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Decentralization Illusion, Voting Democracy and Liquidity Risk in Decentralized Finance

Xiaotong Sun

Submitted in fulfilment of the requirements for the Degree of Doctor of Philosophy in Finance

Adam Smith Business School
College of Social Science
University of Glasgow

January 2024

Abstract

This thesis is made up of four chapters on *Decentralized Finance (DeFi)*. Simply, a blockchain is a distributed ledger that facilitates and records transactions, and DeFi is blockchain-based decentralized financial systems. The execution of transactions in blockchain and DeFi relies on code instead of trusted third party, allowing any agents to access blockchain and DeFi without limitations of space or time. Therefore, decentralization is considered as the most significant virtue of blockchain and DeFi. This thesis answers two important questions. First, is governance truly decentralized in DeFi? Second, is DeFi immune to liquidity risk? Are DeFi users with centralized power the source of liquidity risk?

In DeFi, the most widely adopted solution to decentralized governance is *Decentralized Autonomous Organization (DAO)*, where all DAO participants have the authority for decision-making within the underlying DeFi application. Conceptually, DAOs embody decentralized governance structure. However, but the centralized distribution of decision-making power in influential DAOs is challenging the DeFi supporters' beliefs in true decentralization. In chapter 3, I focus on governance centralization in DeFi and choose MakerDAO and its Maker protocol, the most attention-getting DAO and DeFi application, as a case study. Through an analysis of the voting history in MakerDAO governance, I present novel facts about highly centralized governance, such as low voting participation and concentration of voting power. Furthermore, I investigate the impact of centralized governance on market performance of Maker protocol. The empirical results suggest that governance centralization has complicated influences on DeFi, implying that DeFi users face a trade-off between decentralization and DeFi performance.

The decision-makers in DeFi are not separated individuals, and the interactions between decision-makers may exacerbate governance centralization. In chapter 5, I delve deeper into MakerDAO governance, developing a method to detect potential voter coalitions in MakerDAO. By applying clustering algorithms to voting history of MakerDAO governance polls, I identify three distinguished voter coalitions, with one coalition comprising the most voters and contributing to most total votes. Furthermore, I study the dissimilar effects of voter coalitions on the performance of Maker protocol, where both voting share and group cohesion of voter coalitions matter. Surprisingly, the largest coalition (i.e., the one with the most voters) often exert the opposite influence compared to smaller coalitions. Empirical

results also indicate that voter coalitions can drive cryptocurrency flows issued by Maker protocol in different ways. This chapter seeks to enrich our understanding of governance centralization in DeFi by considering the dynamics of cooperation and competition of voter coalitions.

Beside participating in DeFi governance, DeFi users have other ways to gain centralized power, introducing potential financial risks. In chapter 5, I focus on liquidity risk and market concentration in Lending Protocols (LPs), resembling banks in DeFi ecosystems. Diverging from traditional financial institutions, LPs operate without a trusted third party, with all borrowing and lending activities automated through code. However, this distinction doesn't render LPs immune to financial risks. Given that LP users can easily initiate a loan and withdraw their deposits, concentrated loans and deposits can be a concern. Utilizing Aave protocol as a case study, I find that liquidity risk is very likely to exist, and both regular users (that repeatedly borrow and deposit cryptocurrencies) and large users (that contribute significant amount of loans and deposits) exert complicated influences on the protocol. Additionally, the study uncovers cross-LP effects between liquidity risk and market concentration in Aave, illustrating interconnections among prominent LPs.

Together, these four chapters offer a comprehensive overview of blockchain and DeFi and also novel insights into centralization in DeFi. Through empirical evidence on centralization in DeFi, the research demonstrates that specific users can serve as sources of centralization. Importantly, I also suggest that DeFi users face a trade-off between centralization and the market performance of DeFi.

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Acknowledgement

This thesis marks the end of a long journey of my life as a student. Reflecting on my schooling, I realize that I have constantly evolved, shedding layers of my former self.

As a child, I studied in classrooms without incandescent lamps, which caused my near-sightedness. The facilities at both my primary and middle schools were inadequate, with classrooms often flooded on rainy days. Therefore, I had a strong desire to leave my hometown for better education. Fortunately, I was admitted to one of the best high schools in Shandong, followed by acceptance to Fudan University, an elite university in China. I escaped from the destiny of being a girl confined to a small-town education.

If life were a fairy tale, my life after receiving the offer from Fudan University would have been remarkable. However, the cruel truth is that the life of small-town swots in elite universities is far from idyllic. The competition was great, and my academic performance was disappointing. Compared to my city-born peers, I was behind in mindset and lacked a vision of how the world really works. The lack of cultural and social capital was also a problem. Despite aspiring to an academic career, I faltered in maintaining focus and even questioned my ambitions, abandoning my once-confident self.

In autumn 2018, my study at University of Leeds started. Though the specifics evade me, everything seemed to be better. I regained control over my focus and realigned myself with my academic aspirations. As my time at Leeds almost finished, an advertisement for research assistants at Leeds University Business School caught my eye. Dr. Felix Irresberger offered me an RA position, which I saw as an invaluable opportunity to delve into academic research. Since then, I have started my research on blockchain and DeFi and became captivated by the technology and its myriad applications. This time, I resolved to cast aside all negativity and reignite my pursuit of an academic career.

This narrative would be incomplete without acknowledging the invaluable support of my PhD supervisors, Prof. Charalampos Stasinakis and Prof. Georgios Sermpinis. After the 3.5 years of PhD study, I evolved from an unconfident student with many immature research ideas to an independent researcher capable of constructing solid research projects. This could not happen without my supervisors. I am deeply grateful for their guidance, encouragement, advice, and discipline throughout my PhD journey.

I must also express my gratitude to my coauthors, Michele Fabi and Xi Chen, for their contribution to our collaborative research.

I am eternally grateful to my parents and grandparents for their unconditional love.

I also thank my friends. Friends are the family we choose for ourselves. I would like to extend a special thank you to Yuqing Cai, Ziyang Li, Jian Liu, and Yi Shi for their support.

A special acknowledgement goes to Dr. Pantelis Kazakis for his suggestions and encouragement.

Finally, I would like to thank all families, friends and colleagues who have provided valuable insights, feedback, and support during this journey. Your contributions have been deeply appreciated.

Home is behind. The world ahead.

Author's declaration

I declare, except where explicit reference is made to the contribution of others, that this dissertation is the result of my own work and has not been submitted for any other degree at the University of Glasgow or any other institution.

Name: Xiaotong Sun

Signature:

Chapter 1

Introduction

1.1 General Background and Motivation

Since Satoshi Nakamoto introduced Bitcoin in 2008, blockchain has been a prominent issue and attracted attention from both industry and academia. Blockchain, defined as a distributed ledger, stores all validated transactions in a list of blocks (Zheng et al., 2017). Once a new block is validated, the block, along with the grouped transactions, will be appended to the existing blockchain, and this process does not necessitate the involvement of a trusted third party. This novel property of decentralization is considered disruptive to centralized power structures.

One noteworthy offshoot of blockchain-based applications is Decentralized Finance (DeFi), which replicates many traditional financial services, including lending and asset management (Harvey, Ramachandran, & Santoro, 2021). In essence, DeFi is financial systems and applications that operate on blockchain, and the transactions in DeFi are automatically executed by codes rather than trusted third parties, e.g., central banks. Consequently, DeFi is often regarded as a challenge to traditional finance, leveraging decentralization as a novel virtue. DeFi has grown rapidly, surging from around 600 million USD in total value locked (TVL) in 2020 to over 160 billion USD in TVL at the start of 2022[1]. Despite a decrease in TVL in 2023, it still hovers around 50 billion USD, and the daily volume of DeFi maintains around 3 billion USD. This underscores the significance of DeFi as a growing important financial market.

[1] More details about the overview of DeFi market can be found: https://defillama.com/?volume=false

However, despite removing centralized parties in traditional finance, centralization persists in blockchain and DeFi. Sai, Buckley, Fitzgerald, & Gear (2023) offer an insightful overview of centralization within the blockchain space. For example, key developers often maintain more control power over the blockchain than ordinary users, primarily due to their significant holdings of the native cryptocurrency issued by a blockchain. This ownership grants them centralized decision-making power at the governance level (Hsieh, JP Vergne, & Wang, 2017). Furthermore, key developers are more active in writing improvement proposals, consolidating their centralized control (Gervais, Karame, Capkun, & Capkun, 2014; Yermack, 2017). In DeFi, similar descriptive studies are presented by Goldberg & Schär (2023). By analysing Decentraland (a blockchain-based virtual world), they argue that decision-makers with centralized power can engage in rent extraction behavior and give rise to related problems. These examples underscore that neither blockchain nor DeFi is immune to centralization, as certain participants can become new centralized parties, potentially exerting negative effects.

In addition to centralization, DeFi may face other risks akin to those found in traditional financial markets. Considering the significance of lending activities in DeFi, exploring liquidity risk—a well-discussed issue in the banking sector—is necessary. In DeFi, lending protocols (LPs) function analogously to banks, allowing users to borrow and lend cryptocurrencies without reliance on conventional financial institutions. These activities are automated by codes, introducing the potential for illiquidity under specific circumstances, such as when depositors collectively withdraw their funds. Currently, the primary depositors contribute the majority of liquidity in LPs (Gudgeon, Perez, Harz, Livshits, & Gervais, 2020a), and a small group of borrowers account for most loans (Saengchote, 2023). Therefore, liquidity risk is a valid concern, particularly in understanding how the activities of influential users may impact the likelihood of illiquidity. This exploration is crucial given the evolving dynamic and unique structure of decentralized lending in DeFi market.

1.2 Four chapters

In light of the motivation outlined above, this thesis contributes to the field of blockchain and decentralized finance by presenting novel evidence on governance centralization and liquidity risk and examining their effects on the underlying DeFi systems.

Chapter two Chapter two presents an overview of blockchain technology and DeFi. The chapter begins with definition and classification of blockchain, offering insights into its fundamental concepts. Furthermore, it outlines the primary challenges encountered by blockchain technology. The latter part of the chapter delves into DeFi, commencing with an exploration of its distinctive properties. Among various DeFi applications, the chapter places a particular emphasis on elucidating stablecoins, lending protocols, and decentralized exchanges. Special attention is given to the specific risks associated with these DeFi applications. Finally, the chapter addresses the common risks and challenges in DeFi markets.

Chapter three Chapter three begins from scrutinizing the potential illusion of decentralized governance within the space of DeFi. Decentralized Autonomous Organizations (DAOs) currently stand as the prevailing governance mechanism in DeFi, allowing all DAO members to engage in DAO governance and positing decentralization as a primary difference from corporate governance. In a DAO, members simultaneously hold ownership and managerial roles, ostensibly addressing the agency problem. Decisions are collaboratively made by DAO members, contrasting with the hierarchical decision-making in traditional corporations. Currently, DAO supporters often assert that DAOs are disruptive to traditional corporate structures.

However, the distribution of governance power in DAOs is likely to be centralized, paralleling patterns observed in corporate finance. DAO participants' decision-making power relies on the quantity of governance tokens held, granting larger stakeholders' greater control over DAOs and the potential to significantly influence the underlying DeFi protocol. Drawing on prior research on corporate governance (e.g., Jensen & Warner, 1988; Connelly, Hoskisson, Tihanyi, & Certo, 2010; Fichtner, Heemskerk, & Garcia-Bernardo, 2017), I anticipate identifying ownership concentration in DAOs, potentially accompanied by challenges posed by influential block holders.

For this chapter, MakerDAO, recognized as the most influential DAO in the DeFi market, is selected as a case study. An analysis of voting history in MakerDAO governance polls reveals low voting participation, with a small cohort of voters holding concentrated voting power—an initial indication of governance centralization. Subsequently, several metrics of centralized governance are constructed, and their impact on the Maker protocol is investigated. Empirical results unveil that decentralized governance, exemplified by higher voting participation and more decentralized distribution of voting power, may not necessarily confer advantages to MakerDAO. Interestingly, network adoption of MakerDAO appears to be enhanced when decision-making power is concentrated. Overall, this chapter shows that DeFi users face a trade-off between decentralization and the market performance of a DeFi protocol.

Chapter four Chapter 4 builds upon the insights presented in Chapter 3, extending the analysis to a deeper level. While Chapter 3 primarily examines governance centralization at the individual level, constructing measurements of centralized decision-making power in voting history and the distribution of governance tokens, it does not explore the potential interconnections among DAO participants. In Chapter 4, the focus shifts towards investigating decentralized governance by incorporating the concept of multi-coalition democracy within DAOs. Whether in the context of DAO governance or corporate governance, decision-makers should not be viewed in isolation, necessitating a comprehensive study of potential coalitions. In the corporate finance literature, shareholder coalitions have been extensively scrutinized both theoretically and empirically, elucidating the effects of ownership structure and concentration on firm performance.

Inspired by research on shareholder coalitions, this chapter aims to detect potential voter coalitions in DAOs, and MakerDAO is chosen as a case study. By applying clustering algorithms to voting history in MakerDAO, we cluster voters with similar voting patterns as a potential coalition. This study identifies three voter coalitions, including a dominant coalition and several minoritarian ones. We then construct measurements of their voting power and group cohesion and illustrate the dynamics of these coalitions. After manually collecting information about voters' identities, it is apparent that influential DeFi users in these coalitions often have dissimilar voting patterns, potentially influenced by their private interests.

The results unveil that voter coalitions exert a complex nexus of influences on Maker protocol. First, the concentrated power of the dominant coalition contributes to the DAO's performance, both in terms of value and stability. This can be explained by the incentives for participating in DAO governance by dominant token holders. Furthermore, heightened cohesiveness of the dominant coalition or diminished cohesiveness of minoritarian ones improves political stability, indicating interest conflicts among coalitions. In summary, this chapter demonstrates that shareholder coalitions, a well-explored concept in corporate finance, also manifest within the DeFi space. This underscores that DAOs may not represent lawless solution to decentralized governance.

Chapter five This chapter centres on liquidity risk in DeFi (more specifically, lending protocols). I show that liquidity risk is possible and market concentration is a potential concern that can cause illiquidity.

Utilizing Aave protocol as a case study, we find that available liquidity and utilization are highly volatile, with spikes in utilization closely approaching one. Moreover, regular users and large users contribute to most deposits and loans, indicating market concentration in Aave.

By applying a series of factor analysis, we investigate the effects of liquidity risk and market concentration. Though low amount of available liquidity is not a good signal, we find that the network adoption of Aave protocol may be constrained when there is excess available liquidity. The influence of regular users and large users is intricate, with both positive and negative effects on the market performance of Aave. Additionally, we argue that liquidity risk in Aave has cross-protocol effects, drawing parallels with research on bank competition.

This chapter contributes to research on liquidity risk in the banking sector, where the unacceptable results are addressed. Our findings prove that DeFi is not immune from liquidity risk. However, if the liquidity is underutilized, the lending protocol can be negatively impacted. It is to say, lending protocols need to introduce assessing mechanisms and real-time monitoring of deposits/loans to mitigate liquidity risk. Our research also suggests that behavior analysis can help to detect possibly malicious activities in DeFi.

In general, each chapter includes the specific motivation, empirical results, and contribution. Most chapters are considered for publication, while they are already presented to academic peers through conferences. Chapter 3 is accepted by academic Journal of Financial Stability. Chapter 4 is presented at the 32nd European Financial Management Association (EFMA) conference in Cardiff, UK. It has also been presented in UCSB-Econ DeFi seminar organized by the University of California, Santa Barbara and BlockchainSem@Paris organized by École Polytechnique. Finally, Chapter 5 has been presented in Cryptocurrency Research Conference 2022 in Durham, UK and Cardiff FinTech Conference in Cardiff, UK.

1.3 This Thesis in Current Context

This thesis significantly contributes to the ongoing debates surrounding decentralization in both blockchain and decentralized finance (DeFi). Vitalik Buterin, the co-founder of Ethereum blockchain, proposes blockchain trilemma, claiming that decentralization, security and scalability cannot coexist in blockchain. Mining centralization is one of the most well-known examples of centralization, and Gervais et al. (2014) present empirical evidence in Bitcoin blockchain. Powerful miners can exploit their dominance by either launching various attacks (Eyal & Sirer, 2014; Teutsch, Jain, & Saxena, 2016), bribery (Bonneau, 2016), and selfish mining practices (Nadahalli, Khabbazian, & Wattenhofer, 2021). These malicious activities can hinder normal blockchain users.

In DeFi, centralization is also an inevitable concern. While DeFi eliminates trusted third parties from traditional finance, recent research, such as that by Goldberg & Schär (2023), highlights governance centralization issues. The concentration of voting power, potential rent extraction by powerful voters (Goldberg & Schär, 2023), and instances where core developers make final decisions (Yermack, 2017) reveal the complexities and challenges of achieving decentralized governance in DeFi.

Chapter 3 and chapter 4 contribute to these debates by offering solid evidence on governance centralization in DeFi. These contributions go beyond descriptive studies, such as those conducted by Goldberg & Schär (2023), by delving into the intricate influences of governance centralization on the underlying DeFi protocol. The findings underscore a dilemma faced by DeFi users—a trade-off between decentralization and the market performance of the DeFi protocol.

These two chapters first contribute to research on centralization in blockchain and its applications. Among the centralization issues observed in various layers of blockchain technology, governance centralization stands out as a significant concern (Sai et al., 2023). Despite DeFi being built upon decentralized networks (i.e., blockchain), the existence of centralized governance power suggests that the technology does not inherently guarantee fully decentralized systems. Cong, Tang, Wang, & Zhao (2023) employ the Ethereum blockchain as a case study to provide empirical evidence of concentrated ownership, while Nadler & Schär (2020) investigate ownership concentration through the lens of token distribution in DeFi protocols. In comparison, Chapters 3 and 4 offer a more focused examination, concentrating on the decision-making processes within DeFi. They provide direct evidence of governance centralization and identify the dominant decision-makers involved.

The two chapters also draw connections to corporate governance research, particularly concerning ownership concentration and shareholder coalitions. Classical results, such as Shleifer & Vishny (1997), suggest that decentralization of power may lead to self-serving actions. In contrast, more recent work, including studies by Tran & Turkiela (2020) and Giannetti & Zhao (2019), indicates that centralized governance may result in riskier actions and thus increased volatility in a firm's performance. Chapter 3 and chapter 4 in this thesis bridge this discussion to blockchain and DeFi, offering empirical insights for comparing traditional corporations and blockchain-based organizations (e.g., DAOs).

Chapter 5 delves into liquidity risk and market concentration in DeFi, contributing to research on liquidity risk in traditional finance. Theoretical models of liquidity risks have been developed over the years (Bryant, 1980; Diamond & Dybvig, 1983; Rochet & Vives, 2004; Goldstein & Pauzner, 2005; Fall & Viviani, 2015), and empirical studies have highlighted the severe consequences of liquidity risk, such as bank failures post the 2008 financial crisis (Hong, Huang, & Wu, 2014) and a reduction in banks' long-term investments (Choudhary & Limodio, 2022). However, research on lending in DeFi remains relatively sparse, and this chapter addresses the research gap by examining whether challenges faced by traditional lending systems exist in blockchain-based lending systems. Presently, research on liquidity risk in DeFi predominantly comprises descriptive studies and economic models (e.g., Gudgeon et al., 2020a; Gudgeon et al., 2020b; Bartoletti, Chiang, & Lluch-Lafuente, 2021). Therefore, chapter 5 not only contributes empirical evidence on potential risks in DeFi but also enhances understanding by exploring the parallels with challenges seen in traditional finance.

In the banking sector, the importance of large depositors and borrowers is well-established. Banks often favor a concentrated loan portfolio to optimize returns and manage risk (e.g., Winton, 1999; Mercieca, Schaeck, & Wolfe, 2007; Tabak, Fazio, & Cajueiro, 2011). Large depositors tend to choose systemically important banks, especially during crises (Oliveira, Schiozer, & Barros, 2015). However, DeFi research has yet to thoroughly investigate the distribution of loans and deposits, leaving uncertainty about whether important users, such as large users, exhibit behavior analogous to that in the banking sector. Chapter 5 shows solid evidence on market concentration in DeFi, revealing that a small group of users significantly contributes to most deposits and loans. However, it also highlights the potential for illiquidity in DeFi protocols if these users execute certain strategies, such as collectively withdrawing their deposits. It is to say, these large users wield more influence than smaller users, signalling a new form of centralization in DeFi. In summary, chapter 5 emphasizes the necessity to assess DeFi protocols and closely monitor the behavior of important users.

More broadly speaking, this thesis bridges computer science and finance research. Researchers in computer science have made significant contributions by introducing concepts like the peer-to-peer financial system (e.g., Nakamoto (2008)), designing blockchain consensus mechanisms (e.g., Du, Ma, Zhang, Wang, & Chen (2017)), and exploring security and privacy issues within blockchain (e.g., Zhang, Xue, & Liu (2019)). Studies such as Gudgeon et al. (2020a) delve into potential risks within DeFi by analysing the mechanism design of DeFi protocols. However, these studies often overlook how flaws within DeFi may impact the financial systems, particularly the performance of cryptocurrencies issued by DeFi, or lack substantial empirical investigations of financial risks. This thesis addresses these gaps by closely examining prominent DeFi protocols and studying the behavior of influential participants.

Researchers in finance have extensively discussed blockchain economics, as seen in works like Abadi & Brunnermeier (2022), and many have constructed game theoretical models to analyse the interest conflicts among users of blockchain-based platforms (e.g., Sockin & Xiong (2023); Cong, Tang, Wang, & Zhao (2020)). Additionally, studies on the risks and returns of cryptocurrencies (such as Liu & Tsyvinski (2020)) expand asset pricing research to the emerging market. In comparison, this thesis delves deeper into the on-chain activities of DeFi users and discusses potential risks through empirical analysis.

For DeFi practitioners, this thesis serves as a valuable reference for refining the mechanism design of DeFi protocols. Chapters 3 and 4 highlight the inevitable governance centralization within DAOs following the 'one token, one vote' principle, and suggest that voter coalitions may further hinder decentralized governance. Consequently, there is a need for improved governance mechanisms. Chapter 5 focuses more on on-chain lending, emphasizing the importance of dominant borrowers and depositors. This chapter underscores the necessity of developing risk assessment frameworks for DeFi protocols, especially in monitoring influential users.

In summary, this thesis discusses critical issues in DeFi. Its objective is to offer evidence and insights relevant to the design of robust blockchain-based financial systems. Chapters 3–5 are inspired by centralization challenges within DeFi and aim to address the complex effects of centralization.

Chapter 2

Overview of Blockchain Technology and Decentralized Finance

This chapter provides an introduction to the background knowledge about blockchain and Decentralized Finance (DeFi) to enhance the reader's understanding of the thesis. It begins with exploring various definitions of blockchain, elucidating how on-chain transactions are validated, and highlighting the rapid growth of the blockchain-based finance market. The chapter also introduces the centralization problems in blockchain.

Moving forward, the chapter introduces the concept of DeFi and draws comparisons with traditional financial institutions. Among various DeFi applications, the focus is providing more details about lending protocols (LPs) and decentralized exchanges (DEXes), considering them as primary components in the DeFi market. The chapter concludes with a review of the risks associated with DeFi.

2.1 Definition of blockchain

Nakamoto Satoshi's publication of the Bitcoin blockchain whitepaper in 2008 marked the beginning of widespread awareness and discussion about blockchain technology. Since then, blockchain, along with the cryptocurrencies traded on blockchain, has become a highly controversial and influential topic. Despite the extensive discourse surrounding blockchain, a universally accepted definition is yet to be established, and various definitions are present in the literature.

A prevailing perspective is that blockchain is based on distributed ledger technologies (DLTs). DLTs maintains a ledger of transactions and update status without the need for a trusted third party. These ledgers are accessible to any participating agents, and tampering with the existing ledger is typically challenging. Evolving from DLTs, blockchain has specific attributes, such as decentralization and tamper-resistance. Blockchain’s data structure is often described as 'a chain of blocks,' setting it apart from other DLT implementations with different data structures (Tabatabaei, Vitenberg, & Veeraragavan, 2023).

In line with Abadi & Brunnermeier (2022), a general definition of blockchain characterize it as a type of distributed ledger that maintains a chain of blocks. Typically, the blocks are written by anonymous agents rather than centralized third parties, and any participating agents can contribute to the ledger following established rules, known as consensus.

2.2 Classifications of blockchain

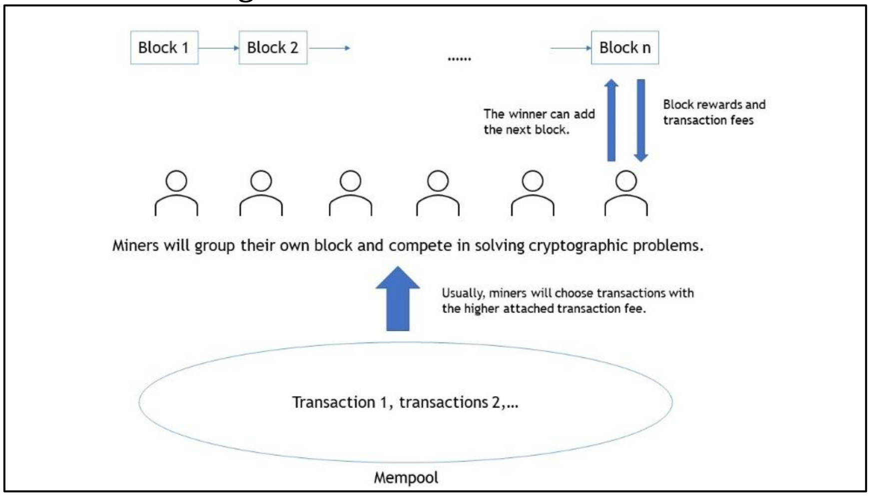
2.2.1 Consensus mechanisms

Blockchains can be categorized based on the consensus mechanisms they employ. Consensus refers to a set of established rules utilized within a blockchain to attain distributed agreement regarding the blockchain's state. Two of the most widely recognized consensus mechanisms are Proof-of-Work (PoW) and Proof-of-Stake (PoS). For additional information on other consensus models, one can refer to the work of Yaga, Mell, Roby, & Scarfone (2018).

Proof-of-Work (PoW) blockchain The Bitcoin blockchain is the most prominent example of a Proof-of-Work (PoW) blockchain. In a PoW system, a node intending to publish a block must demonstrate that it has done significant computational work, typically referred to as "mining." The nodes engaged in this process are commonly known as miners. In PoW blockchains, this computational work involves solving complex cryptographic problems, often in the form of PoW puzzles (Atzei, Bartoletti, & Cimoli, 2017). Miners compete to solve these puzzles.

The figure below presents a simplified overview of how PoW blockchains operate: Miners select transactions submitted by users and construct a block, with decisions on transactions and their order influenced by attached transaction fees (McCorry, Hicks, & Meiklejohn, 2018). Miners then engage in a competitive process of solving cryptographic problems, utilizing their computational power. Only the miner first successfully solving the puzzle can add the next block to the blockchain and receive rewards. These rewards consist of a block reward and transaction fees paid by users sending transactions (Liao & Katz, 2017).

Figure 2.1: Ethereum blockchain



Note: This figure illustrates the validation process in PoW blockchains. Blockchain users can submit transactions (temporarily stored in mempool), and miners will choose transactions and group their own blocks. Only the winning miner can add the next block to the existing blockchain and get rewarded.

Clearly, the PoW mechanism results in intense competition, and one of the most widely observed issues is mining concentration. Currently, the majority of blocks are added by a small group of miners (Gervais et al., 2014). In order to compete with powerful large miners, individual miners can organize themselves into 'pools,' known as mining pools. The consolidated mining power increases the likelihood of winning the mining process, and when a mining pool successfully adds a new block, the rewards are proportionally distributed among its members. However, the emergence of mining pools further exacerbates mining concentration (Gencer, Basu, Eyal, van Renesse, & Sirer, 2018).

Proof-of-Stake (PoS) blockchain A drawback of PoW blockchains is the substantial energy consumption. Solving PoW puzzles involves significant computational expense and consumes a considerable amount of electricity. Benetton, Compiani, & Morse (2019) provide additional empirical evidence on the energy consumption in PoW blockchains. To address the energy expenditure issue in PoW blockchains, King & Nadal (2012) proposed Proof-of-Stake (PoS), first implemented by the Peercoin blockchain. Saleh (2021) later presents a formal economic model of PoS.

Technically speaking, PoS randomly select stakeholders to append blocks to the existing blockchain. Here, stakeholders are participants in the blockchain who invest native tokens in the consensus process. The chance to append a block for a PoS stakeholder is proportional to its stake value. Xiao, Zhang, Lou, & Hou (2020) provide more details about different implementations of PoS blockchains.

However, PoS can introduce new problems. Similar to mining pools, stakeholders in PoS blockchains can join staking pools to increase their chances of winning. Tang, He, Fan, & Wang (2023) argue that large stakeholders tend to concentrate in big (wealthy) staking pools, leading to centralization in PoS blockchains. This concentration may exacerbate the 'rich get richer' phenomenon, although Roşu & Saleh (2021) contend that it does not theoretically exist in PoS.

Ethereum blockchain: from PoW to PoS On September 15th, 2022, Ethereum blockchain, a leading blockchain, transitioned from PoW to PoS. The event is commonly known as ‘The Merge’, which reduced Ethereum’s energy consumption by approximately 99.95% (Ethereum, 2023). While Ethereum became much more environmentally friendly after adopting PoS, a new problem emerged due to the centralized distribution of validation power. After 'The Merge,' a few stakeholders control validations for over 50% of new blocks (Mancino, Leporati, Viviani, & Denaro, 2023), indicating that the shift in consensus did not eliminate centralization. For more information about ‘The Merge’, readers can access the datasets using Dune.xyz.[2]

[2] A dashboard about ‘The Merge’ can be found: https://dune.com/sixdegree/ethereum-the-merge

2.2.2 Permission model

Blockchains can be categorized based on their permission models, which include permissionless blockchains and permissioned blockchains. In simple terms, permission models revolve around a fundamental question: Who can publish new blocks? Importantly, irrespective of whether a blockchain is permissionless or permissioned, it can adopt any consensus mechanism. For a more in-depth exploration of permission models and their respective advantages and disadvantages, insights are provided by Yaga, Mell, Roby, & Scarfone (2018).

Permissionless blockchain Permissionless blockchains, also known as public blockchains, operate as open networks accessible to everyone, allowing anyone to participate in publishing new blocks without requiring permission from a central authority. Usually, the users have the option to remain anonymous, and the blockchain is open-sourced, so permission blockchains are considered more decentralized than permissioned blockchain. However, a notable concern for permissionless blockchains is the potential for malicious users to attack the system by publishing specific types of blocks, such as a series of empty blocks. Therefore, the implementation of incentive mechanisms for block publishers is crucial in the context of permissionless blockchains.

Permissioned blockchain Permissioned blockchains exclusively permit authorized publishers, as designated by a central authority, to maintain the blockchain. Typically developed by private entities, these blockchains offer controlled transparency accessible to authorized users, prioritizing security in comparison to permissionless blockchains. Besides, permissioned blockchains can be customized for specific uses, such as claims settlements and identity verification, making them valuable for organizations seeking control over their blockchain. However, the limited number of publishers in permissioned blockchains raises concerns about potential issues such as corruption and collusion.

2.3 Blockchain-based applications

Blockchain-based applications emerge across various sectors, as comprehensively reviewed by Casino, Dasaklis, & Patsakis (2019). This subsection provides a concise overview of cryptocurrency and other financial applications based on blockchain technology, electronic voting systems, and the use of blockchain in identity management.

2.3.1 Cryptocurrency and other financial applications

The most prominent application of blockchain is cryptocurrency. Since bitcoin was introduced in 2008, numerous cryptocurrencies have surfaced, significantly altering the landscape of financial markets. The programmable features in the Ethereum blockchain have played a pivotal role in fostering the continued growth of the cryptocurrency market. According to Statista[3], the revenue in the cryptocurrency market is projected to exceed $40 billion in 2023.

In addition to tradable cryptocurrencies, blockchain technology facilitates the trading of various financial assets, including securities and financial derivatives. Paech (2017) delves into the capability of blockchain to enable on-chain transactions for traditional financial assets and emphasizes the importance of regulatory considerations in this context. Furthermore, Wu & Liang (2017) provide insights into how blockchain technology contributes to the foreign exchange system and facilitates inter-bank transactions.

Digital payments represent another important blockchain application in finance. For example, Bank of England Santander utilized the technology provided by the payment protocol and exchange network based on Ripple to transfer payments in real time through a mobile application. [4] Papadopoulos (2015) explores the contributions of blockchain technology to digital payments and proposes a viable solution of incorporating

[3] More details can be found: https://www.statista.com/outlook/fmo/digital-assets/cryptocurrencies/worldwide#:~:text=Revenue%20in%20the%20Cryptocurrencies%20market,to%20US%2460.8%20in%202023.

[4] More details can be found: https://www.santander.com/csgs/Satellite?appID=santander.wc.CFWCSancomQP01&c=GSNoticia&canal=CSCORP&cid=1278712674240&empr=CFWCSancomQP01&leng=en_G B&pagename=CFWCSancomQP01%2FGSNoticia%2FCFQ P01_GSNoticiaDetalleMultimedia_PT18

cryptocurrencies into established payment businesses, e.g., PayPal and Visa. Currently, PayPal allow users to trade and transfer cryptocurrencies, and they also issue their own cryptocurrency, namely PayPal USD.[5] Despite the numerous applications in practice, regulatory considerations introduce uncertainties regarding the future of digital payments.

2.3.2 Electronic voting

Blockchain technology can be used for building electronic voting (e-voting) systems, offering potential contributions to political elections and corporate governance voting. E-voting introduces advantages such as remote voting and increased convenience through digital device participation, but it also raises concerns about election tampering if hackers target digital devices or the blockchain (Di Francesco Maesa & Mori, 2020).

Several examples of e-voting systems built on Bitcoin and Ethereum exist. BitCongress, for instance, employed Bitcoin colored coins (representing real-world assets on the Bitcoin blockchain) to authenticate voters and utilized codes deployed on the Ethereum blockchain to tally votes. However, this system has discontinued. Another example is FollowMyVote[6] established by a non-profit organization. FollowMyVote aims to develop blockchain-based voting systems for global political elections, with a focus on enhancing transparency in voting results and safeguarding voters' privacy.

2.3.3 Identity management

An identity management system is designed for identifying entities within a digital system, storing necessary data, and employing specific authentication methods to recognize these entities (Di Francesco Maesa & Mori, 2020). In financial systems, for instance, identity

[5] More details can be found: https://www.paypal.com/us/digital-wallet/manage-money/crypto

[6] https://followmyvote.com/

information can include users' bank data and historical transactions. The security of stored identity information is crucial, as a system breach could lead to unacceptable losses.

Dunphy & Petitcolas (2018) introduce several representative identity management systems built on blockchain, such as uPort[7]. uPort, operating on the Ethereum blockchain, utilizes the Ethereum address as the user identifier. Notably, to safeguard user privacy, the data is not directly stored on the blockchain. For additional information on identity management services utilizing blockchain, readers can refer to Haber & Rolls (2019).

2.4 Centralization in blockchain

Though decentralization is often considered the most crucial virtue of blockchain, it faces various centralization challenges. Theoretically, Vitalik Buterin, the co-founder of Ethereum, has proposed the "blockchain trilemma," asserting that decentralization, security, and scalability cannot coexist in blockchain. Sai et al. (2021) provide a systematic overview of centralization, and this section will delve into mining concentration, governance centralization, and wealth concentration.

2.4.1 Mining concentration

In PoW blockchains, mining centralization is a recognized issue (Gervais et al., 2014), and powerful miners can potentially launch various attacks (Nakamoto, 2008; Teutsch et al., 2017; Eyal & Sirer, 2014). These attacks, often termed "selfish mining attacks," can have significant consequences. A well-known example is the '51% attack,' wherein miners possessing more than 51% of the mining power could manipulate the blockchain's history. In addition to launching attacks, powerful miners can extract profits by reordering transactions. For instance, they may selectively include or exclude certain transactions and,

[7] https://www.uport.me/

at times, engage in arbitrage through transaction reordering. Daian et al. (2020) illustrate how miners employ frontrunning strategies to extract profits and introduce the concept of 'Miner Extractable Value (MEV)' to quantify the maximum profits a miner can earn through transaction-ordering activities. Judmayer, Stifter, Schindler, & Weippl (2023) extend the definitions of MEV, emphasizing the challenges associated with estimating MEV in practical scenarios.

Beside miners' suspicious behavior, risks can arise when miners are subjected to bribery. In such cases, bribery can be seen as a form of collusion between the bribers and the miners (Bonneau, 2016). Depending on the goals of the bribers, bribery can manifest in various categories. Adversaries may bribe miners to tamper the transaction history by initiating blockchain forks (Liao & Katz, 2017; Daian et al., 2020), with such attacks having unacceptable implications for users who have conducted a series of transactions. Anti-blockchain bribers might attempt to append consecutive empty blocks (Bonneau, 2016) to devalue the blockchain. Bribers with a focus on their own interests may aim to execute specific transactions (McCorry, Hicks, & Meiklejohn, 2018) or intentionally ignore others' transactions (Nadahalli, Khabbazian, & Wattenhofer, 2021). Other potential forms of bribery activities are discussed by Winzer, Herd, & Faust (2019) and Judmayer et al. (2021a and 2021b).

2.4.2 Governance centralization

Blockchain governance plays a pivotal role in the dynamic evolution of a blockchain. Narayanan, Bonneau, Felten, Miller, & Goldfeder (2016) provide a concise summary of fundamental questions related to blockchain governance, including inquiries into who holds authority, how governance participants are endowed, and the structures of governance. When viewed through the lens of organizational governance, blockchain-based entities offer alternative models to traditional institutions (Davidson et al., 2016). Since blockchain operates on a software-based framework, it changes traditional principal-agent relationships. In blockchain, governance power is distributed among all stakeholders (Yermack, 2017).

Hsieh et al. (2017) are the first to study the interplay between the value proposition of blockchain and its governance structure. They contend that decentralization stands out as one of the most valuable characteristics from the perspective of blockchain users. However, the reality of blockchain governance often deviates from this ideal, with instances of centralization being prevalent. Early adopters and key developers frequently gain more control than other participants. Wolfson (2015) illustrates that in the Bitcoin market, early users accumulated a significant proportion of Bitcoin during the initial adoption phase.

Similarly, in Ethereum, early investors and developers account for substantial amounts of Ether (ETH), the native cryptocurrency on the Ethereum blockchain (Sai et al., 2021). Through the accumulation of wealth, these users exert more influence than smaller participants who do not hold significant amounts of cryptocurrencies. The other signal of governance centralization is that a small group of blockchain users contribute to most improvement proposals. In Bitcoin and Ethereum, most proposals are written by key developers, and a small group of users account for most discussion about both the cryptocurrencies and the programming languages (Gervais et al., 2014; Azouvi, Maller, & Meiklejohn, 2018). These studies contend that not many users actively participate in blockchain governance, though the network adoption of blockchain is rapidly growing.

2.4.3 Wealth concentration

As in traditional financial markets, wealth concentration is an inherent issue of blockchain, signifying that a small group of users holds a significant proportion of total cryptocurrencies traded on the blockchain. These wealthy users, often referred to as "Whales," possess the capacity to initiate various attacks. For example, Liao & Katz (2017) introduces Whale Transaction Attack. In such an attack, the attacker seeks to induce disagreement among participants by offering a high transaction fee within an already published block. In Ethereum, iFish attack occurred in the summer of 2018[8]. A cryptocurrency named 'iFishYunYu,' possessing no functionalities, was minted and traded extensively. Despite its

[8] https://cryptoslate.com/ethereum-network-under-assault-gas-price-manipulation-may-indicate-covert-eos-attack/

lack of utility, this cryptocurrency experienced substantial trading volume with a high transaction fee in a short period, indicating malicious intent.

Wealth concentration raises concerns, particularly the exacerbation of ‘the rich get richer' phenomenon within blockchain. In Bitcoin, Kondor, Pósfai, Csabai, & Vattay (2014) demonstrate that wealthy nodes in the Bitcoin transaction graph tend to increase their wealth at a faster rate than smaller nodes. The evolution of wealth concentration in Ethereum can be explored using datasets on Dune.xyz[9]. Formally, Srinivasan & Lee (2017) propose methods for evaluating wealth concentration.

2.5 Overview of Decentralized Finance

2.5.1 Definitions and properties

Decentralized Finance (DeFi) can be defined as blockchain-based peer-to-peer financial systems. Werner et al. (2022) highlight four distinctive properties of DeFi: (1) Non-custodial; (2) permissionless; (3) openly auditable; and (4) composable.

Non-custodial DeFi users retain complete control over their cryptoassets at all times. This stands in stark contrast to traditional finance, e.g., bank depositors may not have full control over their funds, as banks can freeze them if necessary.

Permissionless DeFi operates without a centralized third party, allowing anyone to access financial services provided by DeFi without censorship.

Openly auditable DeFi is transparent and open to scrutiny by anyone. This includes the ability for individuals to audit the transaction history and the current state of DeFi systems.

Composable DeFi's financial services are designed to be composable, enabling the execution of complex financial transactions. This composability is likened to building with

[9] An example: https://dune.com/ilemi/Token-Overview-Metrics

Lego models, where various components can be combined to create intricate financial activities.

2.5.2 Components of DeFi

In this subsection, the focus is on providing a brief introduction to the fundamental components of DeFi, including smart contracts, keepers, and oracles.

Smart contracts Smart contracts are coded programs that execute on blockchains. Users can invoke smart contracts, and these contracts can also interact with other smart contracts. A distinctive feature of smart contracts is atomicity, meaning transactions within a smart contract will either fully succeed or fail entirely (Werner et al., 2022). Typically, a DeFi application is composed of several smart contracts.

Keepers In certain blockchain-based systems, external entities, referred to as keepers, are essential when system states require updates. Liquidators in blockchain-based lending systems are an example of keepers. In situations where a borrower's collateral is insufficient, keepers are motivated to initiate liquidation for the borrower's collateral assets.

Oracles Blockchain faces challenges in directly accessing off-chain data, such as stock prices. Oracles serve as tools to bring off-chain data into the blockchain. Oracles have various design mechanisms, primarily classified as centralized oracles and decentralized oracles. The two categories of oracles face different risks (Liu, Szalachowski, & Zhou, 2021). Centralized oracles depend on trusted data providers, posing a risk when these providers exhibit dishonest behavior. On the other hand, decentralized oracles rely on incentive mechanisms to ensure accurate and honest off-chain data. However, specific risks faced by decentralized oracles are discussed by Werner et al. (2022).

2.5.3 Decentralized Finance v.s. Centralized Finance

Qin et al. (2021) provide a comprehensive comparison between Decentralized Finance (DeFi) and Centralized Finance (CeFi), highlighting additional prevalent DeFi properties beyond the advantages discussed in section 2.5.1. These properties include privacy, atomicity, and non-stop market hours.

Privacy While blockchain users can choose not to disclose their real-world identities, blockchain does not offer complete anonymity. Studies by Reid & Harrigan (2011), Harrigan & Fretter (2016), and Harrigan, Shi, & Illum (2018) demonstrate that attackers can create mappings between Bitcoin addresses and users' external information, leading to de-anonymization. Despite limited privacy, DeFi still offers better privacy compared to the Know Your Customer (KYC) and Anti-Money Laundering (AML) practices in CeFi.

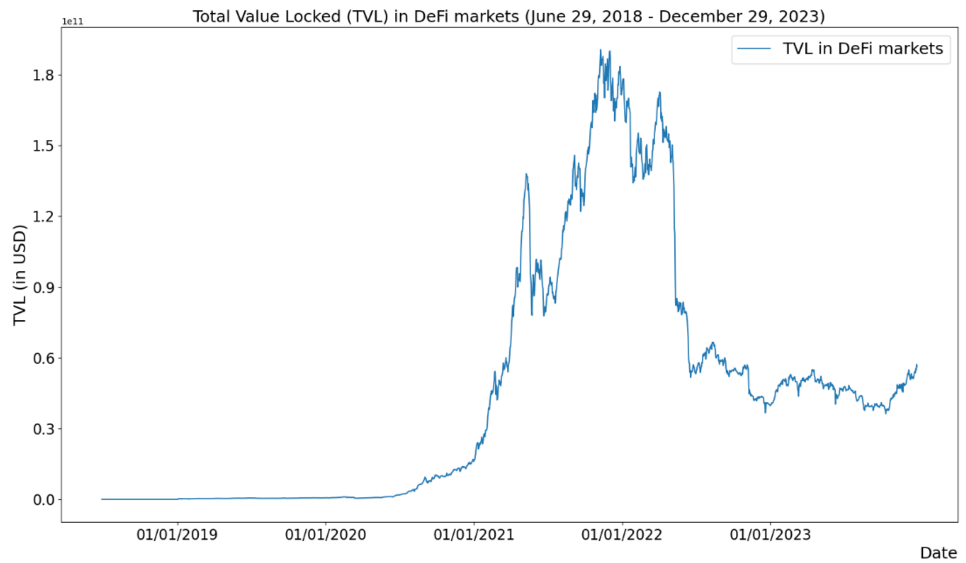
Atomicity DeFi, relying on smart contracts on the blockchain, allows for sequential transactions that can involve multiple financial activities. This combination can be atomic, meaning that the transactions either entirely succeed or entirely fail. This property is not commonly observed in CeFi markets.

Non-stop market hours Different from CeFi markets, DeFi markets operate 24/7, and DeFi users are not restricted by geography. Using GameStop as an example, Qin et al. (2021) explain the absence of pre- or post-market trading in DeFi markets. Brokerage firms in traditional markets can limit customers' purchase and sale of certain financial products, but this restriction does not applicable in DeFi markets. Further research could explore whether DeFi markets offer more benefits to ordinary customers during events like high volatility since there is no such limitation.

2.5.4 Classification of DeFi

Currently, DeFi has the capability to replicate most financial activities found in traditional finance, including lending, asset management, and financial derivatives. DeFi also introduces innovative financial products based on blockchain technology, with stablecoins being a notable example. Since 2021, the DeFi markets have witnessed rapid growth, marked by spikes in Total Value Locked (TVL) exceeding $160 billion around November 2021. Although the DeFi market experienced a downturn since the summer of 2022, the TVL of DeFi markets still hovers around $50 billion in 2023 (see the figure below). Harvey et al. (2021) and Werner et al. (2022) provide comprehensive introductions to various DeFi applications. The following subsections will primarily focus on stablecoins, lending protocols (LPs), and decentralized exchanges (DEXes).

Figure 2.2: Total Value Locked (TVL) in DeFi markets



Note: This figure illustrates the Total Value Locked (TVL) in DeFi markets (June 29, 2018 – December 29, 2023). The data is retrieved from *defillama.com*.

2.6 Stablecoins

Klages-Mundt, Harz, Gudgeon, Liu, & Minca (2020) define stablecoins as ‘cryptocurrencies with an added economic structure that aims to stabilize their price and purchasing power’. Major stablecoin examples, such as Tether (USDT), USD Coin (USDC), and Dai (DAI), are soft-pegged to US dollars, while stablecoins with other peg targets also exist. According to the collateral assets, stablecoins can be divided into custodial and non-custodial stablecoins.

Custodial stablecoins For custodial stablecoins, the common choices of collateral assets are traditional financial assets, such as fiat currencies and bonds. Importantly, this implies that custodial stablecoins are not in the scope of DeFi. These stablecoins are issued to represent the value of the collateral assets; for instance, USDT represents the on-chain value of US dollars. Custodial stablecoins can be categorized into three groups: reserve fund stablecoins (each stablecoin is backed by a unit of the reserve asset), fractional reserve fund stablecoins (stablecoins backed by a mixture of reserve assets and other capital assets), and central bank digital currency (CBDC). For a more detailed introduction, readers can refer to Klages-Mundt et al. (2020). Despite being collateralized by off-chain assets, custodial stablecoins are not entirely risk-free. They face counterparty and censorship risks associated with their collateral assets, akin to risks in traditional assets.

Non-custodial stablecoins Non-custodial stablecoins are cryptocurrencies designed to achieve price stability through collateral assets and additional economic mechanisms. Unlike custodial stablecoins, non-custodial stablecoins operate without reliance on trusted third parties, making them generally considered more decentralized. The value of non-custodial stablecoins is linked to collateral assets, which can be either exogenous or endogenous. An example of stablecoins with exogenous collateral assets is Dai (DAI), issued by Maker protocol.[10] Synthetix's snxUSD is an example of stablecoins with endogenous collateral assets.[11] Klages-Mundt et al. (2020) discuss the economic models of non-custodial stablecoins.

2.6.1 Stability of stablecoins

The literature explores stablecoins around several important research questions. First of all, it is crucial to evaluate the stability of stablecoins. On Thursday March 12th, 2020, cryptocurrency markets suddenly collapsed, and bitcoin prices experienced dramatic decrease in less than a day. Consequently, liquidity evaporation happened, and market panic was caused. The day is usually called 'Black Thursday' in cryptocurrency markets.[12] When this kind of events happen, non-custodial stablecoins can experience high volatility and face deleveraging risks. Klages-Mundt & Minca (2022) construct a mathematical model of over-

[10] https://makerdao.com/en/whitepaper#the-dai-stablecoin

[11] https://docs.synthetix.io/v/v3/for-liquidity-providers/liquidity-positions/minting-and-burning-snxusd

[12] https://blog.kaiko.com/crypto-black-thursday-under-the-microscope-a86770df5c29

collateralized non-custodial stablecoins, and they find that deleveraging spiral can happen during times of shock. In their model, the behavior of speculators is also considered. Klages-Based on the stochastic models of stablecoins, Mundt & Minca (2021) propose design improvements that aim to improve long-term stability of stablecoins.

2.6.2 Regulatory considerations

Adachi, Cominetta, Kaufmann, & Kraajj (2020) explore regulatory considerations related to stablecoins, examining current regulatory gaps and systemic stability risks. Given the financial functions of stablecoins, it is natural for regulators to focus on them. The asset management function of stablecoins could qualify them as issuers of e-money, investment funds, or even banks. In a way, stablecoins play a role similar to "wildcat banks" (Gorton & Zhang, 2021). However, this function also has the potential to pose significant risks to financial stability, especially when a stablecoin achieves a 'global stablecoin' status. A run on a stablecoin arrangement might occur if users lose confidence in the issuer or its network, having negative contagion effects on the financial system.

An example of a stablecoin collapse is the failure of TerraUSD (UST) in May 2022. UST is an algorithmic stablecoin, meaning that its stability relies on mathematical algorithms rather than traditional collaterals. UST's stability is maintained through a two-coin system, with the Luna token (LUNA) acting as the counterweight to mitigate volatility. However, if LUNA's price is under pressure, UST holders may lose confidence, prompting them to exchange UST back to LUNA and then sell LUNA, resulting in a death spiral for UST/LUNA. Briola, Vidal-Tomás, Wang, & Aste (2023) demonstrate that other mainstream cryptocurrencies were negatively affected during this event, highlighting the existence of negative contagion effects in cryptocurrency markets. For further details about this collapse, readers can refer to Briola, Vidal-Tomás, Wang, & Aste (2023) and Liu, Makarov, & Schoar (2023).

The transfer function of stablecoins has also attracted regulatory attention, with components of a global stablecoin arrangement potentially falling under the oversight regime for payment systems. Catalini, Gortari, & Shah (2022) provide insights into stablecoins' payment function, while Liao (2022) discusses the possibility of stablecoins replacing fiat currencies. Empirically, Adachi, Cominetta, Kaufmann, & Kraajj (2020) use Libra as an example to study its performance as a payment tool.

2.7 Lending protocols (LPs)

Lending protocols (LPs) are DeFi protocols that enable users to lend and borrow cryptoassets without relying on any trusted third parties. Unlike traditional banks, the parameters of lending activities, such as interest rates and maturity periods, are determined and executed by smart contracts. Bartoletti, Chiang, & Lluch-Lafuente (2021) present a formal model of LPs, where borrowers and depositors engage with smart contracts to update the state of LPs. Unlike peer-to-peer (P2P) lending, funds in LPs are pooled, creating an open market for loanable cryptoassets without an intermediary role. Compared to banks, LPs lack the function of money creation, making them an innovative presence in lending markets. Therefore, it is inappropriate to view LPs simply as replicas of traditional banks in DeFi.

In LPs, interest rate mechanisms are crucial as they equilibrate the supply and demand for funds. Gudgeon et al. (2020b) explore different interest rate models used by three prominent LPs, namely Compound, Aave, and dYdX. The most widely adopted interest rate models include linear rates, non-linear rates, and kinked rates, all aiming to stabilize interest rates and enhance utilization for borrowers and depositors. Importantly, they observe the existence of arbitrage opportunities in LPs in practice, despite economic mechanisms designed to satisfy non-arbitrage conditions.

2.7.1 Lending pool vulnerabilities

LPs are exposed to various risks, such as unsecured loans or exploitations by malicious actors. For potential attackers, two vulnerabilities stand out in LPs: user collateralization and the presence of free liquidity within LPs. While Bartoletti et al. (2021) provide a detailed analysis of potential attacks on LPs, this subsection aims to offer a more intuitive description of these vulnerabilities.

Risks caused by collateral In LPs, loans are backed by collateral, and liquidations occur when borrowers fail to repay. However, this process is not without risks. When the value of collateral becomes too low, liquidators lack incentives, rendering the loans unrecoverable even after liquidation. In a case study on Compound, Perez et al. (2021) demonstrate that minor fluctuations of just 3% in an asset's dollar price can lead to over $10 million becoming liquidable. Therefore, LPs are highly sensitive to asset prices in the crypto markets, making them susceptible to exploitation by market manipulators. Additionally, Kao et al. (2020) assess the safety of an LP concerning the ratio of undercollateralized loans to the total loan value. In summary, diligent monitoring of collateral assets and their prices within LPs is essential for effective risk management.

Risk caused by utilization Utilization, defined as the ratio of the on-loan value to the total available liquidity in lending protocols (LPs), holds significant importance. Gudgeon et al. (2020b) discuss the crucial role of utilization in LPs, and, practically, it serves as a key parameter in interest rate models employed by platforms like Aave and Compound. Attacks targeting utilization can be categorized into two types: under-utilization attacks and over-utilization attacks. Under-utilization attacks involve malicious users seeking to decrease interest accrual for depositors or discourage borrowing of a cryptocurrency. On the other hand, over-utilization attacks are implemented by a group of malicious users aiming to impede redeems or borrows of a cryptocurrency. For a more in-depth discussion on these attacks, readers can consult Bartoletti et al. (2021).

In addition to attacks, the presence of asymmetric information regarding the quality of assets between borrowers and lenders poses a significant risk. Chiu, Ozdenoren, Yuan, & Zhang (2023) present a dynamic model to discuss this issue. Borrowers who possess private information indicating that their crypto assets are of low quality are more incentivized to borrow compared to those who know their assets are of high quality. Since lenders cannot directly control the collateral, this information asymmetry results in the classic lemons problem (Akerlof, 1970), significantly diminishing gains from trade by driving away high-quality borrowers. Consequently, Chiu et al. (2023) argue that sacrificing a certain degree of decentralization is necessary for enhanced stability in LPs.

2.8 Decentralized Exchanges (DEXes)

Cryptocurrencies are traded on two types of exchanges – centralized exchanges (CEXes) and decentralized exchanges (DEXes). In recent years, prominent CEXes have emerged, including Coinbase and Binance. However, CEXes are associated with counterparty risk. If the private keys of a CEX are leaked, attackers can potentially access the funds. The collapse of FTX, a CEX, in November 2022 had cascading effects on the cryptocurrency market.[13] In simple words, the assets held by Alameda Research (a sister company of FTX) consist mostly of cryptocurrencies created and controlled by FTX and its insiders, rather than fiat currencies or cryptocurrencies with established value. Upon learning this, investors and customers withdrew funds from FTX, creating a situation akin to a 'bank run.' Consequently, FTX's bankruptcy induced high volatility in the cryptocurrency market, negatively impacting investor confidence.

Having observed the failures and inherent risks of CEXes, investors seek to exchange cryptocurrencies in a trustless and secure manner. Currently, DEXes offer an alternative for investors. In a DEX, there is no intermediary exchange acting as a custodian for investors' cryptocurrencies, and the exchange of cryptocurrencies is facilitated by smart contracts. More formally, DEXes can be defined as DeFi protocols that enable users to exchange cryptocurrencies without the need for any centralized counterparty (Aspris, Foley, Svec, & Wang, 2021).

2.8.1 Automated Market Maker (AMM)

Among DEXes employing various market mechanisms, those utilizing Automated Market Makers (AMM) are the most popular. AMM-based DEXes do not rely on a traditional limited order book, allowing for instant trading based on the available liquidity for a given trading pair. Prices are determined according to mathematical formulas. Compared to limited

[13] https://www.investopedia.com/what-went-wrong-with-ftx-6828447

order books, AMM is computationally more efficient and has minimal storage requirements. Additionally, traditional limit order books may not be well-suited for a 'long-tail' of illiquid assets (Aspris et al., 2021).

Most (though not all) of the deployed AMMs take the form of a constant function market maker (CFMM), a market mechanism first suggested and analysed by Angeris, Kao, Chiang, Noyes, & Chitra (2021). In practice, CFMM is adopted by various leading DEXes, such as Uniswap (see Adams, Zinsmeister, & Robinson (2020) and Adams, Zinsmeister, Salem, Keefer, & Robinson (2021)). Here, the explanation of the simplest CFMM is provided using two hypothetical cryptocurrencies, namely cryptocurrency X and cryptocurrency Y. The formula employed by CFMM is as follows:

$$x \times y = k \ (2.1)$$

Under CFMM, the trading pair of X and Y needs to satisfy equation (2.1), where x and y represent the amount of X and Y available liquidity provided on the trading pair, respectively, and k is a constant. Assuming that one exchanges a quantity Δy of Y for a quantity Δx of X, then the quantities to exchange need to satisfy the condition below:

$$x \times y = (x + \Delta x)(y - \Delta y) = k \ (2.2)$$

There are other mathematical models that can be used in AMM-based DEXes. For more details, readers can refer to Xu, Paruch, Cousaert, & Feng (2023).

2.8.2 Security concerns

Primary participants in AMM-based DEXes include liquidity providers, exchange users (or traders), and the protocol foundation (comprising founders, designers, and developers), with various risks associated with liquidity providers and traders.

Heimbach, Wang, & Wattenhofer (2021) present an empirical study on the behavior of liquidity providers, employing Uniswap as a case study. In DEXes, liquidity providers lock their cryptocurrencies into the corresponding liquidity pools and benefit from transaction fees. Despite DEXes allowing users to establish liquidity pools between any pair of tokens, several popular cryptocurrencies tend to dominate the market, potentially leading to illiquidity for less popular cryptocurrencies. Additionally, a small group of liquidity providers contributes the majority of liquidity in the most popular pools, indicating a degree of individual control over the DEX market. This hints at centralization in the DEX market. Moreover, liquidity providers adopt different trading strategies, often focusing on changes in trading volume within stable pools and being influenced by external market factors. Therefore, it becomes crucial for DEXes to devise incentives that encourage significant liquidity providers to remain in the DEX and actively contribute.

Analogous to traditional exchanges, arbitrageurs play a role in the DEX market. Wang, Chen, Deng, & Wattenhofer (2022) delve into cyclic arbitrage in DEXes, wherein a trader can exchange currency A for B, then B for C, and finally C for A again through three distinct trading pools. Analysing transaction-level data on Uniswap, they demonstrate that arbitrage opportunities are more readily exploited in DEXes compared to CEXes.

In addition to cyclic arbitrages, arbitrageurs employ various methods to generate profits. Milionis, Moallemi, Roughgarden, & Zhang (2023) introduce the concept of 'Loss-Versus-Rebalancing (LVR)' in AMM-based DEXes. LVR refers to the costs incurred by AMM liquidity providers due to stale prices exploited by better-informed arbitrageurs. When prices change on centralized exchanges (CEXes), prices on AMM-based DEXes become 'stale' as AMM does not proactively update their price quotes. Arbitrageurs can then capitalize on this discrepancy by executing arbitrage transactions until AMM prices align with CEX prices. Consequently, AMMs incur losses from price slippage. Currently, LVR is a challenging issue for AMM-based DEXes, and perfect solutions have not yet been proposed.

2.9 Risks and challenges in DeFi

Beside risks and security concerns discussed in the previous section, the DeFi market faces common risks and challenges. This section provides a brief introduction to the general risk implications of DeFi. For more in-depth information, readers can refer to Carapella, Dumas, Gerszten, Swem, & Wall (2022) and Capponi, Iyengar, & Sethuraman (2023).

2.9.1 Operational risks caused by smart contracts

Carapella et al. (2022) focus on operational risks in DeFi. While DeFi can reduce some operational risks associated with traditional finance, it introduces new types of operational risks.

Smart contracts may contain mistakes or bugs. In many instances, smart contracts have exhibited design weaknesses that allowed hackers to improperly access funds. A notable example is The Decentralized Autonomous Organization (The DAO) hack on the Ethereum blockchain in June 2016. Before the hack, The DAO had raised over $150 million before the hack, making it one of the largest crowdfunding campaigns on the Ethereum blockchain. Exploiting a flaw in The DAO's smart contracts, a hacker drained around 3.6 million Ether (ETH).[14] Subsequently, a hard fork was implemented in July 2016 to roll back all transactions related to The DAO, enabling contributors to reclaim their funds. This led to the creation of two separate blockchains: Ethereum and Ethereum Classic, as users who did not accept the rollback could choose to use Ethereum Classic. Ethereum Classic has since evolved into a distinct blockchain from Ethereum.

Another concern related to smart contracts is the negotiation cost. In contrast to traditional contracts, smart contract deployers are typically anonymous, making it difficult for parties to renegotiate their contracts. This anonymity may result in higher negotiation costs. Traditionally, most non-smart contracts (e.g., paper contracts) intentionally remain incomplete (Wall, 2016). Parties can specify and negotiate terms in full, creating an opening for renegotiating the contract, which is often more cost-effective. Currently, this challenge lacks effective solutions.

[14] https://www.gemini.com/cryptopedia/the-dao-hack-makerdao#section-origins-of-the-dao

2.9.2 Governance attacks

In DeFi, governance attacks involve malicious actions by attackers aimed at gaining control over a DeFi protocol. Gudgeon et al. (2020a) outline two strategies employed in governance attacks.

The first strategy is crowdfunding, as elucidated by Zoltu (2019). In simple terms, multiple attackers collaborate to acquire a sufficient number of governance tokens through any available means to attain significant control. Subsequently, the attackers draft a governance proposal suggesting the transfer of all collateral assets within the DeFi protocol to them. Following this, the attackers swiftly vote to activate the proposal. The gains from the attack are then distributed among the participating parties. Gudgeon et al. (2020a) present a case study using the Maker protocol, demonstrating the potential for attackers to steal $0.5 billion in locked collateral from the protocol and generate an unlimited supply of DAI stablecoins.

The second strategy for governance attacks involves the use of a flash loan, a noncollateralized loan that remains valid within a single transaction. Presently, several DeFi protocols, including the Aave protocol, offer such financial services.[15] The attack strategy unfolds in three steps: (1) initiation of a flash loan to borrow a sufficient amount of governance tokens, (2) execution of actions designed to extract significant profits, and (3) repayment of the loan along with the associated interest of the flash loan.

An example of governance attacks is Justin Sun’s vote on Compound protocol in February 2022.[16] Initially, Sun borrowed 99,000 COMP tokens, the governance token of the Compound protocol, and subsequently transferred these tokens to Binance, a prominent centralized cryptocurrency exchange. Subsequently, an anonymous user, who had received a substantial amount of COMP from Binance, proposed a governance change advocating for the addition of TUSD token as a new collateral asset on Compound. Given that Justin Sun

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[15] More details about flash loans can be found: https://docs.aave.com/developers/guides/flash-loans

[16] More details can be found: https://www.coindesk.com/tech/2022/02/04/trons-justin-sun-accused-of-governance-attack-on-defi-lender-compound/

is the founder of TRON, the issuer of the TUSD token, there is a reasonable suspicion that he orchestrated these activities.

2.9.3 Illegal activities

Blockchain and DeFi encounter a significant challenge in terms of regulation, as the nature of these activities makes it difficult to be regulated. Instances of abusive behavior, fraud, and episodes of financial instability pose risks to DeFi users and the overall integrity of the DeFi system. However, implementing effective regulation for these activities remains a complex task (Carapella et al., 2022).

In an empirical study focusing on Bitcoin, Foley, Karlsen, & Putniņš (2019) discovered that approximately one-quarter of all users and nearly half of Bitcoin transactions were linked to transactions involving illegal goods, such as drugs. Building upon this, Hiramoto & Tsuchiya (2022) delved into the drug trading in the cryptocurrency market, revealing its influential role in the market's growth. Additionally, cryptocurrencies, particularly Bitcoin, are frequently utilized for transactions on dark web marketplaces. Hiramoto & Tsuchiya (2020) provide evidence regarding the market size, development, and fluctuations of these dark web marketplaces by identifying and tracing Bitcoin addresses associated with illicit activities.

2.10 Theoretical perspectives informing blockchain and DAO

Blockchain facilitates the implementation of experiments in decentralized governance, with Decentralized Autonomous Organizations (DAOs) being characterized as a 'new type of economic institution' (Davidson, Filippi, & Potts, 2018). Consequently, the economic examination of blockchain and DAOs represents a novel domain that enables economists to advance theoretical research. Lumineau, Wang, & Schilke (2021) discuss the distinctions between blockchain governance and traditional contractual and relational governance frameworks. Unlike contractual governance, blockchain governance fosters collaborations without relying on legal frameworks, while diverging from relational governance by not necessitating direct connections between collaborating parties. This subsection will introduce three primary theoretical perspectives applied to blockchain and DAO: transaction cost theory, theory of institutions for collective action, and agency theory. For more detailed systematic literature review, readers can refer to Santana & Albareda (2022).

2.10.1 Transaction cost theory

Among transaction costs, blockchain technology can significantly affect two key costs: the cost of verification and the cost of networking (Catalini & Gans, 2019). This is potentially explained by blockchain's capacity to diminish the market power of intermediaries, consequently reducing costs associated with intermediation. Using startup financing as an illustrative example, Ahluwalia, Mahto, & Guerrero (2020) demonstrate how blockchain technology can mitigate transaction costs by fostering trust. Miscione, Goerke, Klein, Schwabe, & Ziolkowski (2019) examine blockchain as an organizational technology, contending that it can mitigate costs associated with 'double-spending' issues, namely data duplication, without reliance on any central authority. However, in the context of blockchain governance, all involved parties, including developers, miners, and generators, must be considered.

In the context of DAOs, Berg et al. (2019) propose a complete contracting model, elucidating how DAOs can diminish market-based transaction costs. DAOs, on one hand, can mitigate uncertainty and opportunism among investors. On the other hand, they reduce transaction costs related to economic coordination by offering an alternative form of disintermediated economic governance.

2.10.2 Theory of institutions for collective action

The theory of institutions for collective action, originally proposed by Ostrom (1990) for local common-pool resources, pertains to limited resources shared by a community, such as lakes and forests. This theory explains how local users of common-pool resources design self-governing principles to mitigate selfish behavior. Given that blockchain and DAOs are formed by virtual community members, this theory can be re-examined, and scholars are particularly interested in novel power relationships and new hierarchies in blockchain-based governance.

Howell, Potgieter, & Sadowski (2019) and Rozas, Tenorio-Fornés, Díaz-Molina, & Hassan (2021) discuss how the theory of institutions for collective action applies to blockchain governance. Howell et al. (2019) propose that blockchain governance can be analogized to the governance of clubs. Club theory was first proposed by Buchanan (1965) in the context of clubs providing rival and excludable goods and being consumed by volunteer members. Subsequently, significant works by Ostrom (2010) and Ostrom (2014) expanded the discussion to include self-organizing governance systems, demonstrating that common resources could be managed successfully without government regulation or privatization.

Rozas et al. (2021) focus more on the affordances that DAOs can provide to communities, particularly self-enforcement and formalization of rules, autonomous automatization, and decentralization of power over the infrastructure. However, there remain concerns that require further exploration. For example, rules embedded in smart contracts rely on an ex-ante nature rather than an ex-post one (De Filippi & Hassan, 2016), and such rules cannot deal with exceptions very well. Moreover, a DAO cannot ascertain if a person is being coerced to vote in a certain way (Rozas et al., 2021). Given that collective action theory emphasizes ethical issues, such as fraud and corruption, Sulkowski (2019) argues that it is necessary to examine these issues in the context of DAOs.

2.10.3 Agency theory

Agency theory, originally proposed by Fama & Jensen (1983), aims to analyse the ownership and control of owners or investors over managers. Specifically, this theory explores the problems that arise when the 'principal' (owner) and the 'agent' (manager) have conflicting interests, such as differing goals and attitudes towards risk. This issue is commonly known as the principal-agent problem, and Eisenhardt (1989) provides a more detailed discussion.

Blockchain and DAOs are considered alternatives that remove the control and authority of traditional managerial hierarchies. Furthermore, there is no clear separation between ownership and management in DAOs (Nabilou, 2020). Therefore, a series of research has re-examined whether agency theory applies to blockchain and DAOs. Several studies, such as Shermin (2017) and Kaal (2020), argue that blockchain and DAOs can resolve the principal-agent problem. One reason is that they eliminate the need for principals to monitor and control agents, given the integrity and transparency of the underlying peer-to-peer network (Yermack, 2017). Additionally, Sockin & Xiong (2023) and Bena & Zhang (2023) analyse how utility tokens mitigate interest conflicts between platform owners and users, demonstrating that decentralized platforms lead to greater surplus for users compared to centrally governed platforms.

However, there are ongoing debates regarding the complexity of the principal-agent problem in blockchain and DAOs. Murray, Kuban, Josefy, & Anderson (2021) discuss the agency costs that cannot be mitigated by technology, such as excess expenses and compensation for interest alignment. Moreover, there are new roles that wield significant control over blockchain and DAOs, such as developers (Kotsialou et al., 2018) and miners (Gervais et al., 2014).

Chapter 3

Decentralized Illusion in Decentralized Finance: Evidence from Tokenized Voting in MakerDAO Polls

Decentralized Autonomous Organization (DAO) is very popular in Decentralized Finance (DeFi) applications as it provides a decentralized governance solution through blockchain. We analyze the governance characteristics in the Maker protocol, its stablecoin DAI and its governance token Maker (MKR). To achieve that, we establish several measurements of centralized governance. Our empirical analysis investigates the effect of centralized governance over a series of factors related to MKR and DAI, such as financial, network and Twitter sentiment indicators. Our results show that governance centralization influences the Maker protocol and that the distribution of voting power matters. The main implication of this study is that centralized governance in MakerDAO very much exists, while DeFi investors face a trade-off between decentralization and performance of a DeFi protocol. This further contributes to the contemporary debate over whether DeFi can be truly decentralized.

3.1 Introduction

Since the introduction of Bitcoin in 2008 (Nakamoto, 2008), blockchain has deeply changed financial markets. Various debates have evolved around the potential democratization of financial services (Bollaert, Lopez-de-Silanes, & Schwienbacher, 2021), blockchain competition and services improvement (Choi, Guo, Liu, & Shi, 2020; Zhang, Ren, Lan, & Yang, 2022), as well as investment opportunities in new tokenized assets (Howell, Niessner, & Yermack, 2020; Anyfantaki, Arvanitis, & Topaloglou, 2021; Karim, Lucey, Naeem, & Uddin, 2022). It is widely accepted, though, that the main disruption lies in the disintermediation of financial institutions from their centralized role. The absence of centralized third parties, e.g., central banks, in the blockchain universe and circumventing traditional barriers to participation in financial markets are the major attributes of this market revolution. The role of a central authority is limited or absent. Such decentralized frameworks theoretically allow all participants to be part of prominent decision-making and share risk (Abdikerimova & Feng, 2022). Decentralization, therefore, is logically regarded as the core value proposition of blockchain (Harvey et al., 2021).

Decentralized Finance (DeFi) describes blockchain-based financial applications which are designed to replicate most financial activities, e.g., lending and borrowing, in traditional markets. Theoretically, governance in DeFi is decentralized since all members are decision makers. In traditional finance, governance is inevitably centralized, which can be the origin of several problems. The most intractable issue is probably the agency problem, where the owners and managers of an organization have different interests. Managers can pursue their own profits at the expense of owners (Fama & Jensen, 1983). Therefore, the most challenging objective of governance is to align the interests of owners and managers. As discussed by Lee (2019), the decentralized nature of blockchain brings forward the idea of a ‘token economy’, where capital is better directed to those users actually contributing content and services. Within the DeFi context, owners and managers are theoretically identical, which creates an opportunity to investigate the premises of this debate once again. Another crucial intersection between traditional finance and DeFi is stablecoins and their links with the potential introduction of Central Bank Digital Currencies (CBDCs). Even if stablecoins are considered safer than other cryptocurrencies, central banks continue to scrutinize them. Are these tokens really needed to ensure DeFi liquidity, and does introducing CBDCs ensure financial stability from a stablecoin crash?

Stemming from this background, evaluating the efficiency of DeFi is a crucial task. As Momtaz (2022) explains, one pathway to settling this debate is by examining the true decentralized nature of DeFi platforms. Despite the fact that the market size of DeFi exceeds 80 billion dollars (as of April 2022), the debate on whether decentralization is realistic or an illusion still stands (Aramonte, Huang, & Schrimpf, 2021; Carter & Jeng, 2021). Anker-

Sørensen & Zetzsche (2021) argue that innovators prefer less decentralized DeFi platforms for making profits; as a result, governance rights and modes of control in DeFi are highly likely to be centralized. DeFi platforms showcase elements of centralization, usually in the form of ‘governance tokens’ and power concentration to large coin-holders. This phenomenon can lead to collusion among core decision makers during the governance process. It is obvious, then, that governance becomes a critical dimension of the success of true decentralization in DeFi. Decentralized Autonomous Organization (DAO) is one popular solution to decentralized governance and decision making. In a DAO, all members are owners of the organization, and they have decision-making power around its development. Usually, the suggested changes will be written in the form of an Improvement Proposal (IP), which is then voted on through an established poll, where all members can make public their choices. DAO members state their choice through governance tokens. Usually, these governance tokens are also tradable cryptocurrencies. The votes are weighted by the number of governance token held by voters. In other words, governance in DAO is tokenized. Currently, DAO is one of the most common governance mechanisms adopted by DeFi (World Economic Forum, 2021).

So far, voluminous literature focuses on blockchain governance, and the debate revolves around the pros and cons of decentralization. Decentralization will result in slower decision making, implying that the network becomes inefficient (Hsieh et al., 2017). Yermack (2017) argues that, in practice, blockchain governance is not completely decentralized. In some extreme cases, the final decision is taken by only the core developers. For example, Bitcoin core developers once decided to lower transaction fees without discussing it with the related community (Gervais et al., 2014). Recently, Jiang, Li, Wang, & Zhao (2022) discuss blockchain governance by evaluating the trade-off between stability and efficiency through the prism of sensitivity to transaction fees. The authors suggest that the decentralized and audible nature of the blockchain transaction is attractive, but transaction fee movements have led to fork splits and endangered the system’s stability. Their findings show that when users have balanced preferences between efficiency and stability, raising transaction fees reduces congestion in the platform. However, when it comes to DeFi platforms and DeFi governance, the literature is quite silent. What would be the effect of powerful voters proposing and voting on polls that serve their own interests? Tsoukalas & Falk (2020) and Carter & Jeng (2021) provide some insights on this question. Many blockchain-based platforms apply a token-weighted voting mechanism, relying on the premise that tokenized voting incentivizes users towards higher-quality voting and improves system performance. The four mentioned authors explain that this is not always correct, as this voting mechanism discourages truthful votes and decreases the stability of the platform. Recently, Goldberg & Schär (2023) utilize Decentraland, a blockchain-based virtual world (i.e., metaverse), as a case study. By analysing voting behavior, they contend that voting power is not decentralized, which may cause rent extraction behavior and other related problems. Therefore, centralized governance in DeFi could exert negative effects.

Though such papers provide both theoretical models and empirical evidence of governance centralization in blockchain, the literature surprisingly remains silent when it comes to centralization in DeFi. Positioning the centralized governance debate in the DeFi universe at the forefront of the literature is the main motivation of this chapter. We focus on the Ethereum-based DeFi platform, Maker protocol, developed and managed by MakerDAO, as a case study. The rationale behind this choice is simple. MakerDAO is one of the most influential DAOs. Since 2017, when the DeFi universe expanded exponentially, Maker protocol has emerged as the leading lending protocol, which conceptually replicates the operation of a bank in cryptocurrency markets. In the Maker protocol, Maker (MKR) is the governance token. In terms of its value, one token equals one vote in the proposed polls. Apart from this tokenized value, Maker protocol issues DAI, which is a stablecoin soft-pegged to the US Dollar (MakerDAO, 2020). Currently, DAI is one of the most traded stablecoins, with more than ten thousand daily transactions. Although the Maker protocol seems to be a big success of DAO, the way it is governed in practice has not been rigidly examined. To the best of our knowledge, this is the first research that focuses on providing empirical evidence of centralized governance in DeFi.

To achieve that, we collect information for the Maker protocol governance, including all voters, their choice and voting power in Maker governance polls from 5th August 2019 to 22nd October 2021. Our empirical analysis follows two stages. The first stage is to examine governance polls by defining three novel measurements of centralized governance, namely voting participation, centralized voting power and distribution of governance tokens. In the second stage, we investigate the effect of centralized governance on the development of Maker protocol. To achieve this, we expose MKR and DAI to several Maker-specific factors. These factors can be divided into several categories, including financial, network and Twitter sentiment indicators. We also investigate the ratios of collateral assets locked in Maker protocol. Such an empirical setup is consistent with similar studies in the field, such as Liu & Tsyvinski (2020). Beside well-investigated factors, e.g., network factors, we also consider transaction demand (e.g., trading volume), which is a theoretical determinant of token price (Cong et al., 2020). Finally, since users have to lock collateral assets before initiating loans from Maker, acceptable collaterals are a main issue discussed in Maker governance. If collateral is insufficient, theoretically Maker protocol will be less safe due to fewer users participating in it.

The empirical framework brings forward some very interesting findings. By examining governance polls in the Maker protocol, we observe signals of centralized Maker governance. Compared with the rapidly increasing number of users, voters are centralized in a small group, and the most dominant voters are heterogeneous in characteristics. The unevenly distributed voting power, as a preliminary signal of governance centralization, leads to our measurements of governance centralization in Maker protocol. By applying factor analysis, we find a complex nexus of effects of centralized governance around voting participation and distribution of voting power. Intuitively, more voters are a signal of larger voting participation, implying more decentralized governance. Voting participation can directly affect the financial factors of DAI. For example, the trading volume of DAI decreases as more voters vote in governance polls. This suggests that stablecoin can be affected by participation in the polls and that decentralized governance could affect market performance of cryptocurrencies. Centralized distribution of the governance token, i.e., MKR, can decrease the trading volume of MKR and DAI, implying that centralization may bring more serious problems. After expanding our work on other indicators, we find centralized governance exerts complex influence on the adoption of Maker protocol. This is a serious issue, as the more decentralized MakerDAO becomes, the fewer users start using DAI stablecoin. This paints a not very optimistic picture not only for the long-term growth of Maker protocol but also for other DAO-governed DeFi platforms. Finally, voting power distribution appears to play a significant role in the ratios of collateral assets. Consequently, the centralized voting power of large voters may change the proportion of main collateral assets (e.g., stablecoins) locked in the platform. Overall, all the above findings suggest that both the degree of MakerDAO’s centralized governance and its performance pose a relevant trade-off among DeFi investors.

The remainder of this chapter is organized as follows. Section 3.2 provides a summary of the governance process in MakerDAO. The dataset and the measurements of centralized governance in the Maker protocol are defined in section 3.3. The main empirical results are presented in section 3.4, while robustness checks are provided in section 3.5. Section 3.6 provides some concluding remarks. Finally, the appendices provide a description of the utilized factors, the relevant Granger tests, further technical details and robustness tests.

3.2 Governance in the Maker Protocol

3.2.1 Decentralized Autonomous Organization (DAO), MakerDAO and Maker protocol

Decentralized Autonomous Organization (DAO) is a novel mechanism of organizational governance and decision making. The DAO white paper is first proposed by Jentzsch (2016). Technically, DAO can be deployed on blockchain, and, currently, most DAOs rely on Ethereum, which is a programmable blockchain. Ethereum's yellow paper was introduced by Wood (2014), and Ethereum users can write smart contracts in a Turing-complete programming language such as Solidity. By writing and executing smart contracts, users can actualize various interactions and functions, e.g., transactions on Ethereum. The programmable character enables the implementation of DAO. The core of DAO governance is based on standard smart contract code instead of human actors. In other words, DAO's governance is tokenized. In practice, DAO-based protocols usually have their own governance token and governance token holders can vote on changes to the protocols.

MakerDAO was created in 2014, and it has become one of the most influential DAOs. The Maker protocol is a multi-collateral lending system, and the protocol is governed by MakerDAO teams, including individuals and service providers (MakerDAO, 2020). Based on the functions of Maker protocol, it is usually categorized as a Lending Protocol (LP), resembling banks in cryptocurrency markets. Simply, users can lend their tokens to LPs for economic incentives. On the other hand, users can borrow tokens, and LPs usually require collateralization. The economic mechanism, mathematical models and the roles of LPs are well discussed by Bartoletti et al. (2021). Maker protocol issues DAI and the protocol is de facto a Multi-Collateral Dai (MCD) system. DAI is probably the most notable stablecoin, which is soft-pegged to the US dollar. Stablecoins, such as DAI, are cryptoassets designed to cope with the volatility of traditional cryptocurrencies and provide a bridge with fiat currencies (Wang, Ma, & Wu, 2020). As MCD was launched in 2019, in Maker protocol every user can lock any supportive collateral such as ETH and a corresponding number of DAI will be generated as debt.

In addition to DAI, we are also interested in the MKR token. In practice, MKR plays two roles. On the one hand, MKR is the governance token of Maker protocol. MKR holders can vote on changes to the protocol. On the other hand, MKR contributes to the recapitalization of the system. MKR is created or destroyed through the automated auction mechanism of Maker protocol. When the debt of protocol is outstanding, MKR is created and sold for DAI. The protocol sells DAI for MKR and the surplus MKR is destroyed. At the inception of MakerDAO, one million MKR were issued. The protocol sets maximum threshold and minimum threshold of MKR, and the total circulated MKR always fluctuates between the thresholds.

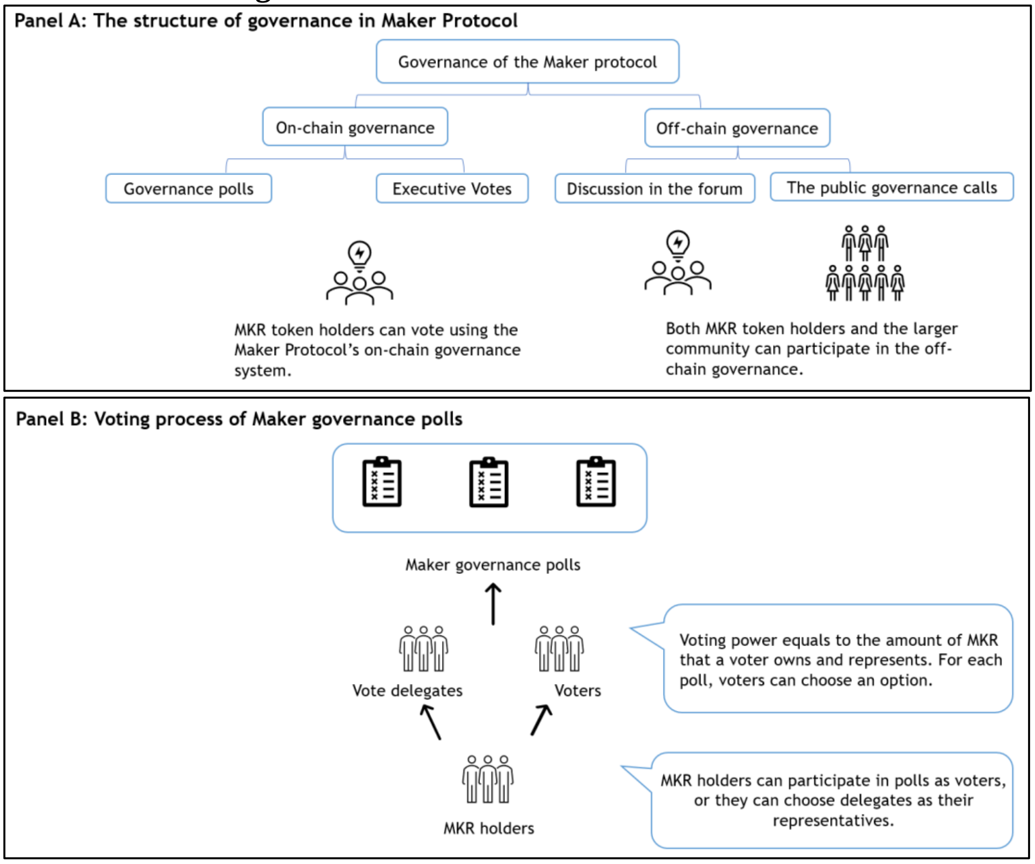
3.2.2 Maker governance structure and voting process

An innovative selling point of the Maker protocol is decentralized governance. In the Maker protocol, governance can be divided into two parts: on-chain governance and off-chain governance. In on-chain governance, there are two types of votes, namely Governance Polls and Executive Votes. Any MKR holders can vote using the Maker Protocol's on-chain governance system. Governance polls, which are about non-technical changes, measure the sentiment of MKR holders. Executive votes "execute" technical changes to the protocol. The voting results are documented on blockchain. Off-chain governance is mainly about informal discussion, e.g., discussion on the MakerDAO forum. Both MKR holders and the larger community can express their opinions. Voting power is weighted by the amount of MKR that a voter owns and represents, making the voting mechanism a token-weighted one (Tsoukalas & Falk, 2020). One MKR equals one vote, and the option with the most votes wins. In the Maker protocol, Maker IPs are structured and formalized for a voting event, and key issues and changes to the system are rigidly defined in Maker IPs. Usually, the Maker Foundation will draft the initial Maker IPs, and any community members can propose competing IPs. Then, the final decisions will be made by MKR voters through the current Maker governance process. The above information is illustrated in Figure 3.1.

MKR holders can be voters and directly choose their options on the Maker Governance Portal. On the other hand, they can choose a Vote Delegate to be their representative. As a result, delegates gain voting power from MKR holders, and these MKR holders can indirectly vote. The voting results are weighted by the amount of MKR voted for a proposal. Noticeably, Vote Delegates were not introduced in the very beginning. On July 30th, 2021, the guidance to Vote Delegates was live in MakerDAO, while on 10th November 2021, 16

Delegates and 65989.65 MKR were delegated. Currently, there are three types of voting in Maker governance, i.e., Forum Signal Threads, Governance Polls and Executive Votes. These are summarized in Table 3.1.

Figure 3.1: Governance in Maker Protocol



Note: Panel A shows the governance structure of Maker protocol. It is divided into two parts, on-chain governance and off-chain governance. Panel B illustrates the voting process of Maker governance polls. MKR holders can participate in polls as voters, or they can choose delegates as their representatives.

Table 3.1: Types of votes in Maker protocol

Type of votes	Functions
Forum signal threads	(1) Determine consensus that something needs to be done in response to a perceived issue, (2) determine consensus for a concrete action to be taken in response to a perceived issue.
Governance polls	(1) Determine governance and DAO processes outside the technical layer of the Maker Protocol, (2) form consensus on important community goals and targets, (3) measure sentiment on potential Executive Vote proposals, (4) ratify governance proposals originating from the MakerDAO forum signal threads, (5) determine which values certain system parameters should be set to before those values are then confirmed in an executive vote, (6) ratify risk parameters for new collateral types as presented by Risk Teams.
Executive votes	(1) Add or remove collateral types, add or remove Vault types, adjust global system parameters, adjust Vault-specific parameters, (2) replace modular smart contracts.

Note: This table describes three types of votes in Maker protocol. Forum signal threads are a part of off-chain governance, and all community members can participate in the discussion on the Maker forum. Governance polls and executive votes are on-chain.

Table 3.1 highlights the functions of the three types of votes. Forum Signal Threads are the least consequential, and the threads are a part of off-chain governance. Governance Polls and Executive Votes occur on-chain, and they can be accessed through the Maker Foundation’s Voting portal. Simply, Governance Polls determine processes outside the technical layer, while Executive Votes are about technical changes to the protocol. Executive Votes use the 'Continuous Approval Voting' model to make the system more secure. The voting model means that new proposals need to surpass the voting weight of the last successful proposal (MakerDAO, 2021).

3.2.3 Governance centralization

Centralization in the governance layer of blockchain has attracted the attention of the academic audience, with the discussion mainly focusing on two problems, namely owner control and improvement protocol (Sai et al., 2021). Gervais et al. (2014) argue that the author Satoshi Nakamoto may accumulate significant Bitcoin since Nakamoto participated in activities at the early stage of Bitcoin blockchain. Similar evidence of owner control exists in Ethereum as well (Bai, Zhang, Xu, Chen, & Wang, 2020). The large proportion of wealth controlled by the owners of blockchains may result in economic manipulation in blockchain. As for improvement protocol, this problem derives from the process of moderation in blockchain. Usually, blockchain and DeFi adopt an improvement proposal system in the decision-making process. By analysing the authors and contributors of improvement proposals, Azouvi, Maller, & Meiklejohn (2018) find that core developers are the main contributors to the development of Bitcoin and Ethereum. In other words, these core developers have more power in the decision-making process.

Apart from the two problems described above, DAO, as a new organizational form to automate governance, may bring both opportunities and challenges. Benefiting from blockchain technology, the ownership is more transparent, and voting can be more accurate (Yermack, 2017). On the other hand, centralization seems to still be inevitable in DAO.

Maker Governance Polls do not attract much participation and MKR held by the dominant voters may theoretically lead to collusion in some polls. However, in order to examine this, we need information from many polls, and this is not an easy task. As shown in the next section, the quest to obtain information from more polls is achieved in this study.

3.3 Data collection and identification

3.3.1 Data collection

In Maker Governance Portal, the details of governance polls, e.g., the number of voters and results, are publicly available. To get the voters' addresses, we query the voting history from MCD Voting Tracker. We investigate governance polls from Poll 16 (deployed on 5th August 2019) to Poll 663 (deployed on 22nd October 2021). The deploy dates of the polls are used to identify when the polls are added to Ethereum blockchain via a transaction. Though the dates might be earlier than the start dates when voters can choose options, the contents of polls are already publicly accessible once the polls are sent to the blockchain. Poll 16 was the first governance poll that MKR holders could participate in. Some polls failed,[17] so they are not documented in the portal. Hence, the dataset consists of a total of 638 successful governance polls, and the voters' public names can be found by searching for their addresses on Etherscan.io and Maker Governance Portal. To study the effects of centralization in Maker governance, we consider two influential crypto assets issued by Maker protocol, namely MKR and DAI.[18]

3.3.2 Measurements of centralized voting power in Maker protocol

[17] Polls 28, 39, 47, 69, 78, 183, 282, 284, 286, and 500 failed.

[18] The Maker portal is available at: https://vote.makerdao.com. The voting tracker is available at: https://beta.mcdgov.info. The DAI and MKR statistics can be found at: https://www.intotheblock.com/.

This section introduces the novel measurements of centralized voting power in Maker protocol, namely voting participation, centralized voting power and distribution of governance tokens. For each of the first two measurements, we initially calculate the value at the poll level. Then, daily measurements can be generated. The distribution of governance tokens can divulgate more information about centralized power of certain Maker protocol users, e.g., MakerDAO delegates and large MKR holders.

Voting participation To proxy voting participation, we use two measurements. One is the total votes of Maker governance polls on a given date. The other is the number of total voters on a given date. Here, a voter refers to an Ethereum address. Intuitively, when these two measurements are higher, there are more voters and votes in governance polls. Assuming that there are n polls and m voters on a date d, we have:

$$Total\ votes_d = \sum_{i=1}^{n} Total\ votes_{i,d} \quad (3.1) \quad \text{and} \quad Voters_d = \sum_{i=1}^{m} Voters_{i,d} \quad (3.2)$$

Centralized voting power In order to capture centralized voting power, we utilize two measures. The first is the Gini coefficient, which is traditionally used to measure inequality (Dorfman, 1979). Assuming that there are l voters in a governance poll, we have:

$$Gini = \frac{\sum_{i=1}^{l}\sum_{j=1}^{l}\left|votes_i - votes_j\right|}{2l^2\overline{votes}} \quad (3.3)$$

where $votes_i$ is the cast votes of voter i, and $\overline{votes}$ is the average votes in a governance poll.

After computing the Gini coefficient for each poll, we can calculate a daily measurement by calculating the average. Assuming that there are n polls on a date d, we calculate the daily Gini coefficient, i.e., $Gini_d$, via maximum likelihood estimation (see Taleb (2015)). The number of voters participating in governance polls can be very different. If we choose arithmetic means to measure the daily Gini coefficient, our measurement can be more biased and suffer from lower accuracy. Maximum likelihood estimation, as an indirect method, can have a considerably lower error rate, especially when the sample sizes (in this case, the voters in a governance poll) vary.

The second proxy for centralized voting power is the largest voter's power in Maker governance polls. Here, largest voter refers to the voter that contributes most votes in a governance poll. The centralized voting power of largest voters can be approximated by the $Largest\ voting\ share$. In that way, we can also reflect on the relative voting power of the largest voter. For each poll, $Order$ refers to the voting order of the largest voter. When $Order$ is smaller, the largest voter will choose their option earlier. Assuming that there are n polls on a date $d,$ we have:

$$Largest\ voting\ share_d = \frac{\sum_{i=1}^{n} Largest\ voting\ share_{i,d}}{n} \quad (3.4)$$

Finally, the voting sequence can actually play a role, as this can be documented in several voting systems (see amongst others, Börgers (2010), Brams (2008), and Brams & Fishburn (2002)). Simply, voters have different strategies, and their voting order preference will vary with their goals. For each poll, we define a variable $order$ to measure the decision speed of the largest voter. Here, the order of the largest voter refers to the order in the whole history. This is to say, the voters with dominant voting power may change their choice later. Assuming that there are k records in the voting history of a governance poll i on a date d, we have:

$$Order_{i,d} = \frac{voting\ order\ of\ the\ largest\ voter}{k} \quad (3.5)$$

Assuming that there are n polls on a date $d,$ we have

$$Order_d = \frac{\sum_{i=1}^{n} Order_{i,d}}{n} \quad (3.6)$$

When $order$ is smaller, the largest voter chooses an option earlier than other voters. All voters can see the existing choices on Maker Governance Portal.

Distribution of governance tokens In addition to the measurements stemming from voting behavior in Maker governance polls, we also consider the distribution of governance tokens in MakerDAO (i.e., MKR), which reveals more information about the characteristics of centralized decision makers. Nadler & Schär (2020) show that token distribution is usually centralized in DeFi, and we suspect such centralization also exists in MakerDAO. First, we calculate the balance of MKR controlled by MakerDAO delegates, which equals the sum of

MKR owned by delegates and represented by delegates.[19] Assuming that there are l delegates, the MKR balance controlled by these delegates on a date d is:

$$delegate_d = \sum_{i=1}^{l} delegate_{i,d} \ (3.7)$$

where $delegate_{i,d}$ is the MKR balance controlled by delegate i on date d. A higher $delegate$ means more voting power is controlled by MakerDAO delegates, implying that the centralized governance is caused by these influential MakerDAO users.

Then, we compute the proportion of MKR controlled by large MKR holders. Here, we consider three categories of MKR holders, including holders with a balance of more than 10,000 MKR, holders with a balance between 10,000 and 100,000 MKR, and holders with a balance of more than 100,000 MKR. On a date d, we assume that there are x, y, z MKR holders in the three categories, respectively. Then, three measurements can be calculated to reflect on the centralized distribution of MKR:

$$> 10k_d = \frac{\sum_{i=1}^{x} > 10k_{i,d}}{total\ circulated\ MKR_d} \ (3.8)$$

$$10k - 100k_d = \frac{\sum_{i=1}^{y} 10k - 100k_{i,d}}{total\ circulated\ MKR_d} \ (3.9)$$

$$> 100k_d = \frac{\sum_{i=1}^{z} > 10k_{i,d}}{total\ circulated\ MKR_d} \ (3.10)$$

where $total\ circulated\ MKR_d$ is the amount of MKR circulating on Ethereum blockchain on date d.

When the three measurements above are higher, more voting power is controlled by large MKR holders. Although governance polls are not deployed on a daily basis, the centralized distribution of MKR is a signal of governance centralization, indicating that voting in MakerDAO is dominated by large MKR holders.

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[19] We query the voting power of MakerDAO delegates from *dune.xyz*.

3.4 Empirical results

This section summarizes the empirical results of this study. The first subsection presents the descriptive statistics of both polls and voters. Then, the centralization in Maker governance polls is described by the calculations of the measurements of centralized governance defined in the previous sections. The second subsection summarizes the factor analysis we perform to investigate the effects of centralized governance on the Maker protocol (MKR, DAI and locked collateral assets).

3.4.1 First stage: Governance polls in the Maker protocol

The collected information from the 638 governance polls is crucial for understanding centralization in the Maker protocol. Table 3.2 presents the descriptive statistics of these polls.

Table 3.2: Descriptive statistics of Maker governance polls

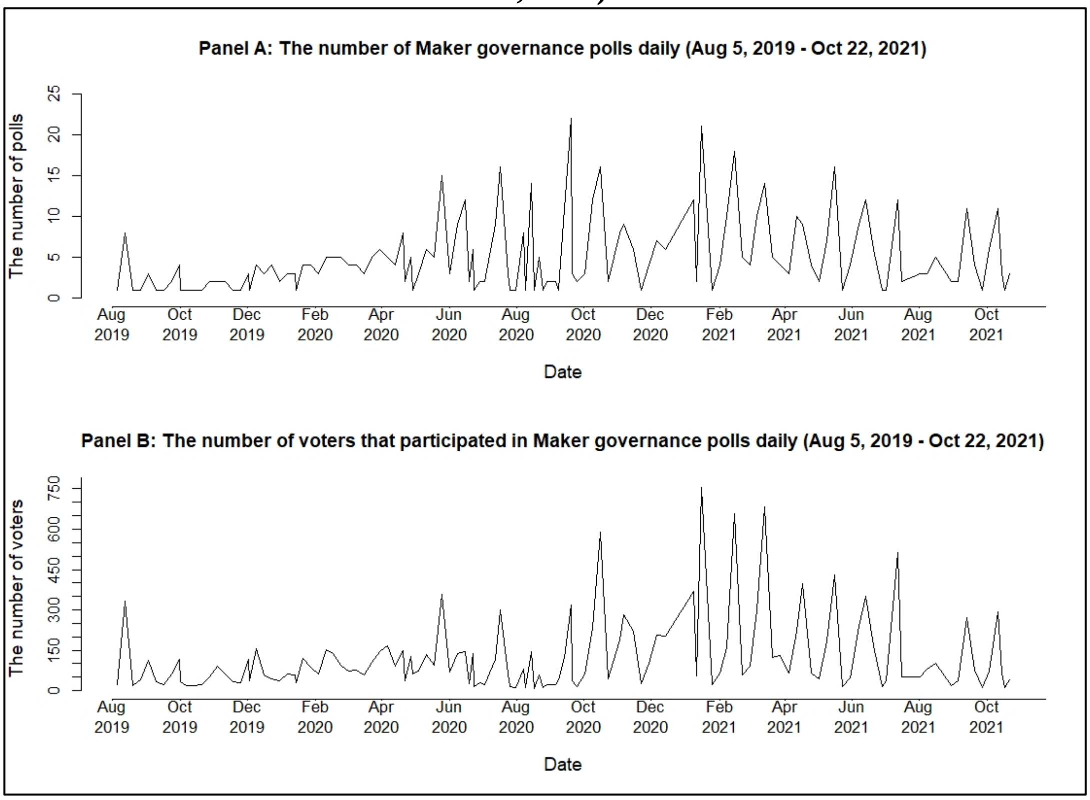
Panel A				
	Total votes	Total voters	Breakdown votes	Breakdown ratio
Mean	36096.52	24.59	31529.94	88.78%
Median	33097.15	23.00	28625.80	98.24%
Maximum	131555.35	146	108694.07	100.00%
Minimum	259.74	5	232.80	13.04%
Std	22383.18	12.76	19998.47	16.67%
Panel B				
	Breakdown voters	Votes of the largest voter	Vote share of the largest voter	
Mean	18.03	16941.61	52.66%	
Median	16.00	17063.93	48.35%	
Maximum	142	39403.85	98.51%	
Minimum	1	203.27	20.28%	
Std	11.63	8452.45	18.02%	

Note: This table reports the descriptive statistics of Maker governance polls. Breakdown votes refers to the votes of the winning option, and breakdown ratio is breakdown votes divided by total votes. Breakdown voters are the number of voters who choose the winning option.

The votes are calculated in MKR tokens, and for each governance poll, breakdown ratio is the proportion of breakdown votes to total votes. In addition to votes and vote share of the largest voter, the order of voting is considered. We also present the daily number of governance polls and voters in Figure 3.2. From the figures we can easily see that within a day, the number of deployed polls is usually less than 25. Usually, no more than 700 voters will vote on the same day. For some polls, no more than ten voters will participate in decision making. The finding implies that not all polls have large voting participation. Compared to the rapid growth of Maker users, voters are a small group. Our analysis extracts a total of 1,250 unique voters in our dataset. For each voter, the number of polls that they participate in can be surprisingly different. To showcase this, we present the following descriptive statistics in Table 3.3.

Examining the total votes and the highest votes that a voter has in a single poll shows that the voting power is not equally distributed across voters. This could be an early sign of voting centralization. However, to make this claim clearer, we need to delve deeper into the composition of the voters and their characteristics. To that end, we identify voters whose identity is publicly available, the top ten voters that participate in most polls, the top ten voters with the largest total votes and the top ten voters that have the largest votes in a single poll. This information is summarized in Appendix A.1.

Figure 3.2: The number of polls and voters in Maker governance (Aug 5, 2019 – Oct 22, 2021)



Note: This figure presents the daily number of polls and voters in Maker governance. Panel A shows the daily number of Maker governance polls, while Panel B presents the number of voters daily in Maker governance polls.

Table 3.3: Descriptive statistics of voters of Maker governance polls

	Involved polls	Total votes	First poll	The highest votes
Mean	12.55	18422.58	278.66	665.39
Median	2.00	1.42	248.00	1.00
Maximum	514	4170786.51	660	39403.85
Minimum	1	0.00	16	0.00
Std	42.46	164269.26	194.65	3372.75

Note: This table reports the descriptive statistics of voters in Maker governance polls. For each voter, we calculate the number of polls that they participate in, their total votes and the highest number of votes in a single poll. Here, votes are calculated in Maker (MKR), which is the governance token of the Maker Protocol. The first poll that a voter participated in is also presented. A lower number means that the voter started to participate in Maker governance polls earlier.

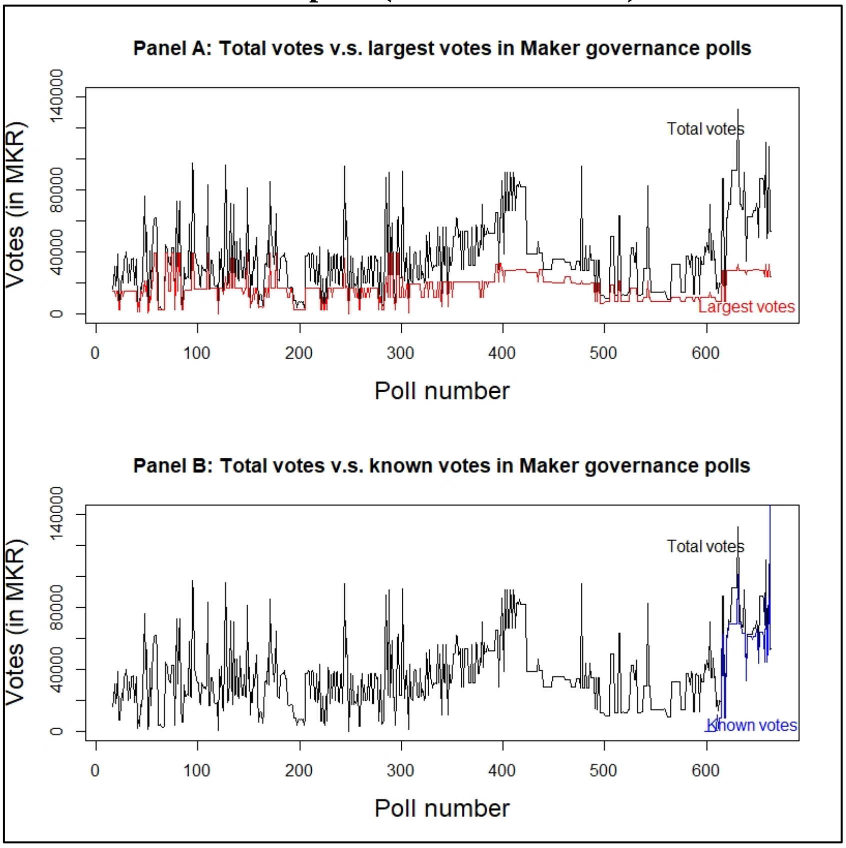
We have some interesting findings towards identifying centralized governance in the Maker protocol. Apart from *a16z,*[20] the known voters are delegates in Maker governance and their identity is publicly available on the Maker governance portal, and more details of these known voters are given as well. The mechanism of voting delegates was introduced in July 2021; therefore, most delegates started participating in governance polls in August 2021. Noticeably, the total votes and the highest votes in a single poll are different among these known voters. Field Technologies, Inc. is the known voter with the largest number of total votes (as of November 1st, 2021). In terms of voters that are participating in polls, none of them has a public name, i.e., their identity is unknown. Voters with the largest total votes are again heterogeneous in characteristics, while only two from the top ten are found to be delegates (Field Technologies, Inc. and a shadow delegate). When accounting for the voters with the largest single votes, we find again a different composition. We identify delegates such as Field Technologies, Inc., Flip Flop Flap Delegate LLC, a shadow delegate and *a16z* being dominant, while the remaining voters appear with unknown identities. Taking a wholistic look at these findings, we notice that some voters may both participate in many polls and have large total votes, namely voters with the addresses *0x4f…3f30* and *0x6a…ab40*. In other cases, some voters might not participate in many polls, but when they do, they have significantly large votes in certain polls. For example, *a16z* only votes for three polls, but their single votes are more than 30,000. These characteristics of the dominant voters suggest that on-chain developments on the protocol are driven by dominant voters and that decentralization does not seem to hold. Voting power appears to be distributed

[20] It is easy to establish by searching for other voters' addresses on *Etherscan.io* that *a16z* represents the venture capital firm Andreessen Horowitz, which is the most influential venture capital in DeFi markets.

unevenly across different known or unknown small groups of voters, especially when total votes and large votes in a single poll are considered.

In order to further show this, we focus now on the notion of centralized voting power in the Maker polls. We compare the largest vote for each poll with the total votes, and we find that the largest voter can account for a significant share of the total votes in most polls. Practically, the largest voter is the pivotal figure in implementing protocol changes, as they tend to account for around one third of the voting share. In terms of the known voters (namely delegates and *a16z*), the trend is similar. These known voters are identified after the delegate regulation change in Maker protocol (after Poll 600) and their dominant power is evident. However, it is hard to say if they were able to play an important role in previous polls. All this information is illustrated in the following figure.

Figure 3.3: Total votes, votes of the largest voter and votes of the known voters in Maker polls (Poll 16 – Poll 663)



Note: Panel A presents the total votes and votes of largest voters in Maker governance polls (Poll 16 – Poll 663). In most polls, the largest voter holds a significant proportion of voting power. Panel B shows the votes from the known voters in Maker governance polls (Poll 16 – Poll 663). The known voters include voting delegates and *a16z* and show strong voting power after Poll 600.

To support the above, we also illustrate the total votes over the breakdown votes and their respective voters, the breakdown ratio, the voting share of the largest voter and average voting share of the largest voter daily. The results show that winning polls are driven by the most votes, the largest voters contribute significant votes to the winning options and the largest voters consistently concentrate at least 30% of the average daily voting share. These voting patterns are presented in Appendix A.1. The key message remains that centralized voting power exists.

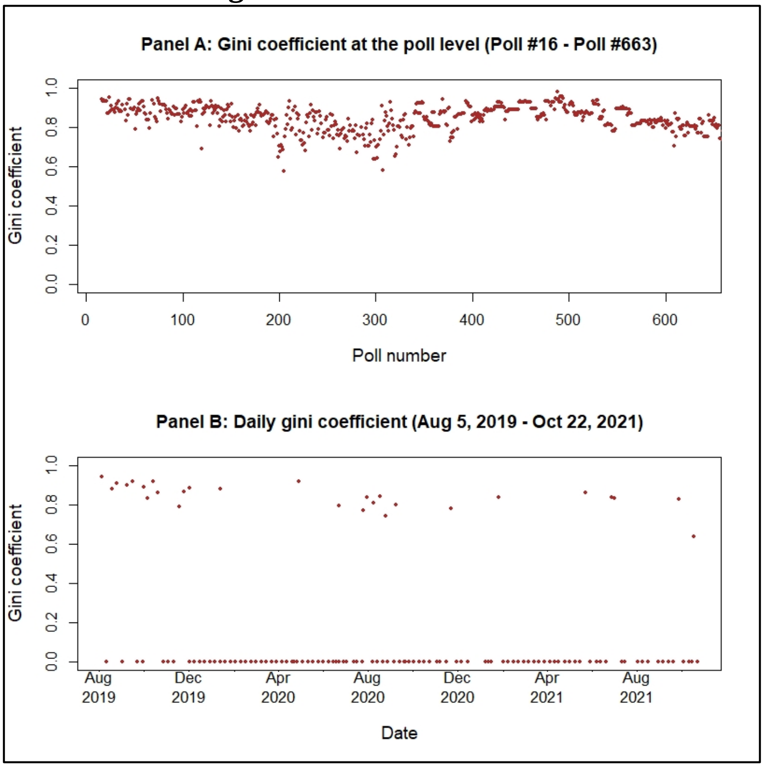
Although the above could happen through descriptive information extracted from our unique dataset, we take further steps to quantitatively establish centralized governance on the Maker protocol. First, we measure the centralized voting power in Maker governance at a poll level and across days by utilizing the Gini coefficient estimations. The results are summarized in the table and figure that follow.

Table 3.4: Gini coefficient in Maker governance polls

	Poll-level	**Daily**
Mean	84.38%	18.57%
Median	85.54%	0.00%
Maximum	98.05%	94.04%
Minimum	57.56%	0.00%
Std	0.06	0.35

Note: This table reports the Gini coefficient in Maker governance polls. In the first column, we calculate the Gini coefficient for each poll. In the second column, we first integrate a voter’s votes within a day, and then we compute the daily Gini coefficient via a maximum likelihood estimation.

Figure 3.4: Gini coefficient

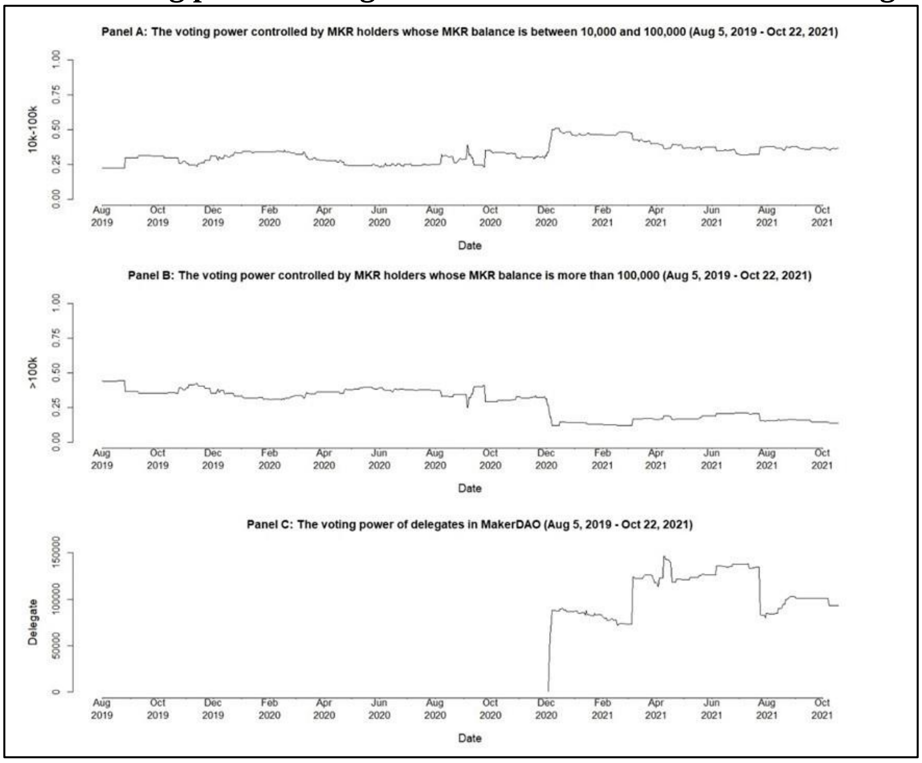


Note: This figure shows the Gini coefficient in Maker governance. Panel A reports the Gini coefficient at the poll level (Poll 16 – Poll 663). Panel B reports the Gini coefficient daily in Maker governance polls (Aug 5, 2019 – Oct 22, 2021).

At a poll level, we find that the Gini coefficient is always more than 50% and exhibits a maximum of 98.05%. Given that the Gini coefficient estimation is higher than 0.60 for most of the polls, highly centralized voting power in the Maker governance is established. We also calculate and illustrate the daily Gini coefficient. The expected daily average Gini coefficient should be around zero, if no centralized voting occurs. However, we observe that there are days that the value is higher than 0.75, again implying strong centralization of voting power on particular days within our period under study. We further highlight the evidence of vote centralization by estimating the Lorenz curve of the cumulative total votes for particular polls. The results support the above findings and are presented in Appendix A.1.

We also illustrate the voting power of large MKR holders and MakerDAO delegates. For MKR holders whose MKR balance is between 10,000 and 100,000 (hereafter, major holders), their voting power is around 25%. For MKR holders with more than 100,000 MKR (hereafter, supermajority holders), their voting power accounts for a significant proportion, though their voting power has decreased since December 2020. The amount of MKR controlled by MakerDAO delegates should not be ignored, given that the spikes of their MKR balances are close to 150,000 MKR.

Figure 3.5: Voting power of large MKR holders and MakerDAO delegates



Note: This figure illustrates the proportion of MKR controlled by large MKR holders and MKR balance controlled by MakerDAO delegates (Aug 5, 2019 – Oct 22, 2021). In Panel A, we calculate the proportion of MKR controlled by holders whose MKR balance is between 10,000 and 100,000. In Panel B, we focus on MKR holders whose MKR balance is more than 100,000. Panel C shows the MKR balance controlled by MakerDAO delegates.

Finally, the other measurements of governance centralization are established based on the definitions given in section 3.3. Their descriptive statistics are provided in the following table.

Table 3.5: Measurements of governance centralization in Maker

	Voters	TotalVotes	LargestShare	Order	10k-100k	>100k	>10k	Delegate
Mean	123.53	181335.26	0.54	0.41	0.33	0.28	0.61	105743.35
Median	68.00	114304.83	0.51	0.39	0.33	0.32	0.63	101145.62
Maximum	756.00	1251962.15	0.96	0.91	0.51	0.44	0.67	146462.93
Minimum	7.00	259.74	0.27	0.00	0.22	0.12	0.49	1151.71
Std	141.27	209387.53	0.16	0.20	0.07	0.10	0.05	23047.70
N of obs.	127	127	127	127	810	810	810	320

Note: This table presents the descriptive statistics of measurement of governance centralization in Maker. The first four columns report measurements of governance centralization in Maker governance polls. We first calculate these measurements for each poll and then convert it to daily level measurements. For example, we first calculate the number of voters for every poll, which we then add to the get the number of daily voters. The last four measurements reflect the influence of large MKR holders and delegates.

To simplify the factor analysis, we implement *Principal Component Analysis (PCA)*. Simply, higher explained variance ratios mean more important measurements. In the following sections, we estimate regressions using the four measurements, including $Gini, Voters, 100k - 100k, > 100k$. $Gini$ and $Voters$ represent voting centralization, while $100k - 100k$ and $> 100k$ describe holding centralization in MakerDAO.[21]

Table 3.6: Principal Component Analysis (PCA) of measurements

Panel A: Measurements related to governance polls			
	Explained Variance Ratio	**Explained Variance**	**N of obs.**
Gini	**51.41%**	**0.15**	**127**
Voters	**19.68%**	**0.06**	**127**
TotalVotes	14.25%	0.04	127
LargestShare	12.56%	0.04	127
Order	0.02%	0.01	127
Panel B: Measurements related to MKR balance			
	Explained Variance Ratio	**Explained Variance**	**N of obs.**
10k-100k	**83.34%**	**0.19**	**810**
>100k	**16.67%**	**0.04**	**810**
>10k	0.00%	0.00	810

Note: This table reports the results for Principal Component Analysis (PCA) of centralization measurements. For each measurement of governance centralization, we present the ratio of explained variance and the variance explained by this measurement, respectively. A higher 'explained variance ratio' implies that the measurement can capture more information included by all measurements. To simplify our empirical results, we only present results related to the measurements with highest 'explained variance ratios'.

3.4.2 Second stage: Factor analysis

In this section, we first apply a series of univariate regressions, with MKR and DAI used as dependent variables and the measurements of centralized governance as independent

[21] The regression results for other measurements can be provided upon request. Beside the four chosen measurements, we also examine the influence of the voting power of MakerDAO delegates in section 3.4, and a measurement 'delegate' is constructed. Compared to other centralization measurements, 'delegate' has fewer observations. We exclude 'delegate' from PCA analysis to evaluate the importance of other centralization measurements more accurately.

variables. We consider financial, network and Twitter sentiment factors. In other words, we estimate the following regressions:

$$factor_{i,t} = \beta_0 + \beta_1 central_t + \varepsilon_t (3.11)$$

where:

- $i = \{MKR, DAI\}$
- $central_t = \{Voters_t, Gini_t, 10k - 100k_t, > 100k_t, Delegate_t\}$

Given i, factors can be defined as a set:

$$factor_{i,t} = \{financial_{i,j,t}, network_{i,k,t}, Twitter\ sentiment_{i,l,t}\}$$

where $j = 1, ..., 7$, $k = 1, \dots, 4$, and $l = 1,2$.

The detailed description of the above set of factors[22] is presented in detail in Appendix A.2. For all statistically significant results, we run the Granger test to address potential reverse causality (see, Appendix A.3). We note that in all cases, the factors pass the Granger causality tests.

Financial factors Maker governance polls are directly related to non-technical changes, e.g., adding a new collateral, to Maker protocol. These changes will add more financial functions or revise the parameters of transactions in the protocol. Therefore, it is crucial to examine whether MKR and DAI factors, such as daily return, market cap, and trading volume, are going to be affected by centralized governance, in the form of the metrics discussed in section 3.3. Market capitalization, trading volume, and daily return are commonly considered key characteristics of cryptocurrencies (Liu et al., 2022). When studying the performance of DeFi, market capitalization and trading volume also emerge as crucial indicators (Makridis, Fröwis, Sridhar, & Böhme, 2023). Measurements of governance centralization can contribute significantly to research on the risks and returns associated with cryptocurrencies. Furthermore, we pay attention to substantial wealth transfers involving MKR and DAI on the Ethereum blockchain, constructing two dependent

[22] To avoid the problems of spurious regressions, we first examine if factors are stationary. For the non-stationary variables, we choose the first differences of the variables instead. Beside the factors presented in section 3.4, we further explore some other factors in Appendix A.4.

variables, namely *volume_l* and *volume_l_usd*. These variables could be associated with manipulation activities in crypto markets, such as pump-and-dump schemes (Dhawan & Putniņš, 2022). By investigating the relationship between governance centralization and large transactions, we can uncover additional drivers behind significant transfers of crypto assets. Further studies can utilize our findings to examine whether governance centralization contributes to manipulation activities.

In addition to the total transaction volume, we also examine transaction volumes on Decentralized Exchanges (DEXes) separately. Makridis et al. (2023) argue that CEX and DEX markets are segmented. Aspris, Foley, Svec, & Wang (2021) contend that DEXes significantly differ from CEXes, particularly in terms of the cryptocurrencies they list, which can lead crypto investors to have varying preferences when choosing cryptocurrency exchanges. By examining the trading volume of MKR and DAI on DEXes, we aim to investigate whether governance centralization in MakerDAO can exert influence on MKR/DAI traders' preferences on cryptocurrency exchanges.

The findings of univariate regression for these factors are summarized in the following table. The two panels of the table bring forward some interesting findings for the effects of centralized governance measures for MKR and DAI. We observe that $10k - 100k$ and $delegate$ have a significant positive effect on MKR volume, while $> 100k$ has the opposite. This conceptually means that the centralized voting power of major MKR holders (i.e., those with 10,000 - 100,000 MKR holdings) and delegates will boost MKR trading activities. However, if supermajority MKR holders (i.e., those with more than 100,000 MKR holdings) accumulate higher MKR balances, the total volume, the volume on DEXes, and the volume of large transactions will decrease. This finding could support the claimed value proposition of MakerDAO, i.e., decentralized governance. The above could parallel the findings of Meirowitz & Pi (2022), who analyze the shareholder's dilemma through the lens of voting and trading. Our results further imply that voting and trading are not substitutes in some cases, and major stakeholders and supermajority stakeholders can have different influences. In the context of DAO, major holders and supermajority holders can even have contrary effects on the trading volume of governance tokens, which implies the complex relationship between governance and trading dynamics in DeFi.

Table 3.7: Financial factors (MKR, DAI)

PANEL A: MKR					
	Voters	Gini	**10k-100k**	**>100k**	**Delegate**
Return	-0.02	0.02	0.01	-0.01	-0.02
	(-0.64)	(1.43)	(1.19)	(-1.06)	(-0.72)
Δ MktC	-0.01	0.00	0.00	0.00	0.00
	(-1.26)	(-0.19)	(0.53)	(-0.44)	(-0.21)
Volume	0.00	0.00	**0.09*** **	**-0.07*** **	-0.04
	(0.45)	(0.22)	**(6.56)**	**(-6.40)**	(-1.14)
Volume_dex	0.02	0.01	**0.12*** **	**-0.10*** **	0.01
	(0.45)	(0.29)	**(7.83)**	**(-8.60)**	(0.27)
Volume_dex_usd	0.03	0.01	**0.12*** **	**-0.12*** **	**0.18*** **
	(0.68)	(0.28)	**(9.38)**	**(-13.52)**	**(3.99)**
Volume_l	0.12	-0.04	**0.11*** **	**-0.09*** **	-0.03
	(0.82)	(-0.76)	**(6.68)**	**(-6.88)**	(-0.74)
Volume_l_usd	0.10	-0.02	**0.09*** **	**-0.10*** **	**0.11*** **
	(1.13)	(-0.70)	**(8.32)**	**(-11.95)**	**(3.00)**
PANEL B: DAI					
	Voters	Gini	**10k-100k**	**>100k**	**Delegate**
Δ Return	0.01	0.00	0.01	-0.01	0.00
	(0.33)	(0.17)	(0.87)	(-1.03)	(0.36)
Δ MktC	0.00	0.00	**0.03*** **	**-0.04*** **	0.00
	(0.00)	(-0.08)	**(3.40)**	**(-4.94)**	(-0.05)
Volume	**0.02***	0.01	**0.05*** **	**-0.05*** **	0.03
	(1.68)	(0.82)	**(6.70)**	**(-9.55)**	(1.29)
Δ Volume_dex	0.02	0.01	**0.12*** **	**-0.10*** **	0.01
	(0.58)	(0.64)	**(7.83)**	**(-8.60)**	(0.27)
Δ Volume_dex_usd	0.02	0.01	**0.12*** **	**-0.12*** **	**0.18*** **
	(0.58)	(0.63)	**(9.38)**	**(-13.52)**	**(3.99)**
Volume_l	**0.02***	0.01	**0.04*** **	**-0.05*** **	0.03
	(1.71)	(0.79)	**(6.28)**	**(-9.07)**	(1.29)
Volume_l_usd	**0.02***	0.01	**0.04*** **	**-0.05*** **	0.03
	(1.70)	(0.80)	**(6.24)**	**(-9.01)**	(1.29)

Note: This table reports the univariate regression coefficients and standard t-statistics in parentheses for the financial factors of MKR (Panel A) and DAI (Panel B). *, ** and *** denote significance levels at the 10%, 5% and 1% levels, respectively. The definitions of the factors are given in Table A.5.

For the case of DAI, we continue to observe significant effects of centralized governance. A higher number of voters has a notable impact on increasing the trading volume of DAI, including total volume and the volume of large transactions. Therefore, a higher voting participation rate proves advantageous for the DAI stablecoin. The DAI market cap is expected to be a metric of the performance of Maker protocol as well. We observe that 10k-100k is positively related to ΔMktC, while >100k has the opposite effect. Regarding the trading volume of DAI, 10k-100k and >100k show inverse influences as well. Therefore, though both major holders and supermajority holders have centralized voting power (compared with small MKR holders), their influences can be different. In corporate governance, holding centralization often serves as a proxy for conflicting interests (Demsets & Villalonga, 2001). Corporate owners with varying levels of ownership can exert different effects on firm performance (Dalton, Daily, Certo, & Roengpitya, 2003), a parallel that resonates with our findings.

However, we do not observe significant results related to how governance centralization affects DAI price or volatility. A decreasing price for DAI, a stablecoin, can be a signal of depegging, implying that decentralized governance can cause problems for it. That in essence defeats the main purpose of stablecoins, namely price stability. For example, Tether (USDT), a stablecoin mostly backed by cash and common cash equivalents, suffered from depegging in late 2022. This created uncertainty on whether its reserves' cushion would be sufficient to meet its obligations during a flood of USDT redemption requests.[23] Based on our analysis, we do not identify a significant relationship between DAI stability and MakerDAO governance.

All the above shows that centralized governance is significantly evident for the financial factors relevant to MKR and DAI. In particular, holding centralization measurements (i.e., 10k-100k and >100k) appear to exert influence on the trading volumes of MKR and DAI, while voting centralization measurements (i.e., Voter and Gini) may not play a primary role. This distinction can be likened to the concept of 'buy-and-hold' in corporate governance, where certain owners are hesitant to actively intervene in governance matters despite observing performance issues in a firm (Connelly et al., 2010). Given that not all MKR holders frequently participate in voting, it becomes evident that holding centralization and voting centralization capture different dimensions of governance centralization, consequently leading to dissimilar effects on the system.

Generally, the results bring forward a trade-off between decentralized governance and volume of these two tokens, and we also contend that the influences of dominant decision makers can be complicated. Although the financial characteristics of coins are quite important, the literature has shown that the researcher needs to expand on other indicators integral to the technical structure of coins, tokens, and protocols in order to capture their potential fundamental value (Kraaijeveld & De Smedt, 2020; Nadler & Guo, 2020; Liu & Tsyvinski, 2020; Nakagawa & Sakemoto, 2022). For that reason, we next turn to other MKR

[23] https://coingeek.com/tether-panics-as-loan-scrutiny-mounts-throws-alameda-under-bus/

and DAI related factors that are non-financial in nature to further establish that centralized governance exists in the Maker protocol.

Network and Twitter sentiment factors In this subsection, we focus on factors capturing network characteristics and social media sentiment. In cryptocurrencies, network adoption is a critical metric that can significantly influence long-term development (Somin Gordon, & Altshuler, 2018; Sockin & Xiong, 2023). Moreover, DeFi is often seen as a more inclusive alternative to traditional finance (Cong et al., 2023). Governance centralization, however, appears to mitigate this effect. Investigating the most important network statistics, such as total addresses, new addresses, active addresses, and their active-to-total ratio should be investigated. This is examined by the univariate regressions presented in Table 3.8.

It is clear that centralized voting affects MKR network factors. For both MKR and DAI, $Gini$ exhibits significant positive effects on the active-to-total ratio. Therefore, centralized voting seems to be advantageous. However, a higher number of voters is associated with a decrease in the growth of new addresses participating in DAI transactions. This implies that network adoption of DAI is negatively affected when MakerDAO governance is more decentralized. Furthermore, our analysis did not reveal how holding centralization is related to network factors. In summary, the network adoption of DAI and MKR appears to benefit from voting centralization in MakerDAO governance, while a higher level of voting participation may not necessarily have a positive impact on network factors. The relationship between governance centralization and network dynamics is complex.

Table 3.8: Network factors (MKR, DAI)

PANEL A: MKR					
	Voters	**Gini**	10k-100k	>100k	Delegate
Δ TotalWithBlc	0.00	0.00	0.00	0.00	0.00
	(-0.24)	(0.47)	(0.02)	(0.03)	(0.05)
Δ New	-0.02	0.02	0.00	0.00	0.01
	(-0.65)	(0.96)	(-0.04)	(0.11)	(0.23)
Δ Active	-0.01	0.01	0.00	0.00	0.00
	(-0.38)	(1.00)	(-0.05)	(0.13)	(0.07)
Δ ActiveRatio	-0.02	**0.03***	0.00	0.00	0.00
	(-0.52)	**(1.75)**	(0.02)	(0.05)	(0.19)
PANEL B: DAI					
	Voters	**Gini**	**10k-100k**	**>100k**	**Delegate**
Δ TotalWithBlc	-0.02	0.00	0.00	0.00	0.00
	(-0.53)	(-0.20)	(0.14)	(0.10)	(-0.08)
Δ New	**-0.08****	0.00	0.00	0.00	-0.01
	(-1.98)	(-0.04)	(-0.14)	(0.28)	(-0.16)
Δ Active	-0.05	-0.03	0.00	0.00	-0.01

	(-1.11)	(-1.02)	(-0.09)	(0.34)	(-0.17)
Δ ActiveRatio	-0.03	**0.04****	0.00	0.00	0.00
	(-0.84)	**(2.22)**	(-0.14)	(0.14)	(0.01)

Note: This table reports the univariate regression coefficients and standard t-statistics in parentheses for the network factors of MKR (Panel A) and DAI (Panel B). *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. The definitions of the factors are given in Table A.6.

In terms of social media sentiment, we focus on Twitter. Currently, Twitter is the main social media platform where DeFi investors express their opinions, and Twitter sentiment analysis has proven to be a valuable tool for predicting cryptocurrency price movements (Kraaijeveld & Smedt, 2020; Naeem, Mbarki, Suleman, & Shahzad, 2020). The crypto community actively engages in discussions and exchanges on this platform, while the Maker protocol also maintains official Twitter accounts. Grover, Kar, Janssen, & Ilavarasan (2019) conducted a study on Twitter users' discussions about blockchain and found that these discussions predominantly focus on the benefits of blockchain rather than its drawbacks. We anticipate that Twitter discussions related to MKR and DAI will be influenced by MakerDAO's governance. By concentrating on Twitter sentiment factors provided by IntoTheBlock.com, we aim to explore whether governance centralization exerts an influence on the negative and neutral sentiment expressed by Twitter users. As shown in Table 2.9, our regression results did not reveal any statistically significant relationships. Based on our analysis, it appears that governance centralization within MakerDAO may not be generating substantial discussion on social media platforms and may not be garnering significant attention from many investors.

Table 3.9: Twitter sentiment factors (MKR, DAI)

PANEL A: MKR					
	Voters	Gini	10k-100k	>100k	Delegate
Δ Neutral	0.00	0.01	0.00	0.00	-0.01
	(-0.26)	(1.09)	(0.05)	(0.02)	(-0.44)
Δ Negative	0.00	0.00	0.00	0.00	0.00
	(-0.03)	(0.08)	(0.04)	(0.03)	(-0.16)
PANEL B: DAI					
	Voters	Gini	10k-100k	>100k	Delegate
Δ Neutral	0.00	0.00	0.00	0.00	0.00
	(0.70)	(-0.44)	(0.05)	(0.02)	(-0.06)
Δ Negative	0.01	0.01	0.00	0.00	-0.01
	(0.16)	(0.37)	(-0.09)	(0.05)	(-0.24)

Note: This table reports the univariate regression coefficients and standard t-statistics in parentheses for the Twitter sentiment factors of MKR (Panel A) and DAI (Panel B). *, ** and *** denote significance at the 10%, 5% and 1%

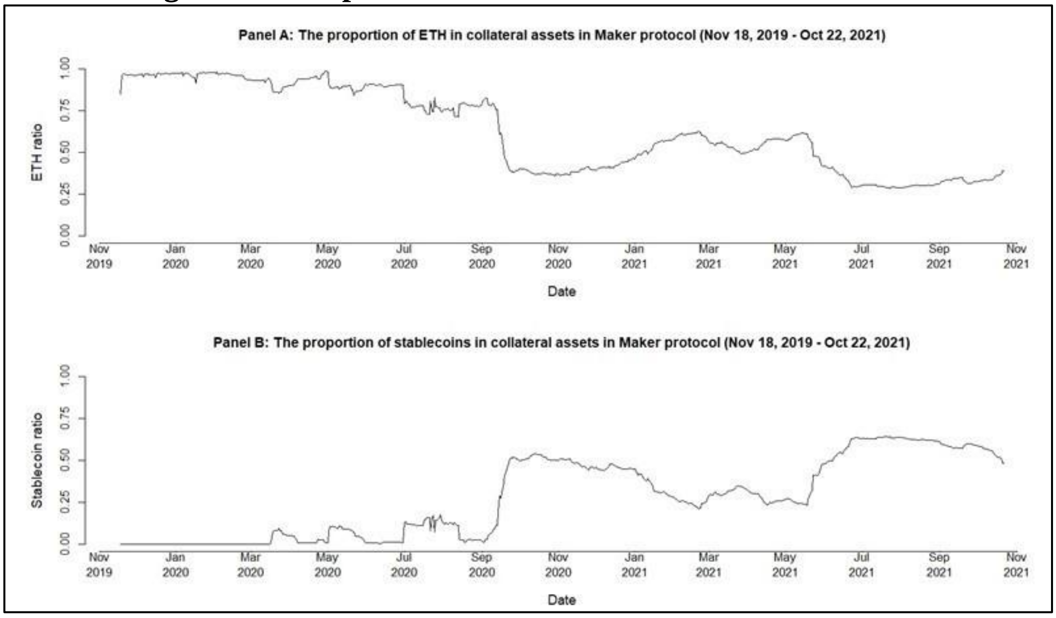
levels, respectively. The definitions of the factors are given in Table A.7.

Collateral ratios Finally, we investigate how centralized governance affects collateral assets locked in Maker protocol. To initiate loans from Maker protocol, Maker users must lock collateral. Therefore, collateral assets accepted by Maker protocol are an important issue in Maker governance. Moreover, if the locked collateral assets become risky, Maker protocol may be affected. In March 2023, DAI was severely influenced by the depegging of USD Coin (USDC),[24] since USDC is one of the most important collateral assets in Maker protocol.

In this subsection, we examine how centralized governance relates to components of collateral assets. We first consider two categories of collateral assets, including Ether (ETH) and stablecoins. The reason for including ETH is intuitive. ETH, as the native cryptocurrency of Ethereum blockchain, is one of the earliest accepted collateral assets in Maker protocol. Stablecoins play a crucial role in Maker protocol. For each category of collateral assets, we compute the proportion of its value (in USD) to the total value of locked collateral assets in Maker protocol. Figure 3.6 shows that ETH was the dominant collateral before September 2020. Since September 2020, ETH ratio has been much lower, while stablecoins become important collaterals. After September 2020, stablecoins usually accounted for more than 25% of value of total collateral assets, and the spikes of stablecoin ratio go above 50%.

[24] https://cointelegraph.com/news/maker-dao-files-emergency-proposal-addressing-3-1b-usdc-exposure

Figure 3.6: Proportions of three different collateral assets



Note: This figure illustrates the proportions of three different collateral assets locked in Maker protocol (Nov 18, 2019 – Oct 22, 2021), including ETH and stablecoins. The datasets are queried from *dune.xyz*.

To explore how collateral assets are driven by centralized governance, we estimate the following regressions:

$$Collateral_t = \beta_0 + \beta_1 central_t + \varepsilon_t (3.12)$$

where:

- $central_t = \{Voters_t, Gini_t, 10k - 100k_t, > 100k_t, Delegate_t\}$

Given i, factors can be defined as a set:

$$Collateral_t = \{\Delta ETH\ ratio_t,\ \Delta Stablecoin\ ratio_t\}$$

The detailed description of the above set of factors is presented in detail in Table A.8 in Appendix A.2. For all statistically significant results, we run the Granger test and the results do not suffer from reverse causality.[25]

[25] More details about results for Granger causality test are given in Appendix A.3.

The picture from Table 3.10 is clear. The distribution of MKR is related to collateral ratios in Maker protocol. Increased voting power of $> 100k$ and $Delegate$ can decrease the growth of ETH ratio, while $10k - 100k$ has the opposite effect. For stablecoins, $10k - 100k$ and $Delegate$ show the contrary influences as well. Again, centralized voting power can affect Maker protocol from the aspect of collateral assets, given that Maker governance decides collateral onboarding and offboarding. Furthermore, MKR holders have dissimilar preferences of collaterals, which may explain why major holders and supermajority holders influence the protocol differently. Overall, our two-stage analysis provides substantial empirical evidence of centralized governance in MakerDAO, as several significant univariate relationships are established across different classes of factors.[26] The next section provides further robustness checks towards that end.

Table 3.10: Collateral ratios

	Voters	Gini	**10k-100k**	**>100k**	**Delegate**
Δ ETH_ratio	0.02	-0.02	**0.02****	**-0.01***	**-0.03*****
	(0.60)	(-1.15)	**(2.04)**	**(-1.73)**	**(-2.88)**
Δ Stablecoin_ratio	-0.01	0.02	**-0.02****	**0.01***	**0.04*****
	(-0.29)	(0.85)	**(-1.96)**	**(1.82)**	**(3.03)**

Note: This table reports the univariate regression coefficients and standard t-statistics in parentheses for collateral ratios in Maker protocol. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. The definitions of the factors are given in Table A.8.

3.5 Robustness checks

3.5.1 Addressing endogeneity: Off-chain governance as an instrumental variable (MKR)

The empirical results presented in section 3.4 could face criticism due to potential endogeneity concerns. To alleviate this issue, we use the instrumental variable approach and estimate two-stage least squares (2SLS) regressions. We construct an instrumental variable (IV) using datasets for forum signal threads, which are a part of the off-chain governance in the Maker protocol (Brennecke, Guggenberger, Schellinger, & Urbach, 2022). Anyone can participate in the discussion and voting in the threads. That means that, unlike the on-chain

[26] Given the extent of the factors and univariate regressions examined, we also present a summary of the relationships in Appendix A.5.

governance investigated previously, off-chain governance does not require MKR in one's account. Even people who do not use blockchain can share their opinions and click an option in the thread. For some signal threads, the informal discussion will eventually turn to Maker IP, where participants can vote.

The results of signal threads are related to on-chain governance. Zhao, Ai, Lai, Luo, & Benitez (2022) describe how off-chain governance acts as the foundation of on-chain governance, and they also show that pre-voting discussions on strategic decisions are beneficial for a DAO in certain cases. Xu, Perez, Feng, & Livshits (2023) show that off-chain governance has growing significance in DeFi governance by analysing the content of off-chain discussion on forums. Reijers, Wuisman, & Mannan (2021) also explain that off-chain governance incorporates the 'one-person, one-vote' principle, unlike on-chain governance where voting rights depend on ownership of tokens or exploitation of hashing power. In MakerDAO governance, forum signal threads are functionally a warm-up for on-chain voting, so off-chain voting in these threads affects Maker protocol via the on-chain voting that follows. This is supported by theoretical and empirical evidence (e.g., Dursun & Üstündağ (2021), Reijers et al. (2021) and Han, Lee, & Li (2023)). For each thread, we document the first post date and the number of unique voters, and the daily number of off-chain voters are utilized as an IV for on-chain governance in MakerDAO.

To further validate off-chain voters as an IV, we conduct an analysis to examine the causal relationship between protocol performance and off-chain governance. Our expectation is that the specific factors of the IV, used as dependent variables, are not affected by the Maker protocol in section 3.4. To address this concern, we add the lagged terms of protocol-specific factors to the first stage regressions and subsequently re-estimate the regressions. The detailed results are presented in Appendix A.6. These results suggest that off-chain governance is a valid IV. The following table presents first and second stage regressions for the financial factors of MKR, and the results show consistency with findings in section 3.4. [27]

[27] For the sake of space, the remaining 2SLS results for MKR and all the equivalent 2SLS results for DAI are provided in Appendix A.5.

Table 3.11: 2-SLS IV regressions (financial factors – MKR)

Panel A: Estimate *10k-100k* using an instrument						
	(1)	(2) Volume	(3)	(4) Volume_dex	(5) Volume_l	(6) Volume_l_usd
Off-chain	0.32*** (6.02)		0.31** (5.81)			
10k-100k		0.22 (1.01)		0.45*** (2.47)	0.16 (0.63)	0.24* (1.64)
Durbin-Wu-Hausman test		0.20		4.36	0.00	0.00
p-value		0.66		0.04	0.95	0.95
Adj. R-sq		-0.01		-0.51	0.02	0.16
N		126		127	127	127

Note: This table reports results of the 2-SLS IV regressions. Panel A, Columns (1) and (4) report the results of the following first stage regression: $10k - 100k_t = \beta_0 + \beta_1 off - chain_t + \varepsilon_t$, where $off - chain$ is an instrumental variable. Columns (2)–(3) and columns (5)–(6) report the results of second stage: $factor_t = \beta_0 + \beta_1\ 10k \widehat{-\ 1}00k_t + \varepsilon_t$. In Columns (1) and (4), partial F-statistics are reported in parentheses. In Columns (2)–(3) and (5)–(6), t-statistics are reported in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

Before using an instrument, we first test if our instrument suffers from weak instruments concerns. The results for the first stage regressions show that our instrument can be used in 2SLS regressions. Then, we are curious whether measurements of centralized governance are endogenous to factors for MKR and DAI. To test the endogeneity, we apply Durbin-Wu-Hausman test. Simply, the test examines whether predictor variables in the univariate regressions are endogenous. Since the null hypothesis is that endogeneity does not exist, usually, we do not observe endogeneity between our measurements and most factors for MKR and DAI, meaning that the corresponding OLS regressions in section 3.4 are reliable. For results where endogeneity is observed (e.g., Column (4), Table 2.11), we compare results of 2SLS regressions and results in section 3.4, and the findings are consistent. Therefore, the measurements of centralized governance are generally not found to be endogenous to MKR and DAI factors.

3.5.2 Regression discontinuity

In September 2020, there was a significant security breach at KuCoin, a centralized exchange, resulting in the theft of approximately $280 million worth of cryptocurrencies (Hui & Zhao, 2020). This event is widely regarded as an exogenous shock to the DeFi market, as highlighted by previous research, such as Makridis et al. (2023). Following their approach, we construct a dummy variable 'shock' to examine the impact of the exogenous shock on our results in section 3.4. The value of 'shock' equals to 1 during the period spanning from Poll 287 (deployed on September 14, 2020) to Poll 412 (deployed on January 11, 2021), when the largest voting share was lower than the average. For the remaining sample, the value of ‘shock’ equals to 0. We estimate the following regression[28]:

$$factor_{i,t} = \beta_0 + \beta_1 central_t + \beta_2 shock_t + \varepsilon_t (3.13)$$

where:

- $i = \{MKR, DAI\}$
- $central_t = \{Voters_t, Gini_t, 10k - 100k_t, > 100k_t, Delegate_t\}$

Given i, factors can be defined as a set:

$$factor_{i,t} = \{financial_{i,j,t}, network_{i,k,t}, Twitter\ sentiment_{i,l,t}\}$$

where $j = 1, ..., 7$, $k = 1, \dots, 4$, and $l = 1, \dots, 2$.

We expect that the influences of governance centralization will not be affected by the KuCoin shock. In other words, the coefficients of centralization measurements in regression (3.13) should be consistent with the results in section 3.4. The table below summarizes the results, which aligns with our findings in section 3.4.[29]

[28] We also estimate the regression: $factor_{i,t} = \beta_0 + \beta_1 central_t + \beta_2 shock_t + \beta_3 central_t \times shock_t + \varepsilon_t$. These results can be provided upon request and resemble the ones presented in the manuscript.

[29] More detailed results for regression discontinuity analysis are presented in Appendix A.7.

Table 3.12: Regression discontinuity (summary)

Panel A: MKR		**Panel B: DAI**		
Measurements	Financial Factors	Measurements	Financial Factors	Network Factors
Voters		Voters	Volume ↑ Volume_l ↑ Volume_l_usd ↑	Δ New ↓
Gini		Gini		Δ ActiveRatio ↑
10k-100k	Volume ↑ Volume_dex ↑ Volume_dex_usd ↑ Volume_l ↑ Volume_l_usd ↑	10k-100k	Δ MktC ↑ Volume ↑ Volume_l ↑ Volume_l_usd ↑	
>100k	Volume ↓ Volume_dex ↓ Volume_dex_usd ↓ Volume_l ↓ Volume_l_usd ↓	>100k	Δ MktC ↓ Volume ↓ Volume_l ↓ Volume_l_usd ↓	
Delegate	Volume_dex_usd ↑ Volume_l_usd ↑	Delegate	Δ Volume_dex ↑ Δ Volume_dex_usd ↑	

Note: This table summarizes the results for regression (3.13), where the KuCoin hack is constructed as a dummy. For example, the first column and second row report *Volume* ↑ , which means that the increase of *10k-100k* leads to a significant increase in *Volume*. The detailed regression results are presented in Appendix A.6.

3.5.3 Certain types of governance polls

Governance polls can be categorized. Their labels are publicly observable on the Maker governance forum. Generally, the label reflects on what a governance poll is focused on. For example, 'collateral onboarding' polls are about new collateral assets that can be used to initiate loans from Maker protocol, while 'MIP' polls discuss improvement proposals of Maker protocol (see Table 3.13). We focus on the label of 'risk parameter', which has the most governance polls. Using the subset, we calculate the centralization measurements again. Table 3.13 summarizes the descriptive statistics. Generally, 'risk parameter' polls have fewer voters and fewer total votes, while the daily Gini coefficient and the largest voters' share is higher. The preliminary results imply that governance is even more centralized in these polls.

Table 3.13: Categories of Maker governance polls

	Number of polls
Risk Parameter	252
Ratification Poll	27
Inclusion Poll	70
Collateral Onboarding	50
Collateral Offboarding	2
Greenlight	146
Real World Asset	28
Misc Governance	18
Misc Funding	3
MakerDAO Open Market Committee	11
MIP	106
Budget	25
Oracle	38
System Surplus	6
DAI Direct Deposit Module	1
Multi-chain Bridge	1
Technical	17
Auction	20
Delegates	0
Peg Stability Module	11
Core Unit Onboarding	17
Dai Savings Rate	28
Black Thursday	4
Multi-Collateral DAI Launch	5
Prioritization Sentiment	2

Note: This table reports the number of governance polls (Poll 16 – Poll 663) in different categories. One poll can have multiple labels.

Table 3.14: Descriptive statistics of 'Voters' and 'Gini' based on 'risk parameter' polls

	Voters	TotalVotes	LargestShare	Order	Gini
Mean	51.58	81514.40	0.56	0.41	0.33
Median	40.00	54565.51	0.53	0.40	0.00
Maximum	206	365383.75	0.96	0.93	0.94
Minimum	7	259.74	0.26	0.00	0.00
Std	39.10	75042.97	0.17	0.22	0.41
N of obs.	107	107	107	107	107

Note: This table presents the descriptive statistics of measurement of governance centralization in Maker, and the measurements are calculated using 'risk parameter' polls. In the first four columns, we first calculate these measurements for each poll and then convert them to daily level measurements. For example, we first calculate the number of voters for every 'risk parameter' poll, then we add them to get the number of daily voters. Daily Gini is calculated using the maximum likelihood method described in section 3.3.

Then, using the subset, we re-estimate the univariate regressions mentioned in section 3.4. Given that 'risk parameter' polls can decide key variables of Maker protocol, e.g., interest rates and debt ceilings, it is not very surprising that governance centralization in these polls can affect financial factors (for both MKR and DAI). Overall, the results prove that more decentralized governance (e.g., a higher number of voters) has positive effects (e.g., an increase in trading volume), while higher *Gini* can negatively affect MKR and DAI, such as lower trading volume of MKR and slower growth of market capitalization of DAI.

Overall, this subsection shows that decentralized governance is advantageous. Further studies can combine the contents of governance polls in different categories with the performance of Maker protocol, revealing which issues are more crucial. We can also investigate voters' voting patterns in different types of polls, in an effort to reveal their private benefits.

Table 3.15: Measurements of governance centralization based on 'risk parameter' polls (summary)

Panel A: MKR			
Measurements	Financial Factors	Network Factors	Twitter Sentiment Factors
Voters	Volume ↑ Volume_dex_usd ↑ Volume_l_usd ↑		
Gini	Volume_dex_usd ↓ Volume_l_usd ↓	∆ New ↑ ∆ Active ↑	∆ Neutral ↑ ∆ Negative ↑
Panel B: DAI			
Measurements	Financial Factors	Network Factors	Twitter Sentiment Factors
Voters	∆ Volume_dex ↑ ∆ Volume_dex_usd ↑	∆ TotalWithBlc ↓	
Gini	∆ Return ↑ ∆ MktC ↓		

Note: This table reports the relationship between measurements of centralized voting power and the factors of MKR and DAI. The measurements are calculated using the datasets for governance polls with the label 'risk parameter'. The detailed regression results are presented in Appendix A.8.

3.6 Conclusion

Decentralization is a crucial innovation of blockchain, and the rapid growth of DeFi relies on decentralization. Complete decentralization is theoretically impossible (Abadi & Brunnermeier, 2022), and empirical evidence of centralization is detected in different layers of blockchain (Sai et al., 2021). In this chapter, we focus on governance in DeFi and particularly on the Maker protocol, which is governed by MakerDAO. Decentralized governance is a crucial domain for DeFi and Maker protocol is an ideal case since its voting history is considered transparent and precise (Beck, Müller-Bloch, & King, 2018). By examining Maker governance polls, we find that voters are centralized in a small group and voting power is unequally distributed among these voters. In most voting activities, the largest voters could account for a significant proportion of votes. Previously, Gervais et al. (2014) and Azouvi et al. (2018) argue that a few key developers have unilateral decision-making power in blockchain governance. This problem might derive from the requirement of programming skills. Our results expand the discussion to the token-weighted voting system in DeFi. Particularly in Maker, any MKR holder can easily participate in governance by clicking an option on the website, which would indicate that governance would be more decentralized. Interestingly, our results show that governance in Maker protocol is highly centralized.

To show that, we first construct two categories of centralization measurements, namely voting centralization (including *Voters* and *Gini*) and holding centralization (including *10k-100k*, *>100k*, and *Delegate*). Voting centralization exerts complex influences on Maker protocol. For example, a higher number of voters can lead to an increase of trading volume of DAI, however, it can also negatively affect the growth of network adoption of DAI. But a higher Gini, usually regarded as a signal of centralized governance, can bring forward more active investors for both MKR and DAI. The findings imply that governance centralization in DAO resembles a double-edged sword.

Holding centralization also exerts influence on Maker protocol. This observation is related to research on ownership structure, where large stakeholders often exert influence through private engagements with management (Jensen & Warner, 1988; Connelly et al., 2010; Fichtner et al., 2017). In DAOs, owners (i.e., governance token holders) and managers (i.e., participants in DAO governance) are theoretically identical, so collusion with management is not necessarily a concern. But our findings show that in DAOs, ownership structure, particularly the governance power held by large stakeholders, remains crucial. The influences of large stakeholders are reflected in on-chain voting. Furthermore, our research presents an intriguing finding: Major stakeholders and supermajority stakeholders have opposing influences on certain cryptocurrencies and the collateral status of DeFi protocol. Future research can explore why that is the case, while it is worthy of investigation whether voting centralization and holding centralization show inconsistent influences across various DAOs.

The optimal governance structure for DeFi remains an open question in the current landscape. When governance is excessively centralized, it leaves DeFi systems vulnerable to manipulation by a select few agents (Hoang & Baur, 2022). This chapter implies that centralized governance in DAO to some extent may contribute to trading activities of the underlying DeFi protocol. With our findings, we make a compelling case in favor of the argument that decentralization in DeFi platforms is an illusion and that the trade-off between market performance and decentralization exists. The trade-off is similar to the ones observed in the corporate world, where unexpected results of governance processes may be caused by different preferences of decision makers (Garlappi. Giammarino, & Lazrak, 2017; Donaldson, Malenko, & Piacentino, 2020).

Although our findings appear conceptually and empirically robust, they should be interpreted with their limitations in mind. First, the identity of the dominant voters is unknown. Anonymity is another character of blockchain and DeFi, and we may not know the identity of voters until they are willing to announce it. Therefore, sybil attacks are a potential problem in our analysis. A single entity can control multiple identities (e.g., blockchain addresses), which can undermine the security of a blockchain-based system by gaining an unfair and overly influential position (Douceur, 2002). Given the difficulty of clustering multiple addresses controlled by an entity, the analysis in this chapter is based on Ethereum addresses. Further research can dive into DAO governance more deeply by implementing more advanced techniques for clustering multiple addresses controlled by a single entity. Second, when studying DAI flows to different on-chain financial systems, we do not track the subsequent transactions of transferred DAI. Nadler & Schär (2020) propose mapping algorithms that can expose the sources of cryptocurrencies stored in an on-chain financial system. This can be a solution towards revealing the real owners of cryptocurrencies traded on DeFi applications. Further studies can investigate the effects of governance centralization in DAO by applying similar methods. Third, we do not investigate the potential voting power of MakerDAO participants. Technically, it is challenging to track the MKR balance of all MKR holders, since that requires to monitor all Ethereum addresses. Agents can purchase MKR using either other cryptocurrencies or currencies, therefore, their potential voting power rely on both balances in their account. As a result, it is practically impossible to precisely estimate potential voting power of MKR holders. Finally, we do not know whether the authors of Maker IPs are dominant voters. If a dominant voter proposes changes to the Maker protocol, the aim of such proposals might be tied to their own vested interests. With their large voting power, this could lead to further centralization of power and potential collusion during the development of Maker protocol. Currently, writing Maker IPs requires both programming skills and understanding of technical structure of DeFi. Assuming that not many voters have such competence, key developers may be the only people that can guide voters by proposing specific Maker IPs, implying that the centralized power of core developers exists in DeFi. This could also be supported by studies suggesting that delegating tasks to a group of experts can lead to better aggregation of information (Fehrler & Janas, 2021). As things stand, though, Maker users rely on developers to provide detailed proposals, the aims of codes and explanations of all possible outcomes in an understandable way. Another possible solution is to make IP authors' addresses publicly available so that users can detect suspicious activities of developers.

Chapter 4

Voter Coalitions and Democracy in Decentralized Finance: Evidence from MakerDAO

In this chapter, we empirically analyze multi-coalition democracy within Decentralized Autonomous Organizations (DAOs), using MakerDAO as a case study. We identify three voter coalitions: a dominant coalition and two minoritarian ones. Concentration of power within the dominant coalition adversely affects the DAO's performance, both in terms of value and stability. This decline in performance can be explained by community's concerns for private-value extraction by dominant token holders. Additionally, increased cohesiveness of the minoritarian ones improves political stability, producing positive effects on the DAO's performance. We also discuss the interlink between MakerDAO's governance and the broader crypto market.

4.1 Introduction

The highest purpose of blockchain technology is to decentralize finance and digital innovation. Yet, whether blockchains can concretely fulfil their aspiration hinges upon the effectiveness of their governance mechanisms, among which the *Decentralized Autonomous Organization (DAO)* is the most popular. In this chapter, we analyze the governance of

DAOs, taking MakerDAO as a case study. We show that DAO governance is exercised through a multi-coalition democracy, where users cluster themselves endogenously into coalitions to compete for power. We identify these coalitions and study their role for the DAO's decentralization and performance.

The distinctive feature of a DAO is the lack of an executive body: All DAO members jointly decide on any suggested action. This property establishes the DAO as the most popular governance structure within Decentralized Finance (DeFi), which is nowadays one of the primary use cases of blockchain technology.[30] A DAO distributes decision-making power by issuing a *governance token*, which is a tradable cryptocurrency. The voting power of users in the DAO is proportional to the amount of governance tokens they own. Voting procedures are automated by smart-contracts and take place through *governance polls*. These polls either fail or lead to the execution of the proposals that collect the majority of votes.

We choose to analyze MakerDAO because it can be considered as the most influential DAO. Besides being one of the most successful DAOs, MakerDAO has set industry standards, such as the ‘one token – one vote’ principle and a combination of “on-chain” governance processes (that are publicly recorded on the blockchain) and “off-chain” discussion. The main role of MakerDAO is to manage the Maker protocol, which is a DeFi lending platform on the Ethereum blockchain. The Maker protocol issues the Dai (DAI) stablecoin, which is pegged to US dollar by the supply-and-demand equilibrium of its tokens. Any market participant can borrow DAI by locking collateral and receiving MakerDAO’s governance tokens, the *MKR token*, in exchange. In other words, the Maker protocol is a multi-collateral DAI system, and MakerDAO decides how this system develops.[31]

Our main empirical finding is that governance in MakerDAO is exercised through a voter-coalition democracy: Users coordinate into coalitions and compete for the control of Maker. We demonstrate that this coalition structure is essential for a decentralized democracy, as it allows minority token holders to defend their interests against large token holders’ proposals.

[30] Capponi, Iyengar and Sethuraman (2023) provides an overview of DeFi.

[31] For more details on MakerDAO’s governance structure, we refer readers to Sun, Stasinakis and Sermpinis (2022).

We examine voter coalitions in MakerDAO by retrieving the voting history of the governance polls deployed from the 15th August 2019 to the 25th July 2022, where all voters' choices and their voting power are publicly observable. Applying the K-means clustering algorithm, we identify three voter coalitions. Although coalition 1 has the most voters and contributes to most of the total votes, the other coalitions still have a chance of winning governance polls, implying power contestability within MakerDAO.

Our second set of findings highlights the influence of voter coalitions on the Maker protocol. We first look at the impact of coalitions' voting share within governance polls on Maker's performances, measured by 30-day volatility of DAI, the growth daily revenues, and the growth of new users of the Maker protocol. We find that the voting share of the largest coalition is positively associated with DAI volatility but has no significant effect on Maker's daily revenues and new users. Conversely, we show that an increase in the voting share of minority voter coalitions is positively associated with DAI stability. These empirical findings highlight the fact that DAO users are sensitive to the distribution of governance power in DeFi, especially voting power controlled by big players. Usually, rent extraction risks from big players are a main concern, and that minority coalitions can hardly mitigate them. But our finding shows a trade-off between governance centralization and the performance of DeFi. Given that DAI is a stablecoin, price stability is its primary goal. In this way, the presence of large voter coalition can cause higher DAI volatility, implying the negative influence of governance centralization.

We then study the effect of political uncertainty in MakerDAO on DAI's performances by measuring and assessing the impact of cohesion among voter coalitions. We measure cohesion using the *Agreement Index (AI)* (Hix, Noury & Roland, 2005), a metric widely used in political science. We find that DAI's performances improve when the smaller coalition becomes more cohesive. Our observation indicates that DAI performances depend on users' aversion towards governance centralization. The increased cohesiveness of the smaller coalition enhances its probability of winning against dominant coalitions, generating more 'decentralized' voting outcomes.

We conclude by studying the interlinks between the Maker protocol and the broader crypto market where the DAI stablecoin is traded. We examine DAI flows towards five types of destinations: *Centralized Finance (CeFi), Decentralized Exchanges (DEXes), Lending*

Protocols (LPs), *External Owned Address (EOA)*, and *Bridges*[32]. Our findings show that voter coalitions drive DAI flows in accordance with their preferences for private value extraction. Notably, the largest coalition exhibits an opposing influence on DAI flows to CeFi compared to that of the minority coalition. Our findings imply that users with similar preferences coordinate within coalitions to direct DAI flows in their favor, thereby extracting higher private benefits.

The remainder of this chapter is organized as follows. Section 4.2 presents a literature review. Section 4.3 describes our dataset, the clustering algorithm that we use to identify coalitions, and their group cohesion measurements. Section 4.4 presents our main empirical results. Section 4.5 concludes.

4.2 Literature review

This chapter contributes mainly to the emerging finance and economics literature on Decentralized Autonomous Organizations. Yet it also addresses questions raised by classical corporate finance doctrine.

The most important contribution for our work is Austgen et al. (2023), which provides the theoretical foundations for our empirical approach. Austgen et al. (2023) lays out a novel methodology to quantify decentralization in a DAO. The beauty of their proposed approach is that it is based on the same principles that we can infer from the analysis of MakerDAO. Namely, coalitions naturally emerge in DAOs because users with similar preferences coordinate to shift DAO policies in their favour. Starting from this idea, Austgen et al. (2023) propose to quantify decentralization with the novel *block-voter entropy*. This metric is the entropy of the token distribution over the voter coalitions that emerge after aggregating users' preferences with a clustering algorithm. Our strategy for identifying voter coalitions can thus be regarded as first step towards quantifying decentralization according to block-voter entropy.

[32] In the context of blockchain, bridges refer to tools that connect two blockchains and allow agents to transfer on-chain assets from one blockchain to the other.

Our work is, to our knowledge, the first one studying voting power concentration at coalition level rather than at voter level. Nevertheless, the risk of voter collusion was already pointed out by early descriptive studies on DAOs (Chohan, 2017; Schär, 2021). Goldberg & Schär (2023) present some preliminary evidence of coalition formation using *Decentraland*, a metaverse-related DAO. They show that voting power is highly concentrated and small voters collude with powerful ones.

The empirical literature on voting power concentration in DAOs is also relevant to us. All the contemporaneous papers find unanimous evidence of voting power concentration in DAOs. Among these papers, Sun, Stasinakis, & Sermpinis (2022), a prequel of this chapter, shows that voting power is highly concentrated in MakerDAO. Fritsch, Müller, & Wattenhofer (2022) present evidence of voting power centralization in three popular DAOs on the Ethereum blockchain: Compound, Uniswap and ENS. Appel & Grennan (2023), Laturnus (2023) and Han, Lee, & Li (2023) find evidence for power centralization in a vast sample of DAOs.

The conclusions that these papers reach on the impact of power concentration on DAO performance are mostly in line with ours. Han, Lee, & Li (2023) find both empirically and theoretically a negative relationship between voting power concentration in DAOs and the value of their underlying platforms. In their model, excessive concentration of power in the hands of large token holders (or “whales”) increases their ability to extract private benefits at the expense of minority token holders. Conversely, Laturnus (2023) finds no significant evidence of a negative effect of power concentration on platform performances. It even shows that concentrated ownership can be beneficial in some cases. A possible reason for this observation is that concentration in the hands of a few voters facilitates coordination. Interestingly, as Fritsch et al. (2022) indicate, voting power concentration can result from voters delegating decisions to a small group of representants. Delegation can thus give rise to concentration of voting power at *coalition level*, which in turn can have a positive overall effect on DAO performances owing to increased involvement of small token holders. Most of these papers also find that voter abstentionism, or *apathy* in the terminology presented by Austgen et al. (2023), is pervasive across DAOs and constitutes an important factor of value loss.

Finally, our findings connect established concepts in corporate finance to the economics of DAOs. The corporate finance literature extensively studied the effects of ownership structure and concentration on firm performances. Shleifer & Vishny (1997) provide a review of these classical results. The broad picture that can be grasped from there, as well as from this chapter, is that decentralized governance is a double-edge sword: Decentralization of power reduces the incentives of influential agents to implement self-serving actions. However, decentralization induces higher uncertainty on the firms' decisions due to the aggregation of the diverse interests of minority stakeholders. Decentralization of ownership by dilution of voting power can also complicate the governance process because small stakeholders lack incentives to participate in corporate governance. The final effect of governance decentralization thus results from the combination of these opposing forces.

Some papers present these concepts discussing power concentration within the board of directors. Tran & Turkiela (2020) and Giannetti & Zhao (2019) show that centralization of power makes it easier for powerful board members to propose risky actions and thus increases the volatility of firm's performance indicators (such as stock returns). Conversely, Bernile, Bhagwat, & Yonker (2018) show that diverse boards tend to hinder the adoption of risky decisions. Iannotta, Nocera, & Sironi (2007) reports analogous findings in the context of bank governance.

Other papers discuss shareholding concentration. They conclude that that large shareholders form coalitions to extract private benefits, while minority shareholders do so to protect their own interests (Sauerwald & Peng, 2013; Hogg, 2000; Zwiebel, 1995; Bennedsen & Wolfenzon, 2000). Some authors discuss the negative effects of ownership concentration: Sauerwald & Peng (2013) show that shareholding concentration can exacerbate conflicts within the shareholder community. Marquardt, Myers, & Niu (2018) shows that ownership concentration in the hands of managers induces the other shareholders to vote strategically. Other authors discuss the positive effects of ownership concentration. For example, Ginzburg, Guerra, & Lekfuangfu (2022) shows that increased voting power makes shareholders more prone to oppose controversial proposals of the management.

Although these corporate finance papers clearly identify the possible effects of ownership centralization (and decentralization), they generally disagree on which effect dominates. Demsetz & Villalonga (2001) even claim that firm performances may not be statistically related to ownership structure. This disagreement is likely caused by data limitations, as discussed by Hermalin & Weisbach (2003) and Adam, Hermalin, & Weisbach (2010). Fortunately, benefiting from blockchain technology, the full voting history of any DAO is publicly available. Therefore, MakerDAO allows us to overcome the data obstacle and better explore the relationship between governance and performance of a DeFi platform.

4.3 Empirical analysis of voter coalitions in MakerDAO

In this section, we outline our data collection methodology. We also present our empirical strategy to identify voter coalitions and measure cohesion.

4.3.1 Data Collection and Description

The core part of our dataset is made of governance polls details and the community voting history; that is, voters' addresses, choices and voting power over the sampled period. We obtain these data from several public online sources. Specifically, we obtain governance poll details, including titles, reviews of proposals, and options from the *Maker Governance Portal*.

We augment the dataset with two sets of auxiliary data. The first are labels that allow us to categorize polls based on their content and purpose.[33] We group under the 'risk parameter' category a set of polls that hold considerable importance within the governance framework. Essentially, 'risk parameter' polls impact the risk profile and overall stability of the Maker protocol, as they involve decisions on parameters such as the interest rates of DAI loans. The second set of auxiliary data is voter identities, which allows us to better understand coalitions' internal structure.

The voting history We query the *MCD Voting Tracker* to obtain the voting history over the sampled period. We investigate governance polls from Poll 16 (deployed on 15th August 2019) to Poll 838 (deployed on 25th July 2022). Poll 16 is the first governance poll that MKR holders can participate in. Our resulting dataset consists of a total of 809 successful

[33] Two examples of labels are 'risk parameter' and 'collateral onboard'.

governance polls.[34] After retrieving voters' addresses, we found 1717 unique voters. We then manually collect voters' public names and labels by searching for their addresses on Maker Governance Portal and *Scopescan.ai*.

The first step of data pre-processing required to apply our clustering algorithm is to replace textual options with numerical values. Most Maker governance polls have three options, including "Yes", "No", and "Abstain". For this type of poll, we assign 1, -1, 0 to "Yes", "No", and "Abstain", respectively. We also assign integer values to different options for the other polls. In all governance polls, we assign 0 to "Abstain".

A hassle we have to deal with are missing values, denoted by NA, that the clustering algorithm generates whenever a voter (e.g., voter i) does not participate in a given poll (e.g., poll j). We deal with them by naturally assuming that a voter i that does not participate in poll j chooses "Abstain". Thus, we replace NAs with zeros.[35]

4.3.2 Identification: Clustering and group cohesion

We pre-process our voting dataset by applying standardization and dimensionality reduction procedures before applying the clustering algorithm and measuring cohesion. To standardize our dataset X, we convert each observation $x \in X$ into a standardized deviation from the sample mean:

$$\frac{x - \bar{X}}{\mathrm{X.std}} \quad (4.1)$$

where $\bar{X}$ is the mean of dataset X and $\mathrm{X.std}$ is its standard deviation.

[34] Some pools failed, and for those we did not find documentation in the portal. The failed pools are Poll 28, 39, 47, 69, 78, 183, 282, 284, 286, 500, 604, 769, 818 and 821.

[35] The two most common solutions are (1) to delete observations with NAs and (2) to fill NAs with the mean. However, none of them suits our context. The first solution would delete too many observations given that only few voters participate to all polls. The second solution would artificially inflate the support for the average option.

For clustering algorithms, each poll in our voting dataset counts as a data-feature. With more than 800 polls, our dataset would be high-dimensional. Hence, we apply dimensionality reduction through *Principal Component Analysis (PCA)* to eliminate the least relevant polls and improve the algorithm's performance. PCA simply computes the principal components of a dataset and keeps only a few among the first ones, which account for most of the variation in the data. In this way, a high-dimensional dataset can be transformed into a lower-dimensional dataset without losing much information. Generally, the new dataset generated by PCA should keep at least 95% of variance in the original dataset. We follow this principle by selecting the first 115 principal components, thereby maintaining 95.01% of the original variance in the resulting lower-dimensional dataset.

Clustering algorithm We cluster users with similar voting patterns into coalitions using the *K-means* clustering algorithm. Our data set consists of a set of voting histories for each voter, $(\boldsymbol{v}_1, \boldsymbol{v}_2, \dots, \boldsymbol{v}_n)$, where n is the number of voters in our sample. Each $\boldsymbol{v}_i$ is a d-dimensional vector that records voter i's choices in all the d governance polls in our dataset. The elements of a voter history v_{ij} denote a vote of voter i in poll j. As we mentioned in SECTION 4.3.1 $v_{i,j}$ is an integer value and is set to 0 if voter i does not participate in poll j.

K-means aims at clustering voters into k $(\leq n)$ sets $V = \{V_1, V_2, \dots V_k\}$, each of which can be regarded as a *voter coalition* that collects voters with similar voting patterns. The resulting set-partition minimizers the *within-cluster sum of squares (WCSS)*:

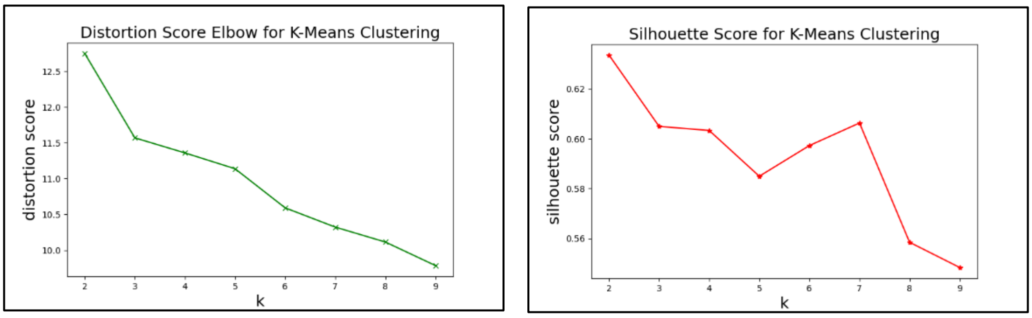
$$V = \underset{\{V_1, V_2, \dots, V_k\}}{\operatorname{argmin}} \sum_{i=1}^{k} \sum_{v \in V_i} \left|\left|v - \mu_i\right|\right|^2 = \underset{\{V_1, V_2, \dots V_k\}}{\operatorname{argmin}} \sum_{i=1}^{k} |V_i| \, Var V_i \quad (4.2)$$

where μ_i is the mean of the points in V_i.

Running the K-means algorithm also requires us to set optimally the number of clusters k. Two common criteria for doing so are the *elbow method* and the *silhouette score*. To put it simply, the optimal number of clusters k^* should have the highest silhouette score and should cause the score function to flatten for k values larger than k^*.[36] We choose $k^* = 3$ based on the results of these tests in Figure 4.1.

[36] A rigorous introduction to these methods can be found in Malik & Tuckfield (2019).

Figure 4.1: Elbow method and silhouette score



Note: This figure shows how we choose the optimal number of clusters when applying K-means algorithm. On the left, we use elbow method and compute distortion score, and this score measures the sum of squared distances from each point to its assigned center. Usually, distortion score could decrease rapidly at first then slowly flatten forming an “elbow” in a line graph, and we will choose the point where the score starts decreasing slowly as the optimal number of clusters. On the right, we calculate silhouette score, which measures how similar a data point is within-cluster compared to other clusters. Usually, we prefer choosing the number of clusters with the highest silhouette score. Combining with the line graph using elbow method, finally we choose 3 as the optimal number of clusters.

Coalition cohesion An important step for our analysis is to measure cohesion within coalitions. To capture cohesion, we employ the modified *Agreement Index (AI)*, introduced by Hix, Noury and Roland (2005).[37] This indicator embeds the idea that a cohesive coalition makes homogeneous choices. Formally, the AI of voter coalition i can be calculated as:

$$AI_i = \frac{\max\{Y_i, N_i, A_i\} - \frac{1}{2}[(Y_i + N_i + A_i) - \max\{Y_i, N_i, A_i\}]}{Y_i + N_i + A_i} \quad (4.3)$$

where Y_i, N_i, A_i denote the number of “yes”, “no” and “abstain” votes, respectively. Similarly, we can expand AI to polls with $j \geq 3$ options as below:

$$AI_i = \frac{\max\{Option_1, \ldots, Option_j\} - \frac{1}{j-1}[(Option_1 + \cdots + Option_j) - \max\{Option_1, \ldots, Option_j\}]}{Option_1 + \cdots + Option_j} \quad (4.4)$$

where $option_j$ denotes the number of votes of option j.

[37] Rice (1928) already developed an index to measure the rate of ‘not voting identically’ before Hix, Noury, & Roland (2005). However, Rice’s index can only describe ‘yes’ – ‘no’ options. The AI instead also applies to voting procedures that consider the “Abstain” option.

AI_i takes a numeric value between 0 and 1, with higher values indicating better group cohesion. If all members of coalition i choose the same option, $AI_i = 1$. Conversely, if the votes of coalition i are equally divided among the available choices, $AI_i = 0$.

4.3.3 Voter participation in governance polls

Before applying K-means we examine voter participation within polls. Table 4.1 provides descriptive statistics of Maker governance polls, ranging from Poll 16 to Poll 838. Both the number of votes and the number of voters exhibit volatility, cycles, and a sharp increase towards the end of the sample period. The number of total votes also shows a mild increasing pattern (see figures B.1 – B.2).

Most polls have fewer than 60 voters. They are thus participated in by a small group of voters in comparison to the total user population of the Maker protocol. This provides us with evidence of pervasive abstentionism, or apathy, among voters. We can conclude that decision-making power is largely controlled by voters who frequently participate in voting polls and possess a significant MKR balance.

Table 4.1: Descriptive statistics of Maker governance polls

	Total votes	Total voters	Breakdown votes	Breakdown ratio	Vote share of the largest voter coalition
Mean	48k	25.97	40k	0.88	0.74
Median	38k	22	34k	0.98	0.72
Maximum	294k	158	177k	1	1.00
Minimum	260	5	233	0.35	0.37
Std	34k	15.92	26k	0.17	0.16

Note: This table shows the descriptive statistics of Maker governance polls. For each poll, we compute the total votes and the number of total voters. ‘Breakdown votes’ refers to the votes of the winning option, and ‘breakdown ratio’ is breakdown votes divided by total votes. Finally, we calculate the largest voter coalition’s voting share, which equals to the votes casted by coalition 0 divided by the total votes.

4.3.4 Detection and analysis of voter coalitions in MakerDAO

Next, we proceed with the detection of voter coalitions using the K-means clustering algorithm. We divide Maker governance polls into two subsets: Poll 16 (started on August 15th, 2019) to Poll 412 (started on January 11th, 2021), and Poll 413 (started on January 18th, 2021) to Poll 838 (started on July 22nd, 2022). To mitigate endogeneity concerns, we apply the K-means algorithm to the first subset and conduct factor analysis on the second subset. We exclude minority voters that account for less than 500 MKR tokens, resulting in 172 remaining voters. Each voter has participated in at least 5 governance polls.

The algorithm reveals the presence of 3 voter coalitions as shown by Table 4.2. Coalition 1 comprises the largest number of members and substantially more votes compared to the other two coalitions. Moreover, coalition 1 has participated in most governance polls. On the other hand, although coalitions 2 and 3 are smaller in size, they account for a meaningful share of the total votes.

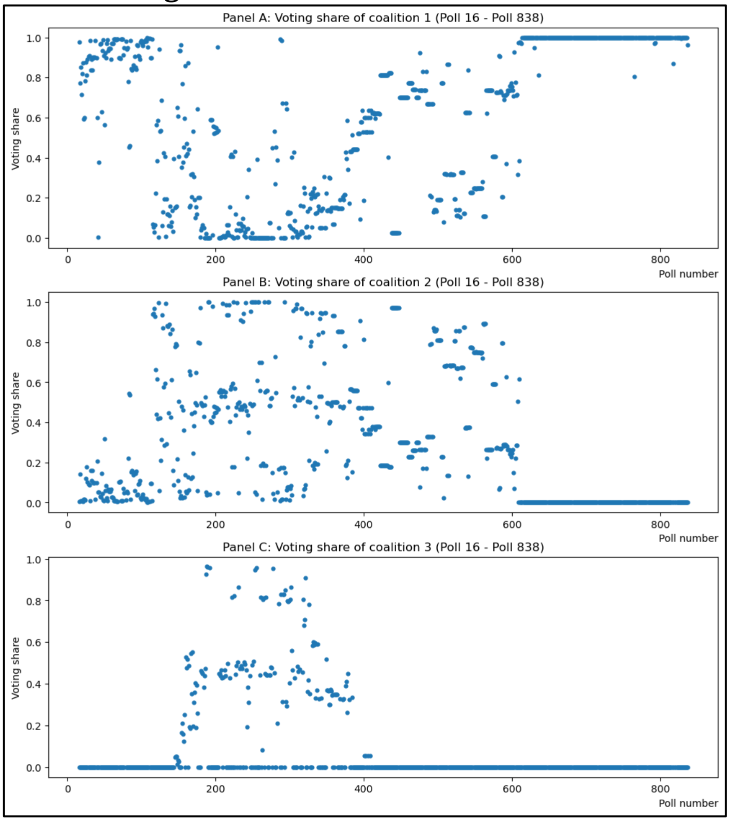
Table 4.2： Descriptive statistics of voter coalitions in MakerDAO

	Involved polls	Total votes	Since
Voter coalition 1	771	28.56m	2017-12-18
Voter coalition 2	650	7.26m	2019-04-11
Voter coalition 3	149	2.36m	2020-04-29

Note: This table presents information about three voter coalitions detected by the K-means algorithm. Voter coalition 1 has the highest voting power and participated in more governance polls than the two smaller coalitions. The column ‘since’ is the first date in which the voters in a coalition made a transaction on the Ethereum blockchain.

Figure 4.2 displays the voting share of the three identified coalitions. It is worth noting that the voting share of the other two coalitions also varies across polls, and in some polls, these two coalitions have accounted for most of the votes. This suggests that coalitions take charge of the leadership of most polls in a rotational manner. As a result, the outcome of these polls could in principle be determined by a single voter coalition.

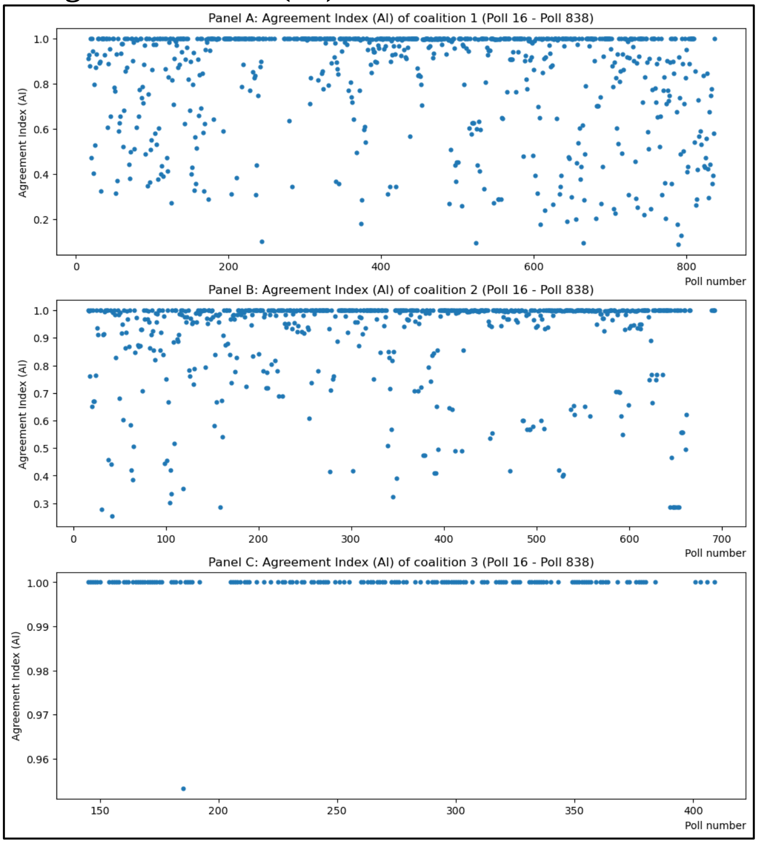
Figure 4.2: Voting share of three voter coalitions in MakerDAO



Note: This figure illustrates the voting share of three voter coalitions in Maker governance polls (Poll 16 – Poll 838). In some polls, the voting share of coalition 0 is close to 1, meaning that they have dominant decision-making power. In some other polls, the voting share of coalition 0 is low, while coalitions 2 and 3 contribute more votes, meaning that two smaller coalitions can win.

We then calculate group cohesion for the identified voter coalitions. The figure below illustrates that the cohesion is generally high within coalitions. However, we also observe opinion differences within certain voting polls, as indicated by a low AI. In this case, low cohesion reflects a level of diversity or divergence of opinions within a given coalition during a specific voting event.

Figure 4.3: Agreement Index(AI) of three voter coalitions in MakerDAO



Note: This figure illustrates the Agreement Index (AI) of three voter coalitions in Maker governance polls (Poll 16 – Poll 838). In some polls, AI of coalition 0 is close to 1, meaning that they concentrate on the same option. In some other polls, AI is low, meaning that their voting power is dispersed.

Table 4.3 provides a breakdown of coalitions' participation within the different poll categories that we identify. We find that coalitions' participation is rather homogeneous across the various poll categories. Both voter coalition 1 and voter coalition 2 show relatively similar levels of participation in the MIP and Greenlight polls. This implies that the coalitions are actively engaged in these types of polls and have a comparable level of influence and interest in shaping their outcomes.

Table 4.3: Voting participation in different categories of governance polls

	Voter coalition 1	**Voter coalition 2**	**Voter coalition 3**
Risk parameter	297	262	52
MIP	181	112	29
Greenlight	173	152	42
Ratification poll	103	33	1
Inclusion poll	70	70	25
Collateral onboarding	63	55	13
Total participated polls	771	650	149

Note: This table presents the number of different categories of governance polls (Poll 16 – Poll 838) that the three voter coalitions participated in. More details about the categories of governance polls are given in Table B.1 in Appendix B.1.

In the last part of our descriptive section, we study coalitions' internal structure by looking at voter identities. In order to provide a more comprehensive description of voters within MakerDAO, we have collected the Ethereum Name Service (ENS) names of voters from the Maker Governance Portal. ENS serves as a unique identifier for blockchain addresses. Subsequently, we have searched for these ENS names on Twitter, as some blockchain users may use their ENS names as their Twitter handles. While most blockchain users tend to prefer anonymity, ENS owners and Twitter users may have a more public presence.

By analyzing voters' historical transactions, we assign labels to describe their behavior, including activities such as decentralized exchange (DEX) trading, liquidity providing, and non-fungible token (NFT) trading. We also consider whether MakerDAO voters are considered "whales," which refers to entities holding a significant number of tokens, or "celebrities" in the DeFi community. We do so by examining voters' historical activities and assigning the appropriate labels leveraging data from scopescan.ai. Identifying known users and delegates within coalitions is important since these can utilize social media platforms like Twitter and the MakerDAO forum to influence the voting behavior of others.

The table below provides an initial overview of the composition of voter coalitions. Coalition 1 comprises the largest number of known users, indicating that the identities of these voters have higher public visibility. On the other hand, voters within coalitions 2 and 3 remain anonymous, as they do not have ENS names or known Twitter accounts. For these coalitions we are however able to retrieve a limited amount of data on trading activities. It is worth noticing that some entities may control multiple addresses, counted by us as individual voters, and split trading activities across them. Nevertheless, if the actions of these accounts are motivated by the same underlying preferences, our clustering algorithm should group them all within the same coalition.

Table 4.4: Internal structure of voter coalitions

	Voter coalition 1	Voter coalition 2
ENS owner	20%	0
Twitter user	10%	0
DEX trader	44%	47%
Liquidity provider	20%	13%
NFT trader	18%	33%
Whale	13%	7%
Delegate	15%	0

Note: This table describes the internal structure of voter coalitions in MakerDAO. For each voter coalition, we list the percentage of identified addresses by category.

We detect several influential entities, such as celebrity voters and MakerDAO delegates, within coalition 1 (more details are given in appendix B.2). Among these we find Andreessen Horowitz (a16z), one of the prominent venture capital firms, who has participated in 6 polls. We also find 23 MakerDAO delegates and voters with names linked to prestigious universities, such as 'Penn Blockchain' and 'Blockchain@Columbia'. Upon reviewing their Twitter accounts, these last turn out to be voters linked to student organizations focused on blockchain and crypto-curious students. Although we may not have information on how they have acquired significant voting power (i.e., a large number of MKR tokens), the presence of voters affiliated with higher education institutions suggests that students from elite universities can exert influence on DeFi by actively participating in DAO governance. Lastly, coalition 1 comprises crypto-native enterprises like Gauntlet[38] and Flipside[39], as well as influencers within the cryptocurrency industry such as Hasu[40] and Chris Blec[41]. The diversity of voters within coalition 1 enhances the intrigue and importance of examining its impact on the Maker protocol.

4.4 The influence of voter coalitions

This section investigates the influence of voter coalitions on the Maker protocol. We focus on the impact of coalitions on three features of Maker ecosystem: DAI volatility, daily

[38] https://gauntlet.network/

[39] https://flipsidecrypto.xyz/

[40] https://twitter.com/hasufl?s=20

[41] https://twitter.com/ChrisBlec?s=20

revenue, and new users. To estimate regressions, two poll-level measurements, i.e., voting share and AI of voter coalitions, are transferred to daily measurements by taking weighted average, where weights are total votes of polls. We provide descriptive statistics of voting share and AI on daily basis in Appendix B.3. The following analysis is based on Poll 413 – Poll 838, where coalition 3 abstained from participating.[42]

4.4.1 DAI Volatility

The primary objective of the DAI stablecoin is to maintain price stability, with 1 DAI intended to be pegged to 1 US dollar. High volatility is generally considered unfavorable for stablecoins (Gans, 2023; Liu, Makarov, & Schoar, 2023). In the field of corporate finance, centralized governance structures have been linked to performance volatility, such as increased volatility in stock returns (Giannetti & Zhao, 2019; Tran & Turkiela, 2020). In the context of DAO governance, centralized voting power held by voter coalitions may have similar effects. Considering this, we estimate the following regression model:

$$
\begin{aligned}
y_t = \beta_0 + \beta_1 voting\ share\ 1_t + \beta_2 voting\ share\ 2_t \\
+ \beta_3 AI\ 1_t + \beta_4 AI\ 2_t + \beta_5 voting\ share\ 1_t \times AI\ 1_t \\
+ \beta_6 voting\ share\ 2_t \times AI\ 2_t + \beta_7 \Delta ETH_t + \beta_8 \Delta RWA_t + \beta_9 Dai\ volume_t \\
+ \beta_{10} Mkr\ return_t + \beta_{11} ETH\ return_t + \beta_{12} ETH\ v30_t + \beta_{13} ETH\ v60_t \\
+ \beta_{14} BTC_t + \beta_{15} UNI_t + \beta_{16} CRV_t + \beta_{17} DeFi\ Pulse_t \\
+ \rho y_{t-30} + \lambda_t + \varepsilon_t \quad (4.5)
\end{aligned}
$$

where y_t denotes 30-day volatility of the DAI stablecoin on day t, y_{t-30} denotes a one-month lagged value of the dependent variable, and λ denotes year fixed effects. We also consider several other explanatory variables that capture three categories of influential factors for the Maker protocol. Detailed definitions of these variables can be found in Table B.4 in Appendix B.4.

[42] In the following regression models, we do not include variables relevant to coalition 3, given that they did not participate in the polls. For the days without any polls, we employ constant interpolation. In the interval between day *t* and day *t+n*, where *n* is the number of days, we assume that the values of voting share and Agreement Index (AI) remain constant, taking on the same values observed on day *t*.

Sun, Zeng, Liu, Ma, & Hu (2024) assess the DeFi market's resilience to risks, with the volume of fiat-backed stablecoins and trading volume emerging as crucial indicators. Kang, Tang, You, & Zeng (2023) demonstrate the relationship between the level of self-collateralization and crypto-runs, while Chiu et al. (2023) discuss the significance of collateral assets in on-chain lending systems. Therefore, we include dependent variables relevant to the collateral assets, and ΔETH and ΔRWA represent the changes in locked Ether (ETH) and Read World Assets (RWA) in the Maker protocol. Typically, ETH serves as the primary collateral asset since it is the native cryptocurrency on the Ethereum blockchain. However, RWA have gained importance as collateral in the Maker protocol recently, and certain governance polls revolve around the acceptance of specific RWAs as collateral. Additionally, we also include *Dai volume* and *Mkr return* as two dependent variables. A higher trading volume indicates a positive market performance for DAI. MKR, as the governance token in the Maker protocol, is akin to stocks in corporate finance. A higher daily return of MKR thus reflects positive expectations on the Maker protocol. Building upon Liu, Tsyvinski, & Wu (2022), we incorporate variables related to mainstream cryptocurrencies in our regression models to capture the dynamics of DeFi markets operating on the Ethereum blockchain, considering cryptocurrency market as crucial factors for risk and return analysis.

The empirical results reveal several interesting findings.[43] Firstly, a higher voting share of coalition 1 is associated with an increase in DAI volatility, while coalition 2's voting share and group cohesion have the opposite effects. This implies that the presence of the smaller voter coalition and its group cohesion contributes to the price stability of DAI, but centralized voting power controlled by the largest voter coalition may cause volatility. These findings are consistent with the results of Bernile et al. (2018), whereby decentralization governance can lead to lower volatility of stock returns, as the firm or bank is more prone to take risky actions. One possible explanation is that power concentration facilitates dominant coalitions to propose risky actions, thereby increasing the volatility of stablecoins. Empirical evidence from the literature of corporate finance, as presented by Tran & Turkiela (2020) and Giannetti & Zhao (2019), underscores the impact of power centralization within the board of directors on decision-making dynamics.

[43] A concern of the empirical results is potential endogeneity. We run Granger causality tests for all statistically significant findings in table 4.5, and the results do not show endogeneity. Furthermore, we re-estimate the regression model using the Newey-West produce with one-day lag to account for potential serial correlation in the data, and the results are also consistent with table 4.5.

Another explanation is rooted in the selfish behavior exhibited by coalitions of large stakeholders. Gudgeon et al. (2020a) provide a case study of a governance attack in the Maker protocol, revealing instances of selfish profit-seeking behavior among large MKR holders. Such stakeholders often form coalitions to extract private benefits, while minority stakeholders may align to protect their interests (Sauerwald & Peng, 2013; Hogg, 2000; Zwiebel, 1995; Bennedsen & Wolfenzon, 2000). Peng (2013) further discusses the conflicts within the shareholder community. Given that maintaining DAI stability is the primary objective of the Maker protocol, minority MKR holders may collaborate to safeguard the system and their interests by making proper choices in MakerDAO governance.

We also find that the prices of mainstream cryptocurrencies show a negative relationship with DAI volatility. This observation further contributes to the ongoing discussion regarding the interconnections between cryptocurrency returns (Guo, Härdle, & Tao, 2022; Şoiman, Duma, & Jimenez-Garces, 2023). Additionally, after controlling time fixed effects, we witness a trade-off between volume and volatility for stablecoins, in line with prior research on return predictors in the cryptocurrency market (Liu, Tsyvinski, & Wu, 2022; Şoiman et al., 2023).

Table 4.5: DAI volatility (30-day) and voter coalitions

	(1)	(2)	(3)	(4)	(5)	(6)
Voting share1	0.25 (1.30)	**0.41***** **(2.61)**	**0.34**** **(2.15)**	**0.31*** **(1.64)**	**0.28**** **(2.31)**	**0.29**** **(2.32)**
Voting share2	-0.30 (-0.67)	**-0.67*** **(-1.90)**	**-0.70**** **(-1.99)**	0.07 (0.15)	-0.09 (-0.31)	-0.08 (-0.30)
AI1	0.06 (0.41)	0.07 (0.63)	0.02 (0.16)	0.03 (0.19)	-0.02 (-0.17)	-0.01 (-0.12)
AI2	**-0.15***** **(-2.56)**	**-0.18***** **(-3.63)**	**-0.16***** **(-3.21)**	-0.06 (-1.00)	**-0.06*** **(-1.63)**	**-0.06*** **(-1.65)**
Voting share1*AI1	0.08 (0.37)	-0.07 (-0.39)	0.02 (0.13)	0.05 (0.25)	-0.04 (-0.26)	-0.04 (-0.31)
Voting share2*AI2	0.68 (1.59)	**0.78**** **(2.25)**	**0.81**** **(2.34)**	0.29 (0.66)	0.21 (0.77)	0.21 (0.75)
Dai volatility^{t-30}	-	-	**-0.13***** **(-2.81)**	-	-	0.01 (0.30)
∆ ETH	-	0.05 (1.23)	0.04 (1.14)	-	**0.07**** **(2.36)**	**0.07**** **(2.36)**
∆ RWA	-	-0.03 (-0.82)	-0.03 (-0.82)	-	-0.03 (-1.00)	-0.03 (-1.00)
Dai volume	-	**0.07**** **(1.99)**	**0.06*** **(1.65)**	-	**-0.09***** **(-3.01)**	**-0.09***** **(-2.98)**
Mkr return	-	-0.04 (-0.83)	-0.04 (-0.82)	-	0.02 (0.51)	0.02 (0.52)
Eth return	-	0.02 (0.40)	0.03 (0.46)	-	-0.01 (-0.29)	-0.01 (-0.30)
Eth v30	-	0.02 (0.27)	-0.08 (-1.06)	-	0.02 (0.43)	0.03 (0.52)
Eth v60	-	**0.11*** **(1.65)**	**0.21***** **(2.84)**	-	**-0.11**** **(-2.15)**	**-0.12**** **(-1.98)**
BTC	-	**-0.62*****	**-0.74*****	-	**-0.79*****	**-0.78*****

		(-7.48)	**(-7.97)**		**(-12.28)**	**(-10.84)**
UNI	-	**0.59*** (3.60)**	**0.78*** (4.42)**	-	0.19 (1.45)	0.17 (1.19)
CRV	-	**-0.27*** (-5.26)**	**-0.24*** (-4.55)**	-	**-0.19*** (-4.68)**	**-0.19*** (-4.64)**
DeFi pulse	-	-0.06 (-0.36)	-0.18 (-1.05)	-	**-0.37*** (-2.85)**	**-0.36*** (-2.70)**
N	540	540	540	540	540	540
Adj. R-sq	0.04	0.43	0.43	0.06	0.65	0.65
Year FE	No	No	No	Yes	Yes	Yes

Note: This table reports the regression coefficients and standard t-statistics in the parentheses for the case of DAI volatility. Columns (1) – (3) present results for regression models without year fixed effects. Columns (4) – (6) present results for regression models with time fixed effects. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics. The definitions of the variables are given in Table B.4.

4.4.2 Total revenue of Maker protocol

The role of the Maker protocol in the DeFi ecosystem is similar to that of banks in the traditional financial system: As in traditional banks, a significant portion of Maker’s revenues come from DAI loans. Various aspects of DAI loans, including interest rates and acceptable collateral assets, are determined through on-chain governance. The decisions made by MakerDAO thus impact loan volumes and, consequently, the revenue generated by the Maker protocol.

To investigate the relationship between protocol revenue and the decision-making power of voter coalitions, we estimate the following regression model:

$$
\begin{aligned}
y_t = \beta_0 &+ \beta_1 voting\ share\ 1_t + \beta_2 voting\ share\ 2_t \\
&+ \beta_3 AI\ 1_t + \beta_4 AI\ 2_t + \beta_5 voting\ share\ 1_t \times AI\ 1_t \\
&+ \beta_6 voting\ share\ 2_t \times AI\ 2_t + \beta_7 \Delta ETH_t + \beta_8 \Delta RWA_t + \beta_9 Dai\ volume_t \\
&+ \beta_{10} Mkr\ return_t + \beta_{11} ETH\ return_t + \beta_{12} ETH\ v30_t + \beta_{13} ETH\ v60_t \\
&+ \beta_{14} BTC_t + \beta_{15} UNI_t + \beta_{16} CRV_t + \beta_{17} DeFi\ Pulse_t \\
&+ \rho y_{t-30} + \lambda_t + \varepsilon_t \quad (4.6)
\end{aligned}
$$

where y_t denotes the growth of daily revenues (in USD) of the Maker protocol on day t, y_{t-30} denotes a one-month lagged value of the dependent variable, and λ denotes year fixed effects. The explanatory variables used here are defined as in regression (4.5).

The table below indicates that the two voter coalitions do not significantly influence the daily revenue of Maker protocol.[44] Intuitively, the primary determinant of daily revenue lies in the transaction fees generated by lending activities within the Maker protocol. While MakerDAO governance undoubtedly affects crucial parameters and acceptable collaterals in lending, the impact is likely more tied to the final voting outcome rather than the voting share of potential coalitions.

Another explanation posits that voter coalitions may not exhibit a direct relationship with the financial performance of DeFi systems, such as daily revenue. Similar observations exist within corporate finance literature, where Demsetz & Villalonga (2001) argue that the financial performance of firms may not be statistically linked to ownership structure. This discrepancy in findings could be attributed to data limitations, as discussed by Hermalin & Weisbach (2003) and Adam, Hermalin, & Weisbach (2010). Further research could explore this issue by constructing more comprehensive datasets for DAOs.

Table 4.6: The growth of daily revenue of Maker protocol and voter coalitions

	(1)	(2)	(3)	(4)	(5)	(6)
Voting share1	-0.06 (-0.29)	0.04 (0.27)	0.04 (0.27)	0.01 (0.08)	0.05 (0.36)	0.05 (0.36)
Voting share2	-0.22 (-0.51)	0.22 (0.69)	0.23 (0.70)	0.18 (0.42)	0.17 (0.51)	0.17 (0.52)
AI1	0.18 (1.24)	0.14 (1.35)	0.14 (1.35)	0.14 (1.00)	0.15 (1.44)	0.15 (1.44)
AI2	**-0.15*** (-2.63)**	0.00 (0.05)	0.00 (0.03)	-0.05 (-0.90)	-0.01 (-0.20)	-0.01 (-0.23)
Voting share1*AI1	-0.29 (-1.32)	-0.21 (-1.28)	-0.21 (-1.27)	-0.32 (-1.48)	-0.21 (-1.30)	-0.21 (-1.29)
Voting share2*AI2	-0.02 (-0.05)	-0.35 (-1.11)	-0.35 (-1.12)	-0.47 (-1.07)	-0.30 (-0.93)	-0.30 (-0.93)
Δ $revenue^{t-30}$	-	-	-0.02 (-0.63)	-	-	-0.02 (-0.66)
Δ ETH	-	**0.63*** (18.68)**	**0.63*** (18.65)**	-	**0.63*** (18.62)**	**0.63*** (18.59)**
Δ RWA	-	**-0.06* (-1.88)**	**-0.06* (-1.88)**	-	**-0.06* (-1.88)**	**-0.06* (-1.89)**
Dai volume	-	0.05 (1.61)	0.05 (1.56)	-	**0.07** (1.99)**	**0.07** (1.95)**
Mkr return	-	0.02 (0.50)	0.02 (0.49)	-	0.02 (0.37)	0.02 (0.35)
Eth return	-	0.05 (1.05)	0.05 (1.07)	-	0.06 (1.12)	0.06 (1.14)
Eth v30	-	-0.02 (-0.41)	-0.02 (-0.34)	-	-0.02 (-0.42)	-0.02 (-0.34)
Eth v60	-	-0.05	-0.06	-	-0.03	0.04

[44] A concern of the empirical results is potential endogeneity. We run Granger causality tests for all statistically significant findings in table 4.6, and the results do not show endogeneity. Furthermore, we re-estimate the regression model using the Newey-West produce with one-day lag to account for potential serial correlation in the data, and the results are also consistent with table 4.6.

		(-0.89)	(-0.98)		(-0.52)	(-0.61)
BTC	-	0.08	0.09	-	0.10	0.11
		(1.11)	(1.20)		(1.33)	(1.42)
UNI	-	-0.23	**-0.25***	-	-0.19	-0.21
		(-1.56)	**(-1.64)**		(-1.28)	(-1.36)
CRV	-	-0.07	-0.07	-	**-0.08***	**-0.08***
		(-1.49)	(-1.57)		**(-1.66)**	**(-1.74)**
DeFi pulse	-	**0.37****	**0.38*****	-	**0.40*****	**0.41*****
		(2.43)	**(2.46)**		**(2.62)**	**(2.65)**
N	540	540	540	540	540	540
Adj. R-sq	0.03	0.52	0.52	0.06	0.52	0.52
Year FE	No	No	No	Yes	Yes	Yes

Note: This table reports the regression coefficients and standard t-statistics in the parentheses for the case of daily revenue of Maker protocol. Columns (1) – (3) present results for regression models without year fixed effects. Columns (4) – (6) present results for regression models with time fixed effects. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics. The definitions of the variables are given in Table B.4.

4.4.3 New users of Maker protocol

Now we analyze what is the impact of voter coalitions on the growth of Maker's user community. This is an important question since network adoption plays a pivotal role in the success of decentralized digital platforms.[45] To investigate this aspect, we utilize the datasets for users of the Maker protocol from *Dune.xyz*. By calculating the growth of new users on a daily basis, we estimate the following regression model:

$$
\begin{aligned}
y_t = \beta_0 + \beta_1 voting\ share\ 1_t + \beta_2 voting\ share\ 2_t \\
+ \beta_3 AI\ 1_t + \beta_4 AI\ 2_t + \beta_5 voting\ share\ 1_t \times AI\ 1_t \\
+ \beta_6 voting\ share\ 2_t \times AI\ 2_t + \beta_7 \Delta ETH_t + \beta_8 \Delta RWA_t + \beta_9 Dai\ volume_t \\
+ \beta_{10} Mkr\ return_t + \beta_{11} ETH\ return_t + \beta_{12} ETH\ v30_t + \beta_{13} ETH\ v60_t \\
+ \beta_{14} BTC_t + \beta_{15} UNI_t + \beta_{16} CRV_t + \beta_{17} DeFi\ Pulse_t \\
+ \rho y_{t-30} + \lambda_t + \varepsilon_t (4.7)
\end{aligned}
$$

where y_t denotes the growth of new users of Maker protocol on day t, y_{t-30} denotes a one-month lagged value of the dependent variable, and λ denotes year fixed effects.

[45] Cong, Li, & Wang (2020) and Xiong & Sockin (2023) have demonstrated how user adoption influences platform growth.

The table below presents the results, and we do not observe significant relationship between voter coalitions and the growth of new users in Maker protocol.[46] Surprisingly, the lagged term of Δ *new user* does not influence the growth of new users. The finance literature usually addresses the importance of network effects on network adoption of financial systems (such as Milne (2006) and Krivosheya (2020)), i.e., the existing users can contribute to the growth of new users. However, our findings argue that the voter coalitions do not exhibit such effects.

Table 4.7: The growth of new users of Maker protocol and voter coalitions

	(1)	(2)	(3)	(4)	(5)	(6)
Voting share1	-0.26 (-1.29)	-0.26 (-1.26)	-0.26 (-1.25)	-0.25 (-1.28)	-0.26 (-1.27)	-0.26 (-1.26)
Voting share2	0.26 (0.57)	0.30 (0.65)	0.29 (0.63)	0.26 (0.57)	0.31 (0.67)	0.31 (0.65)
AI1	-0.12 (-0.80)	-0.13 (-0.83)	-0.13 (-0.82)	-0.12 (-0.80)	-0.13 (-0.84)	-0.13 (-0.83)
AI2	-0.01 (-0.24)	-0.03 (-0.40)	-0.03 (-0.40)	-0.01 (-0.21)	-0.02 (-0.36)	-0.02 (-0.36)
Voting share1*AI1	0.22 (0.99)	0.21 (0.90)	0.21 (0.89)	0.22 (0.99)	0.21 (0.91)	0.21 (0.89)
Voting share2*AI2	-0.34 (-0.79)	-0.45 (-0.97)	-0.44 (-0.95)	-0.35 (-0.77)	-0.46 (-0.99)	-0.45 (-0.97)
Δ New user^{t-30}	-	-	0.02 (0.47)	-	-	0.02 (0.47)
Δ ETH	-	**-0.15*** (-3.00)**	**-0.15*** (-3.00)**	-	**-0.15*** (-2.98)**	**-0.15*** (-2.99)**
Δ RWA	-	0.03 (0.79)	0.03 (0.80)	-	0.03 (0.79)	0.03 (0.80)
Dai volume	-	-0.07 (-1.44)	-0.07 (-1.42)	-	-0.07 (-1.44)	-0.07 (-1.42)
Mkr return	-	0.10 (1.46)	0.10 (1.46)	-	0.10 (1.47)	0.10 (1.48)
Eth return	-	-0.04 (-0.59)	-0.04 (-0.60)	-	-0.04 (-0.60)	-0.04 (-0.61)
Eth v30	-	0.04 (0.46)	0.04 (0.43)	-	0.04 (0.46)	0.04 (0.43)
Eth v60	-	-0.02 (-0.19)	-0.01 (-0.17)	-	-0.02 (-0.23)	-0.02 (-0.21)
BTC	-	-0.01 (-0.13)	-0.02 (-0.15)	-	-0.02 (-0.17)	-0.02 (-0.18)
UNI	-	-0.08 (-0.37)	-0.08 (-0.36)	-	-0.09 (-0.40)	-0.09 (-0.39)
CRV	-	0.01 (0.11)	0.01 (0.11)	-	0.01 (0.13)	0.01 (0.13)
DeFi pulse	-	0.14 (0.63)	0.14 (0.63)	-	0.13 (0.60)	0.13 (0.59)
N	540	540	540	540	540	540
Adj. R-sq	0.00	0.00	0.00	0.00	0.00	0.00
Time FE	No	No	No	Yes	Yes	Yes

[46] A concern of the empirical results is potential endogeneity. We run Granger causality tests for all statistically significant findings in table 4.7, and the results do not show endogeneity. Furthermore, we re-estimate the regression model using the Newey-West produce with one-day lag to account for potential serial correlation in the data, and the results are also consistent with table 4.7.

Note: This table reports the regression coefficients and standard t-statistics in the parentheses for the case of new users of Maker protocol. Columns (1) – (3) present results for regression models without year fixed effects. Columns (4) – (6) present results for regression models with time fixed effects. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics. The definitions of the variables are given in Table B.4.

4.4.4 Following the money: DAI

As DAI is the primary cryptocurrency issued by Maker protocol, we now investigate the link between the decision-making processes within MakerDAO and the flows of DAI towards the crypto-financial broader ecosystem where it is traded. We consider five different destinations of DAI financial flows: *Centralized Exchanges (CeFi)*, *Decentralized Exchanges (DEXes)*, *Lending Protocols (LPs)*, *External Owned Accounts (EOAs)*, and *Bridges*. Simply, EOAs are accounts controlled by people (instead of codes), and bridges enable cross-chain transactions. For more details about these on-chain applications, we refer readers to online appendix 1. To study the influence of MarkerDAO's governance process on DAI flows, we estimate the following regression:

$$\begin{aligned} Dai\ transferred_{i,t} \\ &= \beta_0 + \beta_1 voting\ share\ 1_t + \beta_2 voting\ share\ 2_t \\ &+ \beta_3 AI\ 1_t + \beta_4 AI\ 2_t + \beta_5 voting\ share\ 1_t \times AI\ 1_t \\ &+ \beta_6 voting\ share\ 2_t \times AI\ 2_t + \beta_7 \Delta ETH_t + \beta_8 \Delta RWA_t + \beta_9 Dai\ volume_t \\ &+ \beta_{10} Mkr\ return_t + \beta_{11} ETH\ return_t + \beta_{12} ETH\ v30_t + \beta_{13} ETH\ v60_t \\ &+ \beta_{14} BTC_t + \beta_{15} UNI_t + \beta_{16} CRV_t + \beta_{17} DeFi\ Pulse_t + \lambda_t + \varepsilon_{i,t} \quad (4.8) \end{aligned}$$

where:

- $Dai\ transferred_i = \{CeFi, DEX, LP, EOA, Bridge\}$
- λ denotes year fixed effects

The table below presents the regression results.[47] From the estimated coefficients we can see that coalition 1 significantly increase DAI transferred to LP and EOA but can decrease

[47] A concern of the empirical results is potential endogeneity. We run Granger causality tests for all statistically significant findings in table 4.8, and the results do not show endogeneity. Furthermore, we re-estimate the regression model using the Newey-West produce with one-day lag to account for potential serial correlation in the data, and the results are also consistent with table 4.8.

DAI flows to CeFi, while a higher *voting share 2* can increase DAI flows to CeFi, DEX and bridge. This observation, taken together with the positive coefficient of *AI 2* in columns (1) - (4), leads us to deduce that voter coalition 2 aims at directing more DAI flows towards CeFi and DEX. This finding partly reveals the private interest of coalition 2 and the difference preference in DAI flows to CeFi for the two coalitions.

Additionally, our analysis reveals that collateral structure in Maker protocol can influence DAI flows. An increase in the growth of collateralized ETH will lead to more DAI transferred to EOAs. Considering that ETH is possibly the safest collateral accepted by Maker protocol, a higher quantity of ETH collateral means lower risks within the Maker protocol. Consequently, users exhibit greater willingness to include DAI as part of their cryptocurrency portfolios. Interestingly, other mainstream cryptocurrencies and the status of DeFi market also show influences on DAI flows. Further research can investigate the correlations among leading cryptocurrencies, particularly those issued by leading DeFi protocols.

Table 4.8: DAI flows and voter coalitions

	CeFi		DEX		LP		EOA		Bridge	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Voting share1	-0.41** (-2.39)	-0.33** (-2.05)	-0.01 (-0.15)	0.01 (0.16)	0.50*** (2.81)	0.40*** (2.49)	0.14* (1.86)	0.16** (2.07)	0.19 (1.59)	0.22** (1.99)
Voting share2	1.25*** (3.23)	0.86** (2.39)	0.82*** (4.16)	0.70*** (3.62)	-0.03 (-0.08)	0.42 (1.16)	0.02 (0.11)	-0.05 (-0.27)	0.78*** (3.01)	0.61** (2.40)
AI1	0.03 (0.20)	0.08 (0.72)	-0.30*** (-4.57)	-0.28*** (-4.40)	0.01 (0.07)	-0.06 (-0.50)	-0.15*** (-2.73)	-0.14*** (-2.58)	-0.15* (-1.78)	-0.13 (-1.52)
AI2	0.16*** (3.04)	0.09* (1.71)	0.13*** (4.62)	0.10*** (3.79)	-0.04 (-0.65)	0.05 (1.05)	0.01 (0.34)	-0.01 (-0.21)	0.08** (2.29)	0.05 (1.35)
Voting share1*AI1	-0.17 (-0.85)	-0.19 (-1.05)	0.32*** (3.18)	0.31*** (3.20)	-0.01 (-0.03)	0.02 (0.11)	0.15* (1.73)	0.15* (1.70)	0.13 (1.02)	0.12 (0.97)
Voting share2*AI2	-1.54*** (-4.04)	-1.16*** (-3.26)	-0.65*** (-3.35)	-0.53*** (-2.79)	0.10 (0.26)	-0.34 (-0.96)	0.10 (0.57)	0.16 (0.96)	-0.59** (-2.30)	-0.42* (-1.66)
∆ ETH	0.03 (0.67)	0.01 (0.33)	0.02 (0.73)	0.01 (0.52)	-0.04 (-1.06)	-0.03 (-0.71)	0.04** (2.31)	0.04** (2.19)	-0.06** (-2.16)	-0.07*** (-2.49)
∆ RWA	0.01 (0.29)	0.01 (0.29)	0.03 (1.37)	0.03 (1.40)	0.03 (0.92)	0.04 (1.05)	0.01 (0.91)	0.01 (0.91)	0.04 (1.47)	0.04 (1.50)
Dai volume	0.11*** (2.81)	0.21*** (5.70)	0.00 (0.02)	0.03* (1.66)	-0.09** (-2.20)	-0.21*** (-5.53)	-0.01 (-0.77)	0.00 (0.25)	-0.11*** (-4.35)	-0.07*** (-2.50)
Mkr return	-0.05 (-0.89)	-0.09* (-1.77)	-0.06** (-2.17)	-0.08*** (-2.70)	-0.13** (-2.18)	-0.08 (-1.48)	-0.01 (-0.46)	-0.02 (-0.75)	-0.02 (-0.58)	-0.04 (-1.12)
Eth return	0.10* (1.67)	0.12** (2.22)	0.03 (1.03)	0.04 (1.30)	0.06 (0.94)	0.03 (0.57)	0.01 (0.28)	0.01 (0.43)	0.02 (0.41)	0.03 (0.69)
Eth v30	-0.09 (-1.30)	-0.09 (-1.45)	-0.03 (-0.94)	-0.03 (-0.99)	-0.16** (-2.22)	-0.16** (-2.41)	0.07** (2.13)	0.07** (2.13)	0.07 (1.55)	0.04 (1.57)
Eth v60	0.13* (1.88)	0.28*** (4.14)	0.07** (2.03)	0.12*** (3.31)	0.17** (2.29)	0.00 (0.00)	-0.36*** (-11.32)	-0.33*** (-10.36)	-0.04 (-0.73)	0.03 (0.65)
BTC	0.04 (0.40)	0.16* (1.85)	0.35*** (7.49)	0.38*** (8.45)	-0.40*** (-4.32)	-0.54*** (-6.35)	-0.13*** (-3.19)	-0.11*** (-2.68)	0.31*** (5.16)	0.37*** (6.19)
UNI	-0.38** (-2.09)	-0.11 (-0.63)	-0.17* (-1.89)	-0.09 (-0.98)	1.40*** (7.50)	1.09*** (6.35)	0.40*** (5.00)	0.44*** (5.55)	-0.31*** (-2.58)	-0.19 (-1.60)
CRV	0.38*** (6.73)	0.32*** (6.19)	0.66*** (22.78)	0.64*** (22.67)	0.47*** (8.04)	0.53*** (10.06)	0.17*** (6.75)	0.16*** (6.40)	0.44*** (11.50)	0.41*** (11.15)
DeFi pulse	-0.31* (-1.67)	-0.10 (-0.57)	-0.61*** (-6.54)	-0.55*** (-5.95)	-0.95*** (-5.00)	-1.19*** (-6.90)	-1.00*** (-12.35)	-0.96*** (-11.93)	-0.55*** (-4.45)	-0.45*** (-3.78)
N	540	540	540	540	540	540	540	540	540	540

Adj. R-sq	0.31	0.41	0.82	0.83	0.26	0.40	0.87	0.87	0.69	0.71
Time FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Note: This table reports the regression coefficients and standard t-statistics in the parentheses for the case of DAI flows transferred to different on-chain applications, where variables related to Maker protocol and Ethereum markets are also included. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics. The definitions of the variables are given in Table B.4.

4.4.5 Robustness checks: Known voters in coalition 1

Although we exclude small voters (those with total votes lower than 500 MKR), the distribution of total votes in coalition 1 is centralized. Table B.2 shows that known voters have substantial total votes and thus play a crucial role in coalition 1. To examine the robustness of our results in previous subsections, we calculate daily voting share and AI for these known users and re-estimate regressions (4.5) – (4.8) after replacing *voting share 1* and *AI 1*.

The tables below present the results, which are consistent with our findings in sections 4.4.1 - 4.4.4. This implies that the most influential members in coalition 1 are the known voters. Beside significant decision-making power held, the known voters can influence smaller voters by posting their opinions on social media. In other words, herding behavior may exist. Further research can delve into more details about how small voters are influenced by opinion leaders in DeFi.

Table 4.9: The influence of known voters in coalition 1

	DAI v30				**∆ Revenue**			**∆ New users**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Voting share known	-0.18	**0.77*****	**0.77*****	**0.32***	0.04	0.04	-0.15	-0.07	-0.07
	(-1.03)	**(5.96)**	**(5.95)**	**(1.89)**	(0.32)	(0.30)	(-0.82)	(-0.32)	(-0.31)
Voting share2	-0.04	0.08	0.07	-0.02	-0.04	-0.04	-0.03	-0.04	-0.04
	(-0.50)	(1.44)	(1.35)	(-0.23)	(-0.76)	(-0.78)	(-0.38)	(-0.46)	(-0.44)
AI known	0.45	-0.19	-0.21	-0.33	-0.38	-0.38	0.03	-0.13	-0.13
	(1.16)	(-0.73)	(-0.76)	(-0.87)	(-1.39)	(-1.39)	(0.06)	(-0.30)	(-0.30)
AI2	-0.02	**-0.07****	**-0.07***	**-0.12****	-0.04	-0.04	-0.05	-0.06	-0.06
	(-0.37)	**(-1.95)**	**(-1.85)**	**(-2.24)**	(-1.02)	(-1.06)	(-0.86)	(-0.96)	(-0.95)
Voting share known *AI known	-0.37	-0.02	-0.01	0.03	0.34	0.02	0.12	0.21	0.21
	(-1.01)	(-0.07)	(-0.03)	(0.09)	(1.30)	(0.55)	(0.31)	(0.52)	(0.51)
Voting share2*AI2	**-0.10****	0.00	0.01	0.01	0.02	0.02	-0.03	-0.05	-0.05
	(-1.98)	(0.04)	(0.15)	(0.10)	(0.56)	(0.55)	(-0.53)	(-0.79)	(-0.77)
y^{t-30}	-	-	-0.02	-	-	-0.03	-	-	0.02
			(-0.39)			(-0.90)			(0.34)
∆ ETH	-	-0.04	-0.04	-	**0.65*****	**0.65*****	-	**-0.11***	**-0.11***
		(-1.03)	(-1.05)		**(17.34)**	**(17.36)**		**(-1.87)**	**(-1.87)**
∆ RWA	-	-0.05	-0.05	-	0.02	0.02	-	0.04	0.04
		(-1.52)	(-1.51)		(0.67)	(0.62)		(0.67)	(0.68)
Dai volume	-	**-0.14*****	**-0.14*****	-	0.03	0.03	-	**-0.10***	**-0.10***
		(-3.91)	**(-3.92)**		(0.85)	(0.86)		**(-1.72)**	**(-1.70)**
Mkr return	-	0.02	0.02	-	-0.01	-0.02	-	0.08	0.08

		(0.47)	(0.48)		(-0.27)	(-0.33)		(0.93)	(0.93)
Eth return	-	-0.01	-0.01	-	0.10*	0.10*	-	-0.01	-0.01
		(-0.11)	(-0.12)		(1.84)	(1.88)		(-0.13)	(-0.14)
Eth v30	-	-0.09	-0.10	-	-0.03	-0.03	-	0.00	0.00
		(-1.34)	(-1.37)		(-0.50)	(-0.43)		(-0.02)	(-0.04)
Eth v60	-	0.23***	0.24***	-	-0.01	-0.01	-	-0.02	-0.02
		(2.76)	(2.75)		(-0.07)	(-0.10)		(-0.18)	(-0.17)
BTC	-	-0.74***	-0.76***	-	0.08	0.09	-	-0.05	-0.05
		(-9.99)	(-9.54)		(1.00)	(1.12)		(-0.37)	(-0.38)
UNI	-	0.05	0.07	-	-0.25**	-0.26**	-	-0.02	-0.02
		(0.45)	(0.55)		(-2.01)	(-2.09)		(-0.11)	(-0.11)
CRV	-	-0.21***	-0.21***	-	-0.06	-0.06	-	0.03	0.03
		(-3.63)	(-3.65)		(-0.97)	(-1.08)		(0.37)	(0.36)
DeFi pulse	-	0.00	-0.01	-	0.43***	0.44***	-	0.07	0.07
		(0.02)	(-0.06)		(3.59)	(3.61)		(0.34)	(0.34)
N	381	381	381	381	381	381	381	381	381
Adj. R-sq	0.04	0.62	0.62	0.06	0.60	0.60	0.00	-0.02	0.00
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports the regression coefficients and standard t-statistics in the parentheses for the case of known voters. Columns (1) – (3) present results for the case of Dai volatility. Columns (4) – (6) present results for the case of the growth of daily revenue of Maker protocol. Columns (7) – (9) present results for the case of the growth of new users in Maker protocol. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics. The definitions of the variables are given in Table B.4.

Table 4.10: DAI flows and known voters in coalition 1

	CeFi		DEX		LP		EOA		Bridge	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Voting share known	-0.53***	-0.65***	0.41***	0.40***	0.32**	0.53***	0.80***	0.79***	0.27***	0.26***
	(-3.22)	(-4.12)	(5.35)	(5.21)	(2.06)	(4.08)	(10.43)	(10.28)	(2.76)	(2.64)
Voting share2	-0.05	-0.11	0.02	0.02	-0.26***	-0.16***	0.02	0.02	-0.03	-0.04
	(-0.72)	(-1.62)	(0.66)	(0.54)	(-3.96)	(-2.97)	(0.67)	(0.59)	(-0.77)	(-0.87)
AI known	-1.79***	-1.48***	-0.24	-0.22	1.24***	0.70***	0.16	0.17	0.23	0.26
	(-5.28)	(-4.54)	(-1.49)	(-1.34)	(3.80)	(2.58)	(1.02)	(1.09)	(1.16)	(1.26)
AI2	-0.05	-0.07	0.03	0.03	-0.04	-0.01	-0.01	-0.01	0.00	0.00
	(-1.10)	(-1.56)	(1.42)	(1.36)	(-0.86)	(-0.21)	(-0.29)	(-0.32)	(0.01)	(-0.04)
Voting share known *AI known	1.53***	1.35***	0.12	0.11	-0.98***	-0.67***	-0.39***	-0.40***	-0.16	-0.17
	(4.74)	(4.40)	(0.78)	(0.70)	(-3.16)	(-2.64)	(-2.61)	(-2.64)	(-0.82)	(-0.89)
Voting share2*AI2	0.02	-0.03	-0.02	-0.03	0.05	0.13***	-0.03	-0.03	0.02	0.01
	(0.39)	(-0.63)	(-1.04)	(-1.16)	(1.09)	(3.49)	(-1.34)	(-1.41)	(0.63)	(0.49)
ΔETH	-0.02	-0.05	0.00	0.00	-0.05	0.00	0.01	0.01	-0.01	-0.01
	(-0.47)	(-1.03)	(-0.09)	(-0.16)	(-1.03)	(-0.11)	(0.55)	(0.50)	(-0.33)	(-0.39)
ΔRWA	0.02	0.01	0.04**	0.04*	0.03	0.05	0.03	0.03	0.07***	0.07***
	(0.52)	(0.21)	(1.97)	(1.93)	(0.65)	(1.50)	(1.37)	(1.34)	(2.77)	(2.72)
Dai volume	0.13***	0.21***	0.04*	0.04**	0.02	-0.11***	0.00	0.00	0.01	0.01
	(2.94)	(4.70)	(1.80)	(1.96)	(0.43)	(-3.10)	(-0.19)	(-0.03)	(0.30)	(0.50)
Mkr return	-0.02	-0.06	-0.02	-0.02	-0.09	-0.03	0.01	0.01	-0.02	-0.02
	(-0.34)	(-1.01)	(-0.58)	(-0.66)	(-1.52)	(-0.50)	(0.31)	(0.25)	(-0.40)	(-0.47)
Eth return	0.01	0.04	0.00	0.01	0.06	0.01	-0.01	-0.01	0.02	0.02
	(0.22)	(0.68)	(0.15)	(0.20)	(0.92)	(0.20)	(-0.26)	(-0.22)	(0.55)	(0.60)
Eth v30	0.05	0.05	-0.08**	-0.08**	-0.27***	-0.26***	0.03	0.03	-0.01	-0.01
	(0.62)	(0.57)	(-2.12)	(-2.13)	(-3.36)	(-3.95)	(0.69)	(0.69)	(-0.27)	(-0.28)
Eth v60	-0.53***	-0.34***	0.01	0.02	0.41***	0.08	-0.24***	-0.23***	-0.05	-0.04
	(-5.28)	(-3.43)	(0.13)	(0.37)	(4.25)	(1.01)	(-5.12)	(-4.73)	(-0.90)	(-0.63)
BTC	-0.10	0.03	0.08*	0.08*	-0.62***	-0.83***	-0.32***	-0.31***	-0.10*	-0.09
	(-1.03)	(0.28)	(1.73)	(1.87)	(-6.88)	(-11.04)	(-7.33)	(-7.04)	(-1.83)	(-1.62)
UNI	0.02	0.13	0.03	0.04	1.09***	0.90***	0.44***	0.44***	0.08	0.09
	(0.14)	(0.87)	(0.44)	(0.54)	(7.41)	(7.46)	(6.18)	(6.20)	(0.92)	(1.00)
CRV	0.43***	0.42***	0.59***	0.58***	0.27***	0.29***	0.15***	0.15***	0.40***	0.40***
	(5.91)	(6.05)	(17.11)	(17.07)	(3.85)	(5.07)	(4.43)	(4.41)	(9.20)	(9.17)
DeFi pulse	-0.59***	-0.50***	-0.39***	-0.38***	-0.57***	-0.73***	-0.63***	-0.62***	-0.51***	-0.51***
	(-3.93)	(-3.45)	(-5.50)	(-5.38)	(-3.91)	(-6.15)	(-8.94)	(-8.82)	(-5.77)	(-5.65)
N	381	381	381	381	381	381	381	381	381	381

Adj. R-sq	0.37	0.44	0.86	0.86	0.42	0.61	0.86	0.86	0.78	0.78
Time FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Note: This table reports the regression coefficients and standard t-statistics in the parentheses for the case of DAI flows transferred to different on-chain applications, where variables related to Maker protocol and Ethereum markets are also included. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics. The definitions of the variables are given in Table B.4.

4.5 Conclusion

We presented an analysis of voter coalitions in MakerDAO and discussed the impact of their voting behavior on the financial performances of the underlying Maker protocol. We identified three voter coalitions by applying K-means to voting records of governance polls and brought to light the influence that these coalitions exert on governance by pursuing their private interests. Research on the fundamental properties of decentralized, coalition-based democracy is still at its infancy, and this chapter provides an initial step towards the realization of a broader research plan.

This chapter contributes to theoretical studies on blockchain-based organizations by presenting empirical research on DAO governance. Building upon the work of Schwabe & Ziolkowski (2019), who examine blockchain as an organizational technology and stress the importance of considering all involved parties in blockchain-based governance, such as developers, miners, and generators, and Berg et al. (2019), who discuss how DAOs mitigate uncertainty and opportunism among investors, we further explore the application of the theory of institutions for collective actions. Drawing on the self-organizing governance systems proposed by Ostrom (2010) and Ostrom (2014), we extend the theoretical discussions previously presented by Howell, Potgieter, & Sadowski (2019) and Rozas, Tenorio-Fornés, Díaz-Molina, & Hassan (2021). By considering potential voter coalitions, we investigate novel power relationships and new hierarchies within DAOs.

Furthermore, akin to the arguments of Murray, Kuban, Josefy, & Anderson (2021), our findings demonstrate that novel technology cannot eliminate problems inherent in traditional organizations, particularly those caused by shareholder coalitions in corporate finance. Additionally, our chapter contributes to discussions about ethical issues in DAOs, as highlighted by Sulkowski (2019), which often focus on fraud and corruption but may overlook conflicts within DAO communities.

Additionally, this chapter contributes to the ongoing debates regarding the influence of governance concentration in DAOs, a topic that has elicited varied opinions among researchers along with corresponding empirical evidence. For instance, Han, Lee, & Li (2023) identify a negative relationship between voting power concentration in DAOs and the value of their underlying platforms. They argue that excessive concentration of power in the hands of large token holders may lead to the extraction of private benefits at the expense of minority token holders. Conversely, Laturnus (2023) finds no significant evidence of a negative effect of power concentration on platform performance; in fact, it suggests that concentrated ownership can be beneficial in certain cases. Furthermore, research by Fritsch et al. (2022) focus on DAO delegates and suggest that the concentration of voting power at the coalition level can have an overall positive effect on DAO performance due to increased involvement of small token holders. Building upon these discussions, our chapter delves deeper by considering coalitions within DAO communities, rather than solely focusing on the coalitions between delegates and delegators.

As we mentioned in the introduction, future research can use our dataset to quantify, for MakerDAO, the degree of block-voter entropy (see section 4.1 and Austgen et al. (2023)). Besides quantifying decentralization, an even deeper question would be to understand the latent forces that give rise to our identified coalitions. For example, it would be interesting to understand whether some coalitions originate, for example, because of voter apathy or herding behavior. Assessing these aspects is crucial for addressing crucial design questions for a DAO such as those relating to vote delegation and privacy.

Another problem that requires further academic scrutiny is the extent to which opinion leaders in voter coalitions split their identities over multiple accounts. Coalition identification by clustering would be robust to account-splitting, as all clones of a single entity likely act at unison. However, a deep analysis of account splitting would still provide clues on protocol resilience to this type of behavior (i.e., sybil attacks).

The last topic that we propose for future work is the analysis of the dynamics of voting power and cohesion within coalitions. Pursuing that would however present significant challenges, as it requires matching DAO data with coalition members' activities within the broader cryptofinance ecosystem.

While our findings demonstrate conceptual and empirical robustness, it is important to interpret them within their limitations. Firstly, potential endogeneity issues exist in the empirical analysis. Despite conducting several robustness tests, further research could mitigate endogeneity concerns by employing methodologies such as event studies and identifying suitable instrumental variables. Secondly, despite including dependent variables related to both the Maker protocol and the DeFi market, there remains a possibility of omitted variable bias in the analysis presented in section 4.4. Future research could address this potential issue by identifying appropriate instrumental variables or by developing more comprehensive datasets for DAO governance.

Overall, this chapter presents a pioneering investigation into voter coalitions in blockchain, and the considerations lead us to conclude that there are many important facets of multi-coalition democracy on DAOs that are still unexplored by research. To reach a solid understanding of DAOs, researchers will have to address both empirical and conceptual challenges. We plan to face these challenges in our future works.

Chapter 5

Liquidity Risk and Market Concentration in Lending Protocols: Evidence from Aave

Lending Protocols (LPs), as blockchain-based lending systems, facilitate borrowing and lending cryptocurrencies for any agent. However, liquidity risk is a concern, particularly in scenarios of concentrated deposits and loans. This chapter introduces metrics for assessing liquidity risk, emphasizing both available liquidity and market concentration in LPs. Utilizing Aave as a case study, we find that liquidity risk is highly volatile, and both regular users (that repeatedly borrow and deposit cryptocurrencies) and large users exert complicated influences on the protocol. Furthermore, we investigate cross-LP effects of liquidity risk and market concentration, offering insights into competition among leading LPs.

5.1 Introduction

Financial Technology (FinTech) and its disruptive effects to traditional finance have deeply changed financial markets (An & Rau, 2019). Among all FinTech innovations, *Decentralized Finance (DeFi)* has experienced rapid growth since 2019, and as of September 2021, the size of DeFi reached $110 billion (IMF, 2021). Technically, DeFi protocols can be defined as blockchain-based financial systems, which inherit unique characteristics of blockchain, e.g., openness and transparency. The execution of transactions in DeFi does not rely on a centralized third party, e.g., central banks. Currently, DeFi can replicate most activities in traditional finance (Pereira, Tavalaei, & Ozalp, 2019; Harvey et al., 2021; Werner et al., 2022), e.g., lending, cryptocurrency exchange, and asset management. In this chapter, we focus on *Lending Protocols (LPs)*, resembling banks in DeFi (Gudgeon et al., 2020a; Harvey et al., 2021), and investigate the presence of liquidity risk in LPs, as this will help both investors and policy makers.

Similar to the definition of liquidity risk in the banking sector, liquidity risk in a liquidity pool (LP) refers to a situation where the LP does not maintain sufficient available liquidity to meet the demands of withdrawing and borrowing cryptocurrencies. In LPs, all activities are processed via smart contracts, which are rigidly coded programs, rather than centralized third parties. Therefore, the most crucial roles in LPs are the dominant depositors and borrowers. Liquidity risk can arise if their activities deplete available liquidity, and the situation can worsen if they collectively withdraw deposits. In fact, the concentration of deposits and loans has been a concern for LPs. Unlike lending in traditional finance, LPs offer better transparency, allowing for easy monitoring of lending activities. Currently, the primary depositors contribute the majority of liquidity in LPs (Gudgeon et al., 2020a), and a small group of borrowers account for most loans (Saengchote, 2023). Therefore, liquidity risk is a valid concern, and there is a need to develop metrics for assessing it.

The literature around liquidity risk is voluminous. Theoretically, different models of liquidity risks have been developed over the years (Bryant, 1980; Diamond & Dybvig, 1983; Rochet & Vives, 2004; Goldstein & Pauzner, 2005; Fall & Viviani, 2015). In real life, illiquidity causes unacceptable outcomes. The most influential example may be the bank failures caused by the 2008 financial crisis (Hong et al., 2014). Even worse, bank defaults can cause the failure of the banking sector (Kreis & Leisen, 2018), and illiquidity can reduce banks' long-term investment, leading to negative effects on economic growth (Choudhary & Limodio, 2022). Moreover, if illiquidity occurs, it can spread across financial markets in different countries (Aldasoro & Alves, 2018; Eross, Urquhart, & Wolfe, 2018; Kreis & Leisen, 2018). Beside banks, other financial entities also suffer from illiquidity. If firms cannot recognize liquidity risks, severe results, such as bankruptcy and over-leveraging, will happen (Wang, Xu, & Yang, 2017). Badaoui et al. (2013) show that liquidity risks are also fatal in bond and CDS markets, and a series of research discusses how mutual funds' trading strategies change because of liquidity risks (Anand, Irvine, Puckett, & Venkataraman, 2013; Collin-Dufresne & Fos, 2015; Kacperczyk & Pagnotta, 2019; Anand, Jotikasthira, &

Venkataraman, 2021; Christoffersen, Keim, Musto, & Rzeźnik, 2022). Since illiquidity can be very problematic, Allen & Gale (2004) argue that the role of regulators in reducing liquidity risks is very important.

However, when it comes to liquidity risks in blockchain or DeFi, the literature surprisingly remains silent. By introducing and stress-testing economic models of LPs, liquidity risk is possible in some cases (Gudgeon et al., 2020b). For example, if a large price drop of collateral assets happens, LPs will be undercollateralized, prompting LP users to discard the risky protocols. Consequently, LPs will suffer from illiquidity. Bartoletti et al. (2021) present a formal model of LPs, incorporating important features, such as collateralization, exchange rates and interest rates in LPs. Castro-Iragorri, Remirez, & Velez (2021) study LPs from the perspective of financial intermediation, highlighting liquidity risk as a crucial indicator of LP risk rating. Currently, most LP research revolves about economic models addressing fundamental settings and incentive mechanisms, with limited discussion on empirical evidence of liquidity risk. To fill this gap, we choose Aave, the most successful LP, as a case study, anticipating the intricate effects of liquidity risk on Aave protocol. To the best of our knowledge, this is the first research that provides empirical evidence of liquidity risk in LP.

Aave was founded in 2017 in Switzerland, and it raised more than $16 million in its first initial coin offering (ICO) in 2017. Since then, Aave has grown rapidly and become an industry standard by introducing innovative functions of on-chain lending. We collect information for Aave protocol, including all borrowers, lenders, and all lending-related activities from December 16th, 2019, to January 31st, 2023. By querying the intraday prices of cryptocurrencies traded in Aave, we calculate accurate available liquidity in Aave protocol.

Our empirical analysis follows two stages. The first stage is to examine lending activities in Aave. We first calculate two well-adopted metrics, namely liquidity and utilization, which describes a general sense of Aave protocol. Subsequently, we scrutinize market concentration in Aave, specifically focusing on two categories of users: regular users (repeat borrowers and repeat depositors) and large users (large borrowers and large depositors). Through an analysis of their trading activities, we identify their significant contributions to deposits and loans within Aave. The collective execution of certain strategies by these users may intuitively lead to liquidity risks. It's worth noting that in traditional lending, concentrated loans can reduce default risk for banks and potentially increase a bank's return

(Acharya, Hasan, & Saunders, 2006; Tabak et al., 2011). To understand how regular users and large users impact Aave, we construct several metrics to assess their influence on the protocol.

In the second stage, we explore the effects of liquidity risk and market concentration within the Aave protocol. Empirically, liquidity can affect underlying financial systems (Wang et al., 2017; Papanikolaou, 2018; Momtaz, 2019; Duarte, Galindo, & Montecinos, 2021), therefore, factors specific to Aave protocol may change with potential liquidity risks. We also investigate cross-LP effects, anticipating the existence of contagious illiquidity, as observed in the banking sector (Eross et al., 2018; Kreis & Leisen, 2018). In the banking sector, competition is a pivotal factor influencing banking stability (Fiordelisi & Mare, 2014). Similarly, aside from attracting liquidity, LPs also compete to attract more regular users and large users. Consequently, we expect to observe metrics related to these significant users showing cross-LP effects.

The empirical results bring forward some interesting findings. First, available liquidity and utilization are highly volatile in Aave, with spikes in utilization closely approaching one. Moreover, a significant proportion of deposits and loans are contributed by both regular users and large users, indicating market centralization within. By applying factor analysis, we identify potential issues when available liquidity is not adequately utilized. For instance, the growth of Aave protocol stakeholders may be constrained when there is excess available liquidity. Furthermore, the influence of regular users and large users on Aave is intricate. For instance, an increase in deposits and loans from large users results in the growth of daily revenue and total value locked. However, the growth of market capitalization and the return of the governance token of the Aave protocol are observed to decrease. These findings suggest that such significant users act as a double-edged sword. LPs rely on users to provide liquidity and initiate loans; hence, regular users and large users can stimulate the growth of Aave, given the presence of herding in lending markets (Shao & Bo, 2021) and network effects in the cryptocurrency market (Li, Shin, & Wang, 2023; Xiong & Sockin, 2023). Our research further addresses the potential disadvantages associated with significant users, providing new insights into dominant players in DeFi lending.

More interestingly, liquidity risk and market concentration in Aave affects other LPs. Here, Compound[48] is chosen because it is a leading LP and primary competitor of Aave. The

[48] https://compound.finance/

factor analysis shows the interlinks between Aave and Compound. Factor analysis unveils the interconnectedness between Aave and Compound. For instance, an increase in liquidity in Aave is shown to decrease the growth of stakeholders and market capitalization in Compound. Furthermore, the activities of regular users and large users in Aave can influence Compound, highlighting the intricate relationship between these two leading LPs. Previous literature (e.g., Tolmach, Li, Lin, & Liu, 2021; von Wachter, Jensen, & Ross, 2021) focuses more on composability of DeFi protocols based on the infrastructure of programmable blockchain, while our analysis emphasis on the nature of LPs, i.e., on-chain lending systems. This perspective sheds light on the competition among leading LPs. The findings draw parallels to research on bank competition, where dominant users transfer their funds among banks to mitigate risks (Oliveira et al., 2015), consequently impacting bank performance.

This chapter provides new insights into potential risks associated with FinTech applications. While speculative behavior has been acknowledged as a source of risks in Peer-to-Peer (P2P) lending (Kanga, Oughton, Harris, & Murinde, 2021) and blockchain (Onjewu, Walton, & Koliousis, 2023), our study goes beyond by examining the activities of regular users and large users, whose actions may have complex implications on a LP, even if their activities are not strictly speculative. By investigating the cross-LP effects of liquidity risks, we make a significant contribution to the research on contagious illiquidity (e.g., Aldasoro & Alves, 2018; Eross et al., 2018; Kreis & Leisen, 2018). Despite being competitors, leading LPs are susceptible to the contagion of liquidity risks within the LP ecosystem. Through the presentation of robust empirical evidence, we demonstrate that DeFi is not immune to liquidity risk, with certain users (i.e., regular users and large users) playing a crucial role in this phenomenon.

The remainder of this chapter is organized as follows. Section 5.2 provides a short introduction to LPs. Section 5.3 describes the characteristics of pool-based loans in LPs, the relevant agents and the definitions of liquidity risk measurements. Section 5.4 summarizes the empirical results based on the characteristics of Aave protocol and the associated regressions. Finally, section 5.5 presents the conclusions, while some technical information is summarized in Appendix C.

5.2 Lending protocols (LPs)

Based on blockchain technology, LPs resemble banks in crypto markets, allowing their users to borrow and lend cryptocurrencies (Bartoletti et al., 2021). Any agent can lend their cryptocurrency to an LP. Similar to depositors in banks, LP depositors can earn interest by providing liquidity. For any cryptocurrency, all deposits will be stored in a lending pool, which can be borrowed by anyone. To initiate loans, borrowers should first lock collateral, usually cryptocurrencies accepted by LPs, and both loans and interests should be repaid if a borrower aims to unlock their collateral assets. Beside borrowers and depositors, liquidators also play an important role in LPs. When a borrower fails to repay their loan, liquidators can (partly) repay the failed loan. As a result, liquidators can purchase the borrower's collateral at a discount. Usually, the process is defined as liquidation. Compared to traditional bank lending, a pivotal difference of LPs is that key parameters of loans are not decided by third parties. For example, LPs apply different mathematical models to determine the interest rates. Other suggested changes, e.g., new acceptable collateral, will usually be jointly decided by LP users via voting. For more details, we refer readers to summary research presented by Gudgeon et al. (2020a) and Werner et al. (2022).

Currently, diversified LPs co-exist in DeFi, while several mainstream LPs account for the most lending activities. One of the most widely adopted LPs is Aave[49], which provides service on multiple blockchains. In this chapter, we focus on Aave on Ethereum blockchain. The first version of Aave protocol, i.e., Aave V1, was deployed to the Ethereum mainnet in January 2020. Aave updated to its second version, i.e., Aave V2, in December 2020. As of January 31st, 2023, the total locked value (in USD) in Aave is more than $4.5 billion.

Besides the significant market capitalization, Aave expands its influence by introducing new features. First, Aave allows any user to create lending pools. Theoretically, Aave users can initiate loans in any cryptocurrency that they prefer. This is unlike any relevant flexibility appearing in traditional banking lending. Second, Aave was the first LP to introduce 'flash loans'. Put simply, flash loans do not require any collateral, since the loan will be borrowed and repaid in an atomic transaction group (Qin et al., 2021). More details about utilization of flash loans can be found in Gudgeon et al. (2020a), Wang et al. (2021), and Qin et al.

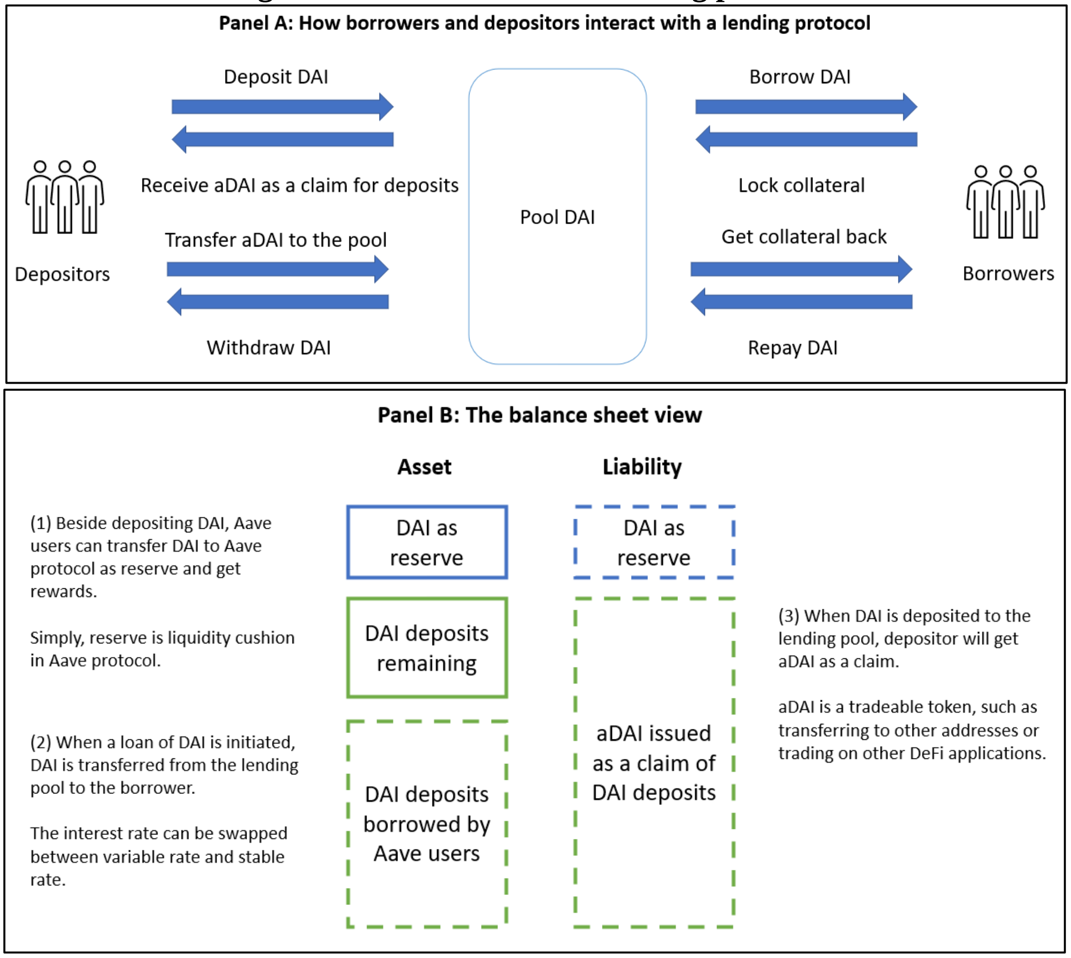
[49] https://aave.com

(2021). This function allows for more on-chain transactions. Aave introduced several innovative features in V2, such as swapping collateral assets and repaying debts with collateral assets (Aave, 2021). These innovative technical features not only increased the adoption of Aave but also made it the main industry standard.

5.3 Pool-based loans in LPs: Depositors, borrowers, liquidators, and associated liquidity risk

In this section, we will present a model to better describe activities in LPs. Our model features three types of agents, i.e., depositors, borrowers, and liquidators; and five types of activities, i.e., borrow, repay, deposit, withdraw, and liquidation. Depositors lend cryptocurrencies to LPs, while borrowers borrow cryptocurrencies by locking collateral assets. Once a borrower fails to repay his loan or his debt is undercollateralized, a liquidator can partly repay the loan and purchase collateral assets at a discounted price. All validated activities are publicly observable by all agents. Figure 5.1 illustrates how borrowers and depositors interact with LPs using DAI stablecoin as an example. If an LP supports a loan of some cryptocurrency, a liquidity pool will be generated, where users can deposit or borrow the cryptocurrency. Panel B presents the balance sheet view of DAI stablecoin in the LP, addressing the importance of sufficient liquidity.

Figure 5.1: Pooled funds in lending protocols



Note: This figure illustrates borrowing and lending in lending protocols. For each token, there will be a pool. Panel A shows how users interact with the lending pool of DAI. Depositors can deposit their token (i.e., DAI) and receive an amount of claim (i.e., aDAI). When depositors want to withdraw their tokens, they need to transfer the claim to the lending protocol. Borrowers need to lock collateral when requiring loans. When they successfully repay loans, the collateral can be returned. Panel B presents the balance sheet view of the lending pool of DAI. Both DAI deposits and DAI reserve are classified as assets[50]. DAI loans represent the debt obligations of borrowers. When an Aave user deposits DAI, aDAI token will be issued as a claim, therefore aDAI is a part of liability.

5.3.1 Depositors

Depositors will receive an amount of claim after transferring cryptocurrencies to an LP. The claim is a cryptocurrency minted by an LP, and it is a proof of deposit. For depositors, the

[50] More details about reserve mechanism in Aave can be found: https://docs.aave.com/aavenomics/incentives-policy-and-aave-reserve

amount of claim received will correspond to the amount deposited. The claim will be redeemable for a value of the same cryptocurrency type of the original deposit. So, when depositors want to withdraw their deposits, they need to transfer their claims to LPs.

Given a cryptocurrency A, we assume there exist N depositors, indexed by $i \in \{1,2,\dots,N\}$, whose deposits on date t are $d_{A,i,t}, i \in \{1,2,\dots,N\}$ and $t \in \{1,2,\dots,T\}$. For depositor i, his withdrawn deposits on date t are $w_{A,i,t}, i \in \{1,2,\dots,N\}$ and $t \in \{1,2,\dots,T\}$.

So, the supply of cryptocurrency A from depositor i on date t is calculate as:

$$supply_{A,i,t} = \sum_{s=1}^{t} (d_{A,i,s} - w_{A,i,s}) \ (5.1)$$

The outstanding deposits of cryptocurrency A on date t is calculated as:

$$outstanding\ deposit_{A,t} = \sum_{i=1}^{N} supply_{i,t} \ (5.2)$$

5.3.2 Borrowers

Borrowers can initiate loans from an LP only if they lock enough collateral. Usually, overcollateralization is required (Bartoletti et al., 2021), meaning that the value of debt is lower than the value of collateral. Collateral can be cryptocurrencies supported by LPs and will be locked in the duration of the loan.

Given a cryptocurrency A, we assume there exist M borrowers, indexed by $j \in \{1,2,\dots,M\}$, whose loans on date t are $b_{j,t}, j \in \{1,2,\dots,M\}$ and $t \in \{1,2,\dots,T\}$. For borrower j, his repaid loans on date t are $r_{j,t}, j \in \{1,2,\dots,M\}$ and $t \in \{1,2,\dots,T\}$.

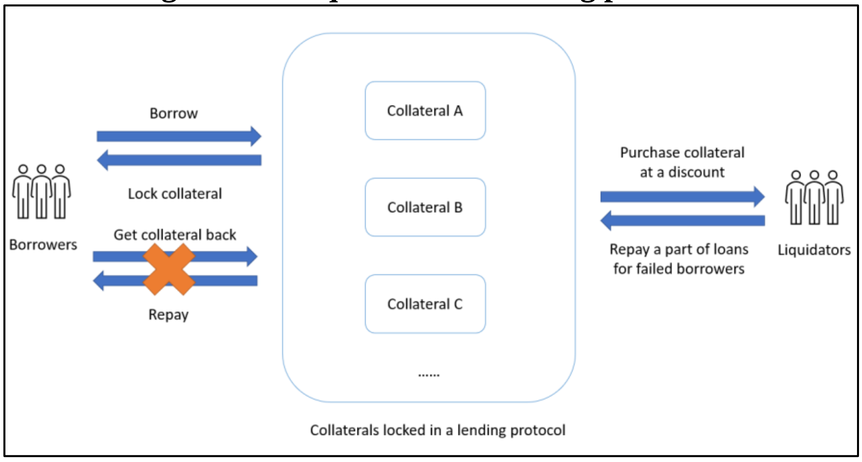
So, the demand of cryptocurrency A from borrower j on date t is estimated as:

$$demand_{A,j,t} = \sum_{s=1}^{t} (b_{A,j,s} - r_{A,j,s}) (5.3)$$

5.3.3 Liquidators

Once borrowers fail to repay their loans, or debt is undercollateralized, liquidators can (partly) repay the loans to acquire a discounted amount of collateral (see Figure 5.2). In LPs, the process is called liquidation. Liquidation thresholds vary between asset markets across different protocols (Gudgeon et al., 2020a).

Figure 5.2: Liquidation in lending protocols



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

Given a cryptocurrency A, we assume there exist L liquidators, indexed by $k \in \{1,2, \dots, L\}$, whose repaid loans on date t are $l_{k,t}, k \in \{1,2, \dots, L\}$ and $t \in \{1,2, \dots, T\}$. On date t, the total loans of cryptocurrency A repaid by all liquidators are calculated as:

$$l_{A,t} = \sum_{s=1}^{t} \sum_{k=1}^{L} l_{A,k,s} (5.4)$$

Consequently, loans will be paid by borrowers and liquidators. The outstanding debt of cryptocurrency A on date t is calculated as:

$$outstanding\ debt_{A,t} = \sum_{j=1}^{M} demand_{A,j,t} - l_{A,t} \quad (5.5)$$

5.3.4 Available liquidity and utilization in LPs

To study liquidity risks in LPs, we choose available liquidity and utilization as two simple and intuitive measurements[51]. For a cryptocurrency in LPs, liquidity means that the total supply is more than the total demand. We can calculate the available liquidity of cryptocurrency A on date t:

$$liquidity_{A,t} = outstanding\ deposit_{A,t} - outstanding\ debt_{A,t} \quad (5.6)$$

Then, the USD value of available liquidity of all cryptocurrencies in an LP on date t can be calculated as:

$$liquidity_{t} = \sum_{A} liquidity_{A,t} \times p_{A,t} \quad (5.7)$$

where $p_{A,t}$ is the price of cryptocurrency A on date t.

The utilization of cryptocurrency A on date t:

$$utilization_{A,t} = \frac{outstanding\ debt_{A,t}}{outstanding\ deposit_{A,t}} \quad (5.8)$$

[51] Traditional examples of measurements of liquidity risks in banking are given by Holmström & Tirole (1998), Berger & Bouwman (2009), and Fall & Viviani (2015). However, these comprehensive measures rely on balance sheet information and how loans are classified. This is not suitable for LPs. In this paper, e choose available liquidity and utilization as two simple and intuitive measurements. In practice, liquidity risks can be triggered by successive withdrawals, especially when depositors with large deposits decide to leave (Alethio, 2020). In this case, available liquidity in LPs will be low, while utilization should be close to one.

The utilization of a LP on date t can be calculated as:

$$utilization_t = \frac{\sum_A outstanding\ debt_{A,t} \times p_{A,t}}{\sum_A outstanding\ deposit_{A,t} \times p_{A,t}} \quad (5.9)$$

where $p_{A,t}$ is the price of cryptocurrency A on date t.

5.4 Empirical results

5.4.1 Measurements of liquidity risk

In this chapter, we focus on Aave on Ethereum blockchain. *Aave: LendingPool V1*[52] and *Aave: LendingPool V2*[53] are the main components of Aave protocol, and these two contracts document events related to deposits and loans in Aave V1 and V2, respectively. Utilizing *Dune.xyz*, we query all transactions in Aave from December 16th, 2019, to January 31st, 2023. For every transaction, we retrieve the real-time prices (in USD) of the borrowed or deposited cryptocurrency; therefore, the statistics, such as the daily volume (in USD) of loans and deposits, can be precisely calculated. Table 5.1 summarizes the details of loans and deposits in Aave. Overall, we do not observe many borrowers or depositors, though the means of daily volume of loans and deposits are more than $20 million. We also consider regular borrowers and depositors in Aave (here after, *repeat borrower* and *repeat depositor*). Compared to new borrowers and depositors, on average, regular users usually contribute more loans and deposits to Aave protocol[54].

Table 5.1: Descriptive statistics of details of loans and deposits in Aave

Panel A: Loan details					
Variable	**Mean**	**Median**	**Maximum**	**Minimum**	**Std**
Borrower	180.26	160	2202	3	137.29
Loan vol USD	74402450.33	44690200.14	1312822432.44	615.84	111355283.92
Loan cnt	257.92	223	2265	9	182.73
New borrower	49.20	34	2113	1	93.23
New loan vol USD	10839280.04	2152363.60	452990005.67	27.91	35010964.38
New loan cnt	58.94	42	2143	1	96.74

[52] The address of 'Aave: LendingPool V1' is 0x398eC7346DcD622eDc5ae82352F02bE94C62d119

[53] The address of 'Aave: LendingPool V2' is 0x7d2768dE32b0b80b7a3454c06BdAc94A69DDc7A9

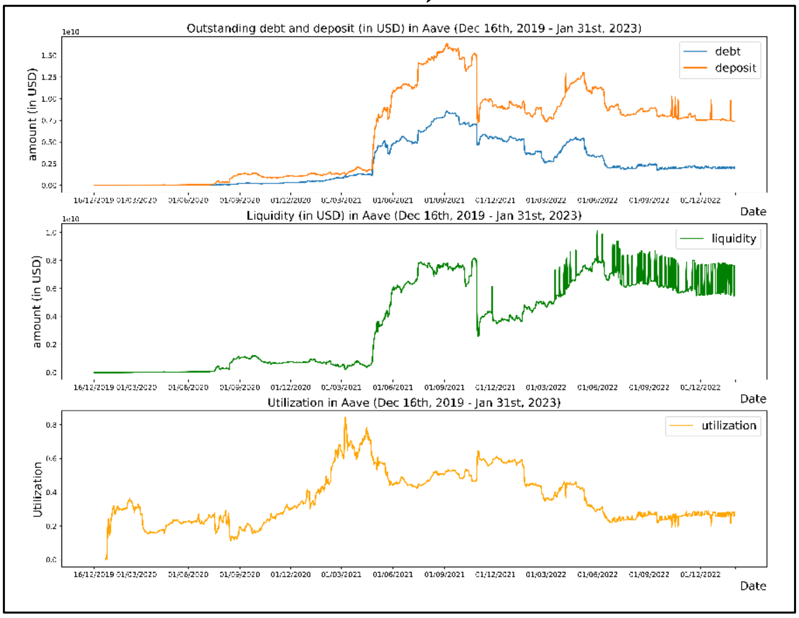
[54] Appendix C.4 presents the results after controlling for the outliers in dependent variables. To achieve that, we windorize dependent variables.

Avg loan USD	279693.06	171118.75	6132660.20	23.69	380383.67
Outstanding loan	2445509004.02	1986428589.00	8583137562.00	0.00	2407001377.99
Liquidation USD	1108629.00	8778.63	182148137.30	0	7192831.19
Repeat borrower	131.07	110	548	0	90.83
Repeat loan vol USD	63563170.29	38763466.99	1293039942.36	0	94246681.88
Repeat loan cnt	198.98	168	903	0	137.70
Panel B: Deposit details					
Variable	**Mean**	**Median**	**Maximum**	**Minimum**	**Std**
Depositor	240.13	210	2315	1	161.27
Deposit vol USD	244207804.95	135861456.56	4353999722.71	3.01	377703443.59
Deposit cnt	478.64	401	2643	1	321.52
New depositor	94.78	73	2117	1	104.30
New deposit vol USD	32321743.93	7459112.17	3238493811.48	3.01	134629694.90
New deposit cnt	121.69	95	2194	1	119.78
Avg deposit USD	555875.97	281998.74	11549070.88	3.01	1026335.57
Outstanding deposit	5953130710.29	7604941310.00	16367590242.00	0	5015574904.39
Repeat depositor	145.34	123	619	0	86.82
Repeat deposit vol USD	211886061.02	117195291.80	4236981879.53	0	326516103.30
Repeat deposit cnt	356.95	296	1985	0	247.94

Note: This table reports details of loans and deposits in Aave v1 and v2 (from Dec 16th, 2019, to Jan 31st, 2023). In this table, we consider all tokens traded in Aave protocol. The definitions of variables are presented in Table C.1.

Figure 5.3 reveals more information about liquidity in Aave protocol. Overall, outstanding debt and deposit (in USD) experienced rapid growth around June 2021 and have shown volatility since then. Noticeably, outstanding debt was extremely close to deposit at some point, implying potential illiquidity. Then, we compute two measurements, i.e., *liquidity* and *utilization*. Daily available liquidity is highly volatile after December 2021, while the spikes of utilization are more than 0.8. All these signals suggest that Aave is not immune to liquidity risks.

Figure 5.3: Outstanding debt and deposit in Aave protocol (Dec 16, 2019 – Jan 31, 2023)



Note: This figure illustrates outstanding debt and deposit (in USD) in Aave protocol; available liquidity (in USD) daily and utilization are also presented. In this figure, we consider all tokens traded in Aave.

To better investigate the influence of repeat borrowers and depositors[55], we construct two ratios related to their activities, namely *repeat loan ratio* and *repeat deposit ratio*. *Repeat loan ratio* is the proportion of daily volume (in USD) of loans contributed by repeat borrowers, while *repeat deposit ratio* equals the proportion of daily volume (in USD) of deposits contributed by repeat depositors. When the two ratios are higher, illiquidity is more likely if repeat borrowers or repeat depositors collectively initiate loans and withdraw deposits. Overall, these two measurements are very volatile and usually higher than 0.8, implying that repeat users are dominant players in Aave.

We also consider large users of Aave. Among all cryptocurrencies traded in Aave, we focus on five mainstream cryptocurrencies, including Ether (ETH), Wrapped Bitcoin (WBTC), Dai (DAI), USD Coin (USDC) and Tether (USDT). For each cryptocurrency, we inspect the top 100 borrowers and depositors in terms of both cryptocurrency amount and frequency of transactions, resulting 980 manually identified addresses. More details about the large users are presented in appendix C.2. After filtering large users, we construct two measurements of liquidity risks, namely *deposit large* and *loan large*. *Deposit large* is defined as the USD value outstanding deposits from large depositors, while *loan large* is the USD value of outstanding loans by large borrowers. Intuitively, the two measurements reflect the significance of contributions of large users, especially how they provide and utilize available liquidity. The table below presents descriptive statistics of the measurements of liquidity risk in Aave.

Table 5.2: Measurements of liquidity risks

	Liquidity	**Utilization**	**Repeat deposit ratio**	**Repeat loan ratio**	**Deposit large**	**Loan large**
Mean	3667536822.32	0.36	0.86	0.86	73340196.69	68734339.56
Median	3924483726.00	0.31	0.92	0.93	32718829.01	29493444.83
Maximum	10122920707.00	0.84	1.00	1.00	1774291874.00	2274180710.00
Minimum	0.00	0	0.00	0.00	0	0
Std	3090386938.75	0.16	0.16	0.16	209519528.48	187300122.38

Note: This table reports descriptive statistics of liquidity risk measurements based on the datasets for Aave V1 and V2 lending pool (from Dec 16th, 2019, to Jan 31st, 2023).

[55] Figures C.3 – C.5 in Appendix C.1 provide more details about repeat borrowers and depositors.

5.4.2 Effects of liquidity risk on Aave protocol

We are interested in how liquidity risks affect Aave protocol. To achieve that, we construct a series of factors specific to Aave protocol; the original datasets are available on *Dune.xyz* and *tokenterminal.com.* Table 5.3 gives a brief introduction of factors related to Aave. In the following subsections, we investigate the influences of repeat users and large users, respectively.

Table 5.3: Aave protocol-specific factors

Factor	Definition
MktC_F	Market cap (in USD) based on the maximum supply of tokens
MktC_C	Market cap (in USD) based on the circulating supply of tokens
AAVE	Daily price (in USD) of AAVE
TVL	Value (in USD) of funds locked in the project's smart contracts
Revenue	The amount of revenue (in USD) that is distributed to AAVE holders
Loan vol USD	Daily volume (in USD) of Aave loans
Deposit vol USD	Daily volume (in USD) of Aave deposits
Liquidation USD	Value (in USD) of collateral liquidated daily in Aave
AAVE holder	The number of Ethereum addresses that have a non-zero balance of AAVE token
Active user	Daily active users of Aave protocol
Developer	Daily active developers of Aave protocol

Note: This table introduces a series of factors related to Aave protocol. The factors can be retrieved from *Dune.xyz and tokenterminal.com*.

Effects of liquidity risk and repeat users Following Saengchote (2023), standards errors are estimated using the Newey-West procedure with one-day lag to account for potential serial correlation in the data. Beside Aave specific variables, we also include ETH returns to capture the market performance of Ethereum blockchain. The regression model is presented below:

$$Protocol_{i,t} = \beta_0 + \beta_1 Risk_{t-1} + \beta_2 Repeat\ deposit\ ratio_{t-1} + \beta_3 Repeat\ loan\ ratio_{t-1} + \beta_2 \Delta Deposit\ vol\ USD_{i,t-1} + \beta_3 \Delta Loan\ vol\ USD_{i,t-1} + \beta_4 \Delta Liquidation\ USD_{i,t-1} + \beta_5 \Delta Active\ user_{i,t-1} + \beta_6 \Delta Developer_{i,t-1} + \beta_7 ETH\ return\ (1d)_t + \beta_8 ETH\ return\ (7d)_t + \beta_9 ETH\ SD\ (30d)_t + \varepsilon_{i,t} (5.10)$$

where:

- $Risk = \{Liquidity, Utilization\}$
- $Protocol = \{\Delta MktC\_F, \Delta MktC\_C, \Delta Revenue, \Delta TVL, \Delta AAVE, \Delta AAVE\ holder\}$
- $i = Aave\ protocol$

The aim in this regression setup is to use dependent variables able to describe the status of Aave protocol. Market cap and total value locked (TVL) are two widely adopted metrics of project performance. Usually, higher market cap and TVL are positive signals. We also consider daily revenue (in USD), which also reflects the state of Aave. Besides, two variables related to *AAVE token* are studied. AAVE token, also a cryptocurrency, is the governance token of Aave protocol, and AAVE holders can participate in autonomous governance of Aave protocol. In a sense, AAVE resembles stocks issued by corporations, while AAVE holders play a similar role to shareholders. Therefore, the return of AAVE and the number of AAVE holders show the market expectations and the evaluation of Aave protocol.

Besides the liquidity risk measurement, several other dependent variables are used to help explain the changes of Aave-specific factors. Building upon Liu, Tsyvinski, & Wu (2022), we incorporate variables related to the native cryptocurrency of Ethereum blockchain (i.e., ETH) in our regression models to capture the dynamics of DeFi markets operating on the Ethereum blockchain, considering cryptocurrency market as crucial factors for risk and return analysis. Given that Aave centers on on-chain lending, we consider the daily volume of loans and deposits. We also consider the value (in USD) of liquidated collateral assets, since Kang et al. (2023) and Chiu et al. (2023) demonstrate that collateralization plays a key role in on-chain lending systems. The number of active users should be included because of the importance of network adoption. In the context of crypto markets, Li et al. (2023) and Xiong & Sockin (2023) contend that better network adoption can boost valuation and long-term development of on-chain financial systems. Finally, we include the number of developers, given that these people can influence the technical updates of Aave protocol.

The results of these regressions are summarized in the following table.[56] First, *repeat loan ratio* appears to positively influence the growth of AAVE holders, with a 1% increase in the *repeat loan ratio* leading to a 7% increase in the growth of AAVE holders. This result is statistically significant at the 1% level. Conversely, *liquidity* demonstrates a negative impact, where a 1% increase in *liquidity* results in a 10% decrease in the growth of AAVE holders.

The economic significance is substantial, particularly when considering the dynamics of total AAVE holders[57]. Given that DeFi lending typically favors borrowers with substantial assets (Aramonte, Doerr, Huang, & Schrimpf, 2022), cultivating regular borrowers becomes essential for LPs. Furthermore, in traditional banking, a concentrated loan portfolio can increase returns and reduce default risk (Tabak et al., 2011), and investors may have similar beliefs in LPs. Higher *repeat loan ratio* indicates a stable customer base, implying positive market expectation on Aave protocol. As a result, AAVE token is regarded as an attractive investment and more AAVE holders will emerge.

Conversely, higher *liquidity* suggests underutilized deposits, negatively affecting the growth of AAVE holders. The influences of *repeat deposit ratio* and *repeat loan ratio* on the growth of TVL differ. Intuitively, a higher *repeat loan ratio* tends to attract more new depositors to Aave, as they are likely to anticipate steady rewards. The economic magnitude is significant, considering the TVL of Aave protocol during the sample period,[58] resulting in the expected more rapid growth of TVL.

On the contrary, a higher *repeat deposit ratio* implies a lower proportion of new deposits, potentially slowing down the growth of TVL. While this finding is statistically significant at the 5% level, it is worthy of discussion as it relates to the literature on bank-depositor relationships. Although Iyer & Puri (2012) discuss the bank-depositor relationship, focusing on loyal depositors (e.g., those with deeper and longer relationships) being less likely to withdraw during a crisis, their research does not explore the potential negative effects of such regular depositors on bank performance.

[56] A concern of the empirical results is potential endogeneity. We run Granger causality tests for all statistically significant findings in table 5.4, and the results do not show endogeneity.

[57] Readers can find more details about AAVE holders: https://app.intotheblock.com/coin/AAVE

[58] Readers can find more details about TVL in Aave protocol: https://defillama.com/protocol/aave

Table 5.4: The effects of liquidity risk and repeat users on Aave

Panel A: Repeat users and liquidity

	(1) ∆ MktC_F	(2) ∆ MktC_C	(3) ∆ Revenue	**(4) ∆ TVL**	(5) ∆ AAVE	**(6) ∆ AAVE holder**
Liquidity	0.00	0.00	0.01	0.01	0.00	**-0.10*****
	(-0.08)	(-0.04)	(1.25)	(1.23)	(-0.08)	**(-8.82)**
Repeat deposit ratio	0.00	0.00	0.00	**-0.04****	0.00	-0.02
	(0.07)	(-0.18)	(-0.11)	**(-2.08)**	(0.07)	(-0.96)
Repeat loan ratio	0.01	0.02	0.01	**0.05*****	0.01	**0.07*****
	(0.52)	(0.96)	(0.56)	**(2.67)**	(0.52)	**(2.76)**
∆ Deposits vol USD	-0.04	-0.05	-0.02	**-0.08***	-0.04	-0.01
	(-0.94)	(-1.24)	(-0.42)	**(-1.71)**	(-0.94)	(-0.15)
∆ Loan vol USD	0.04	0.05	0.03	**0.18*****	0.04	0.09
	(0.94)	(1.09)	(0.74)	**(3.70)**	(0.94)	(1.42)
∆ Liquidation USD	**-0.75*****	**-0.72*****	**-0.27*****	**-0.54*****	**-0.75*****	0.00
	(-11.81)	**(-10.76)**	**(-4.73)**	**(-7.69)**	**(-11.81)**	(-0.03)
∆ Active user	0.03	0.02	-0.01	-0.02	0.03	0.00
	(1.25)	(0.98)	(-0.39)	(-0.94)	(1.25)	(-0.10)
∆ Developer	0.00	0.00	-0.01	-0.02	0.00	0.00
	(0.02)	(0.03)	(-0.35)	(-0.80)	(0.02)	(0.11)
ETH return (1d)	**-0.09*****	**-0.09*****	**-0.09*****	**-0.09*****	**-0.09*****	0.05
	(-2.93)	**(-2.97)**	**(-3.19)**	**(-2.79)**	**(-2.93)**	(1.10)
ETH return (7d)	**0.13*****	**0.13*****	**0.07*****	**0.17*****	**0.13*****	**0.08*****
	(6.64)	**(6.66)**	**(3.82)**	**(8.23)**	**(6.64)**	**(3.20)**
ETH SD (30d)	0.00	0.00	0.00	0.01	0.00	**0.12*****
	(-0.01)	(0.00)	(0.29)	(1.09)	(-0.01)	**(7.34)**
N	791	791	791	789	791	791
Adj R-sq	0.20	0.18	0.05	0.17	0.20	0.20

Panel B: Repeat users and utilization

	(1) ∆ MktC_F	(2) ∆ MktC_C	(3) ∆ Revenue	**(4) ∆ TVL**	(5) ∆ AAVE	(6) ∆ AAVE holder
Utilization	-0.01	-0.01	0.00	0.01	-0.01	0.00
	(-0.82)	(-0.74)	(-0.12)	(0.78)	(-0.82)	(0.22)
Repeat deposit ratio	0.00	0.00	0.00	**-0.04****	0.00	-0.04
	(0.07)	(-0.18)	(-0.05)	**(-2.03)**	(0.07)	(-1.36)
Repeat loan ratio	0.01	0.02	0.01	**0.05*****	0.01	**0.08*****
	(0.45)	(0.90)	(0.50)	**(2.68)**	(0.45)	**(2.97)**
∆ Deposits vol USD	-0.04	-0.05	-0.02	**-0.08***	-0.04	0.00
	(-0.95)	(-1.24)	(-0.43)	**(-1.72)**	(-0.95)	(-0.05)
∆ Loan vol USD	0.04	0.05	0.03	**0.18*****	0.04	0.09
	(0.93)	(1.09)	(0.74)	**(3.70)**	(0.93)	(1.35)
∆ Liquidation USD	**-0.75*****	**-0.72*****	**-0.27*****	**-0.54*****	**-0.75*****	-0.01
	(-11.81)	**(-10.76)**	**(-4.72)**	**(-7.68)**	**(-11.81)**	(-0.09)
∆ Active user	0.03	0.02	-0.01	-0.02	0.03	-0.01
	(1.25)	(0.98)	(-0.36)	(-0.92)	(1.25)	(-0.26)
∆ Developer	0.00	0.00	-0.01	-0.02	0.00	0.01
	(0.04)	(0.03)	(-0.41)	(-0.86)	(0.04)	(0.50)
ETH return (1d)	**-0.09*****	**-0.09*****	**-0.09*****	**-0.09*****	**-0.09*****	0.05
	(-2.95)	**(-2.99)**	**(-3.20)**	**(-2.78)**	**(-2.95)**	(1.13)
ETH return (7d)	**0.13*****	**0.14*****	**0.06*****	**0.17*****	**0.13*****	**0.13*****
	(6.80)	**(6.82)**	**(3.66)**	**(8.06)**	**(6.80)**	**(4.61)**
ETH SD (30d)	0.00	0.00	0.00	0.01	0.00	**0.15*****
	(0.02)	(0.02)	(0.07)	(0.87)	(0.02)	**(8.65)**
N	791	791	791	789	791	791
Adj R-sq	0.20	0.18	0.05	0.17	0.20	0.12

Note: This table reports regression results for the influence of liquidity risk on Aave protocol. In columns (1) – (6) of each panel, the dependent variable is *∆MktC_F*, *∆MktC_C*, *∆ revenue*, *∆TVL*, *∆AAVE*, and *∆AAVE holder*, respectively. T-statistics are reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics.

Effects of liquidity indicators and large users To investigate the influence of large users, we estimate the regression model below:

$$\begin{aligned} Protocol_{i,t} = \beta_0 + \beta_1 Risk_{t-1} + \beta_2 Deposit\ large_{t-1} + \beta_3 Loan\ large_{t-1} \\ + \beta_2 \Delta Deposit\ vol\ USD_{i,t-1} + \beta_3 \Delta Loan\ vol\ USD_{i,t-1} \\ + \beta_4 \Delta Liquidation\ USD_{i,t-1} + \beta_5 \Delta Active\ user_{i,t-1} + \beta_6 \Delta Developer_{i,t-1} \\ + \beta_7 ETH\ return\ (1d)_t + \beta_8 ETH\ return\ (7d)_t + \beta_9 ETH\ SD\ (30d)_t \\ + \varepsilon_{i,t} (5.11) \end{aligned}$$

where:

- $Risk = \{Liquidity, Utilization\}$
- $Protocol = \{\Delta MktC\_F, \Delta MktC\_C, \Delta Revenue, \Delta TVL, \Delta AAVE, \Delta AAVE\ holder\}$
- $i = Aave\ protocol$

The table below presents some noteworthy findings.[59] Firstly, both *Δdeposit large* and *Δloan large* demonstrate a positive impact on the growth of TVL, with *Δloan large* additionally accelerating the growth of Aave's revenue. Specifically, a 1% increase in *Δloan large* can contribute to a 44% increase in the growth of Aave's revenue. Moreover, a 1% increase in *Δdeposit large* and *Δloan large* can result in a 22% and 23% increase in the growth of TVL, respectively. These results carry both statistical and economic significance, indicating the substantial contributions from large users—comprising both borrowers and depositors—in enhancing the performance of the Aave protocol. Analogously, in the banking sector, the importance of both large depositors and borrowers is well-established. Banks often favor a concentrated loan portfolio to optimize returns and manage risk (e.g., Winton, 1999; Mercieca et al., 2007; Tabak et al., 2011). Our findings align with Oliveira et al. (2015) argue that large depositors tend to prefer systemically important banks, emphasizing the positive influence of large depositors.

Unexpectedly, *Δdeposit large* is negatively related to the daily return of AAVE, with the growth of market capitalization experiencing a 10% decline with a 1% increase in *Δdeposit large*. While the statistical significance may not be substantial, it is worth discussing how

[59] A concern of the empirical results is potential endogeneity. We run Granger causality tests for all statistically significant findings in table 5.5, and the results do not show endogeneity.

this finding relates to the banking literature. Higher *Δdeposit large* suggests greater reliance on large depositors, raising concerns if these large depositors were to withdraw. In the banking sector, institutional investors often withdraw significantly during crises (Ben-David, Franzoni, & Moussawi, 2012; Oliveira et al., 2015). Consequently, DeFi investors may be more cautious, leading to lower AAVE return and a slower growth rate of the market cap. Existing literature typically emphasizes the negative dynamics of stock returns after observing liquidity risks (e.g., Roogi & Giannozzi, 2015). Our findings, given that AAVE can be likened to a stock issued by the Aave protocol, suggest that centralized liquidity supply could also negatively impact stock returns.

Table 5.5: The effects of liquidity risks and large users on Aave protocol

Panel A: Large users and liquidity						
	(1)	(2)	**(3)**	**(4)**	**(5)**	**(6)**
	Δ MktC_F	Δ MktC_C	**Δ Revenue**	**Δ TVL**	**Δ AAVE**	**Δ AAVE holder**
Liquidity	0.00	0.00	0.01	0.01	0.00	**-0.10*** **
	(-0.12)	(-0.09)	(1.21)	(1.14)	(-0.12)	**(-8.89)**
Δ Deposit large	**-0.10***	-0.10	0.00	**0.22*** **	**-0.10***	-0.10
	(-1.64)	(-1.55)	(-0.04)	**(3.33)**	**(-1.64)**	(-1.22)
Δ Loan large	0.08	0.08	**0.44*** **	**0.23*** **	0.08	0.07
	(1.28)	(1.26)	**(8.31)**	**(3.51)**	(1.28)	(0.77)
Δ Deposits vol USD	-0.04	0.08	0.00	**-0.07***	-0.04	-0.01
	(-0.91)	(1.26)	(-0.10)	**(-1.67)**	(-0.91)	(-0.19)
Δ Loan vol USD	0.04	0.08	-0.03	**0.13*** **	0.04	0.08
	(0.91)	(1.26)	(-0.70)	**(2.71)**	(0.91)	(1.38)
Δ Liquidation USD	**-0.76*** **	**-0.74*** **	**-0.20*** **	**-0.44*** **	**-0.76*** **	-0.02
	(-11.82)	**(-10.78)**	**(-3.60)**	**(-6.39)**	**(-11.82)**	(-0.27)
Δ Active user	0.02	0.02	0.01	-0.01	0.02	-0.01
	(1.14)	(0.86)	(0.27)	(-0.42)	(1.14)	(-0.29)
Δ Developer	0.00	0.00	-0.01	-0.02	0.00	0.01
	(0.12)	(0.14)	(-0.49)	(-0.94)	(0.12)	(0.34)
ETH return (1d)	**-0.09*** **	**-0.09*** **	**-0.09*** **	**-0.10*** **	**-0.09*** **	0.05
	(-2.90)	**(-2.93)**	**(-3.51)**	**(-2.98)**	**(-2.90)**	(1.19)
ETH return (7d)	**0.13*** **	**0.14*** **	0.07	**0.18*** **	**0.13*** **	**0.09*** **
	(6.72)	**(6.78)**	(4.16)	**(8.78)**	**(6.72)**	**(3.43)**
ETH SD (30d)	0.00	0.00	0.00	0.01	0.00	**0.12*** **
	(-0.12)	(-0.16)	(0.27)	(1.04)	(-0.12)	**(7.03)**
N	791	791	791	789	791	791
Adj R-sq	0.20	0.18	0.17	0.22	0.20	0.19
Panel B: Large users and utilization						
	(1)	(2)	**(3)**	**(4)**	**(5)**	(6)
	Δ MktC_F	Δ MktC_C	**Δ Revenue**	**Δ TVL**	**Δ AAVE**	Δ AAVE holder
Utilization	-0.01	-0.01	0.00	0.01	-0.01	0.00
	(-0.88)	(-0.84)	(-0.21)	(0.60)	(-0.88)	(-0.05)
Δ Deposit large	**-0.10***	-0.10	0.00	**0.21*** **	**-0.10***	-0.09
	(-1.63)	(-1.54)	(-0.07)	**(3.30)**	**(-1.63)**	(-0.98)
Δ Loan large	0.08	0.08	**0.44*** **	**0.24*** **	0.08	0.05
	(1.28)	(1.25)	**(8.33)**	**(3.54)**	(1.28)	(0.55)
Δ Deposits vol USD	-0.04	-0.05	0.00	**-0.07***	-0.04	-0.01
	(-0.91)	(-1.21)	(-0.11)	**(-1.68)**	(-0.91)	(-0.10)
Δ Loan vol USD	0.04	0.05	-0.03	**0.13*** **	0.04	0.09
	(0.91)	(1.05)	(-0.70)	**(2.71)**	(0.91)	(1.33)
Δ Liquidation USD	**-0.76*** **	**-0.74*** **	**-0.20*** **	**-0.44*** **	**-0.76*** **	-0.03
	(-11.82)	**(-10.77)**	**(-3.59)**	**(-6.39)**	**(-11.82)**	(-0.30)
Δ Active user	0.02	0.02	0.01	-0.01	0.02	-0.01
	(1.15)	(0.86)	(0.30)	(-0.40)	(1.15)	(-0.47)
Δ Developer	0.00	0.00	-0.01	-0.02	0.00	0.02
	(0.12)	(0.14)	(-0.54)	(-0.99)	(0.12)	(0.71)
ETH return (1d)	**-0.09*** **	**-0.09*** **	**-0.09*** **	**-0.10*** **	**-0.09*** **	0.05
	(-2.92)	**(-2.95)**	**(-3.52)**	**(-2.97)**	**(-2.92)**	(1.20)

ETH return (7d)	**0.13*** (6.90)**	**0.14*** (6.95)**	**0.06*** (4.01)**	**0.17*** (8.66)**	**0.13*** (6.90)**	**0.13*** (4.91)**
ETH SD (30d)	0.00 (-0.08)	0.00 (-0.12)	0.00 (0.05)	0.01 (0.82)	0.00 (-0.08)	**0.15*** (8.40)**
N	791	791	791	789	791	791
Adj R-sq	0.20	0.18	0.17	0.22	0.20	0.11

Note: This table reports regression results for the influence of liquidity risks on Aave protocol. In columns (1) – (6) of each panel, the dependent variable is *ΔMktC_F*, *ΔMktC_C*, *Δrevenue*, *ΔTVL*, *ΔAAVE*, and *ΔAAVE holder*, respectively. T-statistics are reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics.

5.4.3 Cross-LP effects of liquidity risk

LPs cannot be seen through an isolated lens on blockchain. Benefiting from blockchain infrastructure, DeFi protocols can be built on and interact with other protocols. This element of composability of DeFi (Tolmach et al., 2021; von Wachter et al., 2021) is quite important for the validity of each protocol. For that reason, we should also be investigating illiquidity contagion in LPs, as in traditional financial markets. To examine such cross-LP effects, we choose Compound, which is a leading LP. The definitions of Compound factors are similar to Aave factors[60].

Cross-LP effects of liquidity risk and repeat users in Aave We first examine if cross-LP effects of liquidity risks and repeat users in Aave exist. To address it, we include measurements related to liquidity risks and repeat users in Aave as independent variables, and some Compound-specific factors are also considered. The dependent variables are similar to those in section 4.4.2, which can reflect market performance of Compound protocol. The regression model is presented below:

$$\begin{aligned} Protocol_{i,t} = {} & \beta_0 + \beta_1 Risk_t + \beta_2 Repeat\ deposit\ ratio_{t-1} + \beta_3 Repeat\ loan\ ratio_{t-1} \\ & + \beta_2 \Delta Deposit\ vol\ USD_{i,t-1} + \beta_3 \Delta Loan\ vol\ USD_{i,t-1} \\ & + \beta_4 \Delta Liquidation\ USD_{i,t-1} + \beta_5 \Delta Active\ user_{i,t-1} + \beta_6 \Delta Developer_{i,t-1} \\ & + \beta_7 ETH\ return\ (1d)_t + \beta_8 ETH\ return\ (7d)_t + \beta_9 ETH\ SD\ (30d)_t \\ & + \varepsilon_{i,t} (5.12) \end{aligned}$$

[60] Appendix C.3 presents the definitions of Compound factors.

where:

- $Risk = \{Liquidity, Utilization\}$
- $Protocol = \{\Delta MktC\_F, \Delta MktC\_C, \Delta Revenue, \Delta TVL, \Delta COMP, \Delta COMP\ holder\}$
- $i = Compound\ protocol$

Interestingly, Compound protocol appears unaffected by either liquidity or utilization in Aave.[61] However, measurements related to repeat users influence the growth of COMP holders. First, a 1% increase in the *repeat loan ratio* leads to a 5% increase in the growth of COMP holders, and the result is statistically significant at a 1% level. It is worth noting that the COMP token, a cryptocurrency, serves as the governance token of the Compound protocol, with COMP holders resembling shareholders in corporations. Our findings suggest that a more stable customer base, characterized by regular borrowers, in one LP may contribute to the performance (e.g., more stakeholders) of other LPs. Given that Aave and Compound are two leading LPs, investors are likely to evaluate them collectively when assessing the value of their governance tokens (i.e., AAVE and COMP). The presence of more loans from regular borrowers signifies a positive lending market status in the DeFi ecosystem, potentially making more investors hold governance tokens of LPs. This intuition aligns with Chiu, Ozdenoren, Yuan, & Zhang (2023).

On the other hand, there is a negative relationship between *repeat deposit ratio* in Aave and *ΔCOMP holder*, and liquidity in Aave is also negatively associated with *ΔCOMP holder*. Specifically, a 1% increase in liquidity in Aave can result in an 8% reduction in *ΔCOMP holder*. The finding is intuitive as Aave and Compound are substitutes for each other. When Aave absorbs more liquidity from regular depositors, logically, Compound is negatively affected, potentially leading to fewer investors choosing to hold COMP tokens. This finding draws parallels to research on bank competition. In traditional banking, banks compete to attract and retain large investors, such as institutional investors (Oliveira et al., 2015), with this competition being a key factor influencing banking stability (Fiordelisi & Mare, 2014; Goetz, 2018). Our findings suggest that DeFi competition has complex influences. LPs compete to absorb more liquidity, yet they benefit from higher borrowing demand in the DeFi lending market.

[61] A concern of the empirical results is potential endogeneity. We run Granger causality tests for all statistically significant findings in table 5.6, and the results do not show endogeneity.

Table 5.6: The effects of liquidity risk and repeat users on Compound

Panel A: Repeat users and liquidity

	(1)	(2)	(3)	(4)	(5)	**(6)**
	∆ MktC_F	∆ MktC_C	∆ Revenue	∆ TVL	∆ COMP	**∆ COMP holder**
Liquidity	-0.01	-0.02	-0.01	-0.01	0.00	**-0.08*****
	(-1.30)	(-1.62)	(-1.21)	(-1.55)	(-0.20)	**(-12.60)**
Repeat deposit ratio	-0.03	-0.03	0.00	0.00	0.00	**-0.03****
	(-1.21)	(-1.44)	(-0.17)	(-0.27)	(-0.15)	**(-2.20)**
Repeat loan ratio	0.01	0.01	0.00	0.00	-0.01	**0.05*****
	(0.48)	(0.31)	(-0.06)	(-0.08)	(-0.44)	**(3.47)**
∆ Deposits vol USD	0.01	0.02	0.01	0.03	**0.08***	0.00
	(0.20)	(0.50)	(0.50)	(1.02)	**(1.83)**	(0.16)
∆ Loan vol USD	**-0.16***	-0.07	-0.03	0.04	**0.27*****	**-0.09****
	(-1.68)	(-0.82)	(-0.63)	(0.79)	**(3.64)**	**(-1.99)**
∆ Liquidation USD	**0.43*****	**0.37*****	0.08	**0.34*****	-0.20	0.06
	(2.78)	**(2.66)**	(0.91)	**(3.19)**	(-1.29)	(0.70)
∆ Active user	0.02	0.00	0.06	-0.01	-0.03	0.01
	(0.22)	(0.06)	(1.48)	(-0.25)	(-0.43)	(0.25)
∆ Developer	0.00	-0.01	0.00	0.00	-0.02	0.00
	(0.15)	(-0.49)	(0.21)	(0.26)	(-0.63)	(-0.16)
ETH return (1d)	-0.05	-0.04	-0.03	-0.01	**-0.13*****	0.03
	(-1.25)	(-1.09)	(-1.17)	(-0.54)	**(-3.27)**	(1.41)
ETH return (7d)	0.03	0.02	0.01	0.02	**0.15*****	0.02
	(1.02)	(0.70)	(0.37)	(1.21)	**(6.08)**	(1.61)
ETH SD (30d)	-0.01	-0.02	-0.01	-0.01	-0.01	**0.05*****
	(-0.40)	(-1.26)	(-0.56)	(-0.84)	(-0.77)	**(5.59)**
N	631	631	789	789	790	790
Adj R-sq	0.01	0.01	-0.01	0.01	0.06	0.27

Panel B: Repeat users and utilization

	(1)	(2)	(3)	(4)	(5)	**(6)**
	∆ MktC_F	∆ MktC_C	∆ Revenue	∆ TVL	∆ COMP	**∆ COMP holder**
Utilization	0.01	0.02	0.00	0.02	-0.01	0.01
	(0.80)	(1.06)	(0.01)	(1.46)	(-0.93)	(0.61)
Repeat deposit ratio	-0.03	-0.03	0.00	-0.01	0.00	**-0.04*****
	(-1.34)	(-1.60)	(-0.28)	(-0.43)	(-0.15)	**(-3.01)**
Repeat loan ratio	0.01	0.01	0.00	0.00	-0.01	**0.06*****
	(0.65)	(0.52)	(0.05)	(0.16)	(-0.48)	**(4.34)**
∆ Deposits vol USD	0.01	0.02	0.01	0.03	**0.08***	0.00
	(0.13)	(0.41)	(0.50)	(1.02)	**(1.83)**	(0.13)
∆ Loan vol USD	**-0.16***	-0.07	-0.03	0.04	**0.27*****	**-0.08***
	(-1.71)	(-0.86)	(-0.61)	(0.82)	**(3.64)**	**(-1.67)**
∆ Liquidation USD	**0.42*****	**0.36*****	0.08	**0.33*****	-0.20	0.02
	(2.73)	**(2.60)**	(0.87)	**(3.09)**	(-1.27)	(0.20)
∆ Active user	0.01	0.00	0.06	-0.01	-0.03	0.02
	(0.20)	(0.04)	(1.51)	(-0.22)	(-0.41)	(0.52)
∆ Developer	0.01	-0.01	0.00	0.01	-0.02	0.01
	(0.21)	(-0.41)	(0.29)	(0.43)	(-0.65)	(0.67)
ETH return (1d)	-0.05	-0.04	-0.03	-0.01	**-0.13*****	0.03
	(-1.29)	(-1.14)	(-1.20)	(-0.55)	**(-3.29)**	(1.03)
ETH return (7d)	0.03	0.02	0.01	0.02	**0.15*****	**0.06*****
	(1.33)	(1.08)	(0.60)	(1.51)	**(6.23)**	**(3.68)**
ETH SD (30d)	0.00	-0.01	0.00	-0.01	-0.01	**0.09*****
	(-0.14)	(-0.97)	(-0.23)	(-0.57)	(-0.65)	**(8.61)**
N	631	631	789	789	790	790
Adj R-sq	0.00	0.01	-0.01	0.01	0.06	0.12

Note: This table reports regression results for the influence of liquidity risk in Aave on Compound protocol. In columns (1) – (6) of each panel, the dependent variable is Δ *MktC_F*, Δ *MktC_C*, Δ *revenue*, Δ *TVL*, Δ *COMP*, and Δ *COMP holder*, respectively. T-statistics are reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics.

Cross-LP effects of liquidity risk and large users in Aave We then investigate the influences of large Aave users on Compound protocol. To that end, we estimate the following regression model:

$$\begin{aligned} Protocol_{i,t} = {} & \beta_0 + \beta_1 Risk_t + \beta_2 Deposit\ large_{t-1} + \beta_3 Loan\ large_{t-1} \\ & + \beta_2 \Delta Deposit\ vol\ USD_{i,t-1} + \beta_3 \Delta Loan\ vol\ USD_{i,t-1} \\ & + \beta_4 \Delta Liquidation\ USD_{i,t-1} + \beta_5 \Delta Active\ user_{i,t-1} + \beta_6 \Delta Developer_{i,t-1} \\ & + \beta_7 ETH\ return\ (1d)_t + \beta_8 ETH\ return\ (7d)_t + \beta_9 ETH\ SD\ (30d)_t \\ & + \varepsilon_{i,t} (5.13) \end{aligned}$$

where:

- $Risk = \{Liquidity, Utilization\}$
- $Protocol = \{\Delta MktC\_F, \Delta MktC\_C, \Delta Revenue, \Delta TVL, \Delta COMP, \Delta COMP\ holder\}$
- $i = Compound\ protocol$

The table below summarizes our findings.[62] Notably, large depositors and large borrowers have contrasting effects on the growth of daily revenue in Compound protocol. A 1% increase in *Δloan large* in Aave is associated with a 15% reduction in the growth of revenue in Compound. This outcome aligns with the competitive dynamics between Compound and Aave, where a rise in large loans on Aave may divert activity away from Compound. Conversely, a higher *Δdeposit large* is positively correlated with *Δrevenue* in Compound, highlighting the intricate relationship between these leading LPs, though the statistical significance is not substantial. In Fintech, where long-term relationships between clients and banks are uncommon, understanding user behavior is challenging (Yeh & Chen, 2020). In LPs, the complicated influences of large borrowers and depositors adds an additional layer of complexity to this challenge.

Table 5.7: The effects of liquidity risk and large users on Compound

Panel A: Large users and liquidity						
	(1) Δ MktC_F	**(2) Δ MktC_C**	**(3) Δ Revenue**	(4) Δ TVL	**(5) Δ COMP**	**(6) Δ COMP holder**
Liquidity	-0.02	**-0.02***	-0.01	-0.01	0.00	**-0.08*****

[62] A concern of the empirical results is potential endogeneity. We run Granger causality tests for all statistically significant findings in table 5.7, and the results do not show endogeneity.

	(-1.49)	**(-1.80)**	(-1.25)	(-1.57)	(-0.16)	**(-12.91)**
Δ Deposit large	-0.10	-0.08	**0.09****	0.01	-0.06	-0.01
	(-1.12)	(-1.03)	**(1.95)**	(0.23)	(-0.82)	(-0.14)
Δ Loan large	-0.01	0.00	**-0.15*****	-0.04	**0.17****	0.02
	(-0.09)	(-0.05)	**(-3.09)**	(-0.82)	**(2.03)**	(0.47)
Δ Deposits vol USD	0.01	0.02	0.02	0.03	0.07	0.00
	(0.26)	(0.54)	(0.80)	(1.08)	(1.62)	(0.09)
Δ Loan vol USD	-0.15	-0.06	-0.02	0.04	**0.26*****	**-0.08***
	(-1.57)	(-0.74)	(-0.51)	(0.83)	**(3.53)**	**(-1.90)**
Δ Liquidation USD	**0.42*****	**0.37*****	0.08	**0.34*****	-0.19	0.06
	(2.73)	**(2.63)**	(0.87)	**(3.18)**	(-1.23)	(0.61)
Δ Active user	0.03	0.01	0.06	-0.01	-0.03	0.02
	(0.36)	(0.21)	(1.36)	(-0.27)	(-0.37)	(0.55)
Δ Developer	0.01	-0.01	0.01	0.01	-0.02	0.00
	(0.30)	(-0.34)	(0.34)	(0.31)	(-0.71)	(-0.19)
ETH return (1d)	-0.05	-0.04	-0.03	-0.01	**-0.13*****	0.03
	(-1.35)	(-1.21)	(-1.15)	(-0.55)	**(-3.32)**	(1.40)
ETH return (7d)	0.02	0.01	0.00	0.02	**0.15*****	0.02
	(0.94)	(0.63)	(0.33)	(1.20)	**(6.11)**	(1.44)
ETH SD (30d)	0.00	-0.02	-0.01	-0.01	-0.01	**0.05*****
	(-0.31)	(-1.12)	(-0.56)	(-0.82)	(-0.66)	**(5.28)**
N	631	631	789	789	790	790
Adj R-sq	0.01	0.01	0.01	0.01	0.06	0.26

Panel B: Large users and utilization

	(1) Δ MktC_F	(2) Δ MktC_C	**(3) Δ Revenue**	(4) Δ TVL	**(5) Δ COMP**	(6) Δ COMP holder
Utilization	0.01	0.02	0.00	0.02	-0.01	0.00
	(0.85)	(1.13)	(0.02)	(1.47)	(-0.90)	(0.34)
Δ Deposit large	-0.09	-0.08	**0.09****	0.01	-0.06	-0.01
	(-1.08)	(-0.98)	**(1.94)**	(0.22)	(-0.81)	(-0.24)
Δ Loan large	-0.01	0.00	**-0.15*****	-0.04	**0.17****	0.03
	(-0.08)	(-0.04)	**(-3.07)**	(-0.81)	**(2.04)**	(0.55)
Δ Deposits vol USD	0.01	0.02	0.02	0.03	0.07	0.00
	(0.18)	(0.45)	(0.80)	(1.08)	(1.62)	(0.05)
Δ Loan vol USD	-0.15	-0.07	-0.02	0.04	**0.26*****	-0.07
	(-1.61)	(-0.78)	(-0.49)	(0.86)	**(3.53)**	(-1.56)
Δ Liquidation USD	**0.41*****	**0.36*****	0.08	**0.32*****	-0.19	0.01
	(2.67)	**(2.56)**	(0.82)	**(3.08)**	(-1.21)	(0.08)
Δ Active user	0.03	0.01	0.06	-0.01	-0.03	0.04
	(0.35)	(0.20)	(1.41)	(-0.23)	(-0.36)	(0.93)
Δ Developer	0.01	-0.01	0.01	0.01	-0.02	0.01
	(0.37)	(-0.26)	(0.42)	(0.49)	(-0.74)	(0.66)
ETH return (1d)	-0.05	-0.04	-0.03	-0.01	**-0.13*****	0.02
	(-1.40)	(-1.27)	(-1.18)	(-0.57)	**(-3.33)**	(0.99)
ETH return (7d)	0.03	0.02	0.01	0.02	**0.15*****	**0.06*****
	(1.29)	(1.03)	(0.57)	(1.49)	**(6.26)**	**(3.50)**
ETH SD (30d)	0.00	-0.01	0.00	-0.01	-0.01	**0.08*****
	(-0.01)	(-0.80)	(-0.22)	(-0.55)	(-0.55)	**(8.34)**
N	631	631	789	789	790	790
Adj R-sq	0.00	0.00	0.00	0.01	0.06	0.10

Note: This table reports regression results for the influence of liquidity risk in Aave on Compound protocol. In columns (1) – (6) of each panel, the dependent variable is *ΔMktC_F*, *ΔMktC_C*, *Δrevenue*, *ΔTVL*, *ΔCOMP*, and *ΔCOMP holder*, respectively. T-statistics are reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics.

5.4.4 The shocks of DeFi hacks

DeFi are generally bedevilled due to the fear of hacking. Since codes are the foundation of DeFi, DeFi is vulnerable to hacking and bugs. The table below lists the most severe DeFi hacks from 2020 to 2022. In the banking sector, individual bank defaults are infectious and can cause the failure of the banking sector (Kreis & Leisen, 2018). Moreover, herding behaviour widely exist in crypto markets (Zhao, Liu, & Li, 2022), and a hack may first lead to certain activities of influential investors and then trigger a chain reaction. Though Compound and Aave were not the victims in the chosen hacks, we evaluate if DeFi hacks can affect these two LPs.

Table 5.8: DeFi hacks

Date	Hacked protocol	Date	Hacked protocol	Date	Hacked protocol
2020-02-18	bZx	2021-03-05	Paid Network	2022-01-27	Qubit Finance
2020-03-12	DAOMaker	2021-04-19	EasyFi	2022-02-02	Wormhole Bridge
2020-04-18	Uniswap	2021-04-28	Uranium Finance	2022-03-29	Ronin Bridge
2020-04-19	dForce	2021-05-19	PancakeBunny	2022-04-17	Beanstalk Farms
2020-09-14	bZx	2021-05-30	Belt Finance	2022-06-05	Maiar Exchange
2020-09-29	Eminence	2021-08-10	Poly Network	2022-06-24	Horizon Bridge
2020-10-26	Harvest	2021-09-30	Compound	2022-08-02	Nomad Bridge
2020-11-12	Akropolis	2021-10-27	Cream Finance	2022-09-21	Wintermute
2020-11-14	Value DeFi	2021-11-05	bZx	2022-10-06	BNB Chain
2020-11-21	Pickle Finance	2021-12-02	BadgerDAO	2022-10-11	Mango Markets

Note: This table presents influential DeFi hacks that happened in 2020 – 2022.

To that end, we include a dummy variable *hack* in regression models (5.10) – (5.13). Assuming that a hack in Table 4.8 occurs on date t, the dummy hack is defined as:

- $$Hack_t = \begin{cases} 1, a\ hack\ happend\ between\ day\ t\ and\ day\ t-6 \\ 0, otherelse \end{cases}$$

The tables below present the results, which are consistent with results in section 5.4.2 and 5.4.3. Furthermore, *hack* shows negative effects on the growth of AAVE holders. Given that the chosen hacks are impactful, investors may reassess AAVE token as an investment, potentially leading to a reduction in new AAVE holders. In the case of Compound, *hack* also exerts a negative influence on the growth of COMP holders, addressing the substantial impact of hacks. This finding is consistent with patterns observed in traditional lending market, where fear sentiments among investors can drive them away (Dijk, 2017; Anastasiou

& Drakos, 2021). Specifically, large investors are often more reactive to bad news (Ben-David et al., 2012).

Table 5.9: The effects of liquidity risk and large users on Aave

Panel A: Large users and liquidity						
	(1) Δ MktC_F	(2) Δ MktC_C	**(3) Δ Revenue**	**(4) Δ TVL**	**(5) Δ AAVE**	**(6) Δ AAVE holder**
Liquidity	0.00	0.00	0.01	0.01	0.00	**-0.10*****
	(-0.10)	(-0.08)	(1.16)	(1.11)	(-0.10)	**(-8.82)**
Hack	0.00	0.00	0.01	0.01	0.00	**-0.03*****
	(-0.43)	(-0.40)	(1.29)	(1.05)	(-0.43)	**(-3.54)**
Δ Deposit large	**-0.10***	-0.10	0.00	**0.22*****	**-0.10***	-0.11
	(-1.65)	(-1.55)	(-0.02)	**(3.35)**	**(-1.65)**	(-1.30)
Δ Loan large	0.08	0.08	**0.44*****	**0.23*****	0.08	0.06
	(1.28)	(1.25)	**(8.33)**	**(3.52)**	(1.28)	(0.75)
Δ Deposits vol USD	-0.04	-0.05	0.00	**-0.07***	-0.04	-0.01
	(-0.90)	(-1.21)	(-0.10)	**(-1.67)**	(-0.90)	(-0.19)
Δ Loan vol USD	0.04	0.05	-0.03	**0.13*****	0.04	0.08
	(0.90)	(1.04)	(-0.67)	**(2.73)**	(0.90)	(1.33)
Δ Liquidation USD	**-0.77*****	**-0.74*****	**-0.20*****	**-0.44*****	**-0.76*****	-0.03
	(-11.82)	**(-10.78)**	**(-3.58)**	**(-6.37)**	**(-11.82)**	(-0.33)
Δ Active user	0.02	0.02	0.00	-0.01	0.02	-0.01
	(1.15)	(0.87)	(0.25)	(-0.44)	(1.15)	(-0.23)
Δ Developer	0.00	0.00	-0.01	-0.02	0.00	**0.01**
	(0.14)	(0.16)	(-0.56)	(-1.00)	(0.14)	**(0.55)**
ETH return (1d)	**-0.09*****	**-0.09*****	**-0.09*****	**-0.10*****	**-0.09*****	0.05
	(-2.89)	**(-2.92)**	**(-3.54)**	**(-3.00)**	**(-2.89)**	(1.28)
ETH return (7d)	**0.13*****	**0.14*****	**0.07*****	**0.18*****	**0.13*****	**0.10*****
	(6.73)	**(6.79)**	**(4.10)**	**(8.72)**	**(6.73)**	**(3.61)**
ETH SD (30d)	0.00	0.00	0.00	0.01	0.00	**0.12*****
	(-0.10)	(-0.14)	(0.21)	(0.99)	(-0.10)	**(7.22)**
N	791	791	791	789	791	791
Adj R-sq	0.20	0.18	0.17	0.22	0.20	0.20
Panel B: Large users and utilization						
	(1) Δ MktC_F	**(2) Δ MktC_C**	**(3) Δ Revenue**	**(4) Δ TVL**	**(5) Δ AAVE**	(6) Δ AAVE holder
Utilization	-0.01	-0.01	0.00	0.01	-0.01	0.01
	(-0.84)	(-0.80)	(-0.35)	(0.49)	(-0.84)	(0.32)
Hack	0.00	0.00	0.01	0.01	0.00	**-0.03*****
	(-0.35)	(-0.32)	(1.37)	(1.03)	(-0.35)	**(-3.71)**
Δ Deposit large	**-0.10***	**-0.10***	0.00	**0.22*****	**-0.10***	-0.09
	(-1.64)	**(-1.55)**	(-0.04)	**(3.32)**	**(-1.64)**	(-1.07)
Δ Loan large	0.08	0.08	**0.44*****	**0.24*****	0.08	0.05
	(1.27)	(1.25)	**(8.35)**	**(3.55)**	(1.27)	(0.52)
Δ Deposits vol USD	-0.04	-0.05	0.00	**-0.07***	-0.04	-0.01
	(-0.90)	(-1.21)	(-0.11)	**(-1.68)**	(-0.90)	(-0.10)
Δ Loan vol USD	0.04	0.05	-0.03	**0.13*****	0.04	0.08
	(0.90)	(1.04)	(-0.67)	**(2.73)**	(0.90)	(1.27)
Δ Liquidation USD	**-0.76*****	**-0.74*****	**-0.20*****	**-0.44*****	**-0.76*****	-0.04
	(-11.82)	**(-10.77)**	**(-3.56)**	**(-6.37)**	**(-11.82)**	(-0.38)
Δ Active user	0.02	0.02	0.01	-0.01	0.02	-0.01
	(1.15)	(0.87)	(0.28)	(-0.41)	(1.15)	(-0.41)
Δ Developer	0.00	0.00	-0.01	-0.02	0.00	0.03
	(0.14)	(0.16)	(-0.62)	(-1.05)	(0.14)	(0.93)

ETH return (1d)	**-0.09*** (-2.91)**	**-0.09*** (-2.94)**	**-0.09*** (-3.56)**	**-0.10*** (-2.99)**	**-0.09*** (-2.91)**	0.06 (1.31)
ETH return (7d)	**0.13*** (6.90)**	**0.14*** (6.95)**	**0.06*** (3.96)**	**0.17*** (8.62)**	**0.13*** (6.90)**	**0.14*** (5.06)**
ETH SD (30d)	0.00 (-0.07)	0.00 (-0.11)	0.00 (0.01)	0.01 (0.79)	0.00 (-0.07)	**0.15*** (8.59)**
N	791	791	791	789	791	791
Adj R-sq	0.20	0.18	0.17	0.22	0.20	0.12

Note: This table reports regression results for the influence of liquidity risk on Aave protocol. In columns (1) – (6) of each panel, the dependent variable is *⊿MktC_F*, *⊿MktC_C*, *⊿revenue*, *⊿TVL*, *⊿AAVE*, and *⊿AAVE holder*, respectively. T-statistics are reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics.

Table 5.10: The effects of liquidity risk and repeat users on Aave

Panel A: Repeat users and liquidity

	(1) ∆ MktC_F	(2) ∆ MktC_C	(3) ∆ Revenue	**(4) ∆ TVL**	(5) ∆ AAVE	**(6) ∆ AAVE holder**
Liquidity	0.00 (-0.06)	0.00 (-0.02)	0.01 (1.22)	0.01 (1.20)	0.00 (-0.06)	**-0.10*** (-8.75)**
Hack	0.00 (-0.39)	0.00 (-0.35)	0.00 (0.96)	0.00 (0.82)	0.00 (-0.39)	**-0.03*** (-3.47)**
Repeat deposit ratio	0.00 (0.07)	0.00 (-0.17)	0.00 (-0.12)	**-0.04** (-2.09)**	0.00 (0.07)	-0.02 (-0.93)
Repeat loan ratio	0.01 (0.51)	0.02 (0.95)	0.01 (0.58)	**0.05*** (2.69)**	0.01 (0.51)	**0.07*** (2.71)**
∆ Deposits vol USD	-0.04 (-0.94)	-0.05 (-1.24)	-0.02 (-0.42)	-0.08 (-1.71)	-0.04 (-0.94)	-0.01 (-0.15)
∆ Loan vol USD	0.04 (0.93)	0.05 (1.08)	0.03 (0.76)	**0.18*** (3.71)**	0.04 (0.93)	0.08 (1.35)
∆ Liquidation USD	**-0.75*** (-11.81)**	**-0.72*** (-10.76)**	**-0.27*** (-4.72)**	**-0.54*** (-7.68)**	**-0.75*** (-11.81)**	-0.01 (-0.07)
∆ Active user	0.03 (1.25)	0.02 (0.98)	-0.01 (-0.41)	-0.02 (-0.95)	0.03 (1.25)	0.00 (-0.04)
∆ Developer	0.00 (0.05)	0.00 (0.05)	-0.01 (-0.41)	-0.02 (-0.85)	0.00 (0.05)	0.01 (0.32)
ETH return (1d)	**-0.09*** (-2.92)**	**-0.09*** (-2.96)**	**-0.09*** (-3.21)**	**-0.09*** (-2.81)**	**-0.09*** (-2.92)**	0.05 (1.19)
ETH return (7d)	**0.13*** (6.65)**	**0.13*** (6.67)**	**0.07*** (3.78)**	**0.17*** (8.18)**	**0.13*** (6.65)**	**0.09*** (3.38)**
ETH SD (30d)	0.00 (0.01)	0.00 (0.02)	0.00 (0.25)	0.01 (1.06)	0.00 (0.01)	**0.13*** (7.52)**
N	791	791	791	789	791	791
Adj R-sq	0.20	0.18	0.05	0.17	0.20	0.21

Panel B: Repeat users and utilization

	(1) ∆ MktC_F	(2) ∆ MktC_C	(3) ∆ Revenue	**(4) ∆ TVL**	(5) ∆ AAVE	(6) ∆ AAVE holder
Utilization	-0.01 (-0.79)	-0.01 (-0.71)	0.00 (0.22)	0.01 (0.72)	-0.01 (-0.79)	0.01 (0.58)
Hack	0.00 (-0.32)	0.00 (-0.28)	0.00 (1.02)	0.00 (0.79)	0.00 (-0.32)	**-0.03*** (-3.66)**
Repeat deposit ratio	0.00 (0.07)	0.00 (-0.17)	0.00 (-0.06)	**-0.04** (-2.03)**	0.00 (0.07)	-0.04 (-1.33)
Repeat loan ratio	0.01 (0.45)	0.02 (0.90)	0.01 (0.52)	**0.05*** (2.69)**	0.01 (0.45)	**0.08*** (2.94)**
∆ Deposits vol USD	-0.04 (-0.94)	-0.05 (-1.24)	-0.02 (-0.43)	**-0.08* (-1.72)**	-0.04 (-0.94)	0.00 (-0.04)
∆ Loan vol USD	0.04 (0.93)	0.05 (1.08)	0.03 (0.76)	**0.18*** (3.71)**	0.04 (0.93)	0.08 (1.28)

∆ Liquidation USD	**-0.75*****	**-0.72*****	**-0.27*****	**-0.54*****	**-0.75*****	-0.01
	(-11.81)	**(-10.76)**	**(-4.70)**	**(-7.67)**	**(-11.81)**	(-0.14)
∆ Active user	0.03	0.02	-0.01	-0.02	0.03	-0.01
	(1.26)	(0.98)	(-0.38)	(-0.93)	(1.26)	(-0.20)
∆ Developer	0.00	0.00	-0.01	-0.02	0.00	0.02
	(0.05)	(0.05)	(-0.47)	(-0.91)	(0.05)	(0.71)
ETH return (1d)	**-0.09*****	**-0.09*****	**-0.09*****	**-0.09*****	**-0.09*****	0.05
	(-2.94)	**(-2.98)**	**(-3.22)**	**(-2.80)**	**(-2.94)**	(1.24)
ETH return (7d)	**0.13*****	**0.14*****	**0.06*****	**0.17*****	**0.13*****	**0.13*****
	(6.80)	**(6.82)**	**(3.62)**	**(8.03)**	**(6.80)**	**(4.77)**
ETH SD (30d)	0.00	0.00	0.00	0.01	0.00	**0.15*****
	(0.03)	(0.03)	(0.03)	(0.85)	(0.03)	**(8.84)**
N	791	791	791	789	791	791
Adj R-sq	0.20	0.18	0.05	0.17	0.20	0.13

Note: This table reports regression results for the influence of liquidity risk on Aave protocol. In columns (1) – (6) of each panel, the dependent variable is *∆MktC_F*, *∆MktC_C*, *∆revenue*, *∆TVL*, *∆AAVE*, and *∆AAVE holder*, respectively. T-statistics are reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics.

Table 5.11: The effects of liquidity risk and large users on Compound

Panel A: Large users and liquidity

	(1) ∆ MktC_F	**(2) ∆ MktC_C**	**(3) ∆ Revenue**	(4) ∆ TVL	**(5) ∆ COMP**	**(6) ∆ COMP holder**
Liquidity	-0.02	**-0.02***	-0.01	-0.01	0.00	**-0.08*****
	(-1.58)	**(-1.86)**	(-1.26)	(-1.55)	(-0.14)	**(-12.84)**
Hack	0.01	0.01	0.00	0.00	0.00	-0.01
	(1.60)	(1.12)	(0.19)	(-0.43)	(-0.37)	(-1.61)
∆ Deposit large	-0.09	-0.08	**0.09****	0.01	-0.06	-0.01
	(-1.06)	(-0.98)	**(1.95)**	(0.22)	(-0.82)	(-0.17)
∆ Loan large	0.00	0.00	**-0.15*****	-0.04	**0.17****	0.02
	(-0.07)	(-0.03)	**(-3.08)**	(-0.82)	**(2.03)**	(0.46)
∆ Deposits vol	0.01	0.02	0.02	0.03	0.07	0.00
USD	(0.21)	(0.51)	(0.80)	(1.08)	(1.61)	(0.07)
∆ Loan vol USD	**-0.15***	-0.07	-0.02	0.04	**0.26*****	**-0.08***
	(-1.63)	(-0.75)	(-0.52)	(0.84)	**(3.54)**	**(-1.86)**
∆ Liquidation	**0.42*****	**0.37*****	0.08	**0.34*****	-0.19	0.06
USD	**(2.74)**	**(2.64)**	(0.87)	**(3.18)**	(-1.23)	(0.62)
∆ Active user	0.03	0.01	0.06	-0.01	-0.03	0.02
	(0.37)	(0.21)	(1.36)	(-0.27)	(-0.37)	(0.57)
∆ Developer	0.00	-0.01	0.01	0.01	-0.02	0.00
	(0.17)	(-0.43)	(0.32)	(0.33)	(-0.69)	(-0.13)
ETH return (1d)	-0.05	-0.04	-0.03	-0.01	**-0.13*****	0.03
	(-1.40)	(-1.24)	(-1.15)	(-0.54)	**(-3.31)**	(1.44)
ETH return (7d)	0.02	0.01	0.00	0.02	**0.15*****	0.02
	(0.90)	(0.60)	(0.32)	(1.21)	**(6.12)**	(1.52)
ETH SD (30d)	-0.01	-0.02	-0.01	-0.01	-0.01	**0.05*****
	(-0.41)	(-1.19)	(-0.57)	(-0.79)	(-0.65)	**(5.35)**
N	631	631	789	789	790	790
Adj R-sq	0.01	0.01	0.01	0.01	0.06	0.26

Panel B: Large users and utilization

	(1) ∆ MktC_F	(2) ∆ MktC_C	**(3) ∆ Revenue**	(4) ∆ TVL	**(5) ∆ COMP**	**(6) ∆ COMP holder**
Utilization	0.01	0.02	0.00	0.02	-0.01	0.01
	(0.76)	(1.08)	(0.01)	(1.54)	(-0.86)	(0.59)
Hack	0.01	0.01	0.00	0.00	0.00	**-0.01****

	(1.46)	(0.94)	(0.13)	(-0.68)	(-0.28)	**(-2.08)**
Δ Deposit large	-0.09	-0.07	**0.09****	0.01	-0.06	-0.01
	(-1.02)	(-0.94)	**(1.94)**	(0.20)	(-0.82)	(-0.28)
Δ Loan large	0.00	0.00	**-0.15*****	-0.04	**0.17****	0.03
	(-0.06)	(-0.03)	**(-3.07)**	(-0.81)	**(2.03)**	(0.53)
Δ Deposits vol USD	0.01	0.02	0.02	0.03	0.07	0.00
	(0.14)	(0.42)	(0.80)	(1.07)	(1.61)	(0.02)
Δ Loan vol USD	**-0.15***	-0.07	-0.02	0.04	**0.26*****	-0.07
	(-1.67)	(-0.82)	(-0.50)	(0.87)	**(3.54)**	(-1.51)
Δ Liquidation USD	**0.41*****	**0.36*****	0.08	**0.32*****	-0.19	0.01
	(2.69)	**(2.57)**	(0.82)	**(3.08)**	(-1.21)	(0.08)
Δ Active user	0.03	0.01	0.06	-0.01	-0.03	0.04
	(0.36)	(0.20)	(1.40)	(-0.22)	(-0.35)	(0.95)
Δ Developer	0.01	-0.01	0.01	0.01	-0.02	0.01
	(0.24)	(-0.34)	(0.42)	(0.52)	(-0.72)	(0.74)
ETH return (1d)	-0.06	-0.04	-0.03	-0.01	**-0.13*****	0.03
	(-1.44)	(-1.29)	(-1.18)	(-0.55)	**(-3.33)**	(1.04)
ETH return (7d)	0.03	0.02	0.01	0.02	**0.15*****	**0.06*****
	(1.27)	(1.01)	(0.56)	(1.52)	**(6.26)**	**(3.59)**
ETH SD (30d)	0.00	-0.01	0.00	-0.01	-0.01	**0.08*****
	(-0.08)	(-0.84)	(-0.22)	(-0.54)	(-0.54)	**(8.40)**
N	631	631	789	789	790	790
Adj R-sq	0.01	0.00	0.00	0.01	0.06	0.10

Note: This table reports regression results for the influence of liquidity risk in Aave on Compound protocol. In columns (1) – (6) of each panel, the dependent variable is $\Delta MktC\_F$, $\Delta MktC\_C$, $\Delta revenue$, ΔTVL, $\Delta COMP$, and $\Delta COMP\ holder$, respectively. T-statistics are reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics.

Table 5.12: The effects of liquidity risk and repeat users on Compound

Panel A: Repeat users and liquidity

	(1) **Δ MktC_F**	**(2)** **Δ MktC_C**	(3) Δ Revenue	(4) Δ TVL	(5) Δ COMP	**(6)** **Δ COMP holder**
Liquidity	-0.02	**-0.02***	-0.01	-0.01	0.00	**-0.08*****
	(-1.40)	**(-1.69)**	(-1.21)	(-1.53)	(-0.18)	**(-12.54)**
Hack	**0.01***	0.01	0.00	0.00	0.00	-0.01
	(1.69)	(1.19)	(0.23)	(-0.40)	(-0.41)	(-1.53)
Repeat deposit ratio	-0.03	-0.03	0.00	0.00	0.00	**-0.03****
	(-1.22)	(-1.44)	(-0.18)	(-0.25)	(-0.13)	**(-2.14)**
Repeat loan ratio	0.01	0.01	0.00	0.00	-0.01	**0.05*****
	(0.50)	(0.33)	(-0.06)	(-0.09)	(-0.45)	**(3.43)**
Δ Deposits vol USD	0.01	0.02	0.01	0.03	**0.08***	0.00
	(0.16)	(0.47)	(0.51)	(1.01)	**(1.82)**	(0.13)
Δ Loan vol USD	**-0.16***	-0.07	-0.03	0.04	**0.27*****	**-0.08****
	(-1.74)	(-0.86)	(-0.63)	(0.80)	**(3.64)**	**(-1.95)**
Δ Liquidation USD	**0.43*****	**0.37*****	0.08	**0.34*****	-0.20	0.07
	(2.80)	**(2.67)**	(0.91)	**(3.19)**	(-1.29)	(0.71)
Δ Active user	0.02	0.00	0.06	-0.01	-0.03	0.01
	(0.23)	(0.07)	(1.48)	(-0.24)	(-0.42)	(0.27)
Δ Developer	0.00	-0.02	0.00	0.00	-0.02	0.00
	(0.02)	(-0.58)	(0.20)	(0.27)	(-0.61)	(-0.11)
ETH return (1d)	-0.05	-0.04	-0.03	-0.01	**-0.13*****	0.03
	(-1.30)	(-1.13)	(-1.17)	(-0.53)	**(-3.26)**	(1.44)
ETH return (7d)	0.02	0.02	0.01	0.02	**0.15*****	**0.02***
	(0.97)	(0.67)	(0.35)	(1.22)	**(6.09)**	**(1.68)**
ETH SD (30d)	-0.01	-0.02	-0.01	-0.01	-0.01	**0.05*****
	(-0.50)	(-1.34)	(-0.56)	(-0.82)	(-0.75)	**(5.66)**
N	631	631	789	789	790	790

Adj R-sq	0.01	0.01	-0.01	0.01	0.06	0.27
Panel B: Repeat users and utilization						
	(1) ∆ MktC_F	(2) ∆ MktC_C	(3) ∆ Revenue	(4) ∆ TVL	(5) ∆ COMP	**(6) ∆ COMP holder**
Utilization	0.01	0.01	0.00	0.02	-0.01	**0.01**
	(0.71)	(0.99)	(-0.01)	(1.52)	(-0.89)	**(0.84)**
Hack	0.01	0.01	0.00	0.00	0.00	**-0.01****
	(1.56)	(1.03)	(0.18)	(-0.64)	(-0.31)	**(-1.99)**
Repeat deposit ratio	-0.03	-0.03	0.00	-0.01	0.00	**-0.04*****
	(-1.36)	(-1.61)	(-0.29)	(-0.40)	(-0.14)	**(-2.93)**
Repeat loan ratio	0.02	0.01	0.00	0.00	-0.01	**0.06*****
	(0.68)	(0.54)	(0.06)	(0.15)	(-0.49)	**(4.29)**
∆ Deposits vol USD	0.00	0.02	0.01	0.03	**0.08***	**0.00**
	(0.09)	(0.39)	(0.50)	(1.01)	**(1.82)**	**(0.10)**
∆ Loan vol USD	**-0.16***	-0.08	-0.03	0.04	**0.27*****	-0.08*
	(-1.77)	(-0.90)	(-0.61)	(0.83)	**(3.64)**	(-1.63)
∆ Liquidation USD	**0.42*****	0.36***	0.08	**0.33*****	-0.20	0.02
	(2.75)	(2.61)	(0.87)	**(3.09)**	(-1.27)	(0.20)
∆ Active user	0.02	0.00	0.06	-0.01	-0.03	0.02
	(0.21)	(0.05)	(1.51)	(-0.22)	(-0.41)	(0.55)
∆ Developer	0.00	-0.01	0.00	0.01	-0.02	0.01
	(0.09)	(-0.49)	(0.29)	(0.46)	(-0.64)	(0.75)
ETH return (1d)	-0.05	-0.04	-0.03	-0.01	**-0.13*****	0.03
	(-1.34)	(-1.17)	(-1.20)	(-0.54)	**(-3.28)**	(1.07)
ETH return (7d)	0.03	0.02	0.01	0.03	**0.15*****	**0.06*****
	(1.31)	(1.07)	(0.59)	(1.53)	**(6.24)**	**(3.76)**
ETH SD (30d)	0.00	-0.01	0.00	-0.01	-0.01	**0.09*****
	(-0.20)	(-1.01)	(-0.23)	(-0.55)	(-0.64)	**(8.67)**
N	631	631	789	789	790	790
Adj R-sq	0.01	0.01	-0.01	0.01	0.06	0.12

Note: This table reports regression results for the influence of liquidity risks in Aave on Compound protocol. In columns (1) – (6) of each panel, the dependent variable is *∆MktC_F*, *∆MktC_C*, *∆revenue*, *∆TVL*, *∆COMP*, and *∆COMP holder*, respectively. T-statistics are reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics.

5.5 Conclusion

An important question always posed towards the community of FinTech practitioners and entrepreneurs is whether FinTech can be immune from risks observed in traditional financial markets. This chapter attempts to shed light on this question from the lens of one of the controversial FinTech segments, LPs. Particularly, we focus on the possibility of liquidity risk in LPs. Though liquidity risk has been studied in the context of banking (e.g., Brynat, 1980; Diamond & Dybvig, 1983; Allen & Santomero, 1997; Allen & Gale, 2004; Ryu, Webb, & Yu, 2021) and P2P lending (e.g., Käfer, 2017; Shao & Bo, 2021), LPs as the emerging on-chain lending systems, have not been scrutinized in that regard.

Through an analysis of lending activities in Aave, our findings reveal the very real possibility of liquidity risk, with a smaller group of users, including regular users and large users, contributing to the majority of deposits and loans. Subsequently, we construct metrics to assess liquidity risk, particularly focusing on several measurements related to the significance of regular users and large users, and discover that these metrics exert a complicated influence on the Aave protocol. Our findings contribute new insights to research on lending. In the banking sector, Molyneux & Thornton (1992), among others, show that liquidity can negatively influence profitability. However, opposing arguments, such as those of Bourke (1989) and Al-Matari (2021), are also presented. This chapter further contributes to the debates. Additionally, our research also contributes to the understanding of large depositors and loan concentration in the banking sector. In banking literature, two important research topics are the reason why large depositors shift their resources (such as Oliveira et al. (2015)) and the influences of major borrowers on risk and return of banks (e.g., Acharya et al. (2006); Tabak et al. (2011)). Though we have not understood the motivations of dominant users in LPs, we first provide initial empirical evidence regarding their influences.

We also study how liquidity risk and market users affect the performance of Compound protocol, revealing the complicated relationship among leading LPs. The findings indicate that the two LPs are competitors in terms of attracting liquidity. For example, more liquidity absorbed by Aave will decelerate the growth of market cap and the growth of COMP holders, implying that users tend to adopt LPs with more sufficient liquidity. Moreover, regular users and large users in Aave show complicated influence on financial indicators in Compound, implying that the leading LPs can get better together when the customer base is more stable. Regarding cross-bank effects, literature studies that illiquidity risks of individual banks can cause crises in the banking sector (e.g., Kreis & Leisen, 2018) and addresses the influence of bank competition (e.g., Fiordelisi & Mare, 2014). Our research further contributes to this subfield.

Although our findings appear conceptually and empirically robust, they should be interpreted with their limitations in mind. First, we do not show the identity of regular users and large useres, which can help us understand their trading strategy. However, in blockchain, anonymity is another unique characteristic. Unless these users are willing to announce their identity, we will hardly ever know who they are. Foley, Frijns, Garel, & Roh (2022) attempted to identify the originating country for Bitcoin transactions. Following similar approaches, further study can work on revealing more information about DeFi users. Second, potential liquidity risks can be affected by social networking. Assuming that potential collusion could exist among a group of malicious liquidity providers, the risk of illiquidity attacks could be augmented. This possibility of successful illiquidity attacks is not captured by our constructed liquidity risk measurements. To better predict liquidity risks, we may need private information, such as the relationship of LP users and their strategies in different market conditions, which at this stage is extremely difficult to secure. Thirdly, despite including dependent variables related to both the Aave protocol and the DeFi market, there remains a possibility of omitted variable bias in the analysis presented in section 5.4. Future research could address this potential issue by identifying appropriate instrumental variables or by developing more comprehensive datasets for on-chain lending systems. Finally, better measurements of liquidity risks in LPs may be a good topic for further study. In traditional finance, how to measure liquidity risks is a controversial topic, and risk measures are modified to better adapt to changing markets (Zaevski & Nedeltchev, 2023). Lou & Sadka (2011) argue that liquidity level and liquidity risks are not the same thing. In this chapter, we do not investigate the overall liquidity level of Aave protocol, given that there are various cryptocurrencies traded on Aave. A possible choice is expected default probability (EDF), and Covitz & Downing (2007) and Erkens, Hung, & Matos (2012) show how to apply the measurements. We expect to see new measurements that can better describe liquidity risks in LPs.

Chapter 6

Conclusion

This thesis takes several small steps towards advancing our understanding of the blockchain and DeFi landscape. These advances in our knowledge are designed to help us make better blockchain-based financial systems. More importantly, these steps aim to help draw us closer to risks in the DeFi market.

Chapter 2 provides a comprehensive overview of blockchain technology and DeFi. It commences with the definition and classification of blockchain, followed by an exploration of the risks and intricate challenges inherent in blockchain technology. The chapter then delves into popular DeFi applications, namely stablecoins, lending protocols, and decentralized exchanges, elucidating their properties and specific risks. Finally, the chapter investigates the common risks and challenges in the DeFi market. This thorough exploration equips users with essential background information.

Chapters 3 – 4 focus on DeFi governance and provide solid empirical evidence on governance centralization within the DeFi space, using MakerDAO as a case study. Chapter 3 starts the analysis by examining the voting history in MakerDAO governance. The findings reveal a high degree of centralization in both voting power and decision-making distribution within DeFi. Additionally, the participation of DeFi governance is limited, amplifying the control of active voters with substantial voting power. The empirical analysis results demonstrate that voting participation, the concentration of voting power, and the centralized distribution of governance tokens exert influence over DeFi protocols, which can be either positive or negative.

Chapter 4 builds upon the groundwork laid in Chapter 3, offering a deeper exploration of DeFi governance by examining the presence of voter coalitions in DeFi. Drawing parallels to shareholder coalitions in corporate governance, this research question is investigated through the application of clustering algorithms to voting history. Using MakerDAO as a case study, three distinct voter coalitions are identified, featuring a dominant coalition and two minoritarian counterparts. This underscores that governance centralization extends beyond individual control of decision-making power, emphasizing the importance of considering collective voting behavior among individuals with shared interests. Furthermore, the dominant voter coalition has adverse impacts on the market performance of the underlying DeFi, both in terms of value and stability, highlighting the negative influences of governance centralization. Conversely, higher cohesiveness of minoritarian coalitions yields positive effects, showing that decentralization is a crucial and valuable property of DeFi.

Chapter 5 explores liquidity risk within the DeFi landscape, positing the probable existence of such risk. Through an in-depth analysis of lending activities in Aave protocol, the study reveals that both available liquidity and utilization exhibit high volatility, signalling that the state of the Aave protocol may not consistently be secure, particularly when available liquidity is nearly fully utilized. Notably, both regular users and large users are major participants in Aave, playing pivotal roles in providing deposits and initiating loans. The inherent potential for illiquidity risks becomes apparent when these users collectively withdraw deposits or engage in other malicious strategies. Empirical analysis demonstrates that both available liquidity and influential users can impact the market performance of DeFi, albeit in a complex way. Additionally, the chapter uncovers cross-DeFi effects, indicating that the state of a leading DeFi application can influence other DeFi applications offering similar financial services. The findings suggest that if liquidity risk occurs, the DeFi market may face contagion effects. Overall, this chapter underscores the significance of monitoring the state of DeFi and assessing risks posed by significant users within DeFi protocols.

Despite ongoing debates in blockchain and DeFi with varying opinions, the scarcity of solid empirical studies has been a notable gap. Previous research in blockchain by academics in economics and finance primarily delves into areas such as blockchain economics (such as Abadi & Brunnermeier, (2022)), the design of consensus mechanisms (such as Saleh (2021)), and the examination of how blockchain technology integrates with established financial systems (as explored in Wu & Liang (2017)). Within the cryptocurrency research, a predominant focus lies on the valuation of cryptocurrencies, such as Cong et al. (2020), and the identification of risk factors in the cryptocurrency market, as evidenced in Liu et al. (2022). This thesis contributes by expanding the discussion to blockchain-based financial systems, scrutinizing specific challenges inherent in these systems. By doing so, it aims to provide a nuanced understanding of the risks and returns associated with cryptocurrencies, moving beyond the conventional purview of traditional asset pricing models.

This thesis also bridges the gap of DeFi research between computer science and mainstream finance. Academics in computer science have made significant contributions to DeFi research by introducing and discussing the foundations of DeFi, such as smart contracts (e.g., Werner et al., 2022) and oracles (e.g., Liu et al., 2021), and they also present a comparison between DeFi and traditional finance (e.g., Qin et al., 2021). Furthermore, systematic reviews presented by Werner et al. (2022) and Klages-Mundt et al. (2020), and mathematical models of DeFi presented by Bartoletti et al. (2021) and Gudgeon et al. (2020b), can provide background information and formal theoretical analysis for readers interested in DeFi. However, when it comes to empirical research on DeFi, the literature remains relatively silent, and this thesis contributes to filling the research gap. By analyzing the most influential DeFi applications, this thesis demonstrates that the concerns proposed by academics in computer science, such as governance centralization (Narayanan et al., 2016), and liquidity risks (Gudgeon et al., 2020a, and Gudgeon et al., 2020b), are very likely to exist. Furthermore, this thesis investigates how these concerns affect the underlying DeFi applications by applying econometric techniques, going beyond the theoretical analysis commonly done by computer science researchers.

More specifically, this thesis makes a distinct contribution to corporate governance research by expanding the discussion about ownership concentration to the context of DeFi. The impact of ownership structure and concentration on firm performance has been a pivotal research topic for a long time, with Shleifer & Vishny (1997) summarizing the classical research findings. Recent studies present divergent perspectives on ownership concentration. Tran & Turkiela (2020) and Giannetti & Zhao (2019) provide empirical evidence on higher volatility of firm performance caused by governance centralization. However, Iannotta et al. (2017) and Bernile et al. (2018) hold opposing views. This disagreement may be caused by data limitations, as discussed by Hermalin & Weisbach (2003) and Adam, Hermalin, & Weisbach (2010). Through an examination of DeFi governance, this thesis demonstrates that governance centralization is inevitable in DeFi. The effects of governance centralization are intricate, manifesting both positive and negative outcomes.

Besides, this thesis is associated with banking literature by examining potential liquidity risk in blockchain-based lending markets. Building upon theoretical models of liquidity risk developed over the years (such as Diamond & Dybvig, 1983; Goldstein & Pauzner, 2005;

Fall & Viviani, 2015), empirical studies further explore the significant negative impacts of liquidity risk, such as the bank failures during the 2008 financial crisis (Hong et al., 2014). These negative influences can also spread across financial markets (Urquhart & Wolfe, 2018; Kreis & Leisen, 2018). Given the rapid growth of DeFi markets, it becomes crucial to investigate whether DeFi applications, particularly those facilitating on-chain lending, are exposed to potential liquidity risk. This thesis answers this research question by analyzing transaction-level data in DeFi, demonstrating that liquidity risk can indeed manifest, particularly when certain users contribute significantly to deposits and loans. Furthermore, these influential depositors and borrowers exert complex influences on the market performance of DeFi, contributing to the ongoing debates about the impact of major depositors and borrowers (such as Oliveira et al., 2015; Acharya et al., 2006; Tabak et al., 2011).

In general, this thesis contributes to the advancement of knowledge in the field of financial technology and serves as a bridge between blockchain research in computer science and finance. By addressing two crucial challenges in the DeFi market, namely governance centralization and liquidity risk, the insights presented in this thesis provide valuable guidance for both DeFi users and developers as they navigate the intricacies of this evolving landscape. Regulators can also draw upon this thesis as a reference.

There are several limitations of this thesis. Firstly, the reliance on case studies in the previous chapters necessitates further validation through the utilization of more extensive datasets. Kitzler, Balietti, Saggese, Haslhofer, & Strohmaier (2023) study how DeFi contributors influence DeFi governance, and the dataset include over 800 DAOs with over 980,000 voters, offering a potential avenue for such validation. However, it is important to note that these studies often focus more on network analysis rather than employing econometric methods. The challenges associated with data collection in the DeFi space, especially in constructing comprehensive control variables for DeFi protocols, represent a common obstacle. Secondly, the anonymity of participants in DeFi poses a significant hurdle, preventing the identification of users' true identities. This lack of transparency complicates the understanding of user interactions, such as herding behavior in DeFi governance. Further research can explore innovative methodologies to de-anonymize DeFi participants. Finally, the long-term impacts of governance centralization and potential illiquidity remain unclear. Continuous monitoring and research are essential to capture emerging trends and developments in the evolving DeFi market.

Future research could delve deeper into governance centralization within the DeFi space. In DeFi, understanding decision-makers' behavior can be enhanced by investigating their trading activities, such as lending and arbitrage transactions. Examining their activities before and after the governance process may unveil their private interests. A more comprehensive understanding of DeFi governance could be achieved by exploring the interactions among decision-makers. Off-chain information, such as the real-world identities of decision-makers, could contribute to elucidating the relationships between these key players in DeFi. Ideally, decision-makers with shared interests may form coalitions to gain increased control over DeFi. Future research could investigate whether certain interest groups with substantial governance power manipulate the DeFi market and, if so, explore the implications of governance centralization.

The behavior of minor stakeholders also presents intriguing avenues for research. It is crucial to explore how to incentivize minor voters to actively engage in DeFi governance, given that decentralization is a primary feature of DeFi. Research focused on the design of governance mechanisms could address the issue of low participation. Additionally, herding behavior may exist in DeFi governance, where minor voters follow key opinion leaders. This dynamic could potentially empower influential decision-makers to exert even greater control over DeFi governance. Investigating whether key opinion leaders pursue private interests at the expense of their followers' interests is necessary.

Besides, research on financial risks in DeFi markets offers an opportunity to draw comparisons between mainstream finance and financial technology. Future studies could explore the applicability of effective risk management practices from traditional finance to the DeFi space. New risk measures can be also introduced. Through a detailed analysis of specific market dynamics within these emerging markets, there is potential to develop and enhance innovative risk assessment frameworks. These frameworks can be instrumental in providing improved protection for investors in DeFi.

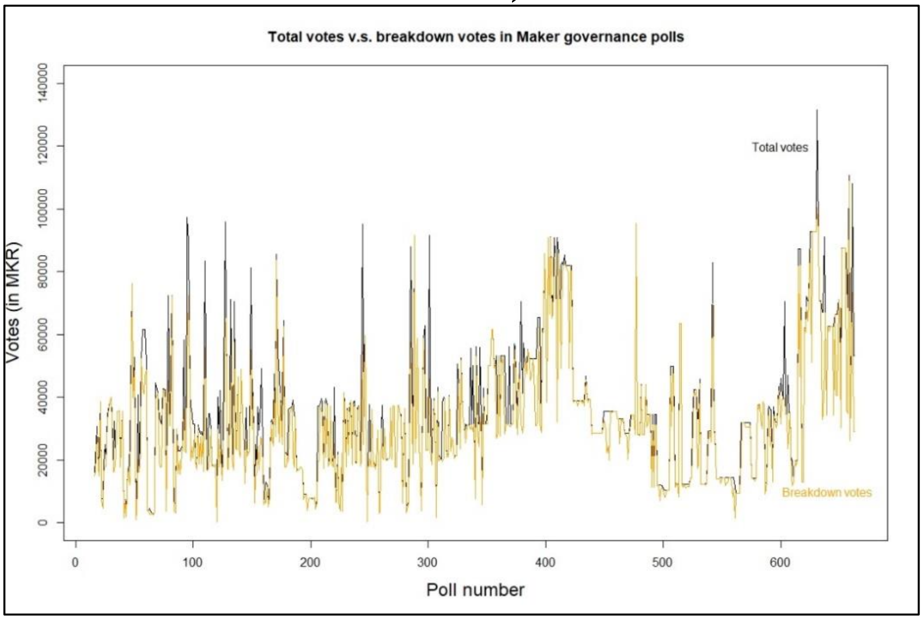
Appendices

Appendix A (Chapter 3)

A.1 Further information for voting patterns

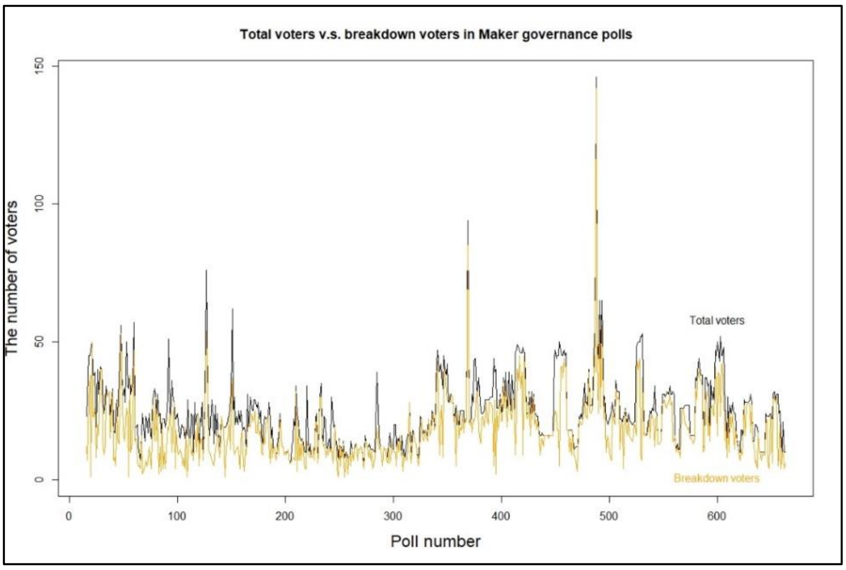
Figure A.1 and Figure A.2 illustrate the votes and voters at the poll level. For each poll, both the total votes and breakdown votes vary; however, the voters are a small group of MKR holders. In Figure A.3, we compare the voting share of the largest voter to the breakdown ratio. For most polls, the largest voter is the pivotal figure. Then, we calculate the average voting share of the largest voter daily in Figure A.4. Most of the time, the largest voters have more than one third of the total voting share. Finally, Figure A.5 shows the Lorenz curve of voting results in Maker governance polls, implying that the total votes are highly centralized for particular polls. All these figures further support our message that centralized voting power is evident in the Maker protocol.

Figure A.1: Total votes and breakdown votes in Maker governance polls (Poll 16 – Poll 663)



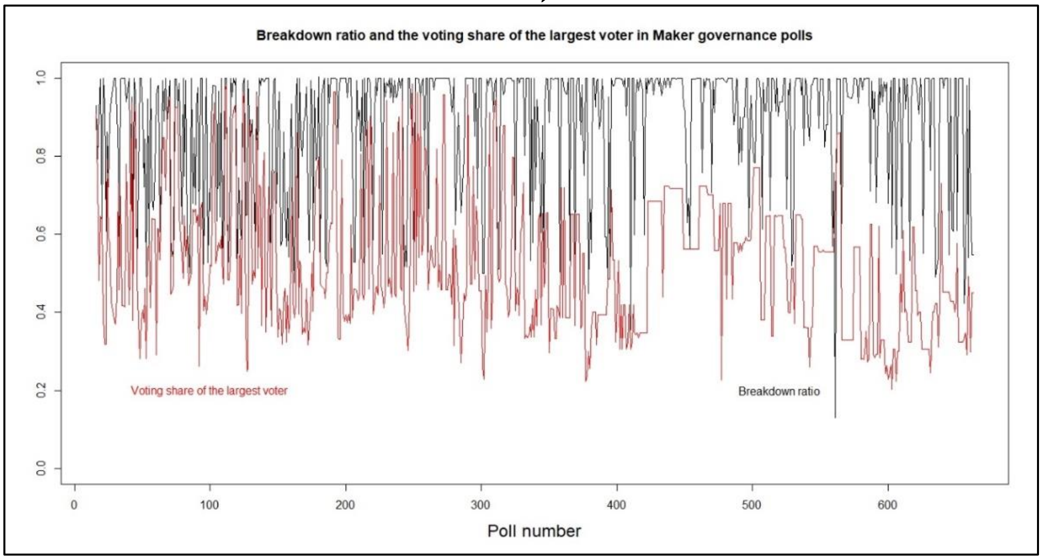
Note: This table shows the total votes and breakdown votes in Maker governance polls (Poll 16 – Poll 663). The winning options tend to get the most votes.

Figure A.2: Total voters and breakdown voters in Maker governance polls (Poll 16 – Poll 663)



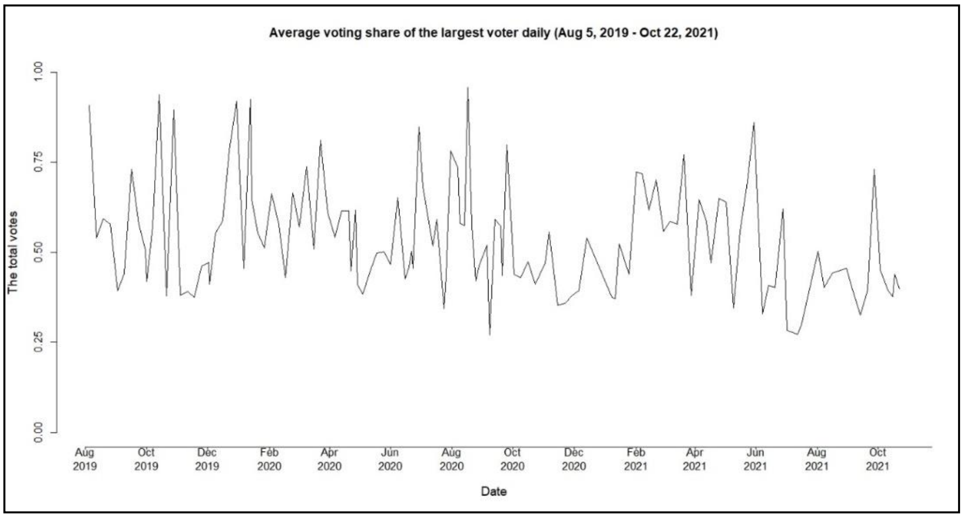
Note: This table shows the total voters and breakdown voters in Maker governance polls (Poll 16 – Poll 663). The winning options are chosen by most voters.

Figure A.3: Breakdown ratio and the voting share of the largest voter (Poll 16 – Poll 663)



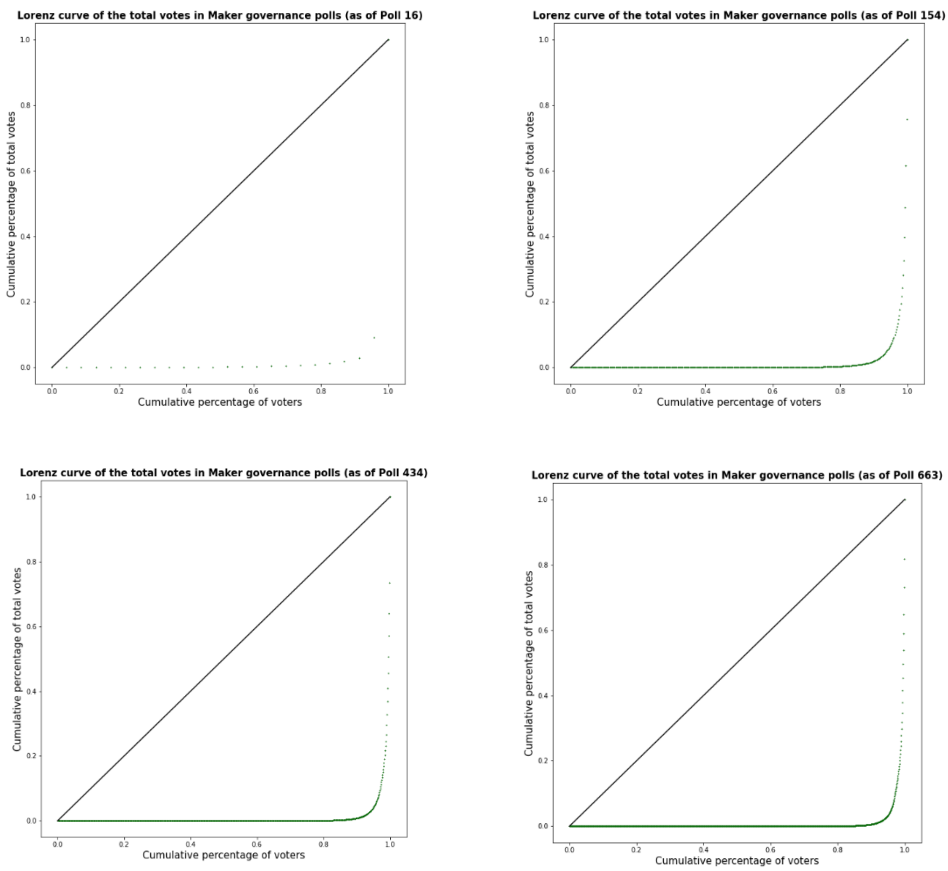
Note: This figure presents breakdown ratio and voting share of the largest voters in Maker governance polls (Poll 16 – Poll 663). In most polls, the largest voters contribute a significant number of votes to the winning options.

Figure A.4: Average voting share of the largest voter daily (Aug 5, 2019 – Oct 22, 2021)



Note: This figure shows the average voting share of the largest voter daily (Aug 5, 2019 – Oct 22, 2021). Most of the time, the largest voters have more than 30% voting share, implying unequally distributed voting power.

Figure A.5: Lorenz curve of the total votes in Maker governance polls



Note: This figure illustrates the Lorenz curve at four time points, i.e., Poll 16 (started on Aug 5, 2019), Poll 154 (started on May 4, 2021), Poll 434 (started on Jan 25, 2021), and Poll 633 (started on Oct 26, 2021). The curves imply that total votes are highly centralized in particular Maker governance polls.

We also present relevant tables regarding the characteristics of the voters. Table A.1 lists the known voters of Maker governance polls, including voting delegates and a16z. Tables A.2-A.4 report the ten voters that participate in most Maker governance polls, the ten voters that have the largest total votes and the ten voters that have the largest single votes, respectively. All these tables give more information about active and powerful voters in the Maker protocol.

Table A.1: Known voters in Maker governance polls

Address	Identity	Involved Polls	Total votes	First poll	The highest votes	Since
0x05e793ce0c6027323ac150f6d45c2344d28b6019	a16z	3	96480.00	631	32160.00	2019-11-08
0x845b36e1e4f41a361dd711bda8ea239bf191fe95	Feedblack Loops LLC	44	53892.24	610	10102.26	2021-08-02
0xad2fda5f6ce305d2ced380fdfa791b6a26e7f281	Field Technologies, Inc.	52	1165679.40	610	28511.07	2021-08-02
0xaf8aa6846539033eaf0c3ca4c9c7373e370e039b	Flip Flop Flap Delegate LLC	53	454657.27	610	23903.23	2021-08-10
0x22d5294a23d49294bf11d9db8beda36e104ad9b3	MakerMan	46	37071.23	610	5061.75	2021-08-13
0x45127ec92b58c3a89e89f63553073adcaf2f1f5f	monetsupply	45	45633.81	610	5139.34	2021-08-09
0x14a4ed2000ca405452c140e21c10b3536c1a98e4	Shadow Delegate	63	12022.10	598	239.50	2021-07-21
0x00daec2c2a6a3fcc66b02e38b7e56dcdfa9347a1	Shadow Delegate	45	936786.68	610	25044.84	2021-08-01
0x2c3b917cceaf41503145ceb4b37c8623d862c4cd	Shadow Delegate	33	66000.00	609	2000.00	2021-08-02
0xefcc3401739427eb0491cc27c7baa06817c7dfdb	Shadow Delegate	28	149405.00	615	5976.20	2021-08-26
0x68b216e9fc96a7b98b5c0028ff72e4c39c5c5a61	Shadow Delegate	5	23605.00	649	4721.00	2021-08-20
0xb21e535fb349e4ef0520318acfe589e174b0126b	ultraschuppi	57	1898.27	607	50.27	2021-07-28

Note: This table reports the known voters of Maker governance polls. For each voter, the number of involved polls, total votes and the highest votes in a single poll are presented. Votes are calculated in MKR tokens. The table highlights the first poll that a voter participated in, and the corresponding date is shown in the column 'Since'.

Table A.2: Ten voters that participate in most Maker governance polls

Address	Involved Polls	Total votes	First poll	The highest votes	Since
0xfdd650e5838fb21ead6479c7430da3f9cb3a833f	514	4493.6	16	9.41	2019-05-07
0x883b94bbd31902c79ab2c2daf89d439c94232319	479	83336.47	18	238.50	2019-04-11
0x4f2161c7eb1dc40d6f0eb24db81bf4a6eb0c3f30	479	1907163.70	17	8002.4	2019-08-11
0xd353bbf69d0dfb2cd6798dfff40bb31ae565ccc2	426	1441.31	18	7.04	2019-08-13
0xe602d1d6a52b5022a81c4ee7020292261bbb6f17	412	8699.84	51	51.14	2019-11-19
0x7a74fb6bd364b9b5ef69605a3d28327da8087aa0	359	32796.53	26	339.79	2019-05-14
0xd818bf36b2751b09efda09e4a4a16dd132612fc1	311	15515.95	305	116.45	2020-09-27
0x6a3000945173ad8905c70fda700ebbe1c41eab40	294	844500.00	17	3000.00	2019-07-26

0xc4abbb0099c3db6e8bebd3693ed66f7fe020f405	277	51739.05	26	203.27	2019-08-22
0xe896bcce9fbb3341a1e98f98ec7a6ffbdea35060	269	13452.21	18	61.75	2019-08-05

Note: This table reports the ten voters that participate in most Maker governance polls. Identity is not presented as a column, as none are found with public names. For each voter, the number of polls that they are involved in, total votes and the highest votes in a single poll are presented. Votes are calculated in MKR tokens. The table highlights the first poll that a voter participated in, and the corresponding date is shown in the column 'Since'.

Table A.3: Ten voters that have the largest total votes in Maker governance polls

Address	Identity	Involved Polls	Total votes	First poll	The highest votes	Since
0x7d6149ad9a573a6e2ca6ebf7d4897c1b766841b4		224	4170786.51	116	20540.06	2020-03-24
0x1ead7050c94c8a1f08071ddbb28b01b3eb1b3d38		86	2019684.05	399	28479.83	2021-01-06
0x4f2161c7eb1dc40d6f0eb24db81bf4a6eb0c3f30		479	1907163.70	17	8002.40	2019-08-11
0x1f29a733cc3827765797e111c7ce7cf870f9ad03		133	1357946.88	168	10526.72	2020-06-03
0xad2fda5f6ce305d2ced380fdfa791b6a26e7f281	Field Technologies, Inc.	52	1165679.40	610	28511.07	2021-08-02
0x1c11ba15939e1c16ec7ca1678df6160ea2063bc5		68	999993.71	16	16763.92	2019-05-15
0x00daec2c2a6a3fcc66b02e38b7e56dcdfa9347a1	Shadow Delegate	45	936786.68	610	25044.84	2021-08-01
0xac39d02cdd60c2851a8441950ac06b0f911400e2		86	905297.92	399	10526.72	2021-01-13
0x6a3000945173ad8905c70fda700ebbe1c41eab40		294	844500.00	17	3000.00	2019-07-26
0x61d2f3a50b8388e1b5ab1cdddbb091331a66b89d		145	725110.20	155	5000.76	2020-05-14

Note: This table reports the ten voters that have the largest total votes in Maker governance polls. For each voter, the number of involved polls, total votes and the highest votes in a single poll are presented. Votes are calculated in MKR tokens. The table highlights the first poll that a voter participated in, and the corresponding date is shown in the column 'Since'.

Table A.4: Ten voters that have the largest single votes in Maker governance polls

Address	Identity	Involved Polls	Total votes	First poll	The highest votes	Since
0x8778b64f999aa8ed59045d8d67998a77ab51e258		17	669865.45	57	39403.85	2019-02-22
0x26732399f47e00739d2b4b0451acc3f93f7e3a14		5	197019.25	288	39403.85	2020-09-11
0xd48d3462c5e5a5d568c8f8ec3366241ed8b46bd1		3	108224.28	132	36074.76	2018-08-29
0x56a176ace5516b0f8525b292ba697a16d5e8a7eb		20	423092.99	145	33001.90	2020-02-22
0x05e793ce0c6027323ac150f6d45c2344d28b6019	a16z	3	96480.00	631	32160.00	2019-11-08
0xad2fda5f6ce305d2ced380fdfa791b6a26e7f281	Field Technologies, Inc.	52	1165679.40	610	28511.07	2021-08-02
0x1ead7050c94c8a1f08071ddbb28b01b3eb1b3d38		86	2019684.05	399	28479.83	2021-01-06
0x00daec2c2a6a3fcc66b02e38b7e56dcdfa9347a1	Shadow Delegate	45	936786.68	610	25044.84	2021-08-01
0xaf8aa6846539033eaf0c3ca4c9c7373e370e039b	Flip Flop Flap Delegate LLC	53	454657.27	610	23903.23	2021-08-10
0xa497573c2481d44381b510ede15bcd6b6e901457		4	95432.00	127	23858.00	2020-04-08

Note: This table reports the ten voters that have the largest single votes in Maker governance polls. For each voter, the number of involved polls, total votes and the highest votes in a single poll are presented. Votes are calculated in MKR tokens. The table highlights the first poll that a voter participated in, and the corresponding date is shown in the column 'Since'.

A.2 Description of utilized factors

The following tables summarize the factors used in our univariate regressions.

Table A.5: Financial factors for MKR and DAI

	Description
Return	Daily return
MktC	Price (in USD) of the tokens times the circulating supply
Volume	Total amount (in tokens) of tokens transferred on Ethereum blockchain within a day
Volume_usd	Total amount (in USD) of tokens transferred on Ethereum blockchain within a day
Volume_dex	Sum of the amount (in tokens) traded on Decentralized Exchanges (DEXes)
Volume_dex_usd	Sum of the amount (in USD) traded on Decentralized Exchanges (DEXes)
Volume_l	Aggregated daily volume, measured in tokens from on-chain transactions of more than $100,000
Volume_l_usd	Aggregated daily volume, measured in USD from on-chain transactions of more than $100,000

Note: The factors are provided by *intotheblock.com*.

Table A.6: Network factors for MKR and DAI

	Description
TotalWithBlc	The number of addresses that actually have a balance
New	The number of new addresses created daily
Active	The number of addresses that made a transaction
Active ratio	The percentage of addresses with a balance of tokens that made a transaction during a given period (Active Addresses / Addresses with a Balance).

Note: The factors are provided by *intotheblock.com*.

Table A.7: Twitter sentiment factors for MKR and DAI

	Description
Positive	The number of tweets that are related to a given token have a positive connotation.
Neutral	The number of tweets that are related to a given token have a neutral connotation.

Negative	The number of Tweets that are related to a given token have a negative connotation.

Note: The Twitter sentiment factors utilize machine learning algorithm to determine if the texts used in the Tweets related to a given token have a positive, neutral or negative connotation. The factors are computed and provided by *intotheblock.com*.

Table A.8: Collateral ratios

	Description
ETH_ratio	The value (in USD) of ETH locked as collateral divided by the total value (in USD) of locked collateral in Maker protocol
Stablecoin_ratio	The value (in USD) of stablecoins locked as collateral divided by the total value (in USD) of locked collateral in Maker protocol

Note: We focus on three types of collateral assets, including ETH, stablecoins and Wrapped Bitcoin (WBTC). The variables are queried on *dune.xyz*.

A.3 Results for Granger test

The following tables summarize the results for the Granger test. For the measurements based on governance polls, the number of observations is not enough for implementing the Granger test. Therefore, we fill the null values using linear interpolation.

Table A.9: Granger test results for MKR (linear interpolation)

PANEL A: Network							
Null Hypothesis	**Obs.**	**df**	**F-stat.**	**Prob.**	**Null Hypothesis**	**F-stat.**	**Prob.**
Gini does not Granger Cause Δ Active ratio	807	2	0.09	0.96	Δ Active ratio does not Granger Cause Gini	4.16	0.13

Note: This table reports the results for Granger tests based on Vector Autoregression (VAR) models. Column ‘df’ shows the optimal lag order. Using the optimal lag order, we run Granger tests for the hypotheses stemming from our empirical findings. For each test, both F-statistics and probability are presented.

Table A.10: Granger test results for MKR (measurements related to MKR distribution)

PANEL A: Financial factors							
Null Hypothesis	**Obs.**	**df**	**F-stat.**	**Prob.**	**Null Hypothesis**	**F-stat.**	**Prob.**
10k-100k does not Granger Cause Volume	804	6	1.70	0.12	Volume does not Granger Cause 10k-100k	1.19	0.31
10k-100k does not Granger Cause Volume_dex	806	4	3.43	0.01	Volume_dex does not Granger Cause 10k-100k	0.15	0.96
10k-100k does not Granger Cause Volume_dex_usd	801	9	1.08	0.37	Volume_dex_usd does not Granger Cause 10k-100k	0.25	0.99
10k-100k does not Granger Cause Volume_l	804	6	2.02	0.06	Volume_l does not Granger Cause 10k-100k	1.47	0.19
10k-100k does not Granger Cause Volume_l_usd	799	11	0.65	0.79	Volume_l_usd does not Granger Cause 10k-100k	0.44	0.94
>100k does not Granger Cause Volume	804	6	1.22	0.29	Volume does not Granger Cause >100k	0.82	0.55
>100k does not Granger Cause Volume_dex	806	4	3.45	0.01	Volume_dex does not Granger Cause >100k	0.60	0.66
>100k does not Granger Cause Volume_dex_usd	801	9	1.18	0.30	Volume_dex_usd does not Granger Cause >100k	0.36	0.95
>100k does not Granger Cause Volume_l	804	6	1.74	0.11	Volume_l does not Granger Cause >100k	0.89	0.50
>100k does not Granger Cause Volume_ l_usd	799	11	0.83	0.61	Volume_l_usd does not Granger Cause >100k	0.10	1.00
Delegate does not Granger Cause Volume_dex_usd	319	1	5.08	0.02	Volume_dex_usd does not Granger Cause Delegate	0.05	0.82
Delegate does not Granger Cause Volume_ l_usd	319	1	3.28	0.07	Volume_ l_usd does not Granger Cause Delegate	0.59	0.44

Note: This table reports the results for Granger tests based on Vector Autoregression (VAR) models. Column ‘df’ shows the optimal lag order. Using the optimal lag order, we run Granger tests for the hypotheses stemming from our empirical findings. For each test, both F-statistics and probability are presented.

Table A.11: Granger test results for DAI (linear interpolation)

PANEL A: Financial factors							
Null Hypothesis	**Obs.**	**df**	**F-stat.**	**Prob.**	**Null Hypothesis**	**F-stat.**	**Prob.**
Voters does not Granger Cause Volume	703	7	0.20	0.99	Volume does not Granger Cause Voters	1.64	0.12
Voters does not Granger Cause Volume_l	704	6	0.24	0.97	Volume_l does not Granger Cause Voters	1.63	0.14
PANEL B: Network							
Null Hypothesis	**Obs.**	**df**	**F-stat.**	**Prob.**	**Null Hypothesis**	**F-stat.**	**Prob.**
Voters does not Granger Cause ∆ New	704	6	1.07	0.38	∆ New does not Granger Cause Voters	0.98	0.44
Gini does not Granger Cause ∆ActiveRatio	695	15	0.23	1.00	∆ActiveRatio does not Granger Cause Gini	0.36	0.99

Note: This table reports the results for Granger tests based on Vector Autoregression (VAR) models. Column 'df' shows the optimal lag order. Using the optimal lag order, we run Granger tests for the hypotheses stemming from our empirical findings. For each test, both F-statistics and probability are presented.

Table A.12: Granger test results for DAI (measurements related to MKR distribution)

PANEL A: Financial factors							
Null Hypothesis	**Obs.**	**df**	**F-stat.**	**Prob.**	**Null Hypothesis**	**F-stat.**	**Prob.**
10k-100k does not Granger Cause ∆MktC	706	4	3.97	0.00	∆MktC does not Granger Cause 10k-100k	0.22	0.93
10k-100k does not Granger Cause Volume	706	4	3.96	0.00	Volume does not Granger Cause 10k-100k	0.22	0.93
10k-100k does not Granger Cause Volume_l	706	4	3.74	0.01	Volume_l does not Granger Cause 10k-100k	0.22	0.93
10k-100k does not Granger Cause Volume_l_usd	706	4	3.71	0.01	Volume_l_usd does not Granger Cause 10k-100k	0.22	0.93
>100k does not Granger Cause ∆MktC	706	4	4.60	0.00	∆MktC does not Granger Cause >100k	0.65	0.63
>100k does not Granger Cause Volume	709	1	65.58	0.00	Volume does not Granger Cause >100k	0.00	1.00
>100k does not Granger Cause Volume_l	709	1	60.72	0.00	Volume_l does not Granger Cause >100k	0.00	0.99

>100k does not Granger Cause Volume_ l_usd	709	1	59.98	0.00	Volume_l_usd does not Granger Cause >100k	0.00	0.99
Delegate does not Granger Cause ΔVolume_dex	315	5	0.57	0.72	ΔVolume_dex does not Granger Cause Delegate	0.53	0.75
Delegate does not Granger Cause ΔVolume_dex_usd	315	5	0.57	0.72	ΔVolume_dex_usd does not Granger Cause Delegate	0.53	0.75

Note: This table reports the results for Granger tests based on Vector Autoregression (VAR) models. Column 'df' shows the optimal lag order. Using the optimal lag order, we run Granger tests for the hypotheses stemming from our empirical findings. For each test, both F-statistics and probability are presented.

Table A.13: Granger test results for collateral ratios

Null Hypothesis	Obs.	df	F-stat.	Prob.	Null Hypothesis	F-stat.	Prob.
10k-100k does not Granger Cause Δ ETH_ratio	700	4	2.80	0.03	Δ ETH_ratio does not Granger Cause 10-100k	0.74	0.57
10k-100k does not Granger Cause Δ Stablecoin_ratio	700	4	1.95	0.10	Δ Stablecoin_ratio does not Granger Cause 10-100k	1.53	0.19
>100k does not Granger Cause Δ ETH_ratio	698	6	3.52	0.00	Δ ETH_ratio does not Granger Cause >100k	1.09	0.36
>100k does not Granger Cause Δ Stablecoin_ratio	698	6	2.79	0.01	Δ Stablecoin_ratio does not Granger Cause >100k	1.90	0.08
Delegate does not Granger Cause Δ ETH_ratio	319	1	4.94	0.03	Δ ETH_ratio does not Granger Cause Delegate	0.65	0.42
Delegate does not Granger Cause Δ Stablecoin_ratio	319	1	4.31	0.04	Δ Stablecoin_ratio does not Granger Cause Delegate	1.12	0.29

Note: This table reports the results for Granger tests based on Vector Autoregression (VAR) models. Column 'df' shows the optimal lag order. Using the optimal lag order, we run Granger tests for the hypotheses stemming from our empirical findings. For each test, both F-statistics and probability are presented.

A.4 Additional results: other Maker protocol-specific factors

We further discuss some other factors specific to Maker protocol, but the results are not immune from endogeneity problem. The findings are summarized across the following tables for readers' information.

Table A.14: Definitions of factors (MKR, DAI)

	Description
Price	Daily price (USD)
Positive	The number of tweets that are related to a given token have a positive connotation.
AvgSize	Total value of transactions (in tokens) divided by the number of transactions
AvgSize_usd	Total value of transactions (in USD) divided by the number of transactions
Txncnt	The number of valid transactions of tokens within a day
Volume_usd	Total amount (in USD) of tokens transferred on Ethereum blockchain within a day
Volume_ex	Sum of the amount (in tokens) entering an exchange plus the amount (in tokens) leaving an exchange
Volume_ex_usd	Sum of the amount (in USD) entering an exchange plus the amount (in USD) leaving an exchange
ETH_ratio	The value (in USD) of ETH locked as collateral divided by the total value (in USD) of locked collateral in Maker protocol
Stablecoin_ratio	The value (in USD) of stablecoins locked as collateral divided by the total value (in USD) of locked collateral in Maker protocol

Note: *ETH_ratio*, *Stablecoin_ratio*, *Volume_dex* and *volume_dex_usd* are queried on *dune.xyz*. Other factors are provided by *intotheblock.com*.

Table A.15: Additional results (MKR, DAI)

PANEL A: MKR					
	Voters	Gini	**10k-100k**	**>100k**	**Delegate**
AvgSizeMkr	0.05	-0.03	0.01	**-0.02****	-0.02
	(0.44)	(-0.92)	(1.45)	**(-2.02)**	(-0.69)
AvgSize_usd	0.11	-0.02	**0.04*****	**-0.05*****	0.03
	(1.40)	(-0.77)	**(6.06)**	**(-10.18)**	(1.32)
TxnCnt	**0.10*****	-0.01	**0.16*****	**-0.11*****	-0.06
	(2.58)	(-0.60)	**(11.14)**	**(-9.65)**	(-1.28)
Volume_ex	0.05	0.00	**0.10*****	**-0.08*****	0.03
	(1.39)	(-0.18)	**(7.71)**	**(-8.95)**	(0.82)
Volume_ex_usd	**0.03****	0.00	**0.08*****	**-0.08*****	**0.12*****
	(2.18)	(-0.17)	**(8.91)**	**(-12.76)**	**(4.16)**
Volume_usd	0.01	0.00	**0.11*****	**-0.12*****	**0.13*****
	(0.79)	(0.47)	**(9.19)**	**(-13.03)**	**(3.20)**

	Voters	Gini	10k-100k	>100k	Delegate
∆ Positive	-0.01	0.01	0.00	0.00	-0.02
	(-0.31)	(0.65)	(0.22)	(-0.04)	(-0.92)
PANEL B: DAI					
	Voters	Gini	**10k-100k**	**>100k**	**Delegate**
AvgSizeDai	0.02	0.00	0.01	**-0.02****	-0.02
	(1.60)	(0.59)	(1.45)	**(-2.02)**	(-0.69)
AvgSize_usd	0.02	0.00	**0.04*****	**-0.05*****	0.03
	(1.58)	(0.62)	**(6.06)**	**(-10.18)**	(1.32)
TxnCnt	0.09	0.01	**0.16*****	**-0.11*****	-0.06
	(1.47)	(0.34)	**(11.14)**	**(-9.65)**	(-1.28)
Volume_ex	0.02	0.04	**0.10*****	**-0.08*****	0.03
	(0.23)	(0.92)	**(7.71)**	**(-8.95)**	(0.82)
Volume_ex_usd	0.01	0.04	**0.08*****	**-0.08*****	**0.12*****
	(0.22)	(0.92)	**(8.91)**	**(-12.76)**	**(4.16)**
Price	**-0.02****	0.01	**-0.11*****	**0.09*****	0.00
	(-2.20)	(1.13)	**(-9.41)**	**(10.23)**	(-0.28)
Volume_usd	**0.02***	0.01	**0.05*****	**-0.05*****	0.03
	(1.68)	(0.83)	**(6.68)**	**(-9.75)**	(1.49)
∆ Positive	**0.07*****	-0.01	0.00	0.00	-0.01
	(2.99)	(-0.47)	(0.31)	(-0.10)	(-0.82)

Note: This table reports the univariate regression coefficients and standard t-statistics in parentheses for the factors of MKR (Panel A) and DAI (Panel B). *, ** and *** denote significance levels at the 10%, 5% and 1% levels, respectively. The definitions of the factors are given in Table A.14.

A.5 Summary of significant patterns across MKR and DAI univariate regression

This study brings forward several empirical findings from numerous univariate regressions and factors for MKR and DAI. For that reason, we also summarize these findings across the following tables.

Table A.16: Financial factors, network factors and twitter sentiment factors (MKR, DAI)

Panel A: Financial factors		
Measurements	MKR factors	DAI factors
Voters		Volume ↑ Volume_l ↑ Volume_l_usd ↑
10k-100k	Volume ↑ Volume_l ↑ Volume_l_usd ↑ Volume_dex ↑ Volume_dex_usd ↑	∆ MktC ↑ Volume ↑ Volume_l ↑ Volume_l_usd ↑ ∆ Volume_dex ↑ ∆ Volume_dex_usd ↑

>100k	Volume ↓ Volume_l ↓ Volume_l_usd ↓ Volume_dex ↓ Volume_dex_usd ↓	∆ MktC ↓ Volume ↓ Volume_l ↓ Volume_l_usd ↓ ∆ Volume_dex ↓ ∆ Volume_dex_usd ↓
Delegate	Volume_l_usd ↑ Volume_dex_usd ↑	∆ Volume_dex_usd ↑
Panel B: Network factors		
Measurements	MKR factors	DAI factors
Voters		∆ New ↓
Gini	∆ ActiveRatio ↑	∆ ActiveRatio ↑

Note: This table reports the relationship between measurements of centralized voting power and the factors of MKR and DAI. These are identified in tables A.5 – A.7. For example, the second column and first row report Price ↓ , which means that the increase of *Voters* leads to a significant decrease in the price of DAI.

Table A.17: Collateral ratios

Measurements	**Collateral ratios**
10k-100k	∆ ETH_ratio ↑ ∆ Stablecoin_ratio ↓
>100k	∆ ETH_ratio ↓ ∆ Stablecoin_ratio ↑
Delegate	∆ ETH_ratio ↓ ∆ Stablecoin_ratio ↑

Note: This table reports the relationship between measurements of centralized voting power and the collateral ratios. These are identified in Table A.8. For example, the second column and first row report ∆ ETH_ratio ↑ , which means that the increase of *Voters* leads to a significant increase in ∆ ETH_ratio.

A.6 Addressing endogeneity: Off-chain governance as an instrumental variable (MKR and DAI)

Table A.18 shows the descriptive statistics of the instrumental variable along with the correlation between off-chain governance and the measurements of centralized governance.

Table A.18: Correlations and descriptive statistics of the instrumental variable

Correlations	**Voters**	Gini	**10k-100k**	>100k	Delegate
Off-chain voters	**3.72***	1.96	**0.26***	-0.12	-0.12
	(0.06)	(0.16)	**(0.09)**	(0.46)	(0.44)
Descriptive Statistics	**Mean**	**Median**	**Maximum**	**Minimum**	**Std**
Off-chain voters	55.80	36.00	393	0	72.17

Note: This table presents correlation between the number of off-chain voters and measurements of centralized governance in Maker. P-values are presented in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. *Voters* and *10k-100k* have significant correlations with the daily off-chain voters.

A main concern about the choice of IV is endogeneity. Our expectation in our analysis is that 'off-chain voter' is not affected by factors specific to Maker protocol. To this end, we use both the IV and a lagged term of Maker protocol-specific factors as independent variables and keep the corresponding Maker protocol-specific factors as dependent variables. Two Ethereum factors are also included to exclude the influences that the market performance of Ethereum blockchain ecosystem could have on DAO. We estimate the regression below:

$$factor_{i,t} = \beta_0 + \beta_1 off - chain_t + \beta_2 factor_{i,t-d} + \beta_3 ETH\ return_t \\ + \beta_4 ETH\ volume\ usd_t + \varepsilon_t (A.1)$$

where:

- $i = \{MKR, DAI\}$
- $d = 7\ days$

Given i, factors can be defined as a set:

$$factor_{i,t} = \{financial_{i,j,t},, network_{i,k,t}, collateral_{i,l,t}\}$$

where $j = 1, ..., 6$, $k = 1$, and $l = 2$.

The following tables summarize the results, which are consistent with our findings in section 2.4 of the manuscript.

Table A.19: Financial factors (MKR, DAI)

PANEL A: MKR					
	Volume	Volume_dex	Volume_dex_usd	Volume_l	Volume_l_usd
Off-chain	-0.03	0.04	0.00	-0.05	-0.05
	(-0.38)	(0.80)	(-0.02)	(-0.50)	(-0.94)
$\boldsymbol{factor_{t-7}}$	0.13	0.07	0.02	0.09	-0.07
	(1.37)	(0.84)	(0.23)	(0.90)	(-0.79)
∆ ETH	**-0.20***	**-0.24*****	**-0.12****	-0.16	-0.05
	(-1.94)	**(-4.50)**	**(-2.40)**	(-1.37)	(-0.94)
ETH volume usd	**0.14***	**0.17*****	**0.33*****	**0.18****	**0.44*****
	(1.80)	**(4.02)**	**(7.14)**	**(2.20)**	**(8.24)**

PANEL B: DAI						
	∆ MktC	Volume	∆ Volume_dex	∆ Volume_dex_usd	Volume_l	Volume_l_usd
Off-chain	0.08	0.01	-0.03	-0.03	0.00	0.00
	(1.63)	(0.17)	(-0.52)	(-0.51)	(0.07)	(0.07)
$\boldsymbol{factor_{t-7}}$	-0.06	0.12	0.14	0.14	0.13	0.13
	(-0.60)	(1.34)	(1.11)	(1.13)	(1.39)	(1.39)
∆ ETH	**0.22*****	**-0.11***	0.00	0.00	**-0.11***	-0.11
	(3.85)	**(-1.78)**	(-0.07)	(-0.07)	**(-1.64)**	(-1.61)
ETH volume usd	0.00	**0.39*****	0.02	0.02	**0.39*****	**0.40*****
	(0.05)	**(6.37)**	(0.52)	(0.51)	**(6.18)**	**(6.19)**

Note: This table reports the results for examining endogeneity of the IV. We include the lagged term of the dependent variable in the regression models. Both the coefficients and standard t-statistics in parentheses for the financial factors of MKR (Panel A) and DAI (Panel B) are presented. *, ** and *** denote significance levels at the 10%, 5% and 1% levels, respectively. The definitions of the factors are given in Table A.5.

Table A.20: Network factors (DAI)

	∆ New
Off-chain	-0.08
	(-1.06)
$\boldsymbol{factor_{t-7}}$	0.01
	(0.15)
∆ ETH	-0.07
	(-0.86)
ETH volume usd	**-0.18*****
	(-3.01)

Note: This table reports the results for examining endogeneity of the IV. We include the lagged term of dependent variable in the regression models. Both the coefficients and standard t-statistics in parentheses for the network factors of MKR (Panel A) and DAI (Panel B) are presented. *, ** and *** denote significance levels at the 10%, 5% and 1% levels, respectively. The definitions of the factors are given in Table A.6.

Table A.21: Collateral ratios

	∆ETH_ratio	∆Stablecoin_ratio
Off-chain	-0.04	0.05
	(-0.79)	(0.95)
$\boldsymbol{factor_{t-7}}$	0.15	0.08
	(1.46)	(0.66)
∆ ETH	**0.19*****	**-0.17*****
	(3.40)	**(-3.07)**
ETH volume usd	-0.02	0.04
	(-0.56)	(0.84)

Note: This table reports the results for examining endogeneity of the IV. We include the lagged term of dependent variables in the regression models. Both the coefficients and standard t-statistics in parentheses for collateral ratios are presented. *, ** and *** denote significance levels at the 10%, 5% and 1% levels, respectively. The definitions of the factors are given in Table A.8.

Table A.22: 2-SLS IV regressions (financial factors – DAI)

Panel A: Estimate *Voters* using an instrument

	(1)	(2) Volume	(3) Volume_l	(4) Volume_l_usd
Off-chain	0.15* (3.58)			
Voters		0.91 (1.46)	0.87 (1.40)	0.88 (1.39)
Durbin-Wu-Hausman test		2.72	2.34	2.31
p-value		0.10	0.13	0.13
Adj. R-sq		-1.04	-0.90	-0.89
N		111	111	111

Panel B: Estimate *10k-100k* using an instrument

	(1)	(2) Δ MktC	(3) Volume	(4) Δ Volume_dex	(5) Δ Volume_dex_usd	(6) Volume_l	(7) Volume_l_usd
Off-chain	0.25* (3.51)						
10k-100k		0.20 (1.04)	0.56* (1.72)	-0.08 (-0.54)	-0.08 (-0.53)	0.54* (1.63)	0.54 (1.61)
Durbin-Wu-Hausman test		1.18	1.64	0.16	0.15	1.41	1.40
p-value		0.28	0.20	0.69	0.70	0.24	0.24
Adj. R-sq		-0.29	-0.25	-0.05	-0.05	-0.22	-0.22
N		111	111	111	111	111	111

Note: This table reports results of the 2-SLS IV regressions. Panel A, Column (1) reports the results of the following first stage regression: $Voters_t = \beta_0 + \beta_1 off-chain_t + \varepsilon_t$, where $off-chain$ is an instrumental variable. Columns (2)-(4) reports the results of second stage: $factor_t = \beta_0 + \beta_1 \widehat{Voters}_t + \varepsilon_t$. In Column (1), partial F-statistics are reported in parentheses. In Columns (2) – (7), t-statistics are reported in parentheses. Panel B, Column (1) reports the results of the following first stage regression: $10k - 100k_t = \beta_0 + \beta_1 off - chain_t + \varepsilon_t$, where $off - chain$ is an instrumental variable. Columns (2)-(7) reports the results of second stage: $factor_t = \beta_0 + \beta_1\, 10k \widehat{-} 100k_t + \varepsilon_t$. In Column (1), partial F-statistics are reported in parentheses. In Columns (2) – (7), t-statistics are reported in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

Table A.23: 2-SLS IV regressions (network factors and Twitter sentiment factors – DAI)

Panel A: Estimate *Voters* using an instrument

	(1)	(2) Δ New
Off-chain	0.15* (3.58)	
Voters		-0.79 (-1.22)
Durbin-Wu-Hausman test		1.83
p-value		0.18
Adj. R-sq		-0.69
N		111

Note: This table reports results of the 2-SLS IV regressions. Panel A, Column (1) reports the results of the following first stage regression: $Voters_t = \beta_0 + \beta_1 off - chain_t + \varepsilon_t$, where $off - chain$ is an instrumental variable. Columns (2) reports the results of second stage: $factor_t = \beta_0 + \beta_1 \widehat{Voters}_t + \varepsilon_t$. In Column (1), partial F-statistics are reported in parentheses. In Column (2), t-statistics are reported in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

Table A.24: 2-SLS IV regressions (collateral ratios)

Panel A: Estimate *10k-100k* using an instrument			
	(1)	(2) ∆ ETH_ratio	(3) ∆ Stablecoin_ratio
Off-chain	0.26* (3.34)		
10k-100k		-0.38 (-1.19)	0.38 (1.19)
Durbin-Wu-Hausman test		4.14	3.24
p-value		0.04	0.07
Adj. R-sq		-1.15	-1.09
N		91	91

Note: This table reports results of the 2-SLS IV regressions. Panel A, Column (1) reports the results of the following first stage regression: $10k - 100k_t = \beta_0 + \beta_1 off - chain_t + \varepsilon_t$, where $off - chain$ is an instrumental variable. Columns (2) and (3) reports the results of second stage: $Collateral_t = \beta_0 + \beta_1\ 10k \widehat{-100}k_t + \varepsilon_t$. In Column (1), partial F-statistics are reported in parentheses. In Columns (2) and (3), t-statistics are reported in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

A.7 Regression discontinuity

Following the methodology employed by Makridis et al. (2023), we use the KuCoin hack as an exogenous shock and construct a dummy variable labeled 'shock.' This 'shock' variable takes on a value of 1 during the period spanning from September 14, 2020, to January 11, 2021, encompassing Poll 287 (deployed on September 14, 2020) to Poll 412 (deployed on January 11, 2021). The results of these analyses are summarized in the following tables.

Table A.25: Financial factors (September 14, 2020 – January 11, 2021)

PANEL A: MKR						
		Voters	Gini	**10k-100k**	**>100k**	**Delegate**
Return	β_1	-0.02 (-1.00)	0.01 (1.30)	0.01 (1.06)	-0.01 (-1.03)	0.00 (-0.16)
	β_2	0.00 (0.27)	0.00 (0.31)	0.01 (0.95)	0.01 (1.07)	**0.02*** **(1.63)**
∆ MktC	β_1	-0.01	0.00	0.00	0.00	-0.01

		(-1.30)	(-0.16)	(1.10)	(-1.45)	(-0.40)
	β_2	0.00	0.00	0.00	0.00	0.00
		(0.41)	(0.18)	(-0.10)	(0.01)	(0.02)
Volume	β_1	0.00	0.02	**0.08*** **	**-0.07*** **	0.03
		(-0.11)	(0.84)	**(5.73)**	**(-6.21)**	(0.64)
	β_2	**0.07*** **	**0.07*** **	**0.04*** **	**0.05*** **	**0.09*** **
		(3.14)	**(3.28)**	**(4.00)**	**(4.65)**	**(4.66)**
Volume_dex	β_1	0.00	0.02	**0.11*** **	**-0.10*** **	0.08
		(0.07)	(0.67)	**(6.96)**	**(-8.36)**	(1.50)
	β_2	**0.05* **	**0.05** **	**0.04*** **	**0.05*** **	**0.10*** **
		(1.90)	**(2.02)**	**(3.81)**	**(4.59)**	**(3.69)**
Volume_dex_usd	β_1	0.03	0.01	**0.12*** **	**-0.13*** **	**0.16*** **
		(0.72)	(0.32)	**(9.44)**	**(-13.23)**	**(3.18)**
	β_2	-0.01	**-0.01**	**-0.03*** **	**-0.02*** **	-0.02
		(-0.45)	**(-0.28)**	**(-3.32)**	**(-2.63)**	(-0.69)
Volume_l	β_1	0.00	0.02	**0.10*** **	**-0.09*** **	0.03
		(-0.01)	(0.81)	**(5.92)**	**(-6.62)**	(0.66)
	β_2	**0.07*** **	**0.07*** **	**0.04*** **	**0.04*** **	**0.08*** **
		(2.94)	**(3.08)**	**(3.18)**	**(3.83)**	**(3.61)**
Volume_l_usd	β_1	0.01	0.01	**0.09*** **	**-0.10*** **	**0.10** **
		(0.65)	(0.83)	**(8.37)**	**(-11.64)**	**(2.31)**
	β_2	0.00	0.00	**-0.02*** **	**-0.02*** **	-0.02
		(0.01)	(0.24)	**(-3.19)**	**(-2.57)**	(-1.01)
PANEL B: DAI						
		Voters	Gini	**10k-100k**	**>100k**	Delegate
Δ Return	β_1	0.00	0.00	0.00	0.00	0.00
		(0.31)	(-0.02)	(0.53)	(-0.38)	(0.02)
	β_2	0.00	0.00	0.00	0.00	0.00
		(0.06)	(0.10)	(-0.29)	(-0.23)	(0.14)
Δ MktC	β_1	0.00	0.00	**0.03*** **	**-0.04*** **	-0.02
		(-0.05)	(-0.04)	**(3.42)**	**(-4.84)**	(-0.45)
	β_2	0.01	0.01	-0.01	0.00	-0.02
		(0.33)	(0.31)	(-1.16)	(-0.67)	(-1.26)
Volume	β_1	**0.02* **	0.01	**0.05*** **	**-0.05*** **	0.02
		(1.66)	(0.88)	**(6.55)**	**(-9.05)**	(0.74)
	β_2	0.00	0.00	**-0.01* **	0.00	-0.02
		(0.11)	(0.46)	**(-1.88)**	(-0.99)	(-1.41)
Δ Volume_dex	β_1	0.01	0.02	0.00	0.00	**0.04*** **
		(0.42)	(0.78)	(0.04)	(0.01)	**(2.72)**
	β_2	0.02	0.02	0.00	0.00	0.00
		(1.08)	(1.25)	(0.11)	(0.11)	(-0.57)
Δ Volume_dex_usd	β_1	0.01	0.02	0.00	0.00	**0.04*** **
		(0.42)	(0.78)	(0.04)	(0.01)	**(2.73)**
	β_2	0.02	0.02	0.00	0.00	0.00
		(1.08)	(1.24)	(0.11)	(0.11)	(-0.57)
Volume_l	β_1	**0.02* **	0.01	**0.04*** **	**-0.05*** **	0.02
		(1.68)	(0.85)	**(6.15)**	**(-8.58)**	(0.71)
	β_2	0.00	0.00	**-0.01* **	0.00	-0.02
		(0.11)	(0.46)	**(-1.90)**	(-1.06)	(-1.50)
Volume_l_usd	β_1	**0.02* **	0.01	**0.04*** **	**-0.05*** **	0.02
		(1.67)	(0.86)	**(6.11)**	**(-8.53)**	(0.71)
	β_2	0.00	0.00	**-0.01* **	0.00	-0.02
		(0.13)	(0.48)	**(-1.87)**	(-1.03)	(-1.50)

Note: This table reports the results for regression (13), including regression coefficients and standard t-statistics in parentheses for the financial factors of MKR (Panel A) and DAI (Panel B). *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. The definitions of the factors are given in Table A.5.

Table A.26: Network factors (September 14, 2020 – January 11, 2021)

		Voters	Gini	10k-100k	>100k	Delegate
PANEL A: MKR						
Δ TotalWithBlc	β_1	0.00	0.00	0.00	0.00	0.01
		(0.05)	(0.23)	(0.09)	(-0.15)	(0.66)
	β_2	**-0.02***	**-0.02***	0.00	0.00	0.00
		(-1.73)	**(-1.69)**	(0.23)	(0.24)	(0.34)
Δ New	β_1	-0.01	0.01	0.00	0.00	0.01
		(-0.28)	(0.68)	(-0.09)	(0.06)	(0.49)
	β_2	**-0.04****	**-0.04****	0.00	0.00	0.01
		(-2.10)	**(-2.04)**	(0.63)	(0.63)	(0.54)
Δ Active	β_1	0.00	0.01	0.00	0.00	0.02
		(0.01)	(0.69)	(-0.01)	(-0.05)	(0.70)
	β_2	**-0.03****	**-0.03****	0.00	0.00	0.01
		(-2.30)	**(-2.21)**	(0.47)	(0.48)	(0.63)
Δ ActiveRatio	β_1	-0.01	0.02	0.00	0.00	0.01
		(-0.21)	(1.49)	(-0.04)	(0.07)	(0.38)
	β_2	**-0.03***	**-0.03***	0.00	0.00	0.00
		(-1.90)	**(-1.73)**	(0.32)	(0.32)	(0.57)
PANEL B: DAI						
		Voters	**Gini**	10k-100k	>100k	Delegate
Δ TotalWithBlc	β_1	0.00	-0.01	0.00	0.00	0.00
		(-0.15)	(-0.54)	(0.11)	(0.05)	(0.07)
	β_2	**-0.05*****	**-0.05*****	0.00	0.00	0.01
		(-2.64)	**(-2.73)**	(0.21)	(0.23)	(0.41)
Δ New	β_1	**-0.07***	-0.01	0.00	0.00	0.01
		(-1.76)	(-0.24)	(-0.19)	(0.24)	(0.24)
	β_2	-0.03	**-0.04***	0.01	0.00	0.02
		(-1.40)	**(-1.67)**	(0.52)	(0.49)	(1.01)
Δ Active	β_1	-0.03	-0.03	0.00	0.00	0.01
		(-0.76)	(-1.38)	(-0.15)	(0.29)	(0.15)
	β_2	**-0.06****	**-0.06*****	0.01	0.00	0.02
		(-2.45)	**(-2.76)**	(0.54)	(0.52)	(0.90)
Δ ActiveRatio	β_1	-0.03	**0.04****	0.00	0.00	0.00
		(-0.75)	**(2.15)**	(-0.14)	(0.14)	(0.38)
	β_2	-0.01	-0.01	0.00	0.00	0.00
		(-0.52)	(-0.39)	(0.02)	(0.00)	(1.03)

Note: This table reports the results for regression (13), including regression coefficients and standard t-statistics in parentheses for the network factors of MKR (Panel A) and DAI (Panel B). *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. The definitions of the factors are given in Table A.6.

Table A.27: Twitter sentiment factors (September 14, 2020 – January 11, 2021)

PANEL A: MKR						
		Voters	Gini	10k-100k	>100k	Delegate
∆ Positive	β_1	-0.01 (0.18)	0.01 (0.43)	0.00 (0.31)	0.00 (-0.22)	-0.02 (-0.66)
	β_2	-0.02 (-1.16)	-0.02 (-1.13)	0.00 (-0.06)	0.00 (-0.02)	0.00 (-0.14)
∆ Neutral	β_1	0.00 (-0.14)	0.01 (0.86)	0.00 (0.06)	0.00 (-0.01)	0.00 (-0.16)
	β_2	-0.01 (-1.14)	-0.01 (-1.04)	0.00 (0.04)	0.00 (0.05)	0.00 (0.12)
∆ Negative	β_1	0.00 (-0.04)	0.00 (-0.08)	0.00 (0.09)	0.00 (-0.08)	0.00 (0.06)
	β_2	-0.01 (-0.52)	-0.01 (-0.54)	0.00 (0.01)	0.00 (0.02)	0.00 (0.12)
PANEL B: DAI						
		Voters	Gini	10k-100k	>100k	Delegate
∆ Positive	β_1	**0.07***** **(3.12)**	-5.23 (-0.55)	5.78 (0.31)	-1.26 (-0.10)	0.00 (-0.85)
	β_2	-0.01 (-1.05)	-0.01 (-0.65)	0.00 (-0.13)	0.00 (-0.08)	0.00 (-0.36)
∆ Neutral	β_1	0.02 (0.74)	-5.78 (-0.48)	5.77 (0.06)	1.35 (0.02)	0.00 (-0.01)
	β_2	0.00 (-0.34)	0.00 (-0.30)	0.00 (-0.46)	0.00 (-0.39)	-0.01 (-0.70)
∆ Negative	β_1	0.00 (0.28)	0.38 (0.27)	-0.23 (-0.09)	0.08 (0.05)	0.02 (0.01)
	β_2	-0.02 (-0.79)	-0.01 (-0.70)	0.00 (-0.08)	0.00 (-0.08)	0.00 (0.01)

Note: This table reports the results for regression (13), including regression coefficients and standard t-statistics in parentheses for the Twitter sentiment factors of MKR (Panel A) and DAI (Panel B). *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. The definitions of the factors are given in Table A.7.

To examine if the results for collateral ratios are affected by the KuCoin shock, we estimate the following regressions:

$$Collateral_t = \beta_0 + \beta_1 central_t + \beta_2 shock_t + \varepsilon_t (A.2)$$

where:

- $central_t = \{Voters_t, Gini_t, 10k - 100k_t, > 100k_t, Delegate_t\}$

Given i, factors can be defined as a set:

$$Collateral_t = \{\Delta ETH\ ratio_t,\ \Delta Stablecoin\ ratio_t\}$$

The results are summarized in the following table, and the findings are consistent with the results in section 2.4.2.

Table A.28: Collateral ratios (September 14, 2020 – January 11, 2021)

		Voters	Gini	**10k-100k**	**>100k**	**Delegate**
Δ ETH_ratio	β_1	0.03	-0.03	**0.02****	**-0.01***	**-0.03****
		(0.81)	(-1.32)	**(2.20)**	**(-1.68)**	**(-2.33)**
	β_2	-0.03	-0.03	-0.01	-0.01	0.01
		(-1.48)	(-1.53)	(-1.62)	(-1.34)	(0.97)
Δ Stablecoin_ratio	β_1	-0.02	0.02	**-0.02****	**0.01***	**0.04*****
		(-0.46)	(0.99)	**(-2.13)**	**(1.77)**	**(2.82)**
	β_2	0.03	0.03	**0.01***	0.01	0.00
		(1.22)	(1.27)	**(1.71)**	(1.43)	(-0.01)

Note: This table reports the results for the regression A.2, including both regression coefficients and standard t-statistics in parentheses for the collateral ratios in Maker protocol. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. The definitions of the factors are given in Table A.8.

A.8 'Risk parameter' governance polls

We observe that 'risk parameter' polls are the most common governance polls. Therefore, we re-estimate the same univariate regressions using a subset of Maker governance polls with the label 'risk parameter'. The findings are summarized across the following tables.

Table A.29: Financial factors (MKR, DAI)

PANEL A: MKR			**PANEL B: DAI**		
	Voters	**Gini**		**Voters**	**Gini**
Return	0.00	-0.01	**Δ Return**	0.00	**0.01*****
	(-0.14)	(-0.43)		(-0.37)	**(2.66)**
Δ MktC	-0.01	-0.01	**Δ MktC**	0.03	**-0.06***
	(-0.56)	(-1.05)		(0.94)	**(-1.82)**
Volume	**0.19*****	-0.02	Volume	0.02	0.01
	(4.51)	(-0.59)		(1.26)	(0.45)
Volume_dex	0.05	-0.05	**Δ Volume_dex**	**0.25*****	0.04
	(0.99)	(-1.28)		**(4.34)**	(0.61)
Volume_dex_usd	**0.05***	**-0.10*****	**Δ Volume_dex_usd**	**0.25*****	0.04
	(1.70)	**(-4.79)**		**(4.34)**	(0.60)
Volume_l	0.22	-0.03	Volume_l	0.02	0.01
	(4.47)	(-0.58)		(1.28)	(0.42)

Volume_l_usd	**0.05****	**-0.05*****	Volume_l_usd	0.03	0.01
	(2.23)	**(-2.90)**		(1.32)	(0.40)

Note: This table reports the univariate regression coefficients and standard t-statistics in parentheses for the financial factors of MKR (Panel A) and DAI (Panel B). *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. The definitions of the factors are given in Table A.5.

Table A.30: Network factors (MKR, DAI)

PANEL A: MKR			PANEL B: DAI		
	Voters	**Gini**		**Voters**	Gini
∆ TotalWithBlc	-0.03	0.01	**∆ TotalWithBlc**	**-0.10****	0.02
	(-1.53)	(0.83)		**(-2.45)**	(0.37)
∆ New	-0.04	**0.04****	∆ New	0.01	0.03
	(-1.18)	**(2.21)**		(0.18)	(0.43)
∆ Active	-0.04	**0.02***	∆ Active	-0.12	0.02
	(-1.48)	**(1.88)**		(-1.65)	(0.28)
∆ ActiveRatio	-0.02	-0.01	∆ ActiveRatio	-0.01	0.00
	(-0.30)	(-0.24)		(-0.99)	(-0.26)

Note: This table reports the univariate regression coefficients and standard t-statistics in parentheses for the network factors of MKR (Panel A) and DAI (Panel B). *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. The definitions of the factors are given in Table A.6.

Table A.31: Twitter sentiment factors (MKR, DAI) (Risk parameter)

PANEL A: MKR			PANEL B: DAI		
	Voters	**Gini**		Voters	Gini
∆ Positive	-0.03	0.00	∆ Positive	-0.01	-0.02
	(-1.01)	(-0.16)		(-0.47)	(-1.29)
∆ Neutral	0.00	**0.01***	∆ Neutral	0.00	0.00
	(0.20)	**(1.84)**		(-0.22)	(-0.19)
∆ Negative	0.07	**0.03***	∆ Negative	-0.03	-0.02
	(1.61)	**(1.84)**		(-0.91)	(-1.05)

Note: This table reports the univariate regression coefficients and standard t-statistics in parentheses for the Twitter sentiment factors of MKR (Panel A) and DAI (Panel B). *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. The definitions of the factors are given in Table A.7.

Table A.32: Collateral ratios (Risk parameter)

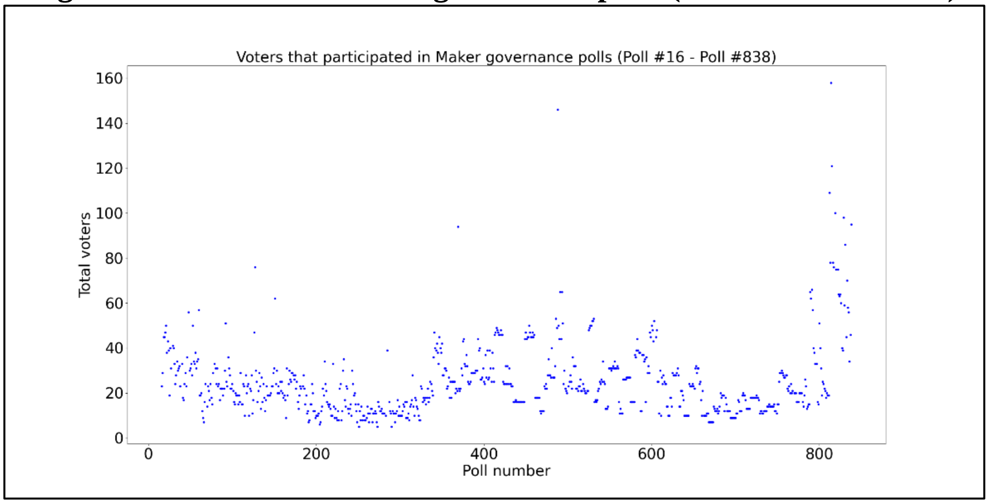
	Voters	Gini
∆ ETH_ratio	0.08	-0.49
	(1.10)	(-0.83)
∆ Stablecoin_ratio	-0.06	0.58
	(-0.88)	(0.99)

Note: This table reports the univariate regression coefficients and standard t-statistics in parentheses for the collateral ratios in Maker protocol. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. The definitions of the factors are given in Table A.8.

Appendix B (Chapter 4)

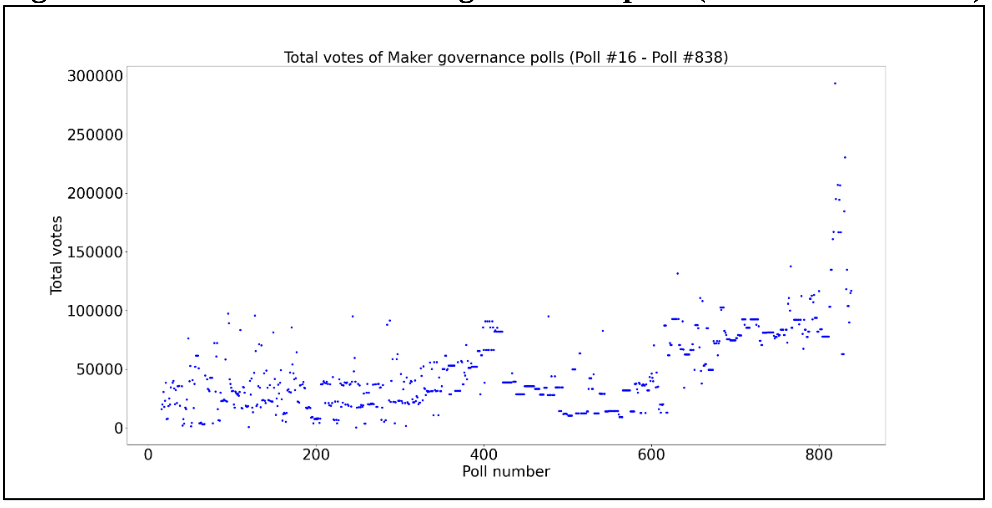
B.1 Details about Maker governance polls

Figure B.1 : Voters of Maker governance polls (Poll #16 – Poll #838)



Note: This figure shows the number of voters in Maker governance polls (Poll #16 – Poll #838). In most polls, the number of voters will not be more than 60.

Figure B.2: Total votes of Maker governance polls (Poll #16 – Poll #838)



Note: This figure illustrates the total votes in Maker governance polls (Poll #16 – Poll #838). Overall, we observe that the total votes are on the increase, while most polls attract less than 100,000 votes.

Table B.1: Labels of Maker governance polls

	Number of polls	Total voters	Total votes
Risk Parameter	297	6125	11620405.21
Ratification Poll	103	3180	9191601.36
Inclusion Poll	71	1514	2419753.25
Collateral Onboarding	63	1370	2864764.94
Collateral Offboarding	19	298	1381079.48
Greenlight	173	5549	7894197.78
Real World Asset	37	1051	2271616.02
Misc Governance	29	1108	1844854.05
Misc Funding	14	569	1480519.35
MakerDAO Open Market Committee	22	476	1294594.31
MIP	182	4800	11667401.86
Budget	61	1636	4511723.76
Oracle	42	761	1383196.90
System Surplus	10	263	721589.11
DAI Direct Deposit Module	10	215	820019.35
Multi-chain Bridge	5	126	385882.47
Technical	20	429	914487.67
Auction	23	421	715394.51
Delegates	5	53	338567.60
Peg Stability Module	14	252	643171.78
Core Unit Onboarding	29	899	1888838.96
Dai Savings Rate	28	662	959804.04
Black Thursday	4	172	265698.72
Multi-Collateral DAI Launch	5	165	192941.15
Prioritization Sentiment	2	55	54826.02

Note: There are several labels related to oracle. For convenience, we merge these labels into one category, namely ‘oracle’.

B.2 Known voters in coalition 1

Table B.2: Voters with known identities and MakerDAO delegates in coalition 1

Address	ENS name	Twitter	Delegate	Total votes	Involved polls
0xaf8aa6846539033eaf0c3ca4c9c7373e370e039b	Flip Flop Flap Delegate LLC	CruzerDefi	1	4555078.4	225
0xb21e535fb349e4ef0520318acfe589e174b0126b	schuppi	schuppi	1	2735238.67	228
0x845b36e1e4f41a361dd711bda8ea239bf191fe95	Feedblack Loops LLC		1	1928371.78	212
0xad2fda5f6ce305d2ced380fdfa791b6a26e7f281	Field Technologies, Inc.	ImperiumPaper	1	1271752.98	67
0x22d5294a23d49294bf11d9db8beda36e104ad9b3	MakerMan			1071135.69	217

0x45127ec92b58c3a89e89f63553073adcaf2f1f5f	monetsupply	monetsupply	1	943768.66	199
0x00daec2c2a6a3fcc66b02e38b7e56dcdfa9347a1			1	936786.68	45
0x4d3ac33ab1dd7b0f352b8e590fe8b62c4c39ead5	ACREinvest	ACREinvest	1	548753.02	130
0xb0b829a6aae0f7e59b43391b2c8a1cfd0c801c8c	gauntlet	gauntletnetwork	1	468000	102
0xcdb792c14391f7115ba77a7cd27f724fc9ea2091	JustinCase		1	463620.37	161
0x74971f1be0afd1bb820668abfe411d164f17b53c			1	403948	12
0xefcc3401739427eb0491cc27c7baa06817c7dfdb			1	394429.2	69
0xafaff1a605c373b43727136c995d21a7fcd08989	Hasu	hasufl	1	390896.15	43
0xf60d7a62c98f65480725255e831de531efe3fe14	GFX Labs	labsGFX	1	274272.97	159
0x8804d391472126da56b9a560aef6c6d5aaa7607b	Doo	DooWanNam	1	213828.87	98
0x05e793ce0c6027323ac150f6d45c2344d28b6019	a16z	a16z		156960	6
0x68b216e9fc96a7b98b5c0028ff72e4c39c5c5a61			1	136909	29
0x84b05b0a30b6ae620f393d1037f217e607ad1b96	Flipside Crypto	Flipsidecrypto	1	116384.68	77
0x2c3b917cceaf41503145ceb4b37c8623d862c4cd			1	102000	59
0x2c511d932c5a6fe4071262d49bfc018cfbaaa1f5	Chris Blec	ChrisBlec	1	91578.52	25
0x7ddb50a5b15aea7e7cf9ac8e55a7f9fd9d05ecc6	Penn Blockchain	PennBlockchain	1	73911.4	67
0xb8df77c3bd57761bd0c55d2f873d3aa89b3da8b7	Blockchain@Columbia	BlockchainatCU	1	22000	22
0x14a4ed2000ca405452c140e21c10b3536c1a98e4			1	15566.5	234
0xaa19f47e6acb02df88efa9f023f2a38412069902	mhonkasalo & teemulau	mhonkasalo;teemulau	1	8023.87	8023
0x4e314eba76c3062140ad196e4ffd34485e33c5f5	Governance House		1	7007	7
0xe84adc0964ee34ce0319df3418636ed6a4117b97	justneedtogetthroughthisweek.eth			6569.84	143
0x14341f81df14ca86e1420ec9e6abd343fb1c5bfc	tylersorensen.eth			6106.56	30
0x4f2fc90212e949ff4aa32def570744163671f22b	00x.eth	00x_eth		818.44	79
0x57db5d6aa783cf29af41330569d24957140fd3eb	dix-sept.eth			736.85	122
0xa7bc2dc8d3ea8ef85faf48d560fa56835abcea88	blockworm.eth			620	10

Note: This table provides detailed information about voters with known identities and MakerDAO delegates in coalition 1. ENS names are publicly available, and the column 'twitter' listed the twitter usernames if a voter is detected as a Twitter user. If a voter is a MakerDAO delegate, the value in column 'delegate' is 1. We find that some delegates do not disclose any public identities (i.e., ENS names and Twitter accounts).

B.3 Descriptive statistics of daily measurements

Table B.3: Descriptive statistics

	Voter coalition 1	Voter coalition 2
Mean	0.15	0.03
Median	0	0
Maximum	1.00	0.97
Minimum	0	0
Std	0.14	0.14
	Voter coalition 1	Voter coalition 2
Mean	0.80	0.91
Median	0.84	0.95
Maximum	1	1
Minimum	0.36	0.54
Std	0.19	0.12

Note: This table summarizes the descriptive statistics of voting shares and Agreement Index (AI) for three voter coalitions in MakerDAO, using the dataset for governance polls from Poll 413 to Poll 838. The statistics related to voter coalition 3 are zero, because we do not find voters in coalition 3 participated in Poll 413 – Poll 838.

B.4 Definitions of variables related to Maker protocol

Table B.4: Definitions of variables

	Definitions
ΔETH	The changes of value of Ether (ETH) locked in Maker protocol as collateral
ΔRWA	The changes of value of Real World Asset (RWA) locked in Maker protocol as collateral
Dai volume	Transaction volume (in USD) of DAI daily
Mkr return	Daily return of Maker (MKR), which is the governance token in Maker protocol
Eth return	Daily return of Ether (ETH), which is the native cryptocurrency in Ethereum blockchain
Eth v30	30-day volatility of Ether (ETH)
Eth v60	60-day volatility of Ether (ETH)
BTC	The price of Bitcoin (BTC)
UNI	The price of Uniswap (UNI), which is the governance token in Uniswap protocol
CRV	The price of Curve DAO token (CRV), which is the governance token in Curve finance protocol
DeFi pulse	The DeFi Pulse Index (DPI) is a capitalization-weighted index that tracks the performance of some of the largest protocols in the decentralized finance (DeFi) space.

Note: This table presents definitions of explanatory variables in the regression models.

Table B.5: Calculation of variables

	Definitions
Dai v30	Annualized 30-day price volatility of Dai (DAI) using 365 days.
Δ revenue	Assuming that $token_i, i = \{1, \ldots, n\}$, are locked in Maker protocol for lending, the variable 'daily revenue' can be calculated as $$\sum_{i=1}^{n} revenue_i$$ Where $revenue_i$ is the value in USD of revenue earned by the locked $token_i$. Subsequently, the growth of daily revenue on day t can be calculated as $$\Delta revenue_t = revenue_t - revenue_{t-1}$$
ΔETH	Assuming that ETH_t is the USD value of Ether (ETH) locked in Maker protocol for lending, the variable 'Δ ETH' can be calculated as $$\Delta ETH_t = ETH_t - ETH_{t-1}$$
ΔRWA	Assuming that RWA_t is the USD value of Real World Assets (RWAs) locked in Maker protocol for lending, the variable 'Δ RWA' can be calculated as $$\Delta RWA_t = RWA_t - RWA_{t-1}$$
Mkr return	Assuming that the closing price of MKR on day t is P_t, the daily returns can be defined by $$V_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$$
ETH return	Assuming that the closing price of ETH on day t is P_t, the daily return can be defined by $$V_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$$
ETH v30	Annualized 30-day price volatility of Ether (ETH) using 365 days.
ETH v60	Annualized 60-day price volatility of Ether (ETH) using 365 days.

Note: This table describes how to calculate variables included in the regression models.

Appendix C (Chapter 5)

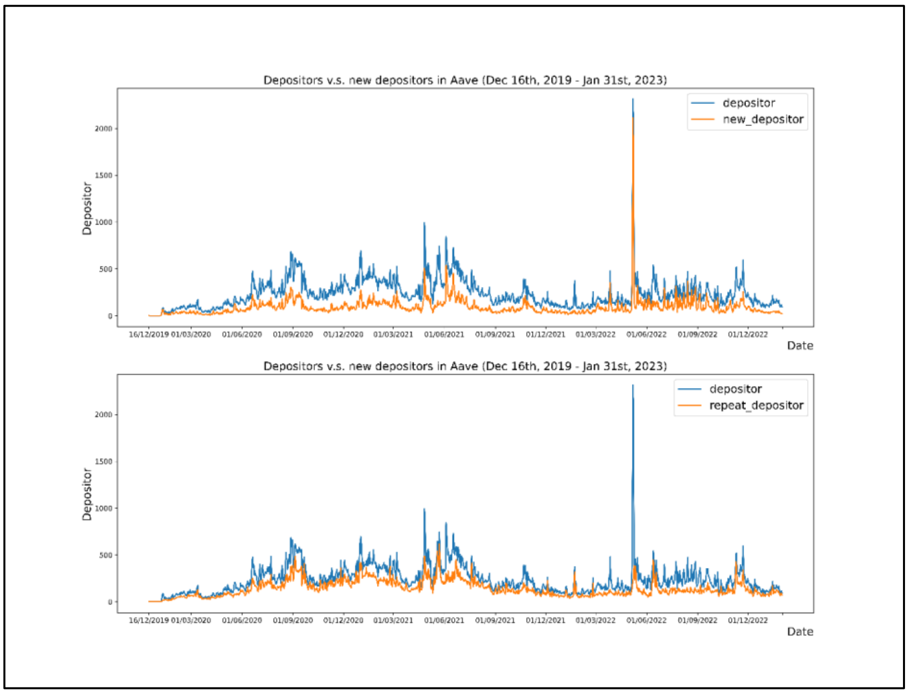
C.1 Details about loans and deposits in Aave

Table C.1: Variables related to loans and deposits in Aave

Panel A: Loan details	
Variable	**Description**
Borrower	The number of borrowers daily
Loan vol usd	Daily volume (in USD) of Aave loans
Loan cnt	The count of Aave loans daily
New borrower	The number of new borrowers daily
New loan vol usd	Daily volume (in USD) of Aave loans initiated by new borrowers
New loan cnt	The count of Aave loans initiated by new borrowers daily
Avg loan usd	Daily volume (in USD) of Aave loans divided by the count of Aave loans daily
Outstanding loan	The value (in USD) of outstanding loans in Aave
Liquidation usd	The value (in USD) of collateral liquidated daily in Aave
Repeat borrower	The number of borrowers daily minus the number of new borrowers daily
Repeat loan vol usd	Daily volume (in USD) of Aave loans initiated by repeat borrowers
Repeat loan cnt	The count of Aave loans initiated by repeat borrowers daily
Panel B: Deposit details	
Variable	**Description**
Depositor	The number of depositors daily
Deposit vol usd	Daily volume (in USD) of Aave deposits
Deposit cnt	The count of Aave deposits daily
New depositor	The number of new depositors daily
New deposit vol usd	Daily volume (in USD) of Aave deposits from new depositors
New deposit cnt	The count of Aave deposits from new depositors daily
Avg deposit usd	Daily volume (in USD) of Aave deposits divided by the count of Aave deposits daily
Outstanding deposit	The value (in USD) of outstanding deposits in Aave
Repeat depositor	The number of depositors daily minus the number of new depositors daily
Repeat deposit vol usd	Daily volume (in USD) of Aave deposits from repeat depositors
Repeat deposit cnt	The count of Aave deposits from repeat depositors daily

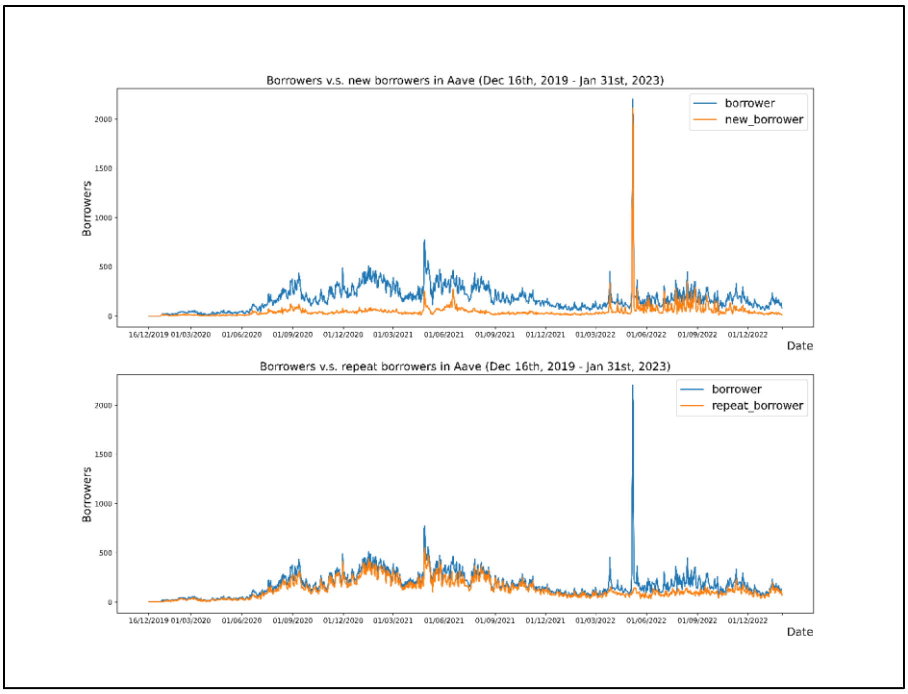
Note: This table introduces the variables related to details of loans and deposits in Aave protocol.

Figure C.1: Depositors in Aave protocol (Dec 16, 2019 – Jan 31, 2023)



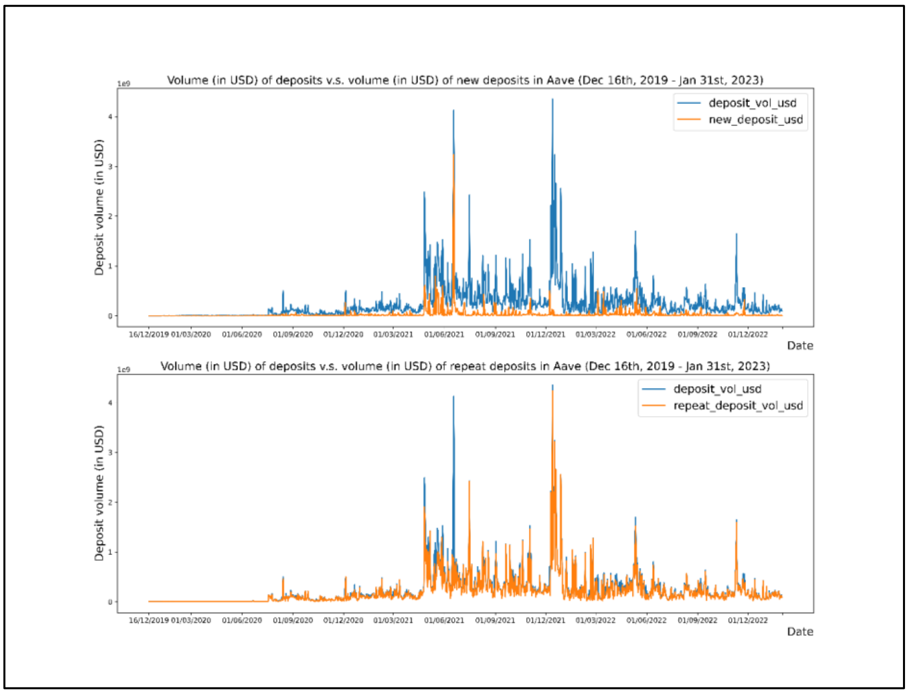
Note: This figure illustrates the number of depositors daily in Aave protocol, and we also show the number of new depositors and repeat depositors daily.

Figure C.2: Borrowers in Aave protocol (Dec 16, 2019 – Jan 31, 2023)



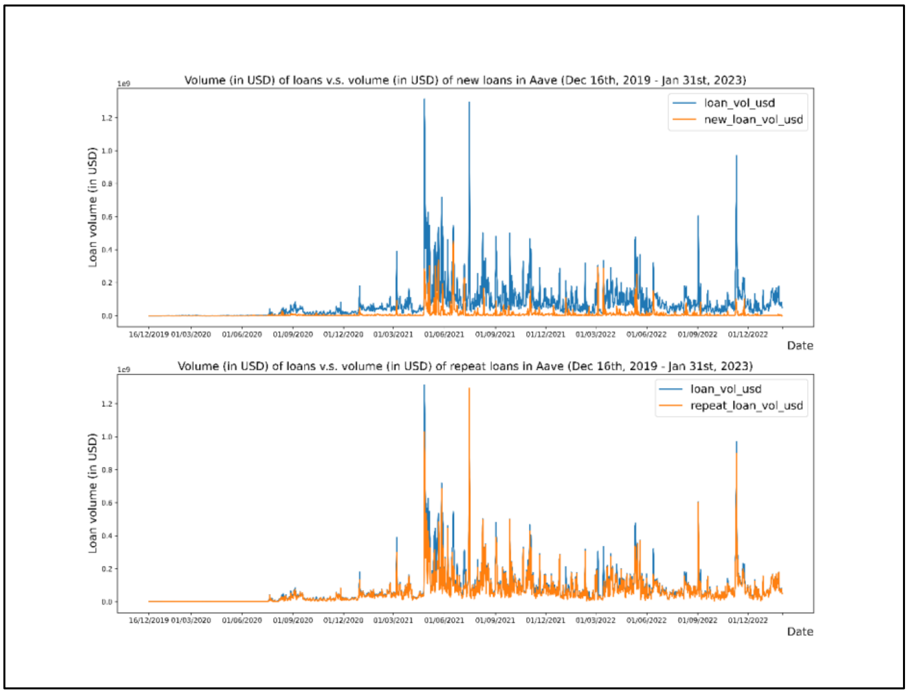
Note: This figure illustrates the number of borrowers daily in Aave protocol, and we also show the number of new borrowers and repeat borrowers daily.

Figure C.3: Deposit volume in Aave protocol (Dec 16, 2019 – Jan 31, 2023)



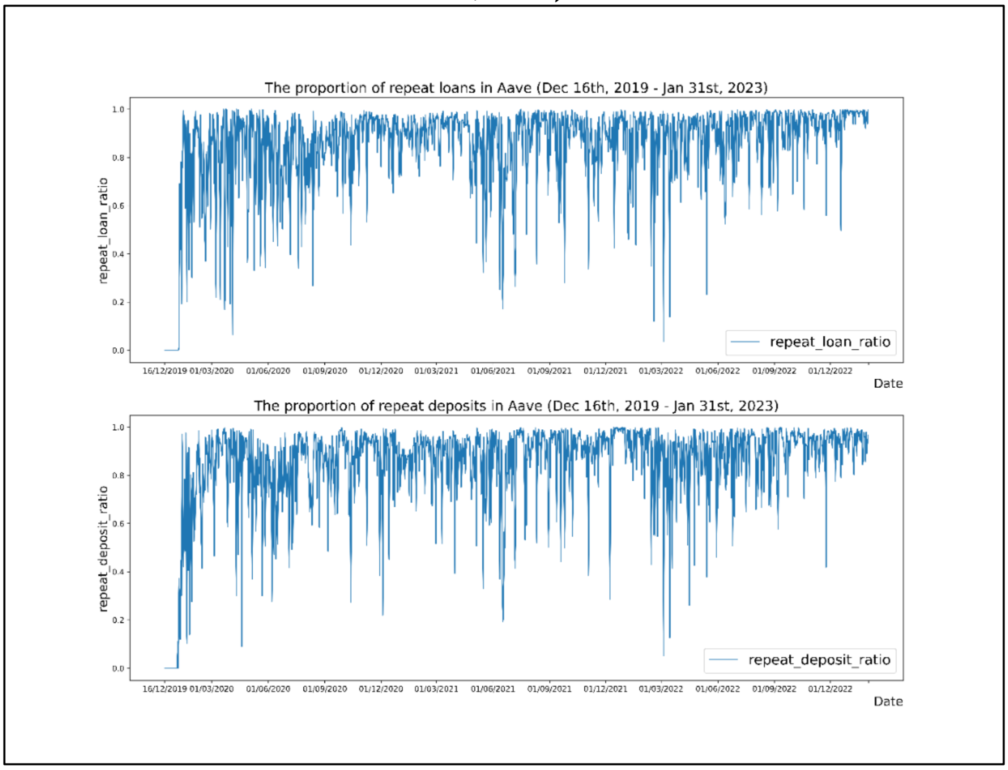
Note: This figure illustrates the volume (in USD) of deposits in Aave protocol, and we also show the volumes (in USD) of deposits from new depositors and repeat depositors.

Figure C.4: Loan volume in Aave protocol (Dec 16, 2019 – Jan 31, 2023)



Note: This figure illustrates the volume (in USD) of loans in Aave protocol, and we also show the volumes (in USD) of loans from new borrowers and repeat borrowers.

Figure C.5: The proportion of repeat deposits and repeat loans (Dec 16, 2019 – Jan 31, 2023)



Note: This figure illustrates the proportion of repeat loans and deposits in Aave protocol, respectively.

C.2 Large addresses in Aave

We construct two measurements of liquidity risks based on the trading activities of large users in Aave. Among all cryptocurrencies traded in Aave, we focus on five mainstream cryptocurrencies, including Ether (ETH), Wrapped Bitcoin (WBTC), Dai (DAI), USD Coin (USDC) and Tether (USDT). For each cryptocurrency, we inspect the top 100 borrowers and depositors in terms of both token amount and frequency of transactions. The large users are 980 unique Ethereum addresses, including 582 borrowers and 639 depositors. Then we manually examine these Ethereum addresses and find they fall into several categories. The table below introduces the different types of Ethereum addresses identified as large users in Aave.

Table C.2: Smart contract and DeFi protocol classification

Classification	Definition
EOA	External Owned Addresses (EOAs) refer to Ethereum addresses controlled by people rather than codes.
DeFi contract	DeFi contracts refer to smart contracts that are a part of DeFi applications.
Wallet application	Wallet applications refer to cryptocurrency wallets. Simply, they are a form of digital wallets designed for on-chain transactions. Users can store and trade cryptocurrencies using cryptocurrency wallets.
MEV bot	MEV bots are software tools built to monitor the Ethereum blockchain, identify profitable opportunities, and automatically execute those transactions for their user.
Yield aggregator	Yield aggregators essentially automate the process of staking and collecting the generated rewards on behalf of DeFi users, to optimize gas fee (i.e., transaction fees on blockchain) spending via different strategies.
Asset management	Similar to asset management in traditional finance, asset management in cryptocurrency market helps investors to manage and optimize their portfolios.

Note: The table introduces the definitions of different types of Ethereum addresses identified as large users.

The table below presents the descriptive statistics of large users in Aave. Panel A summarizes the activities of large depositors, while Panel B focuses on large borrowers. Among the six categories of Ethereum addresses, EOA, DeFi contracts and unidentified contracts are the most important in terms of the USD value of their total deposits and total loans.

Table C.3: Summary statistics of large addresses in Aave

Panel A: Depositors					
	Total deposits (USD m)	Number of unique addresses	Av. Deposits per addresses (USD m)	Standard Deviation (USD m)	Median value of deposits (USD)
EOA	37329.90	333	2.08	14.17	7249.84
DeFi contract	28095.20	213	0.16	2.54	0.00
Wallet application	95.08	4	0.73	5.63	1.00
MEV bot	5969.48	9	2.52	7.14	2058788.79
Yield aggregator	57.26	1	57.26	0.00	57257487.69
Asset management	0	0	0	0	0
Unidentified contract	9086.55	79	1.00	5.59	0.00
All types	80633.47	639	0.40	5.08	0.00
Panel B: Borrowers					

	Total loans (USD m)	Number of unique addresses	Av. loans per addresses (USD m)	Standard Deviation (USD m)	Median value of loans (USD)
EOA	28375.59	329	0.83	6.31	27886.12
DeFi contract	23513.80	123	0.49	5.26	20232.99
Wallet application	0.45	2	0.00	0.00	1301.86
MEV bot	3523.93	12	0.99	2.45	326033.29
Yield aggregator	0	0	0	0	0
Asset management	2032.63	20	0.15	1.85	8618.67
Unidentified contract	17900.47	96	1.02	18.28	22062.52
All types	75346.86	582	0.65	8.62	20779.50

Note: This table reports summary statistics of large addresses in Aave. We consider five cryptocurrencies, including Ether (ETH), Wrapped Bitcoin (WBTC), Dai (DAI), USD Coin (USDC) and Tether (USDT). The large addresses are filtered based on their trading activities, and we focus on their transaction frequency and cryptocurrency amount of their lending and borrowing activities.

C.3 Cross-LP effects

Table C.4: Compound protocol-specific factors

Factor	Definition
MktC_F	Market cap (in USD) based on the maximum supply of tokens
MktC_C	Market cap (in USD) based on the circulating supply of tokens
COMP	Daily price (in USD) of COMP
TVL	Value (in USD) of funds locked in the project’s smart contracts
Revenue	The amount of revenue (in USD) that is distributed to COMP holders
Loan vol usd	Daily volume (in USD) of Compound loans
Deposit vol usd	Daily volume (in USD) of Compound deposits
Liquidation usd	The value (in USD) of collateral liquidated daily in Compound
COMP holder	The number of Ethereum addresses that have a non-zero balance of COMP token
Active user	Daily active users of Compound protocol
Developer	Daily active developers of Compound protocol

Note: This table introduces the definitions of Compound-specific factors.

C.4 Control for the outliers in dependent variables

To exclude the influence of outliers in dependent variables, we windorize the dependent variables at 2.5% and 97.5% and re-estimate regression models (4.10) - (4.13). The following tables present the results, which are consistent with section 4.4.

Table C.5: The effects of liquidity risk and repeat users on Aave

	(1) Δ MktC_F	(2) Δ MktC_C	(3) Δ Revenue	**(4) Δ TVL**	(5) Δ AAVE	**(6) Δ AAVE holder**
Panel A: Repeat users and liquidity						
Liquidity	0.00	0.01	0.05	0.03	0.00	**-0.34*****
	(0.02)	(0.17)	(1.25)	(1.02)	(0.02)	**(-10.75)**
Repeat deposit ratio	-0.02	-0.03	-0.01	-0.07	-0.02	-0.06
	(-0.38)	(-0.59)	(-0.11)	(-1.60)	(-0.38)	(-1.45)
Repeat loan ratio	0.01	0.03	0.03	**0.09****	0.01	**0.12*****
	(0.23)	(0.65)	(0.56)	**(2.23)**	(0.23)	**(3.10)**
Δ Deposits vol USD	**-0.07***	**-0.08****	-0.02	**-0.09****	**-0.07***	0.01
	(-1.75)	**(-1.96)**	(-0.42)	**(-2.16)**	**(-1.75)**	(0.15)
Δ Loan vol USD	0.04	0.04	0.03	**0.15*****	0.04	0.04
	(1.05)	(0.97)	(0.74)	**(3.75)**	(1.05)	(1.05)
Δ Liquidation USD	**-0.18*****	**-0.19*****	**-0.17*****	**-0.22*****	**-0.18*****	0.00
	(-5.18)	**(-5.27)**	**(-4.73)**	**(-6.43)**	**(-5.18)**	(0.02)
Δ Active user	0.01	0.01	-0.01	-0.03	0.01	0.00
	(0.20)	(0.16)	(-0.39)	(-0.90)	(0.20)	(0.08)
Δ Developer	-0.02	-0.02	-0.01	-0.03	-0.02	0.00
	(-0.49)	(-0.48)	(-0.35)	(-0.97)	(-0.49)	(0.14)
ETH return (1d)	**-0.11*****	**-0.12*****	**-0.12*****	**-0.11*****	**-0.11*****	0.04
	(-2.85)	**(-3.07)**	**(-3.19)**	**(-2.94)**	**(-2.85)**	(1.16)
ETH return (7d)	**0.24*****	**0.24*****	**0.15*****	**0.31*****	**0.24*****	**0.12*****
	(6.27)	**(6.38)**	**(3.82)**	**(8.66)**	**(6.27)**	**(3.63)**
ETH SD (30d)	0.02	0.02	0.01	**0.31*****	0.02	**0.26*****
	(0.47)	(0.46)	(0.29)	**(8.66)**	(0.47)	**(8.28)**
N	791	791	791	789	791	791
Adj R-sq	0.08	0.09	0.05	0.15	0.08	0.26
Panel B: Repeat users and utilization						
	(1)	(2)	(3)	**(4)**	(5)	**(6)**
	Δ MktC_F	Δ MktC_C	Δ Revenue	**Δ TVL**	Δ AAVE	**Δ AAVE holder**
Utilization	-0.03	-0.03	0.00	0.05	-0.03	0.03
	(-0.76)	(-0.85)	(-0.12)	(1.42)	(-0.76)	(0.84)
Repeat deposit ratio	-0.02	-0.03	0.00	-0.07	-0.02	**-0.08***
	(-0.37)	(-0.58)	(-0.05)	(-1.56)	(-0.37)	**(-1.88)**
Repeat loan ratio	0.01	0.03	0.02	**0.10****	0.01	**0.14*****
	(0.16)	(0.57)	(0.50)	**(2.30)**	(0.16)	**(3.34)**
Δ Deposits vol USD	**-0.07***	**-0.08****	-0.02	**-0.09****	**-0.07***	0.01
	(-1.75)	**(-1.97)**	(-0.43)	**(-2.17)**	**(-1.75)**	(0.26)
Δ Loan vol USD	0.04	0.04	0.03	**0.15*****	0.04	0.04
	(1.05)	(0.97)	(0.74)	**(3.76)**	(1.05)	(0.98)
Δ Liquidation USD	**-0.18*****	**-0.19*****	**-0.17*****	**-0.22*****	**-0.18*****	0.00
	(-5.18)	**(-5.27)**	**(-4.72)**	**(-6.43)**	**(-5.18)**	(-0.07)
Δ Active user	0.01	0.01	-0.01	-0.03	0.01	0.00
	(0.20)	(0.17)	(-0.36)	(-0.89)	(0.20)	(-0.13)
Δ Developer	-0.02	-0.02	-0.01	-0.03	-0.02	0.02
	(-0.48)	(-0.48)	(-0.41)	(-1.03)	(-0.48)	(0.60)
ETH return (1d)	**-0.11*****	**-0.12*****	**-0.12*****	**-0.11*****	**-0.11*****	0.04
	(-2.87)	**(-3.09)**	**(-3.20)**	**(-2.91)**	**(-2.87)**	(1.20)
ETH return (7d)	**0.24*****	**0.24*****	**0.14*****	**0.31*****	**0.24*****	**0.19*****
	(6.41)	**(6.50)**	**(3.65)**	**(8.51)**	**(6.41)**	**(5.21)**
ETH SD (30d)	0.02	0.02	0.00	0.03	0.02	**0.32*****
	(0.48)	(0.44)	(0.07)	(0.80)	(0.48)	**(9.69)**
N	791	791	791	789	791	791
Adj R-sq	0.08	0.09	0.05	0.16	0.08	0.15

Note: This table reports regression results for the influence of liquidity risk on Aave protocol. In columns (1) – (6) of each panel, the dependent variable is ⊿*MktC_F*, ⊿*MktC_C*, ⊿*revenue*, ⊿*TVL*, ⊿*AAVE*, and ⊿*AAVE holder*, respectively. T-statistics are reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics.

Table C.6: The effects of liquidity risk and large users on Aave

Panel A: Large users and liquidity						
	(1) Δ MktC_F	(2) Δ MktC_C	**(3) Δ Revenue**	(4) Δ TVL	(5) Δ AAVE	**(6) Δ AAVE holder**
Liquidity	0.00 (-0.04)	0.00 (0.10)	0.04 (1.21)	0.03 (0.93)	0.00 (-0.04)	**-0.35*** (-10.82)**
Δ Deposit large	-0.06 (-1.34)	-0.06 (-1.31)	0.00 (-0.04)	0.06 (1.48)	-0.06 (-1.34)	-0.04 (-0.93)
Δ Loan large	0.07 (1.54)	0.06 (1.44)	**0.36*** (8.31)**	0.05 (1.18)	0.07 (1.54)	0.03 (0.69)
Δ Deposits vol USD	**-0.07* (-1.67)**	**-0.08* (-1.90)**	0.00 (-0.10)	**-0.09** (-2.16)**	**-0.07* (-1.67)**	0.00 (0.10)
Δ Loan vol USD	0.04 (0.96)	0.04 (0.90)	-0.03 (-0.70)	**0.13*** (3.31)**	0.04 (0.96)	-0.01 (-0.16)
Δ Liquidation USD	**-0.19*** (-5.17)**	**-0.19*** (-5.27)**	**-0.12*** (-3.60)**	**-0.20*** (-5.77)**	**-0.19*** (-5.17)**	-0.01 (-0.16)
Δ Active user	0.00 (0.13)	0.00 (0.07)	0.01 (0.27)	-0.03 (-0.74)	0.00 (0.13)	0.00 (-0.11)
Δ Developer	-0.02 (-0.50)	-0.02 (-0.47)	-0.02 (-0.49)	-0.03 (-0.97)	-0.02 (-0.50)	0.01 (0.34)
ETH return (1d)	**-0.11*** (-2.87)**	**-0.12*** (-3.08)**	**-0.13*** (-3.51)**	**-0.11*** (-2.97)**	**-0.11*** (-2.87)**	0.04 (1.24)
ETH return (7d)	**0.24*** (6.33)**	**0.24*** (6.47)**	**0.15*** (4.16)**	**0.32*** (8.90)**	**0.24*** (6.33)**	**0.13*** (3.89)**
ETH SD (30d)	0.02 (0.49)	0.01 (0.43)	0.01 (0.27)	0.03 (0.87)	0.02 (0.49)	**0.25*** (7.99)**
N	791	791	791	789	791	791
Adj R-sq	0.08	0.09	0.17	0.16	0.08	0.25
Panel B: Large users and utilization						
	(1) Δ MktC_F	(2) Δ MktC_C	**(3) Δ Revenue**	**(4) Δ TVL**	**(5) Δ AAVE**	(6) Δ AAVE holder
Utilization	-0.03 (-0.75)	-0.03 (-0.88)	-0.01 (-0.21)	0.04 (1.24)	-0.03 (-0.75)	0.02 (0.56)
Δ Deposit large	-0.06 (-1.34)	-0.06 (-1.31)	0.00 (-0.07)	0.06 (1.45)	-0.06 (-1.34)	-0.03 (-0.66)
Δ Loan large	0.07 (1.54)	0.06 (1.44)	**0.36*** (8.33)**	0.05 (1.20)	0.07 (1.54)	0.02 (0.42)
Δ Deposits vol USD	**-0.07* (-1.67)**	**-0.08* (-1.90)**	0.00 (-0.11)	**-0.09** (-2.17)**	**-0.07* (-1.67)**	0.01 (0.20)
Δ Loan vol USD	0.04 (0.97)	0.04 (0.90)	-0.03 (-0.70)	**0.13*** (3.31)**	0.04 (0.97)	0.04 (0.95)
Δ Liquidation USD	**-0.19*** (-5.16)**	**-0.19*** (-5.27)**	**-0.12*** (-3.59)**	**-0.20*** (-5.78)**	**-0.19*** (-5.16)**	-0.01 (-0.21)
Δ Active user	0.00 (0.13)	0.00 (0.08)	0.01 (0.30)	-0.02 (-0.73)	0.00 (0.13)	-0.01 (-0.34)
Δ Developer	-0.02 (-0.50)	-0.02 (-0.47)	-0.02 (-0.54)	-0.03 (-1.02)	-0.02 (-0.50)	0.03 (0.78)
ETH return (1d)	**-0.11*** (-2.89)**	**-0.12*** (-3.11)**	**-0.13*** (-3.52)**	**-0.11*** (-2.94)**	**-0.11*** (-2.89)**	0.05 (1.26)

ETH return (7d)	**0.24*** (6.48)**	**0.24*** (6.61)**	**0.14*** (4.00)**	**0.31*** (8.80)**	**0.24*** (6.48)**	**0.20*** (5.54)**
ETH SD (30d)	0.02 (0.53)	0.02 (0.44)	0.00 (0.05)	0.02 (0.68)	0.02 (0.53)	**0.31*** (9.45)**
N	791	791	791	789	791	791
Adj R-sq	0.08	0.09	0.17	0.16	0.08	0.13

Note: This table reports regression results for the influence of liquidity risks on Aave protocol. In columns (1) – (6) of each panel, the dependent variable is Δ *MktC_F*, Δ *MktC_C*, Δ *revenue*, Δ *TVL*, Δ *AAVE*, and Δ *AAVE holder*, respectively. T-statistics are reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics.

Table C.7: The effects of liquidity risk and repeat users on Compound

Panel A: Repeat users and liquidity						
	(1) Δ MktC_F	(2) Δ MktC_C	(3) Δ Revenue	**(4) Δ TVL**	(5) Δ COMP	**(6) Δ COMP holder**
Liquidity	-0.06	-0.06	-0.05	**-0.08****	-0.02	**-0.52*****
	(-1.32)	(-1.53)	(-1.20)	**(-1.99)**	(-0.50)	**(-19.03)**
Repeat deposit ratio	-0.07	-0.08	-0.01	-0.02	0.01	**-0.13*****
	(-1.33)	(-1.51)	(-0.17)	(-0.49)	(0.12)	**(-4.00)**
Repeat loan ratio	0.03	0.03	0.00	0.00	-0.03	**0.12*****
	(0.55)	(0.61)	(-0.06)	(0.09)	(-0.67)	**(3.81)**
Δ Deposits vol USD	-0.01	0.00	0.02	0.04	0.04	0.01
	(-0.19)	(0.08)	(0.50)	(1.01)	(1.05)	(0.39)
Δ Loan vol USD	-0.07	-0.03	-0.03	0.03	**0.13*****	-0.04
	(-1.34)	(-0.61)	(-0.63)	(0.77)	**(3.30)**	(-1.46)
Δ Liquidation USD	**0.15*****	**0.14*****	0.04	**0.13*****	-0.04	0.01
	(3.19)	**(2.93)**	(0.91)	**(3.40)**	(-0.99)	(0.38)
Δ Active user	0.04	0.04	0.05	0.00	-0.02	0.01
	(0.89)	(0.90)	(1.48)	(-0.06)	(-0.71)	(0.21)
Δ Developer	0.01	-0.01	0.01	0.00	0.00	-0.02
	(0.13)	(-0.36)	(0.21)	(-0.05)	(0.06)	(-0.91)
ETH return (1d)	**-0.07***	**-0.07***	-0.05	-0.04	**-0.11*****	0.04
	(-1.74)	**(-1.68)**	(-1.17)	(-0.93)	**(-2.86)**	(1.51)
ETH return (7d)	0.05	0.04	0.01	0.03	**0.22*****	**0.16*****
	(1.07)	(0.83)	(0.37)	(0.75)	**(5.75)**	**(5.75)**
ETH SD (30d)	0.03	0.00	-0.02	0.00	0.00	**0.25*****
	(0.64)	(0.02)	(-0.55)	(-0.08)	(0.10)	**(9.26)**
N	631	631	789	789	790	790
Adj R-sq	0.01	0.01	-0.01	0.02	0.05	0.48
Panel B: Repeat users and utilization						
	(1) Δ MktC_F	**(2) Δ MktC_C**	(3) Δ Revenue	**(4) Δ TVL**	(5) Δ COMP	**(6) Δ COMP holder**
Utilization	0.05	0.06	0.00	**0.08****	-0.02	**0.06***
	(1.24)	(1.57)	(0.01)	**(2.28)**	(-0.61)	**(1.83)**
Repeat deposit ratio	-0.07	**-0.08***	-0.01	-0.03	0.00	**-0.18*****
	(-1.46)	**(-1.66)**	(-0.28)	(-0.70)	(0.08)	**(-4.71)**
Repeat loan ratio	0.04	0.04	0.00	0.02	-0.03	**0.19*****
	(0.76)	(0.86)	(0.05)	(0.43)	(-0.66)	**(4.82)**
Δ Deposits vol USD	-0.01	0.00	0.02	0.04	0.04	0.01
	(-0.28)	(-0.02)	(0.50)	(1.02)	(1.04)	(0.32)
Δ Loan vol USD	-0.07	-0.03	-0.02	0.03	**0.13*****	-0.04
	(-1.37)	(-0.64)	(-0.61)	(0.80)	**(3.31)**	(-1.01)
Δ Liquidation USD	**0.15*****	**0.14*****	0.03	**0.13*****	-0.04	-0.01
	(3.13)	**(2.86)**	(0.87)	**(3.28)**	(-1.00)	(-0.32)
Δ Active user	0.03	0.03	0.05	0.00	-0.02	0.02
	(0.85)	(0.85)	(1.51)	(-0.04)	(-0.68)	(0.57)
Δ Developer	0.01	-0.01	0.01	0.01	0.00	0.01
	(0.20)	(-0.27)	(0.29)	(0.19)	(0.06)	(0.41)
ETH return (1d)	**-0.08***	**-0.07***	-0.05	-0.04	**-0.11*****	0.03
	(-1.78)	**(-1.72)**	(-1.20)	(-0.94)	**(-2.88)**	(0.91)
ETH return (7d)	0.06	0.05	0.02	0.04	**0.23*****	**0.26*****
	(1.40)	(1.21)	(0.60)	(1.12)	**(5.95)**	**(7.83)**
ETH SD (30d)	0.04	0.01	-0.01	0.01	0.01	**0.39*****

	(0.89)	(0.27)	(-0.22)	(0.27)	(0.32)	**(12.41)**
N	631	631	789	789	790	790
Adj R-sq	0.01	0.01	-0.01	0.02	0.05	0.24

Note: This table reports regression results for the influence of liquidity risks in Aave on Compound protocol. In columns (1) – (6) of each panel, the dependent variable is *∆MktC_F*, *∆MktC_C*, *∆revenue*, *∆TVL*, *∆COMP*, and *∆COMP holder*, respectively. T-statistics are reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics.

Table C.8: The effects of liquidity risk and large users on Compound

Panel A: Large users and liquidity						
	(1)	**(2)**	**(3)**	**(4)**	(5)	**(6)**
	∆ MktC_F	**∆ MktC_C**	**∆ Revenue**	**∆ TVL**	∆ COMP	**∆ COMP holder**
Liquidity	-0.06	**-0.07***	-0.05	**-0.08****	-0.02	**-0.53*****
	(-1.46)	**(-1.69)**	(-1.25)	**(-2.04)**	(-0.44)	**(-19.35)**
∆ Deposit large	0.00	-0.01	**0.09****	0.05	-0.04	0.00
	(0.03)	(-0.12)	**(1.95)**	(1.07)	(-0.84)	(0.05)
∆ Loan large	-0.03	-0.02	**-0.15*****	-0.04	0.06	0.01
	(-0.56)	(-0.43)	**(-3.09)**	(-0.91)	(1.36)	(0.34)
∆ Deposits vol USD	-0.01	0.01	0.03	0.04	0.03	0.01
	(-0.12)	(0.14)	(0.80)	(1.09)	(0.90)	(0.29)
∆ Loan vol USD	-0.06	-0.03	-0.02	0.03	**0.13*****	-0.04
	(-1.30)	(-0.57)	(-0.51)	(0.79)	**(3.23)**	(-1.38)
∆ Liquidation USD	**0.15*****	**0.14*****	0.03	**0.13*****	-0.04	0.01
	(3.17)	**(2.92)**	(0.87)	**(3.41)**	(-0.95)	(0.30)
∆ Active user	0.04	0.04	0.05	0.00	-0.02	0.02
	(0.97)	(1.01)	(1.36)	(-0.09)	(-0.69)	(0.59)
∆ Developer	0.01	-0.01	0.01	0.00	0.00	-0.02
	(0.21)	(-0.27)	(0.33)	(-0.02)	(0.01)	(-0.87)
ETH return (1d)	**-0.08***	**-0.08***	-0.04	-0.04	**-0.11*****	0.04
	(-1.82)	**(-1.76)**	(-1.15)	(-0.92)	**(-2.89)**	(1.42)
ETH return (7d)	0.04	0.03	0.01	0.03	**0.22*****	**0.16*****
	(0.98)	(0.74)	(0.33)	(0.71)	**(5.79)**	**(5.43)**
ETH SD (30d)	0.03	0.00	-0.02	0.00	0.01	**0.25*****
	(0.730	(0.11)	(-0.56)	(-0.04)	(0.21)	**(9.06)**
N	631	631	789	789	790	790
Adj R-sq	0.01	0.01	0.01	0.02	0.05	0.47
Panel B: Large users and utilization						
	(1)	(2)	**(3)**	**(4)**	(5)	(6)
	∆ MktC_F	∆ MktC_C	**∆ Revenue**	**∆ TVL**	∆ COMP	∆ COMP holder
Utilization	0.05	0.06	0.00	**0.08****	-0.02	0.05
	(1.26)	(1.59)	(0.02)	**(2.27)**	(-0.56)	(1.57)
∆ Deposit large	0.00	0.00	**0.09****	0.05	-0.04	0.00
	(0.06)	(-0.09)	**(1.94)**	(1.05)	(-0.84)	(-0.11)
∆ Loan large	-0.03	-0.02	**-0.14*****	-0.04	0.06	0.02
	(-0.55)	(-0.42)	**(-3.07)**	(-0.89)	(1.36)	(0.44)
∆ Deposits vol USD	-0.01	0.00	0.03	0.04	0.03	0.01
	(-0.22)	(0.03)	(0.80)	(1.09)	(0.90)	(0.19)
∆ Loan vol USD	-0.06	-0.03	-0.02	0.03	**0.13*****	-0.03
	(-1.32)	(-0.60)	(-0.49)	(0.83)	**(3.23)**	(-0.91)
∆ Liquidation USD	**0.15*****	**0.14*****	0.03	**0.13*****	-0.04	-0.01
	(3.10)	**(2.83)**	(0.82)	**(3.27)**	(-0.95)	(-0.42)
∆ Active user	0.04	0.04	0.05	0.00	-0.02	0.03
	(0.96)	(0.98)	(1.41)	(-0.03)	(-0.67)	(1.06)
∆ Developer	0.01	-0.01	0.02	0.01	0.00	0.01
	(0.28)	(-0.18)	(0.42)	(0.23)	(0.02)	(0.45)
ETH return (1d)	**-0.08***	**-0.08***	-0.05	-0.04	**-0.11*****	0.03
	(-1.86)	**(-1.81)**	(-1.18)	(-0.94)	**(-2.91)**	(0.79)
ETH return (7d)	0.06	0.05	0.02	0.04	**0.23*****	**0.26*****
	(1.33)	(1.13)	(0.57)	(1.08)	**(5.98)**	**(7.49)**
ETH SD (30d)	0.04	0.02	-0.01	0.01	0.01	**0.39*****
	(1.00)	(0.38)	(-0.22)	(0.30)	(0.41)	**(12.19)**
N	631	631	789	789	790	790
Adj R-sq	0.01	0.01	0.00	0.02	0.05	0.22

Note: This table reports regression results for the influence of liquidity risks in Aave on Compound protocol. In columns (1) – (6) of each panel, the dependent variable is Δ*MktC_F*, Δ*MktC_C*, Δ*revenue*, Δ*TVL*, Δ*COMP*, and Δ*COMP holder*, respectively. T-statistics are reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics.

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