DETERMINANTS OF CRYPTO-LOAN DEMAND

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ABSTRACT

This paper explores multiple factors influencing individual crypto-loan size. We find that past experiences negatively affect current loan size in case of liquidations. In case of past repayments of successful loans, we find a positive effect on current loan size. When we correct for sample heterogeneity, we find that rising transaction costs (gas fees) in return increase the principal loan amount. We observe considerable variation in the estimated effects of exogenous market dynamics for different investor types. These findings are relevant to policy makers and regulatory bodies as the crypto-loan market is currently growing rapidly without any (regulatory) oversight. The effectiveness of future legislation to mitigate associated externalities (money laundering, environmental concerns, monetary stability) could therefore be enhanced by taking these findings into account.

Keywords Cryptocurrency · Decentralized Finance · Ethereum · Quantile regression

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Contents

1 Introduction

With the release of the original bitcoin white paper Nakamoto, 2008, an alternative online electronic payment and financial system has sprung up, namely the cryptocurrency marketplace. At the foundation of this trustless peer-to-pee system is a network of nodes validating financial interactions between different participating parties without much regulatory oversight. With the global crypto market cap now amounting to 1.39 trillion US dollars, derivatives and other financial products have been developed following the increasing interest in crypto. A relatively new phenomena is the world of “Decentralized Finance” (DeFi) where instead of financial intermediaries, code in the form of smart contracts is utilized to offer financial instruments. Processes such as loan origination are fully automated and executed by using a smart contract (ensemble of code on the blockchain) with few regulatory oversight. Where the economic literature on traditional financial products is extensive, it has been limited for their crypto counterparts. It is still unclear whether the dynamics of financial crypto products differ under the influence of several factors such as little regulatory oversight and high market volatility.

In this paper we focus specifically on the loan market of the DeFi crypto space. With the introduction of so-called “stable-coins”[1] , users of crypto-loan platforms can now take out loans which are 1:1 pegged to the US Dollar[2]. This lack of significant volatility(in fiat monetary terms) in comparison to cryptocurrency such as Bitcoin and Ethereum, can be seen as important contributing factor to the rising interest or crypto-loans[3]. We will look at other potential factors determining the size of crypto-loans. This paper specifically addresses whether transaction costs (gas fees) affect individual loan size, when market and user specific characteristics are taken into account. In addition we explore the individual effects of these market and user specific characteristics on individual loan size.

As mentioned before, the economic literature on the DeFi crypto space has been limited. Related recent economic literature has been mainly focussed on Bitcoin’s status as a digital currency and whether it adheres to the efficient market hypothesis(see Section 2). With this paper we try enrich the DeFi literature by collecting extensive individual loan data and match this with market variables at the time. By doing so we obtain a comprehensive dataset which enables us to obtain estimates not only based on aggregated market variables such as prices and volatility. With this new dataset, we will try to not only cast a light on the median loan size of the market as a whole, but also of subsets of investors. This paper will investigate whether small/retail investors differ in their demanded crypto loan size in comparison to large/professional investors. Up to the best of our knowledge, no other article has done such empirical analysis within the DeFi space.

We start our research by collecting key individual data of borrowers on the AAVE platform. This includes past experiences (such as repayments and liquidations of past loans) and current loan parameters such as interest rate and principal loan amount. To ensure the validity of our estimates under changing market circumstances, we collect data for an approximate 1 year timespan. With this relatively long timespan, we have multiple “Boom and Bust” episodes in our dataset. We thereafter estimate a quantile regression model which corrects for investor heterogeneity within our sample. As estimated effects for retail borrowers may not be an accurate reflection of professional borrowers and vice versa. As mentioned, our main focus will be whether gas fees influence the principal loan amount of both borrower groups. In addition we investigate whether past experiences with the platform have any effect on our dependant variable, even though they are not taking into consideration from the viewpoint of AAVE in the loan origination process.

[1] There is a lively debate on the “stability” of some stable-coins such as USD Tether. Although outside the scope of this thesis, external audits and investigations such as “Attorney General James Ends Virtual Currency Trading Platform Bitfinex’s Illegal Activities in New York” (2021) provide insights on this topic

[2] although stable-coins are pegged, micro fluctuations in fiat monetary terms are still observed

[3] see https://defipulse.com/aave for a general historic and current overview

In short we find that gas fees have a positive relationship with individual loan size for both groups of investors. Furthermore we find that past interactions on the platform indeed influence the current loan size. Past "successful" loans (repayments) are associated with a higher median principal loan amount, whereas the effect is negative for past liquidations of underwater loans on AAVE. These effects have been fairly consistent between the different investor quantiles. We also find that exogenous market circumstances such as the liquidity/availability of a cryptocurrency play a role. Although in this case we do find considerable heterogeneity in the estimates for different quantiles. Our findings are among the first to empirically reveal the demand side dynamics of the crypto-loan market. With ongoing debate about regulations surrounding cryptocurrencies, extensive research on DeFi could form a foundation for future regulatory frameworks. Our results implies the need of a more tailored approach which takes into account the heterogeneity of borrowers.

The outline of the article is as follows. Section 2 provides a general overview of relevant past economic literature on cryptocurrencies. In section 3 we develop a basic theoretical model which simulates the investment decision of taking out a crypto-loan. Section 4 sets out the construction and compilation of loan data from the AAVE platform. Here a detailed description of our sample is also provided. Section 5 presents our econometric framework and the tuning of our models. Section 6 discusses the results of our empirical analysis. Section 7 concludes.

2 Literature Review

Extensive economic research has been conducted on the cryptocurrency marketplace, with a special focus on the most prominent currency, Bitcoin. Initial research by Frisby, 2014; Yermack, 2015(among others) has focussed on whether Bitcoin can be classified and used as a currency. While Bitcoin at the time showed promise of being a digital alternative to fiat currency, it in practice has been plagued by scalability issues to evolve as a mature alternative for financial transactions. Besides a potential medium of exchange, Bitcoin has also evolved into a speculative vehicle for investors and traders. Whether the market for Bitcoin, or other cryptocurrency, adhere to the Efficient Market Hypothesis as pioneered by Fama (1970) has been an ongoing debate (Cheah et al., 2018; Köchling et al., 2019; Vidal-Tomás & Ibañez, 2018). Although this fundamental research into the market dynamics of Bitcoin has been important in giving us preliminary insights, the cryptocurrency space has substantially progressed since then with the introduction of newer protocols and currencies.

As evidenced by Corbet et al. (2018) crypto-markets seem to exhibit a certain degree of interconnectedness, regardless of underlying technology or protocol. More precisely, the market for Bitcoin seems to be a vector of spill-over effects to other crypto-markets. Focussing on the determinants of a cryptocurrency's price, Sovbetov (2018) adds to the argument of interconnected crypto-markets. In comparison to other papers, the authors have extend their analysis to alternative cryptocurrencies such as Ethereum and Monero. The findings of interconnectedness here seem to be robust in both the short and long term. The same spill-over and interconnectedness dynamics have been observed for crypto-market volatility by Yi et al. (2018) across a large sample of 52 cryptocurrencies. An more in-depth extension on the spill-over evidence is provided by Giudici and Pagnottoni (2020) and Luu Duc Huynh (2019).

If we take into account that the crypto-market as a whole(Bitcoin and other all other cryptocurrency) seem to be interconnected and inefficiencies are not uncommon, arbitrage trading seems to be a viable strategy as evidenced by Giudici and Pagnottoni (2020). With the introduction of new protocols and currencies, arbitrage and derivative trading has become more mature and prominent within the crypto space Schär (2021). Adding to this "DeFi" literature is an article by Gudgeon et al. (2020) which investigates the dynamics of interest rates.

We try to contribute to this strain of "DeFi" research by empirically testing the contributing factors of crypto loan demand with a sample starting from the advent of commonplace "DeFi" protocols. Up to the best of our knowledge, no study has been conducted on the user characteristics and market dynamics influencing crypto-loan size, which is indicative of demand side dynamics. We try to fill this gap by extracting personal characteristics for each borrower and combine this data with crypto-market data such as gas fees. In particular, we study whether gas fees affects crypto-loan size, corrected for market and personal characteristics.

3 Theoretical Framework

3.1 Retail Trades

3.1.1 costs

First we consider the case of an atomistic borrower whose interactions do not significantly affect current market equilibrium[4]. Here the borrower chooses to post collateral X (denominated at the respective cryptocurrency) at $t = 0$ and either repays or gets liquidated for their loan at a future time-point $t = T$. The borrower furthermore endogenously chooses their Loan to Value ratio (φ) in the set [0 ; $\tilde{\varphi}$]. The LTV ratio is capped at $\tilde{\varphi}$ which is exogenously given as per the terms of condition of AAVE for each cryptocurrency. Therefore the total principal amount of the loan is given by $\varphi \cdot X$. The total running cost of the loan are defined as :

$$\varphi \cdot X \frac{i_r}{365} t - X \cdot \frac{i_c}{365} t \tag{1a}$$

$$X \cdot \frac{t}{365} (\varphi \cdot i_r - i_c) \tag{1b}$$

The borrower obtains a yearly deposit rate[5] of i_c on their collateral (X) and pays a yearly borrow rate (APR) of i_r over their principal amount $\varphi \cdot X$. In our case, the borrower has to post an initial collateral amount on $t = 0$ where they have to incur a gas fee(F_c). This gas fee is an exogenously given market rate for executing transactions on the Ethereum network. Immediately thereafter the borrower opts to move their funds to a final use case either outside or within the AAVE ecosystem, incurring gas fees once again(F_s). Finally at $t = T$, the investor either repays or gets liquidated. In this case the sum of gas fees incurred are :

$$\text{sum gas fees} = \begin{cases} F_c(\Xi_0) + F_s(\Xi_0) + F_e(\Xi_1), & \text{repayment } (p_r) \\ F_c(\Xi_0) + F_s(\Xi_0), & \text{liquidation}(p_l) \end{cases} \text{where} \quad \underbrace{p_r + p_l}_{p_r \geq 0 \,\wedge\, p_l \geq 0} = 1 \tag{2}$$

Where the costs of posting collateral/swapping/closing the loan are functions of the average gas fee ($\Xi_{0,1}$) at their respective time t. The gas fee in itself is a function of Ethereum network congestion. In case of liquidation the borrower does not incur closing costs(F_e) as funds are not moved for repayment. Instead he or she keeps the borrowed amount (whether in cryptocurrency or fiat) and loses the posted collateral.

3.1.2 potential gain

To assess whether he or she takes out a loan, the borrower forms expectations beforehand about the potential pay-off and probabilities of both scenarios (repayment and liquidation). The potential gain of the retail trade are therefore given by the stylized form:

$$\text{potential gain} = \begin{cases} \mathbb{E}[\tau_c] \cdot X + \mathbb{E}[\tau_\alpha]\varphi \cdot X, & \text{repayment } (p_r) \\ \mathbb{E}[\tau_\alpha]\varphi \cdot X + (\varphi \cdot X - X), & \text{liquidation } (p_l) \end{cases} \text{where} \quad \underbrace{p_r + p_l}_{p_r \geq 0 \,\wedge\, p_l \geq 0} = 1 \tag{3}$$

[4]by assumption, slippage is negligible

[5]The earned interest here is continuously added to the account and can be immediately withdraw at any notice.

In the case of successful repayment with probability p_r, the investor receives an expected pay-off $\mathbb{E}[\tau_c]$ on the collateral amount X and $\mathbb{E}[\tau_\alpha]$ on the borrowed amount $\varphi \cdot X$. As both the collateral and the borrowed amount are denominated in cryptocurrency, the expected pay offs can be interpreted as a fluctuation vis à vis the USD. In addition, general market volatility in part also affects the expected pay offs[6]. With probability p_l the investor gets liquidated and only obtains a pay-off on the borrowed amount. In the latter case, the investor in addition loses collateral amount X but keeps the borrowed loan value $\varphi \cdot X$. The net asset position in the repayment case does not change.

3.1.3 gas fees and borrow value

To form a first hypothesis we investigate the effect of a change in gas fees on the loan size of a retail borrower. As per equation 2 the paid gas fees can be interpreted as fixed costs, regardless of the final loan status (repayment or liquidation). As such we have a first indication of a negative effect of gas fees on the potential profit of an individual retail borrower. In order to recoup these fixed costs, the retail borrower either has to take out a larger loan(more exposure to the market), or take on more risk in anticipation of a higher pay-off. Therefore the investor is in theory presented with either posting more collateral (X), raising their LTV ratio (φ), or invest in cryptocurrency with higher associated risks and upside ($\mathbb{E}[\tau_\alpha]$). Therefore our first hypothesis states that for retail trades, higher gas fees results in higher principal loan values.

4 Data

4.1 Loan data and borrower characteristics

In order to build a comprehensive and robust sample we source data from multiple providers. Due to the decentralized and automated nature of cryptocurrency, code integrity[7] becomes a hindrance to data collection. We therefore cross-check data from each provider by randomly comparing it to independent public data from Etherscan. We restrict our sample to loan data from the AAVE platform as it has been the most prominent marketplace within the DeFi space, as evidenced by the 22 billion USD[8] sized liquidity pool. We limit the scope of data to May 2020 till June 2021 with the starting date roughly coinciding with the public release of the AAVE protocol[9]. As there is no central statistical agency curating cryptocurrency data, we build a compiling and matching algorithm (see Appendix, Figure 4), starting by querying loan data.

By using the GraphQL endpoint of AAVE[10] we obtain cross-sectional data for each loan and their associated borrower, to reach a dataset consisting of 86 thousand unique loans. For each observation, loan characteristics such as the interest rate, type of interest rate (fixed or variable) and principal amount denominated in the associated cryptocurrency are compiled. Here the rate type is defined as 1 for variable rates and 0 for the fixed rates. We convert the principal loan amount to USD by making use of the Poloniex public chart data API. We match the associated cryptocurrency with the respective price in USD by pulling data for the corresponding May 2020-June 2021 time period with 30 second

[6] see Section 5 for a more in depth note on volatility

[7] In short, although blockchain data is completely public at its core, data collection of all transactions is computationally costly. Due to the associated costs of compiling and aggregation, data providers impose limits on the provided data. A common occurrence is the combination of crypto-exchange and data provider. This combination gives rise to a potential conflict of interest as it is not necessarily in the interest of the data provider to disseminate data which harms the profitability of the crypto-exchange operations.

[8] as of 10-06-2021

[9] Any on-chain transaction made before 01-05-2020 are therefore not considered, making the loan observations dependant on these transactions also drop out of the sample

[10] as provided by : https://thegraph.com/explorer/subgraph/aave/protocol

increments. Data has been aggregated by taking a daily average price in USD to reduce computational costs[11]. In line with mainstream economic thought, interest rates and potentially interest type are potentially drivers of loan demand. Our main dependent variable is the principal loan amount in USD.

Another possible driver of (individual) loan demand is past interactions. It is not unimaginable that, due to the novelty of crypto-loans, new potential borrowers face a "learning effect" of becoming accustomed to certain dynamics. We therefore incorporate borrower characteristics in our dataset. We start by requesting for each loan the associated wallet address and match this with past interactions on the AAVE platform. In so we obtain for each borrower the number of past liquidation calls of underwater loans, repayments of past loans, redeems/posting of collateral (both in dollar amounts and number of instances). Due to limitations of the GraphQL endpoint, we only obtain a maximum of 100 past interactions for each type (liquidations, redeems or repayments). As an example, if a trader has a history of 156 redeems and 108 repayments, only the most recent 100 redeems and 100 repayments are returned for this specific wallet address. Furthermore we obtain the alternative interest rate of the desired cryptocurrency if borrowers would have altered their rate type (flexible in case of fixed loans and vice versa). For most currencies, AAVE offers both rate types and allows users to switch between. The alternative interest rate controls for a potential "flight to safety" effect observed by practitioners. In short, in times of turmoil (crypto-)market exposure is reduced by investors. While conventional financial markets experience a flight to safe haven assets such as the USD(McCauley & McGuire, 2009), the dynamic in the crypto space differs slightly. While a straight withdrawal from Ethereum to USD might be expected, this becomes problematic due to withdrawal limits[12], especially for larger trades. Instead, investors often opt for "stable-coins", with this increase in demand for stable-coins subsequently causing a surge in (flexible) interest rates.

4.2 Market Dynamics

Aside from user characteristics, (exogenous) market dynamics in addition are a potential import driver of loan demand. We therefore control for the utilization rate of the lending pool[13]. A lending pool is fundamentally the percentage of funds available to borrow, determined by market forces of liquidity providers and borrowers. It is not unlikely that the size of the loan adjusts to the available funds (especially larger trades). To further complement our dataset we obtain the average daily gas fee[14] corresponding to the origination date of the loan. As it is our main independent variable of interest, it is vital to be precise in our specification of gas. Strictly speaking, the average gas fee is determined for each infinitesimal time-step by market forces i.e., higher gas fees in most cases is a sign of more transaction volume on the Ethereum blockchain. To save on computational costs the loan data is rounded to the nearest day and matched with the Etherscan gas data.

4.3 Descriptive statistics

A first glance at the main descriptive statistics reveals interesting preliminary insights. Table 1 presents the summary statistics of the total sample. As evidenced by the statistics for borrow value (principal loan value), balance and user characteristics, there is potential for our group heterogeneity hypothesis. While the average principal loan is approximately 140k USD and associated with an user who had 11 past repayments and 0.62 liquidations, this is not an accurate description of the whole sample as evidenced by the standard deviations. With the standard deviations being larger than the mean for almost all loan and user characteristics, there is preliminary evidence of heterogeneity

[11]Due to congestion spikes on the Ethereum network, not every transaction is executed immediately. We account for this by taking the daily average price in USD

[12]see: https://help.coinbase.com/en/pro/trading-and-funding/trading-rules-and-fees/limits

[13]see appendix Figure 7 for the distinction between lending and liquidity pool

[14]as provided by Etherscan

in the sample. In addition exogenous market dynamics (gas, interest rates) also seem to exhibit considerable volatility by looking at their standard deviations in relation to the mean. We also notice that the interest rate type is indeed endogenously determined as evidenced by figure 5. Although borrowers might have an initial preference for either fixed or flexible rate loans, a shift in the loan type is observed under different (market) circumstances. In a high gas market, borrowers seem to more often opt for a fixed rate loan. Furthermore this effect seem to be more pronounced in larger loans.

In order to specify an appropriate econometric model, we formally test whether our sample is normally distributed based on skewness and kurtosis. As presented in table 2 this seems not to be the case for the total sample based on both metrics. Furthermore if we split the sample for two different quantiles (corresponding to retail and professional trades respectively[15]), we observe the same evidence of non-normally distributed data. Based on these results we assume the a certain degree of non-normally distributed data and tune our econometric models accordingly.

Table 1: Summary table

Total sample

	mean	sd	min	max
borrow_value(USD)	140153.4	1590466	6.00e-13	1.88e+08
interest_rate(%)	7.893613	12.06059	.0001523	307
stable_borrow_alt(%)	20.26365	22.21214	0	69.47873
variable_borrow_alt(%)	16.054	23.42088	.0475522	67.97873
utilization_ratio	.6743425	.3165435	.003019	.9999645
ltv ratio	.1396383	.1759103	2.82e-14	1
repays_exante⋆	10.54449	17.66554	0	100
repays_expost⋆	14.87891	20.59692	0	100
liquidations_exante ⋆	.6216768	2.860902	0	47
liquidations_expost⋆	1.365842	4.572798	0	100
redeems ⋆	3.047893	13.63151	0	100
balance (USD)	3445384	3.54e+07	.0010459	2.23e+09
sum_dep(USD)	3602365	3.61e+07	.0010459	2.23e+09
sum_redeems(USD)	156981.2	2825192	0	2.20e+08
sum_rep_exante (USD)	1488957	1.03e+07	0	3.98e+08
sum_rep_expost(USD)	3530663	2.23e+07	0	7.24e+08
sum_liq_expost(USD)	296632.4	2543823	0	4.24e+07
sum_liq_exante(USD)	99156.36	1217776	0	3.83e+07
rate_type	.7444921	.4361489	0	1
gas (gwei)	113.9163	77.07385	22.17171	709.708
repays_total_number	25.4234	31.04498	0	100
rate_alt (%)	19.33655	22.48741	0	69.47873
N	85649			

⋆ indicates number of instances. Borrow value refers to the principal loan amount. “Dep”= deposits, “Rep”=repays, “liq”= liquidations and “rate alt” refers to the alternative interest rate(e.g. the flexible rate if a fixed rate borrower would have opted for this instead)

[15]We revisit these ad-hoc cut-off quantiles in more detail in later sections.

Table 2: Normality test borrow value

Sample	N	skewness	kurtosis
Total	85649	0.000	0.000
25^{th} quantile	21413	0.000	0.000
95^{th} quantile	81395	0.000	0.000

Estimated p-values for both skewness and kurtosis

5 Methodology

As evidenced by Table:2 the observations in our dataset seem not to be normally distributed, regardless of sample composition. This empirical finding poses challenges from an econometric point of view. To account for differences between quantiles and increasing residuals around the tail ends from non normally distributed data(figure : 6), we make use of non parametric regression models(see Koenker and Bassett Jr (1978)).

5.1 Borrow value and gas fees

Taking into account the sample composition of retail and professional trades, we define a quantile regression for the 25^{th} and 95^{th} quantile regarding the principal loan size in USD[16]. In comparison to OLS based methods, the quantile regression framework is more robust to outliers and non-normal distributed data as the estimates are centred around the median instead of the mean. Furthermore, to account for potential heteroscedasticity we bootstrap our regression to consistently obtain the standard errors[17]. Our quantile regression is given by:

$$ln\left(Q_\tau(Y)\right) = \beta_0(\tau) + \beta_1(\tau)\Xi_t + \sum_{i=2}^{i=n} \beta_i(\tau)X_i + \varepsilon_{\tau,t} \tag{4}$$

Here the dependant variable Y equals the predicted median principal loan amount in USD for percentile Q_τ regressed on the market gas fee rate Ξ at time t. We take the natural logarithm of Y for a more intuitive interpretation of the results. By doing so we obtain semi-elasticities for the loan size, which state a percentage change in principal loan size associated for each absolute change in the vector of variables. As the demand for loans is not only affected by gas fees, but also market and user characteristics, we account for a vector of n control variables. We account for market variables such as the loan's interest rate, the alternative interest rate and the utilization rate of the cryptocurrency, which are all exogenously determined before the loan origination process. We explicitly do not account for market volatility as there has been up to date no reliable proxy for this variable[18].

While the argument for the inclusion of interest rates in our vector of controls is trivial, the utilization rate variable warrants further clarification. From the viewpoint of an uninformed retail trader, the utilization rate of a certain cryptocurrency can interpreted as a "signal" of underlying currency specific factors. Cryptocurrency with a higher utilization rate are potentially more "trustworthy" under normal market circumstances as informed (professional)

[16]Although the percentile cut-off seems to be arbitrary, the corresponding absolute borrow values correspond to 1640 and 400,000 USD respectively. Which seem to accurately reflect the difference between retail and professional trades.

[17]We follow standard practices as laid out by the works of Koenker and Chernozhukov. Formal evidence of "bootstrapping" to account for heteroscedasticity is given by Fan and Lee (2019)

[18]Crypto-equivalent of the VIX measure for stock market volatility have been developed by T3 index (BitVol) and CVI.finance (CVI). However the lack of volume in the former instrument and the latter product still being in the "beta phase" makes these measures unsuited for our research.

traders are taking risks into consideration which are not apparent to the uniformed borrower[19]. In case of larger trades, the utilization rate accounts for a slippage/lack of liquidity effect where a lack of available funds causes the larger professional trade to (in)voluntarily decrease his or her loan size.

As the "DeFi" space is relatively still in its infancy, there is an argument to be made that potential borrowers with little to no experience with crypto-loans are sceptical about the trustworthiness of the AAVE platform and therefore choose lower valued loans than their more experienced counterparts[20]. Although the platform does not take past interactions into consideration during the loan origination process (e.g. users with multiple incidences of liquidations do no get any restrictions), users themselves can restrict their loan sizes based on past events. It is not unimaginable that users who have recently experienced a liquidation are potentially more cautious (smaller loan size/ other behavioural adjustments) as a result. To account for user characteristics in our control vector, we take into consideration past instances of liquidations and repayments of loans for each borrower.

We repeat equation 4 on the median LTV-ratio of the loans to investigate whether any relationship between borrow value and gas fees can be ascribed to investors posting more collateral or taking riskier loans. The analysis is run on the full sample. In case of a positive relationship between the median principal loan amount and the market gas fee with no significant relationship between the LTV-ratio and the market gas fee, the effect of posting more collateral is more prominent and vice versa. The same set of control variables are used as in the initial regression to account for user and market characteristics.

In order to obtain more precise estimates of the effects of different interest rates, we deviate from our initial approach As mentioned in section: 4.1, interest rates are more likely to rise during an increase of market volatility. While any change in volatility is almost immediately priced in at the variable rate, this is by design not always the case for the fixed rate(see Figure:8). As evidenced in the figure, fixed interest rates only adjust in case of extreme episodes of volatility, whereas flexible rates more accurately reflect any changes in market volatility. Moreover the interest rate differential between flexible and fixed rates is approximately 8 percentage points, which implies that fixed rate borrowers are potentially less concerned about the interest rate cost of their loan at origination. Taking both findings into account, we run our regression 4 again on a restricted sample of only fixed rate loans. As mentioned, by design the interest costs of the loans themselves are (almost) insulated of short term market volatility. Therefore any relationship between the principal loan amount and the alternative interest rate is not running through the interest sensitivity of borrowers. By doing so we mitigate confounding bias(Angrist and Pischke (2008)) in our interest rate estimates.

6 Result

As specified in section 5.1 our principal loan amount quantile regression is separately estimated on the 25$^{\text{th}}$ and 95$^{\text{th}}$ quantile. In section6.1we first estimate the basic model with only the gas fee as independent variable. Thereafter we subsequently add in market and user characteristics as control variables. In section 6.2 we repeat the same procedure with the LTV ratio as dependant variable instead.

6.1 Borrow value

[19]A clear example is the different mechanisms employed by stablecoins to maintain their 1:1 peg to the USD. This difference in so called "governance" results in discrepancies in risk premia (see statistics on the AAVE platform) and utilization rates.

[20]The relatively high incidence of near 0 USD loans in the raw data suggests that potential borrowers first take out a "test loan" to assess the trustworthiness/mechanics of the platform before committing to their actual desired principal amount

Table 3: Quantile regression table
principal loan amount semi-elasticity

	(1)	(2)	(3)
		25^{th} quantile	
gas	0.00669***	0.00649***	0.00655***
	(0.000114)	(0.000143)	(0.000132)
interest_rate		0.0172***	0.0154***
		(0.00138)	(0.00134)
liquidations_exante		-0.0591***	-0.0632***
		(0.00208)	(0.00203)
repays_exante		0.0260***	0.0260***
		(0.000471)	(0.000567)
utilization_rate			0.911***
			(0.0472)
rate_alt			-0.00934***
			(0.000563)
Constant	6.676***	6.390***	5.934***
	(0.0162)	(0.0206)	(0.0346)
		95^{th} quantile	
gas	0.00319***	0.00311***	0.00275***
	(0.000270)	(0.000175)	(0.000233)
interest_rate		0.0207***	0.0218***
		(0.00193)	(0.00236)
liquidations_exante		-0.0828***	-0.0752***
		(0.00469)	(0.00570)
repays_exante		0.0339***	0.0323***
		(0.00103)	(0.000908)
utilization_rate			-0.695***
			(0.0716)
rate_alt			-0.00677***
			(0.00103)
Constant	12.50***	11.87***	12.48***
	(0.0386)	(0.0319)	(0.0551)
Observations	85649	85649	85649
User characteristics	No	Yes	Yes
Market characteristics	No	No	Yes

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

As stated our main variable of interest is the market gas fee, which we try to estimate the effect of on principal loan size. Presented in Table 3 are three different models with various controls for both quantiles. In column (1) we see that a straightforward regression of solely gas on the principal loan amount yields a significant and positive relationship for both quantiles. When we control for user and market characteristics (column 2 and 3), the estimated effect for gas remains robust, albeit decreasing in magnitude for both percentiles. For the 25^{th} quantile a 10 point increase in the average daily gas fee results in an approximate 6.6% increase in the median principal loan amount, whereas this effect is 2.8% for the 95^{th} quantile.

Furthermore, previous experiences with the platform seem to affect the principal loan amount for both quantiles, with a negative effect for liquidations and a positive effect for past repayments when we control for ex-ante characteristics. The estimated effect is a 6.3% and 7.5% decrease of the median loan amount for each past liquidation instance for the 25^{th} and 95^{th} quantile respectively. The absolute estimates for repayments are smaller with a 2.6% and 3.2% increase for each instance of repayment for the 25^{th} and 95^{th} quantile respectively. These results provide evidence of past experiences with the AAVE platform influencing current individual loan size.

Counter-intuitive to mainstream economic intuition, there is a positive relation to be found between the interest rate and loan value. As presented in column 3 of Table 3 we find the median loan amount increases by an estimated 1.5% for each percentage point increase of the interest rate at the 25^{th} quantile. The effect is also positive at the 95^{th} with an estimated coefficient of 2.2%. In contrast to these findings are the estimates of the alternative interest rate if investors opted for a different rate type for the same cryptocurrency. In both quantiles the estimates are negative, where a 10 percentage point increase in the alternative interest rate yields a decrease of 9.3% and 6.7% for the 25^{th} and 95^{th} quantile respectively.

If we look at table:4 and compare the interest estimates, the results are comparable for the 25^{th} quantile. Here the estimates are a 1.8% median loan value increase for each percentage point increase in the interest rate. The alternative interest rate also has a negative effect on median loan amount with an associated 11% decrease for each 10 percentage point increase in alternative interest. However for the 95^{th} quantile, the estimates differ from our initial sample. By mitigating potential confounding bias, we obtain non significant estimates for both the interest rate as well as the alternative interest rate. While the results are only indicative, the 95^{th} quantile seems to be relatively more inelastic than the 25^{th} quantile in their demanded loan size under changing interest rates.

The estimated effect of the utilization rate appears to be heterogeneous across the two quantiles. Whereas the effect appears to be positive for the 25^{th} quantile, it is negative for the 95^{th}. While there seems to be evidence of our signalling hypothesis for the 25^{th} quantile, where retail investors are more confident in taking larger loans of highly utilized currencies, the result should be taken with caution. The magnitude of the coefficient is an estimated 91% increase in median loan value for each percentage point increase in utilization rate. For the 95^{th} quantile, the estimate is a 70% decrease for each percentage point increase in utilization rate. The results are in line with our slippage hypothesis (see section 5.1) for higher valued loans, nonetheless the results should be interpreted with caution.

Table 4: Quantile regression table
Restricted sample (only fixed rate)
principal loan amount semi-elasticity

	(1)	(2)	(3)
		25^{th} quantile	
gas	0.00679***	0.00644***	0.00650***
	(0.000322)	(0.000254)	(0.000241)
interest_rate		0.0237***	0.0176***
		(0.00447)	(0.00359)
liquidations_exante		-0.0267***	-0.0238***
		(0.00565)	(0.00663)
repays_exante		0.0247***	0.0239***
		(0.000937)	(0.00105)
utilization_rate			1.100***
			(0.113)
rate_alt			-0.0114***
			(0.000894)
Constant	6.751***	6.367***	5.802***
	(0.0455)	(0.0542)	(0.0976)
		95^{th} quantile	
gas	0.00558***	0.00560***	0.00471***
	(0.000534)	(0.000396)	(0.000537)
interest_rate		0.00887	-0.0000845
		(0.00583)	(0.00533)
liquidations_exante		-0.0826***	-0.0648***
		(0.0144)	(0.0187)
repays_exante		0.0301***	0.0319***
		(0.00160)	(0.00225)
utilization_rate			-1.314***
			(0.149)
rate_alt			-0.00145
			(0.00146)
Constant	11.69***	11.24***	12.44***
	(0.0797)	(0.0912)	(0.145)
Observations	21884	21884	21884
User characteristics	No	Yes	Yes
Market characteristics	No	No	Yes

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6.2 LTV

We run the same model specifications with the median loan to value (LTV) ratio as dependant variable, presented in Table 5. While gas fees seem to positively influence the LTV ratio in our initial model (column 1), the effect dissipates when the vector of controls is included for the 25th quantile. When we consider the 95th quantile, the effect even vanishes (columns 2 and 3). Although we do find statistically significant results for both quantiles the real world impact is negligible. In case of a 3 sigma deviation for gas fees[21] , the median LTV of a retail loan would increase in the neighbourhood of 231 * 0.0000412 = 0.0095 percentage points. If we repeat these calculations for all other parameters, we can conclude that although the estimates may be statistically significant, they bear little economic importance. In other words, changes in leverage are not the main drivers of the principal loan size. Both quantiles do not change the LTV of their loans in response of rising gas fees or any other variable.

[21]as per table :1; 77 *3 = 231 gwei

Table 5: Quantile regression table
LTV semi-elasticity

	25th quantile		
gas	0.0000531***	0.0000412***	0.0000412***
	(0.00000325)	(0.00000304)	(0.00000306)
interest_rate		0.0000831***	0.0000566***
		(0.0000184)	(0.0000145)
liquidations_exante		-0.000963***	-0.00103***
		(0.0000333)	(0.0000346)
repays_exante		-0.000652***	-0.000654***
		(0.00000917)	(0.00000976)
utilization_rate			0.00728***
			(0.000891)
rate_alt			-0.000193***
			(0.00000968)
Constant	0.0167***	0.0317***	0.0311***
	(0.000402)	(0.000400)	(0.000711)
	95th quantile		
gas	0.0000995**	0.0000554	0.0000279
	(0.0000373)	(0.0000290)	(0.0000371)
interest_rate		0.00104***	0.00113***
		(0.000236)	(0.000247)
liquidations_exante		0.000945	0.00188
		(0.00120)	(0.00100)
repays_exante		-0.00600***	-0.00594***
		(0.0000362)	(0.0000474)
utilization_rate			-0.0534***
			(0.00827)
rate_alt			-0.00134***
			(0.000108)
Constant	0.520***	0.549***	0.606***
	(0.00581)	(0.00404)	(0.00770)
Observations	85649	85649	85649
User characteristics	No	Yes	Yes
Market characteristics	No	No	Yes

Standard errors in parentheses
$^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

7 Sensitivity tests

In this section we put the underlying assumptions and specifications of our initial models (see section:5) under scrutiny to credibly form a conclusion based on their results. To reiterate the underlying assumptions and specifications:

- Group heterogeneity (retail and professional)
- Corresponding group cut off quantiles are the 25$^{\text{th}}$ and 95$^{\text{th}}$
- Power-law type distribution at tail ends
- No significant missing ex-ante user characteristics

In addition, we will test whether our quantile regression model suffers from (excessive) over-fitting.

7.1 Group specification

One of the main assumptions of our theoretical and empirical model is the existence of heterogeneity within the group of borrowers. In so, we defined the cut-off points as the 25$^{\text{th}}$ quantile for retail and the 95$^{\text{th}}$ quantile for professional trades. We empirically test whether there is heterogeneity at all, and if so, whether our cut-off points are valid. Based off the works of Chernozhukov et al., 2017; Chernozhukov et al., 2020; Koenker, n.d. we bootstrap equation (4) for each percentile to obtain estimates and confidence intervals of the independent variables[22]The interpretation of any result is straightforward, with the coefficients of the independent variable and their confidence intervals(in grey) on the Y-axis and the corresponding quantile on the X-axis. In case of heterogeneity, the plotted estimates would differ along the X-axis as opposed to the completely homogenous case of a horizontal estimates line (quantiles do not affect the estimated effects).

We obtain estimates for each independent variable along the full quantile range with increments of 1 percentage point. Presented in Figure: 1 we can clearly see that the estimated effects surge in magnitude when approaching the boundary limit of the 100$^{\text{th}}$ quantile. More interestingly, visual inspection confirms our choices of setting our cut-off points roughly around the 25$^{\text{th}}$ and 95$^{\text{th}}$ quantiles. All estimates remain flat along the range [0 ; .25] with gas steadily rising from the 40$^{\text{th}}$quantile onwards. The figure also provides evidence for the 95$^{\text{th}}$ quantile cut-off as almost all estimated variables surge in magnitude from this point, up to the boundary limit. In so we do not find sufficient evidence of rejecting our first two assumptions.

Table 6: Pareto tail distribution

Hill estimation	
Quantile	α
5$^{\text{th}}$	.
25$^{\text{th}}$	.
95$^{\text{th}}$	.65

Although shape parameter estimates for the 5$^{\text{th}}$ and 25$^{\text{th}}$ quantiles are returned, they are undefined under the restriction $\alpha > 0$ for real numbers.

[22]We tune our bootstrap in accordance to Chernozhukov et al., 2017, which has a specific focus on extreme quantiles.

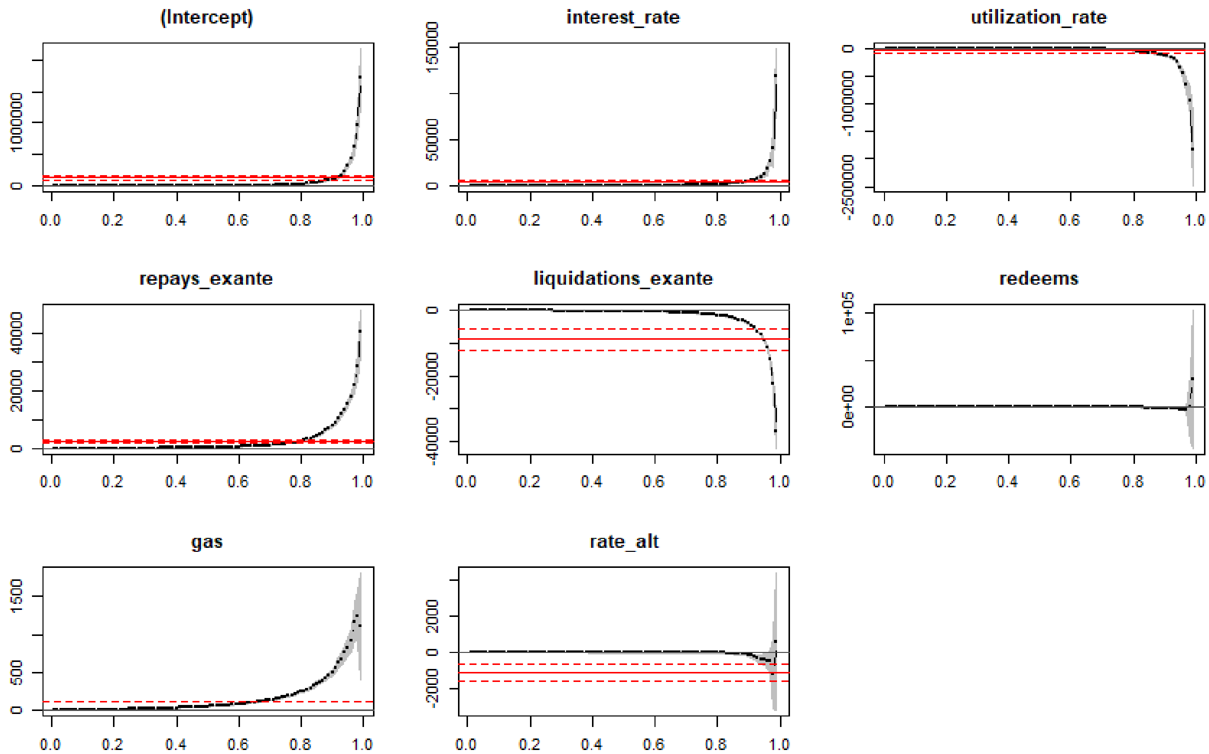

Figure 1: Extreme Value Quantile Inference, bootstrapped based on Chernozhukov et al.
Black dots correspond to the estimated coefficient (Y-axis) for each quantile on the X-axis. In grey are the estimated confidence intervals for each point estimate, with the red solid line as the average effect. The red dotted line indicates the 90 percent confidence interval for the average effect. The returned estimates in the figure are in absolute units, not semi-elasticities.

Both the initial equation (4) and the bootstrapped form theoretically assumes a power-law type distribution in the tails of the dependant variable (Chernozhukov et al. (2017)). We formally investigate this assumption by following the approach of Hill, 1975; Koenker, n.d. In so our hypothesis is that the tails follow a Pareto distribution (power-law probability distribution)with tail index α. We run the test on the tail ends ($5^{th}$and 95^{th} quantile) and the retail cut-off (25^{th} quantile).The results of this is presented in Table 6, where we use the Hill estimator to estimate the tail-end behaviour of our loan data. Although no significant Pareto-type distribution is observed in the lower tail end, it is observed at the 95^{th} quantile. Bootstrapping our equation in line with Chernozhukov et al., 2017 as a precaution is therefore warranted.

7.2 Model specification

So far, in our model specification we have relied on economic intuition to construct the vector of controls. By doing so, our model is potentially suffering from substantial “over-fitting” where the predictive power on out of sample observations is insufficient. To put the vector of controls under scrutiny we first specify a LASSO model which is cross validated by 10 folds of our dataset. By doing so we obtain a “penalty” λ which shrinks our vector of controls to minimize the mean squared error of the model.

Table 7: Additive quantile regression model, LASSO fitted borrow value

	λ = 264
	25$^{\text{th}}$ quantile
gas	0.00655***
	(.00012)
interest_rate	0.0126***
	(.020)
liquidations_exante	-0.0579***
	(.0016)
repays_exante	0.0273***
	(.00048)
utilization_rate	0.209***
	(.0017)
rate_alt	-0.00627***
	(.00039)
redeems	-0.0638***
	(.00074)
Constant	6.51***
	(.019)
	95$^{\text{th}}$ quantile
gas	0.00293***
	(.00022)
interest_rate	0.0178***
	(.0020)
liquidations_exante	-0.0754***
	(.0018)
repays_exante	0.0347***
	(.0010)
utilization_rate	-0.0754***
	(.00086)
rate_alt	-0.0126***
	(.00068)
redeems	-0.0356***
	(.0021)
Constant	12.23***
	(.043)
Observations	85649

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

As the LASSO model does not take into account latent differences stemming from sample heterogeneity, we turn to an additive quantile regression model with the same formula (equation 4). Following the approach of Koenker et al., 2011, we tune the additive model by imposing a penalty λ to prevent over-fitting. The parameter λ is the same λ as provided by the LASSO model. We repeat the process for both the "retail" and "professional" percentiles and compare the estimates with the initial model, with the results presented in Table: 7. If we compare the results with table: 3 we can see that the estimates for gas are similar for both quantiles. While the estimated effects for the interest rate is smaller in magnitude in our LASSO model for both quantiles, the interpretation of the results do not differ . The same holds for user characteristics (liquidations and repayments), as also here the estimated relationships do not differ significantly from our initial estimates. Although the direction of the estimated effect does not differ for the utilization rate, our estimates do differ significantly in magnitude. In our initial analysis we estimated a 91% increase for the 25$^{\text{th}}$ and a 70% decrease for the 95$^{\text{th}}$ quantile respectively with a 1 percentage point increase in the utilization rate. Contrary to this we find a 21% increase and a 7.5% decrease for the same quantiles in our LASSO model. The alternative interest rate in addition only returns slightly muted effects, but no significant deviation from the result of our initial analysis.

Although not an explicit aim of our research, the interest rate type of a loan is an other variable chosen by the investor (aside from the principal amount and the LTV). As the variable is inherently endogenous and determined ex-post, we do not include it in the vector of controls. Nonetheless, if stable rate borrowers significantly differ from their variable rate counterparts, other possible ex-ante user characteristics[23] outside of our model could drive (part of) the demand. We therefore investigate the distribution of the loan value for both rate types, and formally assess any difference by a Kolmogorov–Smirnov test. Importantly, we only compare within the retail and professional quantile respectively. Our hypotheses can be defined as :

- Retail investors choosing a fixed interest rate do not differ in their loan value from their variable rate counterpart.
- Professional investors choosing a fixed interest rate do not differ in their loan value from their variable rate counterpart.

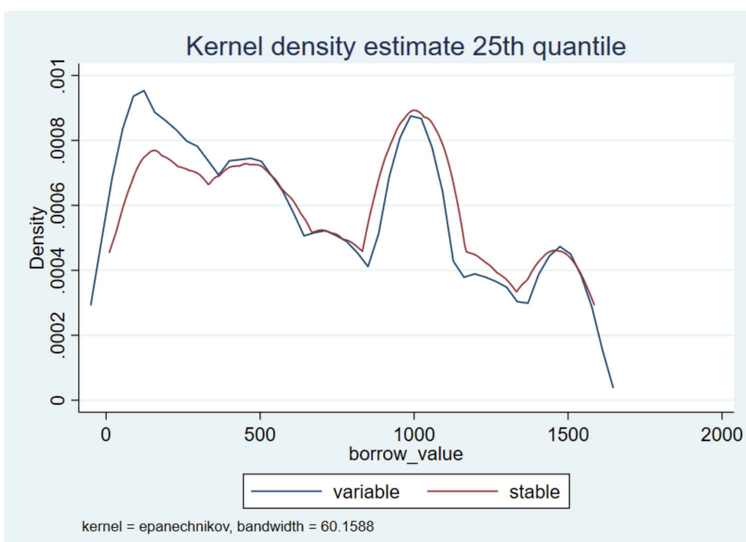

Figure 2: Estimated distribution of variable and stable/fixed rates (retail)

[23] One can possibly think of different values for risk aversion.

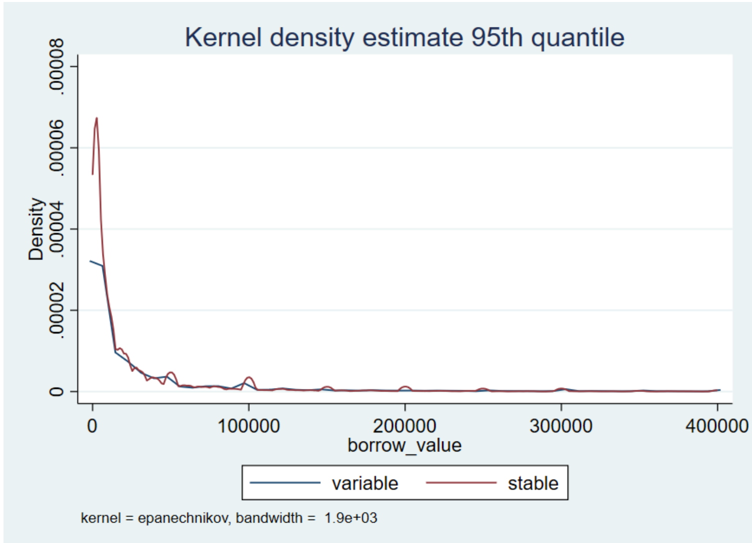

Figure 3: Estimated distribution of variable and stable/fixed rates (professional)

For both quantiles we first separately plot the estimated probability density functions (PDF) for each interest rate type (Figures : 2 and 3). Looking at the graphs we can see that although the distributions bear great resemblance, differences between interest rate type appear for both quantiles. Variable interest rate borrowers seemingly consistently opt for lower valued loans compared to stable rate borrowers, along all borrow value intervals. Formally we test any differences between the PDFs with the Kolmogorov-Smirnov test (Tables: 8 and 9). As evidenced in both tables we can not reject the hypothesis of differences in the PDFs for both quantiles. With the variable rate group having a negative and significant score (-.0745 for the 25^{th} and -.038 for the 95^{th} quantiles.), there is possible evidence of a difference in ex-ante characteristics between the two groups. As our dataset does not contain a vast vector of personal characteristics[24], a speculative explanation would lie in risk aversion. It is not unthinkable that borrowers who opt for fixed rates (and thereby "trading away" interest rate risk) in return are more likely to take out bigger loans[25]. Here the monetary risk of bigger loans is balanced out by having the interest rate risk traded away. In conclusion, we do not find a significant reason to expand our vector of controls.

Table 8: Two-sample Kolmogorov-Smirnov test
25^{th} quantile

Smaller group	D	P-value
Stable rate	0.0009	0.994
Variable Rate	-0.0745	0.000
Combined K-S	0.0745	0.000

D equals the largest observed difference between the distribution functions.

[24]By nature, cryptocurrency reveal almost no personal information, impeding this strain of research
[25]We leave a formal inquiry in this dynamic up to further research

Table 9: Two-sample Kolmogorov-Smirnov test
95 th quantile

Smaller group	D	P-value
Stable rate	0.022	0.000
Variable Rate	-0.038	0.000
Combined K-S	0.038	0.000

D equals the largest observed difference between the distribution functions.

Taking everything into consideration, the LASSO model further strengthens our hypothesis of a positive relationship between gas and loan size. In addition, past interactions on the platform also seem to be influencing the current loan sizes. Past liquidations negatively affect current loan size, while past repayments yield a positive effect. The LASSO model furthermore confirms a positive relationship for the interest rate and a negative effect for the alternative interest rate in both quantiles. Heterogeneous effects are observed for the utilization rate with a positive relationship at the 25^{th} and a negative relationship at the 95^{th} quantile. These results add to the evidence of slippage considerations forcing larger traders to decrease their loan size. In addition the positive relationship at the 25^{th} quantile is in line with our initial estimates and the signalling hypothesis.

8 Conclusion

In this paper we have found that transaction fees(gas fees) cause an increase in the median principal loan amount taken out by investors. The effect is 6.6% for retail (25^{th} quantile) and 2.8% for professional investors(95^{th} quantile) following a 10 point increase in gas fees. This result seems to not be driven by investors pushing the loan to value ratio of their loans, which remains relatively constant. Therefore, in line with our theoretical model, the subsequent rise of the principal loan amount can mainly be attributed to an increase in posted collateral. Furthermore past experiences do shape the current median loan size with a 6.3% decrease for every instance of past loan liquidation and a 2.6% increase for every instance of past repayment for retail investors. For professional investors the estimates are a 7.5% decrease and 3.2% increase respectively. Contrary to mainstream economic intuition we see a positive relation for interest rates at each quantile We estimate an increase of 1.5% and 2.2% for the 25^{th} and 95^{th} quantile respectively for each percentage point increase in the interest rate.

As we have initially hypothesized, exogenous market circumstances indeed affect the median loan size at both quantiles. Although a precise estimate is difficult to isolate, we do have sufficient evidence to conclude a positive relationship between the ex-ante utilization rate of a crypto currency and principal loan amount for the 25^{th} quantile. This result is in line with a potential "signalling" hypothesis where under-informed retail investors interpret the utilization rate of a currency as signal of trustworthiness. For the 95^{th} quantile a negative relationship is uncovered which is in line with potential slippage costs forcing larger trades to be somewhat downsized. As mentioned in the methodology section, the flexible interest rate can proxy for short term market volatility for fixed rate borrowers. We find sufficient evidence for the 25^{th} quantile to conclude a negative relationship for this alternative interest rate. Contrary to this we find no robust relationship for the 95^{th} quantile.

Our analysis and results imply significant effects of user characteristics (past experiences), ,market characteristics(e.g. utilization rate) and transaction fees (gas) on individual crypto loan size. In addition we find evidence of heterogeneity in the composition of borrowers, with retail and professional investors differing in their demanded loan sizes. Our results suggest that potential new legislation and regulation on the DeFi space would have to take these factors into consideration. It may be the case that the semi-elasticities of past experiences will become smaller in magnitude as the DeFi space matures and reaches a broader audience. In addition the semi-elasticity of transaction fees may also decrease in magnitude following the implementation of new protocols to mitigate congestion on the Ethereum network[26]. Future legislation aiming at ensuring a fair financial market should therefore take these dynamics into consideration and also incorporate the heterogeneity of borrowers in the policy making process.

[26] A prominent recent example being the transition from Proof of Work to Proof of Stake

9 Appendix

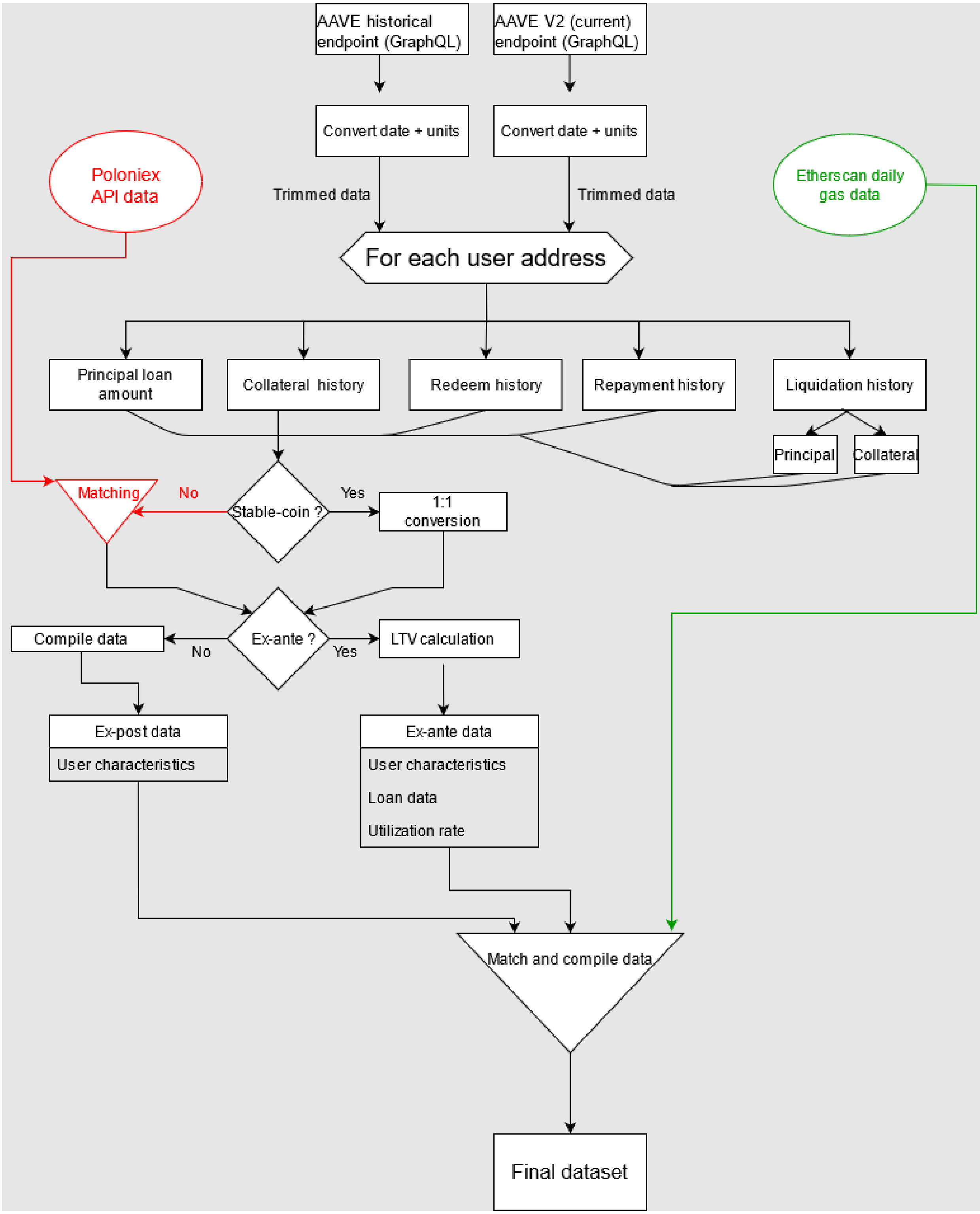

Figure 4: Short overview schematic of data collection
corresponding code is available upon request

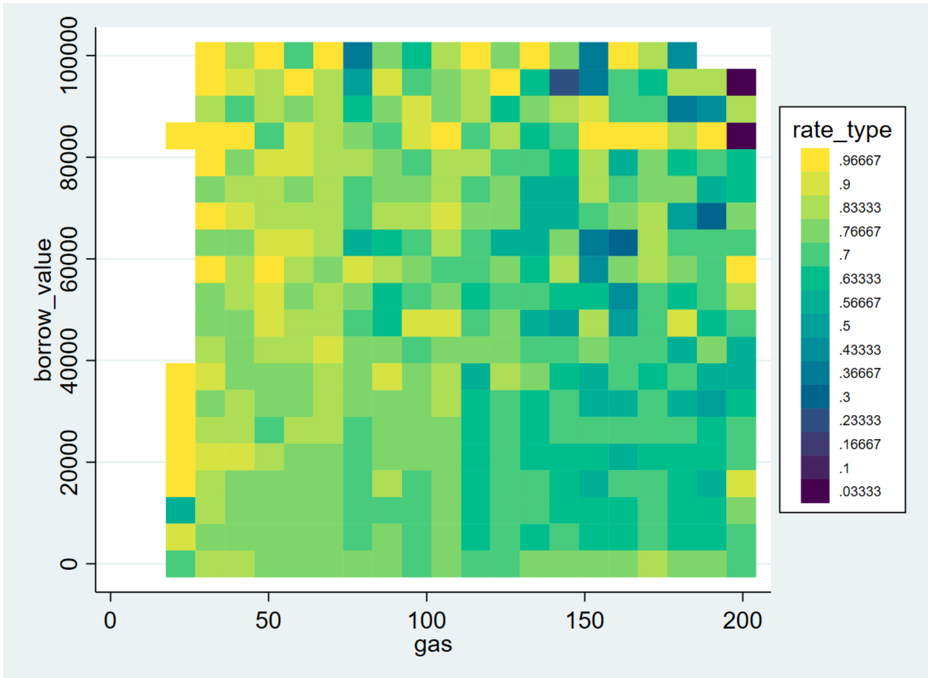

Figure 5: Heatplot of rate types
Gas value in gwei (X-axis) and Borrow value (Y-axis USD). Darker coloured cells indicate more fixed rate type loans. Here only retail trade is considered

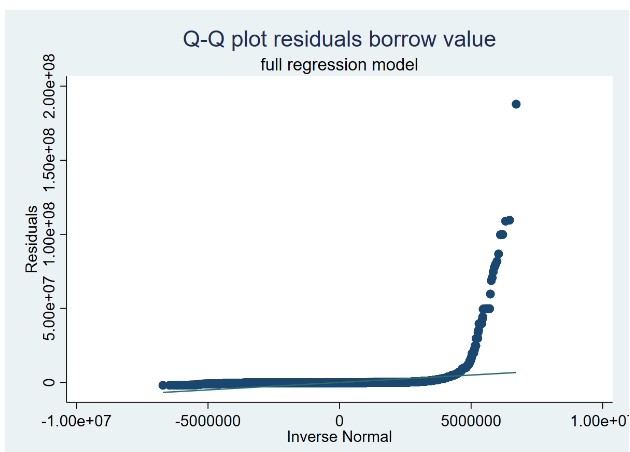

Figure 6: Q-Q plot residuals full regression model complete sample

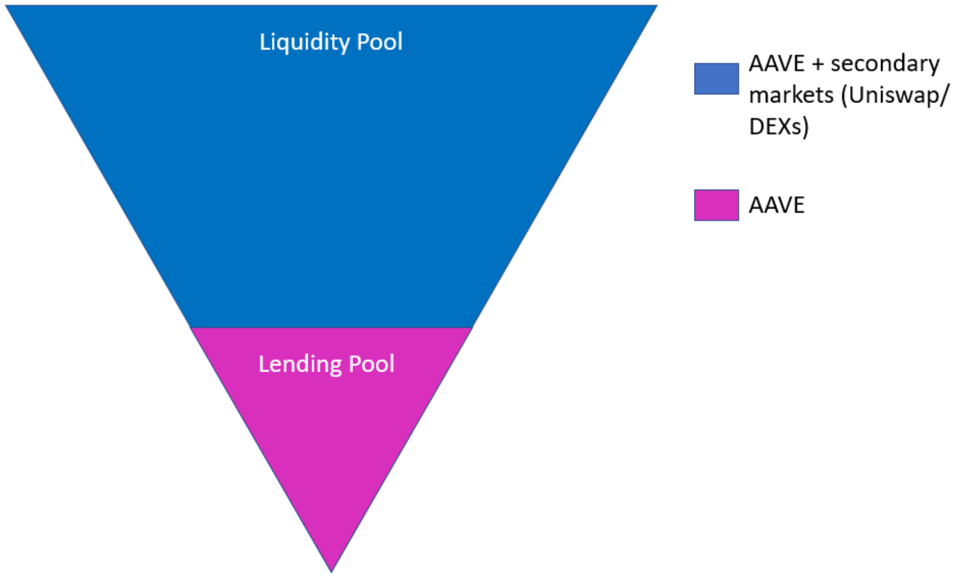

Figure 7: Distinction between lending and liquidity pools
Borrowing and other loan transactions are executed in the pink shaded area. All other transactions such as swaps are executed in the blue shaded area which is not restricted to the AAVE platform.

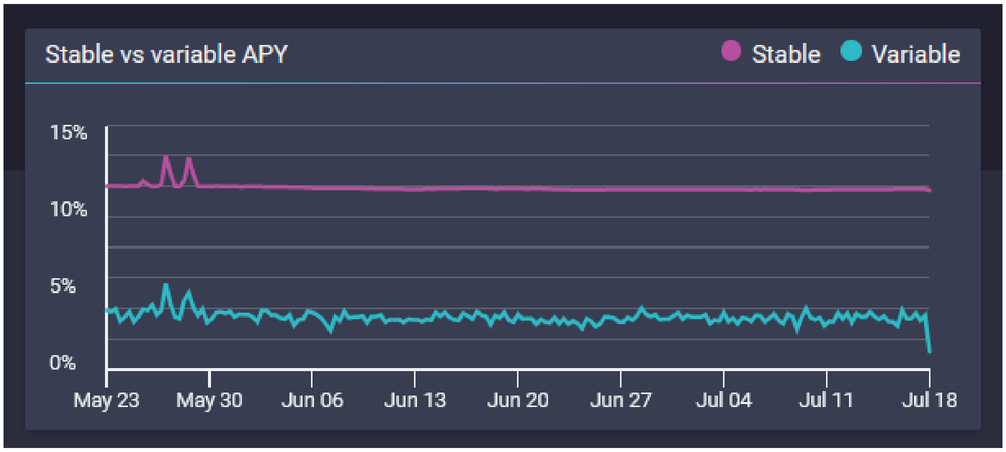

Figure 8: Comparison of stable and variable interest rates
Borrowing rates for the DAI market on the AAVE platform for the period 23-05-2021 till 12-07-2021.

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