-specific risks on Twitter sentiment, we do not find statistically significant results in Table 19. Overall, the results are consistent with illiquidity risks of DAI in Aave.

[Table 15 here]

[Table 16 here]

[Table 17 here]

[Table 18 here]

[Table 19 here]

5. Conclusion

Lending protocols play a role of banks in DeFi ecosystem. Therefore, illiquidity risks are a crucial and inevitable problem in LPs. Theoretically, LPs can be under illiquidity risks when price volatility is higher

(Gudgeon et al., 2020). Empirically, a small group of users contributes to most liquidity in LPs (Saengchote, 2021). The previous findings imply that illiquidity risks can occur, especially when certain users collectively initiate some behaviours, i.e., successively withdraw deposited tokens.

In this paper, we use Aave protocol as a case study, and illiquidity risks of stablecoins are measured. In consideration the trading volume and market influence, we select three stablecoins, namely DAI, USDC and USDT. After analysing the whole history in Aave v2 lending pool, we detect that some users have dual roles, i.e., borrowers and depositors. As these users participate in both supply and demand side of Aave lending pool, they may have different performance from other users. After computing their trading amount of stablecoins, we find these users perform differently from the pool, especially when the stablecoins' price and volatility change. Therefore, for these dual-role users, we establish measurements of illiquidity risks caused by their borrow and deposit events in Aave.

For DAI, volatility is a driver of illiquidity risks. While for other two stablecoins, their illiquidity risks are not driven by price or volatility. For potential illiquidity risks caused by users with dual roles, both price and volatility are crucial. But the effects of price and volatility vary with different stablecoins. As token holders can gain profits by executing other activities in DeFi, they may withdraw and borrow tokens from LPs, thereby causing potential illiquidity risks. But we should realize that token holders will make different decisions when price and volatility change. Therefore, the drivers of illiquidity risks, especially potential risks caused by certain users, are not clear. Besides, the total supply of stablecoins and borrowing rate in Aave are also important drivers of risks caused by selected users, implying that their behaviour depends on cost of obtaining stablecoins.

The effects of illiquidity risks should not be ignored. We consider the effects in four dimensions, including effects on Aave protocol, effects on loans in Aave, effects on ownerships of Aave protocol, and effects on Twitter sentiment of stablecoins. For Aave protocol, higher illiquidity risks can lower the adoption of Aave protocol, e.g., lower market cap and less total valued locked in Aave. But when select users can cause higher potential risks, their activities may have positive influence on Aave. For loans in Aave, with higher illiquidity risks, there will be fewer active borrowers and depositors, and borrowing volume will decrease as well, implying that the risks can negatively influence Aave. But potential risks caused by dual-role users have some positive effects. For example, the loan-to-value ratio will decrease with higher risks caused by selected users, meaning that the risks of loans are lowers. Furthermore, the value of Aave ownership will decrease with higher illiquidity risks. For example, the governance token of Aave, i.e., AAVE, will have a lower price when illiquidity risks are higher. The results imply that investors will perceive the risks in Aave, leading to a lower evaluation of Aave protocol. But when considering users with dual roles, their potential risks will lead to higher value of Aave ownership. Though the mechanism is not clear, the finding implies that some certain users may have influence on LPs, and thereby evaluation of LPs will be affected. Finally, we consider Twitter sentiment of stablecoins. Both positive and negative discussion will be posted with higher risks caused by users with dual roles. Therefore, DeFi users may not easily detect potential risky activities initiated by certain users.

Our results should be interpreted with their limitations in mind. First, we only consider stablecoins in Aave protocol, so the actual illiquidity risks might be higher. But the trading volume of most other tokens is much lower than selected tokens, the measurements of illiquidity risks could reflect on the status of Aave protocol.

Second, we calculate illiquidity risks by selecting certain users, i.e., users that are borrowers and depositors. Though some other users may be more malicious, it is hard to identify the goal of users in Aave simply according to their borrow and deposit events. Finally, there are other well-adopted lending protocols, e.g., Compound. Illiquidity risks might be higher in DeFi ecosystem.

Reference

Aave. 2021. *Changes from v1 to v2 - Developers*. [online] Available at: <https://docs.aave.com/developers/change-from-v1-to-v2> [Accessed 11 December 2021].

Alethio., 2019. *Illiquidity and Bank Run Risk in Defi*.[online] Available at: <https://medium.com/alethio/overlooked-risk-illiquidity-and-bank-runs-on-compound-finance-5d6fc3922d0d> [Accessed 7 December 2021]

Bartoletti, M., Chiang, J. and Lafuente, A., 2021. SoK: Lending Pools in Decentralized Finance. *Lecture Notes in Computer Science*, pp.553-578.

Bryant, J., 1980. A model of reserves, bank runs, and deposit insurance. *Journal of Banking & Finance*, 4(4), pp.335-344.

Chen, L., Cong, L. and Xiao, Y., 2020. A Brief Introduction to Blockchain Economics. *Information for Efficient Decision Making*, pp.1-40.

Chen, W., Zhang, T., Chen, Z., Zheng, Z. and Lu, Y., 2020. Traveling the token world: A graph analysis of Ethereum ERC20 token ecosystem. *Proceedings of The Web Conference 2020*,.

Diamond, D. and Dybvig, P., 1983. Bank Runs, Deposit Insurance, and Liquidity. *Journal of Political Economy*, 91(3), pp.401-419.

Fröwis, M., Fuchs, A. and Böhme, R., 2019. Detecting Token Systems on Ethereum. In *Financial Cryptography and Data Security*. Springer, pp. 93-112.

Goldstein, I. and Pauzner, A., 2005. Demand-Deposit Contracts and the Probability of Bank Runs. *The Journal of Finance*, 60(3), pp.1293-1327.

Grilli, V. and Roubini, N., 1996. Liquidity models in open economies: Theory and empirical evidence. *European Economic Review*, 40(3-5), pp.847-859.

Gudgeon, L., Perez, D., Harz, D., Livshits, B. and Gervais, A., 2020. The Decentralized Financial Crisis. *2020 Crypto Valley Conference on Blockchain Technology (CVCBT)*,.

Gudgeon, L., Werner, S., Perez, D. and Knottenbelt, W., 2020. DeFi Protocols for Loanable Funds. *Proceedings of the 2nd ACM Conference on Advances in Financial Technologies*,.

Harvey, C., Ramachandran, A., Santoro, J., Ehrsam, F. and Buterin, V., 2021. *DeFi and the Future of Finance*. John Wiley & Sons

Kao, H.T., Chitra, T., Chiang, R. and Morrow, J., 2020. *An Analysis of the Market Risk to Participants in the Compound Protocol*. [online] Available at https://scfab.github.io/2020/FAB2020_p5.pdf> [Accessed 30 November 2021].

Kitzler, S., Victor, F., Saggese, P. and Haslhofer, B., 2021. *Disentangling Decentralized Finance (DeFi) Compositions*. [online] arXiv.org. Available at: <https://arxiv.org/abs/2111.11933> [Accessed 30 November 2021].

Klages-Mundt, A., Harz, D., Gudgeon, L., Liu, J. and Minca, A., 2020. Stablecoins 2.0. *Proceedings of the 2nd ACM Conference on Advances in Financial Technologies*,.

Morris, S. and Shin, H., 2004. Coordination risk and the price of debt. *European Economic Review*, 48(1), pp.133-153.

Perez, D., Werner, S., Xu, J. and Livshits, B., 2021. Liquidations: DeFi on a Knife-Edge. *Financial Cryptography and Data Security*, pp.457-476.

Qin, K., Zhou, L., Livshits, B. and Gervais, A., 2021. Attacking the DeFi Ecosystem with Flash Loans for Fun and Profit. *Financial Cryptography and Data Security*, pp.3-32.

Rochet, J. and Vives, X., 2004. Coordination Failures and the Lender of Last Resort: Was Bagehot Right after All?. *Journal of the European Economic Association*, 2(6), pp.1116-1147.

Saengchote, K., 2021. Decentralized Lending and Its Users: Insights from Compound. [online] Available at <https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3925344> [Accessed 30 November 2021].

Somin, S., Gordon, G. and Altshuler, Y., 2018. Network Analysis of ERC20 Tokens Trading on Ethereum Blockchain. *Unifying Themes in Complex Systems IX*, pp.439-450.

Tolmach, P., Li, Y., Lin, S. and Liu, Y., 2021. *Formal Analysis of Composable DeFi Protocols*. [online] arXiv.org. Available at: <https://arxiv.org/abs/2103.00540> [Accessed 30 November 2021].

Victor, F., 2020. Address clustering heuristics for Ethereum. In *Financial Cryptography and Data Security*. Springer, pp. 617-633.

Vogelsteller, F. and Buterin, V., 2015. *EIP-20: Token Standard*. [online] Ethereum Improvement Proposals. Available at: <https://eips.ethereum.org/EIPS/eip-20> [Accessed 7 December 2021].

Victor, F. and Lüders, B., 2019. Measuring Ethereum-Based ERC20 Token Networks. *Financial Cryptography and Data Security*, pp.113-129.

Wachter, V., Jensen, J. and Ross, O., 2021. Measuring Asset Composability as a Proxy for DeFi Integration. *In International Conference on Financial Cryptography and Data Security*. Springer, pp.109–114.

Wang, D., Wu, S., Lin, Z., Wu, L., Yuan, X., Zhou, Y., Wang, H., Ren, K., 2021. *Towards understanding flash loan and its applications in defi ecosystem*. [online] Available at: < https://arxiv.org/abs/2010.12252> [Accessed 7 December 2021]

Wood, G., 2014. Ethereum: A Secure Decentralised Generalised Transaction Ledger. [online] Available at: <https://ethereum.github.io/yellowpaper/paper.pdf> [Accessed 01 December 2021].

Endnotes

1.The address of *Aave: LendingPool V2* is *0x7d2768dE32b0b80b7a3454c06BdAc94A69DDc7A9*.

Tables

Table 1. Most frequently traded tokens

Deposit	Volume	Total deposit	Volume	Borrow	Volume	Total borrow	Volume
DAI	2011389872.52	WETH	5216618523.61	**USDT**	42921181.39	**USDC**	3125210146.91
WETH	147621403.25	**USDC**	3552135180.78	**USDC**	26911470.93	**DAI**	1451590718.31
WBTC	107886536.64	**DAI**	1796141798.28	WETH	13146472.34	**USDT**	944138023.33
USDC	35478033.98	WBTC	1451106719.74	sUSD	12243292.20	WETH	119873286.49
LINK	5456057.84	**USDT**	983893776.69	FEI	10185138.35	TUSD	75149921.57
USDT	5243841.82	LINK	376050079.09	WBTC	1561614.28	sUSD	60864784.92
FEI	1869275.68	AAVE	268040221.93	**DAI**	564451.02	FEI	49125338.19
CRV	891992.68	MKR	135977742.96	RAI	513400.00	WBTC	41319596.77
YFI	273672.63	TUSD	104112983.93	AMPL	178197.00	RAI	21426011.14
BAL	269891.58	FEI	65140235.63	CRV	27360.00	CRV	20773058.91

This table reports the most frequently traded tokens in Aave v2 lending pool (from Dec 1, 2020 to Dec 15, 2021). For deposit and borrow events, we calculate the volume (in USD) on Dec 15, 2021 and total volume (in USD) by Dec 15, 2021. In this table, DAI, USDC and USDT account for significant volume in Aave v2 lending pool.

Table 2. Descriptive statistics

	DAI	USDC	USDT
Deposit events	21353	34300	14959
Unique depositors	7694	10984	6307
Withdraw events	17076	29849	13176
Unique users in withdraw events	4897	8022	4581
Borrow events	18297	45876	29056
Unique borrowers	5877	9713	7242
Repay events	11236	26981	17316
Unique users in repay events	4405	7446	5582
Liquidation events	73	168	0
Unique liquidators	36	93	0

This table reports descriptive statistics of datasets for Aave v2 lending pool (from Dec 1, 2020 to Dec 15, 2021). The datasets include five main categories of events, i.e., *deposit*, *withdraw*, *borrow*, *repay* and *liquidation*. For each token and each category of events, the number of events and unique participants in the events are present.

Table 3. Selected tokens

Token	Brief introduction
Dai (DAI)	Dai is a stablecoin soft-pegged to US dollar. Dai is issued and regulated by MakerDAO. Dai is not backed by US dollars in a bank account.
USD Coin (USDC)	USDC is a stablecoin pegged to US dollar. Each USDC is backed by one dollar or asset with equivalent fair value. The backed assets are held in accounts with US regulated financial institutions.
Tether (USDT)	USDT is a stablecoin pegged to US dollar. Each USDC is backed by one dollar or asset with equivalent fair value. The backed assets are held in accounts with US regulated financial institutions.

This table introduces three selected stablecoins, namely DAI, USDC and USDT are stablecoins. The main goal of stablecoins is price stability.

Table 4. Examples of users with dual roles

Panel A: DAI			
Address	**Deposit events**	**Borrow events**	**Total events**
0x1729f336bb0a90ef3f9c73549a7f197a50ed4294	5	128	133
0x47d73396d148e87b676a0abe7b2e5702357f6d4a	4	122	126
0x208b82b04449cd51803fae4b1561450ba13d9510	1	116	117
0x13e1699a681d48d9b98e0adf64052134559f105c	21	81	102
0xa3ba242f405fc8e93a00d50af162f723d7328631	3	81	84
Panel B: USDC			
Address	**Deposit events**	**Borrow events**	**Total events**
0x208b82b04449cd51803fae4b1561450ba13d9510	6	462	438
0x59655511bc501dec7193f2928aad4dbeea1afbd7	89	309	398
0xaf8609004fe2d76f47207ebba1abdaede4d87503	4	334	338
0xe1d18ae098ffb1ad301e0609180f155b329a710a	10	297	307
0x34a0c4d43ced6dc7149b716f00ba8c70672a1a0d	164	119	283
Panel C: USDT			
Address	**Deposit events**	**Borrow events**	**Total events**
0xf39e7cbfcca8a7f215d5af42c4f05864697856e3	5	167	172
0x9c5083dd4838e120dbeac44c052179692aa5dac5	14	154	168
0xecded8b1c603cf21299835f1dfbe37f10f2a29af	3	163	166
0xcc8b42551400236f5694eb49ad469eb12cf3d593	3	177	120
0xe1d18ae098ffb1ad301e0609180f155b329a710a	9	93	102

This table reports the users with dual roles in Aave. For each stablecoin, we present five examples, and these addresses are both depositors and borrowers. The number of deposit events and borrow events are presented. The total events initiated by these addresses are calculated as well. Besides, we find two addresses, i.e., *0x20…9510* and *0xe1…710a*, shown in different panels.

Table 5. Correlation matrix for borrow events

	Dual-role users			Aave		
	DAI	**USDC**	**USDT**	**DAI**	USDC	**USDT**
Price	0.00 (0.88)	-0.03 (0.30)	-0.02 (0.55)	**0.44***** **(0.00)**	0.00 (0.98)	-0.03 (0.57)
R	**0.06**** **(0.04)**	-0.03 (0.31)	**-0.05*** **(0.08)**	-0.03 (0.56)	-0.03 (0.56)	-0.05 (0.29)
V2	**0.05*** **(0.09)**	**0.05*** **(0.09)**	**0.11***** **(0.00)**	0.00 (0.93)	0.03 (0.52)	0.04 (0.42)
V3	**0.07**** **(0.02)**	**0.06*** **(0.06)**	**0.13***** **(0.00)**	0.02 (0.65)	0.04 (0.48)	**0.10*** **(0.06)**
V4	**0.08***** **(0.01)**	**0.06**** **(0.04)**	**0.14***** **(0.00)**	0.03 (0.55)	0.04 (0.48)	**0.09*** **(0.09)**
V5	**0.09***** **(0.00)**	**0.05*** **(0.08)**	**0.15***** **(0.00)**	0.03 (0.52)	0.02 (0.75)	**0.09*** **(0.07)**
V6	**0.10***** **(0.00)**	**0.06**** **(0.05)**	**0.16***** **(0.00)**	0.02 (0.67)	0.03 (0.58)	**0.12**** **(0.02)**
V7	**0.10***** **(0.00)**	**0.06**** **(0.04)**	**0.17***** **(0.00)**	0.00 (0.94)	0.04 (0.41)	**0.14***** **(0.01)**

This table reports correlation between financial statistics of tokens and the amount of token borrowed by filtered users and Aave pool, respectively. Financial statistics include price, daily return, and historical volatility. P-values are reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics. The selected users' borrowing behaviour will vary with the financial statistics of tokens, while the pool is only sensitive to DAI and USDT. Therefore, selected users and pool have different beliefs on these mainstream tokens, leading to potential different decision on borrow events.

Table 6. Correlation matrix for deposit events

	Dual-role users			Aave		
	DAI	**USDC**	**USDT**	**DAI**	USDC	**USDT**
Price	-0.01 (0.76)	-0.02 (0.60)	**-0.05*** **(0.08)**	0.00 (0.95)	0.00 (0.94)	-0.03 (0.61)
R	0.05 (0.12)	-0.01 (0.63)	**-0.05*** **(0.08)**	0.01 (0.77)	-0.02 (0.70)	-0.02 (0.70)
V2	**0.07**** **(0.03)**	**0.05*** **(0.09)**	**0.10***** **(0.00)**	-0.04 (0.47)	0.03 (0.62)	0.00 (0.92)
V3	**0.09***** **(0.00)**	**0.06*** **(0.06)**	**0.13***** **(0.00)**	-0.05 (0.34)	0.04 (0.42)	0.04 (0.40)
V4	**0.10***** **(0.00)**	**0.06*** **(0.07)**	**0.15***** **(0.00)**	-0.02 (0.66)	0.03 (0.57)	0.07 (0.19)
V5	**0.10***** **(0.00)**	0.05 (0.14)	**0.14***** **(0.00)**	-0.02 (0.77)	0.00 (0.93)	0.07 (0.19)
V6	**0.11***** **(0.00)**	**0.05*** **(0.08)**	**0.15***** **(0.00)**	-0.02 (0.64)	0.02 (0.64)	**0.10**** **(0.05)**
V7	**0.11***** **(0.00)**	**0.06*** **(0.06)**	**0.16***** **(0.00)**	0.05 (0.29)	0.03 (0.57)	**0.13***** **(0.01)**

This table reports correlation between financial statistics of tokens and the amount of token deposited by selected users and Aave pool, respectively. Financial statistics include price, daily return, and historical volatility. P-values are reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics. The selected users' depositing behaviour will vary with the financial statistics of most tokens, while the pool is only sensitive to USDT. Therefore, selected users and pool have different beliefs on these mainstream tokens, leading to potential different decision on deposit events.

Table 7. Descriptive statistics of illiquidity measurements (normalized)

	DAI			USDC			USDT		
	Illiquidity	Illiquidity_share	Risk_share	Illiquidity	Illiquidity_share	Risk_share	Illiquidity	Illiquidity_share	Risk_share
mean	0.00	0.47	0.47	0.01	0.45	0.45	0.01	0.51	0.51
median	0.00	0.58	0.58	0.00	0.55	0.55	0.00	0.69	0.69
max	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
std	0.05	0.38	0.38	0.08	0.36	0.36	0.05	0.36	0.36

This table reports the descriptive statistics of measurements of illiquidity risks. For each token, column *'illiquidity'* measures the illiquidity risks in Aave. Column *'illiquidity_share'* measures illiquidity risks caused by users with dual roles, and *'risk_share'* combines illiquidity risks with liquidation activities of selected users.

Table 8. The drivers of illiquidity risks

	DAI			USDC			USDT		
	Illiquidity	**Illiquidity_share**	**Risk_share**	**Illiquidity**	**Illiquidity_share**	**Risk_share**	Illiquidity	**Illiquidity_share**	**Risk_share**
Price	0.00	0.08	0.08	-0.02	**0.75***	0.75	0.00	**0.23***	**0.23***
	(0.96)	(0.76)	(0.76)	(-0.19)	**(1.63)**	(1.63)	(-0.17)	**(1.76)**	**(1.76)**
Return	-0.01	0.01	0.01	0.03	-0.02	-0.02	0.01	0.00	0.00
	(0.74)	(0.96)	(0.96)	(0.40)	(-0.05)	(-0.05)	(0.32)	(-0.02)	(-0.02)
v2	-0.01	**0.28***	**0.28***	-0.04	**-0.77****	**-0.76****	0.00	-0.10	-0.10
	(0.59)	**(0.06)**	**(0.06)**	(-0.50)	**(-1.98)**	**(-1.96)**	(-0.37)	(-1.10)	(-1.10)
v3	-0.01	**0.27****	**0.27****	0.01	**-0.78****	**-0.77****	0.00	-0.10	-0.10
	(0.58)	**(0.03)**	**(0.03)**	(0.18)	**(-2.20)**	**(-2.18)**	(0.19)	(-1.07)	(-1.06)
v4	-0.01	**0.24****	**0.24****	0.01	**-0.82*****	**-0.81****	0.00	-0.12	-0.12
	(0.48)	**(0.02)**	**(0.02)**	(0.08)	**(-2.47)**	**(-2.44)**	(-0.02)	(-1.18)	(-1.17)
v5	-0.01	**0.23****	**0.23****	-0.01	**-0.86*****	**-0.85*****	0.00	-0.13	-0.13
	(0.42)	**(0.02)**	**(0.02)**	(-0.10)	**(-2.68)**	**(-2.66)**	(-0.30)	(-1.21)	(-1.21)
v6	**0.02***	**0.20****	**0.20****	-0.02	**-0.93*****	**-0.92*****	-0.01	-0.15	-0.15
	(0.06)	**(0.03)**	**(0.03)**	(-0.35)	**(-3.03)**	**(-2.99)**	(-0.54)	(-1.39)	(-1.38)
v7	**0.04*****	**0.16***	**0.16***	-0.03	**-0.98*****	**-0.97*****	-0.01	-0.16	-0.16
	(0.00)	**(0.06)**	**(0.06)**	(-0.54)	**(-3.29)**	**(-3.26)**	(-0.53)	(-1.47)	(-1.46)
Supply	-0.02	**1.36*****	**1.36*****	**-0.07*****	**1.12*****	**1.12*****	**-0.01*****	**1.56*****	**1.40*****
	(-1.60)	**(52.44)**	**(52.46)**	**(-7.55)**	**(46.54)**	**(46.49)**	**(-5.13)**	**(16.08)**	**(10.97)**
Users	**-0.03****	**2.33*****	**2.33*****	**-0.12*****	**1.64*****	**1.63*****	**-0.08*****	**2.64*****	**2.42*****
	(-2.03)	**(52.67)**	**(52.71)**	**(-6.21)**	**(30.37)**	**(30.33)**	**(-3.84)**	**(45.39)**	**(29.95)**
Borrow rate	-0.02	**-1.57*****	**-1.57*****	0.02	**-1.36*****	**-1.36*****	0.00	**-1.26*****	**-1.26*****
	(-1.10)	**(-16.31)**	**(-16.30)**	(0.56)	**(-12.11)**	**(-12.08)**	(-0.29)	**(-14.45)**	**(-14.45)**

This table reports the relationship between financial statistics and risk measurements. Here, financial statistics include token price, daily return, and volatility (from 2-day volatility to 7-day volatility). In the regression models, financial statistics are independent variables, and risk measurements are dependent variables. Standard t-statistics are reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics. For DAI, higher volatility can result in higher illiquidity risks in Aave, while USDC and USDT are not sensitive to financial statistics. For DAI, its illiquidity risks caused by users of dual roles will increase when volatility is higher, while illiquidity risks of USDC will decrease when volatility is higher. Besides, USDT price is a driver of illiquidity risks caused by users of dual role. With more total supply and total users, illiquidity risks will decrease, but risks caused by selected users will be higher. When borrowing rates are lower, risks caused by selected users will be higher.

Table 9. Definition of factors

Factor	Definition
Panel A: Factors of Aave protocol	
Full.MktC	Market Cap based on the maximum supply of tokens in Aave
Circulating.MktC	Market Cap based on the circulating supply of tokens in Aave
Total.Revenue	Total fee paid in Aave protocol
Supply.Revenue	Fee paid to the supply-side participants in Aave protocol
Protocol.Revenue	Fee paid to AAVE holders
P/S	Fully diluted market cap divided by annualized total revenue
P/E	Fully diluted market cap divided by annualized protocol revenue
TVL	Total value locked in smart contracts of Aave protocol
Panel B: Factors of loans in Aave	
Active.Borrower	The number of active Aave borrowers daily
Active.Depositor	The number of active Aave depositors daily
Borrow.Vol	Borrowing volume on Aave protocol
LTV	Loan to value ratio
Deposit	Daily value of total deposits in Aave
Loan	Daily value of total loans in Aave
Excess	Value of total deposits minus value of outstanding loans in Aave
Panel C: Statistics of Aave ownership	
AAVE.P	The price of AAVE
Token.Incentive	Value of AAVE distributed
AAVE.Vol	Trading volume of AAVE
New.Address	New addresses of AAVE holders daily
Total.Address	Total addresses with non-zero AAVE balance
Panel D: Twitter sentiment of stablecoins	
Positive	The number of Tweets related to a stablecoin that have a positive connotation
Neutral	The number of Tweets related to a stablecoin that have a neutral connotation
Negative	The number of Tweets related to a stablecoin that have a negative connotation

This table introduces factors that might be affected by illiquidity risks in Aave Protocol. The factors can fall into four categories, namely, factors of Aave protocol, factors of loans in Aave, statistics of Aave ownership, and Twitter sentiment of stablecoins.

Table 10. Lending pool specific factors in Aave

	DAI			USDC			USDT		
	Illiquidity	**Illiquidity_share**	**Risk_share**	**Illiquidity**	**Illiquidity_share**	**Risk_share**	**Illiquidity**	**Illiquidity_share**	**Risk_share**
Full.MktC	**-1.45e+04*** (-11.50)**	0.02 (0.75)	0.02 (0.76)	**-6.48*** (-12.90)**	**0.08*** (2.97)**	**0.08*** (2.97)**	**-23.80*** (-14.32)**	**0.10*** (3.44)**	**0.10*** (3.44)**
Circulating.MktC	**-1.51e+04*** (12.07)**	**0.06** (2.19)**	**0.06** (2.20)**	**-6.73*** (-13.56)**	**0.12*** (4.32)**	**0.12*** (4.33)**	**-24.83*** (-15.23)**	**0.13*** (4.90)**	**0.13*** (4.90)**
Total.Revenue	**-9311.96*** (-7.62)**	**0.37*** (25.45)**	**0.37*** (25.45)**	**-4.09*** (-8.21)**	**0.35*** (21.12)**	**0.35*** (21.09)**	**-15.68*** (-9.41)**	**0.39*** (26.33)**	**0.39*** (26.32)**
Supply.Revenue	**-9224.54*** (-7.63)**	**0.36*** (24.87)**	**0.35*** (24.87)**	**-4.05*** (-8.21)**	**0.35*** (20.69)**	**0.35*** (20.66)**	**-15.50*** (-9.39)**	**0.38*** (25.73)**	**0.38*** (25.73)**
Protocol.Revenue	**-1.01e+04*** (-7.47)**	**0.43*** (30.37)**	**0.43*** (30.37)**	**-4.45*** (-8.06)**	**0.42*** (24.68)**	**0.42*** (24.65)**	**-17.32*** (-9.41)**	**0.46*** (31.36)**	**0.46*** (31.35)**
P/S	**1.75e+04*** (9.88)**	**-0.61*** (-35.49)**	**-0.61*** (-35.50)**	**7.60*** (10.60)**	**-0.60*** (-29.00)**	**-0.60*** (-28.85)**	**28.31*** (11.86)**	**-0.65*** (-36.74)**	**-0.65*** (-36.73)**
P/E	**1.54e+04*** (8.99)**	**-0.52*** (-24.48)**	**-0.52*** (-24.49)**	**6.88*** (9.92)**	**-0.54*** (-24.07)**	**-0.54*** (-23.90)**	**27.07*** (11.91)**	**-0.58*** (-29.21)**	**-0.58*** (-29.21)**
TVL	**-1.84e+04*** (-9.93)**	**0.67*** (48.33)**	**0.67*** (48.36)**	**-8.10*** (-10.84)**	**0.64*** (29.99)**	**0.64*** (29.96)**	**-31.24*** (-12.77)**	**0.71*** (47.87)**	**0.71*** (47.85)**

This table reports the effects of illiquidity risks on Aave lending pool. The factors of lending pool include fully diluted market cap, circulating market cap, total revenue, supply-side revenue, protocol revenue, P/S ratio, P/E ratio, and total value locked in Aave protocol. In regression models, illiquidity risk measurements are independent variables, and lending pool factors and dependent variables. Standard t-statistics are reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics. For activities on Aave, higher illiquidity risks will decrease market cap, revenue, and total value locked in Aave, while P/S and P/E ratio will increase. For activities of users with dual roles, potential risks caused by them will lead to higher market cap, revenue, and total value locked in Aave. But potential risks caused by these users will lead to lower P/S and P/E ratio.

Table 11. Loan-specific factors in Aave

	DAI			USDC			USDT		
	Illiquidity	**Illiquidity_share**	**Risk_share**	**Illiquidity**	**Illiquidity_share**	**Risk_share**	**Illiquidity**	**Illiquidity_share**	**Risk_share**
Active.Borrower	**-0.29****	0.00	0.00	**-0.42*****	**0.05*****	**0.05*****	**-0.40*****	**0.04****	**0.04****
	(-2.29)	(0.14)	(0.14)	**(-4.99)**	**(3.06)**	**(3.08)**	**(-3.33)**	**(2.28)**	**(2.28)**
Active.Depositor	**-0.27***	**-0.05****	**-0.05****	**-0.21****	-0.01	-0.01	-0.18	-0.03	-0.03
	(0.06)	**(-2.31)**	**(-2.31)**	**(-2.04)**	(-0.35)	(-0.34)	(-1.29)	(-1.32)	(-1.32)
Borrow.Vol	**-1.88e+04*****	**0.84*****	**0.84*****	**-8.26*****	**0.87*****	**0.87*****	**-32.15*****	**0.89*****	**0.89*****
	(-8.19)	**(67.73)**	**(67.75)**	**(-8.83)**	**(62.80)**	**(62.72)**	**(-0.35)**	**(70.92)**	**(70.90)**
LTV	0.01	**-0.15*****	**-0.15*****	0.08	**-0.13*****	**-0.13*****	0.07	**-0.14*****	**-0.14*****
	(0.08)	**(-9.70)**	**(-9.70)**	(0.87)	**(-8.23)**	**(-8.26)**	(0.56)	**(-8.50)**	**(-8.50)**
Deposit	0.12	**-0.58*****	**-0.59*****	**0.34***	**-0.58*****	**-0.58*****	0.32	**-0.60*****	**-0.60*****
	(0.48)	**(-32.38)**	**(-28.61)**	**(1.90)**	**(-28.69)**	**(-28.61)**	(1.29)	**(-30.08)**	**(-30.07)**
Loan	0.12	**-0.66*****	**-0.66*****	0.35*	**-0.66*****	**-0.67*****	0.32	**-0.67*****	**-0.67*****
	(0.40)	**(-34.98)**	**(-34.97)**	(1.74)	**(-30.07)**	**(-30.11)**	(1.16)	**(-30.29)**	**(-30.28)**
Excess	0.10	**-0.46*****	**-0.46*****	**0.28***	**-0.47*****	**-0.47*****	0.26	**-0.48*****	**-0.48*****
	(0.62)	**(-28.99)**	**(-28.98)**	**(1.91)**	**(-26.28)**	**(-26.19)**	(1.31)	**(-27.72)**	**(-27.72)**

This table reports the effects of illiquidity risks on loans in Aave lending pool. The factors of loans include the number of daily active borrowers, the number of daily active depositors, daily borrowing volume (in USD), and loan to value ratio. Besides, we also consider daily value of deposits, loans and excessed deposits (i.e., the deposits minus the outstanding loans). In regression models, illiquidity risk measurements are independent variables, and lending pool factors and dependent variables. Standard t-statistics are reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics. Higher illiquidity risks will decrease the number of active borrowers and depositors in Aave, and the borrowing volume of stablecoins will decrease as well. But the potential risks caused by users with dual roles can be a driver of active borrowers and borrowing volume. For these stablecoins, their loan-to-value ratios will decrease when *illiquidity_share* and *risk_share* are higher, meaning that the risks of loans will be lower. Besides, *illiquidity_share* and *risk_share* will lead to lower value of deposits and loans, implying that the growth of Aave will be affected.

Table 12. Aave Ownership specific factors

	DAI			USDC			USDT		
	Illiquidity	Illiquidity_share	Risk_share	Illiquidity	Illiquidity_share	Risk_share	Illiquidity	Illiquidity_share	Risk_share
AAVE.P	**-0.37****	0.03	0.03	**-0.84*****	**0.09*****	**0.09*****	**-0.74*****	**0.11*****	**0.11*****
	(-2.01)	(1.34)	(0.18)	**(-6.84)**	**(3.46)**	**(3.47)**	**(-4.25)**	**(4.11)**	**(4.11)**
Token.Incentive	**-1.04e+04*****	**0.42*****	**0.42*****	**-4.58*****	**0.42*****	**0.42*****	**-17.91*****	**0.47*****	**0.47*****
	(-6.56)	**(19.51)**	**(19.51)**	**(-7.04)**	**(17.91)**	**(17.89)**	**(-8.21)**	**(22.23)**	**(22.22)**
AAVE.Vol	**-2022.56***	**-0.18*****	**-0.18*****	**-0.87***	**-0.16*****	**-0.16*****	-2.55	**-0.16*****	**-0.16*****
	(-1.71)	**(-9.07)**	**(-9.07)**	**(-1.77)**	**(-7.75)**	**(-7.72)**	(-1.53)	**(-7.67)**	**(-7.67)**
Total.Address	**-0.58****	**0.57*****	**0.57*****	**-1.29*****	**0.54*****	**0.54*****	**-1.15*****	**0.60*****	**0.60*****
	(-2.34)	**(32.74)**	**(32.76)**	**(-8.05)**	**(25.16)**	**(25.13)**	**(-5.00)**	**(3.47)**	**(3.46)**
New.Address	-0.03	**-0.28*****	**-0.28*****	-0.04	**-0.28*****	**-0.28*****	-0.04	**-0.29*****	**-0.29*****
	(0.85)	**(-16.33)**	**(-16.32)**	(0.72)	**(-15.40)**	**(-15.30)**	(-0.25)	**(-16.00)**	**(-16.00)**

This table reports the effects of illiquidity risks on ownership of Aave protocol. In Aave protocol, AAVE is the governance token, and the token holders are theoretically owners of Aave protocol. We consider AAVE price, value of distributed AAVE, and trading volume of AAVE. Besides, we consider the number of AAVE holders and new AAVE holders daily. In regression models, illiquidity risk measurements are independent variables, and statistics of Aave ownership and dependent variables. Standard t-statistics are reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics. Higher illiquidity risks of DAI and USDC will decrease AAVE price, token incentive, trading volume and the number of total AAVE holders. For USDT, its illiquidity risks will lead to lower price and token incentives of AAVE. The number of total AAVE holders will decrease as well. As for potential risks caused by users with dual roles, when these users account for more risks, AAVE price, token incentives and the number of AAVE holders will increase. But AAVE trading volume and the number of new AAVE holders will decrease. For dual-role users in DAI activities, their potential risks will lead to higher token incentives and more AAVE holders. But trading volume and the number of new AAVE holders will decrease.

Table 13. Twitter sentiment of stablecoins

	DAI			USDC			USDT		
	Illiquidity	**Illiquidity_share**	**Risk_share**	**Illiquidity**	**Illiquidity_share**	**Risk_share**	Illiquidity	**Illiquidity_share**	**Risk_share**
Positive	-0.04	0.02	0.02	**-0.27*** **	**0.16*** **	**0.16*** **	-0.02	**0.01***	**0.01***
	(-0.53)	(1.62)	(1.62)	**(-2.72)**	**(8.67)**	**(8.67)**	(-0.45)	**(1.81)**	**(1.80)**
Neutral	-0.02	**0.02*** **	**0.02*** **	**-0.08***	**0.07*** **	**0.07*** **	-0.15	**0.08*** **	**0.08*** **
	(-0.27)	**(2.57)**	**(2.57)**	**(-1.66)**	**(7.60)**	**(7.60)**	(-1.17)	**(4.06)**	**(4.05)**
Negative	-0.04	**0.04*** **	**0.04*** **	**-0.13***	**0.14*** **	**0.14*** **	-0.05	0.01	0.01
	(-0.62)	**(4.25)**	**(4.25)**	**(-1.71)**	**(10.17)**	**(10.18)**	(-0.59)	(0.50)	(0.50)

This table reports the effects of illiquidity risks on Twitter sentiment of stablecoins. Here, we consider the number of Tweets with different connotation daily. In regression models, illiquidity risk measurements are independent variables, and lending pool factors and dependent variables. Standard t-statistics are reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics. For DAI and USDC, higher potential risks caused by users with dual roles will lead to more negative Tweets. Surprising, for USDC and USDT, higher *illiquidity_share* and *risk_share* will bring more positive discussion on Twitter.

Table 14. Descriptive statistics of DAI-specific risk measurement (normalized)

	DAI-specific
mean	0.00
median	0.00
max	1.00
min	0.00
std	0.05

This table reports the descriptive statistics of DAI-specific risk measurement. The calculation is based on equations (13) – (15).

Table 15. Drivers of DAI-specific risk measurement

	DAI-specific
Price	0.00 (0.05)
Return	-0.01 (-0.34)
v2	-0.01 (-0.54)
v3	-0.01 (-0.56)
v4	-0.01 (-0.70)
v5	-0.01 (-0.81)
v6	**0.02*** **(1.86)**
v7	**0.04***** **(3.24)**
Supply	-0.02 (-1.60)
Users	**-0.03**** **(-2.03)**
Borrow rate	-0.02 (-1.10)

This table reports the relationship between financial statistics and DAI-specifc risk measurement. Here, financial statistics include token price, daily return, and volatility (from 2-day volatility to 7-day volatility). We also consider the total supply of DAI, total DAI users, and borrowing rates of DAI on Aave. In the regression models, financial statistics are independent variables, and risk measurements are dependent variables. Standard t-statistics are reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics. DAI-specific risks are driven by 6- day volatility and 7-day volatility. When there are more DAI users, the risks will decrease.

Table 16. Effects of DAI-specific risks on lending pool

	DAI-specific
Full.MktC	**-1.31e+04***** **(-11.09)**
Circulating.MktC	**-1.36e+04***** **(-11.54)**
Total.Revenue	**-7794.98***** **(-6.75)**
Supply.Revenue	**-7732.11***** **(-6.77)**
Protocol.Revenue	**-8373.79***** **(-6.54)**
P/S	**1.47e+04***** **(8.74)**
P/E	**1.27e+04***** **(7.78)**
TVL	**-1.54e+04***** **(-8.75)**

This table reports the effects of DAI-specific risks on Aave lending pool. The factors of lending pool include fully diluted market cap, circulating market cap, total revenue, supply-side revenue, protocol revenue, P/S ratio, P/E ratio, and total value locked in Aave protocol. In regression models, illiquidity risk measurements are independent variables, and lending pool factors and dependent variables. Standard t-statistics are reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics. When DAI-specific risks are higher, market cap, revenue, and total value locked will decrease. But P/E and P/S ratio will be higher.

Table 17. Effects of DAI-specific risks on DAI loans

	DAI-specific
Active.Borrower	**-0.29**** **(-2.29)**
Active.Depositor	**-0.27*** **(-1.89)**
Borrow.Vol	**-1.547e+04***** **(-7.08)**
LTV	0.01 (0.08)
Deposit	0.12 (0.48)
Loan	0.12 (0.40)
Excess	0.10 (0.49)

This table reports the effects of DAI-specific on loans in Aave lending pool. The factors of loans include the number of daily active borrowers, the number of daily active depositors, daily borrowing volume (in USD), and loan to value ratio. Besides, we also consider daily value of deposits, loans and excessed deposits (i.e., the deposits minus the outstanding loans). In regression models, illiquidity risk measurements are independent variables, and lending pool factors and dependent variables. Standard t-statistics are reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics. When DAI-specific risks are higher, there will be fewer active borrowers and depositors, and the borrow volume will decrease as well.

Table 18. Effects of DAI-specific risks on Aave ownership

	DAI-specific
AAVE.P	**-0.37**** **(-2.01)**
Token.Incentive	**-8540.93***** **(-5.69)**
AAVE.Vol	**-2230.67**** **(-2.03)**
Total.Address	**-0.58**** **(-2.34)**
New.Address	-0.03 (-0.19)

This table reports the effects of illiquidity risks on ownership of Aave protocol. In Aave protocol, AAVE is the governance token, and the token holders are theoretically owners of Aave protocol. We consider AAVE price, value of distributed AAVE, and trading volume of AAVE. Besides, we consider the number of AAVE holders and new AAVE holders daily. In regression models, illiquidity risk measurements are independent variables, and statistics of Aave ownership and dependent variables. Standard t-statistics are reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics. When DAI-specific risks are higher, AAVE price, token incentives, trading volume and the number of total AAVE holders will decrease.

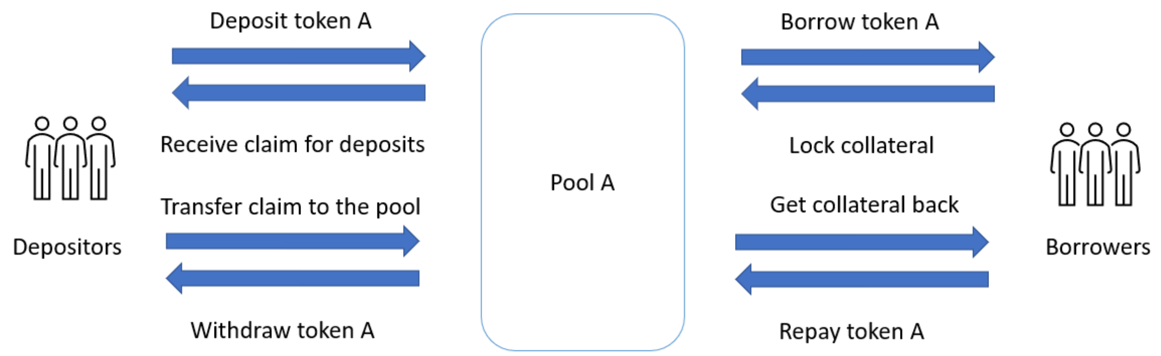
Table 19. Effects of DAI-specific risks on Twitter sentiment of DAI

	DAI-specific
Positive	-0.04 (-0.53)
Neutral	-0.02 (-0.27)
Negative	-0.04 (-0.54)

This table reports the effects of DAI-specific risks on Twitter sentiment of DAI. Here, we consider the number of Tweets with different connotation daily. In regression models, illiquidity risk measurements are independent variables, and lending pool factors and dependent variables. Standard t-statistics are reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics. However, we do not find statistically significant results.

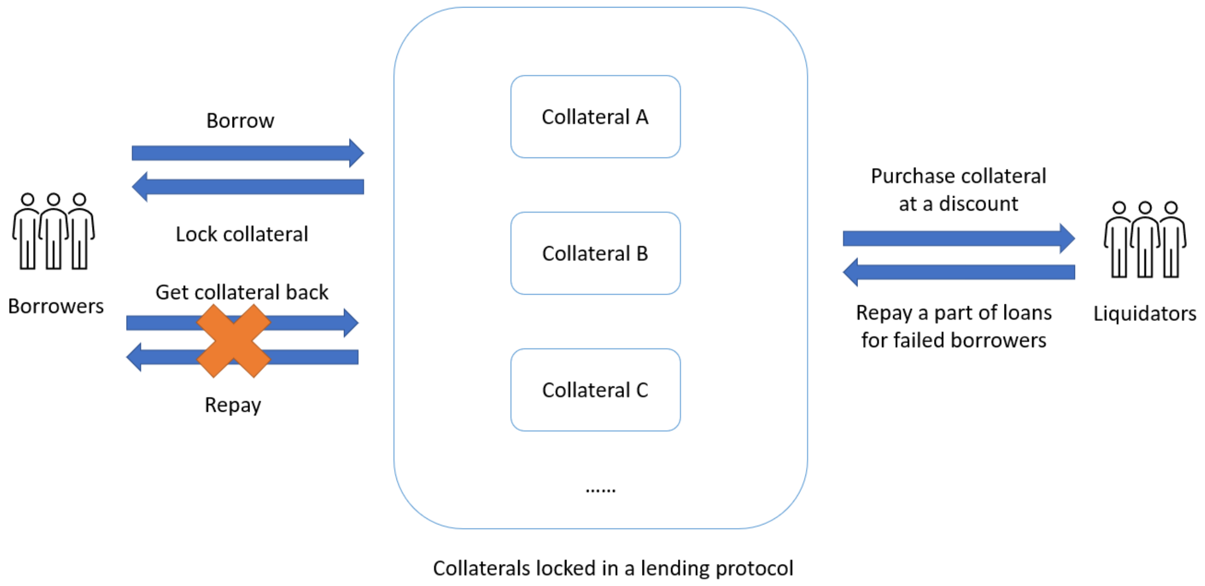
Figures

Figure 1. Pooled funds in lending protocols



This figure illustrates borrowing and lending in lending protocols. For each token, there will be a pool. Depositors can deposit their token and receive an amount of claim. When depositors want to withdraw their tokens, they need to transfer claim to the lending protocol. For borrowers, they need to lock collateral when requiring loans. When they successfully repay loans, the collateral can be returned.

Figure 2. Liquidation in lending protocols



This figure illustrates liquidation in a lending pool. When borrowers fail to repay their loans, liquidators can participate in liquidation. Liquidators can repay a part of loans for failed borrowers. In return, liquidators can purchase collateral of failed borrowers at a discount.