Credit Unions and Low-Income Areas: Implications for Credit Access and Consumer Outcomes

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1 Introduction

Credit unions are unique among financial institutions for being member-owned non-profits with a board elected by the members. Credit unions offer the same portfolio of products as other financial institutions but are more focused on relationship lending than large banks. On aggregate credit unions offer lower interest rates on loans and higher deposit yields than other financial institutions. Because of their structure and mission, credit unions are widely viewed as better equipped to serve low-income and financially underserved populations compared to other financial institutions. Yet whether credit unions meaningfully improve borrower financial outcomes, particularly in disadvantaged areas, and through what mechanisms, remains an open empirical question.

This paper provides new evidence on this question and proposes a mechanism that rationalizes the findings. Using a large, nationally representative panel of consumer credit records linked to geographic identifiers for Low-Income Designated (LID) areas, I show that initiating a credit union relationship leads to substantially lower delinquency rates, conditional on

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observable borrower characteristics. I then demonstrate that the observed patterns in interest rates and delinquency can be rationalized in a simple hidden-information lifecycle model in which lenders differ in their ability to acquire soft information about borrower repayment ability.

Access to reasonably priced credit to smooth consumption is an important issue for borrowers in low-income and financially under-served areas, where liquidity shocks and income volatility are more prevalent. In these areas, the absence of mainstream financial institutions ("banking deserts") can push consumers toward high-cost alternatives such as payday loans or pawn credit, which are associated with worse financial outcomes (Zinman 2010; Bhutta, Goldin, and Homonoff 2016). Understanding whether credit unions expand access to affordable credit—and for whom—is therefore essential for designing effective financial-inclusion policy.

I focus on two major forms of unsecured credit: revolving credit via credit cards and installment credit via small-dollar personal loans. Credit cards are the most widely used form of day-to-day credit, but small-dollar loans are more prevalent among credit union customers. Controlling for borrower characteristics, there are heterogeneous impacts on borrower outcomes across loan types and borrower type at origination. All established borrowers– super-prime, prime, and non-prime– experience lower delinquency on both credit card and small dollar loans after opening a credit union account as opposed to an account with another lender. The credit limit effects are more varied. Borrowers across all three credit tiers have higher credit limits on average after opening a credit card account with a credit union. Prime and non-prime borrowers have lower credit limits on average after taking out a small dollar loan with a credit union. Super-prime borrower credit limits are not statistically different between credit union and other lenders after taking out a small dollar loan. New borrowers receive lower credit limits from credit unions but exhibit meaningfully lower delinquency after opening a credit union credit card account, but on the other hand, meaningfully higher delinquency for small-dollar loans[1].

Taken together, the results imply that credit-union credit cards benefit both established and new borrowers in both dimensions. Whereas credit-union small-dollar installment loans benefit established borrowers on the delinquency front, but are less likely to grow a borrowers credit limit. Because payday lenders—who typically offer more expensive and higher-default products—do not appear in the data, the estimated benefits for non-prime small-dollar borrowers represent a lower bound on the value of credit-union substitution away from high-cost fringe lenders.

To interpret these results, I extend a simple hidden-information lifecycle model from Chatterjee et al. (2025), to include two lenders who differ in their ability to acquire soft information about borrower type. The model shows that modest advantages in soft-information precision for credit unions can rationalize both (i) lower delinquency and (ii) product-specific credit limit differences observed in the data. Credit unions' improved ability to infer borrower type reduces default risk, enabling lower interest rates and more selective limit-setting.

This paper makes two contributions. First, it provides the first large-sample evidence on how credit-union origination affects borrower outcomes across multiple liquidity-oriented credit products and across the credit-score distribution. Prior research focuses primarily on auto loans, mortgages, or local competition in consumer-credit markets (Shahidinejad, Stillerman, and vanRijn (2025); vanRijn, Zeng, and Hellman (2021); Shahidinejad (2025); Gissler, Yu, and Ramcharan (2019); Chen (2025)). I show that credit-union impacts vary systematically by product type and borrower risk, with implications for financial inclusion and inequality in LID communities. Second, I contribute to the literature on asymmetric information by using a unique institutional setting—credit unions versus other lenders—to test predictions of a soft-information screening channel in consumer lending.

[1]At this stage, I am not confident in this result given my matching technique, see discussion and next steps

2 Background and regulatory environment

Credit unions have a small but growing market share for consumer loans. In 2023, 24% of consumers in LID areas have a credit union account across all loan types, 19% have credit union credit card accounts and 58% have small-dollar loans with credit unions (Table 1).

Credit unions are governed by the National Credit Union Administration (NCUA). Credit unions generally have restrictions on membership and loan-portfolios. For instance, credit unions are subject to caps on interest rates and small-business lending. A benefit shared by all credit unions is tax-exempt status which allows them to operate at lower profit margins than traditional banks. This in conjunction with the credit union mission of maximizing borrower welfare (and NCUA imposed interest rate caps) leads to lower aggregate interest rates on loans compared to other financial institutions.

The NCUA selects Low Income Designated (LID) areas as geographies with at least half the population earning 80% less than the national median household income or at least half the population earning 80% less than the average of all wage earners in the U.S. Credit unions located in LID areas can easily obtain Low-Income Designated Credit Union (LIDCU) status. The NCUA's intended purpose for LIDCUs is to expand credit and banking services to underserved populations. The LIDCU designation lifts regulations allowing the credit union to function more similarly to a bank. Credit unions may opt-in to LIDCU for this purpose or they may opt-in to receive special benefits such as fewer regulations on business lending.

3 Data

I retrieve the list of low-income designated (LID) areas as of 2023 from the NCUA. Table 1 compares low-income-designated areas to the rest of the country in 2023. Information is from the Equifax Analytic Dataset unless otherwise noted. By construction, LID areas have lower income than non-LID areas. Fewer people in LID areas have credit reports. The second panel from the top illustrates that LID areas do not vary significantly from non-LID areas in overall credit union usage. The third panel from the top shows that LID areas are slightly more likely to have non-prime borrowers with credit union credit card accounts. The bottom panel shows that there is not a significant difference in small dollar loan usage.

The primary dataset used is the Equifax Analytic Dataset[2]. This dataset has useful borrower-outcome variables such as delinquency rates, credit limits, and credit scores[3]. I also use variable for *estimated* income, which is treated with caution since it is not true consumer income. The data covers a random and anonymous 10% panel of credit reports in the U.S. The panel is at the tradeline-consumer-month level from 2005 to present day. I subsample this panel for only zip-codes classified as LID areas. I take the full subsample for small-dollar loans and credit union originated credit cards. I take a further 10% subsample for the credit card accounts originated by other lenders to balance sample size and computational time. I flag accounts as either credit union or "other" lender. The other lender category for credit cards includes National Credit Card Companies, Banks, Community Banks and Savings and Loan Associations. The vast majority of other lenders in the credit card sample are banks or credit card companies. For small dollar loans, the other category includes banks (34%), national credit card companies (< 1%), and savings and loan associations (< 1%). New borrowers in the system are identified by origination credit scores equal to 4 and no prior credit history. For the main empirical analysis I take a balanced panel at the individual-loan origination level.[4]

Small dollar loans are selected from the "other installment category" and chosen if the loan amount is under $2,000 and the term length is less than or equal to 24 months. I drop observations with account-type or narrative code indicating that the loan will be used for auto-purchases or home improvement. The above criteria are meant to filter the loans to

[2]The Equifax Analytic Dataset set is a loan level data set derived from a 10% random, anonymous sample of US consumers tracked in the Equifax core consumer credit database beginning in 2005.

[3]This paper uses the VantageScore 3.0, which is calculated at time of archive date. It is a credit risk score introduced by VantageScore Solutions LLC in 2013 that predicts the likelihood that a borrower will become 90 days or more delinquent on a credit account.

[4]In some cases, I needed to interpolate variables of interest to get monthly observations.

those most closely resembling credit-builder loans and payday alternative loans[5], which are popular credit union products for improving consumer outcomes.

	Not LID		LID	
	Mean	SD	Mean	SD
Homeowners (ACS)	64.87	10.23	62.69	11.34
Have mortgage (ACS)	39.53	7.00	34.08	6.33
Homeowners, no mortgage (ACS)	24.90	6.10	27.99	8.59
Age (ACS)	52.36	2.64	52.05	3.71
Household Income (ACS)	$118,639.79	$27,678.98	$85,730.33	$12,819.45
Pop. w. credit report (%)	76.51	32.05	72.38	32.07
Consumers with credit union accounts				
All (%)	23.91	8.35	24.12	9.02
New borrowers (%)	11.39	17.66	11.34	18.39
Superprime (%)	20.70	9.96	20.43	11.26
Prime (%)	24.24	10.54	24.09	11.56
Nonprime (%)	26.23	11.00	25.67	11.28
Consumers with credit union credit card accounts				
All	16.89	8.77	18.76	9.48
New	11.32	18.90	12.21	20.96
Superprime	14.03	9.85	14.26	10.96
Prime	15.29	10.97	16.01	12.11
Nonprime	20.92	11.87	23.26	12.53
Consumers with credit union small dollar loans				
All (%)	58.41	26.87	58.22	26.20
New borrowers (%)	38.57	42.57	40.74	42.04
Superprime (%)	66.36	43.85	67.53	43.50
Prime (%)	59.16	34.50	59.18	34.61
Nonprime (%)	54.98	29.94	55.35	28.93

Table 1: Summary Statistics in 2023

4 Empirical Strategy

Credit unions originate both credit card accounts and small-dollar loans to two types of borrowers: established consumers with existing credit histories and new entrants who have no prior records in the system. I analyze these groups separately because new borrowers

[5]Secured loans are more likely credit-builder loans and unsecured loans are more likely to be payday alternative loans.

cannot be matched to historical credit behavior.

To estimate the causal impact of credit-union origination on borrower outcomes, I focus on newly originated credit cards and small-dollar loans. These two loan types are chosen since they are typically available to a wide range of borrowers and are directly beneficial for consumption smoothing. The main concern with simply comparing credit union loan originations to originations by other lenders is bias from selection. To help control for this, I match borrowers on pre-treatment and origination characteristics to find a control group that is most similar to the set of credit union borrowers. For each new origination, I construct matched groups based on borrower characteristics[6] and the origination date of the loan. I retain only matched sets that contain at least one credit-union origination and at least one origination from a non–credit-union lender. This ensures that each matched group includes a treatment observation (credit-union origination) and a comparable control observation with similar pre-origination characteristics.

Using this matched sample, I then estimate a difference-in-differences model to identify the effect of credit-union origination on subsequent borrower outcomes, including delinquency and credit limits.

4.1 Matching

The match is done at the consumer-origination date level. For established borrowers, I match on quarter-year of origination and average vantage score in the 4-quarters prior to origination. Matching on historical vantage score allows me to control for the trajectory of the borrower profile. For brand-new borrowers I match on quarter-year of loan origination, region, and consumer age in 6-10 year buckets.[7]

Table 2 shows the summary statistics of matched and unmatched borrowers. Note that each observation is at the consumer-origination level, so a consumer can appear multiple

[6] Borrower characteristics are measured at the consumer × origination-date level.

[7] The region is given by the first 3 digits of the consumer zip code. The first age bucket includes ages 18-24. The other buckets are in 10-year increments.

times in the matched sample. The top panel contains information from established borrower matches and the bottom panel contains information from the new borrower matches. To be included in the established borrower panel, the consumer must be in the sample for the 12 months prior to the new origination. After this restriction, I am left with 486,951 matched observations. I lose 858,464 observations that do not match with another observation and I lose 210,311 observations that only match with consumer-originations from the same lender-type. Matched consumer-origination portfolios are fairly similar to matched portfolios with no lender variation. Though notably, the dropped observations are more likely to be a credit card than a small dollar loan. There are clear differences between matched borrower vantage scores and never matched borrower vantage scores: unmatched borrowers have lower estimated incomes, lower credit limits, younger credit age, slightly younger consumer, have fewer small dollar loans and more credit card accounts.

New borrowers with no matches have lower credit limits on average and are older. Otherwise, the matched borrowers in the final sample are similar on average to the observations dropped from the sample. Fewer observations are dropped from having no matches for the new borrows compared to the established borrowers. This is because matching on trajectory of vantage score is more restrictive than matching on age and region.

4.2 Difference-in-difference model

I estimate the impact of credit-union loan origination on borrower credit outcomes using the following difference-in-differences specification:

$$Y_{it} = \beta \mathrm{CU}_i \times \mathrm{Post}_t + \gamma \mathrm{CU}_i + \delta \mathrm{Post}_t + \mathbf{X}'_{it}\theta + \alpha_{g(i)} + \varepsilon_{it}$$

Where Y_{it} is either the borrower's credit limit or delinquency rate at time t. Delinquency is measured as percent of accounts 30 or more days past due. Since the treatment varies by date, $t \in [-12, 24]$[8] where $t = 0$ at loan origination (treatment). Post_t is a dummy equal to

[8]For new borrowers $t \in [0, 24]$ since the borrowers are unobserved prior to first loan origination.

	In sample		Dropped from sample			
	Matched		No matches		No lender variation	
	mean	sd	mean	sd	mean	sd
Established borrowers						
Average vantage score after origination	683.73	85.18	644.38	81.59	688.79	86.09
Estimated income ($1000s)	38.29	15.32	35.78	14.67	39.30	15.94
Credit limit ($)	3182.53	4215.34	2662.21	3858.15	3625.31	4284.23
Year of origination	2017.33	5.12	2017.10	5.44	2016.77	5.47
Age of oldest account (bucket)	3.03	1.08	2.81	1.08	3.02	1.05
Current age bin	4.04	1.63	3.62	1.53	3.92	1.60
Fraction with mortgage	0.32	0.47	0.31	0.46	0.36	0.48
Credit union (%)	41.17	49.21	32.79	46.95	23.39	42.33
Other lender (%)	59.11	49.16	67.73	46.75	76.76	42.23
Small dollar loan (%)	42.15	49.38	31.86	46.59	28.40	45.09
Credit card account (%)	58.08	49.34	68.46	46.47	71.77	45.01
Observations	486951		858464		210311	
New borrowers						
Average vantage score after origination	643.90	42.65	636.61	42.09	636.91	48.19
Esimated income ($1000s)	18.16	0.80	18.03	0.35	18.12	1.08
Credit Limit ($)	762.01	908.72	648.34	423.57	861.07	1100.48
Year of origination	2018.04	5.36	2018.48	5.32	2017.26	5.86
Current age bin	1.95	1.40	2.60	1.72	1.86	1.39
Fraction with mortgage	0.00	0.00	0.00	0.00	0.00	0.00
Credit union (%)	43.59	49.59	45.65	49.81	43.52	49.58
Other lender (%)	56.53	49.57	54.48	49.80	56.58	49.57
Small dollar loan (%)	34.22	47.45	41.82	49.33	42.79	49.48
Credit card account (%)	66.24	47.29	58.73	49.23	57.57	49.42
Observations	472433		8890		318684	

Table 2: Characteristics of matched vs unmatched consumer-originations

one if $t > 0$. CU_i is a dummy equal to one if the consumer originated a credit union loan or credit card account and zero if the loan or credit card was originated with a non-credit union lender. $\mathbf{X}'_{it}$ is a vector of borrower and loan level characteristics: estimated income, credit limit (when Y_{it} =delinquency rate), delinquency rate (when Y_{it} =credit limit), number of credit card and small dollar accounts, and loan-term fixed effects. Match-level fixed effects, $\alpha_{g(i)}$ are absorbed and standard errors are clustered at this same level.

I estimate the model for borrowers with either loan type (Table 4) by credit tier: super-prime, prime, and non-prime[9]. I do not separate the effects by loan type in the main analysis since the object of interest is general consumption smoothing debt. Credit card originations and small-dollar loans are analyzed separately in the Appendix (Table 8 and Table 9, respectively). It is important to estimate the empirical model separately for each credit tier since the outcomes are heterogeneous across tiers. I drop credit card observations from t=0 to t=21 in order to eliminate introductory offer effects[10]. Table 10 in the Appendix shows that delinquency results are sensitive to this assumption. When I include the introductory offer period, the non-credit union accounts perform better along the delinquency margin, likely due to balance transfers to 0% APR accounts which are more common among non-credit union accounts. I keep the sample adjustment since this paper aims to quantify longer-term impacts of banking with credit unions.

4.2.1 Established borrower outcomes

	New Borrowers	Superprime	Prime	Nonprime
Either loan				
Delinquency rate	0%	0.016%	1.250%	9.778%
Credit limit	\$792	\$11821	\$7789	\$3328
Just small dollar				
Delinquency rate	0%	0%	0.004%	0.209%
Credit limit	\$712	\$2701	\$1766	\$1317
Just credit cards				
Delinquency rate	0%	0.010%	1.020%	10.847%
Credit limit	\$802	\$11619	\$8232	\$4238

Note: For new borrowers the baseline consists of t=0 values. For existing borrowers, the baseline consists of t=-12 to t=0.

Table 3: Baseline statistics for the matched samples

Table 3 shows the average delinquencies and credit limits in the pre-period for borrowers that open non-credit union accounts. The credit limit is positive even for new borrowers

[9]Super-prime includes vantage scores over 780, prime includes vantage scores between 660 and 780, and non-prime includes vantage scores less than 660

[10]Most credit card introductory offers for 0% APR and balance transfers occur within the first 21 months of account origination

because $t = 0$ includes the new origination. New borrowers have no delinquency since the new origination is their first account. New borrowers have an average credit limit of \$792 for new accounts accounting for either loan type. The average credit limit on first credit card is slightly higher than the small dollar loan size. Established borrowers are characterized by credit tier at origination and the delinquency rates and credit limits follow intuitive patterns. Delinquency rates are lowest for super-prime borrowers and highest for non-prime borrowers. Credit limits are highest for super-prime borrowers and lowest for non-prime borrowers. Super-prime borrowers have near zero delinquency rates and an average credit limit of \$11,821. Prime borrowers have an average baseline delinquency of 1.50% and average credit limit of \$7,789 across either loan type. Non-prime borrowers have an average baseline delinquency of 9.778% and average credit limit of \$3,328. The average delinquency rate is lower for small dollar loans than credit cards, which is understandable given that the small dollar loans are (1) lower credit limit and (2) have a known, set amount to repay at the end of the term. The average credit limit for small dollar loans is lower mechanically since those observations are capped at \$2,000[11].

Table 4 shows the impact of opening either a credit card or a small-dollar loan with a credit union. The main coefficient of interest is interaction term *Credit union flag* × *Post period*, which captures the difference-in-differences treatment effect. The left panel shows the impact of credit union lending on borrower delinquency. Opening a credit union account as opposed to receiving a loan from another lender decreases delinquency for super-prime borrowers by 0.0957 percentage points. This effect is statistically significant but economically negligible given the baseline delinquency for super-prime borrowers is nearly zero: 0.016% (see Table 3). The effect is larger for prime and non-prime borrowers. Opening a credit union account decreases prime delinquency by 1.663 percentage points overtime (relative to 1.250% delinquency rate baseline) and decreases non-prime delinquency by 4.218% overtime (relative to 9.778% baseline).

[11] These baselines also indicate that in the pre-period, there are few borrowers with credit card limits over \$2,000 that also take out small dollar loans

The right panel of Table 4 shows that opening a credit union account increases credit limit by \$1063 for super-prime borrowers. Prime and non-prime borrowers have insignificant treatment effects. A \$1,000 increase in estimated income is associated with a \$146 increase in credit limits for super-prime borrowers, a \$195 increase for prime borrowers, and a \$165 increase for non-prime borrowers. Relative to their respective baseline credit limits (\$11,821 for super-prime, \$7,789 for prime, and \$3,328 for non-prime borrowers), these represent increases of approximately 1.2%, 2.5%, and 5%. This pattern indicates that income is more important for borrowers with lower credit scores: non-prime borrowers receive proportionally larger credit-limit increases in response to income differences, while super-prime borrowers' credit limits respond the least to income.

	(1) Superprime	(2) Prime	(3) Nonprime	(4) Superprime	(5) Prime	(6) Nonprime
	Delinquency rate (%)			Credit Limit ($1000s)		
Credit limit ($1000s)	-0.00310***	-0.0961***	-0.227***			
	(0.000779)	(0.00383)	(0.0137)			
Estimated income ($1000s)	-0.000620	-0.00940***	-0.176***	0.146***	0.195***	0.165***
	(0.000405)	(0.00173)	(0.00739)	(0.00268)	(0.00238)	(0.00329)
Credit union flag	-0.0141	0.250***	0.370*	0.542***	-0.0928	-0.197***
	(0.0141)	(0.0780)	(0.209)	(0.0979)	(0.0565)	(0.0397)
Post period	0.360***	2.962***	8.343***	-0.196***	1.379***	0.314***
	(0.0236)	(0.0835)	(0.180)	(0.0605)	(0.0419)	(0.0304)
Credit union flag	-0.0957*	-1.663***	-4.218***	1.063***	-0.0148	-0.0203
× Post period	(0.0581)	(0.113)	(0.218)	(0.0954)	(0.0506)	(0.0338)
Number of accounts	0.0397***	0.419***	-0.986***	6.835***	4.378***	1.840***
	(0.00890)	(0.0257)	(0.0543)	(0.0440)	(0.0350)	(0.0218)
Delinquency (%)				-0.0297***	-0.0322***	-0.00617***
				(0.00708)	(0.00111)	(0.000324)
_cons	0.0131	1.700***	24.06***	-6.752***	-7.914***	-5.033***
	(0.0256)	(0.0889)	(0.332)	(0.164)	(0.129)	(0.133)
N	1042239	1436203	1523017	1042239	1436203	1523017

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Credit union impact on established borrowers: either loan type

4.3 New borrower outcomes

Table 5 reports the effect of opening a credit card or small-dollar loan on new borrower credit outcomes. As before, the main coefficient of interest is the interaction term Credit union flag $\times$ Post period, which captures the difference-in-differences treatment effect. Periods $t = 1$ to $t = 21$ are dropped for borrowers opening credit card accounts to control for introductory offers. Since new borrowers do not have existing credit history, dropping these months has a smaller effect (Table 11) than the same restriction for established borrowers, indicating that balance transfers are an important factor into established borrower delinquency.

Columns 1 and 2 show the aggregate effect of opening either type of account: opening a credit union account reduces borrower delinquency by 7.221 percentage points and lowers a borrower's credit limit by \$652 relative to a non-credit union account. A larger portion of matched new borrowers open credit card accounts (66,455 borrowers) relative to small dollar loans (3,208 borrowers). Opening a small dollar account leads to a 6.527 percentage point higher delinquency rate and insignificant effects on credit limits. Opening a credit card account with a credit union results in 7.448 percentage points lower delinquency relative to a credit card account from another lender and \$715 lower credit limit.

The above patterns for new borrowers may be explained by the average age of account holders at origination. Credit unions have younger borrowers on average compared to other lenders for credit card accounts, which is likely due to lending to college students. For small dollar loans, credit unions lend to older borrowers on average compared to other lenders. College students without credit are likely different types on average than older borrowers without credit.

4.4 Empirical Discussion

The difference-in-differences results indicate that credit unions vary their credit provision across borrower types in ways that meaningfully affect financial outcomes. For established borrowers, opening a credit union account leads to lower delinquency rates for both credit

	Either type		Small Dollar		Credit Card	
	(1)	(2)	(3)	(4)	(5)	(6)
	DQ (%)	CL ($1000s)	DQ (%)	CL ($1000s)	DQ (%)	CL ($1000s)
high_credit	-1.948***		-5.838***		-1.803***	
	(0.140)		(1.295)		(0.150)	
pim_score	-0.828*	0.485***	-5.457***	-0.0140	-0.704	0.522***
	(0.502)	(0.150)	(0.840)	(0.0198)	(0.712)	(0.181)
FC_flag	1.035***	-0.0628***	1.213	0.0312	0.888***	-0.133***
	(0.232)	(0.0230)	(0.821)	(0.0317)	(0.243)	(0.0278)
FC_flag $\times$ post2	-7.221***	-0.652***	6.527***	0.0849	-7.448***	-0.715***
	(0.575)	(0.0366)	(1.820)	(0.0553)	(0.633)	(0.0439)
1.post2	18.92***	1.087***	10.17***	0.314***	18.23***	1.205***
	(0.498)	(0.0345)	(1.333)	(0.0577)	(0.562)	(0.0425)
numberaccounts_ts	1.869***	1.902***	1.448	0.791***	1.619***	1.989***
	(0.356)	(0.0521)	(1.561)	(0.0743)	(0.389)	(0.0600)
dq30p		-0.0110***		-0.00471***		-0.0130***
		(0.000413)		(0.000560)		(0.000516)
_cons	14.53	-10.00***	93.06***	0.338	12.22	-10.78***
	(9.181)	(2.730)	(15.62)	(0.589)	(13.07)	(3.323)
N	101412	101412	3208	3208	66455	66455

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: New borrowers credit outcomes

cards and small dollar loans. It also results in higher credit limits on credit cards but lower limits on small-dollar installment loans relative to other lenders. In contrast, new borrowers seem to have lower delinquency rates after opening a credit union credit card account and higher delinquency rates after taking out a small dollar loan. This is likely due to incomplete matching and selection.

Despite these heterogeneous credit-limit responses, originating a loan with a credit union is generally associated with improved repayment outcomes. Delinquency rates decline significantly relative to baseline for prime and non-prime borrowers, and new borrowers experience markedly lower credit card delinquency rates.

Taken together, these findings suggest that credit-union expansion in low-income areas is likely to be net-positive for borrower financial health. Importantly, the estimated benefits of credit-union small-dollar lending should be considered a lower bound, as payday lenders—who typically produce substantially worse borrower outcomes—are not included in this dataset.[12]

At the same time, the distribution of benefits is uneven. Super-prime and prime borrowers gain the most in terms of both expanded access to revolving credit and meaningful reductions in delinquency, whereas non-prime borrowers benefit primarily from access to safer small-dollar installment loans. This heterogeneity implies that credit-union growth could unintentionally widen within-neighborhood financial disparities in LID areas. Policies or institutional strategies that emphasize small-dollar lending and targeted underwriting for non-prime borrowers may help ensure that the welfare gains from credit-union expansion are more broadly shared.

5 Model

Borrowing from credit unions results in lower delinquency rates and higher credit limits compared to other lenders. Aggregate data also show that credit unions charge lower interest rates, on average, than other lenders. One possible mechanism consistent with these facts is screening on partially observable effort: because credit unions disproportionately operate through local branches and repeated in person interactions, they observe signals correlate with borrowers' unobserved effort level. In contrast, national banks and credit card companies rely primarily on automated underwriting and cannot observe borrower effort at all.

To formalize this mechanism, I introduce a stylized life-cycle model with hidden borrower types, adapted from Chatterjee et al. (2025), but with two types of lenders that differ in their information sets. The key distinction is that O-lenders (Other lenders) cannot observe

[12] This assumption is supported by a large empirical literature documenting negative borrower outcomes associated with payday loans.

borrower effort; pricing is based only on predicted repayment using credit history whereas CU-lenders (Credit Unions) obtain an informational signal about borrower effort (soft information) and can condition prices on realized effort. Importantly, the CU-lender does not directly incorporate the observed effort into its type-updating. This makes the informational advantage of the credit union purely contemporaneous: the observed soft information on borrower effort is used to price loans within period but does not enter the long-run process[13]. Having two lenders with differing ability to incorporate effort into pricing isolates the informational advantage channel. In the simplified model, borrowers are exogenously assigned to a lender and both lenders profit maximize given their information [14].

5.1 Environment

5.1.1 Borrower problem

Time is discrete, indexed by $t = 1, ..., T$. A unit mass of risk-averse borrowers lives for T periods. Each borrower is characterized by private type $\tau \in \{\tau_H, \tau_L\}$, an observed credit state $\omega_t = (s_t, y_t, a_{jt})$, and an exogenous lender assignment $l \in \{O, CU\}$ fixed for all t. The observable credit state contains the type assessment s_t, income y_t, and asset holdings a_t. Private type τ evolves as a Markov Process: $\tau_{t+1} \sim Q_\tau(\cdot|\tau_t)$ drawn independently across individuals. This captures life-cycle changes in type, consistent with Chatterjee et al. (2025).

CU borrowers are given effort-specific price schedule $q^{CU}(a_{t+1}, e_t, \omega_t)$. Since exerting high effort increases the probability of repayment, the CU offers a higher price schedule (or lower interest rate) to borrowers who exert high effort. Other borrowers are given belief-based price schedule $q^O(a_{t+1}, \omega_t)$ computed from the expected repayment probability integrated over equilibrium effort choice. Because prices differ by lender, the same borrower may optimally choose different effort, borrowing, and default when assigned to CU-lender versus

[13] If the CU-lender did incorporate the observed effort into type-updating, then there would be dynamic separation over time with low-types predominately banking with O-lenders. This would be opposite from what is shown by the data.

[14] section 6 discusses adding choice of lender to the discrete choice borrower problem and making the lender problem more realistic.

O-lender.

The borrower has three sequential discrete choices: effort, default, and asset choice conditional on repayment. Let $\omega_t = (s_t, y_t, a_t, n)$ denote the observable credit state, $\tau_t \in \{\tau_H, \tau_L\}$ the private type, and $\ell \in \{O, CU\}$ the exogenous lender assignment.

Stage 1: Effort choice. At the beginning of period t, the borrower chooses effort $e_t \in \{e_H, e_L\}$, which affects income risk, default probabilities, and (for CU borrowers) the interest rate schedule. Effort incurs cost κ_e and is subject to a Type I extreme value shock α_e Define the effort-stage value function:

$$V_t^e(\omega_t, \tau_t) = \mathbb{E}_{\alpha_e}\left[\max_{e_t \in \{e_H=1, e_L=0\}} \left\{-\kappa_e e_t + V_t^d(\omega_t, \tau_t) + \alpha_e\right\}\right].$$

which generate the type-specific decision rule $\sigma_t^e(\omega, \tau)$.

Stage 2: Default decision. If the borrower has debt, he chooses whether to default, $d_t \in \{0, 1\}$, where $d_t = 1$ denotes default, subject to a Type I extreme value shock α_d. If the borrower has positive assets, there is no option to default and the borrower moves to the next stage.

If the borrower defaults ($d_t = 1$), next-period assets are reset to zero: $a_{t+1} = 0$, and consumption is $c_t^d = y_t + a_t$.

If the borrower repays ($d_t = 0$), he proceeds to Stage 3 and chooses a_{t+1}.

Define the default-stage value:

$$V_t^d(\omega_t, \tau_t) = \mathbb{E}_{\alpha_d}\left[\max\left\{W_t^d(\omega_t, \tau_t),\ W_t^r(\omega_t, \tau_t) + \alpha_{d,t}(0)\right\}\right],$$

where the default value is

$$W_t^d(\omega_t, \tau_t) = u(c_t^d) - \kappa_d + \beta\, \mathbb{E}[\, V_{t+1}(\omega_{t+1}, \tau_{t+1})\,],$$

and the repayment continuation value is

$$W_t^r(\omega_t, \tau_t, e_t) = V_t^a(\omega_t, \tau_t, e_t).$$

This decision problem generate the effort and type-specific decision rule $\sigma_t^{(d,e)}(\omega, \tau)$.

Stage 3: Asset choice. If the borrower repays, he chooses next-period assets a_{t+1}, facing lender-specific prices

$$q^\ell(a_{t+1}, I_\ell(e_t), \omega_t), \quad I_O(e_t) = \emptyset,\ I_{CU}(e_t) = e_t.$$

Consumption is

$$c_t = y_t + a_t - a_{t+1}\, q^\ell(a_{t+1}, I_\ell(e_t), \omega_t).$$

Define the asset-choice value:

$$V_t^a(\omega_t, \tau_t, e_t) = \mathbb{E}_{\alpha_{a,t}}\left[\max_{a_{t+1}} \{u(c_t) + \beta\, \mathbb{E}[\, V_{t+1}(\omega_{t+1}, \tau_{t+1})\,] + \alpha_{a,t}(a_{t+1})\}\right].$$

If the borrower defaults, then $a_{t+1} = 0$. The effort and type specific decision rule is given by $\sigma_t^{(a',e)}(\omega, \tau)$.

Last period. At age N, or $t = T$, the borrower does not choice effort nor next period assets, so the only decision is whether to default.

$$V_T(\omega_T, \tau_T) = \mathbb{E}_{\alpha_d}\left[\max_{d \in \{0,1\}} \left\{U(y(\omega) - \kappa_d) + \alpha_d, U(c_N^R(\omega)) + \alpha_d\right\}\right]$$

where $c_N^R(\omega)$ is the last period consumption under repayment. Note that if the borrower chooses to default, he consumes all his income less the cost of default κ_d.

State transitions. After choices are made:

$$
\begin{aligned}
&y_{t+1} \sim Q_y^e(\cdot \mid y_t, e_t), \\
&\tau_{t+1} \sim Q_\tau(\cdot \mid \tau_t), \\
&s_{t+1} = \Pr(\tau_{t+1} = \tau_H \mid a_{t+1}, d_t, y_{t+1}, \omega_t),
\end{aligned}
$$

where the type assessment s_{t+1} is updated using only observable repayment behavior and income (effort does not enter type updating). The type update is therefore exactly the same as in Chatterjee et al. (2025): the probability of being high-type is given by

$$
\Pr(\tau_{t+1} = \tau_H \mid a_{t+1}, d_t, y_{t+1}, \omega_t) = \sum_{\tau} Q_\tau(H; \tau_t) \frac{\upsilon_t^{(a_{t+1},d)}(y_{t+1}, \tau_t; \omega_t)}{\sum_{\tilde{\tau}} \upsilon_t^{(a_{t+1},d)}(y_{t+1}, \tilde{\tau}_t; \omega_t)}
$$

where

$$
\upsilon_t^{(a_{t+1},d)}(y_{t+1}, \tau_t; \omega) = \mathbb{P}(y_{t+1}, \tau_t | a_{t+1}, d_t, \omega_t)
$$

The next-period observable state is

$$
\omega_{t+1} = (a_{t+1}, y_{t+1}, s_{t+1}, n).
$$

Model timing summary.

0. Borrowers are exogenously assigned to either a CU-lender or O-lender

1. Borrowers begin the lifecycle with unobservable type τ_t and observable state $\omega_t = (a_t, y_t, s_t)$

2. Borrowers choose e_t, taking into account that CU-lenders will condition debt prices on effort (but not type-updating)

3. Borrowers choose whether to default $d_t = 1$ on debt a_t

4. If $d_t = 0$, borrowers make an asset choice a_{t+1} at price $q^l(a_{t+1}, I_l(e_t), \omega_t)$. Otherwise,

$a_{t+1} = 0$.

5. Next-period income y_{n+1} is drawn from Q_y^e and unobservable type is drawn from Q_τ

6. Type assessments are updated according to Bayes' Law: $s_{t+1} = \mathbb{P}(\tau_{t+1} = H | a_{t+1}, d_t, y_{t+1}, \omega_t)$

7. Borrowers leave period n in with observable state $\omega_{t+1} = (a_{t+1}, y_{t+1}, s_{t+1})$

5.1.2 Lender O (Other lender) prices

The O-lender cannot observe borrower effort and therefore cannot condition prices on e_t. The lender offers a contract with next-period asset position a_{t+1} (negative for debt) at price q^O.

Given the current observables ω_t and borrower choice of a_{t+1}, the O-lender sets

$$q_t^O \equiv q_t^{a_{t+1}}(\omega_t) = \frac{1}{1+r}\mathbb{P}(d_{t+1} = 0 | a_{t+1}, \omega_t)$$

where $\mathbb{P}(d_{t+1} = 0 | a_{t+1}, \omega_t)$ is the probability of repayment in the next period. Thus,

$$q_n^O(a_{t+1}, \omega_t) = \frac{1}{1+r}\sum_{\tau,\tau',y'} Q_\tau(\tau_{t+1};\tau_t)\upsilon_n^{(a_{t+1},d_t)}(y_{t+1},\tau_t;\omega_t)(1-\bar{\sigma}_{t+1}^{(0,1)}(a_{t+1}, y_{t+1}, \Upsilon_t^{(0,a_{t+1})}(y_{t+1};\omega_t), \tau_{t+1}))$$

where:

- $Q_\tau(\tau_{t+1};\tau_t)$ is the Markov transition for private type,
- $\upsilon_n^{(a_{t+1},d_t)}(y_{t+1},\tau_t;\omega_t)$ is the joint probability of drawing next period income and private type given a_{t+1}, d_t, and ω_t under the equilibrium borrower decision rules,
- $\Upsilon_t^{(0,a_{t+1})}(y_{t+1};\omega_t)$ is the weighted likelihood of each type today accounting for the transition probability tomorrow,

- $\bar{\sigma}^{(0,1)}_{t+1}(a_{t+1}, y_{t+1}, \Upsilon^{(0,a_{t+1})}_t(y_{t+1};\omega_t), \tau_{t+1})$ is the equilibrium default decision rule at $t+1$, i.e. the probability of defaulting next period for state $(a_{t+1}, y_{t+1}, s_{t+1}, \tau_{t+1})$ summed over effort choices.

Because effort is unobservable, the default probability integrates over the borrower's equilibrium effort choice and type distribution.

5.1.3 Lender CU (Credit union) prices

Credit unions differ from O-lenders only in their information set: they observe the borrower's realized effort e_t within the period and may therefore condition loan prices on e_t. Type updating, however, continues to rely only on observable repayment behavior and income, so effort does not affect beliefs about τ_{t+1}.

The CU-lender offers a contract with next-period asset position a_{t+1} at an effort-specific price q^{CU}. Given current observables ω_t, realized effort e_t, and borrower choice of a_{t+1}, the CU-lender sets

$$q^{CU}_t \equiv q^{a_{t+1},e_t}_t(\omega_t, e_t) = \frac{1}{1+r}\,\mathbb{P}(d_{t+1} = 0 \mid a_{t+1}, e_t, \omega_t),$$

where $\mathbb{P}(d_{t+1} = 0 \mid a_{t+1}, e_t, \omega_t)$ is the probability of repayment next period conditional on today's effort choice.

Using the transition laws for type and income, this can be written as

$$\begin{aligned} q^{CU}_t(a_{t+1}, e_t, \omega_t) = \frac{1}{1+r} \sum_{\tau_t,\tau_{t+1},y_{t+1}} & Q_\tau(\tau_{t+1};\tau_t)\,\upsilon^{(a_{t+1},d_t,e_t)}_t(y_{t+1},\tau_t;\omega_t) \\ & \times \Big(1 - \bar{\sigma}^{(0,1)}_{t+1}\big(a_{t+1}, y_{t+1}, \Upsilon^{(0,a_{t+1})}_t(y_{t+1};\omega_t), \tau_{t+1}\big)\Big). \end{aligned} \tag{1}$$

where:

- $Q_\tau(\tau_{t+1};\tau_t)$ is the Markov transition for private type,

- $\upsilon_t^{(a_{t+1},d_t,e_t)}(y_{t+1},\tau_t;\omega_t)$ is the joint probability of drawing next-period income and type given $(a_{t+1},d_t,e_t,\omega_t)$ under the equilibrium borrower decision rules,

- $\Upsilon_t^{(0,a_{t+1})}(y_{t+1};\omega_t)$ is the likelihood mapping from current observables to next period's type assessment s_{t+1},

- $\bar{\sigma}_{t+1}^{(0,1)}(\cdot)$ is the borrower's equilibrium default probability next period, integrating over possible effort choices in $t+1$.

Since high effort reduces default risk, conditional on borrowers not over-leveraging, credit unions offer a higher price (lower interest rate) to high-effort borrowers:

$$q_t^{CU}(a_{t+1},e_H,\omega_t) > q_t^{CU}(a_{t+1},e_L,\omega_t).$$

5.2 Equilibrium

Fix a lender type $\ell \in \{\mathrm{CU},\mathrm{O}\}$.

An equilibrium is a collection

$$\left\{e_t^*, a_{t+1}^*, d_t^*,\ q^\ell,\ \mu_t\right\}$$

such that:

1. Borrower policies solve the dynamic programming problem given q^ℓ.

2. Prices q^ℓ are set given lender ℓ's information

3. Beliefs μ_t for O-lenders are updated according to Bayes' rule using the equilibrium law of motion for (ω_t,θ_t).

4. The distribution of credit states implied by borrower behavior and lender pricing is stationary within each cohort.

5.3 Parameterization

I utilize moments from low-income-designated (LID) areas and my matched empirical sample wherever possible to parameterize the model. By targeting the matched sample moments such as bankruptcy rates and credit rankings, I am able to focus the model on the intensive margin of borrower outcomes and can abstract away from compositional differences between the CU borrower pool and the O borrower pool[15]. Table 6 shows the model parameters, targeted data moments, and corresponding model moments. As in Chatterjee et al. 2025 the model period is 5 years with 8 age groups ($n \in [1, 8]$) corresponding to ages 21 to 60 in the data. I utilize the same income process as in Chatterjee et al. 2025 but with average log income and variance of log income taken from the LID-specific lifecycle (see Figure 3 in Appendix A). The pattern is roughly the same as the national sample, but with lower peak income and a flatter profile. The high-type discount factor is standard given the risk-free rate and the low-type discount factor is 10% lower. The long run share of H-type borrowers comes from the portion of prime and super prime ('prime+') in the matched data sample. The initial share of H-type borrowers is a fraction of the long-run share of H-type borrowers to account for movements into higher credit rankings over the lifecycle as seen in the data. The exogenous probability of borrowing from a CU, λ_{CU}, is 40%. This corresponds to the fraction of CU borrowers in the matched data sample. The extreme value shocks are lowest for effort and highest for default.

The effort cost κ_e and default cost κ_d are key to mapping the model to the data on interest rates and severe delinquency and default. If effort cost κ_e is too high then no borrowers exert effort making the observable effort channel that is unique to credit unions obsolete. If default cost κ_d is too low then the borrowers over-leverage at the lower interest rates, increasing probability of default and overall CU interest rates.

[15]Credit unions lend to a larger quantity of non-prime borrowers, biasing the observed default rates and credit scores downwards in the full sample.

5.4 Model Discussion

The model in which credit-union lenders (CU-lenders) partially observe borrower effort successfully reproduces the key interest rate and default patterns observed in the data. To construct a model-data comparison, I use NCUA-reported average interest rates and compute a weighted mean across credit cards and fixed-rate unsecured loans, assigning a 95% weight to credit cards based on their prevalence in the matched Equifax sample. Using the calibrated parameters in Table 6, both the model and the data generate an average CU-lender interest rate of approximately 13%. For outside lenders (O-lenders), the model produces an average rate of 15.23%, closely matching the data value of 15.2%. Importantly, with the same underlying parameters, the model automatically reproduces the empirical fact that CU-lender interest rates are lower than O-lender rates.

The quantitative model is able to replicate the pattern in the matched data that CU-borrowers have lower bankruptcy rates than O-borrowers. I use bankruptcy rates rather than the non-payment rates used in section 4 because they more closely align with default in the model[16]. This abstraction is reasonable since the non-payment patterns are the same as bankruptcy patterns in the matched data.

Figure 1 shows the correlations among credit rankings, type scores, and income over the lifecycle for CU and O borrowers. Because CU-lenders do not update type scores using observed effort, income and type-score dynamics evolve similarly for CU and O borrowers (panel c). However, interest-rate differences affect borrowing and default behavior, which feeds into credit rankings. Consequently, CU borrowers exhibit a lower correlation between credit ranking and income relative to their otherwise identical O-lender counterparts (panel b). The divergence in the relationship between credit ranking and type score (panel a) arises from the compounding effects of income, borrowing, and default dynamics over the lifecycle. Differences in soft-information precision alter effort incentives, which then propagate through earnings, leverage, and repayment outcomes.

[16] It is difficult to do the empirical analysis with bankruptcy rates due to sample size

Figure 2 shows the average interest rates by type score, lender, and effort as well as the relative mass of credit rankings in each income tercile by lender. Panels (a) and (b) show that the CU-lender offers lower interest rates conditional on high effort. Overall low-income individuals' interest rates for CU-lenders are lower compared to O-lenders but higher for medium to high income individuals. This aligns with observed borrower choice in the real world. High-income prime and superprime borrowers are more likely to use credit cards from national credit card companies which have more valuable offers for this group (usually through cash and cash-adjacent rewards). The higher interest rates for top income tercile CU-borrowers comes from a relatively larger share of non-prime borrowers at this income level (panel (c)). The interest rate effort incentive leads to low-type borrowers to exerting higher effort, leading to higher income for this group relative to their O-lender counterparts. However, the low-type is more likely to over-leverage on the cheap debt and default placing them in the non-prime category[17].

The model verifies that soft-information screening, even in a simple environment, can generate the interest rate differentials, effort responses, and default patterns observed in the matched data.

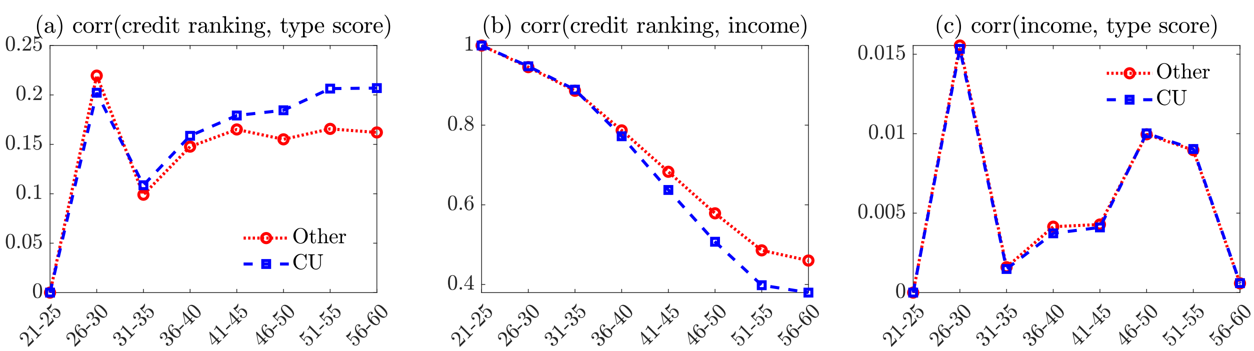

Figure 1: Correlation of credit rankings, income, and type scores across lenders

[17]Recall that the empirical section measures delinquency conditional on being the same type, so these findings are not inconsistent

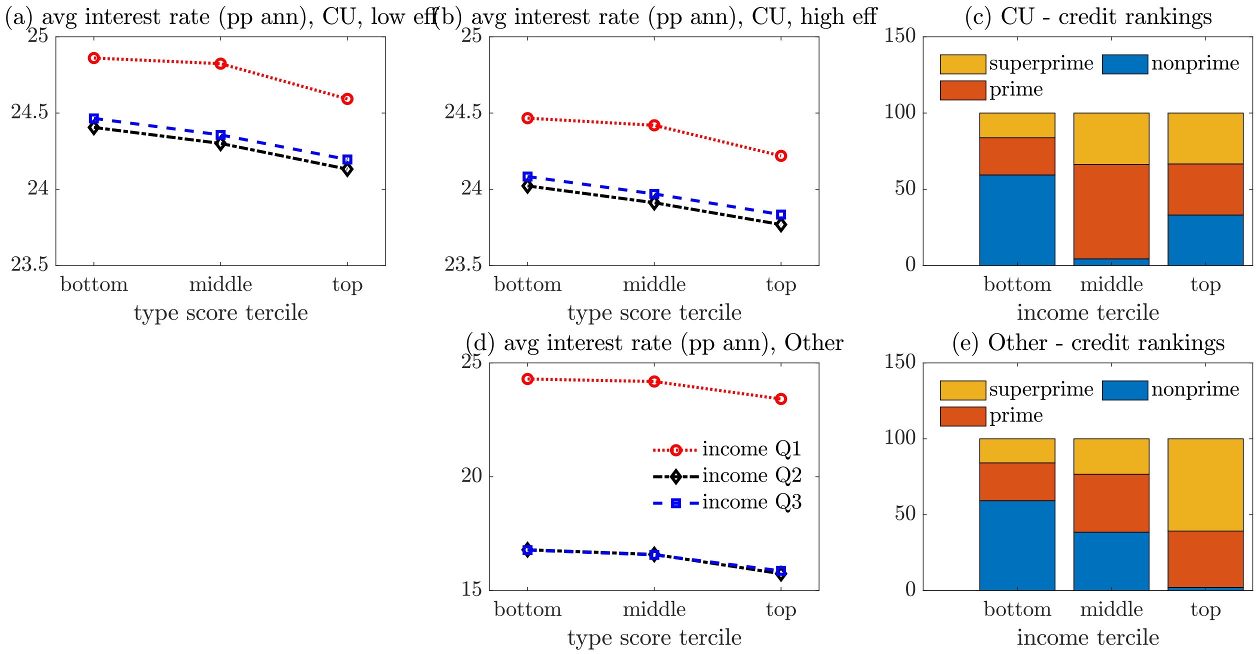

Figure 2: Interest rates and credit rankings aross lenders

6 Conclusion and next steps

Using a large, nationally representative panel of consumer credit records, this paper documents that credit union borrowers in Low-Income Designated (LID) areas experience lower delinquency rates and, for credit cards, higher credit limits than observably similar borrowers who originate accounts with other lenders. A simple two-type, two-lender hidden-information model with a soft-information channel can rationalize the observed delinquency differences and aggregate interest rate patterns across lenders.

While the results for established borrowers are highly robust, the estimates for new borrowers raise concerns about remaining selection bias. The current matching strategy may not adequately control for unobserved borrower characteristics that influence both lender choice and subsequent repayment behavior. Strengthening identification for this subgroup through an instrument for credit-union account origination remains a priority. Another important empirical extension is incorporating geographic access to financial institutions, since market structure may influence borrowers' default decisions. If a borrower only has access to one lender then he may behave differently with respect to delinquency. Finally, expanding the analysis beyond LID areas will help determine whether the effects documented here reflect features specific to underserved markets or generalize to the broader consumer-credit landscape.

On the structural side, the current model assumes exogenous lender assignment, which is sufficient to rationalize the joint credit card and small-dollar results but is not rich enough to explain which borrowers choose credit unions or why credit limits adjust differently across products (Appendix C). To address these limitations, a natural next step is to endogenize lender choice and incorporate differing lender objectives into the equilibrium. Credit unions, by charter, "promote the well-being of their members" and often operate closer to a utility-maximizing breakeven constraint, whereas traditional banks set prices subject to profit-maximization under imperfect competition (e.g., Herkenhoff and Raveendranathan 2024). Embedding these differences in the model will allow me to study how soft-information advantages, borrower sorting, and lender pricing interact in equilibrium and whether the heterogeneous effects across products arise endogenously.

Together, these empirical and structural extensions will sharpen the interpretation of the mechanisms behind credit-union impacts and enable a richer set of counterfactuals for financial inclusion and consumer-credit policy.

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A Income process in LID-areas

Average income in LID-areas follows the same pattern at the national data over the lifecyle. Households begin with low income and then accumulate higher income at a decreasing rate until ages 46-50. After age 50, average income begins to decline. Figure 3 shows that LID areas have lower income than the national sample throughout the lifecycle as well as more muted growth over the lifecycle. The variance in income is strictly increasing over the lifecyle. These values are used to calibrate the income grid and transition matrix in the quantitative model.

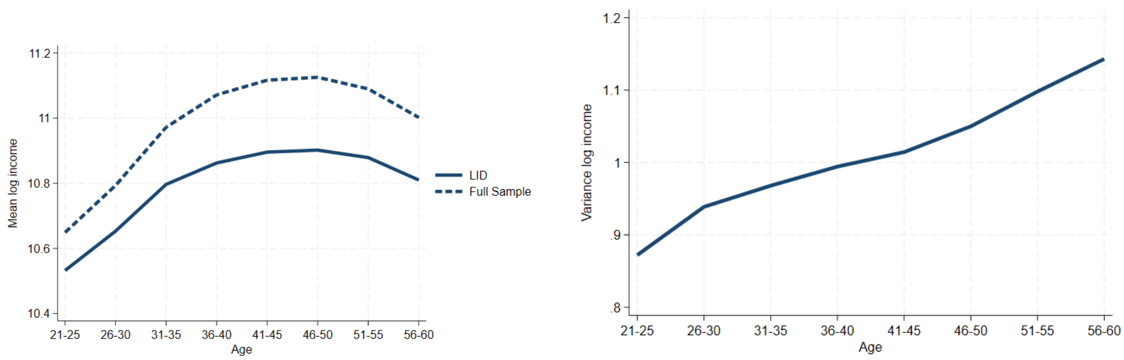

Figure 3: Mean and variance of log household income

B More Tables

Table 7 shows that there is a small overlap in matched consumers that take out credit card and small dollar loans with credit union and other lenders. 11% of matched consumers have originated an account with both types of lenders at some point in the sample. There is a smaller overlap in loan-type. Only 7% of consumers have originated both types of debt in the sample.

C Separating credit cards and small dollar loans

Tables 8 and 9 show the empirical results by each loan type. The left panel of Table 8 shows that the credit union treatment effect on credit card delinquencies is statistically significant and negative across credit tiers. For super-prime borrowers, opening a credit union account leads to a 0.112 percentage point decline in delinquency, but as before, this is economically irrelevant given the baseline delinquency is nearly zero (0.01%). For prime borrowers, opening a credit union account leads to a 1.354 percentage point reduction in delinquency compared to a 1.229% delinquency baseline. Non-prime borrowers experience a 1.149 percentage point reduction in delinquency, relative to the 10.847% baseline. For the new credit card openings, the number of accounts increases delinquency for super-prime and prime borrowers, but reduces delinquency for non-prime borrowers, indicating that non-prime borrowers are relatively more credit constrained. The right panel of Table 8 shows that the treatment effect on credit limits is significant and positive across credit tiers: super-prime borrowers receive $1,115 higher credit limits prime borrowers receive $960 higher credit limits, and non-prime borrowers receive $667 higher credit limits.

The left panel of Table 9 shows the treatment effect on delinquency specifically for small dollar loans. Super-prime and prime borrowers experience negative but insignificant declines in delinquency. Non-prime borrowers 0.459 percentage points less likely to go delinquent on small dollar loans. The right panel shows the treatment effect on credit limits is negative and significant for both prime and non-prime borrowers. Prime borrowers have $291 lower limits and non-prime borrowers have $133 lower limits compared to those who originated loans from non-credit union lenders.

D Robustness check: introductory offers

I drop introductory offers from the main empirical analysis. Large financial institutions are more likely to offer teaser rates and balance transfers in the first 21 months of account openings. Table 10 shows that when this time period is included, non-prime credit union borrowers have a positive but not statistically significant increase in delinquency compared to their counterparts at other financial institutions. This is mechanical since non-prime borrowers are more likely to be credit constrained and utilize offers such as balance transfers, which allow borrowers to delay delinquency decisions.

Parameter		Value	Notes/Target	data	model
A. Assigned externally					
γ	risk aversion	2	Standard CRRA		
r	risk-free rate	2%	$r = (1 + r_{ann})^5 - 1$		
$\bar{\rho}$	long-run share of H-types	0.56	Prime+ share of population in matched data		
λ_{CU}	Exogenous probability of CU lender	0.40	Share of CU borrowers in matched data sample		
$\{\mu_n\}_{n=1}^N$	average log income, age j		path of average log income by age		
$\{\sigma_n\}_{n=1}^N$	SD log income, age j		path of SD log income by age, no effort		
B. Calibrated internally					
B.1 Parameters			***B.2 Targets***		
Type process			*Lifecycle*		
β_H	high-type discount factor	0.906	log income, mean, slope	0.041	0.032
β_L	low-type discount factor	0.815	log income, variance, slope	0.035	0.035
ρ_0	initial share H types	0.373	log consumption, mean, slope	0.013	0.054
ζ	$\mathbb{P}(\tau' = H \vert \tau = L)$	0.100	log consumption, variance, slope	0.026	0.006
			credit ranking, mean, intercept	0.378	0.196
			credit ranking, mean, slope	0.037	0.081
Extreme values			credit ranking, variance, intercept	0.059	0.021
α_e	noise, effort choice	0.001	credit ranking, variance, slope	0.003	0.009
α'_a	noise, asset choice	0.005			
α_d	noise, default choice	0.050	*Credit Market*		
			debt-to-income	0.400	0.055
Earnings and default process			fraction in debt (%)	7.900	8.095
κ_e	effort cost	0.027	average interest rate	14.18	14.35
$\bar{\Delta}^e$	max log income gain from effort	0.400	SD interest rate	7.000	6.819
$\underline{\Delta}^e$	min log income gain from effort	0.100	average interest rate - CU	12.60	13.02
κ_d	default cost	0.100	average interest rate - Other	15.20	15.23
			average bankruptcy rate	0.330	0.648
			bankruptcy rate - CU	0.300	0.628
			bankruptcy rate - Other	0.340	0.662
			corr(credit ranking, income)	0.500	0.714

Notes: Fraction in debt, debt-to-income ratios, and variance in interest rates are taken from SCF (via Chatterjee et al. (2025)) and therefore at the national level rather than LID-level. The consumption data is also from Chatterjee et al. (2025). The bankruptcy rates, credit ranking mean and variance, and correlation between credit ranking and income come from the matched LID Equifax sample described in the Data section. The average interest rates come from the NCUA (March 2025). The rates in this table are a weighted average of credit card and unsecured fixed rate loan interest rates. The log income mean and variance come from CPS data restricted to LID counties.

Table 6: Parameters and Model Calibration

	mean	sd
Vantage score	669.04	82.16
Estimated income ($1000s)	36.49	14.91
Average credit limit ($)	3158.06	3846.40
Fraction with mortgage	0.35	0.48
Have credit union account (%)	42.95	49.50
Have other lender account (%)	68.12	46.60
Have accounts with both types of lenders(%)	11.07	31.37
Have small dollar loan (%)	36.77	48.22
Have credit card account (%)	70.29	45.70
Have both types of loans(%)	7.07	25.63
Observations	560839	

Table 7: Matched accounts consumer-level characteristics

	(1) Superprime	(2) Prime	(3) Nonprime	(4) Superprime	(5) Prime	(6) Nonprime
	Delinquency rate (%)			Credit Limit ($1000s)		
Credit limit ($1000s)	-0.00218**	-0.102***	-0.100***			
	(0.000950)	(0.00534)	(0.0251)			
Estimated income ($1000s)	-0.00105**	-0.0104***	-0.219***	0.139***	0.199***	0.222***
	(0.000420)	(0.00233)	(0.0164)	(0.00316)	(0.00356)	(0.00747)
Credit union flag	-0.0109	0.0859	-1.810***	0.491***	-0.198**	-0.276***
	(0.0102)	(0.111)	(0.454)	(0.115)	(0.0774)	(0.0927)
Post period	0.345***	2.985***	10.80***	-0.165**	1.646***	0.326***
	(0.0225)	(0.106)	(0.377)	(0.0672)	(0.0587)	(0.0798)
Credit union flag	-0.112**	-1.354***	-1.149*	1.115***	0.960***	0.667***
× Post period	(0.0513)	(0.175)	(0.596)	(0.114)	(0.0813)	(0.105)
Number of accounts	0.0393***	0.467***	-1.359***	6.719***	4.479***	1.999***
	(0.0112)	(0.0356)	(0.114)	(0.0516)	(0.0483)	(0.0431)
Delinquency (%)				-0.0211**	-0.0377***	-0.00366***
				(0.00927)	(0.00168)	(0.000894)
_cons	0.0222	1.449***	22.97***	-6.366***	-8.258***	-7.197***
	(0.0288)	(0.120)	(0.671)	(0.193)	(0.192)	(0.298)
N	736029	597066	240923	736029	597066	240923

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Credit union impact on established borrowers: credit cards

	(1) Superprime	(2) Prime	(3) Nonprime	(4) Superprime	(5) Prime	(6) Nonprime
	Delinquency rate (%)			Credit Limit ($1000)		
Credit limit ($1000s)	-0.000528	-0.0317***	-0.122***			
	(0.0237)	(0.00759)	(0.0172)			
Estimated income ($1000s)	-0.000692	-0.00652**	-0.0353***	0.0453***	0.0370***	0.0337***
	(0.0108)	(0.00319)	(0.00337)	(0.0133)	(0.00495)	(0.00190)
Credit union flag	0.0914	-0.00206	-0.00177	-0.216	-0.304***	-0.205***
	(0.0661)	(0.0341)	(0.0375)	(0.165)	(0.0465)	(0.0178)
Post period	0.360	0.638***	2.419***	0.610***	0.462***	0.284***
	(0.246)	(0.0780)	(0.0804)	(0.176)	(0.0434)	(0.0158)
Credit union flag	-0.110	-0.0412	-0.459***	-0.0998	-0.291***	-0.133***
× Post period	(0.272)	(0.0998)	(0.0950)	(0.221)	(0.0541)	(0.0180)
Number of accounts	-0.0821	0.366***	0.206***	6.238***	2.531***	1.547***
	(0.364)	(0.123)	(0.0645)	(0.423)	(0.119)	(0.0493)
Delinquency (%)				-0.000390	-0.00806***	-0.00361***
				(0.0176)	(0.00135)	(0.000253)
_cons	0.106	-0.385*	0.419***	-6.106***	-2.137***	-1.416***
	(0.661)	(0.200)	(0.148)	(0.892)	(0.297)	(0.0968)
N	4267	63822	297477	4267	63822	297477

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Credit union impact on established borrowers: small dollar loans

	(1) Superprime	(2) Prime	(3) Nonprime	(4) Superprime	(5) Prime	(6) Nonprime
	Delinquency rate (%)			Credit Limit ($1000)		
Credit limit ($1000s)	-0.00553***	-0.0811***	-0.233***			
	(0.00136)	(0.00354)	(0.0116)			
Estimated income ($1000s)	-0.00236***	-0.0108***	-0.204***	0.149***	0.208***	0.191***
	(0.000548)	(0.00167)	(0.00707)	(0.00264)	(0.00245)	(0.00370)
Credit union flag	-0.0486***	-0.115	-1.517***	0.376***	-0.0970*	-0.210***
	(0.0149)	(0.0753)	(0.205)	(0.0984)	(0.0576)	(0.0410)
Post period	0.265***	1.211***	3.289***	-0.0159	0.865***	-0.0722***
	(0.0124)	(0.0496)	(0.144)	(0.0479)	(0.0323)	(0.0255)
Credit union flag × Post period	-0.0848***	-0.523***	0.0277	0.889***	0.877***	0.459***
	(0.0263)	(0.0786)	(0.193)	(0.0823)	(0.0439)	(0.0301)
Number of accounts	0.0424***	0.373***	-0.440***	6.894***	4.477***	1.826***
	(0.0111)	(0.0244)	(0.0455)	(0.0410)	(0.0334)	(0.0195)
Delinquency (%)				-0.0296***	-0.0307***	-0.00672***
				(0.00720)	(0.00110)	(0.000297)
_cons	0.134***	1.652***	22.95***	-7.069***	-8.738***	-5.970***
	(0.0292)	(0.0841)	(0.298)	(0.166)	(0.132)	(0.145)
N	2661814	3224488	2790922	2661814	3224488	2790922

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Credit union impact on established borrowers: either loan type, introductory offer period included

	Either type		Small Dollar		Credit Card	
	(1)	(2)	(3)	(4)	(5)	(6)
	DQ (%)	CL ($1000s)	DQ (%)	CL ($1000s)	DQ (%)	CL ($1000s)
Credit limit ($1000s)	-1.195***		-5.808***		-1.078***	
	(0.0874)		(1.277)		(0.0969)	
Estimated income ($1000s)	-0.768	0.466***	-5.453***	-0.0142	-0.983	0.534***
	(0.474)	(0.133)	(0.837)	(0.0199)	(0.627)	(0.186)
Credit union flag	-0.112	-0.138***	1.222	0.0326	0.500**	-0.153***
	(0.220)	(0.0194)	(0.820)	(0.0317)	(0.195)	(0.0206)
Post period	10.41***	0.389***	10.17***	0.315***	9.684***	0.459***
	(0.281)	(0.0134)	(1.331)	(0.0577)	(0.326)	(0.0171)
Credit union flag	-3.195***	-0.239***	6.412***	0.0863	-3.483***	-0.267***
× Post period	(0.352)	(0.0177)	(1.808)	(0.0554)	(0.387)	(0.0199)
Number of accounts	1.806***	1.746***	1.238	0.798***	1.915***	1.833***
	(0.255)	(0.0380)	(1.541)	(0.0740)	(0.295)	(0.0454)
Delinquency (%)		-0.00490***		-0.00472***		-0.00532***
		(0.000270)		(0.000559)		(0.000357)
_cons	12.83	-9.471***	93.23***	0.332	16.62	-10.83***
	(8.681)	(2.438)	(15.57)	(0.590)	(11.52)	(3.414)
N	469513	469513	3220	3220	336348	336348

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Credit union impact on new borrowers: introductory offer period included