Why DeFi lending?

Evidence from Aave V2*

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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.

JEL Classification: G18, G23, O39.

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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 overcollateralisation 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 undercollateralised 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.

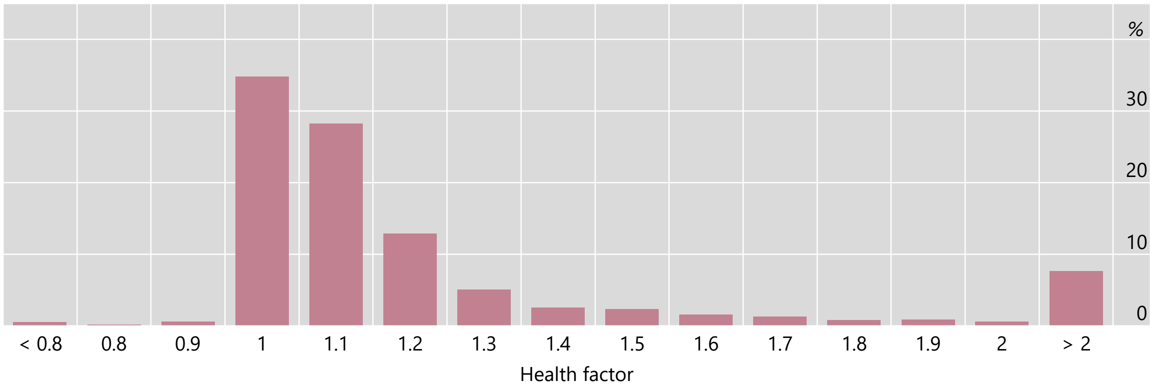
To understand the main determinants of DeFi intermediation activity we use granular transaction level data from Aave, one of the most prominent players in the DeFi lending space.[1] As discussed above, because the value of crypto assets is inherently volatile, borrowers must over collateralise the loans 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.

In this paper, we test three hypotheses. The first hypothesis investigates whether investors deposit funds in DeFi lending protocols primarily for yield-seeking purposes. The second hypothesis explores if investors borrow tokens through DeFi lending protocols for speculative reasons or to temporarily increase their stakes in governance tokens, thereby enhancing their voting power. Finally, the third hypothesis examines whether there is a difference in both depositing and borrowing behaviours between users with small account balances (i.e., retail investors) and those with large account balances. To the best of our knowledge, this paper is the first to empirically investigate the reasons behind investors' use of DeFi lending protocols and to test 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 (Borio and Zhu, 2012; Bruno and Shin, 2015). 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, 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, 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 add to the extant literature in several ways. First, we contribute to a young but

[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.

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 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 – i.e. 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 utilising 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 by trying to explain the economic motivations behind the risks and behaviours 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 (i.e. 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 contrary to what is 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 Schär (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. Carré and Franck (2025) analyse how interest rate rules in DeFi lending protocols on Proof-of-Stake blockchains can be designed to select efficient and secure outcomes by shaping user expectations, especially under uncertainty. 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.

We contribute also to the "search for yield" (or "reach for yield") literature, which primarily focuses on how financial institutions respond to low interest rates. Empirical studies show that when rates are low, banks, mutual funds, and pension funds tend to shift towards riskier assets in pursuit of higher returns (Maddaloni and Peydró, 2011; Jiménez et al., 2014; Di Maggio and Kacperczyk, 2017; Jiang and Sun, 2020). Chen et al. (2019), using randomized investment experiments, demonstrate that individuals also exhibit a stronger preference for risky assets when the risk-free rate is low. Our findings extend this behaviour beyond traditional financial intermediation, showing that low interest rates reduce the opportunity cost for individuals to invest their liquidity in DeFi. By depositing crypto in DeFi protocols, liquidity providers can earn higher returns than through conventional investments, such as bonds or stocks.

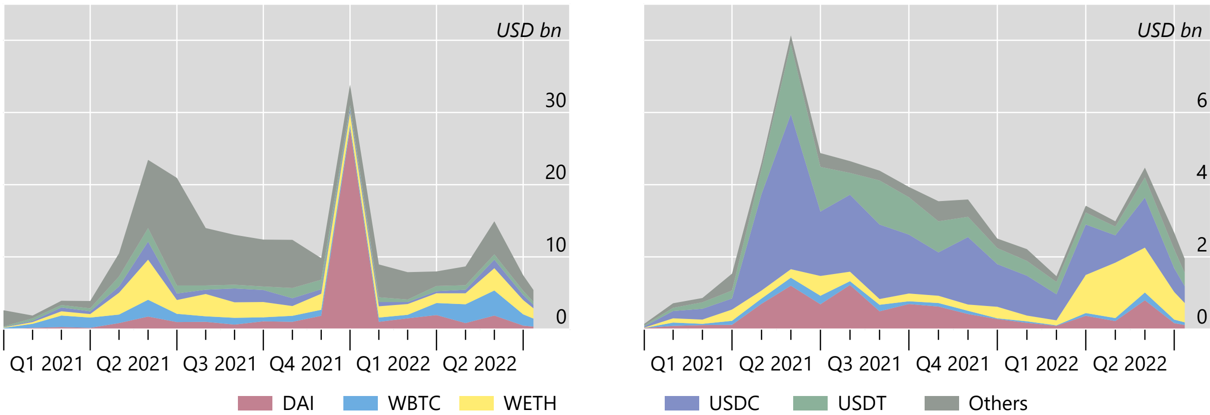
The rest of the paper is organised as follows: section 2 discusses the dataset and some stylised facts, section 4 covers the empirical model and the baseline results, section 5 sheds light on the different motivations of large- vs retail-investors, section 6 reports robustness tests, while section 7 concludes.

2 Data and stylised facts

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).

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.

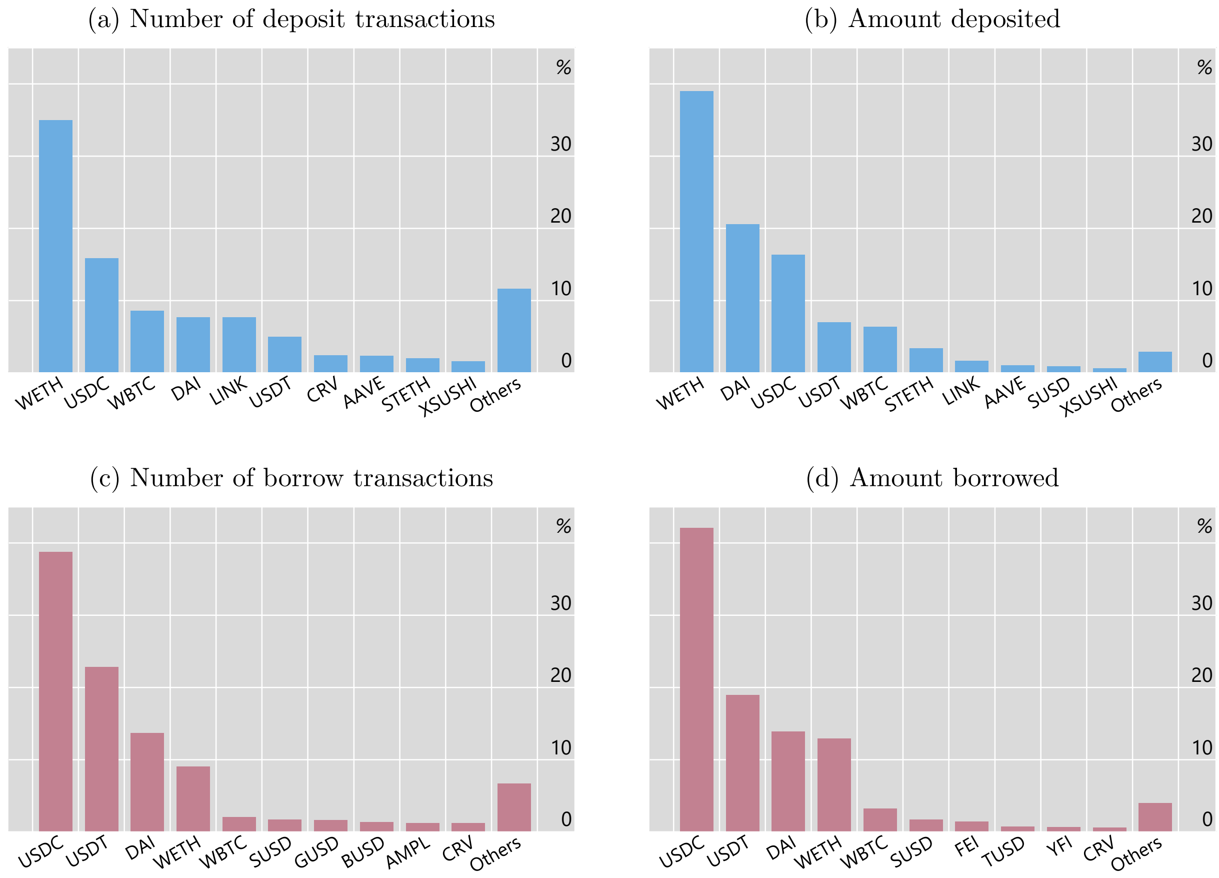
[6]Without loss of generality, we focus on the activity in the main pool of the Aave V2 protocol.

[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 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]

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 acknowledge that the Aave V2 (Ethereum chain) does not capture the entire DeFi

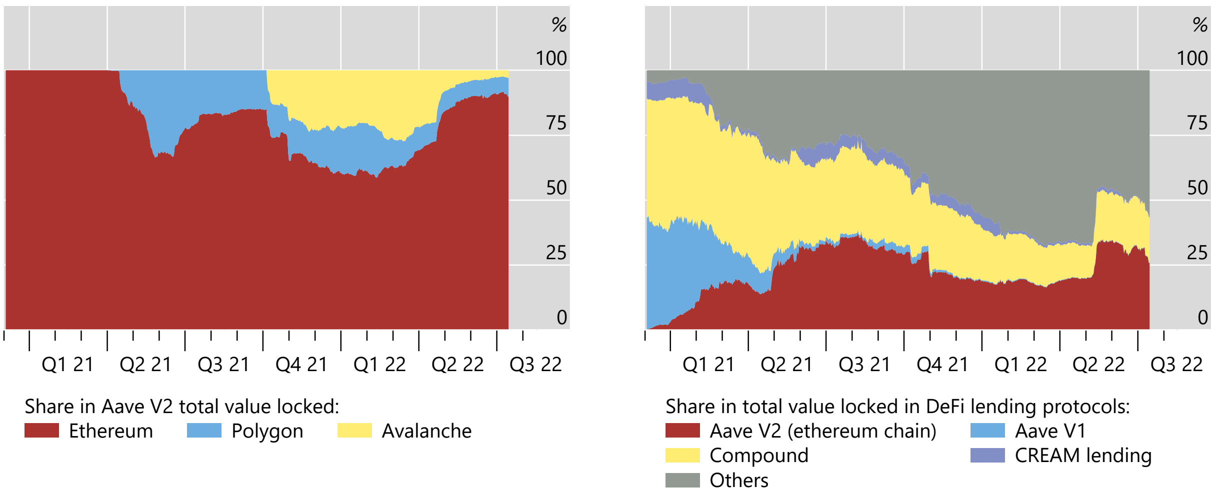
[9]Figure B1 and Table B1 in Appendix B provide more details on the monthly distribution of the number of deposit- and borrow transactions by users, as well as the distribution of deposit and borrowing amounts across deciles by size.

lending universe. However, we argue that it provides a representative sample for our analysis, as shown in panel (a) of Figure 4. Specifically, within the Aave V2 protocol, the Ethereum chain accounts for more than 80% of the total value locked (TVL) in the entire Aave V2 protocol. Panel (b) of the same figure highlights the sustained growth of TVL in the Aave V2 Ethereum chain, which, at its peak, accounted for nearly 40% of the total TVL in DeFi lending protocols. Both panels underscore the significance of Aave V2 on the Ethereum chain as a key component of the DeFi lending market.

Figure 4: **Market share of the Aave V2 (ethereum chain)**

(a) Breakdown of Aave V2 total value locked across blockchains

(b) Breakdown of DeFi lending total value locked across protocols



Note: The graphs show the breakdown of the total value locked in Aave V2 across blockchains (panel (a)) and in DeFi lending across protocols (panel (b)). Sources: DeFiLlama; authors' calculations.

We augment the dataset with additional financial- and crypto-markets variables. The data on the policy rate and on the yield at different maturities for U.S. Treasury securities come from the Federal Reserve Bank of St Louis, FRED. The former is observed (and constant) during non-business days, given that the policy rate depends on monetary policy decisions taken during the FOMC meetings. For the latter, we replace missing values deriving from market closures over non-business days with the latest available trading value. Intuitively, these are the reference values that users observe when transacting in DeFi or crypto markets which are instead open 24/7. We collect data on the *ETH Perpetual Futures Funding rate* from CCData (CryptoCompare formerly) to construct an indicator capturing market expectations about ETH prices (He et al., 2022). Specifically, our measure is computed as the simple average of the ETH perpetual futures funding rates across seven major crypto exchanges (i.e. Binance, Bitget, BitMEX, Bybit, Deribit, Kraken and OKX Exchange). Perpetual futures are derivative contracts that allow users to take leveraged positions in the underlying. Positive funding rates imply that the price of the futures is higher than the spot price (i.e. contango) and that agents holding long positions pay the ones with short positions. Conversely, when funding rates are negative, the contract price is lower than the spot price (i.e. backwardation) and agents holding long positions get paid by the ones with short positions. In other words, positive (negative) funding rates indicate that the market expects ETH prices to go up (down). The price of Ether (*ETH price*) is calculated on ETH pricing data (again) from CCData. Data on the *S&P 500* close price and the *VIX* come from LSEG Workspace. *Borrowing demand* is the sum of all borrowing transactions at the user-reserve level in a given day. *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
3M Gov Bond (%)	230,516	0.214	0.430	-0.002	0.020	0.076	2.324
6M Gov Bond (%)	230,516	0.331	0.630	0.007	0.035	0.088	2.874
1Y Gov Bond (%)	230,516	0.452	0.801	0.033	0.058	0.177	3.125
2Y Gov Bond (%)	230,516	0.674	0.950	0.101	0.147	0.517	3.426
10Y Gov Bond (%)	230,516	1.674	0.591	0.838	1.322	1.658	3.473
Lag ETH Perp Futures rate	230,516	0.050	0.118	-0.358	0.001	0.040	0.692
Ln(ETH price)	230,516	7.710	0.429	6.299	7.497	8.010	8.478
S&P (log)	230,516	8.337	0.065	8.194	8.276	8.388	8.475
Vix (log)	230,516	3.035	0.221	2.712	2.850	3.179	3.616
Borrowing demand (log)	230,516	1.776	12.684	0.00	0.00	0.00	41.418
Panel B. Borrowing Sample							
Borrowing amount (log)	132,382	9.965	2.342	4.546	8.479	11.511	20.209
Lag ETH Perp Futures rate	132,382	0.057	0.119	-0.358	0.008	0.054	0.692
ETH price (log)	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. Sources: Federal Reserve Bank of St Louis, FRED; Aave; CCData; LSEG Refinitiv Workspace; snapshot; The Graph; authors' calculations.

3 DeFi layers and the Aave V2 protocol

3.1 DeFi layers

DeFi can be thought of comprising four main layers: blockchains, smart contracts, protocols and DeFi applications (Dapps).[10] As discussed above, blockchain is a form of permissionless (or "public") distributed ledger in which details of transactions are held in the ledger in the form of blocks of information, while smart contracts allow developers to add functionality beyond simple peer-to-peer transfers.

The other two layers deserve more attention. DeFi protocols are essentially combi-

[10]For a more complete analysis of the different DeFi layers see Aquilina et al. (2025).

nations of smart contracts designed for specific use cases. These use cases include the lending platform analysed in this paper, but also decentralised exchanges (DEXs), and on-chain asset management. Due to the permissionless nature of blockchains, protocols can be accessed by any user and indeed by any application, allowing new products to be built on their foundations. In some sense, protocols can be viewed as collections of more complex smart contracts.

Finally, Dapps provide graphical interfaces that allow users to easily interact with the underlying DeFi protocols, rather than dealing directly with the smart contracts themselves. For all but the most sophisticated users, Dapps serve as the primary gateway to DeFi protocols, typically through computers or smartphones. Despite DeFi's aim to remain fully decentralised, Dapps function - de facto - as centralisation vectors (Schuler et al. (2024)), enabling the development of intermediaries within the DeFi ecosystem.

3.2 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

[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.

borrow without having first deposited funds in the protocol.[12]

4 Empirical model and results

4.1 Demand for deposits transactions

In the first step of our analysis we focus on the motives driving deposit-transactions in DeFi. Specifically, we test the following

Hypothesis 1. Investors deposit funds in DeFi lending protocols for yield-seeking reasons.

To test this hypothesis we specify Equation 1 as follows:

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

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 monetary policy indicator that captures the opportunity cost to invest in alternative forms of liquid investments. We consider, one at the time, 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). 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 one-day lag of the ETH perpetual futures funding rate as a proxy for investors' expectations of ETH prices, the one-day lag of the natural logarithm of the ETH price to control for momentum trading, the one-day lag of the natural logarithm of the closing price of the S&P 500 to control for equity prices in the real economy, and the one-day lag of the natural logarithm of the VIX to control for volatility in equity prices. Finally, users may deposit more funds in the Aave protocol to be able to increase their borrowing activity which, in turn, requires more collateral. To control for this factor, we include in

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

vector Z the natural logarithm of the borrowing demand of user i, for reserve j on the same day.

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. We do not include in the baseline regression the deposit annual percentage rate (APR) as 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 investors' expectations of ETH prices, momentum trade, equity and volatility conditions and borrowing demand, the coefficients for the *FED policy rate* and the yields of U.S. Treasury securities are negative and statistically significant (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 a 60% increase in the amount of deposit in DeFi protocols (column 1).[13] Overall, these results are consistent with investors entering DeFi lending protocols for yield-seeking reasons, supporting hypothesis 1.

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

[13] $exp(-0.4681 * (-1)) - 1$.

can earn higher interest rates than through traditional channels of financial intermediation. For example, providing Tether (USDT) liquidity on Aave yielded a 5.6% APR on average over the sample period, with peaks of more than 15%. The opportunity-cost for users to keep liquidity in DeFi protocols increased in the last part of our sample when interest rates began to normalise.[14]

Table 2: Deposit equation

	Ln(deposit amount)					
	(1)	(2)	(3)	(4)	(5)	(6)
Policy Rate	-0.4681***					
	(0.0638)					
3M Gov Bond		-0.4421***				
		(0.0557)				
6M Gov Bond			-0.3088***			
			(0.0381)			
1Y Gov Bond				-0.2456***		
				(0.0293)		
2Y Gov Bond					-0.2045***	
					(0.0238)	
10Y Gov Bond						-0.2838***
						(0.0298)
Lag ETH Perp Futures rate	0.2476***	0.2524***	0.2576***	0.2655***	0.2812***	0.1732**
	(0.0772)	(0.0767)	(0.0768)	(0.0772)	(0.0778)	(0.0772)
Lag ETH price (log)	1.0513***	1.0165***	1.0194***	1.0308***	1.0398***	1.1953***
	(0.0492)	(0.0491)	(0.0492)	(0.0491)	(0.0491)	(0.0524)
S&P (log)	-1.5562**	-1.2963**	-1.1323*	-0.9703*	-0.6073	-1.7936***
	(0.6165)	(0.5958)	(0.5803)	(0.5707)	(0.5553)	(0.5823)
VIX (log)	0.0649	0.1621	0.2077**	0.2544**	0.2959***	0.0994
	(0.1100)	(0.1053)	(0.1042)	(0.1034)	(0.1026)	(0.1080)
Borrowing demand (log)	0.0072***	0.0071***	0.0071***	0.0071***	0.0071***	0.0071***
	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0016)
Observations	230,516	230,516	230,516	230,516	230,516	230,516
R-squared	0.7492	0.7493	0.7493	0.7493	0.7493	0.7492
User-reserve FEs	✓	✓	✓	✓	✓	✓
Cluster	User-reserve	User-reserve	User-reserve	User-reserve	User-reserve	User-reserve

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.

4.2 Demand for borrowing transactions

There are multiple reasons why participants on the Aave platform might choose to borrow from a lending pool. For instance, an individual might wish to enter into an investment

[14] Table B2 in Appendix B includes the average deposit APR at the pool level as an additional control. The results indicate that the coefficient of the deposit APR is positive and statistically significant. Section 5 shows that we find a similar and consistent result when disentangling small retail- and large investors.

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.

4.2.1 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 that the investor can follow to make the investment. First, assuming that the individual thinks the price of 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 λ. 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 $\lambda S_t^{B/A}$ 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.[15] 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

$$\lambda S_t^{B/A}(r-i)S_{t+1}^{\$/B} + dS_{t+1}^{\$/A} + S_{t+1}^{\$/A} - S_t^{\$/A}. \tag{2}$$

The first term represents the net return from the investment of $\lambda S_t^{B/A}$ 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.[16] After simplifying, this additional aspect changes the expression in Equation 2 to

$$\lambda S_t^{B/A}(r-i)S_{t+1}^{\$/B} + \mathbb{1}_{v=yes}b^A + \lambda \mathbb{1}_{v=yes}b^B + (1+d)S_{t+1}^{\$/A} - S_t^{\$/A}. \tag{3}$$

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

[15]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.

[16]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.

[17]See Equation 14 in Appendix A.2.

transaction was initiated would be $\frac{1\times .8}{.75} = 1.0\dot{6}$.[18]

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 $(1+d)\ell S_{t+1}^{E/A} + \lambda r \frac{S_s^{E/B}}{S_t^{A/B}} * \ell$ and the denominator would be $(\lambda + i)\frac{S_s^{E/B}}{S_t^{A/B}}$, where $s \in (t, t+1]$.[19] 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 $[\lambda + i - \lambda\ell r]\, S_{t+1}^{E/B} > (1+d)\ell S_t^{A/B} S_{t+1}^{E/A}$.

Let $p_{t+1} = Prob\left(\frac{S_{t+1}^{E/B}}{S_t^{A/B} S_{t+1}^{E/A}} > \frac{(1+d)\ell}{\lambda + i - \lambda\ell r}\right)$ 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.[20] Hence, in our example, their payoff is

$$\lambda S_t^{B/A}(r-i)S_{t+1}^{\$/B} + \mathbb{1}_{v=yes} b^A + \lambda \mathbb{1}_{v=yes} b^B + S_{t+1}^{\$/A}((1-\theta)(1+d) - LB^A) - S_t^{\$/A}, \quad (4)$$

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 that gets liquidated by a single liquidation call.[21] The payoff to the borrowing option can

[18] 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.

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

[20] 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.

[21] 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.

therefore be written as

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

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

$$S_t^{B/A}(1+r)S_{t+1}^{\$/B}+\mathbb{1}_{v=yes}b^B-S_t^{\$/A}. \quad (6)$$

The first term in Equation 6 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 5 and Equation 6:

$$(1+d)S_{t+1}^{\$/A}-p_{t+1}(\theta(1+d)+LB^A)S_{t+1}^{\$/A}-S_t^{B/A}(1+(1-\lambda)r+\lambda i)S_{t+1}^{\$/B}+\mathbb{1}_{v=yes}b^A-(1-\lambda))\mathbb{1}_{v=yes}b^B. \quad (7)$$

The sign of the expression in Equation 7 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 $S_t^{B/A}=S_t^{\$/A}$, $S_{t+1}^{\$/B}=1$, and there are likely no governance benefits, so Equation 7 becomes

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

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 7 simplifies to

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

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 λ 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 $d - \lambda i \leq 0$. The second term and third terms are unambiguously negative. Hence, the only possibility for Equation 9 to be positive is if the governance benefits from Coin A are sufficiently large.

4.2.2 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):

$$\lambda S_t^{\$/A}(-i)+(1+\lambda)\mathbb{1}_{v=yes}b^A+(1+\lambda)(1+d)S_{t+1}^{\$/A}-p_{t+1}(LB^A+(1+\lambda)\theta(1+d))S_{t+1}^{\$/A}-(1+\lambda)S_t^{\$/A}. \tag{10}$$

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

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

Taking the difference we get

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

In order for Equation 12 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.

The observations that emerge from Sections 4.2.1 and 4.2.2 are summarized in the following:

Hypothesis 2. Observed borrowing will be higher when price expectations are higher and/or when governance benefits are present.

4.2.3 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 favour borrowing in the absence of relative price appreciation.[22]

[22]While it would be interesting to study to what extent investors lend and borrow to the same pool to obtain governance tokens, identifying such crypto strategies requires establishing a "one-to-one" cor-

We cannot measure individual investor price expectations, but we can get a strong sense of overall market beliefs and sentiment using the ETH perpetual futures funding rate and the price of Ether. The former captures expectations of increases in ETH price through the futures market, while the latter measures speculative behaviour driven by the momentum effect (Liu and Tsyvinski, 2021). Hypothesis 2 can be reformulated, in terms of these variables, as the requirement that level of borrowing will be positively related to the previous day's ETH perpetual futures funding rate and the price of ETH, as well as the activation of voting rights that deliver governance benefits. We therefore specify Equation 13 as follows:

$$Ln(borrow\ amount)_{ijt} = \delta Y_t + \theta_{ij} + \varepsilon_{ijt}, \tag{13}$$

where the dependent variable corresponds to the natural logarithm of the dollar amount of each individual borrowing transaction for user i, reserve j, and timestamp t, and the vector Y includes the two price expectation variables mentioned above and a variable we construct to gauge voting power motives. Specifically, the vector Y includes the one-day lag of the ETH perpetual futures funding rate and the one-day lag of the natural logarithm of the Ether price (*Ln(ETH price)*). In addition, it includes a variable constructed by interacting 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, while the second dummy (*Voting dates*) takes the value 1 for an ongoing vote in correspondence with the execution timestamp of the borrow-transaction. As in Equation 1, Equation 13 also includes user-reserve fixed effects (θ_{ij}).

respondence between the token used as collateral and the token borrowed for each specific borrowing transaction. However, the data available to us only tracks the amounts of collateral deposited with each deposit transaction. Once deposited, these amounts are pooled together, and we lack the visibility into which specific collateral backs each borrowing. Thus, establishing such a one-to-one correspondence is not possible. That said, we provide descriptive statistics at the user level on the proportion of deposits and borrowings made to the same reserve as a percentage of the user's total protocol activity. Figure B2 in appendix B presents data on the top 15 reserves with at least 1,000 users, ranked by the percentage of user deposit and borrowing transactions conducted with the same reserve for the average user. Notably, three of the top ten reserves correspond to governance tokens. On average, users of these reserves conduct between 50% and 70% of their overall transactions with that specific reserve alone.

Table 3 reports the results. Each part of hypothesis 2 is individually supported. We find a positive and statistically significant - at the 1% level across econometric specifications - relationship between our variables capturing the speculative motives (the lag ETH perpetual funding rate and the lag ln(ETH price)) and borrowing volumes, indicating that more positive investors' sentiments coincide with higher borrowing by users in DeFi protocols.[23] The magnitude of the effects is economically meaningful. The coefficients in column 1 suggest that a 1% increase in the previous day ETH perpetual futures funding rate corresponds to about a 0.35% borrowing increase in the DeFi protocol, while an increase of 1% in the one-day lag of the price of ETH results in about 0.77% higher borrowing at the within user-reserve level.[24] This evidence is consistent with DeFi borrowing being driven by expectations of price appreciation 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 with voting days. These results are consistent with investors borrowing through DeFi protocols to increase their voting power to influence tokens' development plans.

Support for the combined statement of hypothesis 2 is mixed. Column 4 reports the results for a complete model where we find, consistently with the implication from the theoretical model in section 4.2, that speculative reasons appear to prevail over voting power motives as the interaction term remains positive but loses statistical significance.[25] The lack of significance of governance benefits could be driven by two factors. One factor is that borrowing data do not capture the additional governance benefits associated with a leverage trade except in some instances where the borrowed token is part of a swap

[23]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.

[24]The effect is calculated as $exp(0.7693 * ln(1.01)) - 1$.

[25]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.

trade. The other factor is the heterogeneous behaviour of the different investor types (i.e. large vs retail). Due to data limitations, we cannot investigate the former factor. We investigate the latter aspect in the next section.

Table 3: Borrowing equation

	Ln(borrow amount)			
	(1)	(2)	(3)	(4)
Lag ETH Perp Futures rate	0.3052***		0.3178***	0.3052***
	(0.0470)		(0.0481)	(0.0470)
Lag ETH price (log)	0.7693***			0.7691***
	(0.0256)			(0.0256)
Governance Token*Voting dates		0.1027*	0.1010*	0.0427
		(0.0538)	(0.0540)	(0.0512)
Observations	132,382	132,382	132,382	132,382
R-squared	0.8389	0.8325	0.8327	0.8389
User-reserve FEs	✓	✓	✓	✓
Cluster	User-reserve	User-reserve	User-reserve	User-reserve

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.

5 Large vs retail investors

In this section, we test whether the depositing and borrowing behaviour of large investors is different relative to retail investors. On the depositing side, 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. On the borrowing side, large investors are the ones having enough weight to influence votes over development proposals. Thus, the may be more interested in borrowing for governance motives relative to retail investors who are anyway "too small" to exert influence. To shed light on this aspect, we create a dummy variable equal to 1 for large investors, i.e. 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), removing users with a cumulative deposit balance in the middle tercile.[26]

The analysis that follows tests the following:

Hypothesis 3a. Retail investors are more responsive to interest rate changes than large investors.

Hypothesis 3b. Relative to retail investors, large investors borrow more for governance motives.

Table 4 shows that the level of interest rate matters for both investor types, albeit being significantly more impactful for retail investors. 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. The effect is statistically and economically significant: a 1% increase in the specific interest rate variable is associated with a drop in the deposit amount ranging from about 35% to nearly 60% depending on the specification. 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 significant. Nonetheless, the size of the effect is significantly smaller: a 1% increase in the specific interest rate variable is associated with a drop in the deposit amount ranging from about 9% to nearly 17% depending on the specification. Taken together, these results indicate that, relative to retail investors, the decision of large investors to deposit in DeFi protocols is considerably less influenced by the policy rate or the yields on U.S. Treasury securities. Hypothesis 3a is thus accepted.

In light of these findings, a reasonable question is what additional factor may be driv-

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

ing 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, which is endogenously determined by the platform matching demand and supply at the reserve level (see Appendix A, subsection A.4). It is possible that, while retail users find traditional investments more attractive 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 for this by augmenting the double interactions specification in Table 4. To alleviate the concern of endogeneity, we capture yield opportunities of the DeFi protocol through the average deposit APR at the pool level (i.e. average across the reserves), which is unlikely to be influenced by the deposit decision of a user in a given reserve. Furthermore, we interact the deposit APR, expressed as a continuous variable, with the dummy Large investor to distinguish the effects on the two types of investors.

Table 4: Deposit equation: Large vs Retail investors

	Ln(deposit amount)					
	(1)	(2)	(3)	(4)	(5)	(6)
Policy Rate	-0.8869***					
	(0.0789)					
Policy Rate*Large investor	0.7003***					
	(0.0979)					
3M Gov Bond		-0.7965***				
		(0.0639)				
3M Gov Bond*Large investor		0.5991***				
		(0.0878)				
6M Gov Bond			-0.5802***			
			(0.0442)			
6M Gov Bond*Large investor			0.4415***			
			(0.0630)			
1Y Gov Bond				-0.4692***		
				(0.0341)		
1Y Gov Bond*Large investor				0.3544***		
				(0.0512)		
2Y Gov Bond					-0.4191***	
					(0.0290)	
2Y Gov Bond*Large investor					0.3258***	
					(0.0459)	
10Y Gov Bond						-0.5356***
						(0.0399)
10Y Gov Bond*Large investor						0.3907***
						(0.0605)
Lag ETH Perp Futures rate	0.2257**	0.2227**	0.2255**	0.2297**	0.2415**	0.1634
	(0.1138)	(0.1133)	(0.1135)	(0.1142)	(0.1155)	(0.1153)
Lag ETH price (log)	1.0722***	1.0468***	1.0490***	1.0583***	1.0662***	1.1875***
	(0.0721)	(0.0724)	(0.0725)	(0.0723)	(0.0721)	(0.0749)
S&P (log)	-1.4833*	-1.3290	-1.2231	-1.1212	-0.8622	-1.7552**
	(0.8621)	(0.8278)	(0.8077)	(0.7931)	(0.7703)	(0.8156)
VIX (log)	0.1580	0.2260	0.2613*	0.2994**	0.3352**	0.1902
	(0.1573)	(0.1504)	(0.1490)	(0.1483)	(0.1477)	(0.1574)
Borrowing demand (log)	0.0088***	0.0088***	0.0088***	0.0088***	0.0088***	0.0088***
	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)
Observations	145,821	145,821	145,821	145,821	145,821	145,821
R-squared	0.7681	0.7682	0.7682	0.7682	0.7682	0.7681
User-reserve FEs	✓	✓	✓	✓	✓	✓
Cluster	User-reserve	User-reserve	User-reserve	User-reserve	User-reserve	User-reserve
Joint coeff	-0.18	-0.19	-0.13	-0.11	-0.09	-0.14
P-value	0.046	0.024	0.022	0.016	0.019	0.00

Standard errors clustered at the user-reserve level in parentheses. ***/**/* indicate 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.

Table 5 shows that the coefficient for deposit APR is positive and statistically significant for both retail- and large investors. Specifically, the coefficient for the interaction term Deposit APR * Large investor is statistically insignificant, suggesting that large investors do not deposit more funds in DeFi protocols following an increase in the deposit APR relative to retail investors (column 1 of Table 5). The F-test for joint significance suggests that the overall effect for large investors is positive and statistically significant. Following a 1 pp increase in the deposit APR, large investors increase the amount deposited in the DeFi protocol by 81 bps (column 1 of Table 5).

In line with the results commented in footnote 12 and reported in Table B2 in Appendix ii, we find that retail investors' behaviour is influenced by changes in the deposit APR (the single coefficient Deposit APR is always positive and 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. Similarly, the results on the overall effect on large investors remain statistically significant when including the deposit APR in the specification, albeit being noticeably smaller relative to the one for retail investors.

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

	Ln(deposit amount)					
	(1)	(2)	(3)	(4)	(5)	(6)
Deposit APR	0.7693***	0.7082***	0.6827***	0.6702***	0.6617***	0.6391***
	(0.1346)	(0.1344)	(0.1342)	(0.1340)	(0.1335)	(0.1342)
Deposit APR*Large investor	0.0482	0.1055	0.1207	0.1241	0.1306	0.1218
	(0.2089)	(0.2086)	(0.2084)	(0.2089)	(0.2096)	(0.2095)
Policy Rate	-0.8943***					
	(0.0792)					
Policy Rate*Large investor	0.7071***					
	(0.0979)					
3M Gov Bond		-0.7998***				
		(0.0644)				
3M Gov Bond*Large investor		0.6074***				
		(0.0878)				
6M Gov Bond			-0.5804***			
			(0.0446)			
6M Gov Bond*Large investor			0.4484***			
			(0.0630)			
1Y Gov Bond				-0.4679***		
				(0.0345)		
1Y Gov Bond*Large investor				0.3597***		
				(0.0513)		
2Y Gov Bond					-0.4169***	
					(0.0294)	
2Y Gov Bond*Large investor					0.3283***	
					(0.0461)	
10Y Gov Bond						-0.5271***
						(0.0404)
10Y Gov Bond*Large investor						0.3927***
						(0.0605)
Lag ETH Perp Futures rate	0.1655	0.1644	0.1691	0.1743	0.1859*	0.1150
	(0.1082)	(0.1079)	(0.1084)	(0.1092)	(0.1105)	(0.1109)
Lag ETH price (log)	1.0477***	1.0230***	1.0259***	1.0354***	1.0431***	1.1605***
	(0.0731)	(0.0734)	(0.0735)	(0.0733)	(0.0731)	(0.0759)
S&P (log)	-1.4488*	-1.2853	-1.1749	-1.0741	-0.8221	-1.6737**
	(0.8697)	(0.8354)	(0.8151)	(0.8002)	(0.7769)	(0.8235)
VIX (log)	0.1790	0.2454	0.2784*	0.3143**	0.3498**	0.2072
	(0.1578)	(0.1507)	(0.1492)	(0.1482)	(0.1477)	(0.1578)
Borrowing demand (log)	0.0089***	0.0088***	0.0088***	0.0088***	0.0089***	0.0088***
	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)
Observations	144,419	144,419	144,419	144,419	144,419	144,419
R-squared	0.7672	0.7673	0.7673	0.7673	0.7674	0.7672
User-reserve FEs	✓	✓	✓	✓	✓	✓
Cluster	User-reserve	User-reserve	User-reserve	User-reserve	User-reserve	User-reserve
F-Test (deposit APR)	0.81	0.81	0.80	0.79	0.79	0.76
P-value (deposit APR)	0.000	0.000	0.000	0.000	0.000	0.000
F-Test (interest rate)	-0.18	-0.19	-0.13	-0.10	-0.08	-0.13
P-value (interest rate)	0.044	0.027	0.028	0.023	0.025	0.006

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.

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. The evidence for the ETH perpetual futures funding rate and the ln(ETH price) is broadly in line with the baseline results suggesting that both large- and retail investors borrow more on the back of expectations of price increases and upward trending crypto prices.

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.[27] In column 3, we also test the stability of the coefficients when the one-day lag of the ETH perpetual futures funding rate, the Governance Token*Voting dates, the one-day lag of ln(ETH price) and their interaction terms are included in the same econometric specification. The point estimates remain stable. Hypothesis 3b is thus accepted.

[27] One should note that the user-reserve fixed effects in Table 6 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.

Table 6: Borrowing equation: Large investors vs Retail users

	Ln(borrow amount)		
	(1)	(2)	(3)
Lag ETH Perp Futures rate	0.3712***		0.3715***
	(0.0592)		(0.0591)
Lag ETH Perp Futures rate*Large investor	-0.1721		-0.1725
	(0.1151)		(0.1151)
Lag ETH price (log)	0.6482***	0.6545***	0.6485***
	(0.0305)	(0.0307)	(0.0305)
Lag ETH price (log) *Large investor	0.2048***	0.1971***	0.2042***
	(0.0576)	(0.0576)	(0.0576)
Governance Token*Voting dates		-0.1497	-0.1522
		(0.1119)	(0.1130)
Governance Token*Voting dates*Large investor		0.2199*	0.2217*
		(0.1339)	(0.1349)
Observations	82,196	82,196	82,196
R-squared	0.8671	0.8670	0.8671
User-reserve FEs	✓	✓	✓
Cluster	User-reserve	User-reserve	User-reserve
Joint coeff (Perpetual Future rate)			0.19
P-value			0.044
Joint coeff (ln(ETH price))			0.85
P-value			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.

6 Robustness checks

6.1 Extending the sample for the deposit analysis

In the period from 26 April 2021 to 20 May 2022, the Aave protocol issued native Aave tokens to reward depositors, thereby incentivising deposit inflows in the platform.[28] One reasonable concern is that our results from the deposit analysis on "search for yield" could be confounded by such incentive plans. In other words, users may deposit more funds in

[28]For more details, see Aave improvement proposal (AIP)-16, AIP-32, AIP-47 and AIP-59.

the Aave protocol to earn such incentive tokens, a practice also known as "yield farming".

To address these concerns, we re-run the deposit analysis from Table 2 on an extended sample covering the period from Dec 2020–Jun 2024 but excluding the period in which yield farming was active (ie 26 Apr 2021 –20 May 2022). Results from Table 7 show that the point estimates remain negative, statistically significant and consistent with the ones from Table 2, albeit being somewhat smaller in magnitude. Specifically, column 1 suggests that a 1 pp increase in the policy rate is associated with a nearly 20 pp drop in the inflows of deposits in the DeFi protocol. Overall, when accounting for incentive plans, the effect of "search for yield" is somewhat smaller, even though consistent, with the evidence from the baseline specification (i.e. Table 2), confirming the robustness of our findings.

Table 7: Deposit equation: removing the yield farming period

	Ln(deposit amount)					
	(1)	(2)	(3)	(4)	(5)	(6)
Policy Rate	-0.2054*** (0.0359)					
3M Gov Bond		-0.2028*** (0.0333)				
6M Gov Bond			-0.2121*** (0.0340)			
1Y Gov Bond				-0.2243*** (0.0343)		
2Y Gov Bond					-0.2447*** (0.0364)	
10Y Gov Bond						-0.3288*** (0.0465)
Observations	200,547	200,547	200,547	200,547	200,547	200,547
R-squared	0.7223	0.7223	0.7224	0.7224	0.7224	0.7220
Controls	Yes	Yes	Yes	Yes	Yes	Yes
User-reserve FEs	✓	✓	✓	✓	✓	✓
Cluster	User-reserve	User-reserve	User-reserve	User-reserve	User-reserve	User-reserve

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 and the same set of controls from Table 2.
Source: Authors' elaboration. The sample covers the period Dec 2020–Jun 2024, excluding the yield farming period (i.e. 26 Apr 2021–20 May 2022).

6.2 Borrowing transaction analysis on the restricted sample of WETH collateral

The argument provided in subsection 4.2 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

$$\text{Health Factor}_{i,t} = \frac{\sum_{a=1}^{N} \left[Collateral_{i,a,t} \text{ in ETH} * \text{liquidation threshold}_{a,t} \right]}{\sum_{d=1}^{N} \left[Borrows_{i,d,0:t} \text{ in ETH} + interest_{i,d,t} \text{ in ETH} \right]} \tag{14}$$

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. Equation 14 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, we can 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 4.2. 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 whom the only collateral deposited in the protocol is WETH, our measures of speculative behaviour driven by expectation of price increases (i.e. ETH perpetual futures funding rate) and by the momentum effect (i.e. ln(ETH price)) are 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 8 shows a positive and statistically significant relationship (at the 1% level) between the previous day ETH perpetual futures funding rate and borrowing volumes, suggesting the our results hold also when we restrict the sample to those users employing the same collateral (WETH) for borrowing. Interestingly, the size of the coefficient increases substantially in comparison to the baseline specification in Table 3. In particular, a one standard deviation increase in the ETH perpetual futures funding rate (i.e. 11.9%) is associated with 10.9% higher borrowing volumes (column 1) relative to the 4.1% 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.[29]

Table 8: Borrowing equation: WETH collateral

	Ln(borrow amount)			
	(1)	(2)	(3)	(4)
Lag ETH Perp Futures rate	0.8704***		-0.3034	0.8702***
	(0.2121)		(0.2069)	(0.2121)
Lag ETH price (log)	1.4192***			1.4194***
	(0.0698)			(0.0698)
Governance Token*Voting dates		0.2178	0.2114	-0.0509
		(0.4596)	(0.4590)	(0.4396)
Observations	16,188	16,188	16,188	16,188
R-squared	0.0958	0.0421	0.0423	0.0958
Reserve FEs	✓	✓	✓	✓
Cluster	Reserve	Reserve	Reserve	Reserve

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: Authors' calculations.

6.3 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 1 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

[29]One should note that these regressions include reserve-fixed effects as the smaller sample size does not allow for 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 9 reports the results. Despite the substantial loss of observations - more than 38,000 - the results yet display a negative and 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 9 the coefficients shrink sizeably 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 is associated with a 14% increase in the amount of deposit in DeFi protocols on a monthly basis (Column 1).

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

	Ln(deposit amount)					
	(1)	(2)	(3)	(4)	(5)	(6)
Policy Rate	-0.1500**					
	(0.0693)					
3M Gov Bond		-0.1513**				
		(0.0734)				
6M Gov Bond			-0.1083**			
			(0.0521)			
1Y Gov Bond				-0.0859**		
				(0.0420)		
2Y Gov Bond					-0.0731**	
					(0.0359)	
10Y Gov Bond						-0.1252**
						(0.0525)
Lag ETH Perp Futures rate	-0.0768	-0.0664	-0.0648	-0.0654	-0.0635	-0.0759
	(0.0576)	(0.0582)	(0.0582)	(0.0584)	(0.0590)	(0.0581)
Lag ETH price (log)	1.0539***	1.0443***	1.0433***	1.0466***	1.0471***	1.0731***
	(0.0700)	(0.0714)	(0.0716)	(0.0716)	(0.0711)	(0.0695)
S&P (log)	-1.2020	-1.0679	-0.9916	-0.9233	-0.7713	-0.9783
	(0.7783)	(0.7717)	(0.7606)	(0.7187)	(0.7187)	(0.7552)
VIX (log)	0.0083	0.0483	0.0614	0.0723	0.0855	0.0568
	(0.1200)	(0.1104)	(0.1074)	(0.1023)	(0.0977)	(0.1055)
Borrowing demand (log)	0.0060***	0.0059***	0.0059***	0.0059***	0.0059***	0.0059***
	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Observations	192,173	192,173	192,173	192,173	192,173	192,173
R-squared	0.7910	0.7910	0.7910	0.7910	0.7910	0.7910
User-reserve-month FEs	✓	✓	✓	✓	✓	✓
Cluster	User-reserve	User-reserve	User-reserve	User-reserve	User-reserve	User-reserve

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: Authors' calculations.

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 ETH perpetual futures funding rate. Following the aforementioned approach, we also augment the results for the borrowing specification with user-reserve-month fixed effects. The results reported in Table 10 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 ETH perpetual futures funding, Governance Token*Voting dates and ln(ETH price) keep sign and statistical significance in line with the baseline results. Similarly to results from Table 9, the magnitudes are somewhat smaller. The stability of the point estimates between Table 10 and Table 3 is reassuring, considering that the estimation of Table 10 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.

Table 10: Including user-reserve-month fixed effects in the borrowing equation

	Ln(borrow amount)			
	(1)	(2)	(3)	(4)
Lag ETH Perp Futures rate	0.1205**		0.3428***	0.1203**
	(0.0482)		(0.0500)	(0.0482)
Lag ETH price (log)	0.8554***			0.8554***
	(0.0636)			(0.0636)
Governance Token*Voting dates		0.1138*	0.1118*	0.1130*
		(0.0638)	(0.0638)	(0.0623)
Observations	110,345	110,345	110,345	110,345
R-squared	0.8777	0.8764	0.8765	0.8777
User-reserve-month FEs	✓	✓	✓	✓
Cluster	User-reserve	User-reserve	User-reserve	User-reserve

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: Authors' calculations.

6.4 Alternative clustering of standard errors

In the baseline specification we cluster standard errors at the user-reserve level. Since the independent variables in our regressions are daily time-series that take a common value for each transaction taking place in a given day, one reasonable concern would be that the standard errors obtained are impacted by this specific feature of our dataset. To address this concern we replicate the baseline analyses by clustering standard errors at the user-reserve and day level. Results from Table 11 on deposit transactions are similar and consistent with the ones from Table 2 confirming the robustness of our baseline results.

Table 11: Deposit equation: two-way standard errors clustering

	Ln(deposit amount)					
	(1)	(2)	(3)	(4)	(5)	(6)
Policy Rate	-0.4681***					
	(0.0728)					
3M Gov Bond		-0.4421***				
		(0.0623)				
6M Gov Bond			-0.3088***			
			(0.0428)			
1Y Gov Bond				-0.2456***		
				(0.0328)		
2Y Gov Bond					-0.2045***	
					(0.0271)	
10Y Gov Bond						-0.2838***
						(0.0354)
Lag ETH Perp Futures rate	0.2476**	0.2524**	0.2576**	0.2655**	0.2812**	0.1732
	(0.1090)	(0.1058)	(0.1059)	(0.1062)	(0.1069)	(0.1087)
Lag ETH price (log)	1.0513***	1.0165***	1.0194***	1.0308***	1.0398***	1.1953***
	(0.0596)	(0.0596)	(0.0598)	(0.0594)	(0.0594)	(0.0622)
S&P (log)	-1.5562**	-1.2963*	-1.1323*	-0.9703	-0.6073	-1.7936***
	(0.6834)	(0.6570)	(0.6433)	(0.6341)	(0.6199)	(0.6516)
VIX (log)	0.0649	0.1621	0.2077*	0.2544**	0.2959**	0.0994
	(0.1194)	(0.1153)	(0.1147)	(0.1145)	(0.1148)	(0.1183)
Borrowing demand (log)	0.0072***	0.0071***	0.0071***	0.0071***	0.0071***	0.0071***
	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)
Observations	230,516	230,516	230,516	230,516	230,516	230,516
R-squared	0.7492	0.7493	0.7493	0.7493	0.7493	0.7492
User-reserve FEs	✓	✓	✓	✓	✓	✓
User-reserve & day cluster	✓	✓	✓	✓	✓	✓

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

Similarly, results from Table 12 are similar and consistent with the ones from Table 3, suggesting, also in the case of borrowing transactions, the robustness of our baseline results.

Table 12: Borrowing equation: two-way standard errors clustering

	Ln(borrow amount)			
	(1)	(2)	(3)	(4)
Lag ETH Perp Futures rate	0.3052***		0.3178***	0.3052***
	(0.0688)		(0.0799)	(0.0688)
Lag ETH price (log)	0.7693***			0.7691***
	(0.0309)			(0.0309)
Governance Token*Voting dates		0.1027*	0.1010*	0.0427
		(0.0572)	(0.0575)	(0.0540)
Observations	132,382	132,382	132,382	132,382
R-squared	0.8389	0.8325	0.8327	0.8389
User-reserve FEs	✓	✓	✓	✓
User-reserve & day cluster	✓	✓	✓	✓

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

6.5 Additional tests

Addressing potential cointegration issues. The identification in Equation 1 and 13 exploit the time series variation of the variables (by using lagged values). However, since the dependent variables are measured in log levels, issues of cointegration may arise. To address these concerns we re-estimate our baseline regressions using log changes of the dependent variable. Table B3 presents the results for the deposit analysis where the dependent variable (deposit amount) is expressed as a log change rather than in levels. Similarly, Table B4 reports the results for borrowing transactions, with the log level of the dependent variable replaced with the log change. The results are consistent with our baseline findings. While the magnitudes of the coefficients differ slightly, the overall direction and statistical significance remain unchanged, reinforcing the robustness of our conclusions.[30]

Instrumental variable regressions. Our results on the borrowing analysis show that speculation is one of the key motives driving users to borrow from DeFi platforms. A potential concern is that some other unobserved variable may be influencing both borrowing behaviour and the independent variables in our regression. To address this concern, we adopt an instrumental variable (IV) approach, leveraging Major League Baseball (MLB) viewership data, inspired by Gorton et al. (2022). In June 2021, MLB and FTX announced a sponsorship deal designating FTX as the"Official Cryptocurrency Exchange" of MLB. This agreement prominently featured the FTX logo on all umpire uniforms starting July 13, 2021, marking the first time umpires wore advertising patches. The umpires displayed the patches during all regular season, post season, and spring training games. Additionally, the sponsorship included promotional activities during nationally televised MLB games, on MLB.com, MLB Network, and social media platforms. Although the monetary value of this sponsorship deal remains undisclosed, it is likely substantial. For reference, FTX has signed other two sports sponsorship deals worth at least 345 million. These deals include a 19-year, 135 million agreement for naming rights for the NBA's Miami Heat stadium and a 10-year, $210 million agreement for naming rights to the esports team TSM. We gather television viewership data for nationally broadcast MLB games from showbuzzdaily.com. This dataset includes a household ratings, which indicates the percentage of households tuning in to each game. The viewership data spans from July 2021 to July 2022, covering the period from when umpires first displayed the FTX logo (starting with the 2021 All-Star game) through the conclusion of our sample period (which is before the collapse of FTX). Specifically, we use the daily averages of the household rating for MLB programmes as instruments for our proxies of the speculative motive - namely, the ETH perpetual futures funding rate and the ETH price.

[30] It is important to note that, these results are based on the monthly log change in the dependent variable. In unreported regression results, we also experimented with using daily log change; however, this approach led to a significant loss of observations, as not all users deposit or borrow on a daily basis.

As documented by Gorton et al. (2022), the identification strategy relies on two key assumptions. First, advertising attracts MLB viewers to the platform, some of whom may subsequently begin trading cryptocurrency after seeing the advertisements. FTX's willingness to invest in costly sponsorship deals aligns with their expectation of increased customer acquisition and trading activity as a result. There is substantial evidence supporting the effectiveness of advertising in influencing consumer behaviour. For example, (Ackerberg, 2003; Sethuraman et al., 2011) provide empirical evidence of advertising's impact, while Bagwell (2007) offers a comprehensive review indicating that advertising is particularly effective among individuals with no prior experience with the brand. Second, the MLB schedule is set well in advance of the season, making it highly unlikely that cryptocurrency developments could impact the timing or viewership of MLB games. This temporal separation ensures that the household ratings are exogenous to developments in the cryptocurrency market, thereby strengthening the validity of the instrumental variable approach.

The first two columns of Table B5 report the results of the first-stage regressions. These results indicate that the instrument is relevant, as both coefficients are positive and statistically significant at the 1% level. Columns 3 and 4 report the results of the second-stage regressions. Specifically, a 1 percentage point increase in the previous day's ETH perpetual futures funding rate is associated with approximately a 3.5% increase in borrowing activity on the DeFi protocol (column 3). Similarly, a 1% increase in the one-day lag of the ETH price corresponds to about a 1.4% increase in borrowing at the within user-reserve level (column 4).

The results are qualitatively similar, supporting the view that speculative motives are driving borrowing in DeFi lending platforms. Moreover, we can notice that both coefficients are significantly larger. This can be due to the fact that the two speculative measures are considered one at the time in the specification and not together.[31]

[31] It is worth noticing that we cannot run a model with both speculative measures together as in column (1) of Table 3. The reason is that we have only one instrument for each endogenous variable.

Placebo tests. To further explore the heterogeneity of the effects we document in the baseline analysis we construct three credible placebo tests. In the first one, we replace the ETH perpetual futures funding rate with the difference between the perpetual futures funding rate of Bitcoin and Ethereum. The results, presented in Table B6, indicate that the coefficients for the BTC-ETH perpetual futures funding rate are not statistically significant. These results suggest that the demand for borrowing is not driven by general speculation in the broader cryptocurrency market.

In a second placebo test, we study how the collapse of Terra Luna and FTX affected the demand for borrowing. During these two episodes, users' trading decisions were likely driven by idiosyncratic motives (e.g. fire sales) that have little in common with the speculative motives posited in our baseline analysis. Therefore, during these periods we expect the results related to speculative motives to lose statistical significance or even reverse sign. To test this, we augment equation 13 as follows:

$$Ln(borrow\ amount)_{ijt} = \delta Y_t + \gamma Y_t \times Event_t^k + \theta_{ij} + \varepsilon_{ijt} \tag{15}$$

where k$\in$ {Terra Luna; FTX} and $Event_t^k$ are indicator variables that take the value of one during the specific event periods: the 5 days of the Terra Luna collapse (9 May–13 May 2022) and the 10 days of the FTX fallout (2 Nov–11 Nov 2022), respectively.

The first two columns of Table B7 report the results for the Terra Luna collapse and the FTX fallout, respectively. The findings support our hypothesis: the double interaction coefficients for the ETH Perpetual Futures funding rate with the Terra Luna and the FTX fallout dummies are not statically different from zero. Similarly, the double interaction coefficient for the ETH price with the Terra Luna fallout dummy is also not statistically significant, while the coefficient with the FTX event dummy is negative, even if only marginally statistically significant.

Finally, we have conduct a third placebo test to study how the "Ethereum Merge" –the upgrade of the Ethereum blockchain that transitioned it from the Proof of Work (PoW) consensus mechanism to the Proof of Stake (PoS) consensus mechanism –affected our results. In a PoW consensus mechanism, transaction validators compete to solve complex problems to win the right to mine the next block in the chain. In contrast, under a PoS consensus mechanism, agents must stake a certain amount of ETH to become validators, and the probability of winning the right to mine the next block is proportional to the amount staked on the chain. Thus, agents may "permanently" prefer to stake their ETH rather than deposit it in DeFi lending protocols for "search-for-yield" motives. In other words, the transition to PoS could have dampened the "search-for-yield" motive identified in our baseline results for deposit transactions. To test this hypothesis, we augmented equation (1) as follows:

$$Ln(deposit\ amount)_{ijt} = \beta X_t + \gamma Z_t \times PoS_t + \theta_{ij} + \varepsilon_{ijt} \tag{16}$$

where PoS_t^k is an indicator variable that takes the value of one after the date of the Merge (i.e. September 15, 2022). Reassuringly, and consistent with our argument, the "search-for-yield" motive remains valid even in the post-Merge period. Results from Table B8 show that none of the interaction terms (i.e. the γ coefficients from equation (2)) are statistically different from zero, with the exception of the interaction terms for the policy rate, which is marginally statistically significant. Conversely, the total effect (obtained summing the level with the interaction terms) remains statistically significant for each of the monetary policy indicators, except for the the 10Y Government Bond. Notably, and consistent with PoS having some influence, the size of the effects, in most of the cases, becomes smaller in absolute value compared to the baseline results.

7 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 decisions are driven by speculative motives, seeking potential high returns through leverage, market movements and price speculation. 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.

Overall, our findings indicate that DeFi intermediation primarily channels funds from savers to speculators, rather than to entrepreneurs engaged in socially productive activities. This result identifies an alternative potential transmission channel from DeFi to the real economy, which could arise financial stability concerns.[32] From a policy perspective, our results underscore the need for heightened attention to the potential risks associated to DeFi. Aquilina et al. (2024) summarize the ongoing debate by highlighting three high level strategies that can be adopted to regulate DeFi which they label "ban", "contain" and "regulate". Outright bans are being advocated mainly by those that believe that DeFi add little to no value while posing substantial risk to the financial system and to

[32] The Financial Stability Board has identified four main channels (FSB (2023)): (i) financial institutions' exposures to crypto assets, related financial products and entities that are financially impacted by cryptoassets; (ii) confidence effects; (iii) wealth effects stemming from the fluctuations in the market capitalisation of cryptoassets; and (iv) the extent of cryptoasset use in payment and settlement.

consumers. The “contain” approach aims at isolating traditional finance (TradFi) from the risks in crypto. Some of the proponents of this approach argue that authorities should “let crypto burn”, and avoid that any regulation could be seen as conferring legitimacy to the sector (Cecchetti and Schoenholtz (2022)). Others, such as the Basel Committee on Banking Supervision (BCBS (2022)) are more concerned with isolating TradFi from any potential spillover caused by the crypto ecosystem. The “regulate” approach (Makarov and Schär (2022)) typically involves addressing the specific market failures described above in a manner comparable to the regulation of TradFi. Our view is that, despite its potential, the unique characteristics of DeFi require tailored governance rules to mitigate speculation and ensure an effective financial intermediation process. This is essential for DeFi to evolve into an efficient alternative for channelling funds from savers to productive investments in the future.

References

Ackerberg, D. A. (2003). Advertising, learning, and consumer choice in experience good markets: an empirical examination. *International Economic Review*, 44(3):1007–1040.

Aquilina, M., Cornelli, G., Frost, J., and Gambacorta, L. (2025). Cryptocurrencies and decentralised finance: functions and financial stability implications. *BIS Papers*, forthcoming.

Aquilina, M., Frost, J., and Schrimpf, A. (2024). Decentralized finance (defi): A functional approach. *Journal of Financial Regulation*, 10(1):1–27.

Aramonte, S., Doerr, S., Huang, W., and Schrimpf, A. (2022). DeFi lending: intermediation without information? BIS Bulletin 57, Bank for International Settlements.

Augustin, P., Chen-Zhang, R., and Shin, D. (2022). Reaching for yield in decentralized financial markets. *Available at SSRN 4063228*.

Bagwell, K. (2007). The economic analysis of advertising. *Handbook of industrial organization*, 3:1701–1844.

Barclay, M. J. and Holderness, C. G. (1989). Private benefits from control of public corporations. *Journal of Financial Economics*, 25(2):371–395.

BCBS (2022). Prudential treatment of cryptoasset exposures. Basel Committee on Banking Supervision, December.

Borio, C. and Zhu, H. (2012). Capital regulation, risk-taking and monetary policy: A missing link in the transmission mechanism? *Journal of Financial Stability*, 8(4):236–251.

Bruno, V. and Shin, H. (2015). Capital flows and the risk-taking channel of monetary policy. *Journal of Monetary Economics*, 71:119–132.

Capponi, A., Iyengar, G., Sethuraman, J., et al. (2023a). Decentralized finance: Protocols, risks, and governance. *Foundations and Trends® in Privacy and Security*, 5(3):144–188.

Capponi, A. and Jia, R. (2024). Liquidity provision on blockchain-based decentralized exchanges. *Available at SSRN 3805095*.

Capponi, A., Jia, R., and Yu, S. (2023b). Price discovery on decentralized exchanges. *Available at SSRN 4236993*.

Capponi, A., Jia, R., and Zhu, B. (2023c). The paradox of just-in-time liquidity in decentralized exchanges: More providers can sometimes mean less liquidity. *Available at SSRN 4648055*.

Carapella, F., Dumas, E., Gerszten, J., Swem, N., and Wall, L. (2022). Decentralized finance (defi): Transformative potential associated risks. *Supervisory Research and Analysis Working Papers, Federal Reserve of Boston*.

Carré, S. and Franck, G. (2025). Estimating investor preferences for blockchain security. *Available at SSRN 4307207*.

Cecchetti, S. and Schoenholtz, K. (2022). Let crypto burn. Financial Times, 17 November.

Chen, L., Ma, Y., and Wang, C. (2019). Low interest rates and risk-taking: Evidence from individual investment decisions. *Review of Financial Studies*, 32:2107–2148.

Chiu, J., Ozdenoren, E., Yuan, K., and Zhang, S. (2022). On the inherent fragility of defi lending.

Di Maggio, M. and Kacperczyk, M. (2017). The unintended consequences of the zero lower bound policy. *Journal of Financial Economics*, 123:59–80.

Dyck, A. and Zingales, L. (2004). Private benefits of control: An international comparison. *The Journal of Finance*, 59(2):537–600.

FSB (2023). The financial stability risks of decentralised finance. Financial Stability Board, February.

Gorton, G. B., Klee, E. C., Ross, C. P., Ross, S. Y., and Vardoulakis, A. P. (2022). Leverage and stablecoin pegs. *NBER Working Paper*, (30796).

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

He, S., Manela, A., Ross, O., and von Wachter, V. (2022). Fundamentals of perpetual futures. *arXiv preprint arXiv:2212.06888*.

Heimbach, L. and Huang, W. (2024). Defi leverage. *BIS Working Papers*, (1171).

Heimbach, L., Schertenleib, E., and Wattenhofer, R. (2023). Defi lending during the merge. *Cornell University Working Paper*.

International Monetary Fund (2022). Shockwaves from the War in Ukraine Test the Financial System's Resilience. Global financial stability report.

Jiang, H. and Sun, Z. (2020). Reaching for dividends. *Journal of Monetary Economics*, 115:321–338.

Jiménez, G., Ongena, S., Peydró, J., and Saurina, J. (2014). Hazardous times for monetary policy: What do twenty-three million bank loans say about the effects of monetary policy on credit risk-taking? *Econometrica*, 82:463–505.

Lehar, A. and Parlour, C. A. (2022). Systemic fragility in decentralized markets. *Available at SSRN 4164833*.

Lehar, A. and Parlour, C. A. (2024). Decentralized exchange: The uniswap automated market maker. *The Journal of Finance*, forthcoming.

Liu, Y. and Tsyvinski, A. (2021). Risks and returns of cryptocurrency. *The Review of Financial Studies*, 34(6):2689–2727.

Maddaloni, A. and Peydró, J. (2011). Bank risk-taking, securitization, supervision, and low interest rates: Evidence from the euro-area and the us lending standards. *Review of Financial Studies*, 24:2121—-2165.

Makarov, I. and Schär, A. (2022). Cryptocurrencies and decentralized finance (defi). *Brookings Papers on Economic Activity*, Spring:141–196.

Messias, J., Pahari, V., Chandrasekaran, B., Gummadi, K. P., and Loiseau, P. (2023). Understanding blockchain governance: Analyzing decentralized voting to amend defi smart contracts. *arXiv preprint arXiv:2305.17655*.

Rivera, T. J., Saleh, F., and Vandeweyer, Q. (2023). Equilibrium in a defi lending market. *Available at SSRN 4389890*.

Saengchote, K. (2023). Decentralized lending and its users: Insights from compound. *Journal of International Financial Markets, Institutions and Money*, 87:101807.

Schuler, K., Cloots, A., and Schär, F. (2024). On defi and on-chain cefi: How (not) to regulate decentralized finance. *Journal of Financial Regulation*, 10(2):213–242.

Sethuraman, R., Tellis, G. J., and Briesch, R. A. (2011). How well does advertising work? generalizations from meta-analysis of brand advertising elasticities. *Journal of marketing research*, 48(3):457–471.

Shleifer, A. and Vishny, R. W. (1986). Large shareholders and corporate control. *Journal of Political Economy*, 94(3, Part 1):461–488.

Zetzsche, D. A., Arner, D. W., and Buckley, R. P. (2020). Decentralized finance (defi). *Journal of Financial Regulation*, 6:172–203.

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 +5.55 WETH	*aToken* +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

$$\text{Health Factor}_{i,t} = \frac{\sum_{a=1}^{N} \left[Collateral_{i,a,t} \text{ in ETH} * \text{liquidation threshold}_{a,t}\right]}{\sum_{d=1}^{N} \left[Borrows_{i,d,0:t} \text{ in ETH} + interest_{i,d,t} \text{ in ETH}\right]} \tag{17}$$

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	*dToken*
5.55 aWETH	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.[33] 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).

[33] 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:

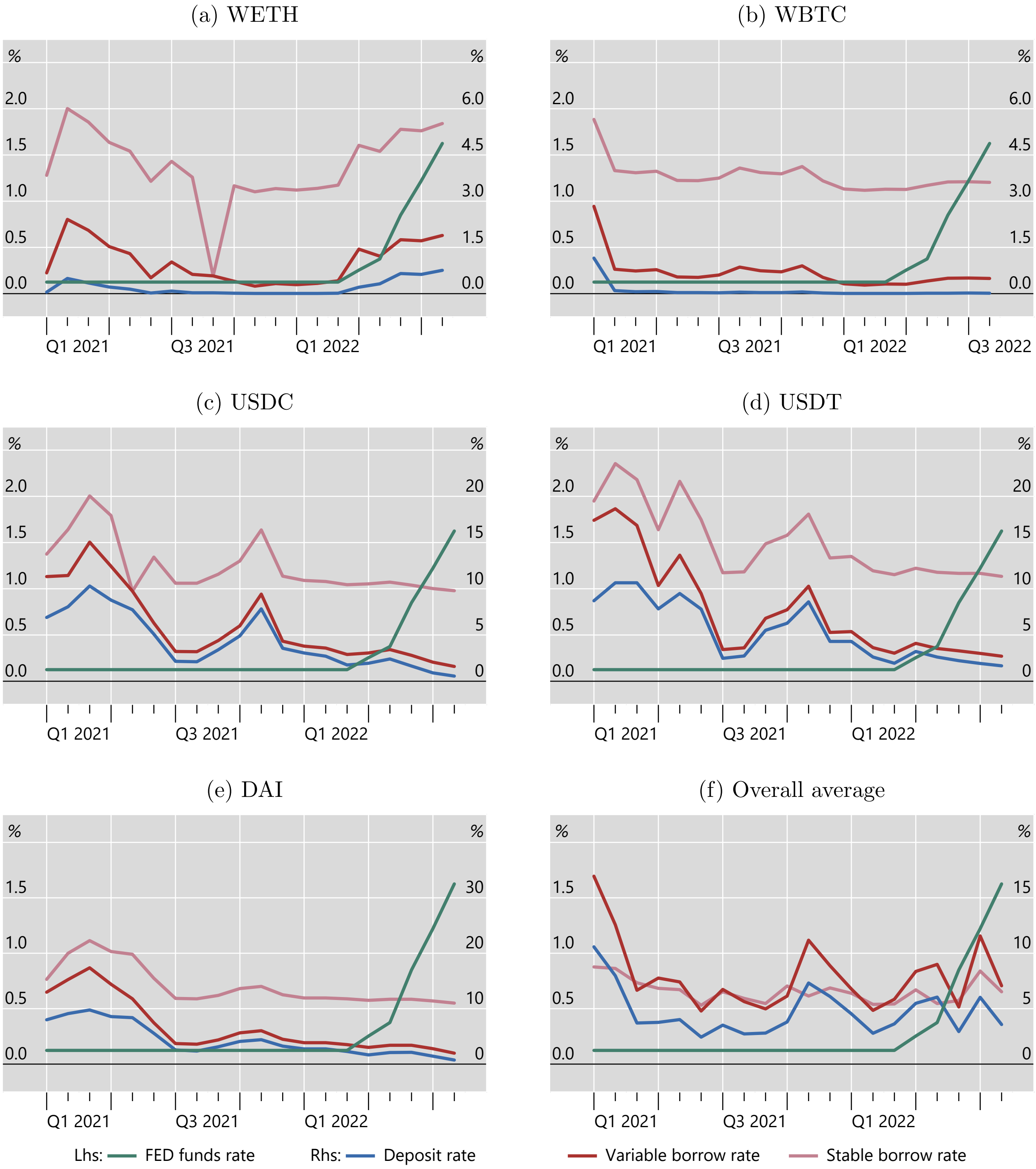
- Base Rate: A fixed rate that serves as the starting point for the calculation.
- Utilization Rate: A critical factor affecting both lending and borrowing rates.
- Slope 1 and Slope 2: Parameters that determine how quickly rates increase as the utilization rate grows. These slopes make the rate adjustment 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**

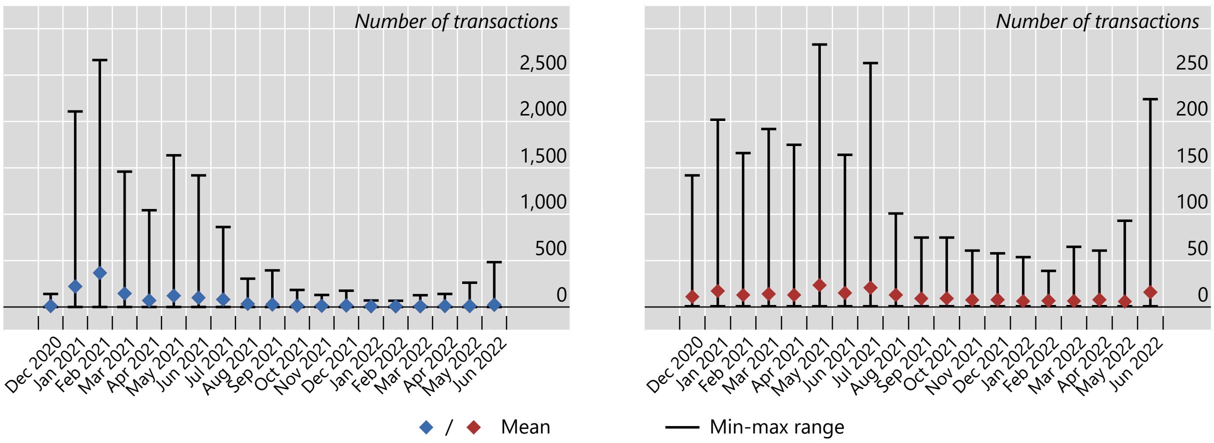


Note: The figures show the FED fund rate, and a daily average of the deposit-, variable borrow- and stable borrow rate in the Aave V2 protocol. The series for the deposit- and the borrow rate in the Aave V2 protocol correspond to daily averages of the transaction-by-transaction data. The overall average 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

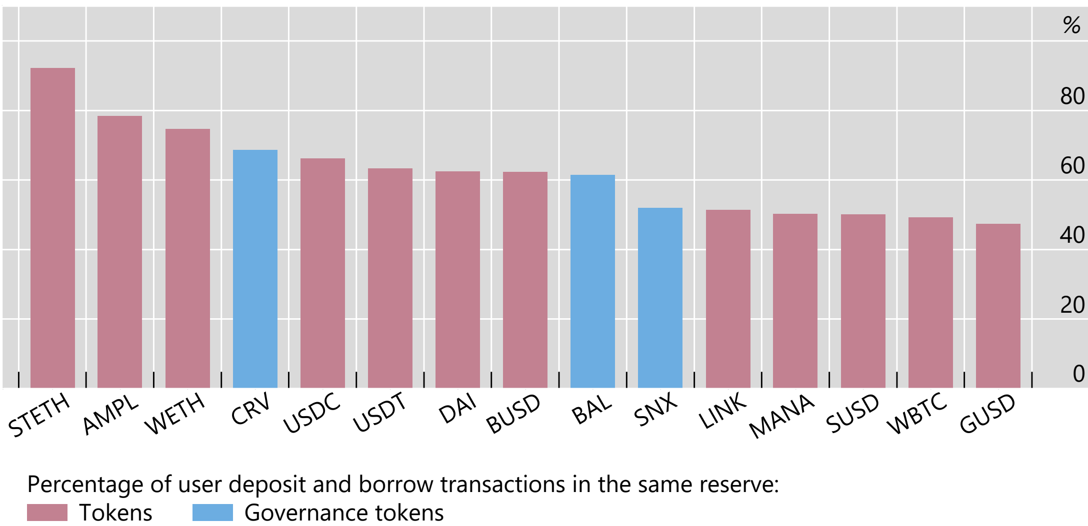
Figure B1: **Distribution of transactions in the Aave V2 protocol by month**

(a) Number of deposit transactions (b) Number of borrow transactions



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.

Figure B2: **Share of deposit and borrowing activity to the same reserve**



Note: The graphs show the top 15 reserves with at least 1,000 users, ranked by the percentage of user deposit and borrowing transactions to the same reserve for the average user. Sources: TheGraphQL; 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: Controlling for deposit APR

	Ln(deposit amount)					
	(1)	(2)	(3)	(4)	(5)	(6)
Policy Rate	-0.4693***					
	(0.0637)					
3M Gov Bond		-0.4382***				
		(0.0557)				
6M Gov Bond			-0.3038***			
			(0.0380)			
1Y Gov Bond				-0.2406***		
				(0.0292)		
2Y Gov Bond					-0.2007***	
					(0.0238)	
10Y Gov Bond						-0.2749***
						(0.0297)
Lag ETH Perp Futures rate	0.1965***	0.2040***	0.2114***	0.2203***	0.2353***	0.1337*
	(0.0741)	(0.0738)	(0.0741)	(0.0745)	(0.0751)	(0.0750)
Lag ETH price (log)	1.0306***	0.9968***	1.0005***	1.0122***	1.0209***	1.1730***
	(0.0498)	(0.0496)	(0.0497)	(0.0497)	(0.0496)	(0.0530)
S&P (log)	-1.5179**	-1.2482**	-1.0806*	-0.9196	-0.5639	-1.7126***
	(0.6206)	(0.5997)	(0.5842)	(0.5746)	(0.5590)	(0.5865)
VIX (log)	0.0866	0.1821*	0.2255**	0.2703***	0.3115***	0.1170
	(0.1107)	(0.1059)	(0.1047)	(0.1039)	(0.1031)	(0.1086)
Borrowing demand (log)	0.0072***	0.0072***	0.0072***	0.0071***	0.0071***	0.0072***
	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0016)
APR deposit rate	0.7239***	0.7021***	0.6824***	0.6710***	0.6760***	0.6438***
	(0.1031)	(0.1033)	(0.1033)	(0.1036)	(0.1042)	(0.1023)
Observations	228,366	228,366	228,366	228,366	228,366	228,366
R-squared	0.7485	0.7487	0.7486	0.7486	0.7486	0.7485
User-reserve FEs	✓	✓	✓	✓	✓	✓
Cluster	User-reserve	User-reserve	User-reserve	User-reserve	User-reserve	User-reserve

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.

Table B3: Results using log changes of the dependent variable

	Δln(deposit amount)					
	(1)	(2)	(3)	(4)	(5)	(6)
Policy Rate	-0.4427***					
	(0.0873)					
3M Gov Bond		-0.3416***				
		(0.0692)				
6M Gov Bond			-0.2399***			
			(0.0503)			
1Y Gov Bond				-0.1654***		
				(0.0403)		
2Y Gov Bond					-0.1311***	
					(0.0340)	
10Y Gov Bond						-0.2130***
						(0.0518)
Lag ETH Perp Futures rate	0.2643	0.2684	0.2729	0.3025	0.3276	0.2145
	(0.2266)	(0.2269)	(0.2267)	(0.2264)	(0.2258)	(0.2319)
Lag ETH price (log)	0.9112***	0.8864***	0.8891***	0.9177***	0.9363***	1.0455***
	(0.1096)	(0.1101)	(0.1101)	(0.1100)	(0.1101)	(0.1120)
S&P (log)	-5.3834***	-5.0402***	-4.8881***	-4.7104***	-4.4701***	-5.4074***
	(0.7436)	(0.7283)	(0.7237)	(0.7199)	(0.7151)	(0.7632)
VIX (log)	0.1896	0.2648**	0.3117**	0.3289**	0.3497***	0.2323*
	(0.1209)	(0.1243)	(0.1281)	(0.1319)	(0.1357)	(0.1235)
Borrowing demand (log)	0.0012**	0.0012**	0.0012**	0.0012**	0.0012**	0.0012**
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Observations	16,202	16,202	16,202	16,202	16,202	16,202
R-squared	0.2217	0.2216	0.2215	0.2211	0.2210	0.2211
User-Reserve FEs	✓	✓	✓	✓	✓	✓
Cluster	User-reserve	User-reserve	User-reserve	User-reserve	User-reserve	User-reserve

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.

Table B4: Results using log changes of the dependent variable

	Δln(borrow amount)			
	(1)	(2)	(3)	(4)
Lag ETH Perp Futures rate	0.9767***		0.9238***	0.9748***
	(0.1761)		(0.1731)	(0.1760)
Lag ETH price (log)	0.1796***			0.1770***
	(0.0533)			(0.0533)
Governance Token*Voting dates		0.6098*	0.6053*	0.5834
		(0.3680)	(0.3665)	(0.3693)
Observations	12,874	12,874	12,874	12,874
R-squared	0.1848	0.1822	0.1843	0.1851
User-reserve FEs	✓	✓	✓	✓
Cluster	User-reserve	User-reserve	User-reserve	User-reserve

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.

Table B5: Borrowing equation: instrumental variable regressions

	Lag ETH Perp Futures rate	Lag ETH Price	Ln(borrow amount)	Ln(borrow amount)
	(1) First stage	(2) First Stage	(3) Second Stage	(4) Second Stage
Lag MLB rating	0.1574***	0.3875***		
	(0.0063)	(0.0232)		
Lag $\widehat{\text{ETH Perp Futures rate}}$			3.5467**	
			(0.5817)	
Lag $\widehat{\text{ETH Price}}$				1.4412***
				(0.2213)
Observations	45,743	45,743	45,743	45,743
F statistic	619	277		
User-Reserve FEs	✓	✓	✓	✓
Cluster	User-Reserve	User-Reserve	User-Reserve	User-Reserve

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.

Table B6: Borrowing equation: placebo test for BTC-ETH perpetual future funding rate

	Ln(borrow amount)			
	(1)	(2)	(3)	(4)
Lag Δ BTC-ETH Perp Futures Rate	0.0136		-0.0296	0.0135
	(0.0416)		(0.0429)	(0.0416)
Lag ETH price (log)	0.7700***			0.7698***
	(0.0256)			(0.0256)
Governance Token*Voting dates		0.1027*	0.1028*	0.0441
		(0.0538)	(0.0538)	(0.0509)
Observations	132,382	132,382	132,382	132,382
R-squared	0.8388	0.8325	0.8325	0.8388
User-Reserve FEs	✓	✓	✓	✓
Cluster	User-Reserve	User-Reserve	User-Reserve	User-Reserve

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

Table B7: Borrowing equation: placebo test for the Terra Luna and FTX fallout

	Ln(borrow amount)	
	(1)	(2)
Lag ETH Perp Futures rate	0.7704***	0.3013***
	(0.0256)	(0.0460)
Terra Luna fallout	3.0597	
	(3.9265)	
FTX fallout		8.7665*
		(5.0100)
Lag ETH Perp Futures rate x Terra Luna fallout	-0.4018	
	(0.5062)	
Lag ETH Perp Futures rate x FTX fallout		-0.6795
		(1.0757)
Lag ETH price (log)	0.3016***	0.8790***
	(0.0471)	(0.0253)
Lag ETH price (log) x Terra Luna fallout	2.7777	
	(1.7903)	
Lag ETH price (log) x FTX fallout		-1.2148*
		(0.6846)
Observations	132,382	162,383
R-squared	0.8389	0.8422
User-Reserve FEs	✓	✓
Cluster	User-Reserve	User-Reserve

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

Table B8: Deposit equation: placebo test for proof-of-stake

	Ln(deposit amount)					
	(1)	(2)	(3)	(4)	(5)	(6)
Policy Rate	-0.3207***					
	(0.0345)					
Policy rate × Proof-of-stake	0.1463*					
	(0.0874)					
3M Gov Bond		-0.2927***				
		(0.0300)				
3M Gov Bond × Proof-of-stake		0.1416				
		(0.0946)				
6M Gov Bond			-0.2464***			
			(0.0255)			
6M Gov Bond × Proof-of-stake			-0.0265			
			(0.1394)			
1Y Gov Bond				-0.2388***		
				(0.0232)		
1Y Gov Bond × Proof-of-stake				-0.0283		
				(0.1392)		
2Y Gov Bond					-0.2363***	
					(0.0216)	
2Y Gov Bond × Proof-of-stake					-0.0322	
					(0.1183)	
10Y Gov Bond						-0.3350***
						(0.0304)
10Y Gov Bond × Proof-of-stake						0.1879
						(0.1221)
Proof-of-stake	-0.1831	-0.2615	0.3348	0.2581	0.1688	-0.7742
	(0.3122)	(0.3738)	(0.6230)	(0.6303)	(0.5198)	(0.4780)
Lag ETH Perp Futures rate	0.1582*	0.1269	0.1496*	0.1476*	0.1420*	0.0532
	(0.0832)	(0.0806)	(0.0827)	(0.0831)	(0.0807)	(0.0789)
Lag ETH price (log)	0.9048***	0.8916***	0.8651***	0.8650***	0.8984***	1.0759***
	(0.1189)	(0.1146)	(0.1167)	(0.1063)	(0.1090)	(0.1009)
S&P (log)	0.0222	0.0380	0.2730	0.3128	0.4499	-0.6306
	(0.9644)	(0.8972)	(0.9385)	(0.8548)	(0.8802)	(0.7836)
VIX (log)	0.1109	0.1808*	0.2276**	0.3186***	0.4577***	0.3084***
	(0.1047)	(0.1037)	(0.0988)	(0.0942)	(0.0966)	(0.1018)
Borrowing demand (log)	0.0008	0.0008	0.0008	0.0008	0.0008	0.0008
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Observations	360,702	360,702	360,702	360,702	360,702	360,702
R-squared	0.7339	0.7339	0.7340	0.7340	0.7339	0.7337
Joint coeff	-0.17	-0.15	-0.27	-0.26	-0.26	-0.14
P-value	0.021	0.074	0.038	0.046	0.022	0.247
User-Reserve FEs	✓	✓	✓	✓	✓	✓
Cluster	User-Reserve	User-Reserve	User-Reserve	User-Reserve	User-Reserve	User-Reserve

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.