Why DeFi lending?

Evidence from Aave V2*

Giulio Cornelli Leonardo Gambacorta
Rodney Garratt Alessio Reghezza

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Abstract

Decentralised finance (DeFi) lending protocols have experienced significant growth recently, yet the motivations driving investors remain largely unexplored. We use granular, transaction-level data from Aave, a leading player in the DeFi lending market, to study these motivations. Our theoretical and empirical findings reveal that the search for yield predominantly drives liquidity provision in DeFi lending pools, whereas borrowing activity is mainly influenced by speculative and, to some extent, governance motives. Both retail- and large investors seek potential high returns through market movements and price speculation, however the latter engage in DeFi borrowing relatively more than the former also to influence protocol decisions and accrue more significant governance rights.

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*Giulio Cornelli (giulio.cornelli@bis.org) is at the Bank for International Settlements and the University of Zurich. Leonardo Gambacorta (leonardo.gambacorta@bis.org) is at the Bank for International Settlements and affiliated with CEPR. Rodney Garratt (rodney.garratt@bis.org) is at the Bank for International Settlements. Alessio Reghezza (alessio.reghezza@ecb.europa.eu) is at the European Central Bank. We thank Kathy Yuan (discussant), Mike Alonso, Matteo Aquilina, Paolo Cavallino, Sean Foley, William Krekel and Tommaso Oliviero for helpful comments and suggestions. We are also grateful to seminar and conference participants at the 2024 ToDeFi - Torino Decentralized Finance Conference at Collegio Carlo Alberto (Turin). The views expressed in this paper are those of the authors and do not necessarily reflect those of the Bank for International Settlements, the European Central Bank or University of Zurich.

1 Introduction

Decentralized finance (DeFi) lending refers to the practice of offering and obtaining loans facilitated directly through blockchain technology and smart contracts, bypassing traditional centralized financial intermediaries such as banks. In this system, participants can lend or borrow assets within a trustless environment, relying on the immutable and transparent nature of blockchain transactions. Interest rates are set by the supply and demand of capital according to a pre-defined function. DeFi lending protocols have witnessed a remarkable growth, reaching a peak in total value locked (TVL) of more than $ 50 billions at times of market buoyancy in early 2022, up from almost zero at end-2020 (Aramonte et al. (2022)).

DeFi lending differs from traditional banking in three key aspects. The first one is anonymity and lack of credit assessment. Unlike traditional banks that rely on extensive credit assessments and personal identification, DeFi operates on the principles of anonymity. Borrowers and lenders interact without revealing their identities, making traditional creditworthiness assessment methods unfeasible.

The second one is the central role of crypto assets as collateral to solve asymmetric information problems. Anonymity and crypto assets volatility leads to reliance on overcollateralization as a risk management tool, as there is no other way to assess the borrower's ability to repay. This is in contrast to traditional banking, where loans are typically undercollateralized or secured with a broader range of assets, including real estate and personal property. DeFi's reliance on crypto assets as collateral also makes it largely self-referential and limits its interaction with the real economy.

The third difference is the use of automation and smart contracts. DeFi utilizes smart contracts based on blockchain technology to automate the lending and borrowing processes. This automation leads to instant loan disbursement and reduced transaction costs compared to traditional banks, where lending involves more manual processing and relationship management. However, this also means DeFi lacks the relationship-building and trust elements inherent in traditional banking, which can play a role in risk assessment and loan recovery. These protocols leverage the capabilities of blockchain and smart contracts to play a role analogous to a credit intermediary in a traditional financial system. Unlike in traditional finance, the business model of DeFi lending protocols is based on funding borrowers that remain anonymous to the platform.

Given the distinct characteristics of DeFi lending compared to traditional forms of intermediation, it is important to understand what the main motivations for Defi lending are. The goal of this paper is to shed light on the motivations driving agents to engage in DeFi borrowing and lending activity, contrasting them with those in traditional finance to highlight the unique nature of DeFi.

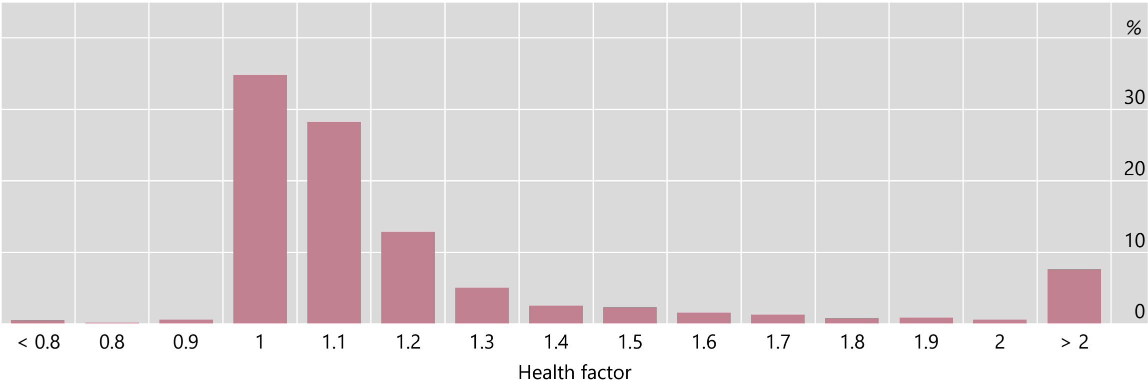
To understand the main determinants of DeFi intermediation activity we use granular transaction level data from Aave, one of the most prominent players in the DeFi lending space.[1] As discussed above, because the value of crypto assets is inherently volatile, borrowers must over collateralize the loans they take in DeFi lending pools. The extent to which borrowers are able to do this is measured by a statistic called the health factor – a weighted-average of the ratio of the value of collateral to the value of borrowings, both expressed in units of Ether (ETH),[2] with weights proportional to the collateral-specific liquidation thresholds. Figure 1 shows that in the Aave protocol more than 98% of the users have a health ratio higher than 1.[3]

[1] We access data on Aave V2 transactions from *The Graph*, an indexing protocol for querying networks like Ethereum.

[2] Ether is the native cryptocurrency of the Ethereum blockchain. It is used to compensate participants who perform computations and validate transactions on the Ethereum network. ETH also acts as a digital currency for making payments and is essential for interacting with many decentralized applications (dApps) on the Ethereum platform.

[3] The data underlying Figure 1 is retrieved as a snapshot of the protocol. For this reason we find that some users have a $HealthFactor$ below 1, and are exactly these users that will be subject to liquidation.

Figure 1: **Distribution of Aave users by level of health ratio**



Note: The graph shows the share of Aave users for different levels of the health ratio (ratio of the value of the collateral to the value of the loan). A health ratio higher than one indicates overcollateralization. Sources: Dune Analytics: @victorljulian; authors' calculations.

Despite its rapid growth, from a macroeconomic perspective DeFi lending volume is still fairly modest. The overall DeFi lending protocols debt outstanding is estimated to be around $ 25 bn (International Monetary Fund (2022)), which is just a tiny fraction compared to the volume of debt outstanding in the overall financial system. Nonetheless, given the rapid evolution of the DeFi ecosystem, a small size today does not guarantee the size stays on such a scale further out in the future. Furthermore, the lack of supervision and the high degree of interconnectedness in the crypto eco-system are just two additional arguments for monitoring this market closely.

Any evaluation of the implications of DeFi lending should be guided by a sound understanding of the reasons attracting investors into these platforms. Deposit transactions are likely explained by a search for yield, something we will test. However, surprisingly, little is know about the motives for borrowing. In fact, given the need for over collateralisation in DeFi lending it is somewhat surprising that there is any borrowing activity on these platforms at all. Why borrow rather than simply liquidate collateral? One explanation would be that the underlying collateral is illiquid, as in the case of some physical assets, like real estate, in the real world. However, in the case of DeFi lending the collateral is typically as liquid as the funds being borrowed. Hence another explanation is required.

We test hypothesis specific to deposit- and borrow-transactions, separately. Furthermore we investigate how the results change when looking at small- vs large-users. To the best of our knowledge, our paper is the first work investigating why investors decide to use DeFi lending protocols and testing empirically these channels.

The main results of our study are the following. First, "search for yield" is a key determinant of liquidity provision in DeFi lending pools, especially for retail users. This effect has been reinforced by the "low-for-long" interest rate environment experienced in advanced economies. Second, investors borrow tokens through DeFi lending protocols for speculative reasons or to increase their voting power by temporarily increasing their stakes in governance tokens, although speculative motives appear to be more important than governance motives.[4] Third, there are key differences in borrowing behaviours between different types of investors. Both retail- (individual, smaller-scale participants) and large investors borrowing decisions are driven by speculative motives, which include seeking potential high returns through leverage, market movements and price speculation. However, while retail investors show "fear-of-missing-out" (FOMO) behaviours, large investors do not. Furthermore, large-scale investors engage relatively more than retail investors in DeFi borrowing for governance motives, such as influencing protocol decisions and accruing more significant governance rights.[5]

We contribute to a young but fast growing literature on DeFi lending. Chiu et al. (2022) highlights how traditional practices of lending based on borrower reputation and financial strength breaks down in a lending market with anonymous participants. However, their analysis assumes that lending pools perform a traditional intermediate role

[4]For a broader discussion on governance tokens see Capponi et al. (2023a).

[5]Our result on the borrowing motivations for large investors is consistent with Shleifer and Vishny (1986); Barclay and Holderness (1989) who document the existence of private benefits associated with large voting power in equity markets and with Dyck and Zingales (2004) who find that the private benefits of control are higher in less developed capital markets and where ownership is more concentrated. The result on the borrowing motivations of retail investors is consistent with Augustin et al. (2022) who show that borrowing in DeFi platforms to chase yield by engaging in leveraged strategies is higher for small investment stakes.

between borrowers with projects that need funding and lenders with available funds. To date there is no direct evidence that lending in DeFi is related to project financing. Nevertheless, our results are consistent with the predictions of their model – ie an increase in ETH price is associated with more borrowing through DeFi protocols. Consistent with our results, Saengchote (2023) shows that users of Compound, another DeFi lending protocol, mainly borrow to engage in leveraged investment strategies. Heimbach and Huang (2024) provide an in-depth analysis of DeFi leverage by utilizing wallet-level data from major DeFi lending platforms. They find that the largest and most active users tend to have higher leverage compared to other users. The authors also find that borrowers with high leverage are more inclined to opt for volatile collateral types when their debt positions approach liquidation thresholds. Our paper complements their analysis trying to explain the economic motivations behind the risks and behaviors associated with high-leverage positions.

Other studies analyse specific aspects of DeFi intermediation activity. Lehar and Parlour (2024) provide evidence of the stability of liquidity pools (ie Automated Market Makers (AMM)), and denote conditions under which AMMs dominate limit order markets. Conversely, Capponi and Jia (2024) document the pitfalls of decentralised exchanges showing that the rent extracted by validators leads to arbitrage losses for liquidity providers and to a higher overall cost of liquidity provision. Furthermore, just-in-time liquidity providers (LPs), those providing liquidity for transactions within a single block, crowd out passive LPs under a sufficiently low elasticity of order volumes relative to the depth of the liquidity pool, and consequently reduce overall market liquidity (Capponi et al., 2023c). Interestingly and contrarily to what expected in a traditional market where informed traders hide their trading intentions, informed traders in decentralised exchanges signal their privileged position by bidding higher fees (Capponi et al., 2023b). Carapella et al. (2022); Harvey et al. (2021); Makarov and Schoar (2022); Zetzsche et al. (2020) discuss the potential opportunities and challenges of DeFi platforms. Rivera et al. (2023) demonstrate that the fixed interest rate structures in DeFi lending tend to be less efficient when compared with those of traditional lending platforms. Lehar and Parlour (2022) investigate the effects of liquidations on prices within DeFi lending, uncovering a potential vulnerability and factor for market spillovers in this emerging financial area. Our study complements the analysis of these papers by presenting new evidence on the motivations of investors to choose DeFi lending.

The rest of the paper is organised as follows: section 2 discusses the dataset and some stylised facts, section 3 covers the empirical model and the baseline results, section 4 sheds light on the different motivations of large- vs retail-investors, section 5 reports robustness tests, while section 6 concludes.

2 Data, stylised facts and testable hypothesis

In this paper we focus on Aave activity taking place on the Ethereum chain.[6] Our database consists of borrow and deposit transaction-by-transaction data from the Aave V2 protocol for the period December 2020, which coincides with the launch of the V2 version of the protocol, to mid-July 2022.[7] In this period, more than \$ 220 bn have been cumulatively deposited in the protocol (Figure 2, left-hand panel).[8] Borrowing activity has witnessed a sustained growth in the first months after Aave V2 roll-out. The total amount borrowed quickly spiked, exceeding \$ 8 bn, and progressively slowed down in the following months (right-hand panel).

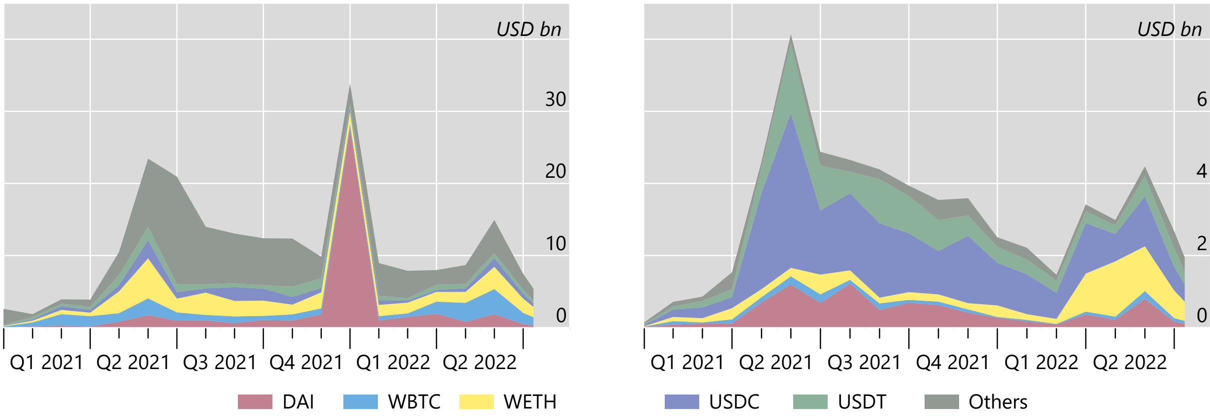
[6]Without loss of generality, we focus on the activity in the main pool of the Aave V2 protocol.

[7]To avoid the possible presence of structural changes in the functioning of the blockchain, we conclude our analysis prior to September 15, 2022. This is when the Ethereum blockchain transitioned from a proof-of-work (PoW) consensus mechanism to a proof-of-stake (PoS) consensus by merging the Ethereum Mainnet with the PoS Beacon Chain. Heimbach et al. (2023) investigate the effects of this 'merge'. Their analysis finds that borrowing rates were extremely volatile. Despite this, no spike in mass liquidations or irretrievable loans materialized. They also quantify and analyse 'hard-fork-arbitrage', which involves profiting from holding debt in the native blockchain token during a hard fork.

[8]The spike in DAI deposits in December 2021 corresponds to the launch of Balancer boosted pools on Aave. This development aimed to enhance liquidity provider yields through optimized pool strategies. For further details see Balancer Launches Boosted Pools to Increase LP Yields.

Figure 2: **Aave V2 protocol activity**

(a) Total amount deposited (b) Total amount borrowed

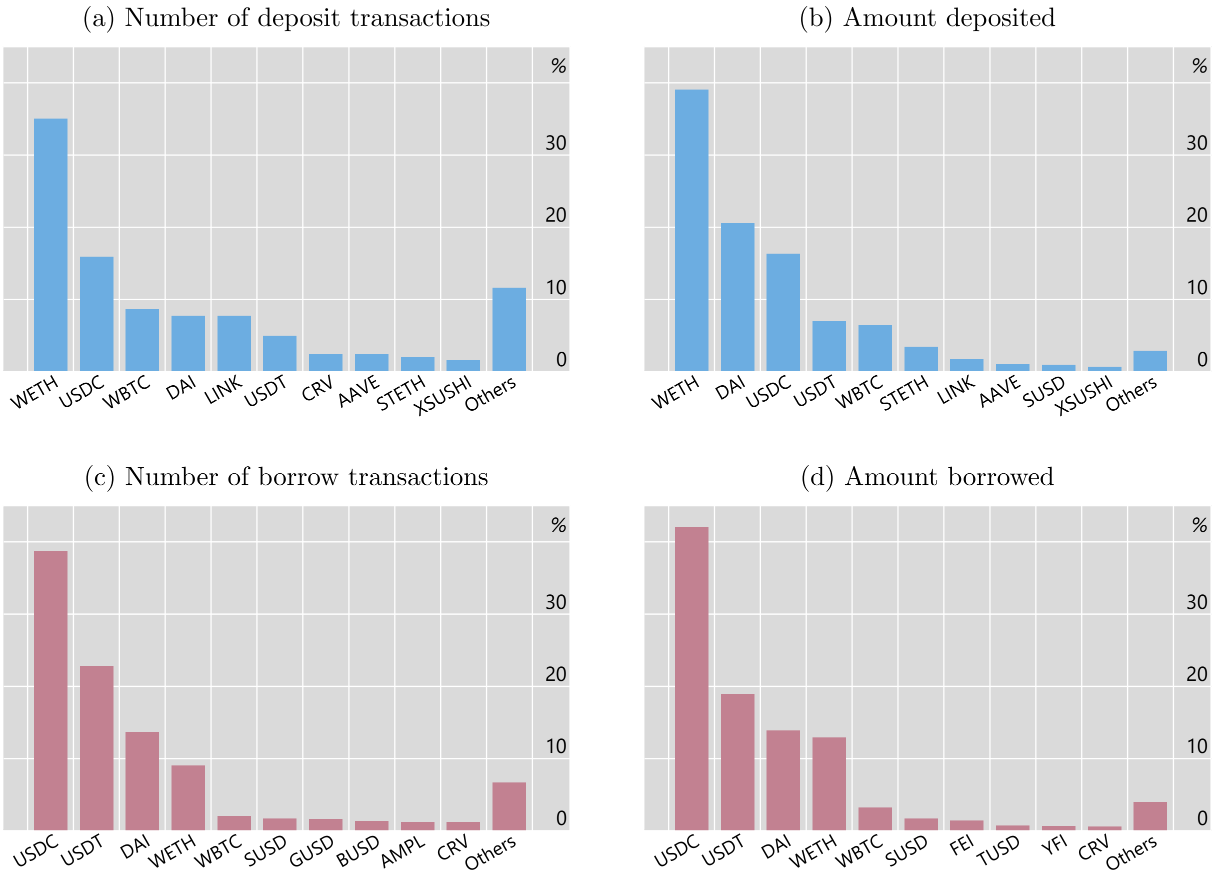


Note: The graphs show the flows of total amounts deposited and borrowed on the Aave V2 protocol for Dai (DAI), wrapped Bitcoin (WBTC), wrapped Ether (WETH), USD Coin (USDC), Tether (USDT) and other 34 tokens. Data up to 13 July 2022.
Sources: The Graph; authors' calculations.

Figure 3 shows the distribution of deposit- and borrow transactions by token. Wrapped Ether (WETH) is the most deposited token both by number of transactions and by amount deposited (Panels (a) and (b)). Conversely, borrowing transactions are dominated by stablecoins. Panels (c) and (d) show that USD Coin (USDC), Tether (USDT), and DAI are the tokens borrowed in about 75% of the transactions, either by number of transactions or amount borrowed.[9]

[9] Figure B1 and Table B1 in Appendix B provide more details on the monthly distribution of the number of deposit- and borrow transactions by users, as well as the distribution of deposit and borrowing amounts across deciles by size.

Figure 3: **Distribution of transactions in the Aave V2 protocol by token**



Note: The figures show the distribution of deposit- (upper panels) and borrow transactions (bottom panels) by token. The left-hand panels are based on the transactions. The right-hand panels are based on the amount (converted into USD) transacted. Based on transaction-by-transaction data for the period from December 2020 to mid-July 2022. Sources: The Graph; authors' calculations.

We augment the dataset with additional financial- and crypto-markets variables. The data on the yield at different maturities for U.S. Treasury securities comes from the Federal Reserve Bank of St Louis, FRED. We collect data on the *Crypto Fear & Greed index* from *Alternative*. The index is a proxy for the sentiment of the Bitcoin market, and it ranges between 0 ("extreme fear") and 100 ("extreme greed"which corresponds to fear-of-missing-out (FOMO) behaviours). [10] The standard deviation of the price of

[10]The index is based on a mix of market-based factors, such as volatility, maximum drawdowns, and volumes relative to the last 30/90 days, as well as other factors like interactions on social media (e.g., X), surveys on expectations about the crypto market, changes in Google Trends search volumes, and Bitcoin's dominance relative to other cryptocurrencies.

Ether (*SD ETH price*) is calculated on ETH pricing data from CCData (CryptoCompare formerly). *Governance Token* is a dummy variable that takes a value of one for those tokens that allow the holders to vote on projects development/enhancement proposals and zero elsewhere. *Voting dates* is a dummy that takes value one in correspondence of periods with ongoing votes for the specific token and zero elsewhere. We source the calendar of votes for each governance token from *snapshot*.

Table 1 provides the summary statistics for the final dataset used for our analysis.

Table 1: Summary statistics

Variables	N. Obs	Mean	St. Dev.	Min	P(25)	P(75)	Max
Panel A. Depositing Sample							
Deposits amount (log)	230,516	9.992	2.914	2.310	8.357	11.770	16.397
Policy Rate (%)	230,516	0.248	0.339	0.125	0.125	0.125	1.625
10Y Gov Bond (%)	167,354	1.679	0.592	0.913	1.322	1.669	3.473
2Y Gov Bond (%)	167,354	0.681	0.954	0.104	0.149	0.584	3.426
1Y Gov Bond (%)	167,354	0.457	0.807	0.033	0.058	0.208	3.125
6M Gov Bond (%)	167,354	0.336	0.636	0.015	0.035	0.091	2.874
3M Gov Bond (%)	167,354	0.218	0.435	-0.002	0.020	0.076	2.324
Crypto Fear & Greed (Index)	230,516	44.67	28.03	6.00	21.00	73.00	95.00
SD ETH price	230,516	2.646	1.000	0.596	1.975	3.302	5.272
Panel B. Borrowing Sample							
Borrowing amount (log)	132,382	9.965	2.342	4.546	8.479	11.511	20.209
Crypto Fear & Greed (Index)	132,382	48.67	27.23	6.00	23.00	74.00	95.00
Ln(ETH price)	132,382	7.755	0.432	6.299	7.514	8.078	8.478
Governance Token (Dummy)	132,382	0.273	0.163	0.00	0.00	0.00	1.00
Voting dates (Dummy)	132,382	0.011	0.104	0.00	0.00	0.00	1.00

Daily data for the period December 2020 –mid-July 2022. Bond yield indicators have fewer observations compared to the other variables due to market closures over weekends. However, given that DeFi and crypto markets are open 24/7, we have data on DeFi indicators for weekends. The policy rate has a higher number of observations relative to bond yields because, given that the policy rate depends on monetary policy decision taken during the FOMC meetings, it is observed (and constant) during weekends. Sources: Aave; Alternative; CryptoCompare; Federal Reserve Bank of St Louis, FRED; snapshot; The Graph; authors' calculations.

In this paper we test three hypotheses. First, whether investors deposit funds in DeFi lending protocols for yield-seeking reasons. Second, whether investors borrow tokens through DeFi lending protocols for speculative reasons, and/or whether they exploit DeFi lending protocols to increase their voting power by temporarily increasing their stakes in governance tokens. Third, if there is any difference in the behaviour of users with a small account balance (ie retails) vis-á-vis those with a large account balance.

3 Empirical model and results

3.1 Architecture of the Aave V2 protocol

The Aave V2 protocol is composed of two lending pools.[11] Each lending pool is organized into multiple reserves, with one reserve designated for each token. These reserves function similarly to wallets. Users can perform transactions such as deposits and/or borrowings directly with these reserves via smart contracts. These contracts, in conjunction with the protocol, ensure that the respective balances are accurately maintained.

Each transaction in the Aave protocol is executed through a contract. Users enter the Aave protocol by depositing cryptocurrencies (ie a deposit-transaction). Once in the protocol, users start to earn a staking- or deposit-yield and decide to perform other transactions like borrowing other tokens or redeeming their holdings to exit the protocol. It is important to note that a borrowing transaction is consequential to a deposit transaction. In other words, an individual user can deposit without borrowing, but a user cannot borrow without having first deposited funds in the protocol.[12]

3.2 Demand for deposits transactions

In the first step of our analysis we focus on the motives driving deposit-transactions in DeFi. Specifically, we test whether investors deposit funds in DeFi lending protocols for

[11] The functioning of a DeFi lending protocol is discussed for the Aave protocol, but the same generic concepts hold for other DeFi lending protocols too.

[12] See Appendix A1–A3 for more details on the specifics of each transaction type.

yield-seeking reasons. We specify Equation 1 as follow:

$$Ln(deposit\ amount)_{ijt} = \beta X_t + \gamma Z_t + \theta_{ij} + \varepsilon_{ijt} \tag{1}$$

where the dependent variable is the natural logarithm of the dollar amount of each individual deposit transaction for user i, reserve j, and timestamp t. X is a vector of monetary policy variables such as the *FED policy rate*, and the yields on U.S. Treasury securities at different maturity buckets (3-month, 6-month, 1-year, 2-year and 10-year). These represent the opportunity costs of alternative forms of investments. Z is a vector of control variables included to capture the possibility that other factors may motivate users to deposit funds in DeFi lending protocols. In particular, we include the *Crypto Fear & Greed* as proxy for investors' sentiment towards cryptocurrencies and the *standard deviation of Ether price* to control for the volatility in the DeFi ecosystem (Aramonte et al. (2021)).

Equation 1 is saturated with granular user-reserve fixed effects (θ_{ij}), included to capture time-invariant unobserved heterogeneity at the user-reserve level. The rationale behind the inclusion of user-reserve fixed effects is determined by the possibility that DeFi users may have a heterogeneous degree of financial literacy, income or preference towards depositing crypto in specific reserves. Consequently, estimating the between-user/reserve relationship among the amount deposited in DeFi protocols and the level of interest rate would be prone to a potential omitted variable bias. On the contrary, the inclusion of user-reserve fixed effects allows us to capture the within-user-within-reserve variation between the amount deposited and our variables of interest. In this first step of the analysis, we do not include the deposit annual percentage rate (APR) that is endogenously determined by the platform matching demand and supply (see Appendix A.4).

Table 2 reports the results from estimating Equation 1. Controlling for the Crypto Fear and Greed index and the standard deviation of Ether price, the coefficients for the *FED policy rate* and the yields of U.S. Treasury securities are negative and statistically significant (mostly at the 1% level) across the spectrum of maturities, with the size of the coefficients decreasing along with the maturity term of the securities. The effect is also economically meaningful. *Ceteris paribus*, a 1 percentage point (pp) reduction in the FED policy rate results in about 35% increase in the amount of deposit in DeFi protocols (column 1). Overall, these results are consistent with investors entering DeFi lending protocols for yield-seeking reasons. The "low-for-long" interest rate environment experienced in advanced economies since the outbreak of the global financial crisis has been a key contributing factor to this search-for-yield behaviour. Indeed, by depositing crypto in DeFi protocols, liquidity providers can earn higher interests than through traditional channels of financial intermediation. For example, providing Tether (USDT) liquidity on Aave yielded 5.6% APR on average over the sample period with peaks of more than 15%.

Table 2: Deposit equation

	Ln(deposit amount)					
	(1)	(2)	(3)	(4)	(5)	(6)
Policy Rate	-0.3486***					
	(0.0614)					
3M Gov Bond		-0.2797***				
		(0.0569)				
6M Gov Bond			-0.1829***			
			(0.0400)			
1Y Gov Bond				-0.1330***		
				(0.0311)		
2Y Gov Bond					-0.1050***	
					(0.0264)	
10Y Gov Bond						-0.0817**
						(0.0336)
Crypto Fear & Greed	0.0028***	0.0024***	0.0023***	0.0024***	0.0024***	0.0026***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0008)
SD ETH price	0.3635***	0.3609***	0.3663***	0.3734***	0.3838***	0.3959***
	(0.0210)	(0.0227)	(0.0222)	(0.0217)	(0.0209)	(0.0194)
Observations	230,516	160,259	160,259	160,259	160,259	160,259
R-squared	0.7493	0.7467	0.7466	0.7466	0.7465	0.7464

Standard errors clustered at the user-reserve level in parentheses. ***/**/* indicates statistical significance at the 1/5/10% level. All the regressions include user-reserve fixed effects.
Source: Authors' elaboration.

Nevertheless, the opportunity-cost for users to keep liquidity in DeFi protocols increases as interest rates begin to normalise because "real-world" assets are less volatile, more predictable and they function within well-established regulatory frameworks.[13]

The evidence from Table 2 allows us to understand what happens to the amount deposited when interest rates increase by 1 pp. However, it says nothing about the dynamic of such an effect. In principle, one would expect to observe a statistically significant contraction in the amounts deposited in DeFi protocols over the months following FED's decision to raise the policy rate (March 2022). On the contrary, the effect should be statistically insignificant for the months preceding the monetary policy tightening. A proper understanding of these dynamics requires to calculate dynamic estimates that we represent mathematically with the following equation:

$$Ln(deposit\ amount)_{ijt} = \sum_{t=Dec\ 2020}^{t=Jul\ 2022} \delta X_t' + \gamma Z_t + \theta_{ij} + \varepsilon_{ijt} \tag{2}$$

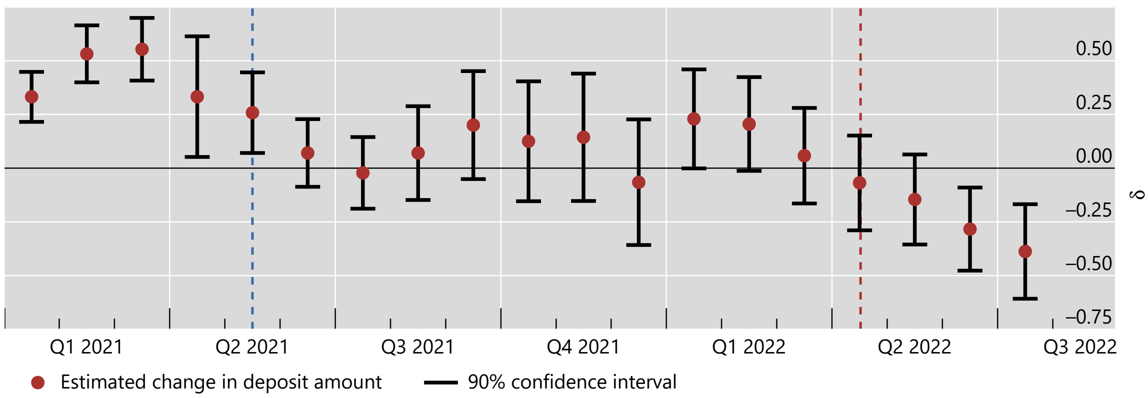
where X_t' is a vector of indicator variables taking value 1 for each year-month of our sample period, and 0 for the base dummy (December 2020). For consistency with Equation 1, the specification includes the same vector (Z) of control variables and it is saturated with the same combination of user-reserve fixed effects (θ_{ij}).

The results derived from Equation 2 are reported in Figure 4 where the blue vertical dotted line indicates when US inflation started to be above target, and the red vertical dotted line the starting point of US monetary policy tightening. First, consistently with our yield-seeking hypothesis, they suggest that low interest rates encourage depositors to shift from traditional real-world-low-yielding assets to DeFi platforms. This is indicated by the positive and statistically significant trend in deposit volumes ahead of the increase in inflation/interest rate expectations (the coefficients before the blue dashed line denote the first period in which inflation was below the target level and the policy rate was at zero). Indeed, in the five quarters leading up to the inflation increase, the amount

[13] Table B2 in Appendix B includes the deposit APR as an additional control. The results indicate that the coefficient of the deposit APR is positive but not statistically significant. Section 4 shows that this result changes when disentangling small retail- and large investors. As outlined in Section 4, these two distinct groups of investors exhibit markedly different behaviours.

deposited into Aave grew by 40%, on average, relative to December 2020. As inflation started to be above its target level and, consequently, interest rate expectations began to materialise (coefficients between the two vertical dashed lines), our results show no significant difference in the amount deposited into Aave relative to December 2020. This can be seen in the part of Figure 4 between the two vertical lines where the confidence intervals overlap at zero. This may indicate that uncertainty about the evolution of interest rates and monetary policy deterred individuals to deposit into DeFi. Finally, as interest rates started to increase (red dashed line) the average amount deposited in Aave declined significantly by about 27% in the three quarters following the start of the monetary policy tightening, compared to December 2020 (Figure 4, coefficients after the red dashed line). This trend indicates a withdrawal from DeFi protocols, consistent with the explanations provided in the preceding paragraphs.

Figure 4: **Dynamic effect of monetary policy decisions on deposit transactions**



Note: The graph shows the coefficients of a panel-OLS regression associated with month-year indicator variables (ie the coefficients δ from equation 2). The dependent variable is the natural logarithm of deposit amounts. Regression include the crypto and fear index and the standard deviation of the ETH price as controls and user-reserve fixed effects. The omitted dummy corresponds to December 2020. The blue vertical dotted line indicates when US inflation started to be above target and the red vertical dotted line the starting point of US monetary policy tightening. The two vertical lines delimit a period of US inflation above the target and therefore expectations of interest rate increases. Sources: Authors' calculations.

3.3 Demand for borrowing transactions

There are multiple reasons why participants on the Aave platform might choose to borrow a lending pool. For instance, an individual might wish to enter into an investment using a cryptocurrency that they do not currently hold, or acquire an exchange token to earn voting benefits. In these instances the platform participant's desire to borrow the alternative token, rather than sell their current holding and buy it outright, will depend on their expectations for the future price of the token they currently hold. In particular, the consumer will borrow if they are sufficiently optimistic about the future price of the cryptocurrency they currently hold.

An alternative motive would be to leverage their existing position in a cryptocurrency. For example, suppose an individual holds Coin A and they think its price will go up. This individual can leverage their position by posting Coin A as collateral in a lending pool, borrowing a stablecoin and then trading that stablecoin for more of Coin A. This person will earn more off their original stake of Coin A if its price rises. Additionally, if Coin A earns governance benefits they may also gain by increasing their holdings of this coin.

In what follows, we formally model these two motivations, abstracting from transaction costs, and illustrate how the decision to borrow from a lending pool depends on price expectations and possible governance benefits.

3.3.1 Borrowing to acquire an alternative (investment) token

Consider an individual that holds 1 unit of Coin A but has an opportunity to earn a return from an alternative Coin B. There are two options the investor can follow to make the investment. First, assuming the individual thinks the price of the Coin A is going to rise during the life of the investment, the individual might prefer to post Coin A as collateral and borrow Coin B to make the investment. Alternatively, the second option would be for that individual to sell Coin A and buy Coin B outright.

In the first option, suppose a lending pool contract requires a loan to value (LTV) ratio of 0.75. Let $S_t^{B/A}$ denote the period t exchange rate of Coin A for Coin B. Then an individual with 1 unit of Coin A can borrow $.75S_t^{B/A}$ units of Coin B. Suppose the Coin B investment opportunity pays r percent in one period, the per-period deposit interest rate on posted collateral (ie deposited funds) is d, and the per-period interest rate on borrowed funds is i.[14] Then the per-unit return to posting Coin A as collateral to obtain Coin B and then investing the Coin B for one period is

$$.75S_t^{B/A}(r-i)S_{t+1}^{\$/B} + dS_{t+1}^{\$/A} + S_{t+1}^{\$/A} - S_t^{\$/A}. \tag{3}$$

The first term represents the net return from the investment of $.75S_t^{B/A}$ units of Coin B, the second term is the reward paid on the Coin A posted as collateral, and the difference in the last two terms is the capital gain or loss on 1 unit of Coin A held over the time period, where all returns are measured in dollars.

The impact of governance tokens can be included in the model by introducing positive constants b^A and b^B that reflect the per-unit benefit to holding governance tokens A and B, respectively (these benefits could reflect discounts on trading platforms or the ability to vote on protocol rules) multiplied by an indicator function $\mathbb{1}_{v=yes}$ which equals 1 if voting benefits apply during the investment period.[15] After simplifying, this additional aspect changes the expression in Equation 3 to

$$.75S_t^{B/A}(r-i)S_{t+1}^{\$/B} + \mathbb{1}_{v=yes}b^A + .75\mathbb{1}_{v=yes}b^B + (1+d)S_{t+1}^{\$/A} - S_t^{\$/A}. \tag{4}$$

There is also a liquidation risk that results from the potential for deterioration in the investor's *Health Factor*, an indicator measuring solvency of each Aave user. The health

[14]To provide the intuition necessary to motivate the empirical analysis it is sufficient to consider a one-period investment. In reality the loans we are describing would be taken for open ended time frames.

[15]This assumes that governance benefits of the borrowed tokens are delegated to the borrower, as appears to be possible on the Aave platform (Messias et al., 2023). If this is not the case, then indicator function takes value 0.

factor is defined as the ratio of assets posted as collateral (subject to a haircut known as the *Liquidation Threshold*) over liabilities (borrowing plus interest).[16] In the case of our example where the only transaction the investor did on Aave was to borrow Coin Busing 1 unit of Coin A, if the LTV = .75 and the Liquidation Threshold = .8, then the health factor at time t when the transaction was initiated would be $\frac{1\times .8}{.75}$.[17]

After the initial borrowing transaction, the value of assets appreciates by the yield earned on the collateral and the investment, and the value of liabilities increases according to the interest on the loan. Fluctuations in cryptocurrency prices will cause further variation in the value of the investor's assets and the liabilities, which are evaluated in terms of Ether by the protocol. Specifically, the numerator would be $(1+d).8S_{t+1}^{E/A} + .75r\frac{S_s^{E/B}}{S_t^{A/B}} * .8$ and the denominator would be $(.75+i)\frac{S_s^{E/B}}{S_t^{A/B}}$, where $s \in (t, t+1]$.[18] If, for example, at any point during the investment period the price of Ether fell relative to Coin B (ie $S_s^{E/B}$ increased), holding the relative prices of Coin A and Ether constant, then the health factor could drop below 1 and the investment will be liquidated. For simplicity, we assume that if the health factor falls below 1, it does so precisely at $t+1$. Then liquidation occurs at time $t+1$ if and only if $[.75 + i - .6r]\, S_{t+1}^{E/B} > (1+d).8S_t^{A/B}S_{t+1}^{E/A}$.

Let $p_{t+1} = Prob\left(\frac{S_{t+1}^{E/B}}{S_t^{A/B}S_{t+1}^{E/A}} > \frac{(1+d).8}{.75+i-.6r}\right)$ denote the probability of liquidation at $t+1$. If an investor's portfolio is liquidated they lose their collateral and have to pay a liquidation bonus to the liquidator.[19] Hence, in our example, their payoff is

$$.75S_t^{B/A}(r-i)S_{t+1}^{\$/B} + \mathbb{1}_{v=yes}b^A + .75\mathbb{1}_{v=yes}b^B + S_{t+1}^{\$/A}((1-\theta)(1+d) - LB^A) - S_t^{\$/A}, \quad (5)$$

where $LB^A \in (0, Collateral - LTV]$ corresponds to the liquidation bonus that the borrower pays to to the liquidator and $\theta \in [0, 0.5]$ corresponds to the fraction of the borrowing

[16] See Equation 16 in Appendix A.2.

[17] We could ignore this aspect if we assumed the investor had additional assets posted so that their Health factor was well above 1. However, as Figure 1 demonstrates, this is not true for most investors.

[18] For simplification we assume, without loss of generality, that the liquidation threshold for Coin B is also equal to 0.8.

[19] Each single liquidation calls in the Aave V2 protocol has a close factor of 0.5. Thus, a single liquidation call can liquidate up to 50% of the amount deposited as collateral.

that gets liquidated by a single liquidation call.[20] The payoff to the borrowing option can therefore be written as

$$.75S_t^{B/A}(r-i)S_{t+1}^{\$/B}+\mathbb{1}_{v=yes}b^A+.75\mathbb{1}_{v=yes}b^B+(1+d)S_{t+1}^{\$/A}-p_{t+1}(\theta(1+d)+LB^A)S_{t+1}^{\$/A}-S_t^{\$/A}. \tag{6}$$

The second option is a round trip scenario where the investor goes from Coin A into Coin B in period t, invests Coin B for one period, and then returns back into Coin A. Ignoring exchange fees, the per-unit dollar return to this investment is

$$S_t^{B/A}(1+r)S_{t+1}^{\$/B}+\mathbb{1}_{v=yes}b^B-S_t^{\$/A}. \tag{7}$$

The first term in Equation 7 is the dollar return from investing $S_t^{B/A}$ units of Coin B and the last term is the dollar cost of the initial investment.

If the investor believes that the price of Coin A will increase from period t to period $t+1$ then she may prefer to borrow Coin B rather than sell Coin A and purchase Coin B to make the investment. We can see this by looking at the difference between Equation 6 and Equation 7:

$$(1+d)S_{t+1}^{\$/A}-p_{t+1}(\theta(1+d)+LB^A)S_{t+1}^{\$/A}-S_t^{B/A}(1+.25r+.75i)S_{t+1}^{\$/B}+\mathbb{1}_{v=yes}b^A-.25\mathbb{1}_{v=yes}b^B. \tag{8}$$

The sign of the expression in Equation 8 depends not only on what happens to the dollar price of Coin A, but also on the dollar price of Coin B. The sign is more likely to be positive when the dollar price of Coin A increases and the dollar price of Coin B decreases, so that Coin A appreciates relative to Coin B.

An interesting, and empirically relevant, case is when Coin B is a stablecoin. Then

[20] To simplify the mathematical formulation, without loss of generality, we assume that a single liquidation call is sufficient to bring the health factor above 1.

$S_t^{B/A} = S_t^{\$/A}$, $S_{t+1}^{\$/B} = 1$, and there are likely no governance benefits, so Equation 8 becomes

$$(1+d)S_{t+1}^{\$/A} - p_{t+1}(\theta(1+d) + LB^A)S_{t+1}^{\$/A} - (1 + .25r + .75i)S_t^{\$/A} + \mathbb{1}_{v=yes}b^A. \quad (9)$$

Here we can see immediately that investors who are sufficiently confident that there will be increase in the dollar price of Coin A will believe that in expectation this expression will be strictly positive. For these investors, borrowing a stablecoin will be the preferred investment strategy.

It is also interesting to note that if the prices of Coin B and Coin A are perfectly (positively) correlated so that $S_t^{B/A} = S_{t+1}^{B/A}$, and hence there is no potential for the price of Coin A to increase relative to the price of Coin B. Then, Equation 8 simplifies to

$$(d - .75i)S_{t+1}^{\$/A} - .25(rS_{t+1}^{\$/A} + \mathbb{1}_{v=yes}b^B) - p_{t+1}(\theta(1+d) + LB^A)S_{t+1}^{\$/A} + \mathbb{1}_{v=yes}b^A. \quad (10)$$

The first term is the net payoff to borrowing. The second term is the opportunity cost of foregone investment that arises from the fact that under this strategy the individual is only able to invest .75 of their initial holding of Coin A rather than 1 unit due to the over-collateralisation requirement. The third term is the expected liquidation cost, and the final terms give the net governance benefits. Conditions under which the first term is positive are unlikely to persist. In this simple example we treat the rates i and d as exogenous, but in reality they adjust based on borrowing demand and amount of deposits (see Appendix A.4). If market participants found the isolated act of borrowing to be beneficial, then i would increase and d would decrease until the point where $d - .75i \leq 0$. The second term and third terms are unambiguously negative. Hence, the only possibility for Equation 10 to be positive is if the governance benefits from Coin A are sufficiently large.

3.3.2 Borrowing for leverage

Using the same notation as the previous subsection we can write the payoff in USD to an investor who deposits Coin A in a lending pool, borrows a stablecoin and then sells that stablecoin to purchase more of Coin A (e.g. through a swap):

$$.75S_t^{\$/A}(-i) + 1.75\mathbb{1}_{v=yes}b^A + 1.75(1+d)S_{t+1}^{\$/A} - p_{t+1}(LB^A + 1.75\theta(1+d))S_{t+1}^{\$/A} - 1.75S_t^{\$/A}. \tag{11}$$

For leveraging to make sense this payoff has to exceed the payoff to simply holding Coin A for one period:

$$(1+d)S_{t+1}^{\$/A} + \mathbb{1}_{v=yes}b^A - S_t^{\$/A}. \tag{12}$$

Taking the difference we get

$$.75S_t^{\$/A}(-i) + .75\mathbb{1}_{v=yes}b^A + .75(1+d)S_{t+1}^{\$/A} - p_{t+1}(LB^A + 1.75\theta(1+d))S_{t+1}^{\$/A} - .75S_t^{\$/A}. \tag{13}$$

In order for Equation 13 to be positive it must be the case that additional governance benefits combined with a price increase are sufficient to offset the expected costs of leveraging.

3.3.3 Empirical analysis

The above scenarios demonstrate that an increase in the expected price of an investor's collateral relative to an alternative investment currency may make borrowing preferred and borrowing seems unlikely to be desirable if investors expect the relative price to decrease. Governance benefits may also make borrowing more likely, but these benefits alone may not be enough to make the investor favor borrowing in the absence of relative price appreciation.

We cannot measure individual investor price expectations, but we can get a strong sense of overall market sentiment using the Crypto Fear & Greed index and the price of Ether. When these measures rise, the above calculations suggest that more and more investors are likely to favor borrowing rather than selling collateral to fund their investments.

Our hypotheses are that the level of borrowing will be positively related to the Crypto Fear & Greed index, the price of Ether and the activation of voting rights that deliver governance benefits. We therefore specify Equation 14 as follows:

$$Ln(borrow\ amount)_{ijt} = \delta Y_t + \theta_{ij} + \varepsilon_{ijt} \tag{14}$$

where the dependent variable corresponds to the natural logarithm of the dollar amount (*Ln(borrow amount)*) of each individual borrowing transaction for user i, reserve j, and timestamp t. Ln(borrow amount) is regressed on a set of variables Y employed to capture whether users borrow crypto either for speculative and/or voting power motives. The vector Y includes *Crypto Fear & Greed* and the natural logarithm of the Ether price (*Ln(ETH price)*) that measure crypto market sentiments and, therefore, capture speculative behaviours. Specifically, the former captures speculative behaviours driven by FOMO, while the second measures speculative behaviours driven by the momentum effect (Liu and Tsyvinski, 2021). In order to gauge voting power motives, we interact two dummies: the first dummy (*Governance Token*) takes the value 1 for those tokens that give holders voting rights over proposed revisions to smart contracts at issuing protocols whilst the second dummy (*Voting dates*) takes value one for an ongoing vote in correspondence of the execution timestamp of the borrow-transaction. As in Equation 1, Equation 14 also includes user-reserve fixed effects (θ_{ij}).

Table 3 reports the results. We find a positive and statistically significant - at the 1% level across econometric specifications - relationship between our variables capturing the speculative motives (the Crypto Fear and Greed index and the Ln(ETH price)) and borrowing volumes, indicating that more greedy investors' sentiments coincide with higher borrowing by users in DeFi protocols.[21] The magnitude of the effects are economically meaningful. A 1% increase in the price of ETH results in about 0.35% higher borrowing in the DeFi protocol,[22] while an increase in 1pp in the Crypto Fear and Greed index leads to about 18 bps borrowing increase at the within user-reserve level. This evidence is consistent with DeFi borrowing being driven by FOMO and investors betting that prices will go up even further. Additionally, the positive and statistically significant coefficients for the interaction term in columns 2 and 3, indicate about 10% higher borrowing volume for governance tokens in correspondence of voting days. This result suggests that investors borrow through DeFi protocols to increase their voting power to influence tokens' development plans. Column 4 reports the results for a complete model where we find, consistently with the implication from the theoretical model in section 3.3, that speculative reasons appear to prevail over voting power motives as the interaction term remains positive but loses statistical significance.[23]

The lack of significance of governance benefits could be driven by two factors. One factor is that borrowing data does not capture the additional governance benefits associated with a leverage trade except in some instances where the borrowed token is part of a swap trade. The other factor is the heterogeneous behaviour of the different investor types (ie large vs retail). Due to data limitations we cannot investigate the former factor. We investigate the latter aspect in the next section.

[21] Our results on the positive relationship between borrowing and ETH prices are consistent with the finding of Chiu et al. (2022). Specifically, the model developed by Chiu et al. (2022) predicts that DeFi lending is positively associated with prices of cryptocurrencies, due to a price-liquidity feedback loop.

[22] The effect is calculated as $exp(0.7564 * ln(1.01)) - 1$.

[23] This finding is consistent with other, purely price driven motives for borrowing. An investor that believes the price of a cryptocurrency will rise may borrow simply to leverage their position and increase returns in the state where prices actually do increase. Some platforms provide automated leverage trades, known as Boosts.

Table 3: Borrowing equation

	Ln(borrow amount)			
	(1)	(2)	(3)	(4)
Crypto Fear & Greed	0.0018***		0.0026***	0.0018***
	(0.0003)		(0.0004)	(0.0003)
Governance Token*Voting dates		0.1027*	0.1082**	0.0509
		(0.0538)	(0.0540)	(0.0515)
Ln(ETH price)	0.7564***			0.7563***
	(0.0256)			(0.0256)
Observations	132,382	132,382	132,382	132,382
R-squared	0.8388	0.8325	0.8329	0.8388

Standard errors clustered at the user-reserve level in parentheses. ***/**/* indicates statistical significance at the 1/5/10% level. All the regressions include user-reserve fixed effects.
Source: Authors' calculations.

4 Large vs retail investors

In this section, we test whether the depositing and borrowing behaviour of large investors is different relative to retail investors. Retail investors may "fly to safety" quickly as interest rates start to normalise from very low levels, while large investors might be more interested in the upside potentials coming from volatile crypto prices, yield opportunities or market sentiment driven by greed. To shed light on this aspect, we create a dummy variable equal to 1 for large investors, ie those users that have a cumulative deposit balance in the top tercile of the distribution, and 0 otherwise. Specifically, we modify our baseline regressions and compare transactions for users with a cumulative deposit balance in the bottom tercile (retail users) with those in the top tercile (large users), ie removing users with a cumulative deposit balance in the middle tercile.[24]

Table 4 shows that the level of interest rate matters only for retail investors.

[24]The average cumulative deposit balance is around $1,000 for retail investors and around $2 million for large investors.

Table 4: Deposit equation: Large vs Retail investors

	Ln(deposit amount)					
	(1)	(2)	(3)	(4)	(5)	(6)
Policy Rate	-0.4773***					
	(0.1175)					
Policy Rate*Large investor	0.4697***					
	(0.1133)					
3M Gov Bond		-0.2944**				
		(0.1286)				
3M Gov Bond*Large investor		0.2967**				
		(0.1285)				
6M Gov Bond			-0.2073**			
			(0.0910)			
6M Gov Bond*Large investor			0.2101**			
			(0.0927)			
1Y Gov Bond				-0.1555**		
				(0.0737)		
1Y Gov Bond*Large investor				0.1660**		
				(0.0765)		
2Y Gov Bond					-0.1260*	
					(0.0669)	
2Y Gov Bond*Large investor					0.1425**	
					(0.0706)	
10Y Gov Bond						-0.2245***
						(0.0602)
10Y Gov Bond*Large investor						0.2490***
						(0.0678)
Large investor	5.8021***	5.6011***	5.9214***	5.9401***	5.9435***	5.9488***
	(0.2289)	(0.2937)	(0.2675)	(0.2563)	(0.2531)	(0.2505)
Crypto Fear & Greed	-0.0003	-0.0007	-0.0006	-0.0006	-0.0007	-0.0007
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
SD ETH price	0.2128***	0.2253***	0.2243***	0.2214***	0.2185***	0.2176***
	(0.0245)	(0.0214)	(0.0232)	(0.0242)	(0.0248)	(0.0255)
Observations	138,558	96,244	96,244	96,244	96,244	96,244
R-squared	0.8869	0.8857	0.8857	0.8857	0.8857	0.8857
F-Test	0.02	0.00	0.01	0.19	0.65	0.56
P-value	0.879	0.957	0.930	0.664	0.418	0.455

Standard errors clustered at the user-reserve level in parentheses. ***/**/* indicates statistical significance at the 1/5/10% level. All the regressions include user-reserve fixed effects. Large investors correspond to users with account balance in the top tercile; retail users, in the bottom tercile.
Sources: Authors' elaboration.

The single coefficients of the Policy rate and the yields on U.S. Treasury securities are negative and statistically significant across the spectrum of interest rate maturities, suggesting that the "low-for-long" interest rate environment pushed retail investors to search-for-yield by depositing cryptocurrencies within DeFi protocols. At the same time, the F-test for the joint significance of the coefficients of the Policy rate and the yields on U.S. Treasury securities and their interaction with the dummy Large investor are statistically insignificant. This indicates that the decision of large investors to deposit in DeFi protocols is not influenced by the policy rate.

Thus, a reasonable question is what is driving deposit decisions of large investors? To answer this question, we look at the role played by the APR for deposits on the Aave V2 protocol, that is endogenously determined by the platform matching demand and supply (see Appendix A.4). It is possible that, while retail users find more attractive traditional investments as soon as interest rates in traditional financial markets increase, large users - perfectly integrated in the DeFi ecosystem - may instead be more interested in harvesting the yield offered by the DeFi protocol. We test this hypothesis by augmenting the double interactions specification of Table 4. We capture yield opportunities of the DeFi protocol through the deposit APR, distinguishing the effects on the two types of investors. In particular, we interact the deposit APR, expressed as a continuous variable, with the dummy Large investor.

Table 5 shows that the deposit APR is statistically significant only for large investors both in relative and absolute terms. Specifically, the coefficient for the interaction term Deposit APR * Large investor indicates that a 1 pp increase in the deposit APR results in 31 bps larger inflow of deposits in the DeFi protocol for large investors relative to retail investors (column 1 of Table 5). The F-test for joint significance suggests that the overall effect is also statistically significant. Following a 1 pp increase in the deposit APR, large investors increase the amount deposited in the DeFi protocol by 45 bps (column 1 of Table 5).

Table 5: Deposit equation: Large vs Retail investors (interaction with deposit APR)

	Ln(deposit amount)					
	(1)	(2)	(3)	(4)	(5)	(6)
Deposit APR	0.0014	0.0004	0.0006	0.0007	0.0007	0.0008
	(0.0016)	(0.0019)	(0.0019)	(0.0018)	(0.0018)	(0.0018)
Deposit APR*Large investor	0.0031*	0.0040*	0.0041*	0.0041*	0.0041*	0.0044**
	(0.0018)	(0.0022)	(0.0022)	(0.0021)	(0.0022)	(0.0022)
Policy Rate	-0.4862***					
	(0.1185)					
Policy Rate*Large investor	0.4696***					
	(0.1136)					
3M Gov Bond		-0.3001**				
		(0.1293)				
3M Gov Bond*Large investor		0.2961**				
		(0.1289)				
6M Gov Bond			-0.2116**			
			(0.0914)			
6M Gov Bond*Large investor			0.2100**			
			(0.0930)			
1Y Gov Bond				-0.1581**		
				(0.0740)		
1Y Gov Bond*Large investor				0.1661**		
				(0.0769)		
2Y Gov Bond					-0.1271*	
					(0.0672)	
2Y Gov Bond*Large investor					0.1422**	
					(0.0710)	
10Y Gov Bond						-0.2233***
						(0.0602)
10Y Gov Bond*Large investor						0.2466***
						(0.0678)
Large investor	5.7979***	5.5956***	5.9132***	5.9312***	5.9347***	5.9404***
	(0.2282)	(0.2909)	(0.2669)	(0.2555)	(0.2521)	(0.2494)
Crypto Fear & Greed	-0.0006	-0.0010	-0.0009	-0.0010	-0.0010*	-0.0010*
	(0.0006)	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
SD ETH price	0.2157***	0.2303***	0.2295***	0.2257***	0.2219***	0.2207***
	(0.0262)	(0.0221)	(0.0242)	(0.0253)	(0.0261)	(0.0269)
Observations	137,432	95,462	95,462	95,462	95,462	95,462
R-squared	0.8855	0.8839	0.8839	0.8841	0.8841	0.8842
F-Test (interest rate)	0.11	0.01	0.00	0.11	0.55	0.51
P-value (interest rate)	0.744	0.927	0.958	0.741	0.458	0.457
F-Test (deposit APR)	26.68	23.20	22.70	21.88	20.72	19.50
P-value (deposit APR)	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors clustered at the user-reserve level in parentheses. ***/**/* indicates statistical significance at the 1/5/10% level. All the regressions include user-reserve fixed effects. Large investors correspond to users with account balance in the top tercile; retail users, in the bottom tercile.
Sources: Authors' elaboration.

In line with the results commented in footnote 8 and reported in Table B2 in Appendix B, we find that retail investors' behavior is not influenced by changes in the deposit APR (the single coefficient Deposit APR is always positive but never statistically significant across the econometric specifications). Nonetheless, the result of retail investor sensitivity to the interest rates in traditional financial markets remains robust to the inclusion of the deposit APR among the controls.

Table 6 reports the results for differential effects in borrowing behaviour between retail and large investors. Interestingly, it reveals some peculiarities in comparison to the baseline results presented in Table 3. While the evidence for the Ln(ETH price) are broadly in line with the baseline results suggesting that both large- and retail investors borrow more on the back of upward trending crypto prices, there are noticeable differences between large and retail investors with respect to speculative behaviours driven by FOMO. Specifically, while retail investors tend to buy when the market sentiments are greedy (the single coefficient for the Crypto Fear & Greed index is positive and statistically significant at the 1% level), large investors tend to increase borrowing in DeFi protocols when the market fears crypto prices are going down, consistent with a "buy low, sell high" strategy, both relative to retail investors (the interaction term Crypto Fear and Greed*Large investor) and in absolute terms (column 1). In other words, the overall effect for large investors which is given by the sum of the coefficients for the Crypto Fear and Greed index and the interaction term is negative and statistically significant at the 5% level, as indicated by the F-test for joint significance.

Second, the interaction term between the Governance Token*Voting dates and the Large investor indicator variable is positive and statistically significant at the 10% level (column 2) suggesting that, relative to retail investors, large investors borrow more through DeFi protocols to increase their voting power to influence tokens' development plans. Arguably this strategy is more appealing for large investors as they are able to significantly increase their voting power over projects' development proposals through borrowing.[25] In column 3, we also test the stability of the coefficients when the Crypto

[25]One should note that the user-reserve (user-reserve-month) fixed effects in Table 6 (Table C2) subdue the coefficients for Governance and Governance*Large investors. Therefore, it is not feasible to calculate the overall effect of governance tokens for retail versus large investors during these periods.

Fear and Greed index, the Governance Token*Voting dates and their interaction terms are included in the same econometric specification. The point estimates hold up well even when the variables of interest are included in the same specification.

Table 6: Borrowing equation: Large investors vs Retail users

	Ln(borrow amount)		
	(1)	(2)	(3)
Crypto Fear & Greed	0.0030***		0.0030***
	(0.0004)		(0.0004)
Crypto Fear & Greed*Large investor	-0.0041***		-0.0040***
	(0.0006)		(0.0006)
Governance Token*Voting dates		-0.3801*	-0.3668*
		(0.2036)	(0.2018)
Governance Token*Voting dates*Large investor		0.4206*	0.3918*
		(0.2153)	(0.2137)
Ln(ETH price)	0.4662***	0.4659***	0.4744***
	(0.0373)	(0.0374)	(0.0373)
Ln(ETH price)*Large investor	0.0137	0.0056	0.0139
	(0.0505)	(0.0506)	(0.0504)
Large investor	3.9569***	3.9569***	4.0824***
	(0.3826)	(0.3826)	(0.3819)
Observations	80,940	80,940	80,940
R-squared	0.9381	0.9381	0.9383
F-Test (Crypto Fear & Greed)	4.95		
P-value	0.026		
F-Test (ln(ETH price))	238.29	225.95	
P-value	0.000	0.000	

Standard errors clustered at the user-reserve level in parentheses. ***/**/* indicates statistical significance at the 1/5/10% level. All the regressions include user-reserve fixed effects. Large investors correspond to users with account balance in the top tercile; retail users, in the bottom tercile.
Sources: Authors' calculations.

5 Robustness checks

5.1 Borrowing transaction analysis on the restricted sample of WETH collateral

The argument provided in subsection 3.3 to derive the hypotheses for the regression coefficients was somewhat simplified because we did not consider the possibility that the investor might post collateral other than Ether. To see why this might matter we must take a closer look at how the *Health Factor* is defined. Its formula is

$$\text{Health Factor}_{i,t} = \frac{\sum_{a=1}^{N}\left[Collateral_{i,a,t} \text{ in ETH} * \text{liquidation threshold}_{a,t}\right]}{\sum_{d=1}^{N}\left[Borrows_{i,d,0:t} \text{ in ETH} + interest_{i,d,t} \text{ in ETH}\right]} \tag{15}$$

where a indicates the token deposited as collateral, and d the token borrowed, $Collateral_{i,a,t}$ corresponds to the tokens deposited and the interest accrued on the position up to time t, $\textit{liquidation threshold}_{a,t}$ corresponds to a haircut on the collateral value, $Borrows_{i,d,0:t}$ corresponds to borrowings contracted from time 0 and still outstanding at time t, and $interest_{i,d,t}$ corresponds to the interest accrued on the borrowings up to time t. Equation 16 shows that the Health Factor is a function of the exchange rate of the token posted as collateral, and the token borrowed vis-á-vis ETH. To fully incorporate the volatility of the two exchange rates in our model, one would need to establish a one-to-one correspondence between the token used as collateral and the one borrowed for each specific borrowing transaction. However, when calculating the Health Factor the collateral deposited is pooled all together and the resulting value is "converted" into ETH. For this reason, establishing such a one-to-one correspondence is not possible.

Nevertheless, what we can do is to eliminate the variability in the value of the numerator of the Health Factor by focusing on those users for which the collateral is entirely constituted by tokens with value pegged to Ether —ie WETH —and show that our results hold in the setting used in subsection 3.3. In other words, if the collateral posted is

Ether, then the numerator of the health factor does not change as Ether price goes up and down. Furthermore, by restricting our sample to those users for which the only collateral deposited in the protocol is WETH, our measure of speculative behaviour driven by the momentum effect (ie ln(ETH price)) is not confounded by any change in the relative price of each token vs ETH.

Thus, as a first robustness check, we replicate the analysis from Table 3 and Table 6 on the sample of users that have deposited WETH as the only form of collateral throughout their full history. One should note that this sample does not include all the borrowing transactions from all the users that have deposited WETH –and hence backed to some extent by WETH collateral –but only the ones carried out by users that have deposited WETH as the only form of collateral through their whole history. In other words, for this test, we are not including in our sample those users that have deposited a token different from WETH in at least one of the deposit transactions performed throughout their whole history. By adopting this strict definition we ensure that we isolate those users for which the variability in the Health Factor is purely driven by the correlation of the token borrowed (which in most of the cases is a stablecoin pegged to the US dollar) and ETH. This test yields very similar and consistent results corroborating our modelling assumptions.

Table 7 shows a positive and statistically significant relationship (at the 1% level) between the Crypto Fear and Greed index and borrowing volumes, suggesting the our results hold also when we restrict the sample to those users employing the same collateral (WETH) for borrowing. The size of the coefficient for the Crypto Fear and Greed index increases substantially in comparison to the baseline specification in Table 3. In particular, a 1 pp increase in the Crypto Fear and Greed index results in 48 bps higher borrowing volumes (column 1) relative to the 18 bps recorded in Table 3.

Notwithstanding, the interaction term between Governance Token and Voting dates loses statistical significance, suggesting that (on average) the benefit from holding governance tokens is not the main motivation driving borrowing transactions in DeFi platforms.[26]

Table 7: Borrowing equation: WETH collateral

	Ln(borrow amount)			
	(1)	(2)	(3)	(4)
Crypto Fear & Greed	0.0046***		0.0031***	0.0046***
	(0.007)		(0.0007)	(0.0007)
Governance Token*Voting dates		0.2178	0.2526	0.0130
		(0.4255)	(0.4256)	(0.4135)
Ln(ETH price)	1.3758***			1.3757***
	(0.0451)			(0.0452)
Observations	16,188	16,188	16,188	16,188
R-squared	0.0949	0.0421	0.0432	0.0949

Standard errors clustered at the reserve level in parentheses. ***/**/* indicates statistical significance at the 1/5/10% level. All the regressions include reserve fixed effects.
Source: Aave; Alternative; CryptoCompare; Federal Reserve Bank of St Louis, FRED; The Graph; authors' calculations.

5.2 Alternative fixed effects specifications

In Table 2 we find an inverse relationship between the amount deposited in DeFi protocols and the level of interest rates, confirming our hypothesis that investors deposit funds in DeFi protocols for yield-seeking reasons. Although the regressions are saturated with user-reserve fixed effects, we left out time fixed effects to avoid multicollinearity (or an excessive data variation reduction) with our interest rate variables. However, it may be argued that other time-variant factors at the within user-reserve level may affect the decision to deposit funds into Aave other than the policy rates –eg COVID-19. To control for this possibility, we augment our econometric specification with user-reserve-month fixed effects. Arguably, this specification is particularly demanding as it omits estimates in which interest rates do not have within-month variation, as in those months interest

[26]One should note that these regressions include reserve-fixed effects as the smaller sample size does not allow to have enough data variation to include user-reserve fixed effects as done in the analysis conducted on the pooled borrowing transactions backed by different types of collateral.

rates would be collinear with monthly fixed effects as well as users that deposit/borrow only once in a particular month.

Table 8 reports the results. Despite the substantial loss of observations - more than 38,000 (28,000) in column 1 (columns 2 - 6) - the results yet display a negative and, in most of the econometric specifications, statistically significant relationship between the amount deposited in DeFi protocols and the level of interest rates, corroborating our baseline results. It is also worth noting that in Table 8 the coefficients shrink by almost half in comparison to the results reported in Table 2. Nevertheless, the point estimates are still economically meaningful. *Ceteris paribus*, a 1 pp reduction in the FED policy rate results in about 19% increase in the amount of deposit in DeFi protocols on a monthly basis (Column 1).

Table 8: Including user-reserve-month fixed effects in the deposit equation

	Ln(deposit amount)					
	(1)	(2)	(3)	(4)	(5)	(6)
Policy Rate	-0.1948***					
	(0.0726)					
3M Gov Bond		-0.1472*				
		(0.0751)				
6M Gov Bond			-0.1029**			
			(0.0516)			
1Y Gov Bond				-0.0751*		
				(0.0396)		
2Y Gov Bond					-0.0587*	
					(0.0328)	
10Y Gov Bond						-0.0584
						(0.0536)
SD ETH price	0.3810***	0.3854***	0.3785***	0.3739***	0.3702***	0.3685***
	(0.0352)	(0.0374)	(0.0382)	(0.0383)	(0.0380)	(0.0379)
Observations	192,173	131,825	131,825	131,825	131,825	131,825
R-squared	0.7909	0.7909	0.7909	0.7909	0.7909	0.7909

Standard errors clustered at the user-reserve level in parentheses. ***/**/* indicates statistical significance at the 1/5/10% level. All the regressions control for the Crypto Fear and Greed index and include user-reserve-month fixed effects.
Source: Authors' elaboration.

In a similar way, unobservable time-varying user-specific characteristics, potentially correlated with our variables of interest, may also affect investors' decision to borrow funds in DeFi protocols. Again, the outbreak of the pandemic could have a heterogeneous effect on users' propensity to borrow funds for speculative reasons which are not necessarily captured by the *Crypto Fear & Greed* index. Following the aforementioned approach, we also augment the results for the borrowing specification with user-reserve-month fixed effects. The results reported in Table 9 hold at the inclusion of the triple fixed effects interaction, confirming the validity of the baseline borrowing results of Table 3. Indeed, the coefficients of the Crypto Fear & Greed and Governance Token*Voting dates keep sign, statistical significance and magnitude in line with the baseline results. The stability of the point estimates between Table 9 and Table 3 is reassuring, considering that the estimation of Table 9 presents a drop of around 22,000 observations, determined by the omission of those users that do not borrow multiple times on a monthly basis.[27]

Table 9: Including user-reserve-month fixed effects in the borrowing equation

	Ln(borrow amount)			
	(1)	(2)	(3)	(4)
Crypto Fear & Greed	0.0019***		0.0037***	0.0019***
	(0.0006)		(0.0006)	(0.0006)
Governance Token*Voting dates		0.1138*	0.1183*	0.1146*
		(0.0638)	(0.0635)	(0.0623)
Ln(ETH price)	0.8358***			0.8357***
	(0.0616)			(0.0616)
Observations	110,345	110,345	110,345	110,345
R-squared	0.8777	0.8764	0.8766	0.8777

Standard errors clustered at the user-reserve level in parentheses. ***/**/* indicates statistical significance at the 1/5/10% level. All the regressions include user-reserve-month fixed effects. Source: Aave; Alternative; CryptoCompare; Federal Reserve Bank of St Louis, FRED; The Graph; authors' calculations.

[27] Tables C1 and C2 in Appendix C report the results where the econometric specifications employed for the analyses of large vs retail investors (Tables 4 and 6) are also augmented with user-reserve-month fixed effects. The results are qualitatively similar to the results presented in Section 4 further corroborating the validity of the choice of user-reserve fixed effects.

6 Conclusions

The paper analyses investors' behaviour in DeFi lending protocols. To understand the main determinants of DeFi intermediation activity, we use granular transaction-level data from Aave, one of the most prominent players in the DeFi lending space.

The main results of our study are as follows. First, "search for yield" in a low interest rate environment is a key determinant of liquidity provision in DeFi lending pools, especially for retail users. Second, investors borrow tokens through DeFi lending protocols for speculative reasons or to increase their voting power by temporarily increasing their stake in governance tokens, although the speculative motive prevails over the governance motive. Third, there are key differences in lending behaviour between different types of investors. Both retail and large investors borrowing decision is driven by speculative motives, seeking potential high returns through leverage, market movements and price speculation. However, while retail investors show "fear-of-missing-out" behaviours, large investors don't. Finally, large-scale investors engage relatively more than retail investors in DeFi borrowing for governance motives, such as influencing protocol decisions and accruing more significant governance rights.

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Appendix A

A How does the Aave platform work?

A.1 Depositing

A user initiates a deposit transaction by transferring funds into the Aave V2 protcol. For example, a user β would like to deposit 5.55 ETH in the protocol. First, the ETH tokens need to be converted in the corresponding ERC-20 tokens, thus transferring ETH in wrapped ETH (WETH), which are supported by a smart contract. In essence, a WETH token is backed one-to-one by an ETH token and represents it within a smart contract. To convert ETH into WETH, a user sends ETH to the WETH smart contract and, in return, receives an equivalent amount of WETH tokens. The 5.55 WETH can then be deposited into the corresponding Aave V2 reserve. Upon deposit, the liquidity in the receiving WETH reserve increases by the same amount. Figure A1 gives a ledger representation of this transaction.

Figure A1: **Graphical representation of a deposit transaction**

User β	
Crypto 5.55 WETH	

WETH reserve	
Available liquidity +5.55 WETH	

Contextually, the protocol issues 5.55 aWETH, which are allocated to the depositing user. *aTokens*, minted upon deposit of assets in an Aave V2 reserve, have their value pegged at a one-to-one ratio to the corresponding supplied asset. These *aTokens*, enabling storage or trade among users on the Aave V2 protocol, accrue interest. This interest is distributed directly to the holders by continuously increasing their wallet balance. Following the ledger representation of the deposit transaction, the liabilities of the WETH reserve increase by 5.55 aWETH and, correspondingly, the assets of user β increase (Figure A2).

Figure A2: **Graphical representation of a deposit transaction**

User β	
aToken	
5.55 aWETH	

WETH reserve	
Available liquidity	*aToken*
+5.55 WETH	+5.55 aWETH

Upon completion of the transaction, the protocol updates the reserve utilization rate which reflects the ratio of total borrows to the total liquidity of a reserve. This metric monitors the proportion of the reserve's total liquidity that is borrowed at any given time. As the utilisation rate increases, the liquidity available for borrowing becomes more scarce.

A.2 Borrowing

After depositing tokens on the platform, a user has the option to borrow tokens from the reserve, either from the same reserve where he deposited funds or from one corresponding to a different token. Continuing with our example, user β decides to borrow 7,500 USDC from the relevant reserve. As depicted in Figure A3 through a ledger representation, the liquidity of the USDC reserve decreases by the corresponding amount. Subsequently, the protocol updates the USDC reserve utilization rate and determines the interest rates applicable to the loan, based on the updated liquidity balance. Contextually, the protocol issues an equivalent amount of *dTokens*, analogous to *aTokens*. Unlike *aTokens*, which accrue interest in favour of the holder (ie *aToken yield*), *dTokens* accumulate interest that the holders are obliged to pay.

Figure A3: **Graphical representation of a borrow transaction**

User β	
aToken 5.55 aWETH	
aToken yield 0.05 aWETH	

USDC reserve	
Available liquidity -7500 USDC	

As Figure A4 shows, *dTokens* can be represented as a liability for user β and an asset for the USDC reserve. Loans have no fixed term, however, as time passes, the amount of interest accruing on the loans for borrowers increases. This mechanism contributes to a deterioration of the user *Health Factor* –an indicator measuring the solvency of each Aave user. Specifically, the general formula of the *Health Factor* for user i at time t is mathematically represented by

$$\text{Health Factor}_{i,t} = \frac{\sum_{a=1}^{N}\left[Collateral_{i,a,t} \text{ in ETH} * \text{liquidation threshold}_{a,t}\right]}{\sum_{d=1}^{N}\left[Borrows_{i,d,0:t} \text{ in ETH} + interest_{i,d,t} \text{ in ETH}\right]} \tag{16}$$

where a indicates the token deposited as collateral, and d the token borrowed. $Collateral_{i,a,t}$ corresponds to the tokens deposited and the interest accrued on the position up to time t, *liquidation threshold*$_{a,t}$ corresponds to a haircut on the collateral value, $Borrows_{i,d,0:t}$ corresponds to borrowings contracted from time 0 and still outstanding at time t, and $interest_{i,d,t}$ corresponds to the interest accrued on the borrowings up to time t.

Figure A4: **Graphical representation of a borrow transaction**

User β	
aToken 5.55 aWETH	*dToken* 7500 dUSDC
aToken yield 0.05 aWETH	
dToken 7500 dUSDC	

USDC reserve	
Available liquidity -7500 USDC	

As the *Health Factor* reaches the value of 1, the user collateral –ie the *aTokens* –is automatically liquidated at a discount. As the threshold is breached, liquidators compete to repay the loan to the platform and, consequently, claim the collateral from the insolvent user in addition to a liquidation bonus.[28] This mechanism incentivises borrowers to over collateralise their positions, while the threat of a collateral liquidation disciplines users' borrowing decisions.

A.3 Repaying

At a certain point, users may wish to reduce their exposure by repaying their borrowings either partially or in full. This action is facilitated through repay transactions. Continuing with our example, user β opts to repay 1,500 USDC of the 7,500 USDC outstanding borrowing. Consequently, user β's liability decreases from 7,500 to 6,000 USDC and, simultaneously, the liquidity available in the USDC reserve is augmented by the same amount (Figure A5).

[28] For more information on liquidation bonuses see Aave V2 Risk Parameters.

Figure A5: **Graphical representation of a repay transaction**

User β	
aToken	*dToken*
5.55 aWETH	6000 USDC
aToken yield	
0.06 aWETH	
dToken	
6000 dUSDC	

USDC reserve	
Available liquidity	
+1500 USDC	

At this stage, the protocol updates the USDC reserve utilization rate and determines the new interest rate, as well as the interest accrued on the *dToken* that have been burned in the repay transaction. Assuming transaction fees amount to 4 USDC, the liquidity in the USDC reserve increases by 1,512 units which correspond to principal and interests repaid by user β. Concurrently, the outstanding loan amount in the liabilities of user β decreases by 1,484 units reflecting the principal amount repaid minus the sum of interest and transaction fees (Figure A6).

Figure A6: **Graphical representation of a repay transaction**

User β

aToken 5.55 aWETH	*dToken* −1484 dUSDC
aToken yield 0.05 aWETH	
dToken 6016 dUSDC	

USDC reserve

Available liquidity +1512 USDC	

A.4 Dynamic Interest rate mechanisms in Aave

The Aave platform calculates borrowing and lending rates based on a dynamic model that aims to balance the supply and demand for funds within the platform.

Lending rates are determined by the liquidity available in the Aave protocol for a specific asset. When the liquidity (the supply of funds available for lending) is high, and the demand (the amount of funds being borrowed) is low, the lending rate tends to decrease. Conversely, if the liquidity is low and the demand is high, the lending rate will increase. This mechanism ensures an incentive balance for depositors and borrowers.

Analogously, borrowing rates are calculated based on the utilization rate of a specific asset in the protocol, which is the ratio of the total borrowed amount to the total liquidity available. The borrowing rate increases as the utilization rate goes up, making it more expensive to borrow assets when a large portion of the available liquidity is already in use. This system aims to prevent the liquidity pool from being depleted and ensures that lenders are compensated appropriately for the risk of lending their assets.

Aave uses algorithmic models to dynamically adjust these rates in real time based on the supply and demand conditions. The specifics of these algorithms are complex, incorporating factors like:

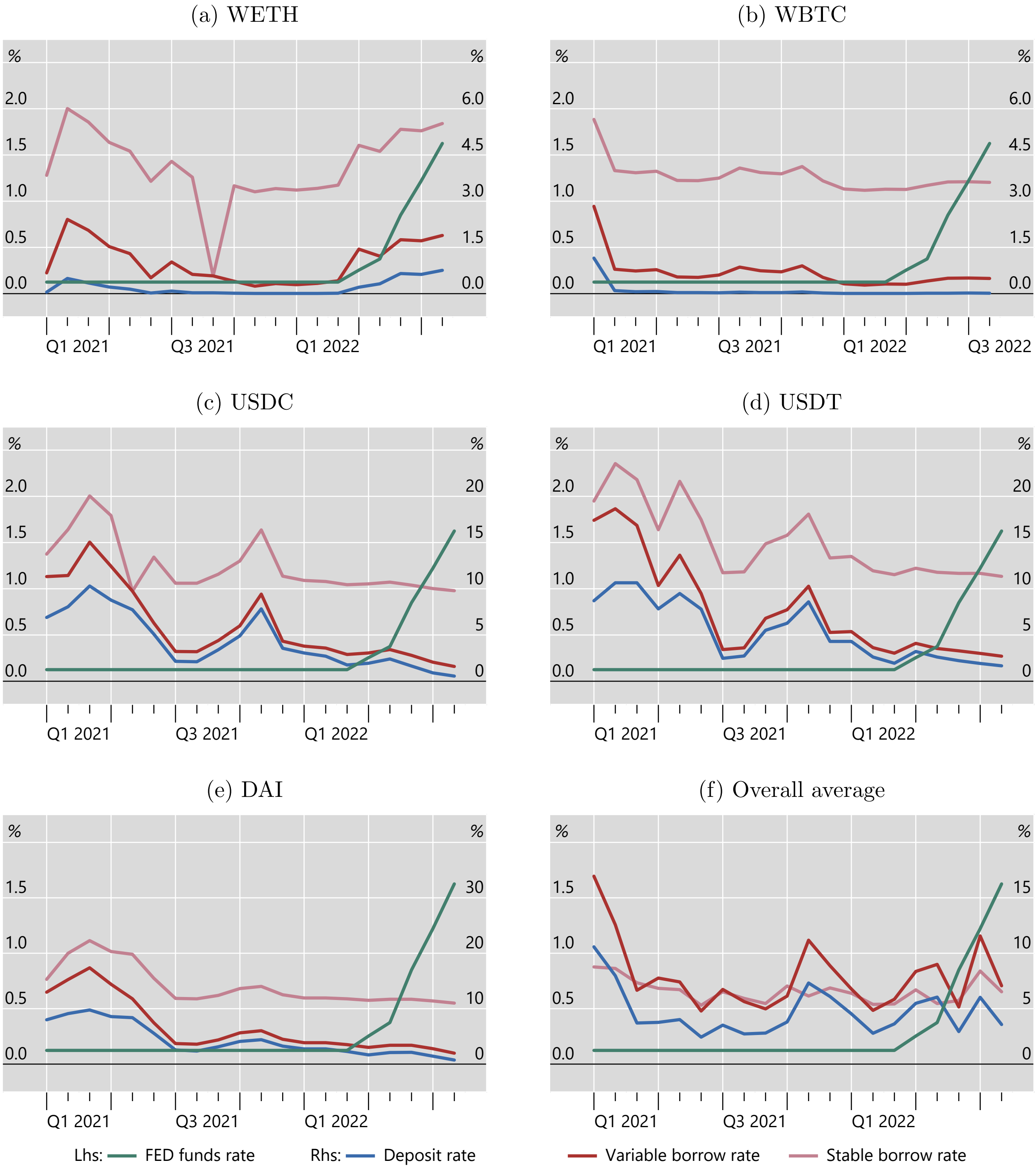
- Base Rate: A fixed rate that serves as the starting point for the calculation.
- Utilization Rate: A critical factor affecting both lending and borrowing rates.
- Slope 1 and Slope 2: Parameters that determine how quickly rates increase as the utilization rate grows. These slopes make the rate adjustment non-linear, with rates accelerating as the liquidity pool gets closer to being fully utilized.

Aave offers both stable and variable interest rates for borrowers:

- Variable Rates change according to the supply and demand dynamics described above.
- Fixed Rates offer borrowers a fixed rate for a certain period. These rates are recalculated at intervals based on the platform's algorithm and market conditions, but they provide more predictability over the loan term.

In summary, Aave's borrowing and lending rates are designed to dynamically adjust to market conditions, ensuring liquidity is maintained in the protocol while providing fair compensation to lenders and affordable borrowing costs to borrowers. Figure A7 shows the evolution of the FED fund rate and of the deposit- and the borrow rates for selected tokens and for the overall Aave V2 protocol.

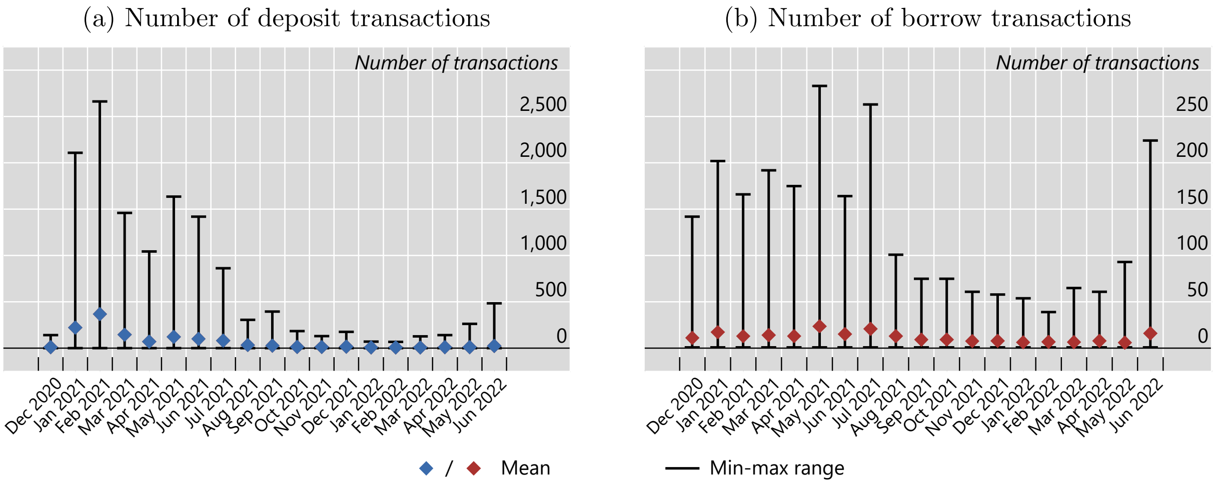
Figure A7: **FED funds rate and deposit- and borrow rates in the Aave V2 protocol**



Note: The figures show the FED fund rate, and a daily average of the deposit-, variable borrow- and stable borrow rate in the Aave V2 protocol. The series for the deposit- and the borrow rate in the Aave V2 protocol correspond to daily averages of the transaction-by-transaction data. The overall average corresponds to a weighted average with weights proportional to transaction amounts over 41 tokens. Data for the period from December 2020 to mid-July 2022. Sources: The Graph; authors' calculations.

Appendix B

Figure B1: **Distribution of transactions in the Aave V2 protocol by month**



Note: The figures show the distribution of the number of deposit- (left-hand panel) and borrow transactions (right-hand panel) by month. Based on transaction-by-transaction data for the period from December 2020 to mid-July 2022.
Sources: The Graph; authors' calculations.

Table B1: Distribution of amount deposited and borrowed by decile

Quantile	N. Obs	Mean	St. Dev.	Median	Min	Max
Panel A. Depositing Sample						
1	31,590	38	37	26	0	122
2	31,590	432	221	400	122	901
3	31,590	1,585	498	1,505	901	2,566
4	31,590	4,228	1,041	4,157	2,567	6,228
5	31,590	9,530	1,979	9,679	6,228	13,590
6	31,590	20,253	4,231	19,956	13,590	28,747
7	31,590	41,955	8,644	40,988	28,749	59,020
8	31,590	91,204	20,892	90,813	59,021	135,501
9	31,590	248,250	90,114	224,561	135,502	470,186
10	31,590	6,554,432	29,000,000	1,261,297	470,213	769,000,000
Total	315,900	697,182	9,364,196	13,590	0	769,000,000
Panel B. Borrowing Sample						
1	16,496	78	118	16	0	420
2	16,496	1,065	399	1,004	420	1,915
3	16,496	2,841	664	2,902	1,915	4,021
4	16,496	5,644	1,024	5,219	4,021	7,939
5	16,496	10,301	1,421	10,024	7,939	13,917
6	16,496	19,019	3,278	19,915	13,918	25,089
7	16,496	37,040	7,954	35,631	25,090	50,126
8	16,496	77,832	18,856	76,450	50,126	108,626
9	16,496	207,733	71,793	199,662	108,636	383,144
10	16,496	3,358,033	12,100,000	1,000,757	383,192	598,000,000
Total	164,960	371,943	3,966,214	13,918	0	598,000,000

The table reports the distribution of the amount of deposit- (Panel A) and borrow transactions (Panel B) converted into US dollars by decile. Based on transaction-by-transaction data for the period from December 2020 to mid-July 2022. Sources: Aave; The Graph; authors' calculations.

Table B2: Deposit equation

	Ln(deposit amount)					
	(1)	(2)	(3)	(4)	(5)	(6)
Policy Rate	-0.3498***					
	(0.0616)					
3M Gov Bond		-0.2800***				
		(0.0567)				
6M Gov Bond			-0.1824***			
			(0.0398)			
1Y Gov Bond				-0.1321***		
				(0.0310)		
2Y Gov Bond					-0.1039***	
					(0.0263)	
10Y Gov Bond						-0.0814**
						(0.0335)
Crypto Fear & Greed	0.0027***	0.0026***	0.0023***	0.0023***	0.0023***	0.0022***
	(0.0007)	(0.0008)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
SD ETH price	0.3626***	0.3963***	0.3838***	0.3732***	0.3656***	0.3597***
	(0.0213)	(0.0194)	(0.0209)	(0.0217)	(0.0222)	(0.0227)
APR deposit rate	0.1003	0.0690	0.0932	0.1029	0.1207	0.1411
	(0.0738)	(0.0876)	(0.0879)	(0.0874)	(0.0867)	(0.0864)
Observations	230,516	160,259	160,259	160,259	160,259	160,259
R-squared	0.7493	0.7467	0.7466	0.7466	0.7465	0.7464

Standard errors clustered at the user-reserve level in parentheses. ***/**/* indicates statistical significance at the 1/5/10% level. All the regressions include user-reserve fixed effects.
Source: Authors' elaboration.

Appendix C

Table C1: Deposit equation: Large vs Retail investors including user-reserve-month fixed effects

	Ln(deposit amount)					
	(1)	(2)	(3)	(4)	(5)	(6)
Policy Rate	-0.5475***					
	(0.1436)					
Policy Rate*Large investor	0.4697***					
	(0.1133)					
3M Gov Bond		-0.3461**				
		(0.1536)				
3M Gov Bond*Large investor		0.2725*				
		(0.1588)				
6M Gov Bond			-0.2625**			
			(0.1090)			
6M Gov Bond*Large investor			0.2073*			
			(0.1108)			
1Y Gov Bond				-0.2024**		
				(0.0862)		
1Y Gov Bond*Large investor				0.1691*		
				(0.0897)		
2Y Gov Bond					-0.1721**	
					(0.0774)	
2Y Gov Bond*Large investor					0.1509*	
					(0.0816)	
10Y Gov Bond						-0.2850***
						(0.1060)
10Y Gov Bond*Large investor						0.2574**
						(0.1093)
Large investor	6.1016***	5.9120***	6.2430***	6.2653***	6.2708***	6.2796***
	(0.1960)	(0.2923)	(0.2200)	(0.2096)	(0.2071)	(0.2059)
Crypto Fear & Greed	-0.0003	-0.0003	-0.0003	-0.0003	-0.0003	-0.0002
	(0.0008)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
SD ETH price	0.2035***	0.2147***	0.2107***	0.2063***	0.2021***	0.2021***
	(0.0278)	(0.0294)	(0.0290)	(0.0287)	(0.0285)	(0.0287)
Observations	114,212	78,662	78,662	78,662	78,662	78,662
R-squared	0.9088	0.9094	0.9094	0.9094	0.9094	0.9094
F-Test	0.27	0.72	0.87	0.58	0.38	0.21
P-value	0.601	0.397	0.350	0.448	0.539	0.647

Standard errors clustered at the user-reserve level in parentheses. ***/**/* indicates statistical significance at the 1/5/10% level. All the regressions include user-reserve-month fixed effects. Large investors correspond to users with account balance in the top tercile; retail users, in the bottom tercile.
Sources: Authors' elaboration.

Table C2: Borrowing equation: Large investors vs Retail users investors including user-reserve-month fixed effects

	Ln(borrow amount)		
	(1)	(2)	(3)
Crypto Fear & Greed	0.0029***		0.0029***
	(0.0008)		(0.0008)
Crypto Fear & Greed*Large investor	-0.0036***		-0.0036***
	(0.0011)		(0.0011)
Governance Token*Voting dates		-0.4720*	-0.4721*
		(0.2603)	(0.2603)
Governance Token*Voting dates*Large investor		0.5535*	0.5503*
		(0.2878)	(0.2881)
Ln(ETH price)	0.4260***	0.4478***	0.4262***
	(0.0893)	(0.0933)	(0.0892)
Ln(ETH price)*Large investor	0.1872	0.1707	0.1874
	(0.1163)	(0.1186)	(0.1162)
Large investor	3.0969***	3.0525***	3.0912***
	(0.8990)	(0.9062)	(0.8998)
Observations	66,282	66,282	66,282
R-squared	0.9531	0.9531	0.9531
F-Test (Crypto Fear & Greed)	-0.0007		
P-value	0.393		
F-Test (ln(ETH price))	71.04	63.67	
P-value	0.000	0.000	

Standard errors clustered at the user-reserve level in parentheses. ***/**/* indicates statistical significance at the 1/5/10% level. All the regressions include user-reserve-month fixed effects. Large investors correspond to users with account balance in the top tercile; retail users, in the bottom tercile.
Sources: Authors' calculations.