Real Effects of Search Frictions in Consumer Credit Markets

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Credit-Market Imperfections

• How are credit markets special?

• Key household finance question: what credit-market imperfections prevent optimal consumption?
  ○ Adams, Einav, Levin (2009) – Adverse selection and moral hazard
  ○ Scharfstein & Sunderam (2017) – Credit market concentration

• This paper: use auto-loan setting to document importance of search frictions in consumer finance
Relevance of costly search in credit markets

- SCF: Many people report doing “almost no searching” for loan.
- Bhutta et al. (2018): 96% of mortgagors think they got the best rate.
- Adams et al. (2019): UK depositors overestimate shopping time
- Our data: Average borrower 15 min drive from branch
  - contrast with U.S. average commute time 26 min
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- Frictions in credit markets affect durable consumption
- Importance of physical distance surprising in digital world,
  - especially salient in an era of declining bank branches.
What we document in this paper

Search frictions in auto loan markets:

1. Lead to price dispersion / interest-rate markups
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Search frictions in auto loan markets:

1. Lead to price dispersion / 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 consumption $\Rightarrow$ DWL
Welfare Consequences of Search Frictions

- Usual sequential search model: inelastic unit demand for a homogenous final good
- Firm $j$ charges
  \[ p_j = MC + \text{markup}_j \]
- Given search cost distribution, markup distribution adjusts
- For each consumer having drawn price $p$
  \[ E(p_j) - p \leq k \]
- In equilibrium, buyers stay with first seller
- Costly search consequence: transfer from buyer to seller
Reality: Elastic Demand, Complements

Reality: DWL has two components.

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

2. For complements/intermediate goods, distorts final good consumption

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

   → Credit market specialness
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search frictions ⇒ credit markups ⇒ smaller loans ⇒ 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, more than credit cards
- 114m outstanding loans \(\approx 0.9\) per U.S. household
- 85\% of car purchases are financed (Consumer Reports, 2013)
- Vehicles 50\%+ of low-wealth HHs total assets (Campbell, 2006)
Data Source

- Data from a private software services company
- 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, ethnicity
- Ex-ante loan variables: Interest rate, LTV, channel
- Collateral variables: make, model, year, purchase price
- Ex-post loan performance: delinquency, charge-off, ΔFICO
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Equilibrium Price Dispersion

- Price dispersion: same good sold for different prices
- Null hypothesis: Law of One Price holds
- Classic explanation: information/search frictions

- Theory: P.D. sustainable when some consumers only know one price

- Empirical challenge: ruling out product heterogeneity
Extensive empirical literature on price dispersion and search

- Prescription drugs: Sorensen (2000)
- Credit cards: Stango and Zinman (2016)
- Cars: Goldberg and Verboven (2001)
- Airfares, houses, auto insurance, electronics, books, fish...

→ Open Questions:
  - All of these assume inelastic demand! How 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 (obscured by models with inelastic demand)
- Develop several comparative statics and testable predictions
- Results apply more broadly to the demand for any two complements.
Borrowers

- Continuum of borrowers ex-ante identical with quasi-linear indirect utility

\[ U(r, p, W) = V(r, p) + W \]

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

- Assume that demand for loans and durables downward sloping
  \[ \Rightarrow V(\cdot, \cdot) \text{ is strictly decreasing in both its arguments.} \]

- Do not implicitly assume cross-price elasticities to be zero!
  - e.g., car loans and car services are strong complements.
Borrower Search

- Borrowers believe $r \sim F$ on $[r, \bar{r}]$ 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
  \[ \int_r^{r'} [V(r, p) - V(r', p)]dF(r) - k \]
- Optimal search: reservation price $m(k)$ (De Groot, 1970; Lippman and McCall, 1976)
- Impt to use $V(\cdot, \cdot)$ instead of just markups $r$
  - Incorporates elastic demand + complements
  - Markups lead to smaller loans and less durable consumption
Lenders

- Lenders $j \in J$ have marginal costs $c_j \sim G$ on $[c, \bar{c}]$ to lend $1$
- Lenders are perfectly informed of $k$ and $F(\cdot)$
- Choose an interest rate $r_j$ to max expected profits

$$E\pi_j = \begin{cases} (r_j - c_j)q(r_j, p)E(N_j) & \text{for } r_j \leq m(k) \\ 0 & \text{for } r_j > m(k) \end{cases}$$

- $N_j$ is the number of borrowers that each take out $q(r_j)$
Equilibrium

- Pure-strategy Nash Equilibrium with price dispersion
- Given demand elasticity $\eta_r$, lender FOC satisfied when
  \[ r_j = \frac{c_j \eta_r}{\eta_r + 1} \]
- Borrower indifference over further search
  \[ \int_r^{m(k)} [V(r, p) - V(m(k), p)]dF_{m(k)}(r) = k \]
  \[ \Rightarrow m(k) \text{ depends also in how interest rates paid affect the utility received from the corresponding loan sizes and durable consumption through } V(\cdot, \cdot). \]
- For given $k$, \( \{m(k), F_{m(k)}(\cdot)\} \) constitute an equilibrium
Welfare

Deadweight loss has three components:

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

$$DWL = \int_{c_{\text{}}}^{c_{\text{}}} \int_{q(r^*(c),p)} q(c,p) (r(q) - c) dq dG(c) + \int_{c_{\text{}}}^{c_{\text{}}} \int_{0}^{q(r^*(c),p)} (c - c) dq dG(c)$$

- $r(q)$ is inverse demand
- $q^m(c, p)$ is the quantity lent by a monopolistic lender with constant marginal cost $c$
- $q^*(c, p)$ is the perfect-competition $q$

\textbf{n.b.,} under inelastic demand, $q^m = q^* \Rightarrow DWL = 0!$
Model Implications and Testable Predictions

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

- We put each borrower $i$ into a cell $\ell$ matched by
  - Origination time (two-quarter window)
  - Loan maturity (in years)
  - FICO Score (5-point bins)
  - Car value (in $1,000 bins)
  - Debt-To-Income (10-point bins)
  - Commuting Zone

- Calculate the Difference from Lowest Available Rate

\[ DLAR_{i\ell} \equiv r_i - \min_{j \in \ell} r_j \]
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• Calculate the Difference from Lowest Available Rate

$$DLAR_{i\ell} \equiv r_i - \min_{j \in \ell} r_j$$

• Lower bound given data coverage (but multiple providers still big leap over existing lit)
Estimated Price Dispersion

- Mean: 234 bp, Median: 125 bp, 46% of borrowers get best rate
- Average markup 27 bp higher in high search-cost markets
Potential Reasons for Observed Price Dispersion

1. Costly price discovery
2. Measurement Error
3. Unobserved heterogeneity
Potential Reasons for Observed Price Dispersion

1. Costly price discovery
2. Measurement Error
3. Unobserved heterogeneity
   - Strategy: test for #1 in a setting where we can rule out #2 and #3
   - Exploit quasi-experimental variation in *benefits* to search
   - Measure search behavior and link to measures of search costs
   - Estimate consequences of costly search by comparing people with high return to search in high vs. low search cost areas
Real Effects of Search Frictions

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Example Credit Union with three discontinuities
Detecting Discontinuities

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

\[ r_{il} = \alpha + \sum_{b} \delta_b \mathbb{1}(FICO_i \in Bin_b) + \varepsilon_{il} \]

- 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 noise)
Example Credit Union with five discontinuities
Wide heterogeneity across institutions in policies
Empirical Strategy

- Regression Discontinuity around detected lending thresholds $\mathcal{D}$
- Form discontinuity sample using loans $\pm 19$ FICO-point window around the threshold
- Normalize FICO scores to each cutoff and estimate
  \[
  r_{iglt} = \sum_{d \in \mathcal{D}} 1(FICO_{il} \in \mathcal{D}_d) \left( \delta \cdot 1(FICO_{id} \geq 0) + f(FICO_{id}; \pi) + \psi_{dl} \right) + \alpha_g + \delta_t + \epsilon_{iglt}
  \]
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  - Quadratic RD function of running variable
    \[ f(FICO; \pi) = \pi_1 FICO + \pi_2 FICO^2 + 1(FICO \geq 0) \left( \pi_3 FICO + \pi_4 FICO^2 \right) \]
  
  - Uniform kernel: $1(FICO_{il} \in D_d)$ indicates loan $i$ within 20 points of discontinuity $d$ at lender $l$
  
  - Discontinuity $\times$ lender, Commuting Zone, and quarter fixed effects
First stage for FICO = 600 cutoff
First stage for FICO = 640 cutoff
First stage for FICO = 700 cutoff
First stage: 130 bp difference in $r$

<table>
<thead>
<tr>
<th></th>
<th>(1) Loan Rate</th>
<th>(2) Loan Term</th>
</tr>
</thead>
<tbody>
<tr>
<td>Discontinuity</td>
<td>-0.0127***</td>
<td>0.822***</td>
</tr>
<tr>
<td>Coefficient</td>
<td>(0.004)</td>
<td>(0.187)</td>
</tr>
<tr>
<td>Discontinuity x Lender FEs</td>
<td>✓ ✓</td>
<td>✓ ✓</td>
</tr>
<tr>
<td>Lender FEs</td>
<td>✓ ✓</td>
<td></td>
</tr>
<tr>
<td>Quarter FE</td>
<td>✓ ✓</td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>514,834</td>
<td>514,834</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.169</td>
<td>0.083</td>
</tr>
</tbody>
</table>

-127 bp on average car loan is $\Delta PMT$ of $13$ and $\Delta PV$ of $440$

- Heterogeneity by FICO
Discontinuities provide variation in benefits of searching

Difference in means: 70 bps
Placebo test: no difference w/o discontinuity
LHS borrowers face high returns to search across lenders

RHS of cutoff: offered this rate
LHS of cutoff: offered this interest rate

Distribution of interest rates for a given (time, value, DTI, MSA) cell
Are LHS and RHS borrowers different along any observable dimension?
  - e.g., (un)awareness of pricing policies correlated with quality

Rule out selection via smoothness of observables at discontinuity:
  ✔ Application loan size
  ✔ Application Debt-to-Income
  ✔ Borrower age
  ✔ Borrower gender
  ✔ Borrower ethnicity
Balance checks: Application Debt-to-Income Ratio
Balance checks: Application Loan Amount
Balance checks: Applicant Age
Balance checks: Applicant Ethnicity

![Graph showing average probability of being white against FICO score relative to threshold. The graph includes error bars and a polynomial fit of order 4.]

- Sample average within bin
- Polynomial fit of order 4
Balance checks: Applicant Gender
No bunching in running variable: Application Counts
## Ex-ante Smoothness

<table>
<thead>
<tr>
<th>Application Loan Amount (1)</th>
<th>Application Debt-to-Income (2)</th>
<th>Number of Loan Applications (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Discontinuity</td>
<td>Coefficient</td>
<td></td>
</tr>
<tr>
<td>128.43</td>
<td>(187.75)</td>
<td>-270.18</td>
</tr>
<tr>
<td>-0.084</td>
<td>(0.447)</td>
<td></td>
</tr>
<tr>
<td>Discon. × Lender FE</td>
<td></td>
<td></td>
</tr>
<tr>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Institution FE</td>
<td></td>
<td></td>
</tr>
<tr>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Quarter FE</td>
<td></td>
<td></td>
</tr>
<tr>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>N</td>
<td>117,985</td>
<td>91,923</td>
</tr>
<tr>
<td>117,985</td>
<td>91,923</td>
<td>39</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.058</td>
<td>0.009</td>
</tr>
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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
  - Can matter 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
Bringing costly search to the data

To ask whether costly search inhibits price discovery, we need

1. A measure of borrower search
   - 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

37/48
Bringing costly search to the data

To ask whether costly search inhibits price discovery, we need

1. A measure of borrower search
   - Total number of applications per borrower
   - Accepting/Rejecting approved loans from application data
   - Takeup \( \equiv 1(\text{Offered loan is accepted}) \)

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 \( \equiv 1(\leq 10 \text{ lenders within 20 minute drive}) \)
Direct measure of search varies with search costs

<table>
<thead>
<tr>
<th></th>
<th>High Search Costs (1)</th>
<th>Low Search Costs (2)</th>
<th>Difference (1) - (2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>1.342</td>
<td>1.409</td>
<td>-0.067***</td>
</tr>
<tr>
<td>S.D.</td>
<td>(0.009)</td>
<td>(0.004)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>N</td>
<td>6,042</td>
<td>44,655</td>
<td></td>
</tr>
</tbody>
</table>

- Data coverage makes this a lower bound
- n.b., in Stahl equilibrium, all shoppers buy from first seller they query.
Indirect measure of search varies with search costs

\[
\text{takeup}_{igt} = \sum_{d \in D} 1(FICO_{il} \in D_d) \left( \delta \cdot 1(FICO_{id} \geq 0) + f(FICO_{id}; \pi) + \psi_{dl} \right) + \alpha_g + \delta_t + \varepsilon_{iglt}
\]

- Estimate for high/low search cost areas
- Investigate if markups more consequential in low search-cost areas
- Verify markups comparable across high/low search-cost areas
- Check robustness to possible endogeneity of search-cost measure
Indirect measure of search varies with search costs

<table>
<thead>
<tr>
<th>Search Costs</th>
<th>Full (1)</th>
<th>High (2)</th>
<th>Low (3)</th>
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<tr>
<td>Dependent Variable = 1(Loan Offer Accepted)</td>
<td></td>
<td></td>
<td></td>
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<td>Discontinuity Coefficient</td>
<td>0.121*** (0.015)</td>
<td>0.020*** (0.005)</td>
<td>0.137*** (0.016)</td>
<td>-0.116*** (0.006)</td>
</tr>
<tr>
<td>Discon. × Lender FE</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
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<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>Commuting Zone FE</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>30,743</td>
<td>4,436</td>
<td>26,307</td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.27</td>
<td>0.45</td>
<td>0.25</td>
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- Discon. × Lender FE: ✓ ✓ ✓
- Quarter FE: ✓ ✓ ✓
- Commuting Zone 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
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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...

- Check for selection: Do LHS borrowers have worse ex-post outcomes?
  - ✓ # days delinquent
  - ✓ default (90+ days past due)
  - ✓ charge-off (was loan written off by lender)
  - ✓ ΔFICO score since origination
## Validating conditional on take-up results

<table>
<thead>
<tr>
<th></th>
<th>(1) Days Delinq.</th>
<th>(2) Charge-off</th>
<th>(3) Default</th>
<th>(4) ΔFICO</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Discontinuity Coefficient</strong></td>
<td>4.185 (3.101)</td>
<td>0.004 (0.003)</td>
<td>0.002 (0.003)</td>
<td>0.001 (0.003)</td>
</tr>
<tr>
<td><strong>Discon. × Lender FE</strong></td>
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<td>✓</td>
<td>✓</td>
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<tr>
<td><strong>N</strong></td>
<td>331,590</td>
<td>514,834</td>
<td>514,834</td>
<td>405,236</td>
</tr>
<tr>
<td><strong>$R^2$</strong></td>
<td>0.162</td>
<td>0.073</td>
<td>0.091</td>
<td>0.015</td>
</tr>
</tbody>
</table>
Real Effects: Loan Choice Impacts Real Consumption

<table>
<thead>
<tr>
<th></th>
<th>(1) Price</th>
<th>(2) Loan Amount</th>
<th>(3) LTV</th>
<th>(4) Payment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Discontinuity Coefficient</td>
<td>376.58**</td>
<td>566.21***</td>
<td>0.0130**</td>
<td>0.17</td>
</tr>
<tr>
<td></td>
<td>(175.72)</td>
<td>(167.93)</td>
<td>(0.005)</td>
<td>(1.02)</td>
</tr>
</tbody>
</table>

Discon. × Lender FE ✓ ✓ ✓ ✓ ✓
Commuting Zone FE ✓ ✓ ✓ ✓ ✓
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

<table>
<thead>
<tr>
<th></th>
<th>(1) Car Value</th>
<th>(2) Car Value</th>
<th>(3) Car Age</th>
</tr>
</thead>
<tbody>
<tr>
<td>Discontinuity</td>
<td>344.69***</td>
<td>79.71</td>
<td>-1.76***</td>
</tr>
<tr>
<td>Coefficient</td>
<td>(123.78)</td>
<td>(49.25)</td>
<td>(0.043)</td>
</tr>
</tbody>
</table>

- Discon. × Lender FE: ✓ ✓ ✓
- Commuting Zone FE: ✓ ✓ ✓
- Quarter FE: ✓ ✓ ✓
- Make-Model FE: ✓ ✓
- Year-Make-Model FE: ✓

<table>
<thead>
<tr>
<th>N</th>
<th>468,800</th>
<th>468,800</th>
<th>468,800</th>
</tr>
</thead>
<tbody>
<tr>
<td>R²</td>
<td>0.353</td>
<td>0.767</td>
<td>0.352</td>
</tr>
</tbody>
</table>

- Costly search ⇒ market power ⇒ each lender faces downward sloping demand ⇒ consumption response to price dispersion ⇒ DWL: fewer and lower quality goods
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
Ruling out alternative explanations

1. Selection into takeup
2. Exclusivity of credit unions
3. Measurement error in interest rates
4. Digital search
5. Risk-based pricing on other dimensions
6. Lender price discrimination
7. Steering by car dealers to lenders
Conclusion

- Auto loans market full of price dispersion, search frictions
- Used rich data to isolate exogenous variation in the benefits of search
- Provided direct evidence that search costs influence search behavior
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- Search costs $\Rightarrow$ finance less, buy older, $400$ less car
Conclusion

- Auto loans market full of price dispersion, search frictions
- Used rich data to isolate exogenous variation in the benefits of search
- Provided direct evidence that search costs influence search behavior
- Transmission of interest rates to durables inhibited by search frictions
- Search costs ⇒ finance less, buy older, $400 less car
- In the real world, elastic demand + costly search ⇒ DWL
- Costly-search fueled markups affect consumer welfare through both extensive and intensive margins
  
  search frictions ⇒ credit markups ⇒ smaller loans ⇒ lower consumption
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 less diverse (73% estimated to be white vs. 64.5% in census data).
- Median FICO at origination is 711 (vs. 695 for US borrowers)
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
### Example rate sheet

**New Auto Loans: Model Years 2015 and Newer**

<table>
<thead>
<tr>
<th>Repayment Period</th>
<th>Minimum Loan Amount</th>
<th>Credit Score 740+</th>
<th>APR^</th>
<th>DPR</th>
<th>Credit Score 739 to 700</th>
<th>APR^</th>
<th>DPR</th>
<th>Credit Score 699 to 660</th>
<th>APR^</th>
<th>DPR</th>
<th>Credit Score 659 to 610</th>
<th>APR^</th>
<th>DPR</th>
<th>Credit Score 609 to 560</th>
<th>APR^</th>
<th>DPR</th>
<th>Credit Score 559 or below</th>
<th>APR^</th>
<th>DPR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Up to 36 Months¹</td>
<td>$500</td>
<td>2.24%</td>
<td>0.0061%</td>
<td>2.74%</td>
<td>0.0075%</td>
<td>3.99%</td>
<td>0.0075%</td>
<td>8.24%</td>
<td>0.0226%</td>
<td>13.49%</td>
<td>0.0370%</td>
<td>14.49%</td>
<td>0.0397%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>37 - 60 Months</td>
<td>$5,000</td>
<td>2.74%</td>
<td>0.0075%</td>
<td>3.24%</td>
<td>0.0089%</td>
<td>4.49%</td>
<td>0.0116%</td>
<td>8.74%</td>
<td>0.0239%</td>
<td>13.99%</td>
<td>0.0383%</td>
<td>14.99%</td>
<td>0.0411%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>61 - 66 Months</td>
<td>$6,000</td>
<td>2.99%</td>
<td>0.0082%</td>
<td>3.49%</td>
<td>0.0096%</td>
<td>4.74%</td>
<td>0.0116%</td>
<td>8.99%</td>
<td>0.0246%</td>
<td>14.24%</td>
<td>0.0390%</td>
<td>15.24%</td>
<td>0.0418%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>67 - 75 Months</td>
<td>$10,000</td>
<td>3.24%</td>
<td>0.0089%</td>
<td>3.74%</td>
<td>0.0102%</td>
<td>4.99%</td>
<td>0.0130%</td>
<td>9.24%</td>
<td>0.0253%</td>
<td>14.49%</td>
<td>0.0397%</td>
<td>15.49%</td>
<td>0.0424%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>76 - 84 Months²</td>
<td>$15,000</td>
<td>3.49%</td>
<td>0.0096%</td>
<td>3.99%</td>
<td>0.0109%</td>
<td>5.24%</td>
<td>0.0158%</td>
<td>9.49%</td>
<td>0.0260%</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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.
Pricing Discontinuities Largest for low FICOs
Older cars generally have higher mileage.
Robustness to varying definition of high search cost

(high - low) difference in RD estimates
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

\[
\#PFIs_{ct}^{Bartik} = \#PFIs_{c,1990} \times \frac{\#PFIs_{-,c,t}}{\#PFIs_{-,c,1990}}
\]

• Define High Search Costs if \( \#PFIs_{ct}^{Bartik} \leq 10 \)
Results with Bartik Instrument

\[ \text{takeup}_{ict} = \eta_{cz(i)} + \delta_t + \gamma \cdot \text{FICO}_{ict} + \delta \cdot 1(\text{FICO}_{ict} \geq 0) + \beta \cdot \text{FICO}_{ict} \cdot 1(\text{FICO}_{ict} \geq 0) + \varepsilon_{ict} \]

<table>
<thead>
<tr>
<th>Bartik Search Costs</th>
<th>High (1)</th>
<th>Low (2)</th>
<th>Diff (1)-(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Discontinuity Coefficient</td>
<td>0.050 (0.045)</td>
<td>0.135*** (0.037)</td>
<td>-0.085*** (0.006)</td>
</tr>
<tr>
<td>Discontinuity $\times$ Lender FE</td>
<td>✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>CZ $\times$ Quarter FE</td>
<td>✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>5,591</td>
<td>25,152</td>
<td></td>
</tr>
</tbody>
</table>
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

\[
\text{takeup}_{igt} = \eta_g + \delta_t + \gamma \cdot \overline{FICO}_{ict} + \delta \cdot 1(\overline{FICO}_{ict} \geq 0) + \beta \cdot \overline{FICO}_{ict} \cdot 1(\overline{FICO}_{ict} \geq 0) + \varepsilon_{ict}
\]
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
     \[ \text{takeup}_{igt} = \eta_g + \delta_t + \gamma \cdot \tilde{FICO}_{ict} + \delta \cdot 1(\tilde{FICO}_{ict} \geq 0) + \beta \cdot \tilde{FICO}_{ict} \cdot 1(\tilde{FICO}_{ict} \geq 0) + \varepsilon_{ict} \]
  2. Difference-in-differences design that focuses on changes to search cost status
     \[ \text{takeup}_{igt} = \eta_g + \delta_t + \gamma \text{High Search Cost}_{gt} + \beta \text{FICO}_{igt} + \varepsilon_{igt} \]
     \[ \Delta \text{takeup}_{gt} = \eta_{cz(g)} + \delta_{t,\Delta t} + \gamma \Delta \text{High Search Cost}_{gt} + \beta \Delta \text{FICO}_{gt} + \varepsilon_{gt} \]
Zip8 FEs in RD Design

\[ \text{takeup}_{igt} = \eta_g + \delta_t + \gamma \cdot \text{\textit{FICO}}_{ict} + \delta \cdot 1(\text{\textit{FICO}}_{ict} \geq 0) + \beta \cdot \text{\textit{FICO}}_{ict} \cdot 1(\text{\textit{FICO}}_{ict} \geq 0) + \varepsilon_{ict} \]

<table>
<thead>
<tr>
<th>Search Costs Sample</th>
<th>High</th>
<th>Low</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Discontinuity Coefficient</td>
<td>0.066 (0.057)</td>
<td>0.190*** (0.035)</td>
<td>-0.125 (0.009)</td>
</tr>
<tr>
<td>8-digit Zip-code FE</td>
<td>✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>Quarter FE</td>
<td>✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>Number of Observations</td>
<td>4,436</td>
<td>26,307</td>
<td></td>
</tr>
</tbody>
</table>
Takeup difference-in-differences

\[ \text{takeup}_{igt} = \eta_g + \delta_t + \gamma \text{High Search Cost}_{gt} + \beta \text{FICO}_{igt} + \varepsilon_{igt} \]

\[ \Delta \text{takeup}_{gt} = \eta_{cz(g)} + \delta_{t, \Delta t} + \gamma \Delta \text{High Search Cost}_{gt} + \beta \Delta \text{FICO}_{gt} + \varepsilon_{gt} \]

<table>
<thead>
<tr>
<th>Levels</th>
<th>Differences</th>
</tr>
</thead>
<tbody>
<tr>
<td>High Search Cost Area</td>
<td>0.11**</td>
</tr>
<tr>
<td>(0.04)</td>
<td>(0.017)</td>
</tr>
<tr>
<td>FICO</td>
<td>-0.00004</td>
</tr>
<tr>
<td>(0.0003)</td>
<td>(0.00003)</td>
</tr>
<tr>
<td>Geographic Fixed Effects</td>
<td>Zip9</td>
</tr>
<tr>
<td>Time Fixed Effects</td>
<td>Quarter</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>608</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.60</td>
</tr>
</tbody>
</table>

Robust standard errors clustered by quarter

→ Borrowers in areas that became high search cost more likely to accept
Are search costs just a catch all for imperfect competition?

<table>
<thead>
<tr>
<th>Search Costs</th>
<th>Competition</th>
</tr>
</thead>
<tbody>
<tr>
<td>LOW</td>
<td>LOW</td>
</tr>
<tr>
<td>LOW</td>
<td>0.12</td>
</tr>
<tr>
<td></td>
<td>[3.49]</td>
</tr>
<tr>
<td>HIGH</td>
<td>-0.03</td>
</tr>
<tr>
<td></td>
<td>[-0.24]</td>
</tr>
</tbody>
</table>