Credit Constraints and Search Frictions in Consumer Credit Markets

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What we ask in this paper:

1. Do credit constraints exist in the auto loan industry and do they distort consumption?

2. If so, why do these credit constraints persist in equilibrium?

Open Question: Why do credit constraints persist?

The continued prevalence of credit constraints is noteworthy and somewhat puzzling in its own right: for all of the advances in risk-based pricing, mechanism design, nonlinear contracting etc., prices are still quite far from clearing consumer credit markets! –Zinman (2014)

Data Source

- Data from a private software services company
- 5.6 million auto loans from 326 lending institutions in 50 states
- 83% of loans were originated by credit unions
- ≈70% of sample was originated between 2012 and 2015
- 2.2 million loan applications originating from 46 institutions
- Exclude indirect loans
- Variables:
    - Ex-ante borrower variables: FICO, DTI, gender, age
    - Ex-ante loan variables: Interest rate, LTV, channel
    - Collateral variables: make, model, year, purchase price
    - Ex-post loan performance: delinquency, charge-off, ΔFICO
- Representativeness

Benchmark: Permanent Income Hypothesis

$$\max \sum_t \frac{u(c_t)}{(1+\delta)^t}$$

$$s.t. \sum_t \frac{c_t}{(1+r^*)^t} \leq \sum_t \frac{y_t}{(1+r^*)^t} + (1+r^*)A_t$$

- yields Euler equation

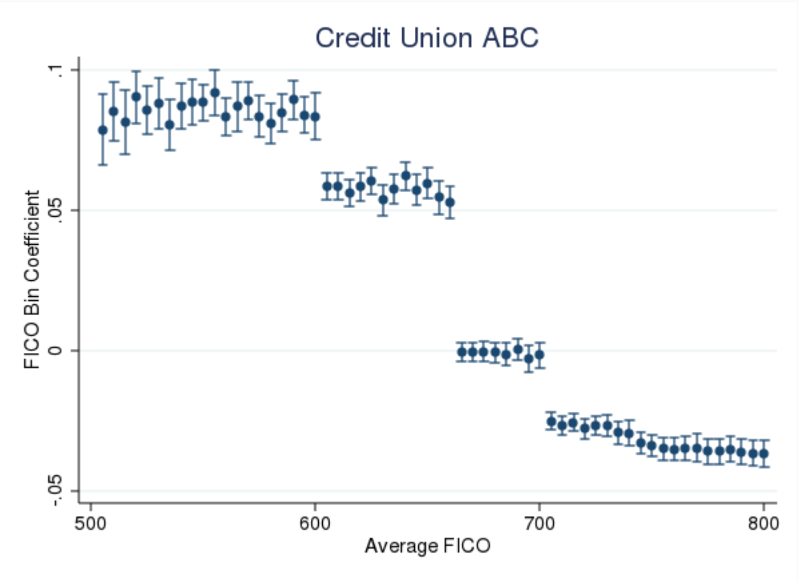
$$u'(c_t) = \frac{1+r^*}{1+\delta} u'(c_{t+1})$$

* Requires access to borrowing/saving technologies @ break-even rate r^*
- If not: distorts consumption decisions from efficient benchmark

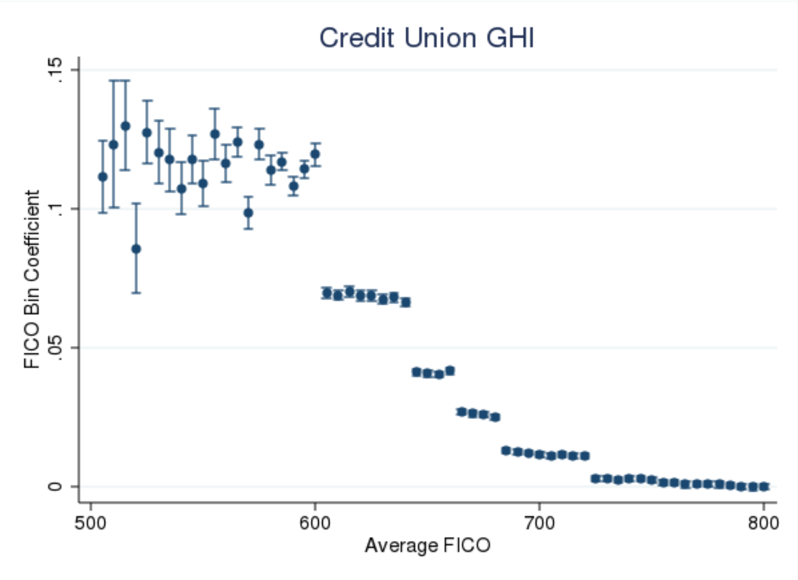
- This paper: rule-of-thumb lending rules $\Rightarrow r > r^*$

Example Credit Union

▸ Discontinuity Algorithm



Credit Union with five discontinuities



1. Is there selection around interest-rate discontinuities?

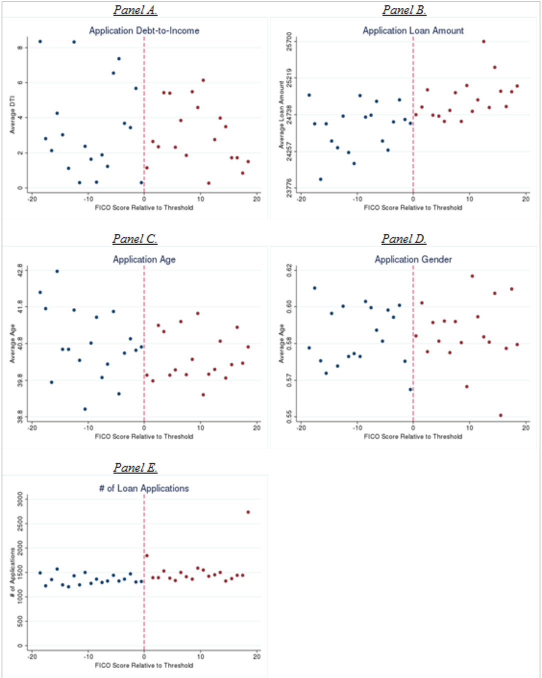
- Are LHS borrowers different from RHS borrowers along financially meaningful dimensions?
- Rule out heterogeneity via several checks:
  - Smoothness of observables at discontinuity:
    - ✓ Application Debt-to-Income
    - ✓ Application loan size
    - ✓ Borrower age
    - ✓ Borrower gender
  - Smoothness of loan performance and borrower credit quality.

Empirical strategy

- RD around lending thresholds.
- To avoid cross-treatment contamination, filter the dataset to include thresholds with $>$100,000 loans in the $\pm$19 FICO points window around the threshold
  - Keep institutions w/o another threshold within 19 FICO points.
  - Results in 489,993 loans originating from 173 institutions.
- Normalize FICO scores to cutoff and estimate

$$\begin{aligned} y_{ict} &= \eta_c + \delta_t + \gamma \cdot normfico_{ict} + \delta \cdot 1(normfico_{ict} \geq 0) \\ &\quad + \beta \cdot normfico_{ict} \cdot 1(normfico_{ict} \geq 0) + \varepsilon_{ict} \end{aligned}$$

- Use bias-corrected RD estimator of Calonico et al. (2014)


Panel A.
Application Debt-to-Income
Average DTI
FICO Score Relative to Threshold
Panel B.
Application Loan Amount
Average Loan Amount
FICO Score Relative to Threshold
Panel C.
Application Age
Average Age
FICO Score Relative to Threshold
Panel D.
Application Gender
Average Age
FICO Score Relative to Threshold
Panel E.
# of Loan Applications
# of Applications
FICO Score Relative to Threshold

Ruling out soft information in sorting

	(1) Days Delinquent	(2) Charge-off	(3) Default	(4) ΔFICO
Discontinuity	-3.76	-.0008	-.002	.0004
Coefficient	[-1.12]	[-.64]	[-1.17]	[.18]
Institution FE	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓
N	336,961	489,315	489,315	369,679

Robust t-stats in brackets.

2. Cutoffs affect consumption decisions

- No apparent sorting across discontinuities.
- Cutoffs appear as good as randomly assigned.
- If cutoffs affect consumption, this is inefficient.

First stage: Discontinuities in loan terms

	(1) Loan Rate	(2) Loan Term
Discontinuity Coefficient	-0.015***	1.38***
	[-29.74]	[5.12]
Institution FE	✓	✓
Quarter FE	✓	✓
N	489,315	489,315

Robust t-stats in brackets.

Second stage: Discontinuities affect purchases

	(1) Car Value	(2) Loan Amount	(3) LTV	(4) Monthly Payment
Coefficient	978.867***	1,479.67***	0.027***	9.67***
	[11.86]	[13.63]	[5.03]	[6.28]
Institution FE	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓
N	489,315	489,315	489,315	489,315

Robust t-stats in brackets.

Evidence on Substitution Patterns

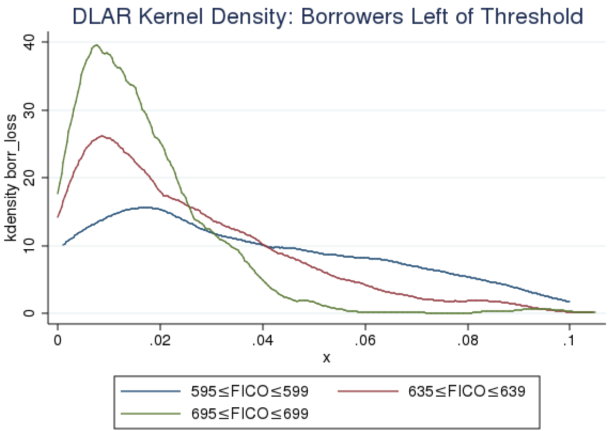
	(1) Car Value	(2) Car Value	(3) Car Age
Coefficient	887.69***	84.62	-.40***
	[10.84]	[1.56]	[-20.86]
Institution FE	✓	✓	✓
Quarter FE	✓	✓	✓
Make-Model FEs	✓		✓
Year-Make-Model FE		✓	
N	448,017	448,017	448,017

Robust t-stats in brackets.

But are there really better loan terms out there?

- For each borrower, we put them into a cell matched by:
  - Origination time (two-quarter window)
  - Car value (in $1000 bins)
  - FICO Score (5-point bins)
  - Debt-To-Income (5-point bins)
  - MSA
- For all cells with at least 2 borrowers, we calculate the Difference from Lowest Available Rate (DLAR)

Better "Opportunity" Set for LHS Borrowers



Measuring Search

- It's difficult to observe search behavior directly.
- In application data, we can observe whether loan was accepted/declined.
- Measure propensity to search with dummy for offered loan accepted by borrower.

$$\begin{aligned} Accept_{ict} &= \eta_c + \delta_t + \gamma \cdot normfico_{ict} + \delta \cdot 1(normfico_{ict} < 0) \\ &\quad + \beta \cdot normfico_{ict} \cdot 1(normfico_{ict} \geq 0) + \varepsilon_{ict} \end{aligned}$$

- Measure search costs using the Driving-time density, i.e. the number of lending institutions within a 20 minute drive.

Single Search Cost Sorts

- Borrowers in low search cost areas are relatively less likely to accept poor loan terms

	(1)	(2)	(3)
	Dependent Variable: 1(Accept Offered Loan)		
Coefficient	0.172	.142	0.196
	[7.06]	[3.98]	[6.54]
Institution FE	✓	✓	✓
Quarter FE	✓	✓	✓
N	48,679	24,446	24,233
Data Subset	Full	**Low Driving-time Density**	**High Driving-time Density**

Errors clustered at the FICO score level - t-stats in brackets.

Direct Measures of Search

	# Applications/Vehicle		
	(1)	(2)	Diff
Mean	1.60	1.65	-.05
Standard Deviation	1.242	1.30	[5.76]
Institution FE	YES	YES	
Quarter FE	YES	YES	
N	42,878	42,878	
Data Subset	**1st quintile Driving-time Density**	**5th quintile Driving-time Density**	

Conclusion

- Consumers are credit constrained (one reason for this is arbitrary pricing policies), which distorts consumption
- One reason that these credit constraints persist, i.e. consumers do not avail themselves of superior available terms, is because search is costly.

Are search costs just a catch all for imperfect competition?

		Competition	
		LOW	HIGH
Driving Density (20m)	LOW	0.12 [2.36]	0.272 [1.97]
	HIGH	0.193 [3.69]	0.478 [4.79]

Representativeness

- Top 5 states by number of loans:
  - Washington (770,334 loans)
  - California (476,791 loans)
  - Texas (420,090 loans)
  - Florida (314,718 loans)
  - Utah (292,523 loans)
- Our data are slightly less diverse (73% estimated to be white vs. 64.5% in census data).
- Median FICO at origination is 715 (vs. 695 for US borrowers)
- Back

Auto loans are ubiquitous

- 85% of car purchases are financed
- Vehicles over 50% of total assets for low-wealth households
- 3rd largest category of consumer debt, 100 million outstanding loans
- Over $1 trillion outstanding auto loans with $400 bn/year originated

Detecting Discontinuities

- Regress loan interest rates onto a series of dummies representing 5-point FICO bins, for a given institution c:

$$r_{ic} = \alpha + \sum_{b=1}^{60} \delta_{bc} \mathbb{I}_{ib} + \varepsilon_{ic}$$

$$\mathbb{I}_{bit} = \begin{cases} 1 & \text{if } 500 + 5(b-1) \leq \text{FICO}_{it} < 500 + 5b \\ 0 & \text{otherwise} \end{cases}$$

- Define a discontinuity as a FICO score cutoff with
  - a 50 bps difference in adjacent coefficients (economically significant)
  - p-value of difference less than .001 (statistically significant)
  - p-values between the leading and following bins $>.1$ (not just noise)