The Determinants of Liquidity in Decentralized Lending

Minh Nguyen, Binh Nguyen, Tra Pham, Huy Pham

The Business School, RMIT University, Vietnam

Minh Nguyen *(Corresponding author)

PhD Candidate at The Business School, RMIT University, Vietnam

University of Economics and Business, Vietnam National University, Hanoi, Vietnam

Email: minh.nguyen291@rmit.edu.vn

Binh Nguyen

The Business School, RMIT University, Vietnam

Email: binh.nguyenthanh@rmit.edu.vn

Tra Pham

The Business School, RMIT University, Vietnam

Email: tra.pham@rmit.edu.vn

Huy Pham

The Business School, RMIT University, Vietnam

Email: huy.phamnguyenanh@rmit.edu.vn

The Determinants of Liquidity in Decentralized Lending

Abstract

Decentralized Lending is a new concept in finance. Based on blockchain and smart contracts, the innovative design of DeFi lending allows pseudonymous participants to lend and borrow money on a large scale without the need for financial intermediaries. Although in the theory of financial intermediation, DeFi Lending is claimed to have certain advantages; it has multiple hurdles to overcome. In contrast to traditional banks, where governments can bail out, or deposit insurance can work, DeFi, as an unregulated market, must deal with illiquidity problems. Moreover, it is considered a main source of financial instability because of the increasing connection between cryptocurrency and traditional financial products. Given that the main reason for these lending platforms' instability is the liquidity shortage, this study investigates the interconnectedness of liquidity between DeFi Lending platforms and the determinants affecting liquidity in DeFi Lending. While many studies have approached this issue at a conceptual level or using aggregate data, this study aims to explore DeFi lending using transaction-level blockchain data. This study applies the time-varying parameter vector autoregression (TVP-VAR) to measure the liquidity connectedness between DeFi Lending platforms, and then the ARDL model and a novel dynamic ARDL simulation are employed to find the factors that affect liquidity in the DeFi Lending platform. The results indicate that even DeFi Lending platforms are highly competitive to each others, it has an extreme liquidity connectedness and Aave is founded to be the net transmitter of liquidity spillovers to other DeFi platforms. The finding also shows that the market power of users and interest rate are two main entrain points that should be looked at in the design of DeFi lending to manage the liquidity in these platforms.

Keywords: *Decentralized Finance, Lending, Borrowing, Liquidity, TVP-VAR, ARDL*

1. Introduction:

Historically, intermediaries have played a crucial role within traditional financial markets (CeFi). They serve as brokers and agents of trust, settlement, liquidity and security. As the complexity of the financial system increases, the range and value of intermediaries have risen throughout the years to fulfill those requirements. Since the 2008 Global Financial Crisis, greater focus has been placed on recognizing the inefficiencies, inequity gaps, and hidden risks of the CeFi system (Adrian et al., 2018). Decentralized Finance (DeFi) was created to offer financial services free from central intermediaries, which are similar to and potentially beyond current ones provided by traditional financial systems (Wharton 2021). The roots of DeFi come from the idea of Bitcoin. Based on the technology behind Bitcoin, Ethereum was created with the functions of smart contracts[1] to host programs being added, which means that Ethereum allows software developers to make blockchain-based decentralized applications for financial services (Buterin, 2014). The rise of many Blockchain platforms such as Polygon, Solana, Polkadot, Cardano, and Binance Smart Chain with functions like Ethereum has created a new financial system called DeFi. DeFi is considered to have the potential to reduce and/or transform the role of financial intermediaries (Grassi et al. 2022; Harwick & Caton, 2020; Kumar et al.,2020). There are different financial services similar to traditional intermediaries that DeFi can provide. Among them, Decentralized Lending and Borrowing (DeFi Lending) platforms are the most prominent protocols in the DeFi ecosystem. DeFi Lending, for the first time, allows pseudonymous participants to lend and borrow money on a large scale without the need for financial intermediaries (Schär, 2021). They have locked in the highest proportion of the value in the DeFi ecosystem, with around $25.68 billion of the total $70 billion at the time of writing (Defilama.com). Their goal is to mimic the functions of traditional banks, one of the most important financial intermediaries of the conventional financial system. More recently, Grassi et al. (2022) highlighted the need to look carefully at the lending sector of DeFi, among other points, to DeFi.

DeFi, in general, or DeFi Lending, also play an important role in the recent growth of the cryptocurrency market (Gogel, 2021). According to coinmarketcap.com, there were 22,131

[1] Smart contracts, which are integrated in blockchains, allow the two parties to enforce the contractual terms of an agreement automatically despite the absence of the third party Zheng, Z., Xie, S., Dai, H.-N., Chen, W., Chen, X., Weng, J., & Imran, M. (2020). An overview on smart contracts: Challenges, advances and platforms. *Future Generation Computer Systems*, *105*, 475-491. .

cryptocurrencies on 27th December 2022. The cryptocurrency market has seen exponential growth in recent years and soaring investments by individual investors and traditional financial institutions. However, the DeFi lending or cryptocurrency market has many limitations related to extreme price volatility, usability, fraud, and regulatory uncertainty (Chen & Bellavitis, 2020; Lucey et al., 2022). DeFi lending platforms stand at the centre of the recent crypto turmoil, which created concerns about rampant speculation and financial instability (Aramonte et al., 2022). In 2022, the collapse of Anchor on the Terra blockchain shook confidence and stopped the rapid ascent of crypto lending. The instability of DeFi lending could lead to many harmful consequences.

In contrast to traditional banks, where governments can bail out, or deposit insurance can work, DeFi, as an unregulated market, must deal with illiquidity problems. As the illiquidity problem occurs in DeFi Lending platforms, there is no intervention of regulatory authority (i.e., Deposit insurance as introduced in the seminal paper of Diamond and Dybvig (1983)). Participants in these platforms could suffer a significant loss due to limited regulation related to financial consumer protection. Moreover, the composability property in DeFi and the increased correlation of crypto assets and DeFi with traditional financial markets through new emerging products such as stablecoins raises the risk of contagion not only from DeFi to the cryptocurrency market but also from cryptocurrency to traditional financial markets (IMF, 2022; Gottlich, 2022; OECD 2022). Non-bank financial intermediaries such as DeFi lending are considered potential primary sources of financial instability because of the increasing connection with traditional financial products and the possibility of spillovers of investor sentiment between asset classes (BIS, 2022).

One of the main reasons for these lending platforms' instability is the liquidity shortage (Aramonte et al., 2022). In traditional banks, suppose banks cannot ensure the appropriate funding liquidity. In that case, it can face the problem of liquidity risk, bank runs and can spread through the financial network, which can end up in a collapse of the financial system, i.e. systemic risk (Allen & Gale, 2004; Diamond & Rajan, 2005). Similar to the definition of funding liquidity in banks, funding liquidity in DeFi lending is understood as the ability of lending platforms to settle the obligations of borrowers and lenders (Gudgeon, Werner, et al., 2020). Liquidity risk in DeFi is “the possibility that there will be insufficient funds or assets available to realize the value of a financial asset. Failure of liquidity for a borrower means the position is involuntarily liquidated and the available assets allocated to owners or creditors. Insufficient liquidity also magnifies market inefficiencies” (Wharton 2021). This risk is also called “Protocol debt” for a DeFi lending platform. By running a simulation, Gudgeon, Perez, et al. (2020a) provide evidence that the failure of a DeFi lending protocol may lead to transmission mechanisms and lend itself to systemic risk, leading to a decentralized financial crisis. This is analogue to the 2008 financial crisis; however, one distinctive property in DeFi could make the systemic risk in DeFi even more severe than the traditional financial system, which is composability. Therefore, funding liquidity is crucial to the stability of DeFi Lending platforms in particular and the whole market. However, this instability risk may be reduced through logical governance and carefully designed incentives to maintain stable liquidity (Wharton 2021).

Given the importance of liquidity in DeFi lending, some papers approach different aspects related to liquidity in lending (Bartoletti et al., 2021; Castro et al., 2021; Gudgeon, Perez, et al., 2020a; Gudgeon, Werner, et al., 2020; Saengchote, 2021a; Xu & Vadgama, 2022). However, little attention has been paid from the literature to quantify the liquidity connectedness between DeFi Lending platforms and study the determinants affecting the liquidity in DeFi Lending to understand the source of liquidity risk. This study contributes to the literature by investigating the interconnectedness of liquidity between DeFi Lending platforms, applying the theoretical framework in traditional lending to DeFi lending and addressing their differences to investigate the factors affecting liquidity in DeFi lending.

2. Literature Review

2.1. Liquidity Connectedness in DeFi Lending

DeFi lending has one distinctive property compared to CeFi Lending: composability. Composability is "the ability to build a complex, multi-component financial system on top of crypto-assets" (Gudgeon, Perez, et al., 2020a, p. 1). This property is often compared with the metaphor 'Money Lego' (Popescu, 2020) which promises to solve the lack of interoperability problem in CeFi. One of the main problems of banking system design is siloed and suffers high switching costs. Different institutions have their own ledgers and are not interoperable; thus, moving capital and value across silos can be unduly lengthy and complicated (Chen & Bellavitis, 2020; Harvey et al., 2021). In contrast, the DeFi system is highly interoperable, allowing for seamless capital flow across different institutions and borders. The composability property of DeFi enables any individual to integrate, fork, or rehash multiple protocols to create entirely new applications. This flexibility creates an open financial system that allows for an unprecedented and ever-expanding variety of financial services (Schär, 2021). For example, supplied positions cannot be repurposed for other investment opportunities in centralized banking. In contrast, tokenized positions via cTokens (Compound) or aToken (Aave) can be used to turn statics into yield-generating assets (Harvey et al., 2021).

However, composability property also brings concern about systematic risk. A major downside of composability is that an intertwined system of debts and obligations is created (Gudgeon, Perez, et al., 2020a). For example, DAI - a stablecoin cryptocurrency created in MakerDAO[2] can be used as collateral in other protocols such as Compound[3], dY/dX[4], or Uniswap[5]. The interconnectedness between DeFi projects allows risk transfer from one project to another and expands outward (Harvey et al., 2021). Also, DeFi services are not limited to countries or business segments but operate in a worldwide marketplace. Moreover, one of the significant issues in DeFi is that there is no circuit breaker; thus, the government cannot step in to stop the trading of assets, for example. Therefore, the systemic defaults due to contagion in DeFi maybe even more server than CeFi.

As aforementioned, the interconnectedness between DeFi projects allows risk transfer from one project to another and expands outward (Harvey et al., 2021). In traditional finance, the financial network structure has received significant attention from academic literature. Allen and Gale (2004) suggest that liquidity services can serve as a potential source of contagion risk among banks, with the potential for liquidity shocks to trigger the collapse of entire financial systems (Diamond & Rajan, 2005). Lee (2013) argue that the complex interconnectivity makes liquidity an issue that affects the entire system. Elliott et al. (2014) and Acemoglu et al. (2015) find that the structure of an interbank network can significantly impact systemic risk, which in turn can influence the contagion of liquidity shocks. DeFi Lending is claimed to be even more interoperable than banks; therefore, it is essential to measure the connectedness between DeFi lending platforms and to see how it can affect the systematic risk of the entire system. Consequently, we can evaluate

[2] The Maker Foundation. 2019. MakerDAO. https://makerdao.com/en/. MakerDAO provides a decentralized stablecoin called DAI that is pegged to the US dollar, while still functioning financially similar to a lending and borrowing platform

[3] Compound Finance. 2019. Compound Finance. https://compound.finance/. Compound is a lending market that offers several different ERC-20 assets for borrowing and lending.

[4] dYdX. 2020. dYdX. https://dydx.exchange/. dYdX is divided into two sub-protocols, one for trading, borrowing, lending and one that also supports futures markets.

[5] Uniswap is a decentralized exchange (DEX) and was first launched on November 2, 2018 on the Ethereum mainnet

the benefits and drawbacks of this new property in DeFi. To the best of our knowledge, this is the first study to examine this topic.

2.2. Determinants of Funding Liquidity in DeFi Lending

In traditional finance, many factors can affect the funding liquidity of a bank. This study applies ideas in theoretical and empirical research on the traditional market to DeFi lending but also addresses differences between these two.

Interest Rate

According to the financial liberalization hypothesis, McKinnon (1973) and Shaw (1973) argue that interest rate ceilings in the current financial systems distort credit allocation and may lead to underinvestment in profitable projects. Therefore, the financial sector should be liberalized for the interest rate to be determined by the interplay of demand and supply. Based on the Rational choice theory, the interest rate will incentivize borrowers to repay or borrow the loan that maximizes their utility. In this case, the interest rate will affect the deposits and loans, thus affecting funding liquidity.

The McKinnon-Shaw hypothesis was criticized by Stiglitz and Weiss (1981) and Besley (1994), who believe that interest rates cannot function as an allocator of credit. Due to the information asymmetry, interest rates may act as a screening device, and borrowers willing to pay high-interest rates may undertake riskier projects. This could decrease the bank's profit due to default; thus, banks prefer to ration credit rather than adopt risky borrowers. In this case, the interest rate cannot be used to equate the supply and demand of loanable funds, and credit rationing occurs. Both theoretical and empirical studies have shown that credit rationing causes financial constraints for firms, and on an aggregate level, this can result in lower overall economic growth (Amable et al., 2004; Banerjee & Moll, 2010; Bencivenga & Smith, 1993; Craig et al., 2007; Yu & Fu, 2021).

In traditional banks, banks have the power to control loanable funds. In contrast to DeFi lending, no intermediaries exist to control deposits and loans to extract high economic rent. Another distinction is that central banks in traditional finance primarily set interest rates via a base rate and function as a key lever in managing credit in economies (i.e., Federal Reserve Board, Bank of England). There is a strand of literature on the role of monetary policy transmission and bank lending channels in both theoretical and empirical (Bernanke & Blinder, 1988, 1992; Bernanke &

Gertler, 1995; Brissimis & Delis, 2009; Ehrmann et al., 2001; Ehrmann & Worms, 2004). Recent studies show that banks may aggressively expand liquidity creation after the central bank relaxes monetary policy by cutting interest rates (Berger & Bouwman, 2017; Beutler et al., 2020; Dang & Huynh, 2022; Hussain & Bashir, 2019; Zhang & Deng, 2020). In contrast, interest rates in DeFi lending are determined algometric by the supply and demand for each token.

The mechanism used to set these rates is a crucial aspect of protocol design because it provides the preconditions to reach the equilibrium and ensure the funding liquidity of the protocol (Gudgeon, Werner, et al., 2020). The interest rate models employed by the DeFi lending protocol can be classified into three categories: linear, nonlinear, and kinked rates (Gudgeon, Werner, et al., 2020). Popular protocols like Compound or Aave often use the kinked interest rate model. The idea is that if the utilization of the pool, which is used to measure funding liquidity, is above the optimum (predetermined utilization rate for each token), then the borrowing rate rises sharply to discourage further borrowing and encourage the payment of outstanding loans. On the other hand, a utilization below the optimum is accompanied by a low borrowing rate to encourage further borrowing. This mechanism is quite similar to the financial liberalization hypothesis of McKinnon-Shaw (1973). Therefore, DeFi lending is an ideal example to empirically test the financial liberalization hypothesis to see whether interest rates can play the role as it is expected without the need for a central third party to adjust the funding liquidity. The first hypothesis is then formulated as follows:

H1: Interest rate (Variable borrow rate) has a significant impact on the funding liquidity of DeFi Lending.

Market Power of Users

According to Shepherd (1970, p. 3), "Market power is the ability of a market participant or group of participants (persons, firms, partnerships, or others) to influence price, quality, and the nature of the product in the marketplace".

Most of the studies in traditional finance are concerned with intermediaries' monopoly or oligopoly power. This is a market with the "absence of competition", creating a situation where a few specific person or enterprise is the only supplier of a particular thing, therefore dominating a market. In the banking industry, market power received significant attention in the literature. There are two opposite views on the role of the concentrated banking sector on financial stability. In the conventional credit market, almost all transactions have to go through financial intermediaries like banks. Therefore, banks have the market power to control financial transactions. In turn, bank market power can lead to an oligopoly market with imperfect competition, resulting in inefficient usage of market liquidity. Thus, utilitarian societal welfare is not maximized. On the one hand, concentrated banking systems could increase market power and enhance bank profits, thus, providing a "buffer" against adverse shocks. In addition, supervision of a few banks in a concentrated will be easier and more effective than lots of banks in a diffuse banking system, thus cognition risk and the probability of systemic crisis less pronounced in a concentrated banking system (Besanko & Thakor, 1995; Boot & Greenbaum, 1993; Hellmann et al., 2000; Matutes & Vives, 2000). According to Allen and Gale (2000), the U.S is an example supporting the "concentration–stability" view because a financial system with lots of banks in the U.S shows much greater financial instability in history than Canada or the U.K, where a few larger banks dominate the banking system. On the other hand, the "concentration–fragility" view argues that banks in concentrated systems are considered "too important to fail"; thus, they tend to receive larger subsidy policies. This support intensifies risk-taking incentives and increases the probability of banking system fragility and systemic distress (De Nicoló et al., 2006; Mishkin, 1999).

In contrast with monopoly or oligopoly, the market might face a monopsony or oligopsony problem, which relates to a few entities' control of a market to purchase a good or service, therefore a few sellers dominating a market. This situation is quite similar to the case of DeFi lending platforms. In contrast to CeFi, DeFi protocols are highly competitive to offer better services for users. The open-source blockchain and smart contracts' public nature allow users to identify flaws and inefficiencies in a DeFi project and "forked away" by copying and improving the flawed project (Harvey et al., 2021). Therefore, the market power of the platform is not likely to occur in DeFi. However, this can transmit to the market power of users, which is often measured as the percentage of funds in the platform that a user address hold. Some empirical papers in DeFi lending find that most supplied funds are controlled by a tiny number of user accounts. For example, only three accounts in Compound control about 50.3% of the total value locked DAI. Likewise, the same number of accounts control 60.0% and 47.3% for ETH and USDC, respectively (Gudgeon, Werner, et al., 2020). Saengchote (2021a) also shows that the distribution of accounts in the Compound platform is skewed, with the top 100 depositors and borrower addresses accounting for

75% and 78% of all deposits and loans, respectively. This high concentration of buyers can result in an oligopsony problem, where buyers pay lower prices than what would be found in perfect competition. This leads to resources not being allocated appropriately and producers receiving less income from their products. In DeFi lending, a few users could drastically diminish liquidity or cause full illiquidity even in times of high liquidity (Gudgeon, Werner, et al., 2020). In this case, oligopsony may be a problem in the DeFi market, affecting funding liquidity. Will the decentralisation goal still occur if major users have market power in DeFi lending? Or does it just transfer from the government to big players? Therefore, the oligopsony issues deserve strong consideration in the DeFi lending industry and policy debates; however, very few studies specifically address this problem to date. Based on the above argument, this study postulates that the concentration of the fund in user accounts may affect funding liquidity in DeFi lending. Hence, the second hypothesis is as follows:

H2: The market power of users has a significant impact on the funding liquidity of DeFi lending.

Protocol Depositor

Depositors in DeFi lending platforms deposit their tokens to a liquidity pool. In exchange, they will receive equal claim tokens minted by the pool. This token proves that they have made a deposit and can be used to redeem the same type of token that was initially put into the pool. If someone wishes to withdraw their deposits, they must transfer the claim tokens back to the liquidity pool.

The role of depositors is to supply the fund to the pools; therefore, similar to traditional banks, when there are more depositors, it can increase banks' liquidity. In contrast, in the case of a bank run (Diamond & Dybvig, 1983), the cascade withdrawal of depositors will cause bank liquidity shortages, leading to bank failure.

Because of the inability to collect users' data across banks, this indicator has not been tested in empirical studies in traditional banks (Ghenimi et al., 2020; Moussa, 2015; Vodova, 2011). However, in blockchain, information is publicly available (Chen & Bellavitis, 2020); therefore, we can easily know the number of depositors in each protocol. As the number of depositors varies, it can affect the liquidity provided in the market, thus, affecting the liquidity in lending pools. Hence, the thirds hypothesis is as follows:

H3: The number of protocol depositors significantly impacts the funding liquidity of DeFi lending.

Protocol Borrower

Borrowers in DeFi lending platforms can initiate loans from a liquidity pool if only they lock in enough collateral. The collateral will be locked in the loan duration. When they borrow from a liquidity pool, the liquidity of the token in that pool will decrease if everything stays the same. Therefore, as the number of borrowers increases or decreases, it can also affect the liquidity in lending pools. Hence, the fourth hypothesis is as follows:

H4: The number of protocol borrowers significantly impacts the funding liquidity of DeFi lending.

3. Data and Methodology

3.1. Data Collection

This research focuses on DeFi lending platforms. At the time of writing, the most prominent lending platforms are Aave ($15.7 billion), Maker ($13.19 billion), and Compound ($10.83 billion) (defipulse.com). The total value locked in these protocols accounts for approximately 60% of the market size in the DeFi Lending market (defilama.com); therefore, this study will focus on these three platforms to investigate the liquidity connectedness between them. We collect the aggregate daily liquidity of these platforms on all chains. We collect the aggregate daily liquidity of these platforms on all chains. The data is collected through API from tokenterminal.com and defillama.com. This study chose the sample period starting from the launch of Aave V2[6] to ensure time consistency across platforms. Aave V2 launched in December 2020; therefore, to reduce the uncertainty of the first-month transfer from Aave V1 to Aave V2, the sample is from 1/1/2021 to 30/12/2022.

As our first analysis of liquidity connectedness shows that Aave is the net transmitter of liquidity spillovers in the DeFi lending market, the second part investigates the determinants of funding

[6] Aave began as ETHLend in 2017 after it raised $16.2 million in an Initial Coin Offering (ICO) to create a decentralized peer-to-peer lending platform. Later, they rebranded to Aave when they switched to a liquidity pool model. Aave launched the Aave Protocol in 2020, an open-source and non-custodial liquidity protocol where users can earn interest on deposits and borrow assets. Aave introduces several innovative features in V2, such as swapping collateral assets and repaying debts with collateral assets, making it industry standard.

liquidity in the Aave lending platform. Aave is the largest DeFi lending platform, measured by the total value locked. Aave provides services on multiple blockchains; however, Ethereum is the most popular and attracts the largest transaction. Therefore, this study focuses on Aave on the Ethereum blockchain. This study chooses five cryptocurrencies, including Wrapped Bitcoin (WBTC), Wrapped Ether (WETH), and three stablecoins (DAI, USDC, USDT), because they represent over 80% of the market size in the platform. For example, these coins account for approximately 89% of the market size in Aave as of Jan 24, 2022 (aave.com). Therefore, the findings of this study can apply to the DeFi lending sector of other platforms with a similar mechanism.

The data of the studied DeFi lending platforms, such as the total amount borrowed, total supply, interest rate, number of depositors, and borrowers, are publicly available in Ethereum's blockchain. The transaction data (i.e., interest rate) accrued based on floating rates every block (i.e.,15 seconds). Since the data is stored as transactions in the ledger, different solutions have come out to ease fetching and querying this data. Some papers (Faqir-Rhazoui et al., 2021; Gudgeon, Werner, et al., 2020; Schär & Gronde, 2021) have used The Graph[7]. The Graph is a popular protocol for Ethereum-based Decentralized applications as it indexes blockchain data and makes the associated databases accessible through an API. This data can be queried using the GraphQL language[8]. In essence, blockchain is open-source, allowing anyone to crawl the same data and check the reliability and validity of that data. Similar to the first research question, this study chose the sample period starting from the launch of Aave V2. The sample period is from 1/1/2021 to 31/7/2022. This study will collect 5-minute, hourly, and daily data transactions for studied variables of each coin in the platform in the sample period.

As discussed in the literature, we will divide the sample into the bull and bear markets phase based on the Crypto Fear and Greed Index from Alternative.me[9]. This index is developed by gathering data on the emotions and sentiments of investors from five different sources, including volatility, market momentum, social media, dominance, and trends. The index ranges from 0 (extreme fear) to 100 (extreme greed). A high index level may indicate that investors are greedy and bullish on

[7] https://thegraph.com/
[8] https://graphql.org/
[9] https://alternative.me/crypto/fear-and-greed-index/

the market. In contrast, a low index level may show investors are concerned about the market's instability. Therefore, the bull and bear market phases are divided as in Figure 1 below.

[Insert Figure 1 here]

3.2. Variables Measurements

In traditional finance, the Basel Committee of Banking Supervision defines funding liquidity as "the ability to fund increases in assets and meet obligations as they come due, without incurring unacceptable losses" (BCBS 2008, p.1). The International Monetary Fund (IMF) defines funding liquidity as "the ability of a solvent institution to make agreed-upon payments in a timely fashion" (IMF 2008, p. 11). In traditional banking and finance, there are various methods to measure funding liquidity in banks (i.e., Berger & Bouwman, 2009; Boudt et al., 2017; Holmström & Tirole, 1998). However, these comprehensive measures rely on the balance sheet and how loans are classified, which may not be suitable for DeFi lending.

Similar to the definition of funding liquidity in traditional banks, funding liquidity in DeFi lending is understood as the ability of lending platforms to settle the obligations of borrowers and lenders (Gudgeon, Werner, et al., 2020). According to Gudgeon, Werner, et al. (2020), the available liquidity in a DeFi lending pool is measured by the difference between the total supply and total borrows of funds in the protocol. Recent papers in the DeFi literature also use this method to measure the funding liquidity in the DeFi lending pool (Cirikka, 2021; Gudgeon, Perez, et al., 2020a; Sun, 2022). Therefore, this study chooses available liquidity in DeFi Lending platforms as the measurement of funding liquidity in these protocols for investigating the liquidity connecnessted between DeFi Lending platforms. The following equation express the measurement of funding liquidity.

Funding liquidity – Method 1:

$$\text{Funding liquidity}_t = \text{Total deposit}_t - \text{Total borrow}_t$$

where Funding liquidity_t is the available liquidity of a DeFi lending platform on date t. Total deposit_t is the average value of funds locked into the protocol's smart contracts on date t. Total borrow_t is the average value of outstanding borrows on the protocol on date t.

For the next part of my research, as other variables in our model are rate variables, another measurement that can also be used to measure the liquidity in DeFi Lending is the Utilization rate. These two measurements can be used interchangeably in the previous research (Cirikka, 2021; Gudgeon, Perez, et al., 2020a; Sun, 2022). In essence, this calculation is still based on the total deposit and total borrow for each token in the lending pool.

Funding liquidity – Method 2: Utilization rate of token i at time as follow:

$$\text{Utilizationrate}_{i,t} = \text{Total borrow}_{i,t} / \text{ Total deposit}_{i,t}$$

where Total $\text{borrow}_{i,t}$ represents the total amount borrowed of token i at time t, Total $\text{deposit}_{i,t}$ is the total amount supply of token i at time t in the lending pool.

The Utilization rate method is quite similar to the LDR (loan to deposit) ratio often used in banking research (i.e., Marozva, 2015; Van den End, 2016). As this rate is close to 1, the lending pool experiences periods of near-illiquidity and all supplied funds are almost loaned out. The value of these two measurements is the opposite, which can be observed clearly in Figure 10 and Figure 11.

The measurement of other variables in our analysis is explained in Table 1.

[Insert Table 1 here]

3.3. Method

3.3.1. Time-varying Parameter VAR (TVP-VAR) Model

The most popular econometric method for examining connectedness is one proposed by (Diebold & Yilmaz, 2009). Diebold and Yilmaz (2009) introduce a connectedness index derived from a Cholesky-type VAR model's factor error variance decomposition (FEVD). Diebold and Yilmaz (2012) further developed the connectedness index by introducing two improvements to the technique proposed in their 2009 paper. First, the generalized VAR framework is used to replace the Cholesky-type VAR, thus eliminating the issue of variable ordering when obtaining variance decompositions from the VAR model. The second improvement is the introduction of net connectedness and directional connectedness between markets, as opposed to the prior framework, which only considered total connectedness. Diebold and Yılmaz (2014) then demonstrated how their proposed measures of connectedness are related to crucial connectedness measurements in network theory. This method is employed to track contagions in a predetermined network to mitigate the adverse effects caused by a specific economic shock.

However, the Diebold and Yilmaz (2009, 2012, 2014) approach has one limitation: it depends on a randomly chosen rolling window size of the changing connectedness. To address this issue, Antonakakis et al. (2020) proposed using the mean squared prediction error of the applied rolling window VAR to select the best window size. Antonakakis et al. (2020) combine the TVP-VAR method of Koop and Korobilis (2013) with the connectedness index computation of Diebold and Yilmaz (2009, 2012, 2014) to overcome the shortcomings of the rolling-window approach. This method is more advantageous than the rolling-window approach in at least three ways. First, it eliminates the necessity of deciding upon a window size which is usually an arbitrary decision without any statistical basis. Second, it prevents the loss of observations which would be equal to the width of the window size as opposed to the rolling sample analysis. Third, the Kalman Filter is used to generate coefficients that are matched to every piece of data in the sample, whereas the rolling window technique does not allow for the recognition of data points that cause a spike or decrease in the connectedness index within a given window.

Therefore, this study takes advantage of the time-varying parameter VAR (TVP-VAR) model of Antonakakis et al. (2020) to look into liquidity connectedness across the three main DeFi Lending platforms. The following present the TVP-VAR connectedness approach in combination with Diebold and Yilmaz's original technique.

The TVP-VAR(p) model can be expressed as:

$$y_t = \beta_t x_{t-1} + \epsilon_t \qquad \epsilon_t | F_{t-1} \sim N(0, R_t) \tag{1}$$

$$vec(\beta_t) = vec(\beta_{t-1}) + v_t \qquad v_t | F_{t-1} \sim N(0, S_t) \tag{2}$$

in which y_t and $x_{t-1} = [y_{t-1}, \dots, y_{t-p}]'$ represent $N \times 1$ and $Np \times 1$ dimensional vectors, respectively. β_t is an $N \times Np$ dimensional time-varying coefficient matrix, ϵ_t is an $N \times 1$ dimensional vector of error disturbance with a corresponding $N \times N$ time-varying variance-covariance matrix, R_t. $vec(\beta_t), vec(\beta_{t-1})$, S_t is an $N^2p \times N^2p$ dimensional matrix. and v_t are $N^2p \times 1$ dimensional vectors.

The next step is to use the Wold representation theorem to transform the TVP-VAR into a TVP-VMA, which will allow for the calculation of the generalized impulse response functions (GIRF) and the generalized forecast error variance decomposition (GFEVD) (Koop et al., 1996; Pesaran & Shin, 1998):

$$y_t = \sum_{j=0}^{\infty} L' W_t^j L \epsilon_{t-j} \tag{3}$$

$$y_t = \sum_{j=0}^{\infty} A_{it} \epsilon_{t-j} \tag{4}$$

where $L = [I_N, \dots, 0_p]'$ is an $Np \times N$ dimensional matrix, $W = [\beta_t; I_{N(p-1)}, 0_{N(p-1)\times N}]$ is an $Np \times Np$ dimensional matrix.

The GIRFs represent the response of all variables to a shock in variable i by computing the differences between a *J*-step-ahead forecast with and without the shock. The calculation is as follows:

$$GIRF_t(J, \delta_{j,t}, F_{t-1}) = E(Y_{t+J} | \epsilon_{j,t} = \delta_{j,t}, F_{t-1}) - E(Y_{t+J} | F_{t-1}) \tag{5}$$

$$\varphi_{j,t}^{g}(J) = \frac{A_{J,t} S_t \epsilon_{j,t}}{\sqrt{S_{ij,t}}} \frac{\delta_{j,t}}{\sqrt{S_{ij,t}}} \qquad , \qquad \delta_{j,t} = \sqrt{S_{ij,t}} \tag{6}$$

$$\varphi_{j,t}^{g}(J) = S_{jj,t}^{-1/2} A_{J,t} S_t \epsilon_{j,t} \tag{7}$$

Where *J* is the forecast horizon, $\delta_{j,t}$ represents selection vector, which has the value of one on the *j*-th position and zero otherwise, F_{t-1} is the information set up to time $t-1$, and $\varphi_{j,t}^{g}(J)$ represents the GIRFs of variable *j*,

Then, GFEVD is calculated, which is the amount of variation that one variable has on other variables. The calculation is given by:

$$\tilde{\phi}_{ij,t}^{g}(J) = \frac{\sum_{t=1}^{J-1} \varphi_{ij,t}^{2,g}}{\sum_{j=1}^{N} \sum_{t=1}^{J-1} \varphi_{ij,t}^{2,g}} \tag{8}$$

where $\sum_{j=1}^{N} \tilde{\phi}_{ij,t}^{g}(J) = 1$ and $\sum_{i,j=1}^{N} \tilde{\phi}_{ij,t}^{N}(J) = N$. Then, the total connectedness index (TCI) is built based on the GFEVD:

$$C_t^{g}(J) = \frac{\sum_{i,j=1, i\neq j}^{N} \tilde{\phi}_{ij,t}^{g}(J)}{\sum_{i,j=1}^{N} \tilde{\phi}_{ij,t}^{g}(J)} \times 100 = \frac{\sum_{i,j=1, i\neq j}^{N} \tilde{\phi}_{ij,t}^{g}(J)}{N} \times 100 \tag{9}$$

Next, this connected approach allows investigation of how a shock in one variable spills over to other variables. First, we can define the *total directional connectedness TO others,* which means the shock transmitted from variable *i* to all other variables *j*.

$$C^{g}_{i\to j,t}(J) = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\phi}^{g}_{ij,t}(J)}{\sum_{j=1}^{N} \tilde{\phi}^{g}_{ij,t}(J)} \times 100 \tag{10}$$

Second, we can define the *total directional connectedness FROM others, which means* the shock that variable *i* receives from all other variables *j*.

$$C^{g}_{i\leftarrow j,t}(J) = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\phi}^{g}_{ij,t}(J)}{\sum_{j=1}^{N} \tilde{\phi}^{g}_{ij,t}(J)} \times 100 \tag{11}$$

Finally, the *net total directional connectedness* can be calculated by subtracting the *total directional connectedness TO others* from *the total directional connectedness FROM others*:

$$C^{g}_{i,t} = C^{g}_{i\to j,t}(J) - C^{g}_{i\leftarrow j,t}(J) \tag{12}$$

The *net total directional connectedness* of variable i can be understood as its influence on the analyzed network. If $C^{g}_{i,t}$ is positive, then this suggests that variable i has a greater effect on the network than it is affected by it, meaning that it is a *shock transmitter.* In contrast, if $C^{g}_{i,t}$ is negative, then variable i is more influenced by the network, making it a *shock receiver*.

3.3.2. An autoregressive distributed lag (ARDL) model

For investigating the determinants of funding liquidity in Aave, the endogeneity issue is particularly relevant for our time series data, as the variables may be determined simultaneously. An Autoregressive distributed lag (ARDL) is a least-squares regression that includes lags of the dependent variable and explanatory variables. A key advantage of the ARDL approach is that it allows treating all the variables series as potentially endogenous (Pesaran & Shin 1999). This method is used due to several proven advantages over other methods to deal with time-series data, such as Vector Autoregression (VAR) or co-integration techniques. The ARDL model allows dealing with data that have a mixture of orders of integration (i.e., I(0) and/or I(1)), which are usually present when a structural break problem occurs. Therefore, the ARDL approach circumvents the pre-testing issues that require variables already classified into standard cointegration, I(0) or I(1) (Pesaran et al., 2001). Moreover, Pahlavani et al. (2005) argue that the

ARDL model helps avoid making many difficult choices, such as the order of VAR, the treatment of deterministic elements, and the optimal number of lags to be used. The reason is that the ARDL technique's estimation procedure allows the utilization of various optimal numbers of lags for different variables in the model. The results of unit root tests are presented in Table 5, revealing that the variables are a mix of orders of integration I(0) and I(1)) and none of the variables is I(2). Therefore, according to Shrestha and Bhatta (2018), this study applies the ARDL model.

The ARDL model for this study can be defined as follows:

$$FL_{i,t} = \beta_0 + \sum_{i=1}^{P} \gamma i FL_{i,t-i} + \sum_{j=0}^{k=1} \sum_{i=1}^{q_j} \boldsymbol{X}_{ij,t-i}{}' \beta_{j,i} + \varepsilon_t \quad \text{(I)}$$

where $FL_{i,t}$ denotes the current value of funding liquidity of cryptocurrency "i" at time t. Where its number of lags is represented by *p – past value of* funding liquidity. p is optimal lag length which is determined by information criteria such as SIC (Schwarz Information Criterion) or AIC (Akaike information criterion). Current and past values of independent variables, including the variable borrow Interest rate (IR), Market power of users (HHI), number of depositors (De), and borrowers (Bo), are represented by the matrix X, where the number of lags of current and past values of each variable is represented by q_k. In our analysis, the past value of funding liquidity and the current and past values of explanatory variables (i.e., VB, HHI, De, Bo) function as dynamic regressors of the current funding liquidity value.

Bounds test for co-integration

The ARDL method also allows assessing simultaneously the short-term and long-term coefficients associated with the studied variable. The dynamic relationship between the dependent variable and explanatory variables can be analyzed using an ARDL model, which can then be converted into a long-run representation (Pesaran et al., 2001). Therefore, this study further performs the ARDL bounds test to check whether the variable has a long-term cointegration.

Novel dynamic ARDL simulation

In addition to understanding the factors that affect the funding liquidity of the DeFi Lending platform, this study examines the impact of shocks on that liquidity. The simulation can be a good source for policy consideration. Therefore, we apply the novel dynamic ARDL simulation (Jordan & Philips, 2018) to capture the future shocks of the market power of users and variable borrow rates variables on the DeFi Lending platform's liquidity. The application of novel dynamic ARDL simulation to our data followed the steps proposed by Jordan and Philips (2018) and the guidelines from Sarkodie and Owusu (2020). Figure 2 below illustrates the steps used in carrying out the empirical analysis.

[Insert Figure 2 here]

4. Results and discussion

4.1. Liquidity Connectedness between DeFi Lending platforms

4.1.1. Descriptive statistics

Figure 3 exhibits the evolution of the liquidity series of three main DeFi lending platforms during the sample period. We observe the common patterns between time series during the 2021-2022 period. MakerDAO has the largest available liquidity, followed by Aave and then Compound. All platforms witnessed a sharp decrease in available liquidity in the second half of 2022, which is quite similar to the cryptocurrency market volatility during this time.

[Insert Figure 3 here]

The first requirement to conduct the TVP-VAR method is to ascertain whether these three liquidity series are stationarity. As our variables are not stationary according to the unit root test statistics developed by Elliott et al. (1996), we use their first-differenced series, which can be seen as a percentage change of these variables. Figure 4 illustrates the pattern of these series.

[Insert Figure 4 here]

Table 2 reports the summary statistics of the transformed series. The variance shows that liquidity in MakarDAO is the most volatile variable, while Aave's liquidity is the least volatile. Next, the Skewness and Kurtosis tests show that all of the series are leptokurtic and significantly right-skewed. The Jarque and Beranormality test shows that all variables are not normally distributed. The ERS test indicates that all series are stationary at 1% significance level. Therefore, these series meet the requirement to conduct the TVP-VAR method and can be used in level to compute the FEVD for building dynamic liquidity connectedness indices. Finally, we find evidence suggesting that series are autocorrelated and exhibit ARCH/GARCH errors, making a TVP-VAR model with time-varying covariances an appropriate choice to estimate interlinkages between the considered variables.

[Insert Table 2 here]

4.1.2. The dynamic liquidity spillovers among DeFi Lending platforms

Table 3 reports the average liquidity connectedness analysis results from the TVP-VAR model.

[Insert Table 3 here]

Table 3 reports the average funding liquidity variations of any DeFi Lending protocol due to cross-protocol liquidity connectedness during the studied period is 42.97. Figure 5 displays a graphical plot of how the TCI has changed over time. This index is relatively high over time and spikes to over 70 in some period, which indicate extreme liquidity connectedness across different DeFi lending platforms, which confirms the composability of DeFi. The TCI values were above the sample average in late 2021 and most of the time in 2022, a period of high volatility in the cryptocurrency market. This indicates that the liquidity connectedness across DeFi platforms was very responsive to uncertain events in the cryptocurrency market.

[Insert Figure 5 here]

Total directional liquidity connectedness TO other platforms

The results in Table 3 indicate that Aave is the largest transmitter of liquidity spillovers to other platforms (Total TO value is 52.49%), while the transmitter of Compound and MakerDAO are lower, with a value of 31.21% and 45.21%, respectively. Figure 6 shows the evolution of each total directional liquidity connectedness to the other platforms during the sample period. We can see that Aave has been actively transmitting its liquidity shocks to different DeFi Lending markets, while Compound's influence is comparatively insignificant.

[Insert Figure 6 here]

Total directional liquidity connectedness FROM other platforms

Table 3 results show that MakerDAO receives the highest average liquidity spillovers from other DeFi Lending markets, with a value of 48.93% of its 10-day-ahead FEVD being caused by shocks in Aave and Compound. The second greatest receiver of liquidity spillovers is Aave (Total FROM value is 41.3%), and the last is Compound (Total FROM value is 38.67%). Figure 7 plots the evolution of each total directional liquidity connectedness from the other platforms during the sample period. The figure reveals that MakerDAO had the highest absorption of liquidity spillovers compared to the Aave and Compound platforms.

[Insert Figure 7 about here]

Net liquidity connectedness

Table 3 and Figure 8 show that Aave is the net transmitter of liquidity spillovers, whereas Compound and MakerDAO serve as net receivers. Only the NET value of Aave is positive (11.19%), whereas the NET value of Compound and MakerDAO are (-7.47%) and (-3.72%), respectively. These results mean that Compound receives 7.47% more liquidity spillovers than it transmits, while the corresponding number for MakerDAO is 3.72%. Figure 8 also shows that the Net total directional connectedness index for Aave was greater than zero throughout the sample period, whereas the corresponding value for Compound and MakerDAO are negative in most of the given time. This result is also described visually in Figure 9

[Insert Figure 8 here]

[Insert Figure 9 here]

In sum, we can see that liquidity in all DeFi Lending platforms is highly interconnected, which brings concern about systematic risk because it allows for risk transfer from one project to another and expands outward. Therefore, DeFi Lending may also face a similar problem as traditional banks as Allen and Gale (2004) suggest that liquidity services can serve as a potential source of contagion risk among banks, with the potential for liquidity shocks to trigger the collapse of entire financial systems (Diamond & Rajan, 2005). In the case of DeFi Lending, Aave (one of the largest total value locked DeFi Lending protocols) is founded to be the net transmitter of liquidity spillovers to other DeFi platforms (Figure 9), and the total connectedness index is relatively high over time with the average value of 64.46%.

This result contributes to the literature on the spillover effect in the new emerging financial market – DeFi (Cevik et al., 2022; Karim et al., 2022; Piñeiro-Chousa et al., 2022; Qiao et al., 2023; Ugolini et al., 2023; Umar et al., 2022). While previous studies focus on the connectedness between DeFi tokens to other financial asset classes such as cryptocurrencies, NFTs, stock, oil, and gold, this research focuses on the connectedness within the DeFi ecosystems. While the composability of DeFi has been discussed extensively in the literature (Meegan & Koens, 2021; Saengchote, 2021b; Schär, 2021; Tolmach et al., 2021; von Wachter et al., 2021), limited research quantifies the composability property of DeFi. This study is the first to apply the time-varying parameter vector autoregression method (TVP-VAR) of Antonakakis et al. (2020) to quantify the degree of liquidity connectedness across DeFi Lending platforms over time. The research results show that liquidity in DeFi Lending is extremely interconnectedness. These findings align with the literature on liquidity in the traditional market. In both DeFi and CeFi markets, liquidity is always an important concern for high connectedness (Allen & Gale, 2004; Diamond & Rajan, 2005; Elliott et al., 2014). Although DeFi protocols are highly competitive to offer better services for users, investors, designers, and governance token holders should aware that protocols are connected at a high level. Therefore, the shocks to one platform could lead to contagion risk to the DeFi system. Therefore DeFi users should be aware of the potential systematic risk in this entire new ecosystem. Moreover, as discussed above, the increasing connection between DeFi and the traditional financial market (BIS 2022, OECD 2022) potentially causes instability in the financial market. Therefore, policymakers should be aware of this source of risk when making decisions.

4.2. Determinants of Liquidity in Decentralized Lending

4.2.1. Descriptive statistics

[Insert Table 4 here]

Table 4 shows descriptive statistics of variables for 5-minute transaction data. Because the sample period is from 1/1/2021 to 31/7/2022, therefore, there are 166,167 observations during that period. The mean utilization rate variable of USDT is the highest (0.8023), followed by USDC and DAI, with values of 0.7566 and 0.7144, respectively. In contrast, the mean utilization rate of WBTC and WETH is much lower, with values of 0.0460 and 0.1376, respectively. This result is suitable with the value of available liquidity for WBTC and WETH pool, which is relatively much higher than for three stablecoins. One of the reasons is that both WBTC and WETH pools have the highest number of depositors but relatively low borrowers.

[Insert Figure 10 here]

[Insert Figure 11 here]

The value of two liquidity measurements, as mentioned in Section 3.2, is the opposite. Figures 10 and 11 illustrate the available liquidity (measurement of funding liquidity used in the first part of our analysis) and the utilization rate (measurement of funding liquidity used in the second part of our analysis) for five studied tokens in Aave, respectively. As we can see, for three stablecoins (USDC, USDT, DAI), as available liquidity in liquidity pools will be low, the utilization rate should be high and close to 1. In contrast, for WETH and WBTC, the available liquidity is relatively high; therefore, the utilization rate is quite low.

4.2.2. Stationary test

To deal with time series data, we first need to know the type of data to find the suitable method (Shrestha & Bhatta, 2018). Therefore, this study first examines the stationary existence of the studied variables. We applied two unit root tests, including the Phillips and Perron - PP test (Phillips & Perron, 1988) and the Augmented Dickey-Fuller – ADF test (Dickey & Fuller, 1979). The results of unit root tests are presented in Table 5, revealing that variables used in model I are a mix of orders of integration I(0) and I(1). And none of the variables is I(2) because both the ADF and PP test for the first-difference variables shows no unit root at 1% significance level. Therefore, as discussed in the research method, this study applied the ARDL model.

[Insert Table 5 here]

4.2.3. ARDL model estimation and cointegration test

Bounds test for co-integration

The following step in the ARDL method is the bounds test to check whether the variable has a long-run cointegration. The Bounds test is used to analyze the relationship between variables in the long run. This is completed by performing a joint significance F-test on the coefficients of variables associated with lagged levels. Co-integration means that the variables move together and do not diverge from the long-run equilibrium over time. Table 6 shows the results of the calculated F-statistics from the bounds test (Pesaran et al., 2001) for co-integration analysis with unrestricted constant and no trend for the 5-minute data. The F-statistic results in Table 6, being above the upper bound critical value for all tokens, allow us to reject the null hypothesis of no existence of the long-run relationship. These results imply that there is an existence of co-integrating relationships, which suggests that the connection between the variables has been substantial over the studied period. Consequently, independent factors have critical roles in influencing the funding liquidity of each token in the long run. Almost the pattern in the short run still exists in the long run.

[Insert Table 6 here]

Table 7 shows the short-run relationship of the concerned independent variables

[Insert Table 7 here]

The results from Table 7 show that the market power of users has a significant impact on the funding liquidity of each token pool in the DeFi Lending platforms. This result confirms the H2 hypothesis that the market power of users had a significant effect on funding liquidity in DeFi Lending platforms. For DAI and USDC, the sign of coefficients is negative in the bull market and positive in the bear market. In contrast, for USDT, the sign of coefficients is positive in the bull market and negative in the bear market. The coefficients of WETH and WBTC are relatively low (nearly zero) compared to the three stablecoins, indicating that the market power of users in these two lending pools is less significant. This result is quite explicable with the fact that the HHI index of these two tokens is lower than 1500 during almost the sample period, indicating a competitive marketplace (Figure 12). Therefore, when the market power of the user is low, it will have less impact on the funding liquidity of the pool. In contrast, three stablecoins have the HHI index at the level of moderately concentrated and highly concentrated at some specific time; therefore, the market power of users in these platforms will have a higher impact on liquidity compared to WETH and WBTC.

[Insert Figure 12 here]

Even to be claimed as a decentralized system, the centralized property still exist in other forms in DeFi. The HHI index provides evidence that the oligopsony problem exists in the DeFi Lending market. In contrast with the monopoly problem that often exists in the traditional financial market, DeFi protocols are highly competitive to offer better services for users. However, this can transmit to the oligopsony problem, which is the market power of users. This paper is among the first to measure the market power of users index in DeFi Lending and investigate their impact on the platform's liquidity. The results show that the higher the market power of users, the higher effect it has on the liquidity of DeFi Lending, and the magnitude of the impact is even higher in the bear market than in the bull market. Therefore, during the market uncertainty period, the market power of users is a big concern for the liquidity problems in the DeFi market.

These results align with the stream of literature that argues that a form complete "decentralization" of finance may hard to fully achieved and is ultimately chimerical because finance involves irreducible dilemma aspects, even in simple and direct forms; it cannot be done purely algorithmically (Harwick & Caton, 2020; Zetzsche et al., 2020). Brown & Oates (1987) argue that a fully decentralized system will be suboptimal and may need central participation in their particular use case. The evidence shows that inefficiency problems still exist in the DeFi market.

Interest rate

The analysis results show that the variable borrow rate positively impacts the utilization rate for all tokens. Therefore, interest rates variable have a negative impact on the funding liquidity of DeFi Lending. These findings mean that the higher borrowing rate does not lower the Utilization rate for each token in the DeFi Lending pool. Therefore, the result rejects the first hypothesis (H1). At the same time, the magnitudes of coefficients are higher in the bear than in the bull market.

From the research results of the interest rate factor, we should be aware that the current purely algometric interest model in DeFi Lending is inefficient in controlling liquidity. Although increasing the borrowing rate could lower liquidity in the long term through the simulation results, the immediate impact of this interest rate model is the opposite. Even though DeFi is claimed to be a financial liberalization market in which the interest rate is adjusted due to the supply and demand of loanable funds, this interest rate model does not work as expected. One possible reason for the inefficiency of obtaining optimal supply and demand based on the interest rate is the existence of investor behavior. The explanation for that can be based on the prospect theory, also known as the loss-aversion theory, developed by Daniel Kahneman and Amos Tversky in 1979. It aims to explain how people act rather than what decisions they would make if they were perfectly rational (as rational choice theory proposes). The concept of prospect theory states that investors have different reactions to gains and losses, with a greater emphasis placed on potential gains than losses. When given the option between two equal choices, an investor is more likely to select the one associated with possible profits since losses cause a more significant emotional impact. People may not always be risk-averse and tend to be more afraid of risk in profit rather than the risk of losing money. People opt for taking a risk rather than accepting certain losses to elude any damage. They are willing to gamble and believe they will not suffer any repercussions.

This theory explains the phenomenon of the irrational behavior of investors. As the borrowing rate increases, if the borrower repays the loan immediately, they have to bear the transaction fee and loss the potential gain in other investments (if the health factor does not exceed the limit to activate the automated liquidation). Therefore, the current interest rate model does not work effectively to control the liquidity in the pool. This result is in line with the literature that has looked into the behavior of investors when it comes to investing in cryptocurrencies. These studies have found that investors engage in herding behavior rather than being rational and are influenced by the hype surrounding cryptocurrencies. This leads to irrational investment decisions that affect other investors who invest in cryptocurrencies without considering the underlying fundamentals (Ajaz & Kumar, 2018; Bouri et al., 2018; Jalal et al., 2020; Vidal-Tomás et al., 2019). The empirical evidence shows that the assumption of financial liberalization with everything pure algometric seems hard to be achieved in the DeFi market. The reason is that due to prospect theory, irrational behavior exists in the cryptocurrency market, making the predesigned interest model not follow the rational choice theory to ensure the liquidity of platforms.

Depositor & Borrower

For the number of depositors variable, the results show a similar pattern for all tokens, the number of depositors in each token pool has a negative impact on the Utilization rate, meaning that an increase in the number of depositors in the lending pool leads to a decrease in the Utilization rate, increase the funding liquidity. These findings confirm the third hypothesis (H3). In contrast, for the number of borrowers variable, the results show that the number of borrowers in each token pool has a positive impact on the Utilization rate, meaning that an increase in the number of borrowers in the lending pool leads to an increase in the Utilization rate, lower the funding liquidity. These results confirm the fourth hypothesis (H4).

Moreover, the magnitudes of coefficients of the two variables for the three stablecoins are higher than for WETH and WBTC, which means the change in the number of depositors and borrowers has more impact on the funding liquidity of these stablecoins than for WETH and WBTC. One possible reason is that both WBTC and WETH pools have many depositors, which is much higher than the number of borrowers, and the availability of liquidity in these pools is relatively high;

therefore, the change in the number of depositors and borrowers has not much impact of the funding liquidity.

4.2.3. Robustness checks and diagnostic measures

As mentioned above, the endogeneity problem is a major concern in our model due to the potential correlation between the explanatory variable and the error term. Unobserved heterogeneity or omitted variables can cause this issue. To deal with this, Pesaran & Shin (1999) declared that if the ARDL model does not have any residual correlation, endogeneity is less of a problem. In order to check the residual correlation, this study applies the popular Breusch-Godfrey LM statistics test. The results of LM tests shown in table 7 do not indicate autocorrelation in the error term; therefore, endogeneity is not an issue for our model. At the same time, Pesaran & Shin (1999) have noted that the appropriate lag order in the ARDL model can address both serial correlation and endogeneity issues.

In addition, cumulative sum tests for the parameter are conducted to investigate if there is any structural change in the estimated coefficient over time. The result from the cumulative sum test revealed that the statistic of the estimates does not surpass the 95% confidence boundary, suggesting that the estimated coefficient over time remains stable (Table 7).

This study also uses both 5-minute and 1-hourly data for analysis. The analysis results from 1-hourly data, as reported in Table 8 and Table 9, show a similar pattern to the analysis of 5-minute data and the results continue to hold.

[Insert Table 8 here]

[Insert Table 9 here]

4.2.4. Dynamic ARDL simulations

This section discusses the result of the market power of user simulation and variable borrow rate simulation using a novel dynamic ARDL simulation. In this case, we use the daily data to capture the impact of counterfactual shock in the long run. In this simulation, we assume that the time at which the shock occurs is 15 days after, and the total range of the simulation is 50 days.

For the case of market power of user simulation, other variables are constant, and the simulation is based on a + 30% change in the HHI index, which means that the level of concentration can increase to the next level (i.e., from competitive marketplace to moderately concentrated or from moderately concentrated to highly concentrated). The outcome of the dynamic ARDL parameters is presented in Figure 13.

[Insert Figure 13 here]

For USDC, USDT, and WETH, the counterfactual shock immediately impacts the utilization rate, which means that a shock that increases the concentration of users, leading to immediate lower liquidity. For DAI, for the first five days, it has no impact, but after that, it also lowers the liquidity. For WBTC, one month later, we can see the effect of the shock, and it is also relatively low.

For the case of variable borrow rate simulation, other variables are constant. The simulation is based on a + 30% change in the variable borrow rate, which means that when the token's price has a high fluctuation, interest rates have to be adjusted according to the supply and demand of the token. The borrowing rate must be increased to encourage people to repay the loans to increase liquidity. The outcome of the dynamic ARDL parameters is exposed in Figure 14.

[Insert Figure 14 here]

5. Conclusion

This study contributes to the existing DeFi literature by providing the first empirical evidence on the connectedness between DeFi Lending platforms and the determinants that affect the liquidity in DeFi Lending.

As mentioned in the introduction, one of the main differences between DeFi and CeFi is that DeFi is an unregulated market. Therefore, as the illiquidity problem occurs in DeFi Lending platforms, there is no intervention of regulatory authority (i.e., a bailout from governments or Deposit insurance as introduced in the seminal paper of Diamond and Dybvig (1983)). Therefore, the empirical research questions evaluate the importance of liquidity in DeFi Lending platforms and find internal factors that can be adjusted through governance and the design of the DeFi platform to stabilize liquidity.

Our results demonstrated that one drawback of the DeFi Lending system compared to the traditional system is the extreme liquidity connectedness between DeFi lending platforms, given that this property has many benefits for improving interoperability in the financial market. In the case of DeFi Lending, Aave (one of the largest total value locked DeFi Lending protocols) is found to be the net transmitter of liquidity spillovers to other DeFi platforms, and the total connectedness index is relatively high over time, with the average value of 64.46%.

DeFi, as an unregulated market, must deal with illiquidity problems without the intervention of regulatory authorities. Therefore to find the solution to stabilize the liquidity in DeFi lending to reduce the risk for users, we need to understand the factors that can impact the liquidity in DeFi Lending. Our results indicate that the interest rate and the market power of users are two main entrain points that should be looked at in the design of DeFi lending to manage the liquidity in these platforms. Designers should be aware that the pure algometric interest model in DeFi Lending is not as efficient as expected due to the irrational behavior of investors in the cryptocurrency market. Besides, the amount of funds each user can hold should be considered carefully. The counterfactual shock simulation also suggests that an unexpected event can significantly affect the platform's liquidity.

Moreover, due to the extreme interconnectedness between DeFi lending protocols, as demonstrated above, it can face the problem of systematic risk. Therefore, users should be careful while using these services. Governance token holders and regulators should consider these factors in the platforms' stability management. By focusing on internal factors that can be adjusted through governance and design of the platform, this study, in particular, is a good complement to other research focus on external factors such as price volatility (Cirikka, 2021; Gudgeon, Perez, et al., 2020b). So combined with previous studies, this study provides a complete picture of the determinants that affect funding liquidity in DeFi Lending.

Lastly, our results align with the literature that supposes purely "decentralization" of finance may be hard to fully achieve (Harwick & Caton, 2020; Zetzsche et al., 2020). Therefore, it is essential to regulate DeFi in an appropriate way to deal with its decentralized nature. DeFi can only replace intermediaries if it performs functions similar to and better than traditional ones. At the moment, DeFi Lending still has inherent problems that need to address.

References

Acemoglu, D., Ozdaglar, A., & Tahbaz-Salehi, A. (2015). Systemic risk and stability in financial networks. *American Economic Review*, *105*(2), 564-608.

Adrian, T., Kiff, J., & Shin, H. S. (2018). Liquidity, leverage, and regulation 10 years after the global financial crisis. *Annual Review of Financial Economics*, *10*, 1-24.

Adrian, T., Iyer, T., & Qureshi, M. S. (2022). Crypto prices move more in sync with stocks, posing new risks. IMF Blog. Available online: https://www. imf. org/en/Blogs/Articles/2022/01/11/crypto-prices-move-more-in-sync-with-stocks-posing-new-risks/(accessed on 11 January 2022)

Ajaz, T., & Kumar, A. S. (2018). Herding in crypto-currency markets. *Annals of Financial Economics*, *13*(02), 1850006.

Allen, F., & Gale, D. (2000). Financial contagion. *Journal of Political Economy*, *108*(1), 1-33.

Allen, F., & Gale, D. (2004). Financial fragility, liquidity, and asset prices. *Journal of the European Economic Association*, *2*(6), 1015-1048.

Amable, B., Chatelain, J.-B., & Ralf, K. (2004). Credit rationing, profit accumulation and economic growth. *Economics Letters*, *85*(3), 301-307.

Anscombe, F. J., & Glynn, W. J. (1983). Distribution of the kurtosis statistic b 2 for normal samples. *Biometrika*, *70*(1), 227-234.

Antonakakis, N., Chatziantoniou, I., & Gabauer, D. (2020). Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. *Journal of Risk and Financial Management*, *13*(4), 84.

Aramonte, S., Doerr, S., Huang, W., & Schrimpf, A. (2022). *DeFi lending: intermediation without information?*

Banerjee, A. V., & Moll, B. (2010). Why does misallocation persist? *American Economic Journal: Macroeconomics*, *2*(1), 189-206.

Basel Committee on Banking Supervision (BCBS), 2008, Principles for Sound Liquidity Risk Management and Supervision.

Bartoletti, M., Chiang, J. H.-y., & Lafuente, A. L. (2021). *SoK: lending pools in decentralized finance* International Conference on Financial Cryptography and Data Security,

Bencivenga, V. R., & Smith, B. D. (1993). Some consequences of credit rationing in an endogenous growth model. *Journal of Economic Dynamics and Control*, *17*(1-2), 97-122.

Berger, A. N., & Bouwman, C. H. (2009). Bank liquidity creation. *The Review of Financial Studies*, *22*(9), 3779-3837.

Berger, A. N., & Bouwman, C. H. S. (2017). Bank liquidity creation, monetary policy, and financial crises. *Journal of Financial Stability*, *30*, 139-155.

Bernanke, B. S., & Blinder, A. S. (1988). Credit, money, and aggregate demand. *The American Economic Review*, *78*(2), 435-439.

Bernanke, B. S., & Blinder, A. S. (1992). l992. the federal funds rate and the channels of monetary transmission. *American Economic Review*, *82*(4), 90-92.

Bernanke, B. S., & Gertler, M. (1995). Inside the black box: the credit channel of monetary policy transmission. *Journal of Economic Perspectives*, *9*(4), 27-48.

Besanko, D., & Thakor, A. V. (1995). 10 Relationship banking, deposit insurance and bank portfolio choice. *Capital Markets and Financial Intermediation*, 292.

Besley, T. (1994). How do market failures justify interventions in rural credit markets? *The World Bank Research Observer*, *9*(1), 27-47.

Beutler, T., Bichsel, R., Bruhin, A., & Danton, J. (2020). The impact of interest rate risk on bank lending. *Journal of Banking & Finance*, *115*.

BIS (2022), Non-bank financial intermediaries and financial stability.

Boot, A. W., & Greenbaum, S. (1993). Bank regulation, reputation and rents: theory and policy implications. *Capital Markets and Financial Intermediation*, *9*(1), 7-25.

Boudt, K., Paulus, E. C. S., & Rosenthal, D. W. R. (2017). Funding liquidity, market liquidity and TED spread: A two-regime model. *Journal of Empirical Finance*, *43*, 143-158.

Bouri, E., Das, M., Gupta, R., & Roubaud, D. (2018). Spillovers between Bitcoin and other assets during bear and bull markets. *Applied Economics*, *50*(55), 5935-5949.

Brissimis, S. N., & Delis, M. D. (2009). Identification of a loan supply function: A cross-country test for the existence of a bank lending channel. *Journal of International Financial Markets, Institutions and Money*, *19*(2), 321-335.

Brown, C. C., & Oates, W. E. (1987). Assistance to the Poor in a Federal System. *Journal of Public Economics*, *32*(3), 307-330.

Buterin, V. (2014). A next-generation smart contract and decentralized application platform. *white paper*, *3*(37).

Castro, C., Ramirez, J., & Velez, S. (2021). *Financial intermediation and risk in decentralized lending protocols*.

Cevik, E. I., Gunay, S., Zafar, M. W., Destek, M. A., Bugan, M. F., & Tuna, F. (2022). The impact of digital finance on the natural resource market: Evidence from DeFi, oil, and gold. *Resources Policy*, *79*, 103081.

Chen, & Bellavitis, C. (2020). Blockchain disruption and decentralized finance: The rise of decentralized business models [Article]. *Journal of Business Venturing Insights*, *13*, Article e00151.

Cirikka, S. (2021). Liquidity risks in the decentralized finance protocol Aave. In.

Craig, B. R., Jackson III, W. E., & Thomson, J. B. (2007). Small firm finance, credit rationing, and the impact of SBA-guaranteed lending on local economic growth. *Journal of Small Business Management*, *45*(1), 116-132.

D'Agostino, R. B. (1970). Transformation to normality of the null distribution of g1. *Biometrika*, 679-681.

Dang, V. D., & Huynh, J. (2022). Bank funding, market power, and the bank liquidity creation channel of monetary policy. *Research in International Business and Finance*, *59*.

De Nicoló, M. G., Boyd, J. H., & Jalal, A. M. (2006). *Bank risk-taking and competition revisited: New theory and new evidence*. International Monetary Fund.

DeFi Beyond the Hype: The Emerging World of Decentralized Finance. Gogel, D., 2021, May. In collab. with Wharton Blockchain and Digital Asset Project and World Economic Forum. Wharton. url: https://wifpr. wharton. upenn. edu/wp-content/uploads/2021/05/DeFi-Beyond-the-Hype. pdf.

Diamond, D. W., & Dybvig, P. H. (1983). Bank runs, deposit insurance, and liquidity. *Journal of Political Economy*, *91*(3), 401-419.

Diamond, D. W., & Rajan, R. G. (2005). Liquidity shortages and banking crises. *The Journal of Finance*, *60*(2), 615-647.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, *74*(366a), 427-431.

Diebold, F. X., & Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal*, *119*(534), 158-171.

Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, *28*(1), 57-66.

Diebold, F. X., & Yılmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, *182*(1), 119-134.

Ehrmann, M., Gambacorta, L., Martínez-Pagés, J., Sevestre, P., & Worms, A. (2001). Financial systems and the role of banks in monetary policy transmission in the euro area. *Available at SSRN 356660*.

Ehrmann, M., & Worms, A. (2004). Bank networks and monetary policy transmission. *Journal of the European Economic Association*, *2*(6), 1148-1171.

Elliott, G., Rothenberg, T. J., & James, H. (1996). Stock. 1996."Efficient tests for an autoregressive unit root.". *Econometrica*, *64*(4), 813-836.

Elliott, M., Golub, B., & Jackson, M. O. (2014). Financial networks and contagion. *American Economic Review*, *104*(10), 3115-3153.

Faqir-Rhazoui, Y., Arroyo, J., & Hassan, S. (2021). A comparative analysis of the platforms for decentralized autonomous organizations in the Ethereum blockchain. *Journal of Internet Services and Applications*, *12*(1), 1-20.

Fisher, T. J., & Gallagher, C. M. (2012). New weighted portmanteau statistics for time series goodness of fit testing. *Journal of the American Statistical Association*, *107*(498), 777-787.

Ghenimi, A., Chaibi, H., & Omri, M. A. B. (2020). Liquidity risk determinants: Islamic vs conventional banks. *International Journal of Law and Management*.

Grassi, L., Lanfranchi, D., Faes, A., & Renga, F. M. (2022). Do we still need financial intermediation? The case of decentralized finance–DeFi. *Qualitative Research in Accounting & Management*.

Gudgeon, L., Perez, D., Harz, D., Livshits, B., & Gervais, A. (2020a). *The Decentralized Financial Crisis* [Conference Paper]. Proceedings - 2020 Crypto Valley Conference on Blockchain Technology, CVCBT 2020,

Gudgeon, L., Perez, D., Harz, D., Livshits, B., & Gervais, A. (2020b). The decentralized financial crisis. 2020 Crypto Valley Conference on Blockchain Technology (CVCBT),

Gudgeon, L., Werner, S., Perez, D., & Knottenbelt, W. J. (2020). DeFi Protocols for Loanable Funds: Interest Rates, Liquidity and Market Efficiency.

Harvey, C. R., Ramachandran, A., & Santoro, J. (2021). *DeFi and the Future of Finance*. John Wiley & Sons.

Harwick, C., & Caton, J. (2020). What's holding back blockchain finance? On the possibility of decentralized autonomous finance. *The Quarterly Review of Economics and Finance*.

Hellmann, T. F., Murdock, K. C., & Stiglitz, J. E. (2000). Liberalization, moral hazard in banking, and prudential regulation: Are capital requirements enough? *American Economic Review*, *90*(1), 147-165.

Holmström, B., & Tirole, J. (1998). Private and public supply of liquidity. *Journal of Political Economy*, *106*(1), 1-40.

Hussain, M., & Bashir, U. (2019). Impact of monetary policy on bank lending: does market structure matter? *International Economic Journal*, *33*(4), 620-648.

IMF (2008), Global Financial Stability Report.

Jalal, R. N.-U.-D., Sargiacomo, M., Sahar, N. U., & Fayyaz, U.-E. (2020). Herding behavior and cryptocurrency: Market asymmetries, inter-dependency and intra-dependency. *The Journal of Asian Finance, Economics and Business*, *7*(7), 27-34.

Jarque, C. M., & Bera, A. K. (1980). Efficient tests for normality, homoscedasticity and serial independence of regression residuals. *Economics Letters*, *6*(3), 255-259.

Jordan, S., & Philips, A. Q. (2018). Cointegration testing and dynamic simulations of autoregressive distributed lag models. *The Stata Journal*, *18*(4), 902-923.

Karim, S., Lucey, B. M., Naeem, M. A., & Uddin, G. S. (2022). Examining the interrelatedness of NFTs, DeFi tokens and cryptocurrencies. *Finance Research Letters*, *47*, 102696.

Koop, G., & Korobilis, D. (2013). Large time-varying parameter VARs. *Journal of Econometrics*, *177*(2), 185-198.

Koop, G., Pesaran, M. H., & Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics*, *74*(1), 119-147.

Lee, S. H. (2013). Systemic liquidity shortages and interbank network structures. *Journal of Financial Stability*, *9*(1), 1-12.

Lucey, B. M., Vigne, S. A., Yarovaya, L., & Wang, Y. (2022). The cryptocurrency uncertainty index. *Finance Research Letters*, *45*, 102147.

Marozva, G. (2015). Liquidity and bank performance. *International Business & Economics Research Journal (IBER)*, *14*(3), 453-562.

Matutes, C., & Vives, X. (2000). Imperfect competition, risk taking, and regulation in banking. *European Economic Review*, *44*(1), 1-34.

McKinnon, R. (1973). *Money and capital in economic development*. Washington, DC: Brookings Institution.

Meegan, X., & Koens, T. (2021). *Lessons Learned from Decentralised Finance (DeFi)*.

Mishkin, F. S. (1999). Financial consolidation: Dangers and opportunities. *Journal of Banking & Finance*, *23*(2-4), 675-691.

Moussa, M. A. B. (2015). The determinants of bank liquidity: Case of Tunisia. *International Journal of Economics and Financial Issues*, *5*(1), 249.

OECD (2022), Why Decentralised Finance (DeFi) Matters and the Policy Implications,

Pahlavani, M., Wilson, E., & Worthington, A. C. (2005). Trade-GDP nexus in Iran: An application of the autoregressive distributed lag (ARDL) model.

Pesaran, H. H., & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics Letters*, *58*(1), 17-29.

Pesaran, M. H., Shin, Y., (1999). An autoregressive distributed lag modeling approach to cointegration analysis. Econometrics and Economic Theory in the 20th Century: The Ragnar Frisch Centennial Symposium in (ed) S Strom, chapter 11, Cambridge University Press, Cambridge

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, *16*(3), 289-326.

Phillips, P. C., & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika*, *75*(2), 335-346.

Piñeiro-Chousa, J., López-Cabarcos, M. Á., Sevic, A., & González-López, I. (2022). A preliminary assessment of the performance of DeFi cryptocurrencies in relation to other financial assets, volatility, and user-generated content. *Technological Forecasting and Social Change*, *181*, 121740.

Popescu, A.-D. (2020). Decentralized finance (defi)–the lego of finance. *Social Sciences and Education Research Review*, *7*(1), 321-349.

Qiao, X., Zhu, H., Tang, Y., & Peng, C. (2023). Time-frequency extreme risk spillover network of cryptocurrency coins, DeFi tokens and NFTs. *Finance Research Letters*, *51*, 103489.

Saengchote, K. (2021a). Decentralized lending and its users: Insights from Compound. *Available at SSRN 3925344*.

Saengchote, K. (2021b). Where do DeFi stablecoins go? A closer look at what DeFi composability really means. *A closer look at what DeFi composability really means.(July 26, 2021)*.

Sarkodie, S. A., & Owusu, P. A. (2020). How to apply the novel dynamic ARDL simulations (dynardl) and Kernel-based regularized least squares (krls). *MethodsX*, *7*, 101160.

Schär, F. (2021). Decentralized finance: On blockchain-and smart contract-based financial markets. *FRB of St. Louis Review*, *103*, 153-174.

Schär, F., & Gronde, F. (2021). *Flash Loans and Decentralized Lending Protocols: An In-Depth Analysis*.

Shaw, E. S. (1973). *Financial deepening in economic development*.

Shepherd, W. G. (1970). *Market power and economic welfare: an introduction*.

Shrestha, M. B., & Bhatta, G. R. (2018). Selecting appropriate methodological framework for time series data analysis. *The Journal of Finance and Data Science*, *4*(2), 71-89.

Stiglitz, J. E., & Weiss, A. (1981). Credit rationing in markets with imperfect information. *The American Economic Review*, *71*(3), 393-410.

Sun, X. (2022). Liquidity Risks in Lending Protocols (LPs): Evidence from Aave Protocol. *arXiv preprint arXiv:2206.11973*.

Tolmach, P., Li, Y., Lin, S.-W., & Liu, Y. (2021). Formal analysis of composable DeFi protocols. Financial Cryptography and Data Security. FC 2021 International Workshops: CoDecFin, DeFi, VOTING, and WTSC, Virtual Event, March 5, 2021, Revised Selected Papers 25,

Ugolini, A., Reboredo, J. C., & Mensi, W. (2023). Connectedness between DeFi, cryptocurrency, stock, and safe-haven assets. *Finance Research Letters*, 103692.

Umar, Z., Polat, O., Choi, S.-Y., & Teplova, T. (2022). Dynamic connectedness between non-fungible tokens, decentralized finance, and conventional financial assets in a time-frequency framework. *Pacific-Basin Finance Journal*, *76*, 101876.

Van den End, J. W. (2016). A macroprudential approach to address liquidity risk with the loan-to-deposit ratio. *The European Journal of Finance*, *22*(3), 237-253.

Vidal-Tomás, D., Ibáñez, A. M., & Farinós, J. E. (2019). Herding in the cryptocurrency market: CSSD and CSAD approaches. *Finance Research Letters*, *30*, 181-186.

Vodova, P. (2011). Liquidity of Czech commercial banks and its determinants. *International Journal of Mathematical Models and Methods in Applied Sciences*, *5*(6), 1060-1067.

von Wachter, V., Jensen, J. R., & Ross, O. (2021). Measuring asset composability as a proxy for defi integration. Financial Cryptography and Data Security. FC 2021 International Workshops: CoDecFin, DeFi, VOTING, and WTSC, Virtual Event, March 5, 2021, Revised Selected Papers 25,

Xu, J., & Vadgama, N. (2022). From banks to DeFi: the evolution of the lending market. In *Enabling the Internet of Value* (pp. 53-66). Springer.

Yu, J., & Fu, J. (2021). Credit rationing, innovation, and productivity: Evidence from small-and medium-sized enterprises in China. *Economic Modelling*, *97*, 220-230.

Zetzsche, D. A., Arner, D. W., & Buckley, R. P. (2020). Decentralized Finance. *Journal of Financial Regulation*, *6*(2), 172-203.

Zhang, J., & Deng, X. (2020). Interest rate liberalization and bank liquidity creation: evidence from China. *China Finance Review International*, *10*(4), 377-391.

Zheng, Z., Xie, S., Dai, H.-N., Chen, W., Chen, X., Weng, J., & Imran, M. (2020). An overview on smart contracts: Challenges, advances and platforms. *Future Generation Computer Systems*, *105*, 475-491.

Table 1. Variable measurement

Variable	Notation	Measurement
Dependent variable		
Funding Liquidity (FL)	AL	Available liquidity$_t$ = Total deposit$_t$ - Total borrow$_t$ In which, Funding liquidity$_t$ is the available liquidity of a DeFi lending platform on date t. Total deposit$_t$ is the average value of funds locked into the protocol's smart contracts on date t. Total borrow$_t$ is the average value of outstanding borrows on the protocol on date t.
	U	Utilizationrate$_{i,t}$ = Total borrow$_{i,t}$/ Total deposit$_{i,t}$ where, Total borrow$_{i,t}$ represents the total amount borrowed of token i at time t, Total deposit$_{i,t}$ is the total amount supply of token i at time t in the lending pool.
Independent variables		
Interest rate	VB	Collect from the platform in percentage (APY). There are three types of interest rate in Aave, including: deposit rate, stable borrow rate, variable borrow rate[10]. This study use the variable borrow rate to match with the hypothesis.
Market power of users	HHI	The Herfindahl-Hirschman Index (HHI) is a common measure in order to assess the level of industry/sectoral concentration. This index has been applied in many industry and research. This study applies the HHI index to estimate the user

[10] https://docs.aave.com/risk/v/aave-v2/liquidity-risk/borrow-interest-rate

		concentration level in DeFi lending protocol. Formula: $$\text{HHI} = s_1{}^2 + s_2{}^2 + \ldots + s_n{}^2$$ where s_i: the percentage amount of a token hold by depositor i compared to the total amount of that token in the lending pool. n: number of accounts have token deposit in the pool. HHI Index can vary from close to 0 to 10,000. A lower values on the HHI indicates a less concentrated market; a HHI value of less than 1,500 is seen as a competitive market, between 1,500 and 2,500 is considered moderately concentrated, and above 2,500 is highly concentrated.
Protocol depositors	De	The logarithm of total numbers of depositors in the lending pool for each token.
Protocol borrowers	Bo	The logarithm of total numbers of borrowers in the lending pool for each token.

Table 2: Summary statistics

	AAVE	Compound	MakerDAO
Mean	-0.004	-0.002	0.001
Variance	0.023	1.184	1.256
Skewness	0.411***	-0.124	0.398***
	(0.000)	(0.171)	(0.000)
Ex.Kurtosis	8.197***	349.643***	355.670***
	(0.000)	(0.000)	(0.000)
JB	2058.674***	3708265.383***	3837217.479***
	(0.000)	(0.000)	(0.000)
ERS	-8.511***	-17.411***	-20.455***
	(0.000)	(0.000)	(0.000)
Q(10)	36.001***	178.369***	187.791***
	(0.000)	(0.000)	(0.000)
Q2(10)	195.060***	181.726***	181.798***
	(0.000)	(0.000)	(0.000)

*Notes: *, **, and *** denote significance at 10%, 5% and 1% significance levels respectively. Skewness is tested using the D'Agostino (1970) test; Kurtosis: Anscombe and Glynn (1983) test; JB: Jarque and Bera (1980) normality test; ERS: Elliott et al. (1996) unit root test; Q(10) and Q^2(10): Fisher and Gallagher (2012) weighted portmanteau test.*

Table 3: Average Liquidity Connectedness from TVP-VAR Model

	From (i)			
To (j)	**AAVE**	**Compound**	**MakerDAO**	**Total FROM**
AAVE	58.70	15.35	25.96	41.30
Compound	19.42	61.33	19.25	38.67
MakerDAO	33.07	15.86	51.07	48.93
Total TO	52.49	31.21	45.21	128.91
NET	11.19	-7.47	-3.72	**64.46/42.97** cTCI/TCI

Notes: AAVE, Compound and MakerDAO is the funding liquidity measure for AAVE, Compound and MakerDAO platforms, respectively. Each column of Table 3 corresponds to the forecast error variance that has been contributed to a single variable from the other variables, and each row shows the individual contribution of each variable to the forecast error variance of all other variables in the network. Total TO is the total directional connectedness TO others, which means the spillovers from variable i to all other variables j, excluding its own spillovers. Total FROM indicates the total directional connectedness FROM others, which means the shock that variable i receives from all other variables j, excluding its own spillovers. Net connectedness (NET) is computed by subtracting the Total FROM from the Total TO amount. Values reported in the Table are average variance decompositions based on 10-step ahead forecasts from a TVP-VAR model with lag length chosen via the Bayesian information criterion (BIC). Total Connectedness Index (TCI) is the value in bold.

Table 4: Descriptive statistics (5-minute data)

Token	Variable	Obs	Mean	Std. Dev.	Min	Max
DAI	U	166,167	0.7144	0.1491	0.1931	0.9997
	AL	166,167	275,000,000	162,000,000	6,655	506,000,000
	HHI	166,167	0.1327	0.0580	0.0219	0.2825
	VB	166,167	6.46	6.90	1.65	78.90
	De	166,167	3653.00	1033.60	612	4443
	Bo	166,167	1881.65	521.45	311	2390
USDT	U	166,167	0.8023	0.1254	0.3634	1
	AL	166,167	169,000,000	123,000,000	0	607,000,000
	HHI	166,167	0.1362	0.0506	0.0350	0.3343
	VB	166,167	7.31	8.52	1.79	64.00
	De	166,167	2052.60	715.60	268	2695
	Bo	166,167	2233.32	717.41	292	2915
USDC	U	166,167	0.7566	0.1853	0.1848	1.0000
	AL	166,167	622,000,000	425,000,000	112	1,560,000,000
	HHI	166,167	0.1021	0.0649	0.0105	0.2819
	VB	166,167	6.02	6.97	1.29	64.00
	De	166,167	4723.50	1735.83	445	6795
	Bo	166,167	4372.49	3128.54	409	13874
WBTC	U	166,167	0.0460	0.0261	0.0137	0.2426
	AL	166,167	1,150,000,000	564,000,000	47,600,000	2,250,000,000
	HHI	166,167	0.0829	0.0392	0.0205	0.2109
	VB	166,167	0.57	0.32	0.17	2.99
	De	166,167	1778.26	552.63	369	2309
	Bo	166,167	227.81	69.83	37	331
WETH	U	166,167	0.1376	0.1433	0.0140	0.4983
	AL	166,167	2,980,000,000	2,190,000,000	48,300,000	9,090,000,000
	HHI	166,167	0.0569	0.0318	0.0095	0.1150

	VB	166,167	1.06	0.78	0.18	3.83
	De	166,167	7818.15	3098.28	972	12729
	Bo	166,167	758.86	311.41	128	1373

Notes: U, AL, VB, HHI, De, and Bo indicate available liquidity in each lending pool, utilization rate in each lending pool, variable borrow interest rate, market power of users, numbers of depositors, and numbers of borrowers in each lending pool for each token, respectively. Measures of these variables are defined in Table 1.

Table 5: Unit Root Test Results (5-minute data)

DAI

Variable	Level.ADF	Δ.ADF	Level.PP	Δ.PP
FL	-2.299	-457.642***	-1.830	-458.234***
VB	-18.582***	-458.347***	-16.647***	-459.853***
HHI	-2.079	-383.160***	-2.322	-384.089***
De	-30.574***	-397.951***	-25.902***	-406.236***
Bo	-19.202***	-395.354***	-15.785***	-404.249***

USDC

Variable	Level.ADF	Δ.ADF	Level.PP	Δ.PP
FL	-1.587	-436.232***	-1.427	-435.996***
VB	-22.891***	-468.467***	-19.343***	-475.554***
HHI	-1.238	-364.907***	-1.548	-367.645***
De	-19.579***	-395.737***	-16.362***	-403.276***
Bo	39.615	-236.233***	12.198	-363.932***

USDT

Variable	Level.ADF	Δ.ADF	Level.PP	Δ.PP
FL	-8.841***	-435.407***	-5.391***	-437.807***
VB	-29.503***	-432.858***	-25.954***	-441.022***
HHI	-3.066	-407.398***	-3.666	-407.501***
De	-15.994***	-404.533***	-13.642	-410.528***
Bo	-19.398***	-388.931***	-14.833***	-404.447***

WBTC

Variable	Level.ADF	Δ.ADF	Level.PP	Δ.PP
FL	-1.405	-33.269***	-1.244	-83.043***
VB	-4.697***	-400.343***	-5.658***	-407.327***
HHI	-1.498	-27.600***	-0.363	-71.667***
De	-13.229***	-404.524***	-12.258***	-406.032***
Bo	-3.808***	-407.701***	-3.809***	-407.701***

WETH

Variable	Level.ADF	Δ.ADF	Level.PP	Δ.PP
FL	-0.147	-370.374***	-0.549	-375.941***
VB	-2.290	-366.254***	-2.797	-371.055***
HHI	-1.812	-465.796***	-1.701	-462.843***
De	-14.921***	-388.269***	-12.104***	-397.293***
Bo	-0.459	-408.783***	-0.458	-408.800***

*Notes: Level.ADF and Δ.ADF represent the level and first-*difference *of the Augmented-Dickey Fuller unit root test (Dickey & Fuller, 1979); Level.PP and Δ.PP represent the level and first-difference of Phillips-Perron unit root test (Phillips & Perron, 1988). ***denotes rejection of the null hypothesis of no unit root at 1% significance level. FL, VB, HHI, De, and Bo indicate funding liquidity in each lending pool, variable borrow interest rate, market power of users, numbers of depositors, and numbers of borrowers in each lending pool for each token, respectively. Measures of these variables are defined in Table 1.*

Table 6. Linear ARDL model: Bounds test for co-integration analysis (5-minute data)

	Market Phase	F_statistic	Critical value Significance	Bounds I0 Bound	I1 Bound
DAI	Bull 1	986.724	10%	2.448	3.507
			5%	2.863	3.995
			1%	3.746	5.013
	Bear 1	1023.927	10%	2.448	3.507
			5%	2.863	3.995
			1%	3.746	5.013
	Bull 2	485.818	10%	2.449	3.507
			5%	2.864	3.995
			1%	3.746	5.013
	Bear 2	1570.139	10%	2.45	3.507
			5%	2.865	3.995
			1%	3.747	5.012
USDC	Bull 1	952.695	10%	2.448	3.507
			5%	2.863	3.995
			1%	3.746	5.013
	Bear 1	292.235	10%	2.447	3.507
			5%	2.862	3.995

			1%	3.745	5.014
			10%	2.449	3.507
	Bull 2	420.974	5%	2.864	3.995
			1%	3.747	5.013
			10%	2.45	3.507
	Bear 2	5136.233	5%	2.865	3.995
			1%	3.747	5.012
			10%	2.448	3.507
	Bull 1	1084.889	5%	2.864	3.995
			1%	3.746	5.013
			10%	2.447	3.507
	Bear 1	432.726	5%	2.862	3.995
USDT			1%	3.744	5.014
			10%	2.448	3.507
	Bull 2	349.012	5%	2.863	3.995
			1%	3.745	5.013
			10%	2.449	3.507
	Bear 2	804.663	5%	2.864	3.995
			1%	3.746	5.012
	Bull 1	339.029	5%	2.863	3.995
			1%	3.745	5.013
			10%	2.449	3.507
	Bear 1	5695.532	5%	2.865	3.995
WETH			1%	3.747	5.013
			10%	2.449	3.507
	Bull 2	1479.931	5%	2.864	3.995
			1%	3.747	5.013
			10%	2.45	3.507
	Bear 2	3350.87	5%	2.865	3.995
			1%	3.748	5.012
			10%	2.448	3.507
	Bull 1	475.272	5%	2.863	3.995
			1%	3.746	5.013
			10%	2.448	3.507
	Bear 1	356.852	5%	2.864	3.995
WBTC			1%	3.746	5.013
			10%	2.449	3.507
	Bull 2	587.891	5%	2.865	3.995
			1%	3.747	5.013
			10%	2.459	3.507
	Bear 2	14730.43	5%	2.865	3.995
			1%	3.748	5.012

Table 7. Linear ARDL model for 5-minute data

DAI – 5m				
VARIABLES	**Bull 1**	**Bear 1**	**Bull 2**	**Bear 2**
HHI	-0.265***	1.469***	0.858***	0.783***
	(0.031)	(0.084)	(0.034)	(0.002)
VB	0.294***	0.594***	0.293***	20.634***
	(0.005)	(0.014)	(0.008)	(0.234)
De	-0.021	-0.460**	-0.134**	0.268***
	(0.107)	(0.189)	(0.056)	(0.021)
Bo	0.313***	0.134	0.263***	0.054***
	(0.071)	(0.165)	(0.090)	(0.014)
Observations	37,980	21,854	32,797	73,421
R^2	0.833	0.587	0.673	0.994
Adjusted R^2	0.8324	0.586	0.6723	0.9939
Diagnostic tests				
LM test	0.7204	0.8418	0.8801	0.7833
CUSUM	Stable	Stable	Stable	Stable

USDC – 5m				
	Bull 1	**Bear 1**	**Bull 2**	**Bear 2**
HHI	-0.287***	0.193***	-0.240***	0.086***
	(0.063)	(0.022)	(0.020)	(0.001)
VB	0.198***	0.281***	0.195***	19.189***
	(0.005)	(0.025)	(0.006)	(0.120)
De	-0.387***	-0.417***	-0.378***	0.054***
	(0.107)	(0.160)	(0.040)	(0.012)
Bo	0.305***	0.843***	0.267***	0.001
	(0.092)	(0.159)	(0.052)	(0.003)
Observations	37,983	21,852	32,812	73,401

R^2	0.640	0.223	0.835	0.997
Adjusted R^2	0.639	0.220	0.834	0.997
Diagnostic tests				
LM test	0.7234	0.1187	0.9189	0.7262
CUSUM	Stable	Stable	Stable	Stable

USDT - 5m				
	Bull 1	**Bear 1**	**Bull 2**	**Bear 2**
HHI	0.223***	-0.623***	0.459***	-1.546***
	(0.018)	(0.055)	(0.039)	(0.045)
VB	0.248***	0.223***	0.243***	0.355***
	(0.006)	(0.011)	(0.008)	(0.014)
De	-0.261*	-0.450	-0.161	-2.934***
	(0.145)	(0.373)	(0.494)	(0.535)
Bo	0.785***	0.899***	0.640	1.265***
	(0.128)	(0.289)	(0.494)	(0.427)
Observations	37,984	21,852	32,796	73,397
R^2	0.664	0.558	0.549	0.482
Adjusted R^2	0.663	0.555	0.548	0.481
Diagnostic tests				
LM test	0.9383	0.3185	0.6203	0.2215
CUSUM	Stable	Stable	Stable	Stable

WETH - 5m				
VARIABLES	Bull 1	Bear 1	Bull 2	Bear 2
HHI	0.012***	0.007***	0.004***	-0.293***
	(0.002)	(0.000)	(0.000)	(0.044)
VB	5.384***	8.037***	7.398***	4.730***
	(0.131)	(0.080)	(0.086)	(0.077)

De	0.001	0.003***	0.004***	-0.080
	(0.001)	(0.001)	(0.001)	(0.114)
Bo	0.000	0.000	0.000**	0.110***
	(0.000)	(0.000)	(0.000)	(0.009)
Observations	37,980	21,865	32,796	73,421
R^2	1.000	1.000	1.000	0.235
Adjusted R^2	1.000	1.000	1.000	0.234
Diagnostic tests				
LM test	0.6017	0.6852	0.3311	0.458
CUSUM	Stable	Stable	Stable	Stable

WBTC - 5m				
VARIABLES	**Bull 1**	**Bear 1**	**Bull 2**	**Bear 2**
HHI	0.0002***	-0.0005***	0.0020***	0.0011***
	(0.000)	(0.000)	(0.000)	(0.001)
VB	7.104***	7.807***	6.239***	8.118***
	(0.155)	(0.185)	(0.133)	(0.030)
De	0.0002***	0.0000	0.0008***	0.0010***
	(0.000)	(0.000)	(0.000)	(0.000)
Bo	0.0000	0.0000	0.0000**	0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	37,982	21,865	32,818	73,424
R^2	1.0000	1.0000	1.0000	0.9998
Adjusted R^2	1.0000	1.0000	1.0000	0.9998
Diagnostic tests				
LM test	0.9999	0.9976	0.7091	0.9723
CUSUM	Stable	Stable	Stable	Stable

The dependent variable is funding liquidity of each token pool in the DeFi Lending platform, which is measured by the Utilization rate for that token. HHI, VB, De, and Bo indicate market power of users, variable borrow interest rate, numbers of depositors, and numbers of borrowers in each *lending pool for each token, respectively. Measures of these variables are defined in Table 1. Standard errors are reported in parentheses. *, **,and *** indicate significance levels of the coefficients at the 10%, 5% and 1% levels, respectively.*

Table 8. Linear ARDL model: Bounds test for co-integration analysis (1-hour data)

	Market Phase	F_statistic	Critical value Significance	Bounds	
				I0 Bound	I1 Bound
DAI	Bull 1	818.391	10%	2.451	3.509
			5%	2.867	3.998
			1%	3.753	5.020
	Bear 1	1312.646	10%	2.453	3.511
			5%	2.870	4.001
			1%	3.758	5.025
	Bull 2	1823.057	10%	2.452	3.510
			5%	2.868	3.999
			1%	3.754	5.021
	Bear 2	420.215	10%	2.450	3.508
			5%	2.865	3.996
			1%	3.749	5.016
USDC	Bull 1	2656.624	10%	2.452	3.509
			5%	2.868	3.998
			1%	3.754	5.019
	Bear 1	469.405	10%	2.453	3.511
			5%	2.870	4.001
			1%	3.758	5.025
	Bull 2	303.064	10%	2.448	3.509
			5%	2.864	3.999
			1%	3.750	5.022
	Bear 2	882.565	10%	2.451	3.508

			5%	2.866	3.996
			1%	3.750	5.016
USDT	Bull 1	645.906	10%	2.450	3.509
			5%	2.866	3.998
			1%	3.752	5.020
	Bear 1	269.691	10%	2.450	3.511
			5%	2.867	4.001
			1%	3.755	5.026
	Bull 2	581.269	10%	2.451	3.509
			5%	2.868	3.999
			1%	3.754	5.021
	Bear 2	2115.454	10%	2.451	3.508
			5%	2.867	3.996
			1%	3.751	5.016
WETH	Bull 1	5.70E+06	10%	2.452	3.509
			5%	2.868	3.998
			1%	3.754	3.754
	Bear 1	972.949	10%	2.453	3.511
			5%	2.870	4.001
			1%	3.758	5.025
	Bull 2	1.05E+07	10%	2.450	3.509
			5%	2.866	3.999
			1%	3.753	5.021
	Bear 2	2307.254	10%	2.451	3.508
			5%	2.867	3.996
			1%	3.751	5.016
WBTC	Bull 1	542.647	10%	2.450	3.509
			5%	2.866	3.998
			1%	3.752	5.020
	Bear 1	1.18E+10	10%	2.453	3.511

			5%	2.870	4.001
			1%	3.758	5.025
	Bull 2	192.765	10%	2.448	3.509
			5%	2.864	3.999
			1%	3.750	5.022
	Bear 2	9.80E+06	10%	2.451	3.508
			5%	2.867	3.996
			1%	3.751	5.016

Table 9. Linear ARDL model for 1-hourly data

DAI – 1 hour				
VARIABLES	**Bull 1**	**Bear 1**	**Bull 2**	**Bear 2**
HHI	-0.294***	1.608***	0.485***	0.050***
	(0.028)	(0.075)	(0.053)	(0.004)
VB	0.028***	0.308***	0.293***	22.584***
	(0.004)	(0.011)	(0.006)	(0.057)
De	-0.193***	-0.600***	-0.085	0.281***
	(0.074)	(0.134)	(0.112)	(0.057)
Bo	0.395***	0.185*	0.139*	0.163***
	(0.074)	(0.073)	(0.058)	(0.028)
Observations	3,164	1,822	2,734	6,116
R-squared	0.899	0.783	0.842	0.996
Adj R-squared	0.899	0.783	0.842	0.996
Diagnostic tests				
LM test	0.5274	0.6343	0.1966	0.2363
CUSUM	Stable	Stable	Stable	Stable

USDC – 1 hour				
VARIABLES	**Bull 1**	**Bear 1**	**Bull 2**	**Bear 2**
HHI	-0.139**	0.213***	-0.110***	0.135***
	(0.070)	(0.025)	(0.038)	0.005
VB	0.194***	0.194***	0.188***	23.520***
	(0.004)	(0.016)	(0.006)	0.034
De	-0.311***	-0.446***	-0.367**	0.098***
	(0.079)	(0.105)	(0.195)	(0.017)
Bo	0.500***	0.308***	0.379***	0.001
	(0.073)	(0.091)	(0.140)	(0.003)
Observations	3,166	1,822	2,731	6,117
R-squared	0.808	0.564	0.850	0.999
Adj R-squared	0.808	0.563	0.849	0.999
Diagnostic tests				
LM test	0.5354	0.881	0.8147	0.5118
CUSUM	Stable	Stable	Stable	Stable

USDT – 1 hour				
VARIABLES	**Bull 1**	**Bear 1**	**Bull 2**	**Bear 2**
HHI	0.144***	-0.618***	0.536***	-1.810***
	(0.046)	(0.088)	(0.064)	(0.042)
VB	0.199***	0.219***	0.281***	0.403***
	(0.004)	(0.013)	(0.009)	(0.013)
De	-0.255**	0.137	-0.340	-3.769***
	(0.128)	(0.311)	(0.333)	(0.354)
Bo	0.445***	0.830***	0.569*	1.137***
	(0.104)	(0.261)	(0.335)	(0.287)
Observations	3,164	1,821	2,733	6,118
R-squared	0.848	0.749	0.753	0.757

Adj R-squared	0.847	0.747	0.753	0.756
Diagnostic tests				
LM test	0.4972	0.1602	0.3003	0.653
CUSUM	Stable	Stable	Stable	Stable

WETH – 1hour				
VARIABLES	**Bull 1**	**Bear 1**	**Bull 2**	**Bear 2**
HHI	0.0178***	0.0066***	0.0070***	-0.3789***
	(0.0034)	(0.0002)	(0.0003)	(0.0505)
VB	8.1384***	8.1426***	8.1417***	5.7584***
	(0.0030)	(0.0012)	(0.0023)	(0.1228)
De	0.0014	0.0026***	0.0017***	-0.0668
	(0.0011)	(0.0005)	(0.0005)	(0.1352)
Bo	-0.0002	0.0000	0.0000	0.2101***
	(0.0004)	(0.0001)	(0.0001)	(0.0328)
Observations	3,166	1,822	2,728	6,118
R-squared	1.000	1.000	1.000	0.654
Adj R-squared	1.000	1.000	1.000	0.653
Diagnostic tests				
LM test	0.7947	0.8504	0.7732	0.9131
CUSUM	Stable	Stable	Stable	Stable

WBTC – 1hour				
VARIABLES	**Bull 1**	**Bear 1**	**Bull 2**	**Bear 2**
HHI	0.0003***	-0.0005***	0.0028***	0.0011***
	(0.0000)	(0.0000)	(0.0001)	(0.0001)
VB	8.1256***	8.1255***	8.1412***	8.1211***

	(0.0001)	(0.0001)	(0.0013)	(0.0022)
De	0.0002***	0.0000	0.0020***	0.0009***
	(0.0000)	(0.0000)	(0.0002)	(0.0004)
Bo	0.0000**	0.0000	0.0001	0.0002*
	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Observations	3,163	1,822	2,730	6,118
R-squared	1.000	1.000	1.000	1.000
Adj R-squared	1.000	1.000	1.000	1.000
Diagnostic tests				
LM test	0.7912	0.6786	0.1479	0.3548
CUSUM	Stable	Stable	Stable	Stable

*The dependent variable is funding liquidity of each token pool in the DeFi Lending platform, which is measured by the Utilization rate for that token. HHI, VB, De, and Bo indicate market power of users, variable borrow interest rate, numbers of depositors, and numbers of borrowers in each lending pool for each token, respectively. Measures of these variables are defined in Table 1. Standard errors are reported in parentheses. *, **,and *** indicate significance levels of the coefficients at the 10%, 5% and 1% levels, respectively.*

Figure 1: Crypto Fear and Greed Index

Market Phase	Period
Bull 1	1/1/2021 – 12/05/2021
Bear 1	13/05/2021 – 27/07/2021
Bull 2	28/07/2021 – 18/11/2021
Bear 2	19/11/2021 – 31/07/2022

Data Source: https://alternative.me/crypto/fear-and-greed-index/

Figure 2: Empirical scheme

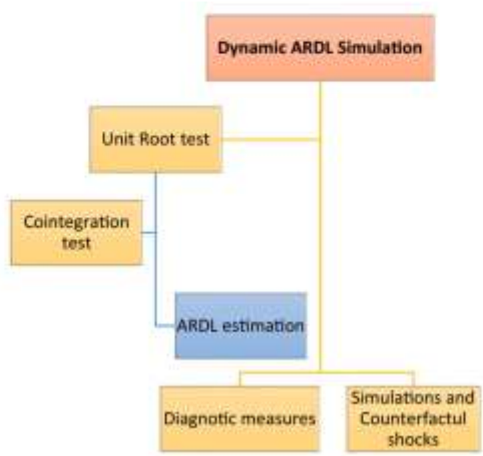


Figure 3: Funding Liquidity in top three Lending protocols

Figure 4: First difference of Funding Liquidity variable in the top three Lending protocols

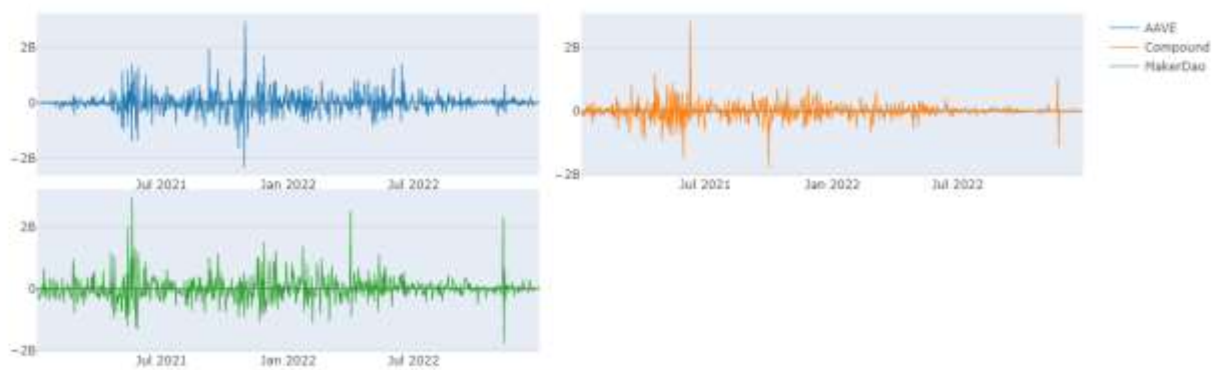
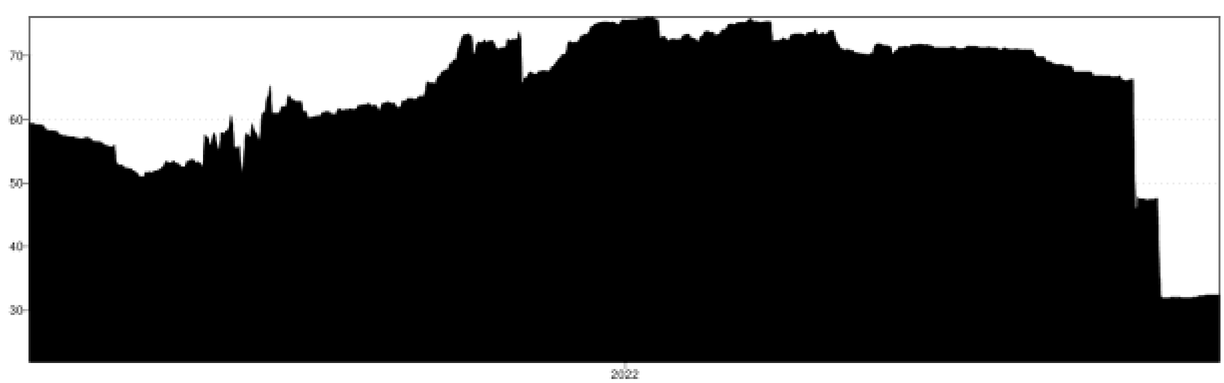
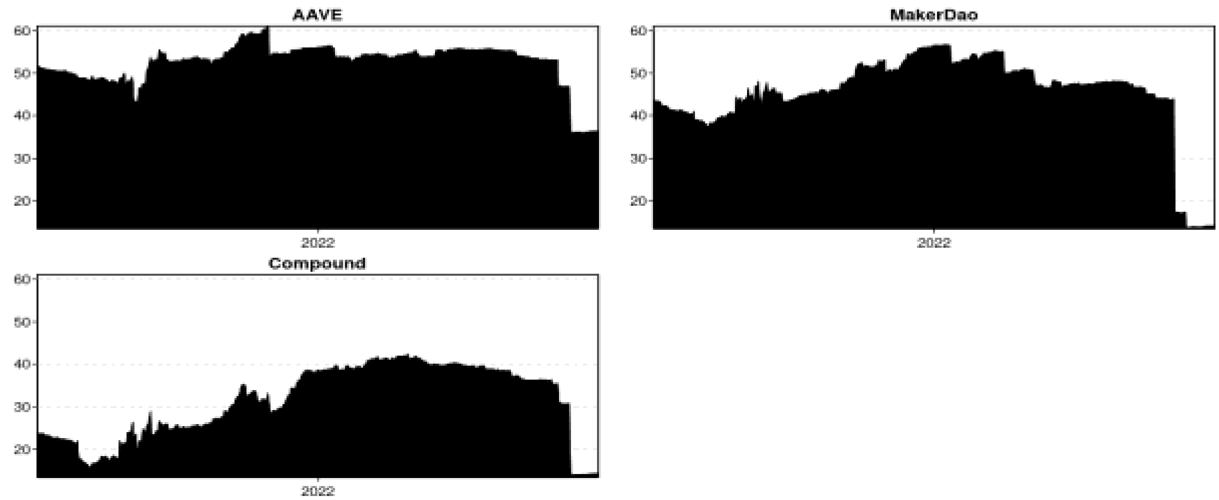


Figure 5: Dynamic total connectedness



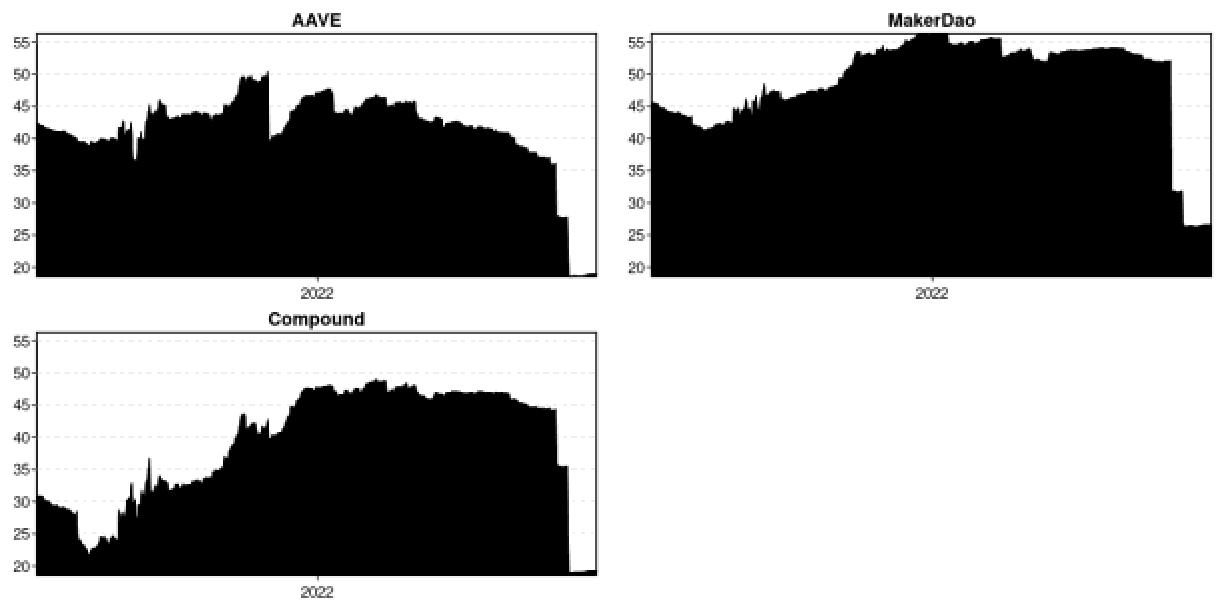
Notes: The graph plots the evolution of the total directional connectedness index (TCI) of the three DeFi Lending platforms - Aave, Compound, MakerDAO, as determined by the TVP-VAR model with lag length as selected by the Bayesian information criterion (BIC).

Figure 6: Total Directional Liquidity Connectedness TO other platfoms



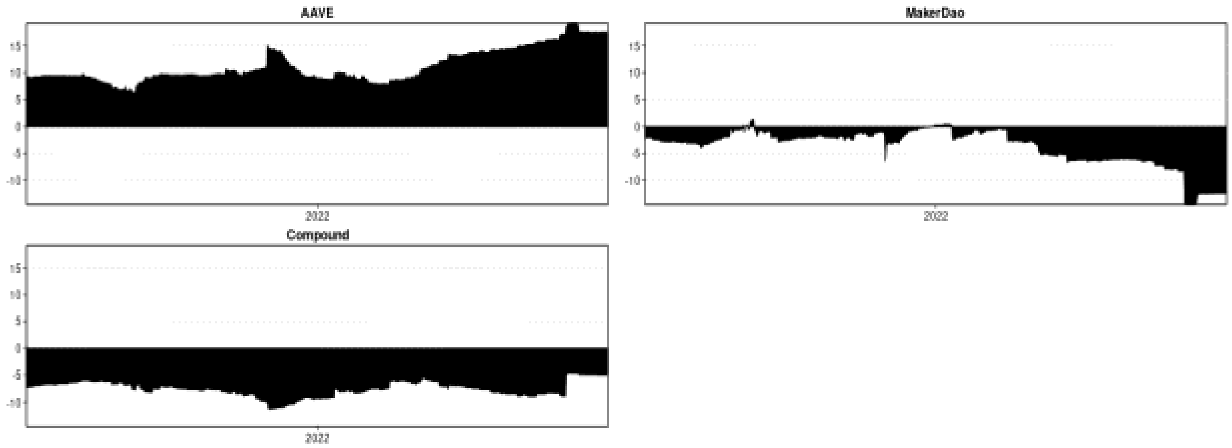
Notes: This graph plots the evolution of the total directional liquidity connectedness of each of the three DeFi Lending platforms (i.e., Aave, Compound, MakerDAO) TO the other two markets, as determined by the TVP-VAR model with lag length as selected by the Bayesian information criterion (BIC).

Figure 7: Total Directional Liquidity Connectedness FROM other platforms



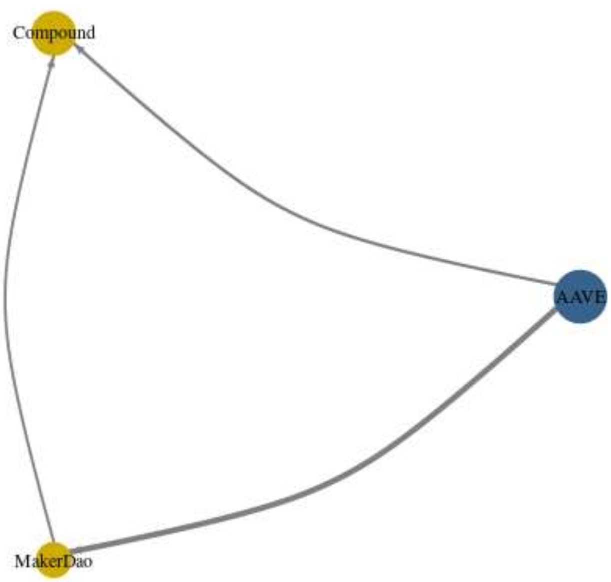
Notes: This graph plots the evolution of the total directional liquidity connectedness of each of the three DeFi Lending platforms (i.e., Aave, Compound, MakerDAO) FROM the other two markets, as determined by the TVP-VAR model with lag length as selected by the Bayesian information criterion (BIC).

Figure 8: Net total directional connectedness



Notes: This graph plots the evolution of the net directional liquidity connectedness of each of the three DeFi Lending platforms (i.e., Aave, Compound, MakerDAO), calculated by subtracting the FROM directional connectedness from the TO directional connectedness as determined by the TVP-VAR model with lag length as selected by the Bayesian information criterion (BIC).

Figure 9: Network plot in liquidity spillovers



Notes: This figure illustrates the net directional spillovers among all possible pairs of variables. The blue color node shows that a variable is a net transmitter of shocks to other variables, while yellow nodes indicate that it is a receiver of shocks from other variables. The thickness of the arrows reflects the magnitude of the average spillover between each pair. This was determined based on the generalized forecast error variance decomposition (GFEVD) from the estimation of TVP-VAR model with 10-step ahead forecasts. The lag length is selected by the Bayesian information criterion (BIC).

Figure 10: Utilization rate for each token in Aave

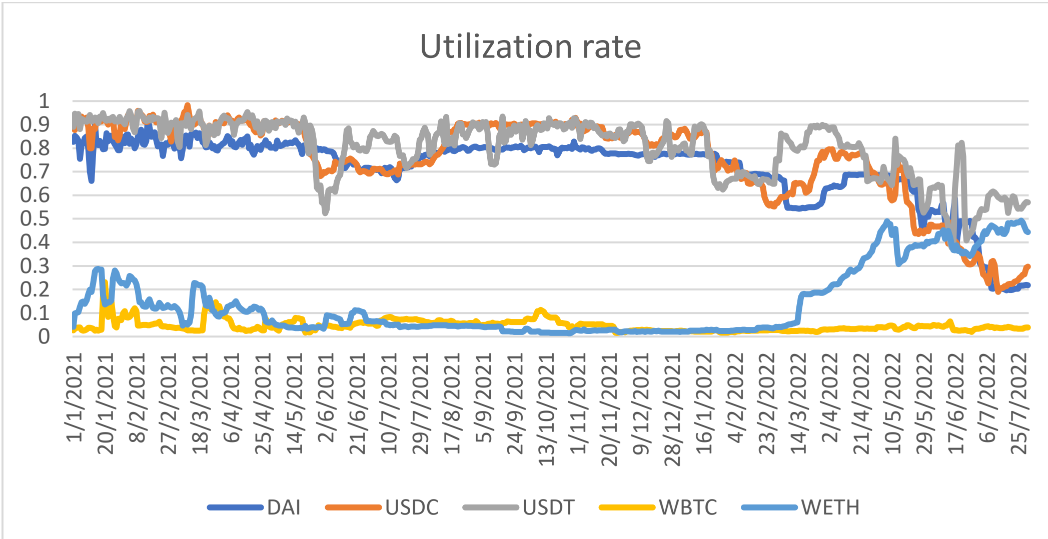


Figure 11: Available liquidity for each token in Aave

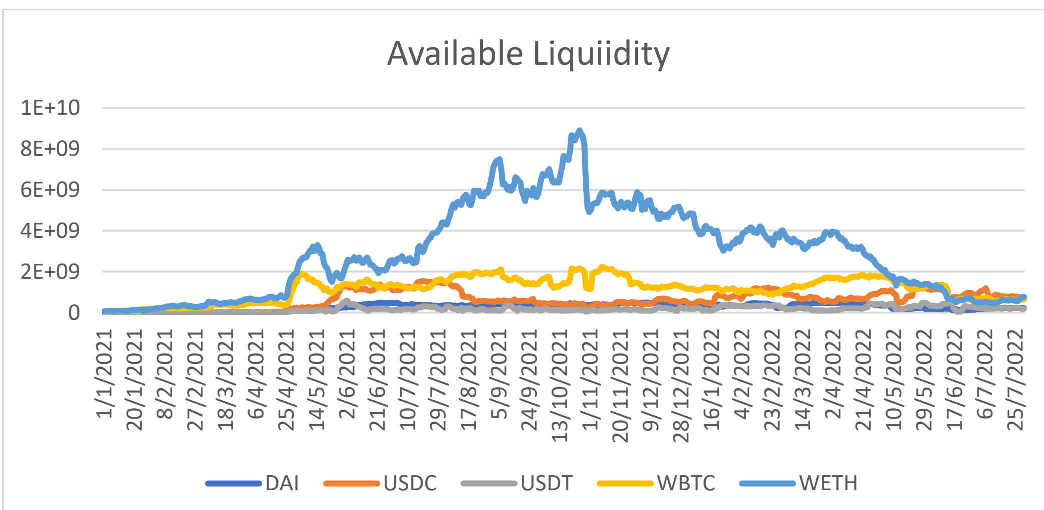
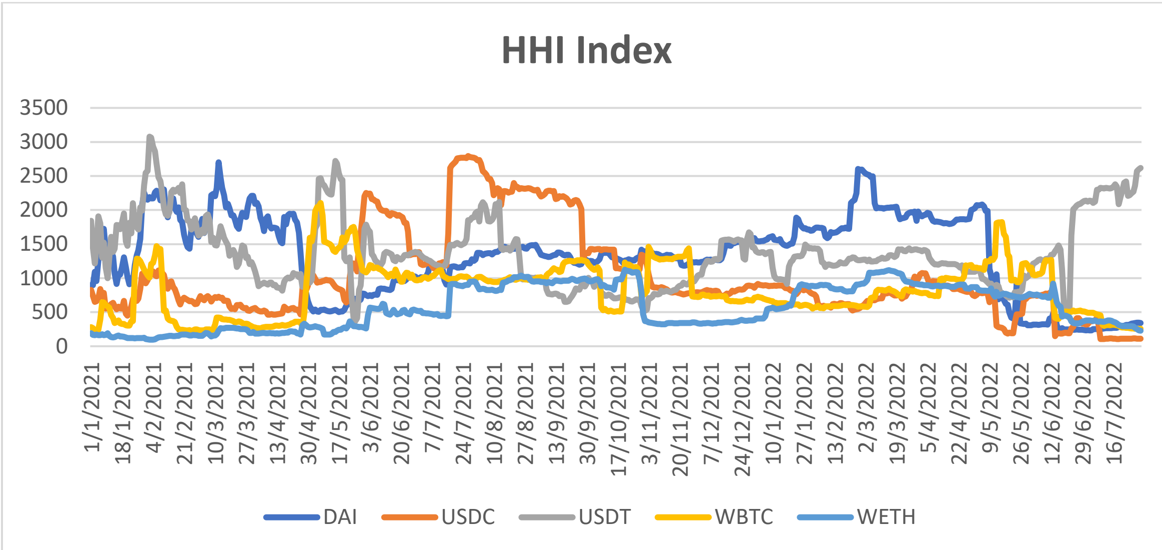


Figure 12: HHI Index

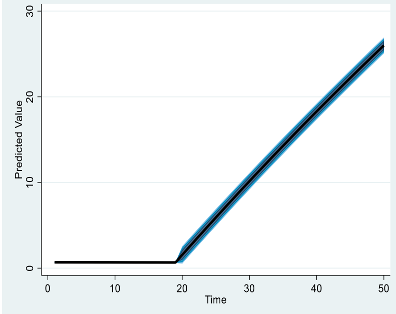
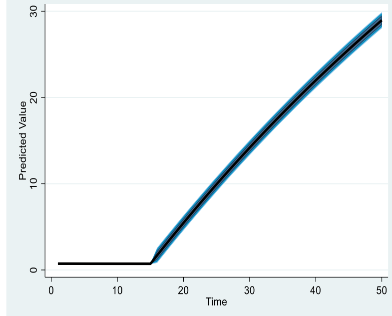
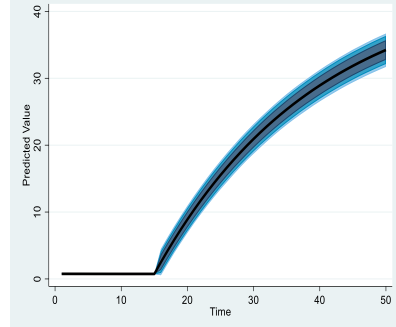


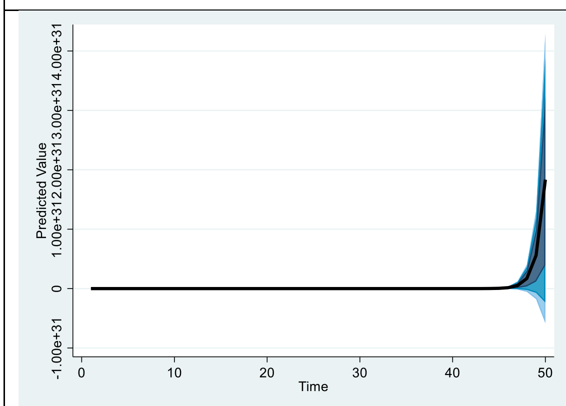
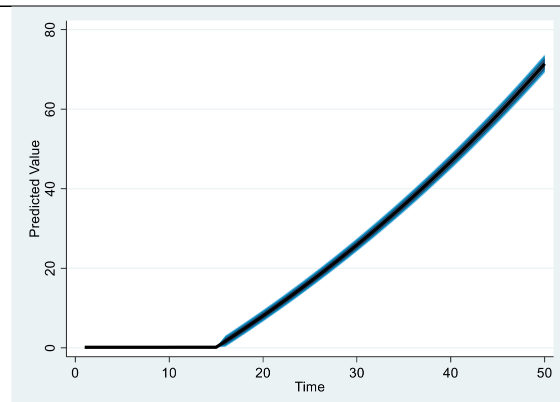
HHI < 1,500: competitive marketplace

HHI: 1,500 - 2,500: moderately concentrated

HHI > 2,500: highly concentrated

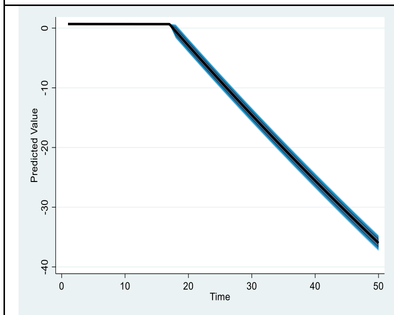
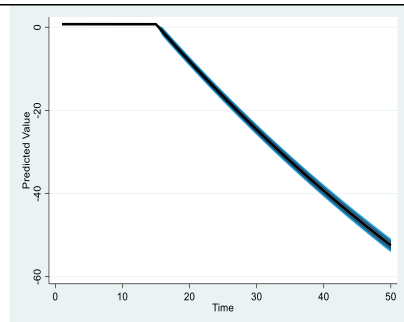
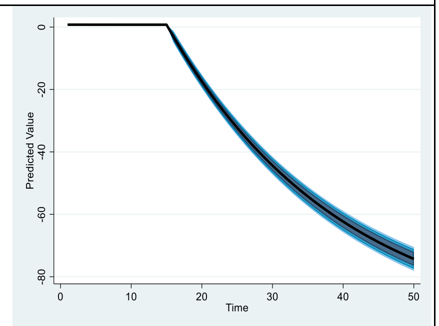
Figure 13. Counterfactual shock in predicted HHI using dynamic ARDL simulations.

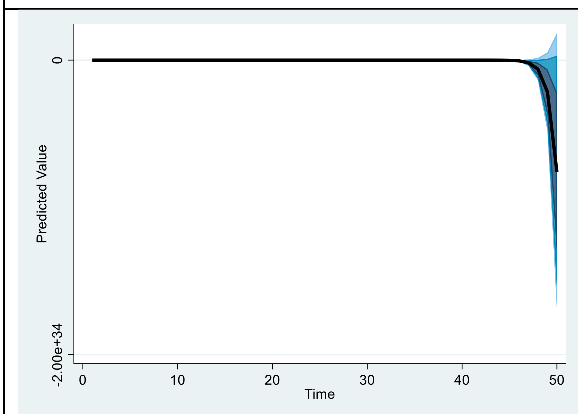
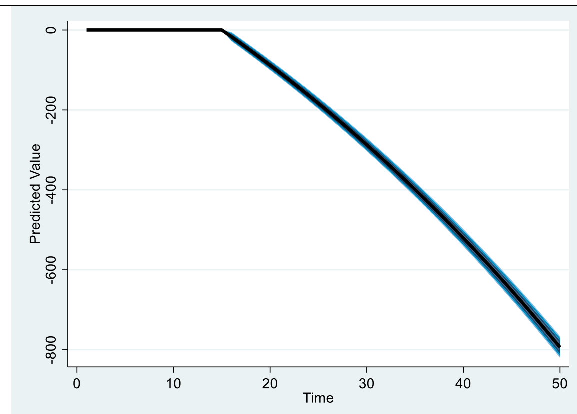
<table>
<tr><th>DAI</th><th>USDC</th><th>USDT</th></tr>
<tr>
<td>
</td>
<td>
</td>
<td>
</td>
</tr>
</table>

<table>
<tr><th>WBTC</th><th>WETH</th></tr>
<tr>
<td>
</td>
<td>
</td>
</tr>
</table>

Note: Dots show average predicted value. Shaded lines show (from darkest to lightest) the 75, 90, and 95 percent confidence intervals

Figure 14. Counterfactual shock in predicted variable borrow rate using dynamic ARDL simulations

DAI	USDC	USDT
		

WBTC	WETH
	

Note: Dots show average predicted value. Shaded lines show (from darkest to lightest) the 75, 90, and 95 percent confidence intervals