Real Effects of Search Frictions in Consumer Credit Markets

Bronson Argyle
BYU

Taylor Nadauld
BYU

Christopher Palmer
MIT and NBER

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Credit-Market Imperfections

- How are credit markets special?
- Key household finance question: what credit-market imperfections prevent optimal consumption?
  - Zeldes (1989), Gross & Souleles (2002) – Borrowing constraints
  - Adams, Einav, Levin (2009) – Adverse selection and moral hazard
  - Scharfstein & Sunderam (2017) – Credit market concentration
  - Agarwal et al. (2018) – Heterogenous pass-through of credit expansions
  - Kuchler and Pagel (2020) – Behavioral biases
  - Nelson (2020) – Private information
- This paper: document importance of search frictions in consumer finance

Costly Search in Credit Markets ⇒ Real Effects

Search frictions in market for auto loans:

1. Lead to price dispersion and interest-rate markups

Costly Search in Credit Markets $\Rightarrow$ Real Effects

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Costly Search in Credit Markets $\Rightarrow$ Real Effects

Search frictions in market for auto loans:

1. Lead to price dispersion and interest-rate markups
2. Explain borrowers' propensity to shop around for a loan
3. Limit both extensive and intensive margin of borrowing
4. Distort intensive margin of durable consumption through demand response $\Rightarrow$ DWL

Usual Sequential Search Model: No DWL from Search Frictions

- Usual sequential search model: inelastic unit demand for a homogenous final good
- Firm j charges

$$p_j = MC + markup_j$$

- Given distribution of search costs k, markup distribution adjusts
- For each consumer having drawn price p'

$$p' - E(p_j) \leq k_i$$

- In equilibrium, buyers stay with first seller
- Costly search consequence: transfer from buyer to seller

Reality: Elastic Demand, Complements

Reality: efficiency loss from demand response on two dimensions.

1. If demand is elastic, $Q^{search} < Q^*$
   - $\rightarrow$ Could result in fewer and/or smaller transactions

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1. If demand is elastic, $Q^{search} < Q^*$
   - $\rightarrow$ Could result in fewer and/or smaller transactions
2. For complements/intermediate goods, distorts final good consumption

$$Q_2(p_1^{search}, p_2) < Q_2(p_1^*, p_2)$$

   - $\rightarrow$ Highlights credit market specialness

search frictions $\Rightarrow$ credit markups $\Rightarrow$ smaller loans $\Rightarrow$ older, cheaper cars

Outline

1. **Auto loans setting and data**
2. Search model with elastic demand
3. Measuring interest rate dispersion
4. Discontinuous pricing policies
5. Direct evidence on search costs and search behavior
6. Consequences of search frictions on loans and consumption

Auto loans are ubiquitous, important

- \$1.3 trillion outstanding (NY Fed, 2019)
- 3rd largest consumer debt category, larger than credit cards
- 114m outstanding loans $\approx$ 0.9 per U.S. household
- 85% of new car purchases financed (Consumer Reports, 2013)
- Vehicles 50%+ of low-wealth HHs total assets (Campbell, 2006)

Data Source

- Data from private software services company focusing on retail financial institutions
- 2.4 million auto loans from 326 lending institutions in 50 states
- Majority originated by credit unions
- 70% of sample was originated between 2012 and 2015
- 1.3 million loan applications originating from 41 institutions
- Exclude indirect loans and refinances
- Representativeness

Variables

- Ex-ante borrower variables: FICO, DTI, gender, age, $\widehat{\text{ethnicity}}$
- Application variables: Approval, take-up
- Loan variables: Interest rate, LTV, channel
- Collateral variables: VIN, make, model, year, purchase price
- Ex-post loan performance: delinquency, charge-off, ΔFICO

$\approx$ HMDA + Deeds + LPS

Also in the family

- Argyle, Nadauld, Palmer, and Pratt (2018)
  - Financing conditions capitalized into prices buyers pay for a car
  - Focus on loan maturity shocks at *car* level that vary payment sizes
  - Heterogenous incidence of credit supply shocks in durables markets
- Argyle, Nadauld, and Palmer (2019)
  - Monthly Payment Targeting, mental accounting
  - Households make decisions using categorical monthly budgets
  - Most sensitive to payment size, even liquidity unconstrained
  - Monthly payments bunch at salient $100-multiples

→ Predictive power of lender-specific pricing rules predicated on costly search

Extensive empirical literature on price dispersion and search

- Mortgages: Woodward & Hall (2012), Allen et al. (2014), Alexandrov & Koulayev (2017), Bhutta et al. (2018)
- Credit cards: Stango and Zinman (2016)
- Mutual funds: Hortaçsu and Syverson (2004)
- Cars: Goldberg and Verboven (2001)
- Online shopping: De Los Santos, Hortaçsu, Wildenbeest (2012), Ellison & Ellison (2009)
- Prescription drugs, airfares, houses, auto insurance, electronics, books, fish...

→ Open Questions:
  - Generally, these assume inelastic demand. Does this matter?
  - How are search frictions in *credit* markets special?
  - Are the welfare consequences of credit-market search frictions?

Search Model with Elastic Demand

- Adapt Reinganum (1979) to credit market with elastic demand for loans and durables
- Demonstrate equilibrium price dispersion
- Characterize DWL (assumed away by models with inelastic demand)
- Develop several comparative statics and testable predictions
- Results apply more broadly to the demand for any two complements.

Model Setup

- Borrowers believe $r \sim F$ on $[\underline{r}, \overline{r}]$ but don't know price locations
- Pay search cost k for each interest-rate quote
- When current quote is r', expected utility gain from search is

$$\int_{\underline{r}}^{r'} [V(r,p) - V(r',p)] dF(r) - k$$

  $V(\cdot,\cdot)$ is the indirect utility of facing prices r and p for loans and durables

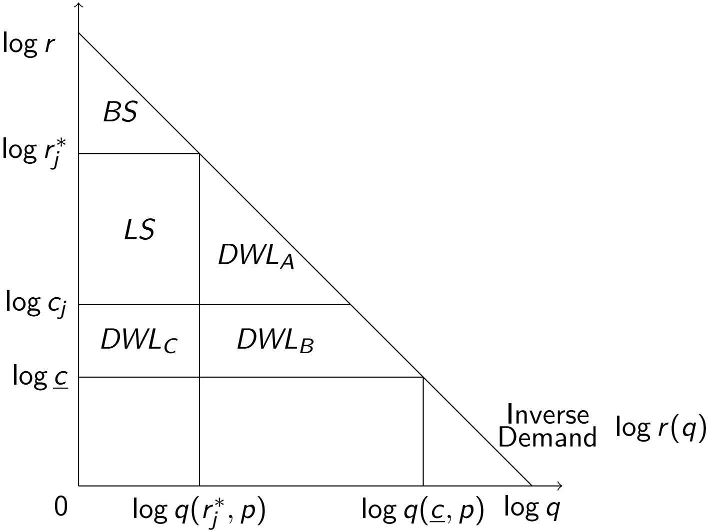
- Especially for credit, important to use $V(\cdot,\cdot)$ instead of just r
  - Incorporates elastic demand + complements
  - Markups lead to smaller loans and less durable consumption

Welfare

Deadweight loss has three components:

1. Lenders monopoly power $\Rightarrow$ lenders other than the lowest-cost lender survive
2. Each lender marks up cost c_j to charge monopoly prices
3. Elastic demand $\Rightarrow$ borrower demand less loans $+$ goods

Components of DWL



Model Implications and Testable Predictions

1. Price dispersion and loan markups increasing in search costs
2. Loan sizes decreasing in search costs
3. Durable consumption decreasing in search costs
4. Welfare loss increasing in search costs (and elasticity of demand)
5. Market shares invariant to markups when search costs are high

$\rightarrow$ Identification: quasi-experimental variation in draw of r'

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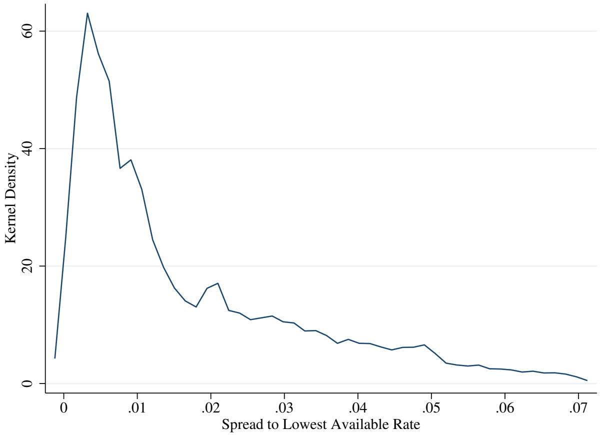
Estimated Price Dispersion



- Match on $(t, T, \text{FICO}, P, \text{DTI}, \text{CZ})$
- Average borrower paying 130 bp more than observationally similar borrower
- Avg 3 price quotes required to find best r
- Average markup 27 bp higher in high-search-cost markets

Potential Reasons for Observed Price Dispersion

1. Costly price discovery
2. Unobserved (borrower/product) heterogeneity
3. Measurement error

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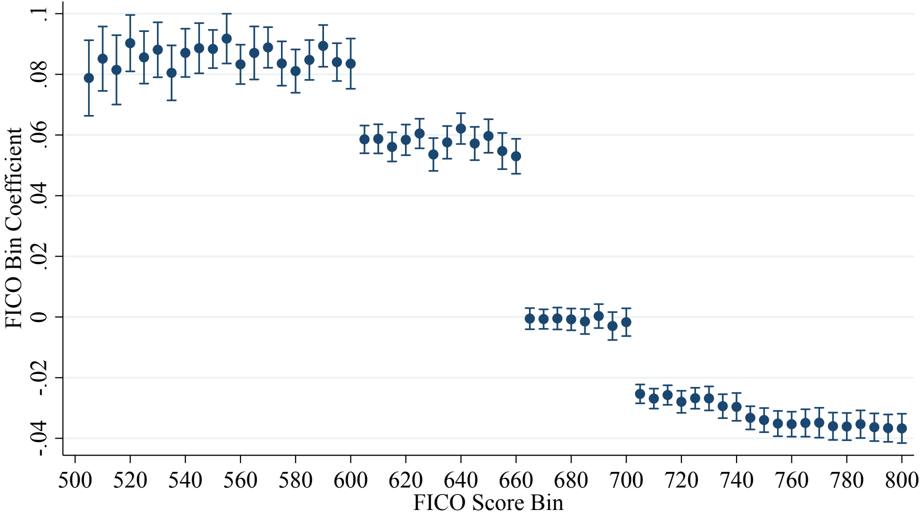
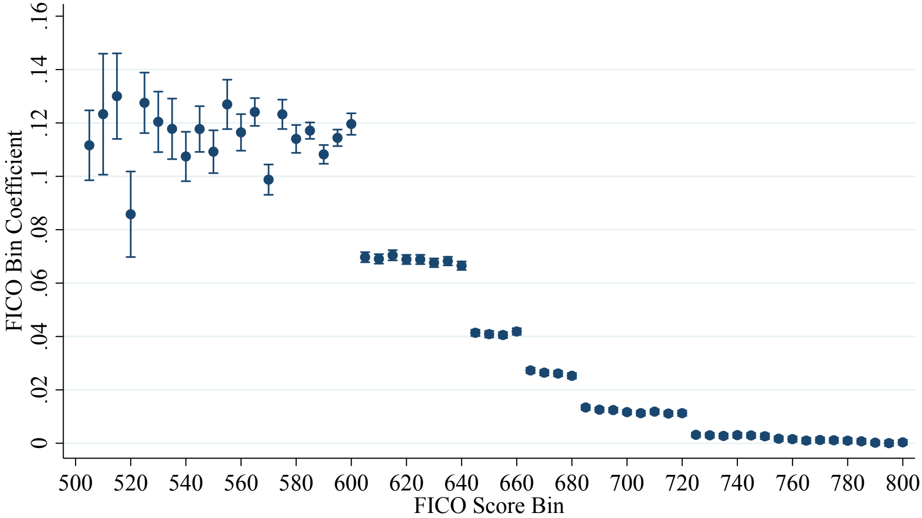
- Strategy: test for #1 in a setting where we can rule out #2 and #3
- Exploit quasi-experimental variation in *benefits* to search
- Endgame: estimate *consequences* of costly search by comparing people with high return to search in high- vs. low-search-cost areas

Outline

Example Credit Union with three discontinuities



Example Credit Union with five discontinuities



Heterogenous

Empirical Strategy

- Regression Discontinuity around detected lending thresholds $\mathcal{D}$
- Normalize FICO scores to each cutoff and estimate

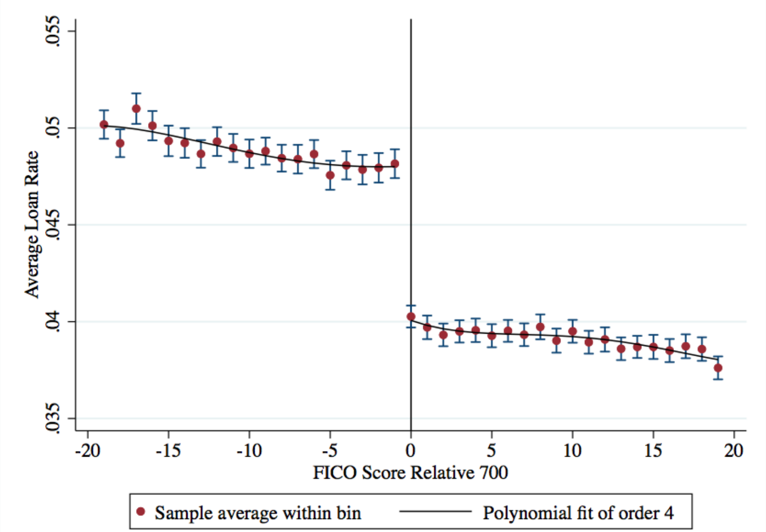
$$r_{iglt} = \sum_{d \in \mathcal{D}} 1(FICO_{il} \in \mathcal{D}_d) \left(\delta \cdot 1(\widetilde{FICO}_{id} \geq 0) + f(\widetilde{FICO}_{id}; \pi) + \psi_{dl} \right) + \alpha_{gt} + \varepsilon_{iglt}$$

- Quadratic RD function of running variable

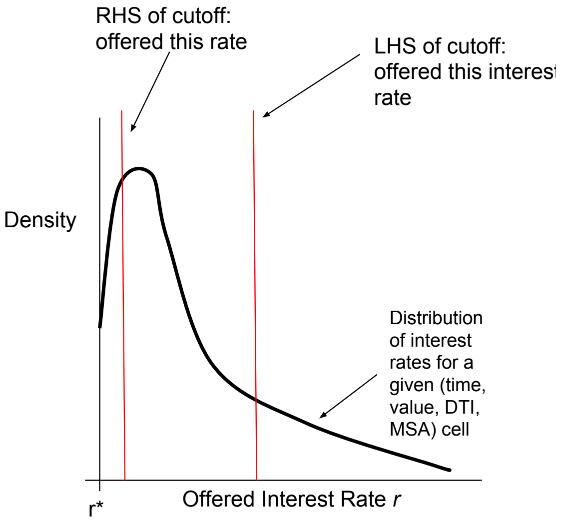
$$f(\widetilde{FICO}; \pi) = \pi_1 \widetilde{FICO} + \pi_2 \widetilde{FICO}^2 + 1(\widetilde{FICO} \geq 0) \left(\pi_3 \widetilde{FICO} + \pi_4 \widetilde{FICO}^2 \right)$$

- Uniform kernel: $1(FICO_{il} \in \mathcal{D}_d) \equiv$ loan i within 20 points of discontinuity d at lender l
- Discontinuity $\times$ lender, Commuting Zone $\times$ quarter fixed effects
- Detection details

First stage for FICO = 700 cutoff



LHS borrowers face high returns to search across lenders

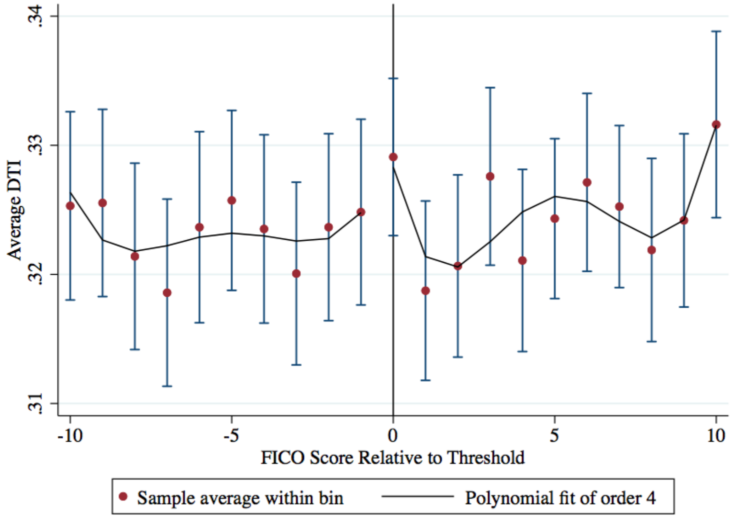


Is there selection around interest-rate discontinuities?

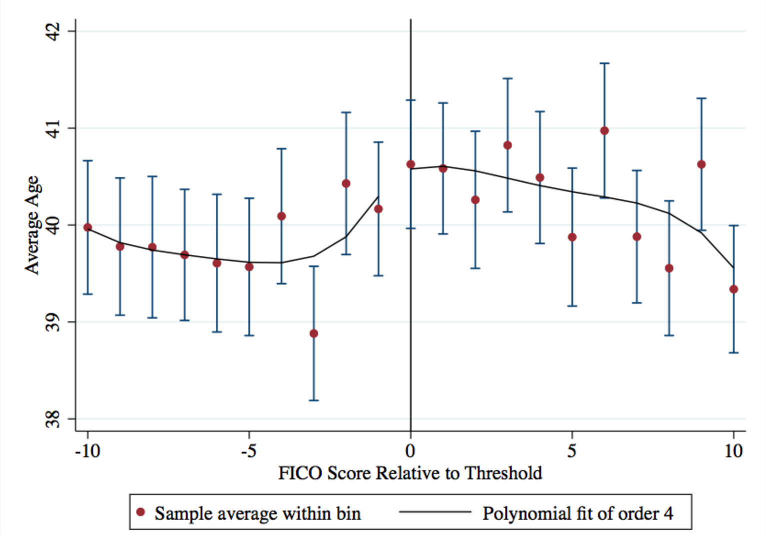
- Are LHS and RHS borrowers ex-ante different along any observable dimension?
  - e.g., (un)awareness of pricing policies correlated with demand, riskiness

- Rule out selection via smoothness of observables at discontinuity:
  - ✓ Application loan size
  - ✓ Application Debt-to-Income
  - ✓ Borrower age
  - ✓ Borrower gender
  - ✓ Borrower ethnicity
  - ✓ No bunching in applications around discontinuities

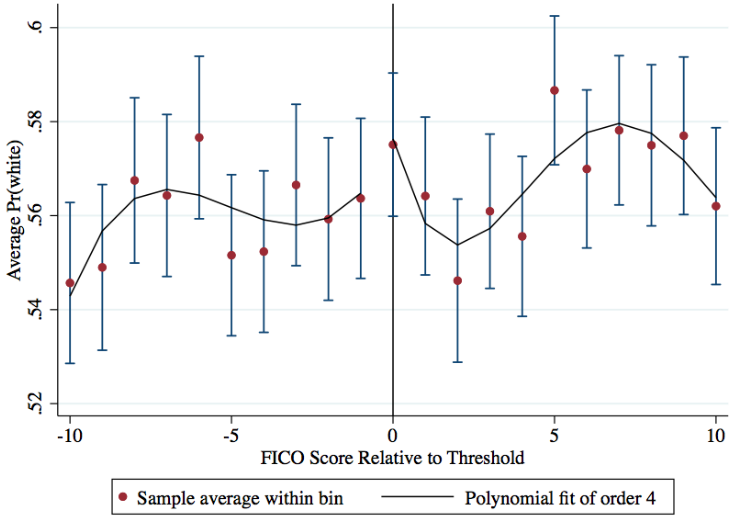
Balance checks: Application Debt-to-Income Ratio



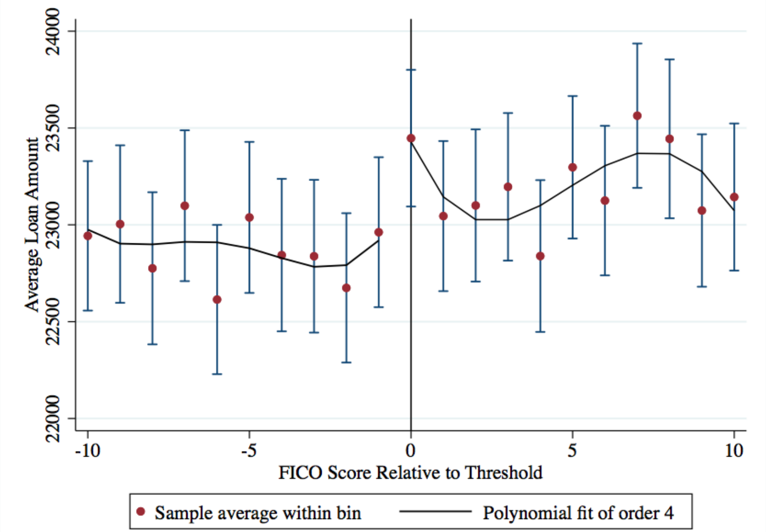
Balance checks: Applicant Age



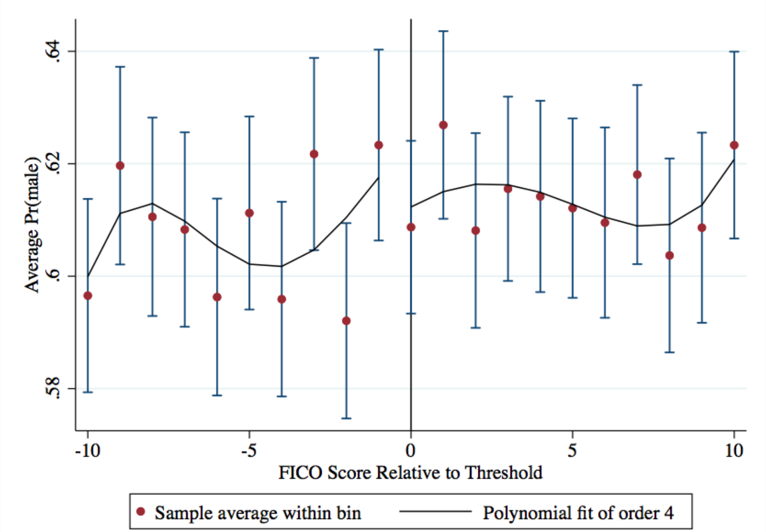
Balance checks: Applicant Ethnicity



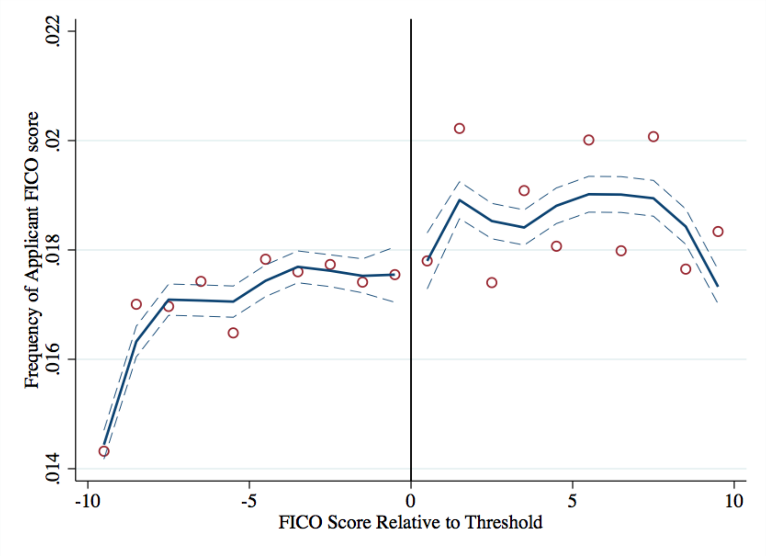
Balance checks: Application Loan Amount



Balance checks: Applicant Gender



No bunching in running variable: Application Counts



Why don't borrowers on LHS find better available rates?

- Dimensions of search costs
    - Temporal specificity (given car/price may expire)
    - Cost of attention to stressful/overwhelming financial paperwork
    - Concerned with impact of FICO pulls (Liberman et al., 2017)
    - Beliefs about price dispersion or time to search
- Our focus: physical search plays important role
    - Average commute: 26 min, average borrower: 15 min drive to lender
- Why would physical distance matter?
    - Paperwork, brand awareness, individual-level pricing, tight timing
    - Evidence matters in lending (Degryse and Ongena, 2005 and Nguyen, 2016)

Bringing costly search to the data

To ask whether costly search inhibits price discovery, we need

1. A measure of borrower search

2. Variation in search costs

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   - Total number of applications per borrower
   - Accepting/Rejecting approved loans from application data
   - Takeup $\equiv 1$(Offered loan is accepted)
2. Variation in search costs

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   - Total number of applications per borrower
   - Accepting/Rejecting approved loans from application data
   - Takeup $\equiv 1$(Offered loan is accepted)
2. Variation in search costs
   - Geocode FDIC+NCUA branch data to calculate driving times
   - For each borrower: # of institutions within a 20-minute drive
   - High search costs $\equiv 1(\leq 10$ lenders within 20 minute drive)

Indirect measure of search varies with search costs

$$takeup_{iglt} = \sum_{d \in \mathcal{D}} 1(FICO_{il} \in \mathcal{D}_d) \left(\delta \cdot 1(\widetilde{FICO}_{id} \geq 0) + f(\widetilde{FICO}_{id}; \pi) + \psi_{dl} \right) + \alpha_{gt} + \varepsilon_{iglt}$$

- Estimate for high/low search cost areas
- Investigate if markups more consequential in low search-cost areas
- Verify discontinuities similar across high/low search-cost areas
- Check robustness to possible endogeneity of search-cost measure
- Validate with structural estimates from Hortaçsu Syverson (2004) + market shares

Indirect measure of search varies with search costs

Search Costs	Full	High	Low	Difference
	(1)	(2)	(3)	(2) - (3)
	Dependent Variable = 1(Loan Offer Accepted)			
Discontinuity	0.121***	0.020***	0.137***	-0.116***
Coefficient	(0.015)	(0.005)	(0.016)	(0.006)
Discon. × Lender FE	✓	✓	✓	
CZ × Quarter FE	✓	✓	✓	
N	30,743	4,436	26,307	
R^2	0.27	0.45	0.25	

→ Low–search-cost borrowers relatively less likely to accept markups

- Robust to varying definition of high search cost area ▸ Results ▸ Endogeneity

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Selection into take-up?

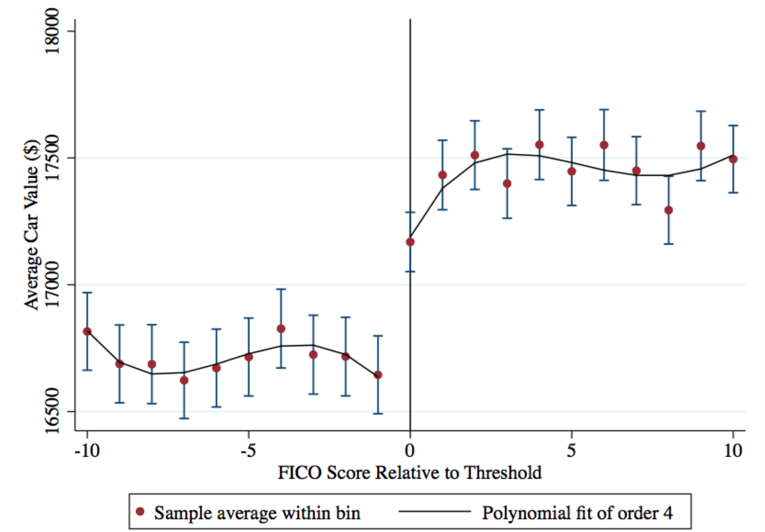
- Want to show real effects of costly search *given* take-up
- But *accepting* a dominated loan offer is an endogenous choice...
- Conditional on take-up: check for balance of application Xs + ex-post ys
  - ✓ # days delinquent
  - ✓ default (90+ days past due)
  - ✓ charge-off (was loan written off by lender)
  - ✓ ΔFICO score since origination

▸ Results

Real Effects: Loan Choice Impacts Real Consumption

	(1) Price	(2) Loan Amount	(3) LTV	(4) Payment
Discontinuity	376.58**	566.21***	0.013**	0.17
Coefficient	(175.72)	(167.93)	(0.005)	(1.02)
Discon. × Lender FE	✓	✓	✓	✓
CZ × Quarter FE	✓	✓	✓	✓
N	514,834	514,834	514,834	514,834
R^2	0.052	0.059	0.029	0.056

Second stage plot: Purchase prices



Evidence on Substitution Patterns

▸ Mileage

	(1) Car Value	(2) Car Value	(3) Car Age
Discontinuity	344.69***	79.71	-1.76***
Coefficient	(123.78)	(49.25)	(0.043)
Discon. × Lender FE	✓	✓	✓
CZ × Quarter FE	✓	✓	✓
Make-Model FE	✓		✓
Year-Make-Model FE		✓	
N	468,800	468,800	468,800
R^2	0.353	0.767	0.352

- Costly search $\Rightarrow$ market power $\Rightarrow$ each lender faces downward sloping demand $\Rightarrow$ consumption response to price dispersion $\Rightarrow$ DWL: fewer and lower quality goods

Ruling out alternative explanations

1. Market concentration
2. Selection into take-up
3. Exclusivity of credit unions
4. Endogeneity of search cost measure
5. Risk-based pricing on other dimensions
6. Steering by car dealers to lenders

Conclusion

- Market for auto loans full of price dispersion, search frictions
- Used rich data to isolate exogenous variation in the benefits of search
- Evidence that search costs influence search behavior

- Search costs $\Rightarrow$ finance less, buy older, \$400 less car

- In the real world, elastic demand + costly search $\Rightarrow$ DWL
- Costly-search fueled credit markups affect welfare through extensive + intensive margins

costly search $\Rightarrow$ credit markups $\Rightarrow$ smaller loans $\Rightarrow$ lower consumption

Representativeness

- Credit-union clientele skew slightly older
- Less diverse (73% estimated to be white vs. 64.5% in Census)
- Median FICO at origination is 711 (vs. 695 for US borrowers)
- Could be a population with preference for local
- Still representative of very large segment of market
- Back

Aside: why would lenders price this way?

- Hard coded from pre-Big Data era (Hutto & Lederman, 2003)
- Persistence of rate-sheet pricing
- Particular processing cost structure (Bubb & Kauffman 2014; Livshitz et al. 2016)
- Worry about overfitting (Al-Najjar and Pai 2014; Rajan et al. 2015)

* n.b., costly search makes it hard to gain market share by undercutting

- While interesting curiosity, justification less impt for our purposes

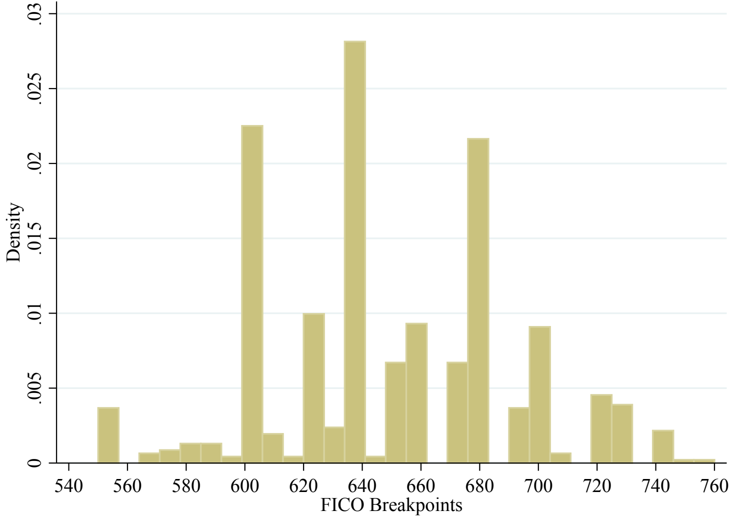
Example rate sheet

Unitus COMMUNITY CREDIT UNION

Consumer Loan Rate Sheet
Effective March 1, 2017

New Auto Loans: Model Years 2015 and Newer													
Repayment Period	**Minimum Loan Amount**	**Credit Score 740 +**		**Credit Score 739 to 700**		**Credit Score 699 to 660**		**Credit Score 659 to 610**		**Credit Score 609 to 560**		**Credit Score 559 or below**	
		APR^	**DPR**	**APR^**	**DPR**	**APR^**	**DPR**	**APR^**	**DPR**	**APR^**	**DPR**	**APR^**	**DPR**
Up to 36 Months[1]	$500	**2.24%**	0.0061%	**2.74%**	0.0075%	**3.99%**	0.0075%	**8.24%**	0.0226%	**13.49%**	0.0370%	**14.49%**	0.0397%
37 - 60 Months	$5,000	**2.74%**	0.0075%	**3.24%**	0.0089%	**4.49%**	0.0116%	**8.74%**	0.0239%	**13.99%**	0.0383%	**14.99%**	0.0411%
61 - 66 Months	$6,000	**2.99%**	0.0082%	**3.49%**	0.0096%	**4.74%**	0.0116%	**8.99%**	0.0246%	**14.24%**	0.0390%	**15.24%**	0.0418%
67 - 75 Months	$10,000	**3.24%**	0.0089%	**3.74%**	0.0102%	**4.99%**	0.0130%	**9.24%**	0.0253%	**14.49%**	0.0397%	**15.49%**	0.0424%
76 - 84 Months[2]	$15,000	**3.49%**	0.0096%	**3.99%**	0.0109%	**5.24%**	0.0158%	**9.49%**	0.0260%	**N/A**		**N/A**	
2015 and newer hybrid vehicles qualify for an additional 0.25% rate reduction.													
We may finance up to 100% Retail NADA or KBB unless the vehicle has over 100,000 miles in which case we may lend up to 100% of NADA or KBB for Tier 1 borrowers and up to 80% of NADA or KBB for Tier 2-6 borrowers. Maximum term for vehicles with over 100,000 miles is 66 months.													

Wide heterogeneity across institutions in policies



back

Detecting Discontinuities

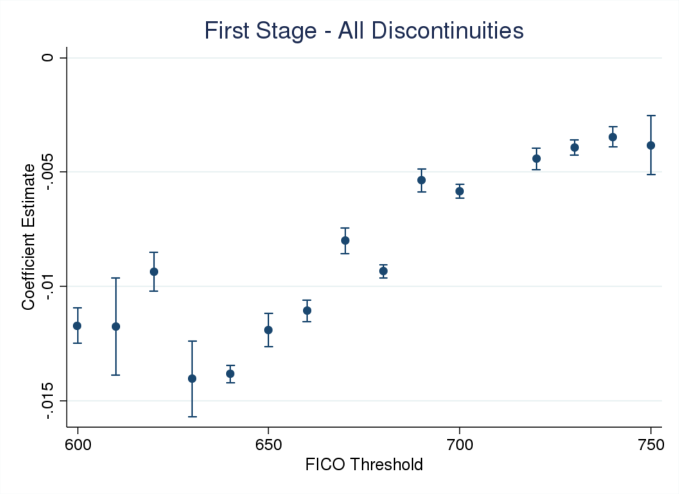
- Regress loan interest rates onto 5-point FICO bin dummies for a given lender l

$$r_{il} = \alpha + \sum_b \delta_{bl} 1(FICO_i \in Bin_b) + \varepsilon_{il}$$

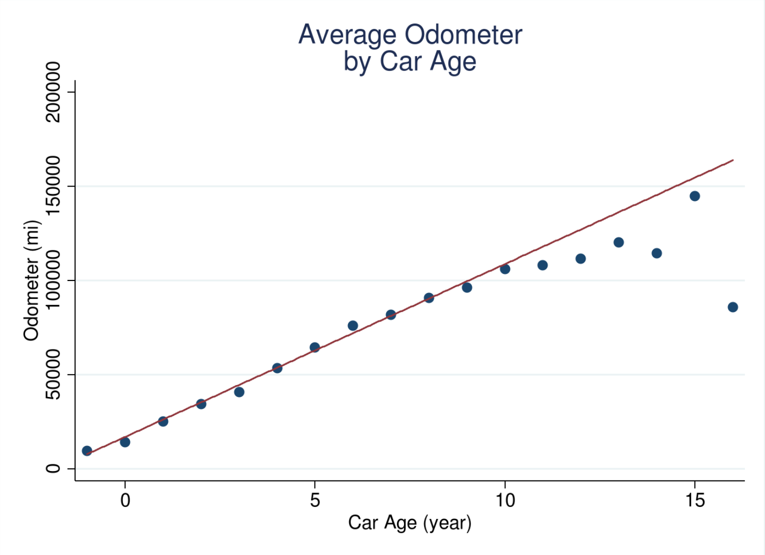
- Define a discontinuity as a FICO score cutoff with
  - a 50 bps difference in adjacent coefficients (economically significant)
  - p-value of difference less than .001 (statistically significant)
  - p-values between the leading and following bins $>.1$ (not just volatility)

back

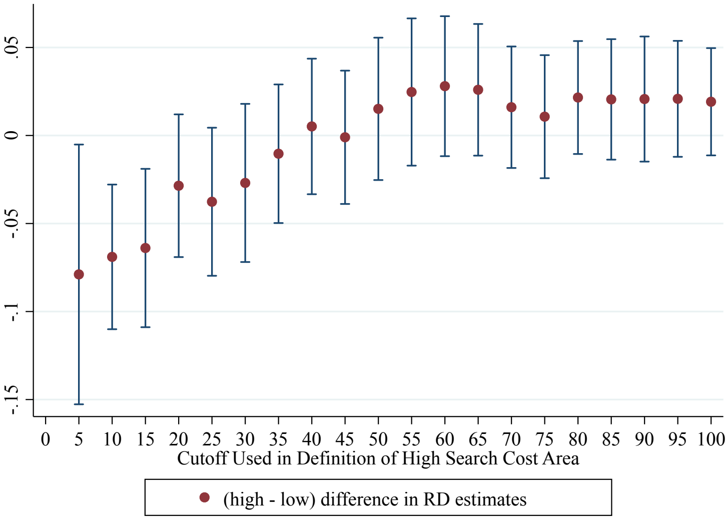
Pricing Discontinuities Largest for low FICOs



Older cars generally have higher mileage ▸ Back



Robustness to varying definition of high search cost



Addressing endogeneity of search-cost measure

- Number of proximate financial institutions possibly correlated with
  1. time-varying differences (local economic shocks, etc.) and/or
  2. time-invariant differences (financial sophistication, etc.)

Addressing endogeneity of search-cost measure

- Number of proximate financial institutions possibly correlated with
  1. time-varying differences (local economic shocks, etc.) and/or
  2. time-invariant differences (financial sophistication, etc.)
- Address (1) with Bartik instrument using 1990 branch network
- Address (2) with
  (a) zip8 FEs and
  (b) diff-in-diffs around branch closings

Back

Time-varying endogeneity of search costs

- Easy to think of time-varying joint endogeneity between takeup and search costs, e.g. endogenous branch closings
- Abstract away from *time-varying* endogeneity of search costs with shift-shares instrument for number of proximate financial institutions
- Use NETS, FDIC, and NCUA data

$$\#PFIs_{ct}^{Bartik} = \#PFIs_{c,1990} \times \frac{\overline{\#PFIs}_{-c,t}}{\overline{\#PFIs}_{-c,1990}}$$

- Define High Search Costs if $\#PFIs_{ct}^{Bartik} \leq 10$

Results with Bartik Instrument

$$takeup_{ict} = \eta_{cz(i)} + \delta_t + \gamma \cdot \widetilde{FICO}_{ict} + \delta \cdot 1(\widetilde{FICO}_{ict} \geq 0) + \beta \cdot \widetilde{FICO}_{ict} \cdot 1(\widetilde{FICO}_{ict} \geq 0) + \varepsilon_{ict}$$

	$Takeup_{ict}$= 1(Loan Offer Accepted)		
Bartik Search Costs	High	Low	Diff
	(1)	(2)	(1)-(2)
Discontinuity Coefficient	0.050	0.135***	-0.085***
	(0.045)	(0.037)	(0.006)
Discontinuity×Lender FE	✓	✓	
CZ×Quarter FE	✓	✓	
N	5,591	25,152	

Back

Time-invariant endogeneity

- Remaining problem is whether branch proximity is correlated with other things *that determine effect of discontinuity*
- Time-invariant characteristics may determine branch network and takeup, e.g., financial sophistication
- Usual problem with Bartik instruments: possibility of endogenous initial conditions
- Looking within CZ may not be enough—CZs large

Addressing time-invariant endogeneity

- Two solutions given Bartik robustness:

1. Zip8 fixed effects in RD, identify off how RD differs for places that changed their

$$takeup_{igt} = \eta_g + \delta_t + \gamma \cdot \widetilde{FICO}_{ict} + \delta \cdot 1(\widetilde{FICO}_{ict} \geq 0) + \beta \cdot \widetilde{FICO}_{ict} \cdot 1(\widetilde{FICO}_{ict} \geq 0) + \varepsilon_{ict}$$

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2. Difference-in-differences design that focuses on *changes* to search cost status

$$takeup_{igt} = \eta_g + \delta_t + \gamma High\ Search\ Cost_{gt} + \beta FICO_{igt} + \varepsilon_{igt}$$

$$\Delta takeup_{gt} = \eta_{cz(g)} + \delta_{t,\Delta t} + \gamma \Delta High\ Search\ Cost_{gt} + \beta \Delta FICO_{gt} + \varepsilon_{gt}$$

Zip8 FEs in RD Design

$$takeup_{igt} = \eta_g + \delta_t + \gamma \cdot \widetilde{FICO}_{ict} + \delta \cdot 1(\widetilde{FICO}_{ict} \geq 0) + \beta \cdot \widetilde{FICO}_{ict} \cdot 1(\widetilde{FICO}_{ict} \geq 0) + \varepsilon_{ict}$$

Search Costs Sample	High	Low	Difference
Discontinuity Coefficient	0.066	0.190***	-0.125
	(0.057)	(0.035)	(0.009)
8-digit Zip-code FE	✓	✓	
Quarter FE	✓	✓	
Number of Observations	4,436	26,307	

Takeup difference-in-differences

$$takeup_{igt} = \eta_g + \delta_t + \gamma High\ Search\ Cost_{gt} + \beta FICO_{igt} + \varepsilon_{igt}$$

$$\Delta takeup_{gt} = \eta_{cz(g)} + \delta_{t,\Delta t} + \gamma \Delta High\ Search\ Cost_{gt} + \beta \Delta FICO_{gt} + \varepsilon_{gt}$$

	Levels	Differences
High Search Cost Area	0.11**	0.03*
	(0.04)	(0.017)
FICO	-0.00004	-0.0002***
	(0.0003)	(0.00003)
Geographic Fixed Effects	Zip9	CZ
Time Fixed Effects	Quarter	Quarter Pair
Number of Observations	608	29,321
R-squared	0.60	0.05

Robust standard errors clustered by time.

→ Borrowers in areas that became high search cost more likely to accept

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Validating conditional on take-up results

	(1) Days Delinq.	(2) Charge-off	(3) Default	(4) ΔFICO
Discontinuity	4.185	0.004	0.002	0.001
Coefficient	(3.101)	(0.003)	(0.003)	(0.003)
Discon. $\times$ Lender FE	✓	✓	✓	✓
Commuting Zone FE	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓
N	331,590	514,834	514,834	405,236
R^2	0.162	0.073	0.091	0.015

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Are search costs just a catch all for imperfect competition?

Search Costs	Competition: LOW	Competition: HIGH
LOW	0.12 [3.49]	0.11 [3.38]
HIGH	-0.03 [-0.24]	-0.02 [-0.23]