DeFi Leverage[1]

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Abstract

In decentralised finance (DeFi), lending protocols are governed by predefined algorithms that facilitate automatic loans – allowing users to take on leverage. This paper examines DeFi leverage – i.e., the asset-to-equity ratio – using wallet-level data. The overall leverage ranges between 1.4 and 1.9, while the largest and most active wallets exhibit higher leverage. Leverage is mainly driven by loan-to-value requirements and borrow cost, as well as crypto price movements and sentiments. Higher borrower leverage undermines lending resilience. Borrowers with higher leverage are more likely to tilt towards volatile collateral when their debt positions are about to be liquidated.

JEL classification: G12, G23, O36

Keywords: Leverage, collateralised borrowing, decentralised finance, automated algorithm.

1 Introduction

Decentralized finance (DeFi) has witnessed a meteoric rise since 2020, disrupting traditional financial services by offering users an alternative way of conducting transactions. Among the plethora of DeFi protocols, lending platforms have emerged as a cornerstone, facilitating collateralised borrowing activities on an economically significant scale (Aramonte, Huang, and Schrimpf, 2021; Chiu, Ozdenoren, Yuan, and Zhang, 2022). At their zenith, these platforms held over \$35 billion in deposits and \$25 billion in outstanding debt, underscoring their significance within the DeFi ecosystem (IOSCO, 2022; FSB, 2023b). Despite its importance, the intricacies of user behavior and pool dynamics within DeFi lending remain largely unexplored.

Borrowing with collateral and the associated leverage, however, are not new topics in traditional finance. The role of collateral and leverage has been thoroughly investigated in general equilibrium models (Geanakoplos, 2001; Geanakoplos, 2010), in financial intermediary theory (Adrian and Shin, 2010; Adrian and Shin, 2014) and in asymmetric information problems (Acharya and Viswanathan, 2011), as well as in eventful markets such as the repurchase agreements (i.e., repo) (Infante, 2019). However, obtaining detailed data on user-level leverage has proven to be challenging, resulting in sporadic empirical analyses (with few exceptions such as Ang, Gorovyy, and Van Inwegen, 2011; Kahraman and Tookes, 2017).

This paper aims to bridge these knowledge gaps by providing a comprehensive analysis of leverage taking behavior in collateralised borrowing. The contribution of the paper is three-fold. Firstly, to the best of our knowledge, we are the first to document individual DeFi wallets' leverage – which is defined as the asset-to-equity ratio (i.e., the leverage concept in Adrian and Shin (2010) and Adrian and Shin (2014)). Using granular data from the Ethereum blockchain, our paper provides an extensive examination of DeFi leverage, elucidating its overall trends, group disparities, and driving factors. Secondly, our analysis presents new empirical evidence on the systemic risk impact of high leverage on DeFi lending platforms. We focus on lending resilience and strategic substitution behaviour, based on individual wallets' investment portfolio data. Last but not least, although DeFi remains a predominantly self-referential system, the lessons gleaned from DeFi lending – a real world laboratory – could be relevant to understanding financial stability concerns, in particular in repo and securities lending markets given the similarities they share. We systemically review the similarities, as well as the distinctions, between DeFi lending and traditional collateralised borrowing, such as repo.

The main findings consist of three parts. Firstly, we examine the overall trends of DeFi leverage. Throughout our sample period (January 2021 - March 2023), the overall leverage of DeFi users[1] ranges from 1.4 to 1.9. This leverage tracks the market-wide price movements with an approximately 3-month lag – a pattern probably reflecting speculative motives in crypto trading (Biais, Bisiere, Bouvard, Casamatta, and Menkveld, 2020; Auer, Cornelli, Doerr, Frost, and Gambacorta, 2023). This asset-to-equity ratio type of leverage is significantly lower than the leverage permitted by the loan-to-value (LTV) ratio (i.e., the leverage concept in Geanakoplos (2001) and Fostel and Geanakoplos (2014)), which ranges from 3.4 to 4.8.

User leverage exhibits heterogeneity across groups. We identify three distinct user groups: those with the largest outstanding debt, the most frequent users interacting with lending protocols, and the earliest adopters of DeFi lending platforms. Our observations reveal that both the largest and most active wallets exhibit higher leverage compared to the remaining users, with their average leverage often exceeding 2. In addition, we classify all wallets into those with long volatile asset positions and those with short volatile asset positions. The long wallets pledge volatile coins as collateral and borrow stablecoins and the short wallets pledge stablecoins as collateral and borrow volatile coins. The leverage of short and long wallets is negatively correlated. When volatile assets appreciate, the leverage of long wallets decreases while that of short wallets increases. Because long wallets' collateral value increases and short wallets' debt value increases.

Next, we explore various hypotheses to identify the factors that are associated with high borrower leverage. Our findings indicate that a user's leverage is higher when they face higher LTV-permitted leverage, lower net borrowing cost, and higher market sentiment. It is striking that the actual leverage is significantly lower than the (maximum) leverage allowed by the LTV ratio required by the lending platforms. This gap can be explained by two channels. For one, since borrowers face substantial losses upon automatic liquidation, they generally avoid leveraging to the maximum extent, opting instead for a more conservative approach with a sizeable buffer. For another, when DeFi users experience asset appreciation (i.e., higher past returns), they deposit more

[1] In the context of DeFi, which is pseudo-anonymous, we use "wallets" and "users" interchangeably. Because wallets are standalone units, largely isolated from the broader balance sheet of the entity.

crypto assets in the lending platforms without taking debts, leading to higher amounts of assets and lower leverage *ceteris paribus*.

Our third finding pertains to the systemic impact of high borrower leverage on DeFi lending platforms. Leverage can propagate shocks via rising liquidity demands that stem from the fluctuations of the collateral value (FSB, 2023a). We first investigate how borrower leverage affects DeFi lending resilience. We assess lending resilience using two metrics: value-at-risk (VaR) and liquidation share. The former gauges the share of loans that are close to being liquidated in total loans, while the latter represents the share of loans that are liquidated. We find that higher borrower leverage contributes to increased VaR, signifying heightened risk within lending pools. In terms of liquidation share, however, borrower leverage does not appear to have a significant influence, as liquidations are predominantly event-driven (Lehar and Parlour, 2022). Last but not least, although borrowers in DeFi can adjust their collateral portfolios as long as meeting the LTV ratio requirements, we find that most borrowers on the brink of liquidation do not shift towards more volatile collateral. This is probably due to the fact that the LTV ratio requirement is more stringent for more volatile assets. However, conditional on those that do tilt towards volatile collateral, higher borrower leverage is associated with more aggressive strategic collateral adjustment. This is consistent with the asymmetric information problem stemming from the pooling of collateral across borrowers (Chiu, Ozdenoren, Yuan, and Zhang, 2022).

We contribute to three relevant strands of literature. The first one is the rapidly evolving literature on DeFi lending.[2] Aramonte, Huang, and Schrimpf (2021) provide a primer on the essential building blocks in DeFi, highlighting the illusion of decentralisation. Carapella, Dumas, Gerszten, Swem, and Wall (2022) discuss the potentials and risks of DeFi platforms. Chiu, Ozdenoren, Yuan, and Zhang (2022) construct a theoretical model of DeFi lending that captures the distinct feature of collateral pooling across borrowers and the associated asymmetric information problem.

[2]Another strand of the literature relates to *trading* in DeFi and in crypto in general. Interested readers can refer to Aoyagi and Ito (2021); Lehar and Parlour (2021); Capponi and Jia (2021); Barbon and Ranaldo (2021); Hasbrouck, Rivera, and Saleh (2022); Capponi, Jia, and Yu (2022); Loesch, Hindman, Richardson, and Welch (2021); Qin, Zhou, and Gervais (2022); Heimbach, Wang, and Wattenhofer (2021); Heimbach, Schertenleib, and Wattenhofer (2022); Malinova and Park (2023); Milionis, Moallemi, Roughgarden, and Zhang (2022); Milionis, Moallemi, and Roughgarden (2023); Milionis, Moallemi, and Roughgarden (2023); Fritsch (2021); Berg, Fritsch, Heimbach, and Wattenhofer (2022) and Torres, Camino, et al. (2021) for the former, and Cong and He (2019); Biais, Bisiere, Bouvard, Casamatta, and Menkveld (2020); Makarov and Schoar (2021); Schmeling, Schrimpf, and Todorov (2022) and Auer, Cornelli, Doerr, Frost, and Gambacorta (2023) for the latter.

Chaudhary, Kozhan, and Viswanath-Natraj (2023) study the interest rate parity in DeFi lending and identify a relationship between the interest rate differential and the futures premium. Gudgeon, Werner, Perez, and Knottenbelt (2020) empirically analyze the differing interest rate rules of DeFi lending protocols, whereas Rivera, Saleh, and Vandeweyer (2023) show that the pre-determined interest rate curves of DeFi lending are less efficient compared to traditional lending platforms. Lehar and Parlour (2022) study the price impact of liquidations in DeFi lending, identifying a potential source of fragility and spillover factor in this nascent financial segment. Similarly, Perez, Werner, Xu, and Livshits (2021) and Qin, Zhou, Gamito, Jovanovic, and Gervais (2021) empirically study liquidations in DeFi and the risks that stem from them. Heimbach, Schertenleib, and Wattenhofer (2023) examine a recent episode in which the available liquidity of a lending pool was entirely depleted and analyse the underlying issues and counterfactual. Yaish, Tochner, and Zohar (2022) discuss how cryptocurrency miners could manipulate their interest rate on DeFi loans by adjusting the block rate, whereas Heimbach, Schertenleib, and Wattenhofer (2023) dissect a recent price manipulation attack on a lending protocol. Finally, Tovanich, Kassoul, Weidenholzer, and Prat (2023) study financial contagion in Compound, i.e., the second biggest DeFi lending protocol on the Ethereum blockchain. Our research complements this strand of literature by presenting new evidence on DeFi leverage and its consequent effect on lending resilience.

The second strand of literature relates to leverage in traditional markets. McGuire and Tsatsaronis (2008) put forth a "regression-based" methodology for estimating hedge fund leverage using publicly available data. Ang, Gorovyy, and Van Inwegen (2011) provide an in-depth analysis of hedge fund leverage based on supervisory data. Adrian and Shin (2014) examine the impact of leverage on financial stability, as well as its procyclicality. Kahraman and Tookes (2017) use the unique features of India's margin trading system to establish a causal relationship between traders' leverage and a stock's market liquidity. Utilising the granular transaction data, we contribute to this literature by identifying the distinct driving factors behind leverage and the impact of high borrower leverage.

We also contribute to the literature on repo markets. Krishnamurthy, Nagel, and Orlov (2014) find that repo volume backed by private asset-backed securities falls to near zero during the global financial crisis. In contrast, Copeland, Martin, and Walker (2014) present evidence suggesting that there was no system-wide run on repo, using confidential data on tri-party repo. Infante (2019) develops a model of repo intermediation that reconciles the discrepancy in the aforementioned analysis on repo market runs. We enrich this strand of literature by understanding an alternative approach to collateralised borrowing.

The rest of the paper is organised in the following. We first explain the mechanics of DeFi lending and contrast that to repo trading and securities lending in Section 2. In Section 3, we show the stylised facts on DeFi leverage, describing the trend as well as the group features. To understand the driving factors, we run wallet-day level panel regressions to test several hypotheses. Section 4 looks into the impact of leverage on lending pool resilience. Section 5 examines how high leverage affects borrowers' collateral selection when their positions are close to being liquidated. Section 6 concludes.

2 Institutional background and data

How DeFi lending works. On DeFi lending platforms, a user can deposit crypto assets into a lending pool and receives a claim on their share of the pool. Smart contracts behind these platforms enable the user to use this claim as collateral to borrow from the same asset or other assets, subject to loan-to-value (LTV) ratios (Figure 1). Table 1 reports the LTV ratio as of the end of March 2023 for major crypto assets. For instance, on Aave v2, the LTV ratio of USDC – a main stablecoin – is 80%, which means that for a collateral value of \$100 USDC, one can have a debt value of up to \$80. Thus, the associated haircut requirement of USDC is 20% and the implied maximum leverage is 5 ($= \frac{1}{1-\text{LTV ratio}}$). The LTV ratio varies across collateral and time depending on the risk management of the DeFi lending platforms. Appendix A provides a detailed description of how the LTV ratio and borrowing/deposit rates are determined in DeFi lending. We note here that the LTV ratio is set and updated by the protocol governance – a decentralised autonomous organisation (DAO) – based on risk assessment on smart contract security, counterparty risk, and market risk.

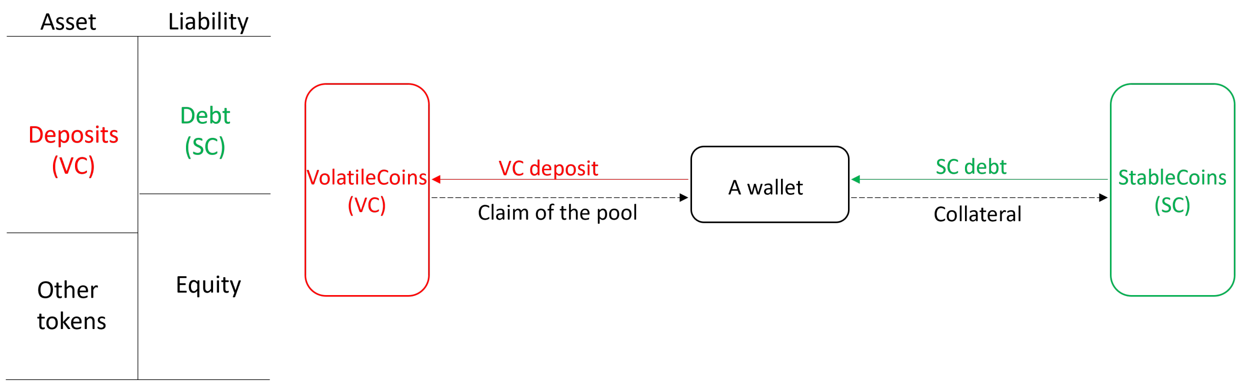
There are two leverage concepts. One is the leverage requirement imposed by the lending platforms – i.e., the maximum leverage implied by the LTV ratio – which is a key variable in the leverage cycle proposed by Geanakoplos (2010); Fostel and Geanakoplos (2014). The other concept is the actual leverage in a user's portfolio, which measures to what extent the user's assets

Table 1. Loan-to-value ratio and implied leverage. LTV is loan-to-value ratio. Haircut is the corresponding discount of the collateral value. Leverage^I is the implied leverage requirement from the LTV ratio. The data is from lending platforms as of 31 March 2023.

	Aave v2			**Compound**		
	LTV	Haircut	Leverage^I	LTV	Haircut	Leverage^I
USDC	0.800	0.200	5.000	0.855	0.145	6.897
USDT	0.000	1.000	1.000	0.000	1.000	1.000
DAI	0.750	0.250	4.000	0.835	0.165	6.061
ETH	0.825	0.175	5.714	0.825	0.175	5.714
BTC	0.720	0.280	3.571	0.700	0.300	3.333

are support by their own equity – i.e., the asset-to-equity ratio (Adrian and Boyarchenko, 2012; Adrian and Shin, 2014). Figure 1 shows a stylised balance sheet of a user that uses volatile coins (VC) as collateral to borrow stablecoins (SC). From the user's perspective, their assets include the deposits on these platforms and other coins they held external to DeFi lending platforms. Their liabilities consist of (collateralised) debt on these platforms. The difference between assets and debt constitutes the user's equity. Both concepts capture different aspects of leverage. Given the focus of this paper is on the users' borrowing behaviours, the term "leverage" refers to the asset-to-equity ratio, while "(LTV-)implied leverage" refers to the leverage (or margin) requirement imposed by the platform.

Figure 1. Mechanics of DeFi lending. This figure shows the balance sheet of a user that borrows stablecoins (SC) using volatile coins (VC) as collateral.



How DeFi lending differs from repo and securities borrowing. DeFi lending bears similarities to repo and securities borrowing but also exhibits unique characteristics. Table 2 summarises the key differences. First, DeFi lending counterparties tend to be pseudonymous, whereas repo counterparties are usually known. Second, DeFi lending pools collateral across borrowers, as the pool claim is used as collateral (Chiu, Ozdenoren, Yuan, and Zhang, 2022), while repo collateral is typically segregated among borrowers (Copeland, Martin, and Walker, 2014).

Third, DeFi lending features predefined borrow rates and haircuts, with borrow rates dependent on the utilisation rate, or the proportion of the pool asset lent out (Rivera, Saleh, and Vandeweyer, 2023). Conversely, repo rates and haircuts are determined flexibly through dealer interactions with cash investors and borrowers (Geanakoplos, 2010). In addition, the maturity in DeFi lending is typically perpetual, although borrowers can choose to repay early. Repos are short-term instruments, often overnight.

Furthermore, as DeFi lending platforms strive to automate the whole lending procedure, they typically put in place liquidation mechanisms to protect lenders from borrowers' defaults. When the LTV ratio rises above a liquidation threshold, the debt position becomes available for liquidation and its collateral is auctioned off at a discount to liquidators in exchange for repaying the debt (see Appendix A). As a result, the close-out process in DeFi lending is automatic and the settlement is instant, while that in traditional repo and securities lending typically takes time and is initiated by the non-defaulting party. Note that, with such an automatic close-out process in DeFi, a loan can still turn out to be bad debt (which is a debt position whose value is larger than the collateral value) when no liquidators are willing to take on the collateral. This could happen typically when (i) the collateral price spirals downwards so that the discount is not profitable or (ii) the loan value is so small that the profit from the discount does not cover transaction costs such as gas fees. Lastly, DeFi lending also allows users to deposit without borrowing.

Table 2. Key differences between DeFi lending and repo/securities borrowing.

	DeFi lending	Repo/securities borrowing
Counterparty	pseudo-anonymous	identifiable
Collateral	pooled across borrowers	segregated
Borrow rate	pre-defined function of utilisation	flexible
Haircuts	pre-defined	flexible
Maturity	perpetual, borrower's option to repay early	short-term
Close-out process	automatically done by liquidators	non-defaulting party starts the process

Data collection. We run an erigon Ethereum archive execution client and a Lighthouse consensus client to collect DeFi lending protocol data. In particular, we analyze data for Aave v1, Aave v2, and Compound v2 – the biggest lending platforms on the Ethereum blockchain. Together, they account for approximately 80% of the value locked in lending protocols.[3]

For all wallet addresses that borrow from Aave and Compound, we collect their daily debt and deposit values on the platforms from 1 January 2021 through 31 March 2023. We have an observation for a user, if they have outstanding debt at the end of the day and do not have bad debt (because bad debt positions can have negative leverage when collateral value is smaller than debt value). In addition, we collect the daily values of other crypto assets held by these wallets outside of the lending platforms.[4] We also get price information from oracles – i.e., data sources used by these lending platforms. All values are in USD and we use "wallets" and "users" interchangeably.[5] Appendix B reports the step-by-step data cleaning procedures.

3 DeFi leverage and drivers

3.1 Overview of DeFi user leverage

We start our analysis by providing the summary statistics of our data sample in Table 3. In total, we have 11,130,928 observations for 55,948 users (Panel A). Not all users are active across the whole sample period. A typical user is active – i.e., with outstanding debt on DeFi lending platforms – for about 200 days in our sample. On average, a user's daily outstanding debt amounts to around \$0.6 million, with a daily outstanding asset of around \$1.2 million. This leads to an average daily equity of around \$0.6 million. These large numbers suggest that lending activities in DeFi are economically significant. Out of the three platforms, Aave v2 is the most popular one, with the highest number of active users and of observations. Compound v2 has especially large outstanding positions, with an average daily debt reaching \$1 million. In comparison, Aave v1

[3] https://defillama.com/protocols/lending/Ethereum

[4] We track the balances of ETH, as well as the biggest 20 ERC-20 tokens in terms of market capitalization on Ethereum, which represent 95% of the total market capitalization and should therefore provide us with good estimate of the value of the tokens held in a wallet.

[5] Note that a wallet can represent funds from multiple investors and an investor can have multiple wallets. Our data do not allow analysis of the actual ownership structure. Interested readers can refer to Victor (2020) for Ethereum address clustering heuristics.

and v2 have smaller positions, with average daily debt positions of around \$0.2 million and \$0.3 million, respectively.

The average daily statistics are biased by large users. Panel B in Table 3 shows the heterogeneity across users. The median debt is less than 0.7% of the mean debt, i.e., a few extremely large positions drive up the mean significantly. A similar pattern emerges for the assets and equity. In terms of leverage, the sample does not look as skewed. The average leverage of a wallet is 1.6, while the median is 1.4 and the top quantile is 1.9. However, the maximum leverage could reach above 7.5. Regarding the LTV-implied leverage, the mean and median are materially higher, amounting to 4.3 and 4.0 respectively. The maximum implied leverage, however, is just slightly above the maximum actual leverage.

Table 3. Summary statistics. In panel A, #Wallets is the number of wallets, #Obs is the number of observations and ratio represents the ratio between the number of observations and the number of wallets. For debt, assets, and equity, we first aggregate across days for each wallet and report the average across users. In panel B, we report the distribution statistics across users.

			Panel A: Overall sample			
Platform	#Wallets (Unit)	#Obs (Unit)	Ratio (Unit)	Avg daily debt (\$)	Avg daily asset (\$)	Avg daily equity (\$)
AAVEV1	4,629	1,358,940	293	224,498	607,759	383,261
AAVEV2	42,123	9,625,813	228	340,479	685,142	344,662
CompoundV2	16,836	5,862,197	348	985,870	1,752,627	766,757
Total	57,555	13,094,094	227	580,497	1,168,491	587,995
			Panel B: Heterogeneity across users			
Variable	Mean	Std	25%	Median	75%	Max
Debt (\$)	580,497	13,258,569	72	4,038	36,644	1,123,007,715
Assets (\$)	1,168,492	22,937,139	1,080	15,824	121,712	2,828,857,418
Equity (\$)	587,995	11,825,693	793	10,069	76,905	1,833,842,618
Leverage (Unit)	1.644	0.731	1.140	1.431	1.861	7.554
Leverage^{I} (Unit)	4.229	1.130	3.428	4.000	5.068	7.692

Figure 2 presents the time variation of user leverage (blue solid line) and juxtaposes it with crypto market price movements (grey dotted line) and LTV-implied leverage (black dashed line). In the same spirit in Liu, Tsyvinski, and Wu (2022), the crypto market index is calculated as an outstanding-debt-weighted average of crypto assets that are available on the three DeFi lending platforms.

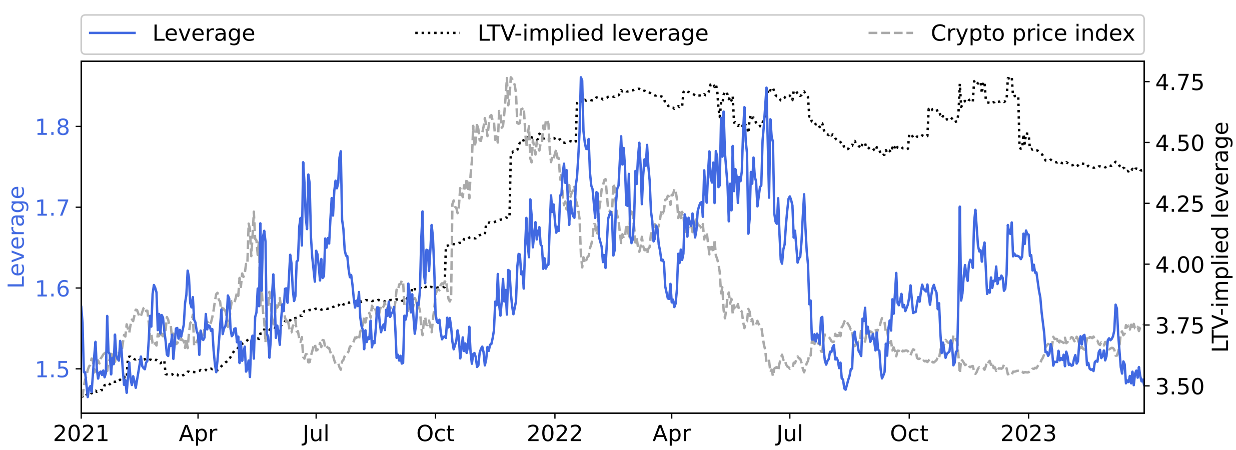
There are three takeaways from this figure. First, the overall leverage ranges from 1.4 to 1.9 in our sample period[6]. It is similar to the level of hedge fund leverage, which is around 1.5 after

[6]Note that Table 3 reports distribution statistics across *users*, while Figure 2 first aggregates leverage across wallet

the Great Financial Crisis (Ang, Gorovyy, and Van Inwegen, 2011). Second, DeFi user leverage appears to track the crypto market price movements closely, but with around a 3-month lag. This is consistent with the speculative trading motives in crypto documented in Biais, Bisiere, Bouvard, Casamatta, and Menkveld (2020) and Auer, Cornelli, Doerr, Frost, and Gambacorta (2023).

Third, the actual leverage taken by DeFi users is significantly lower than the LTV-implied leverage, which ranges from 3.5 to 4.8 in our sample period. This suggests that DeFi users are very conservative in taking up leverage. There could be two potential reasons. The first relates to the loss generated from the automatic close-out process, i.e., the liquidation loss. When a user's LTV ratio rises above a certain threshold, their collateral will be auctioned to liquidators at a considerable discount, incurring material losses for the borrower (as explained in Section 2 and in Appendix A). Hence, borrowers tend to be conservative and maintain a sizeable buffer. The second reason could be a search-for-yield motive. Users may be attracted to these pools because deposits in DeFi lending pools can deliver relatively high returns and they are not actively using these deposits as collateral to borrow. Thus, their actual leverage is not as high as the LTV-implied leverage.

Figure 2. Leverage vs LTV-implied leverage. We plot the time series of average daily leverage (blue solid line) and implied leverage (black dashed line) across all wallets with outstanding debts. The grey dotted line in the background indicates the market-wide price movements of crypto assets.



for each day and then report the average across *time*.

3.2 Leverage of different user groups

Given the heterogeneity across users, we classify them into the following three groups to understand how leverage varies. The first group is the largest users, which are the 1000 users with the largest average outstanding debts. The second group is the most active users, which are the 1000 users with the highest number of borrowing activities during the sample period. The third group is the earliest users, which are the first 1000 wallets that took out debt on each lending platform. There is overlap between the groups: 194 wallets are both amongst the largest and most active. The overlap between the earliest users and the largest and most active is very small. Appendix B provides more detail on the distribution across the three groups.

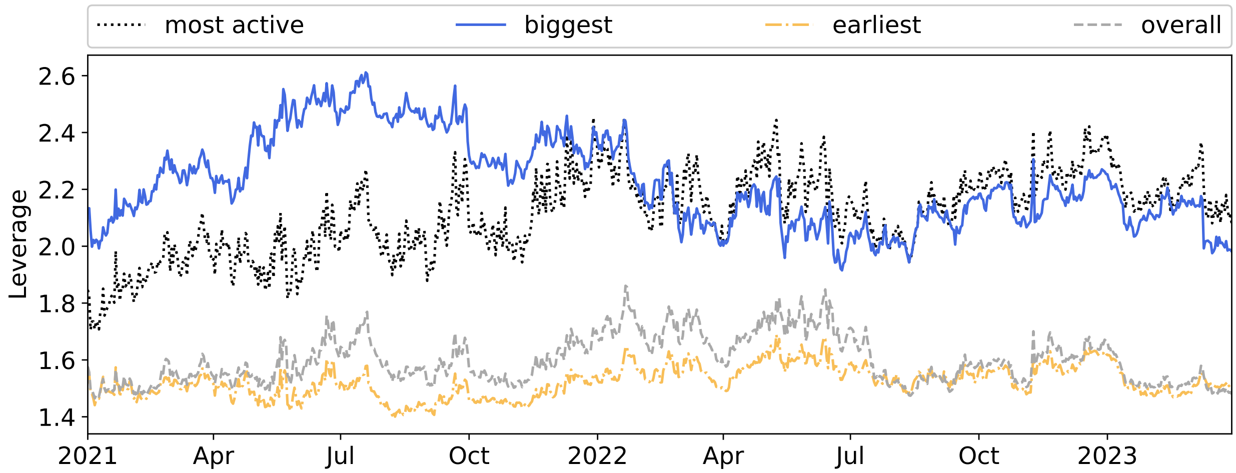
Panel A of Figure 3 presents the time series of leverage of the three groups. The largest and most active users have higher leverage compared to the rest. Their average leverage tends to exceed 2, potentially reflecting economies of scale. Typically, larger and more active borrowers are better able to monitor their positions in real time, which enables them to effectively access higher leverage. The earliest users, on the other hand, exhibit a lower leverage than the rest. The underlying reason could be that these users are testing accounts as they typically have very small debt positions (< \$100). Additionally, given all three lending platforms launched before the start of our sample period, a significant fraction of the earliest users are no longer active during our sample period.

Furthermore, we differentiate two types of users: the ones with long leverage and those with short leverage. A user that deposits volatile coins (VC) such as Bitcoin and borrows stablecoins (SC) such as USDC has long leverage. This trade is similar to a repurchase agreement (repo). VC is on the asset side and SC is on the liability side. We consider a user with long leverage if at least 80% of their debt are SC and at least 80% of the collateral are VC. Alternatively, a user can deposit SC and use that claim of the pool as collateral to borrow VC. The user has short leverage and this transaction is similar to securities borrowing. VC is on the liability side and SC is on the asset side. We consider a user with short leverage if at least 80% of their collateral are SC and at least 80% of the debt are VC.

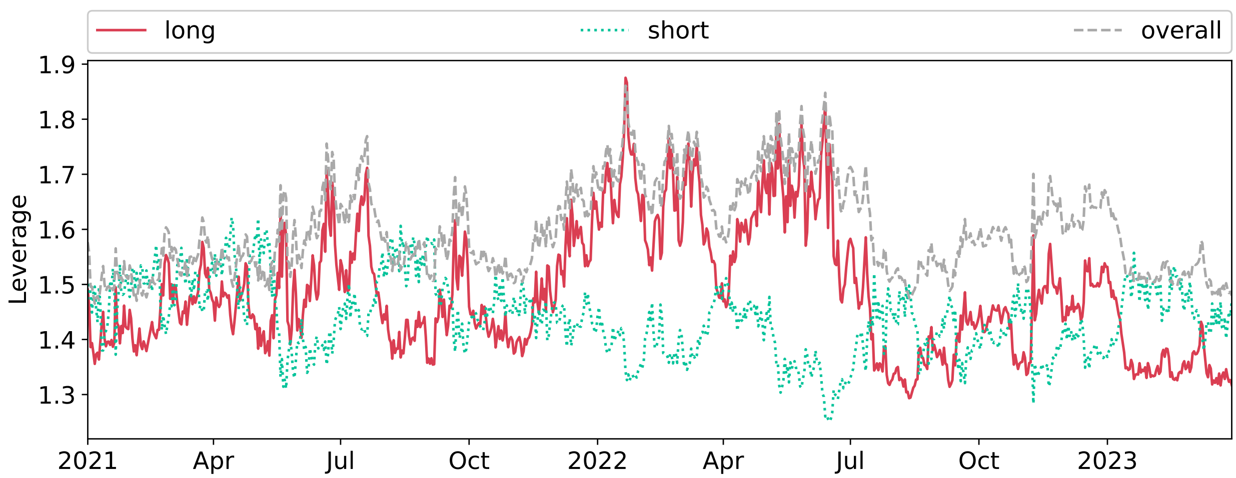
Panel B of Figure 3 shows the time series of the average leverage of the long users (red solid line) and that of the short users (green dashed line). One striking feature is that the leverage

Figure 3. Leverage across groups.

(a) Leverage of the most active, the largest, and the earliest. We plot the mean daily leverage of the most active (black dotted line), the largest (blue solid line), the earliest (yellow dashed-dotted line), and all (grey dashed line) wallets with open loans across time.



(b) Long and short leverage time series. We plot the mean daily leverage of long (red solid line) and short (green dotted line) leverage wallets with open loans across time. The grey dashed line in the background indicates the average leverage of all wallets.



of the short and long users are negatively correlated. This likely reflects the impact of crypto asset price fluctuations on DeFi user leverage. When VC price appreciates, the collateral value of long users increases while their SC debt value remains unchanged, leading to a decrease in their leverage. On the contrary, in this case, the collateral value of short users remains unchanged, while their VC debt value increases, leading to an increase in their leverage. Thus, the VC price movements have opposite effects on the leverage of the long and short users, giving rise to a negative correlation between the leverage of the two groups. An additional observation is that the long users experienced significant deleveraging after the Celsius bankruptcy in June 2022. A similar pattern, however, does not hold for the short users.

Table 4 reports the distribution of leverage amongst users with long and short leverage. The first observation is that users typically have long leverage. The number of observations with long leverage exceeds that with short leverage by more than a factor of ten. The long leverage users tend to be more active, with an average of active day reaching about 200 days, which is twice as much as that for the short leverage users. Secondly, on average and across the various quantiles, the leverage of the short users is higher than that of the long users, even though this is not apparent in Figure 3b (because the reported statistics weigh the average leverage of each wallet equally independent of the number of days they were active for).

Table 4. Distribution of leverage amongst wallets with long and short leverage. We first aggregate the leverage across days for each wallet and report the statistics across wallets. We further report the number of observations and unique wallets with long and short leverage, as well as the ratio to indicate the mean number of observations per wallet.

	Mean	Std	25%	50%	75%	#Wallets	#Obs	Ratio
Long	1.511	0.516	1.119	1.380	1.730	42,647	8,615,139	202
Short	1.725	0.736	1.190	1.532	2.015	4,554	526,361	115

3.3 Factors that are associated with high leverage

3.3.1 Hypothesis development

Next, we are going to study the factors associated with high DeFi leverage. There are two critical contractual terms in collateralised borrowing: haircuts (implied by LTV) and borrow rates. When an asset has a lower haircut, a user can pledge it to borrow a higher amount of debt, i.e., with a higher LTV ratio and thus a higher implied leverage (Fostel and Geanakoplos, 2014). As indicated in Figure 2, one would expect that a user that faces a higher LTV-implied leverage (i.e., a looser haircut requirement) will have higher actual leverage.

Hypothesis 1. *A user has higher leverage when the LTV-implied leverage is higher.*

To test Hypothesis 1, we construct a wallet-day level variable of the LTV-implied leverage. We first get the daily time series of the LTV ratio for each crypto asset j and convert them into a time series of the implied leverage:

$$Leverage^I_{j,t} = \frac{1}{1 - LTV_{j,t}}. \quad (1)$$

For each wallet i, we then calculate the debt-weighted implied leverage across all crypto assets that are in the wallet's debt portfolio J (in which $Debt_{i,j,t}$ is the outstanding debt of crypto asset j of wallet i on day t):

$$Leverage^I_{i,t} = \frac{\sum_J (Debt_{i,j,t} \times Leverage^I_{j,t})}{\sum_J Debt_{i,j,t}}. \quad (2)$$

Thus, $Leverage^I_{i,t}$ captures the LTV-implied leverage for wallet i on day t. For the actual leverage, we get the total asset and total debt for each wallet-day, and calculate the equity as the difference between the asset and debt. $Leverage_{i,t}$ is the asset-to-equity ratio for wallet i on day t. Hypothesis 1 implies that $Leverage_{i,t}$ increases in $Leverage^I_{i,t-1}$.

The second hypothesis pertains to the borrowing cost. In the case of floating rate debts, when the cost of taking leverage is higher, that should suppress a user's actual leverage.

Hypothesis 2. *A user has lower leverage when they face higher borrowing costs.*

To test Hypothesis 2, we first get the daily time series of the (floating) borrow rate and deposit rate for each crypto asset. For each wallet-day, we calculate the debt-weighted average borrow rate across all crypto assets that are in the wallet's floating debt portfolio for that day (similar to Equation 2). Thus, $BorrowRate_{i,t}$ captures the borrowing cost faced by wallet i on day t. Similar to the construction of $BorrowRate_{i,t}$, we build $DepoRate_{i,t}$, i.e., the deposit-weighted average of deposit rate across all crypto assets that are deposited by wallet i on day t. Then $NetBorrowCost_{i,t}$ is the difference between $BorrowRate_{i,t}$ and $DepoRate_{i,t}$, capturing the net borrowing cost faced by wallet i on day t. Note that most debts on DeFi lending platforms are floating rate debts (as known as "variable rate debts" in the crypto terminology). In our sample, over 95% of the debts are floating rate debts. Hypothesis 2 implies that $Leverage_{i,t}$ decreases in $NetBorrowCost_{i,t-1}$.

The third hypothesis relates to a typical feature of crypto activities: speculation and momentum types of trading. Auer, Cornelli, Doerr, Frost, and Gambacorta (2023) document that crypto price movements are closely related to the enthusiasm, or sentiment, in crypto markets. They show that a key driving factor for Bitcoin price movements is the number of active users of crypto exchanges. This is consistent with the earlier literature that reports the speculative activities/motives in crypto market (Biais, Bisiere, Bouvard, Casamatta, and Menkveld, 2020; Aramonte, Huang, and Schrimpf, 2021). In the context of DeFi lending, Chiu, Ozdenoren, Yuan, and Zhang (2022) models some key features in DeFi lending and finds that sentiment matters. Thus, we hypothesise that market sentiment will increase a user's actual leverage.

Hypothesis 3. *A user has higher leverage when the sentiment is higher.*

To test Hypothesis 3, we construct a market sentiment variable that is particularly relevant for DeFi lending. We first get the daily time series of the utilisation rate for each crypto asset, i.e., the proportion of a crypto asset that has been lent out in the total deposit amount of that asset. A high utilisation rate, thus, indicates that the crypto asset is "popular" in the lending platform. For each wallet-day, we then calculate the debt-weighted utilisation rate across all crypto assets that are in the wallet's floating debt portfolio for that day (in the same spirit of Equation 2). Thus, $Utilisation_{i,t}$ captures the popularity, or the market sentiment, of the debt portfolio of wallet i on day t. Thus, it is a user-specific measure of market sentiment, which reflects individual users' own exposures to market sentiment. Hypothesis 3 implies that $Leverage_{i,t}$ increases in $Utilisation_{i,t-1}$.

There is a closely related, yet fundamentally different, mechanism on how crypto price movements could affect user leverage. As shown in Panel B of Figure 3, price movements of the volatile coins (VC), which also captures essentially the crypto market price movements given the stablecoin (SC) prices are relatively stable, have opposite effects on the actual leverage of a long user and that of a short user. When VC depreciates, a long user has higher leverage as their VC collateral value decreases and SC debt value remains unchanged. On the contrary, a short user has higher leverage when VC appreciates. Hypothesis 4 summarises these effects.

Hypothesis 4. *A long user has lower leverage when (volatile) crypto assets appreciate. On the opposite, a short user has higher leverage when crypto assets appreciate.*

To test Hypothesis 4, we first construct a variable that indicates a user's direction of lending on a given day: +1 for long position and −1 for short position, following the categorisation methodology in Figure 3b and Table 4.

$$Sign_{i,t} = \begin{cases} +1, \text{if at least 80\% of debt are SC and at least 80\% of collateral are VC;} \\ -1, \text{if at least 80\% of debt are VC and at least 80\% of collateral are SC;} \\ 0, \text{others.} \end{cases} \quad (3)$$

We then multiply $Sign_{i,t}$ with the crypto market price index on day t shown in Figure 2, which is the outstanding-debt weighed average of prices across all crypto assets that can be borrowed in the three lending platforms. Thus, we have a wallet-day level variable that captures the opposite effects of crypto price movements on long and short users: $SignedVCPrice_{i,t}$. Hypothesis 4 implies that $Leverage_{i,t}$ decreases in $SignedVCPrice_{i,t-1}$.

Our final two hypotheses aim to elucidate the gap between actual and LTV-implied leverage as shown in Figure 2. In traditional finance, the LTV-implied leverage is typically also the actual leverage taken out by a borrower. This discrepancy in the DeFi lending sphere could be attributed to two distinguishing features. The first is the automatic close-out process and the associated material liquidation loss for borrowers. Different from traditional finance in which intermediaries like dealers or central counterparties issue margin calls when the LTV ratio of a debt position rises, DeFi lending deploys automatic liquidation algorithms – i.e., auctioning off the collateral to liquidators at a discount *as soon as* a user's LTV ratio rises above a certain threshold. Such liquidation algorithms expose borrowers to great risks of unexpected liquidation, especially in volatile markets. Furthermore, Lehar and Parlour (2022) document that there are "predatory liquidations", i.e., liquidators strategically target debt positions teetering on the brink of liquidation thresholds, artificially suppress the collateral price to trigger a liquidation event, and subsequently acquire and resell the collateral at a profit. Given these unique factors, DeFi users may avoid leverage to the maximum extent and the volatility of a user's collateral will affect such conservativeness. Thus, we hypothesize that all else being equal, users with more volatile collateral will opt for a more conservative approach, hence lower actual leverage.

Hypothesis 5. *A user has lower leverage when their collateral is more volatile.*

To test Hypothesis 5, we first construct daily time series of the realised volatility for all crypto assets that are eligible as collateral in DeFi lending platforms. Then, we calculate the collateral-weighted average volatility across all assets that are deposited by wallet i on day t: $Volatility_{i,t}$. Hypothesis 5 suggests that $Leverage_{i,t}$ decreases in $Volatility_{i,t-1}$.

The other feature of DeFi lending that could lead to the gap between the actual leverage and the LTV-implied leverage relates to a search-for-yield motive. As crypto markets are rather self-referential (Aramonte, Huang, and Schrimpf, 2021), asset holders do not have many real use cases but hope that their crypto assets may appreciate. Thus, when users experience higher return of their crypto assets, they are incentivised to deposit even more to these platforms, anticipating for future price appreciations. Instead of using them to borrow actively, users only deposit the assets to reach for yields. Such behaviours increase their assets without expanding their debt, leading to lower leverage.

Hypothesis 6. *A user has lower leverage when they face higher collateral returns.*

Similar to the construction of $BorrowRate_{i,t}$, we build $CollateralReturn_{i,t}$ in two steps. First, we calculate the time series of the past 30-day returns for crypto assets that can be deposited on the three DeFi lending platforms. Then, we calculate the deposit-weighted return $CollateralReturn_{i,t}$ across all crypto assets that are deposited by wallet i on day t. Hypothesis 6 implies that $Leverage_{i,t}$ decreases in $CollateralReturn_{i,t-1}$.

3.3.2 Regression results

To formally test these hypotheses, we estimate the following panel regressions:

$$\begin{aligned} Leverage_{i,t} = \beta_0 + \beta_1 Leverage^{I}_{i,t-1} + \beta_2 NetBorrowCost_{i,t-1} + \beta_3 Utilisation_{i,t-1} \\ + \beta_4 SignedVCPrice_{i,t-1} + \beta_5 Volatility_{i,t-1} + \beta_6 CollateralReturn_{i,t-1} + \gamma_i + \mu_t + \varepsilon_{i,t} \end{aligned} \tag{4}$$

We include time and user fixed effects to capture the omitted variations across time (i.e., market-wide developments like interest rate movements of fiat currencies and concentration in borrowing and lending) and across users (i.e., user-specific but time-invariant characteristics). To ensure robustness, we estimate the double-clustered standard errors following Petersen (2008).

Table 5 reports the regression results. The first column is estimated on the whole sample. As expected, leverage increases in LTV-implied leverage and decreases in the net borrowing cost. When utilisation – the proxy for sentiment and popularity – is higher, leverage increases. For long (short) leverage wallets, their leverage decreases (increases) when VC collateral (debt) appreciates. In addition, users' actual leverage decreases when their collateral is more volatile and when the collateral return is higher, suggesting that the gap between the actual leverage and the LTV-implied leverage is driven by both the looming threat of automatic liquidation and the search-for-yield motive.

Given the skewness of the sample, we exclude the largest 1% and smallest 1% wallets and run the regression on a winsorised sample (the second column in Table 5) and find that the results are robust. We further examine the three groups of wallets identified before (the third to the last columns) and observe that the patterns are mostly consistent. The noticeable exception is on the impact of collateral volatility, indicating that the looming threat of automatic liquidation does not lower these three groups' leverage. Particularly, for the earliest users, their leverage is higher when their collateral is more volatile. However, this is likely due to the fact that these wallets are typically testing accounts, most of which are no longer active during our sample period.

Additionally, we conduct several robustness tests in Appendix C. One concern could be the multicollinearity between *NetBorrowCost* and *Utilisation* given these variables are interlinked in the pre-defined interest rate functions (see Appendix A). Although multicollinearity still yields unbiased estimated coefficients, it inflates their variance. To address this issue, we run panel regressions in which these variables are included separately. The results remain qualitatively unchanged.

Another concern could stem from the construction of *SignedBVCPrice*, in which the 80% cut-off is an ad-hoc choice. We rerun all the regressions in the main analysis with various cut-off levels. The results are not sensitive to the cut-off choices.

4 The systemic impact of leverage on lending resilience

We next investigate the effect of leverage on the resilience of DeFi lending pools. As discussed in Section 2, DeFi lending relies on overcollateralisation to prevent defaults and the associated losses. When collateral values decline, however, borrowers could still default. To mitigate such risk, DeFi

Table 5. Driving factors of DeFi leverage. We report the regression results for the following model $Leverage_{i,t} = \beta_0 + \beta_1 Leverage^I_{i,t-1} + \beta_2 NetBorrowCost_{i,t-1} + \beta_3 Utilisation_{i,t-1} + \beta_4 SignedVCPrice_{i,t-1} + \beta_5 Volatility_{i,t-1} + \beta_6 CollateralReturn_{i,t-1} + \gamma_i + \mu_t + \varepsilon_{i,t}$. We estimate the double-clustered standard errors following Petersen (2008). T-stats are reported in brackets.

	All	**Winsorised**	**Largest**	**MostActive**	**Earliest**
Leverage^I	0.074***	0.074***	0.082	0.181***	0.093***
	(16.030)	(15.989)	(1.609)	(6.293)	(4.204)
NetBorrowCost	-0.021***	-0.021***	-0.232**	-0.124***	-0.056**
	(-3.300)	(-3.200)	(-1.965)	(-4.230)	(-2.395)
Utilization	0.031**	0.028**	0.436***	0.367***	0.010
	(2.456)	(2.159)	(2.692)	(3.494)	(0.224)
SignedVCPrice	-0.043***	-0.042***	-0.103***	-0.056***	-0.014
	(-17.108)	(-16.394)	(-4.678)	(-3.819)	(-1.438)
Volatility	-3.697**	-3.8882**	14.439	0.176	7.347***
	(-2.418)	(-2.426)	(1.144)	(0.029)	(3.124)
CollateralReturn	-0.154***	-0.155***	-0.269***	-0.172***	-0.049***
	(-20.658)	(-20.794)	(-7.012)	(-5.076)	(-3.435)
Time FE	✓	✓	✓	✓	✓
User FE	✓	✓	✓	✓	✓
No. Observations	12345871	12026304	173034	327793	435770
R-squared	0.0181	0.0175	0.0429	0.0459	0.0205

platforms allow anyone to liquidate a loan when the loan-to-value ratio exceeds a certain threshold, i.e., the so-called "liquidation threshold". The liquidation threshold is higher than the LTV ratio but remains below 1 to ensure the loan stays overcollateralised.

To understand how borrower leverage may generate systemic risk for the lending platforms, We examine two DeFi-lending-specific resilience measures. One is the value-at-risk (VaR) of the pool, i.e., the share of the pool that is close to being liquidated. The other is the share of the pool that has been actually liquidated. The former indicates how many debt positions in a given crypto asset pool are at risk of liquidation, while the latter signals the materialisation of such risk.

Panel A of Figure 4 shows the average VaR on Aave v2 (black dotted line) and juxtaposes that with the borrower leverage (blue solid line) and the crypto price index (grey dashed line). It is remarkable that the VaR of the pool tracks closely the debt-weighted average of borrower leverage, especially in the first half of the sample. It suggests that when the borrowers take higher leverage, a higher share of the pool is close to being liquidated. In other words, lending resilience deteriorates when borrower leverage increases.

Panel B of Figure 4 shows the share of liquidation volume in the outstanding debt (yellow solid line). Large liquidation spikes often coincide with significant price fluctuations in crypto assets. Notably, before mid-2021, the spikes of liquidation share were more frequent as the lending pools were relatively small. However, since 2022, these spikes have become more event-driven, as evidenced by incidents such as the USD Terra crash (the first vertical line), the Celsius bankruptcy (second vertical line), the FTX collapse (third vertical line), an attack on Aave in November 2022 (fourth vertical line), and the USDC depegging due to the SVB collapse (fifth vertical line). It appears that the spiky share of liquidation volume is not that closely related to borrower leverage.

To better understand the impact of leverage on pool resilience, we estimate the following panel regressions:

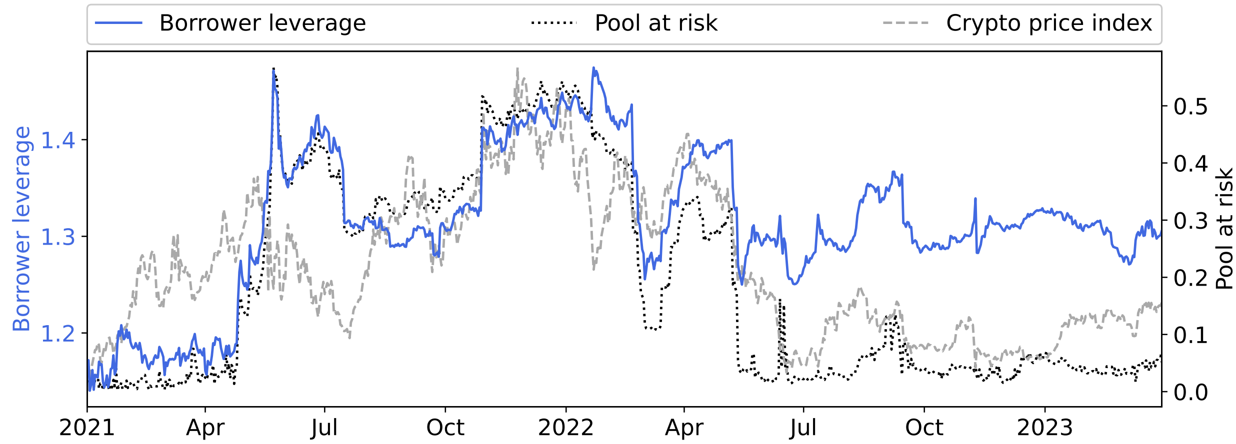
$$PoolResilience_{j,t} = \alpha + \beta BorrowerLeverage_{j,t-1} + \theta Control_{j,t-1} + \gamma_j + \mu_t + \varepsilon_{j,t} \tag{5}$$

where the dependent variable is the pool-day resilience measure (i.e., Value-at-Risk or liquidation share), and the key explanatory variable is borrower leverage. We include relevant control variables such as the liquidation threshold, the loan-to-value ratio (LTV), the realised volatility, and the concentration index (HHI) of borrowers, as well as the time and pool fixed effects.

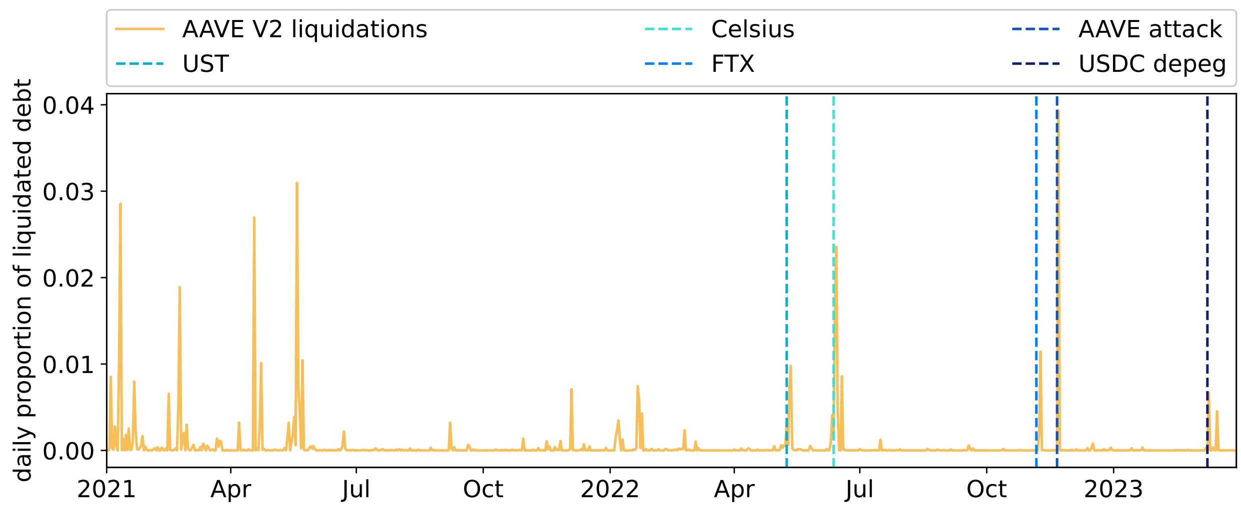
Table 6 reports the regression results. Panel A is for the lending pools in Aave v2 and Panel B is for Compound. The first three columns present the results of the panel regressions with the dependent variable being pool VaR and the sample being the full, VC only, and SC only. The key take-away is that when borrower leverage is higher, VaR is higher, signaling higher risk in lending pools. This pattern is broadly consistent in Aave v2 and in Compound pools. The last three columns report the results of the regressions with the dependent variable being liquidation share. Coefficients of borrower leverage are generally positive but not significant, likely due to the fact that liquidations are rather event-driven and tend to be self-amplifying (Lehar and Parlour, 2022). The pattern is consistent with Figures 4. When the borrower leverage is higher, a large

Figure 4. Lending resilience.

(a) Daily proportion of debt at risk on Aave v2. We consider a debt position at risk if the position's health factor drops below 1.1 (see Appendix A). The black dotted line is the value-at-risk of the pool. The blue solid line is the debt-weighted average of borrower leverage. The grey dashed line is the crypto market price index.



(b) Daily proportion of liquidated debt on Aave v2. The grey line in the background indicates the ETH price and the vertical lines indicate major events.



share of the pool is close to being liquidated. However, the higher leverage does not significantly affect the share of the pool that has actually been liquidated.

In Appendix C, we conduct robustness checks around the cut-off values in the pool VaR measure. The results are not sensitive to the cut-off choices.

Table 6. DeFi leverage and pool resilience. We report the regression results for the following model $PoolResilience_{j,t} = \alpha + \beta BorrowerLeverage_{j,t-1} + \theta Control_{j,t-1} + \gamma_j + \mu_t + \varepsilon_{j,t}$ where the dependent variable is the pool-day resilience measure (i.e., Value-at-Risk or liquidation share), and the key explanatory variable is borrower leverage. Control variables include the liquidation threshold, the loan-to-value ratio (LTV), the realised volatility, and the concentration index (HHI) of borrowers. We also include the time and pool fixed effects. We estimate the double-clustered standard errors following Petersen (2008). T-stats are reported in brackets.

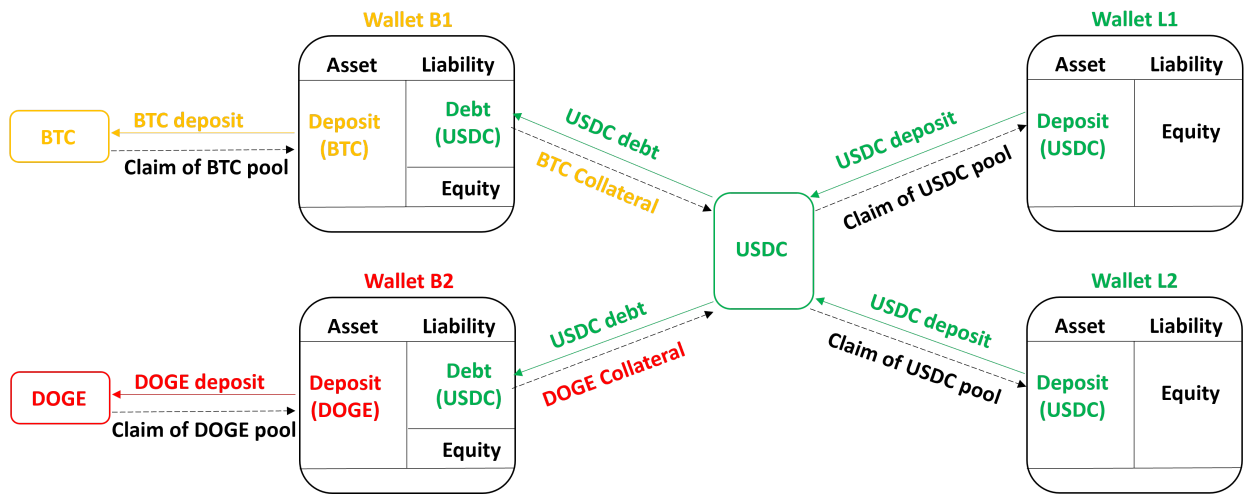
	Pool Value-at-Risk			**Liquidation share**		
	All	**Volatile coins**	**Stablecoins**	**All**	**Volatile coins**	**Stablecoins**
			Panel A: Aave v2			
BorrowLeverage	0.9178***	0.6265***	1.0833***	0.0055*	0.0074	0.0034
	(6.0587)	(2.6351)	(7.4830)	(1.9227)	(1.6242)	(0.9485)
Controls	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Pool FE	✓	✓	✓	✓	✓	✓
No. Observations	21157	13952	7205	22816	15568	7248
R-squared	0.3473	0.1435	0.6554	0.0018	0.0028	0.0015
			Panel B: Compound			
BorrowLeverage	1.2050***	1.1563***	0.4677*	0.0035*	0.0037*	0.0004
	(4.1348)	(2.8542)	(1.7666)	(1.7078)	(1.7215)	(0.2164)
Controls	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Pool FE	✓	✓	✓	✓	✓	✓
No. Observations	11137	7286	3851	11848	7928	3920
R-squared	0.2685	0.3371	0.5272	0.0003	0.0011	0.0013

5 Collateral selection at liquidation

One unique feature of DeFi lending is the pooling of collateral *across borrowers*. Figure 5 illustrates how this works via a simple example. Suppose there are two borrowers B1 and B2 and two lenders L1 and L2 for the pool of USDC. Borrower B1 collateralises their USDC loan with Bitcoin (BTC) while B2 uses Doge coin (DOGE) as collateral. Consider the following three cases, each as a more stressful case than the previous one.

Case 1 is when the DOGE price decreases and B2's loan-to-value (LTV) ratio rises above the liquidation threshold. In this case, B2's DOGE collateral is auctioned off to liquidators at a discount to repay their USDC debt. The lenders can choose to redeem their claims of the USDC pool, but only to the extent that is available in the USDC pool as some of the USDC are still "occupied" by

Figure 5. Pooling of collateral across borrowers. This figure shows a stylised example of how collateral is pooled across borrowers, focusing on the users of the USDC pool (green). Wallet B1 and B2 are borrowers of USDC, using BTC (yellow) and DOGE (red) as collateral, respectively. Wallet L1 and L2 are the lenders of USDC.



B1's debt positions.

Case 2 is when both BTC and DOGE prices decrease and both B1's and B2's USDC debt positions are liquidated. Similar to case 1, both BTC and DOGE collateral are auctioned off to liquidators at discounts to repay the USDC debt. The lenders can choose to redeem all their claims.

Case 3 is when both BTC and DOGE prices plummeted and only B1's debt position was liquidated successfully while B2's position turned to bad debt. In other words, the DOGE price decreases so fast that the collateral value falls below the debt value. In this case, whoever among the two lenders redeems first their claim of the USDC pool will make it whole, while the other lender will end up with bad debt.

This simple example shows that the composition of the collateral that backs the debt positions is extremely fluid and difficult to monitor by lenders, which also features in the novel setup in Chiu, Ozdenoren, Yuan, and Zhang (2022). The authors find that with this feature, there exists self-fulfilling sentiment equilibria, i.e., the overall quality of the collateral declines when the market sentiment deteriorates. The reason is that, due to the pooling of collateral across borrowers, borrowers have information advantage over lenders on the quality of the collateral. Thus, borrowers can substitute low quality collateral for high quality collateral when they expect their debt positions to be liquidated. In the example in Figure 5 in which the quality of BTC is assumed to be higher than that of DOGE, borrower B1 could potentially choose to deposit DOGE and withdraw

BTC – hence swapping BTC collateral for DOGE collateral without affecting their USDC debt – when they expect their debt positions to be liquidated due to bad sentiment.

The granular wallet-level data allows us to investigate if borrowers who are about to be liquidated adjust their collateral composition towards lower quality assets. In total 1,526 wallets were liquidated in our sample. For each one of these wallets, we calculate the portfolio-weighted collateral volatility 30 days ahead of its liquidation $CollateralVol_{i,t}$ where t runs from -29 to 0. In addition, we construct a "simulated" volatility measure $SimulatedVol_{i,t}$ that fixes the portfolio composition on day -29.

$$CollateralVol_{i,t} = \frac{\sum_K (CollateralValue_{k,i,t} \times Vol_{k,t})}{\sum_K CollateralValue_{k,i,t}}, \tag{6}$$

$$SimulatedVol_{i,t} = \frac{\sum_K (CollateralValue_{k,i,-29} \times Vol_{k,t})}{\sum_K CollateralValue_{k,i,-29}}, \tag{7}$$

$$Diff_i = CollateralVol_{i,0} - SimulatedVol_{i,0}. \tag{8}$$

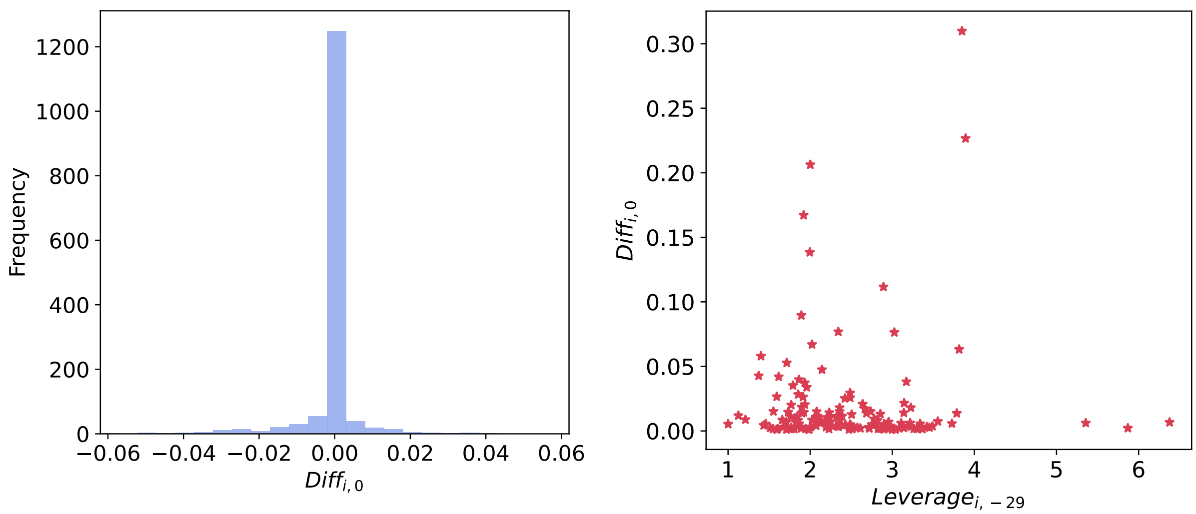
where K is the set of collateral of wallet i on day t, $CollateralValue_{k,i,t}$ is the collateral value of crypto asset k of wallet i on day t and $Vol_{k,t}$ is the volatility of crypto asset k on day t.

If $SimulatedVol_{i,0}$ is lower than $CollateralVol_{i,0}$ – i.e., $Diff_i > 0$ – it means that wallet i tilts towards more volatile, hence lower quality, assets as collateral on the day when it was liquidated. Figure 6a shows the distribution of $Diff_i$ across all wallets that were liquidated in our sample. The key result is that most of these wallets did not modify their collateral composition 30 days ahead of the final liquidation, i.e., no strategic collateral selection at close to liquidation. This result likely reflects the fact that the LTV requirement of more volatile collateral is more stringent than that of less volatile one. For instance, in the example above, when borrower B1 swaps DOGE collateral for BTC collateral, they would need to put in more DOGE than BTC they withdraw because the LTV requirement for DOGE is more restrictive than that for BTC. Hence, to the extent that the LTV requirements take into account the quality of collateral perfectly, such strategic collateral selection should not take place and should not expose lenders to higher risk even if that type of activity takes place.

That said, a small amount of wallets indeed tilted towards to more volatile collateral as indicated by the right tail of the distribution. Figure 6b zooms in on the wallets that have positive $Diff_i$, i.e., those that tilted towards volatile collateral, and plots $Diff_i$ against leverage. The plot indicates some positive correlation between the two variables, i.e., when a wallet's leverage is higher, it tilts towards more volatile collateral.

Figure 6. Collateral selection. Panel A plots the histogram for $Diff_i$ of all wallets that were liquidated in our sample. Panel B is a scatter plot. The x-axis is the actual leverage 30 days ahead of the liquidation. The y-axis is $Diff_i$. The sample includes only the wallets that have positive $Diff_i$.

(a) Histogram of $Diff_i$. **(b) Leverage vs $Diff_i$.**



We run the following cross-sectional regression to investigate the relationship between leverage and the behaviour of collateral selection:

$$Diff_i = \beta_0 + \beta_1 Leverage_i + Debt_i + \varepsilon_i \tag{9}$$

where $Leverage_i$ is the wallet's leverage 30 days ahead of the liquidation, and $Debt_i$ is the wallet's outstanding debt 30 days ahead of the liquidation.

Table 7 reports the regression results. The first column shows that when the wallet's leverage is higher, the difference between the actual collateral volatility and the simulated one that keeps the collateral composition unchanged is higher. In addition, when the wallet's implied-leverage requirement (from the LTV ratio) is higher, it is also titled towards more volatile collateral, as indicated by the second column. This is likely due to the fact that crypto assets that are more stable typically have higher implied-leverage from the LTV ratio. When a user initially has more stable collateral, it is easier to move to more volatile collateral. Column 3, to some extent, confirms this intuition. When the difference between the implied leverage and the actual leverage is higher for a wallet, it has more "room" to migrate to volatile collateral and thus has a higher *Diff*.

Table 7. The impact of leverage on collateral selection. We report the regression results for the following cross-sectional regression $Diff_i = \beta_0 + \beta_1 Leverage_i + Debt_i + \varepsilon_i$ where the dependent variable is $Diff_i$ defined in Equation 8, $Leverage_i$ is the wallet's leverage 30 days ahead of the liquidation, and $Debt_i$ is the wallet's outstanding debt 30 days ahead of the liquidation. T-stats are reported in brackets.

	Diff	**Diff**	**Diff**
Leverage	0.0078***		
	(4.561)		
Leverage^I		0.0050***	
		(5.594)	
Leverage^I - Leverage			0.0100***
			(6.067)
Debt	-0.0001	-0.0002	0.0000
	(-0.595)	(-0.990)	(0.214)
No. Observation	145	145	145
R-squared	0.1754	0.1836	0.1383

6 Conclusion

In this paper, we document individual wallets' leverage in DeFi for the first time in the literature. Throughout our sample period between January 2021 and March 2023, the overall leverage of DeFi lending protocol users ranges from 1.4 to 1.9. Users with the highest volume of activity and those managing the largest amounts of outstanding debt consistently demonstrate higher levels of leverage compared to their counterparts, with average leverage frequently surpassing 2.

Our analysis reveals that user-level leverage is primarily influenced by LTV-implied leverage and borrow rates, as well as the crypto market sentiment and price movements. However, the actual leverage is markedly lower than the LTV-implied leverage. This discrepancy may be attributed to the distinctive feature of automatic liquidation inherent in DeFi lending. The looming risk of liquidation and the subsequent potential losses appear to prompt DeFi borrowers to maintain a more conservative approach, ensuring a substantial buffer. These behaviours suggest that while the automation of traditional intermediaries may curtail the rents extracted by these intermediaries, it may concurrently give rise to new forms of friction.

We investigate the impact of high borrower leverage on DeFi lending platforms. While higher borrower leverage raises the proportion of loans nearing liquidation, it does not significantly impact the incidence of liquidation itself, as liquidations entail substantial costs and are typically triggered by specific events. In addition, although DeFi borrowers can modify their collateral portfolios as long as meeting the LTV ratio requirements, we find that most borrowers nearing liquidation do not shift towards more volatile collateral, probably due to more stringent LTV requirements for such assets. However, among borrowers that do tilt towards volatile collateral, higher borrower leverage is associated with more aggressive strategic collateral adjustment.

Our findings in DeFi lending also contribute to improvement and adaptation within traditional financial systems. Notably, major global banks are pioneering in blockchain networks for intraday repo transactions (see e.g., Bloomberg (2021)). Large asset managers are also venturing into the realm of tokenized collateral settlements (see e.g., Bloomberg (2023)). Our results highlight the importance of considering user behaviour, market dynamics, and automated risk mitigation in the design and management of collateralized borrowing platforms with emerging tokenized assets.

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A Lending Protocol Background

Lending protocols utilise pre-defined rules executed through smart contracts, which automate and regulate the protocol's operations. To become a lender, individuals must lock their assets in the protocol's smart contract and will receive a deposit rate in return for providing the collateral. On the other hand, borrowers can obtain loans by depositing collateral and borrowing against it. It is important to note that borrowers are subject to a substantial collateral haircut, ranging from 10% to 40%, based on the type of collateral provided. The haircut is expressed by the loan-to-value ratio in lending protocols and is pre-defined by the protocol governance[7]. A unique feature of DeFi lending is that borrowers pay a borrow rate on their debt, but also receive a deposit rate for their collateral.

DeFi lending protocols typically offer loans with an open-ended repayment period, allowing borrowers to repay the loan at their convenience. A user can take out debt, as long as the value of value of the collateral after the collateral haircut is applied, exceeds the value of the debt. To be precise, a user can take out debt, as long as

$$\sum_{i \in A} (C_i \cdot LTV_i) \geq \sum_{i \in A} D_i,$$

where A are the platform's assets, while C_i is the collateral amount in asset i and D_i is the debt amount in asset i. Additionally, LTV_i is the loan-to-value ratio for asset i.

The LTV ratio is voted by the decentralised autonomous orgranisation (DAO) based on risk rating analysis (conducted by the lending platform or related third-party risk consultants) that looks into three risk factors: smart contract risk, counterparty risk, and market risk. Smart contract risk assesses the technical safety of an asset and its vulnerability to potential hacks. Counterparty risk examines the governance and control of the asset. Market risks look into liquidity and volatility, alongside market size and demand fluctuations. Based on the assessment, a rating is assigned to each asset ranging from A+ (lowest risk) to D- (highest risk). Voting coin holders can propose and vote on the LTV ratio for each asset.

[7] Aave and Compound are governed by a decentralized autonomous organization (DAO). A DAO decision-making process is governed by code. The stakeholders in a DAO hold voting power that is proportional to their stake in the DAO's native token, enabling them to participate in the decision-making process and propose changes to the protocol's rules or parameters.

The interest rate charged on the borrowed amount is applied periodically and is typically a floating rate, determined by the current utilisation of the borrowed asset. The borrow rate is applied periodically by adjusting the borrower's debt balance. An asset's a utilisation at time t can be calculated as the ratio of the total outstanding debt (D_t^a) to the collateral (C_t^a), i.e.,

$$U_t^a = \frac{D_t^a}{C_t^a}.$$

In the following we describe how borrow and deposit rates are set on Aave and Compound. As the specifics vary slightly, we will go through them one by one. Aave allows borrowers to choose between fixed and floating interest payments. A floating borrow rate loan is always charged at the current fixed borrow rate, while a fixed borrow rate is supposed to remain fixed for the duration of the loan. It can only be adjusted in special circumstances[8]. The borrow rate for asset a at time t is given by

$$r_t^a = \begin{cases} r_0^a + \dfrac{U_t^a}{U_{\text{optimal}}^a} r_{\text{slope}_1}^a & \text{if } U_t^a \leq U_{\text{optimal}}^a, \\ r_0^a + r_{\text{slope}_1}^a + \dfrac{U_t^a - U_{\text{optimal}}^a}{1 - U_{\text{optimal}}^a} r_{\text{slope}_2}^a & \text{if } U_t^a > U_{\text{optimal}}^a. \end{cases}$$

In the previous, U_t^a is the asset's utilisation. The remaining parameters (r_0^a, $r_{\text{slope}_1}^a$, $r_{\text{slope}_2}^a$, U_{optimal}^a) are parameters set by the protocol governance to reflect the risks related to the asset. It's worth noting that the parameters for fixed and floating loans of the same asset can vary, with the parameters for fixed loans being more cautious. Moreover, U_{optimal}^a represents the desired utilisation of the protocol, and if the utilisation surpasses U_{optimal}, the borrowing rates increase rapidly.

The deposit rate d_t^a for lenders at time t is then determined as follows

$$d_t^a = U_t^a (D_t^{a,s} \tilde{r}_t^{a,s} + D_t^{a,v} r_t^{a,v})(1 - R^a),$$

where D_t^s denotes the share of fixed loans, r_t^s represents the average fixed borrow rate, D_t^v represents the share of floating loans, and r_t^v denotes the floating borrow rate. Additionally, R^a is the reserve factor, which indicates the minimum shares of borrow rate payments that are directed towards the protocol's treasury. It is important to note that lenders can withdraw their assets at any time,

[8] https://medium.com/aave/aave-borrowing-rates-upgraded-f6c8b27973a7

provided that the utilisation level allows it. In other words, there must be adequate funds available that are not currently being borrowed.

As opposed to Aave, Compound only offers variable interest rate loans. Furthermore, while Aave indicates annualized rates and then charges for the time the money was borrowed, Compound charges a per block rate. The borrow rate of assets on Compound either follows the standard interest rate model, where the borrow rate for asset a at time t is

$$r_t^a = r_0^a + U_t^a \cdot r_{\text{slope}}^a,$$

or using the jump interest rate model, where similarly to Aave, the borrow rate is computed as

$$r_t^a = \begin{cases} r_0^a + U_t^a r_{\text{slope}_1}^a & \text{if } U_t^a \leq U_{\text{optimal}}^a, \\ r_0^a + U_{\text{optimal}}^a r_{\text{slope}_1}^a + U_t^a - U_{\text{optimal}}^a r_{\text{slope}_2}^a & \text{if } U_t^a > U_{\text{optimal}}^a. \end{cases}$$

where U_t^a is again the asset's utilisation and the configuration parameters ($r_0^a, r_{\text{slope}_1}^a, r_{\text{slope}_2}^a, U_{\text{optimal}}^a$) are pre-defined parameters set by the protocol governance. Finally, the deposit rate on Compound follows a similar logic to the deposit rate on Aave and is then given by

$$d_t^a = r_t^a \cdot U_t^a(1 - R^a),$$

where r_t^a is the borrow rate and R^a the reserve factor.

Liquidations. Both Aave and Compound have liquidation mechanisms in place for loans that are close to becoming under-collateralized, i.e., the lower-than-market value of collateral no longer exceeds the value of the debt. To express this lending protocols compute a position's health factor. To be precise, a position's health factor is given by

$$H = \frac{\sum_{i \in A} (C_i \cdot l_i)}{\sum_{i \in A} D_i}. \tag{A1}$$

Here, A refers to the assets that are available on the platform, while C_i represents the collateral amount of the loan position in asset i and D_i represents the debt amount of the loan position in asset i. Additionally, l_i is a pre-defined parameter that represents the liquidation threshold for asset i. In Compound, the liquidation threshold corresponds to the loan-to-value ratio, which determines whether a position can be opened. On the other hand, Aave implements a more relaxed liquidation threshold compared to the loan-to-value ratio.

A position becomes available for liquidation if the health factor drops below. Consider the following example, if the value of the debt exceeds 80% of the collateral value, a position with a liquidation threshold of 80% is considered under-collateralized. When a position becomes eligible for liquidation, its collateral is auctioned off at a discount to liquidators in exchange for repaying the debt.

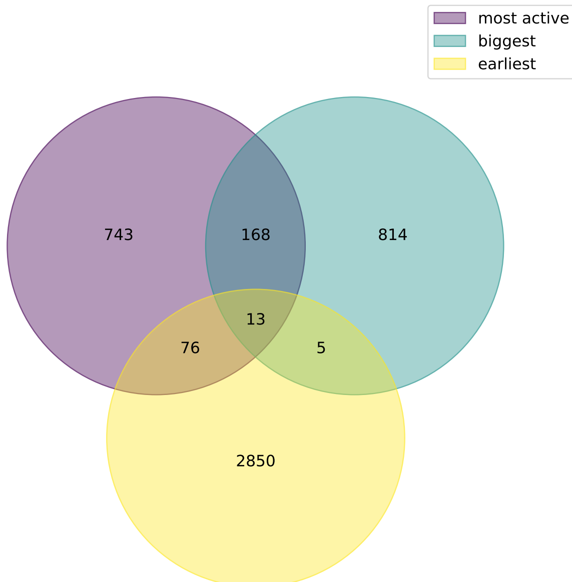
B Data Collection and Cleaning

Wallet-Level Data. We collected information on daily debt, collateral, and asset balances for all wallets that borrowed from any of the three protocols. The original dataset consisted of 19,618,615 observations of active wallets with outstanding debt, out of a total of 68,213 wallets. For the wallet-level analysis, we removed observations with bad debt, which refers to a negative weighted average health factor (cf. Appendix A) across the three lending protocols. This was necessary to avoid distorting the data set due to the infinite or even negative leverage that can result from bad debt. Additionally, we excluded observations from wallets whose debt never exceeds $1. After this data cleaning process, we were left with 13,094,094 observations from 57,555 unique wallets.

Further, we identify three groups: (1) the 1000 most active users in terms of the number of borrows during our observation period, (2) the biggest users in terms of average outstanding debt on their active days, and (3) the 1000 earliest users on each of the three lending protocols. We show the overlap between these three groups in Figure A1.

Pool-Level Data. In addition to gathering daily data for all lending protocol users, we also gather daily data regarding the pool configuration, i.e., borrow rate, deposit rate, LTV, and liquidation threshold. We combine this with the full wallet-level data (i.e., without removing small positions or positions with bad debt) to obtain the pool-level variables outlined in Section 4.

Figure A1. Venn diagram showing overlap between different groups.



Decentralized Exchange Data. Finally, we gather data on the following decentralized exchange platforms: Uniswap V2, Uniswap V3, SushiSwap, and Curve. For all lending protocol users, we then collect information regarding their end-of-day liquidity positions in liquidity pools where all the pool's currencies are amongst ETH, BTC, DAI, USDT, and USDC. In total, there are ten pools that fit this description on Uniswap V2, 63 on Uniswap V3, eight on SushiSwap, and two on Curve.

We find that of the 57,555 unique wallets in our wallet-level dataset, we have observations for 16,593 of these having liquidity positions on decentralized exchanges during our data collection period. In total, we have 4,146,041 observations with non-zero liquidity balances on decentralized exchanges.

C Robustness

We run several robustness checks. The first set of regressions addresses issues in the analysis of factors associated with high leverage (Section 3). The second set is for results in the pool level analysis (Section 4).

C.1 Robustness checks for factors associated with high leverage

To address the multicollinearity issue between *NetBorrowCost* and *Utilisation*, we run panel regressions (i.e., Equation 4) in which these three variables are included separately. Table A1 shows the results for the full sample (Column (1) to (3)) and for the winsorised sample (Column (4) to (6)). Compared to Table 5, both the coefficients and the t-statistics remain relatively unchanged.

Table A1. Driving factors of DeFi leverage (addressing multicollinearity). We report the results for wallet level regressions. The dependent variable is the actual leverage $Leverage_{i,t}$. The independent variables include the LTV-implied leverage $Leverage^{I}_{i,t-1}$, the signed crypto market price movement $SignedVCPrice_{i,t-1}$, the collateral volatility $Volatility_{i,t-1}$ and the collateral return $CollateralReturn_{i,t-1}$, as well as $NetBorrowCost_{i,t-1}$ and $Utilisation_{i,t-1}$ where the latter two variables are added separately due to concerns on multicollinearity. Time and user fixed effects are included. The regressions are run on the full sample and the winsorised sample that excludes the largest 1% and smallest 1% wallets. We estimate the double-clustered standard errors following Petersen (2008). T-stats are reported in brackets.

	All		**Winsorised**	
	(1)	**(2)**	**(3)**	**(4)**
Leverage^{I}	0.0738***	0.0737***	0.0736***	0.0734***
	(16.051)	(16.018)	(16.015)	(15.977)
NetBorrowCost	-0.0168***		-0.0168***	
	(-2.9922)		(-2.9348)	
Utilization		0.0281**		0.0248**
		(2.2605)		(1.9644)
SignedVCPrice	-0.0416***	-0.0430***	-0.0408***	-0.0420***
	(-17.215)	(-17.076)	(-16.550)	(-16.362)
Volatility	-3.6362**	-3.6934**	-3.8265**	-3.8780**
	(-2.4136)	(-2.4243)	(-2.4074)	(-2.4164)
CollateralReturn	-0.1543***	-0.1540***	-0.1552***	-0.1549***
	(-20.860)	(-20.799)	(-20.721)	(-20.663)
Time FE	✓	✓	✓	✓
User FE	✓	✓	✓	✓
No. Observations	12345871	12345871	12026304	12026304
R-squared	0.0180	0.0180	0.0175	0.0175

Another concern of the wallet-level regressions could arise from the construction of $SignedVCPrice_{i,t}$, in which the 80% cut-off is an ad-hoc choice. We rerun all the regressions in the main analysis with various cut-off levels. Table A2 and Table A3 report the results of a 70% cutoff and a 90% cutoff, respectively. The results are not sensitive to the cut-off choices.

Table A2. Factors associated with high leverage (with a 70% cutoff in *SignedVCPrice*). We report the regression results for the following model $Leverage_{i,t} = \beta_0 + \beta_1 Leverage^I_{i,t-1} + \beta_2 NetBorrowCost_{i,t-1} + \beta_3 Utilisation_{i,t-1} + \beta_4 SignedVCPrice_{i,t-1} + \beta_5 Volatility_{i,t-1} + \beta_6 CollateralReturn_{i,t-1} + \gamma_i + \mu_t + \varepsilon_{i,t}$. We estimate the double-clustered standard errors following Petersen (2008). T-stats are reported in brackets.

	All	**Winsorised**	**Largest**	**MostActive**	**Earliest**
Leverage^I	0.0735***	0.0732***	0.0785	0.1785***	0.0932***
	(16.020)	(15.977)	(1.5580)	(6.2361)	(4.2133)
NetBorrowCost	-0.0225***	-0.0221***	-0.2452*	-0.1289***	-0.0543**
	(-3.4397)	(-3.3393)	(-2.0579)	(-4.3673)	(-2.3418)
Utilization	0.0399***	0.0365***	0.4702***	0.3870***	0.0036
	(3.1726)	(2.8595)	(2.9081)	(3.6857)	(0.0823)
SignedVCPrice	-0.0462***	-0.0453***	-0.1136***	-0.0614***	-0.0109
	(-18.098)	(-17.375)	(-5.0785)	(-4.0787)	(-1.0801)
Volatility	-3.6910**	-3.8725**	13.373	-0.1652	7.3714***
	(-2.4263)	(-2.4182)	(1.0920)	(-0.0273)	(3.1474)
CollateralReturn	-0.1537***	-0.1547***	-0.2615***	-0.1709***	-0.0491***
	(-20.731)	(-20.597)	(-6.8972)	(-5.0446)	(-3.4392)
Time FE	✓	✓	✓	✓	✓
User FE	✓	✓	✓	✓	✓
No. Observations	12345871	12026304	173034	327793	435770
R-squared	0.0191	0.0185	0.0483	0.0471	0.0198

C.2 Robustness checks for results about pool-level regressions

The pool value-at-risk measure in the main analysis is constructed as the share of the pool outstanding debt with a health factor lower than 1.1, in which the health factor is defined in Equation A1. To ensure the robustness of the results in Section 4, we rerun the regressions with different cut-off values. Table A4 reports the results when the pool VaR measures use 1.05 and 1.2 as the cut-off values. The results are qualitatively unchanged compared to Table 6.

Table A3. Driving factors of DeFi leverage (with a 90% cutoff in *SignedVCPrice*). We report the regression results for the following model $Leverage_{i,t} = \beta_0 + \beta_1 Leverage^I_{i,t-1} + \beta_2 NetBorrowCost_{i,t-1} + \beta_3 Utilisation_{i,t-1} + \beta_4 SignedVCPrice_{i,t-1} + \beta_5 Volatility_{i,t-1} + \beta_6 CollateralReturn_{i,t-1} + \gamma_i + \mu_t + \varepsilon_{i,t}$. We estimate the double-clustered standard errors following Petersen (2008). T-stats are reported in brackets.

	All	**Winsorised**	**Largest**	**MostActive**	**Earliest**
Leverage^I	0.0742***	0.0739***	0.0833	0.1822***	0.0933***
	(16.079)	(16.038)	(1.6126)	(6.3313)	(4.2123)
NetBorrowCost	-0.0193***	-0.0188***	-0.2253**	-0.1154***	-0.0536**
	(-3.1462)	(-3.0435)	(-1.9382)	(-3.8174)	(-2.3023)
Utilization	0.0210	0.0177	0.3988***	0.3376***	0.0021
	(1.6679)	(1.3812)	(2.5393)	(3.2321)	(0.0475)
SignedVCPrice	-0.0400***	-0.0389***	-0.0956***	-0.0501***	-0.0109
	(-16.271)	(-15.532)	(-4.6445)	(-3.4767)	(-1.1104)
Volatility	-3.6638**	-3.8571**	16.467	1.3911	7.3622***
	(-2.4214)	(-2.4136)	(1.3332)	(0.2313)	(3.1444)
CollateralReturn	-0.1544***	-0.1553***	-0.2740***	-0.1735***	-0.0491***
	(-20.879)	(-20.743)	(-7.1168)	(-5.1216)	(-3.4436)
Time FE	✓	✓	✓	✓	✓
User FE	✓	✓	✓	✓	✓
No. Observations	12345871	12026304	173034	327793	435770
R-squared	0.0171	0.0166	0.0396	0.0444	0.0199

Table A4. DeFi leverage and pool resilience (with different cut-offs on pool Value-at-Risk). We report the regression results for the following model $VaR_{j,t} = \alpha + \beta BorrowerLeverage_{j,t-1} + \theta Control_{j,t-1} + \gamma_j + \mu_t + \varepsilon_{j,t}$ where the dependent variable $VaR_{j,t}$ has different cut-off values of 1.05 and 1.2. The key explanatory variable is borrower leverage. Control variables include the liquidation threshold, the loan-to-value ratio (LTV), the realised volatility, and the concentration index (HHI) of borrowers. We also include the time and pool fixed effects. We estimate the double-clustered standard errors following Petersen (2008). T-stats are reported in brackets.

	Pool Value-at-Risk at 1.05			**Pool Value-at-Risk at 1.2**		
	All	**Volatile coins**	**Stablecoins**	**All**	**Volatile coins**	**Stablecoins**
			Panel A: Aave v2			
BorrowLeverage	0.6080***	0.2379***	0.7909***	1.0190***	0.8182***	1.1098***
	(2.9293)	(3.2956)	(3.0795)	(7.2684)	(3.3500)	(7.5975)
Controls	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Pool FE	✓	✓	✓	✓	✓	✓
No. Observations	20515	13420	7095	21963	14717	7246
R-squared	0.2751	0.0649	0.6067	0.2790	0.1533	0.5114
			Panel B: Compound			
BorrowLeverage	1.1304***	1.1824***	0.1976	1.3561***	1.1794***	0.8332***
	(3.4044)	(2.5736)	(1.1110)	(6.7055)	(4.6142)	(2.0698)
Controls	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Pool FE	✓	✓	✓	✓	✓	✓
No. Observations	10925	7128	3797	11444	7563	3881
R-squared	0.2792	0.3946	0.5628	0.2722	0.2868	0.3860