Real Effects of Search Frictions in Consumer Credit Markets

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Consumer Credit Market Imperfections

- Key question for household finance: what credit-market imperfections prevent optimal consumption?
  - Adams, Einav, Levin (2009) – Adverse selection and moral hazard
  - Scharfstein & Sunderam (2016) – Credit mkt concentration + MP
  - Agarwal et al. (2017) – Mismatch in who gets/wants credit expansion

- This paper: use auto-loan setting to document importance of search frictions in consumer finance
We find that 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

Relevance of costly search in credit markets

- SCF: Many people report doing “almost no searching” for loan.
- Our data: Average borrower 15 min drive from branch
  - contrast with U.S. average commute time 26 min
- Importance of physical distance surprising in digital world, especially salient in an era of declining bank branches
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Outline

1. Auto loans setting and data
2. Measuring interest rate dispersion
3. Discontinuous pricing policies
4. Direct evidence on search costs and search behavior
5. Consequences of search frictions on loans and consumption
6. Pass-through of interest rates
Auto loans are ubiquitous, important

- $1.2$ trillion outstanding (NY Fed, 2016)
- Fastest growing consumer debt category, 3rd largest
- 100m outstanding loans $\approx 0.8$ per U.S. household
- 85% of car purchases are financed (Consumer Reports, 2003)
- Vehicles 50%+ of low-wealth HHs total assets (Campbell, 2006)
Data Source

- Data from a private software services company
- 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
- 2.2 million loan applications originating from 46 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)
- **Mortgages**: Woodward & Hall (2012), Alexandrov & Koulayev (2017)
- **Credit cards**: Stango and Zinman (2016)
- **Mutual funds**: Hortacsu and Syverson (2004)
- **Cars**: Goldberg and Verboven (2001)
- **Online shopping**: De Los Santos, Hortacsu, and Wildenbeest (2012), Ellison & Ellison (2009)
- **Airfares, houses, auto insurance, electronics, books, fish**...
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→ **Open Questions**:
  - How are search frictions in consumer credit markets special?
  - What are the welfare consequences of credit-market search frictions?
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

\[ DLAR_{i\ell} \equiv r_i - \min_{j \in \ell} r_j \]
Estimated Price Dispersion

Mean: 173 bp, Median: 119 bp, 19% of borrowers in populated cells get best rate.
DLAR bins: 5 pt FICO, $1,000 collateral, same maturity, 10 pt DTI, same CZ, same 6 months
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 variation in potential benefits to search (Sorensen, 2000)
- Measure search behavior and link to measures of search costs
- Estimate consequences of costly search
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Example Credit Union #1

Real Effects of Search Frictions
Discontinuous pricing policies

FICO Score Bin vs. FICO Bin Coefficient

- The graph illustrates the relationship between FICO Score Bin and FICO Bin Coefficient for Example Credit Union #1.

- The x-axis represents FICO Score Bin, ranging from 500 to 800.

- The y-axis represents FICO Bin Coefficient, ranging from -0.04 to 0.1.

- Each data point indicates the coefficient for a specific FICO Score Bin, with error bars showing the variability.

- The data suggests a discontinuous pattern in pricing policies, especially noticeable in the FICO Score Bin range of 600 to 700.
Detecting Discontinuities

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

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

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

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

The chart illustrates the density of FICO breakpoints across various credit scores. The x-axis represents different FICO breakpoints ranging from 540 to 760, while the y-axis shows the density ranging from 0 to 0.03. The chart reveals a high density of breakpoints around the FICO scores of 640 and 700, indicating significant market discontinuities in these areas.
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)
- 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
### 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>Credit Score 739 to 700</th>
<th>Credit Score 699 to 660</th>
<th>Credit Score 659 to 610</th>
<th>Credit Score 609 to 600</th>
<th>Credit Score 599 or below</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>APR^</td>
<td>DPR</td>
<td>APR^</td>
<td>DPR</td>
<td>APR^</td>
<td>DPR</td>
<td>APR^</td>
</tr>
<tr>
<td>Up to 36 Months</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>
</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>
</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>
</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>
</tr>
<tr>
<td>76 - 84 Months</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>
</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.
Empirical Strategy

- Regression Discontinuity around lending thresholds.
- To avoid cross-treatment contamination, form discontinuity sample to include thresholds with >100,000 loans in the ±19 FICO points window around the threshold
  - Keep institutions w/o another threshold within 19 FICO points
  - Normalize FICO scores to cutoff and estimate

\[
 r_{ict} = \beta_1 \tilde{FICO}_{ict} + \beta_2 \mathbb{I}(\tilde{FICO}_{ict} \geq 0) \\
+ \beta_3 \tilde{FICO}_{ict} \cdot \mathbb{I}(\tilde{FICO}_{ict} \geq 0) + \alpha_c + \delta_t + \varepsilon_{ict}
\]

- Use bias-corrected RD estimator of Calonico et al. (2014)
- Cluster by \( \tilde{FICO} \)
First stage for FICO = 600 cutoff
First stage for $\text{FICO} = 640$ cutoff

![Graph showing the relationship between FICO score relative to 640 and average loan rate. The graph includes a polynomial fit of order 4 and sample average within bin markers.](image-url)
First stage for FICO = 700 cutoff
First stage: 150 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 Coefficient</td>
<td>-0.0146***</td>
<td>1.19***</td>
</tr>
<tr>
<td></td>
<td>[-17.25]</td>
<td>[4.60]</td>
</tr>
<tr>
<td>Commuting Zone FE</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Quarter FE</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>274,029</td>
<td>274,029</td>
</tr>
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</table>

-150 bp on average car loan is $\Delta PMT$ of $25$ and $\Delta PV$ of $1300$

- Heterogeneity by FICO
Discontinuities provide variation in benefits of searching

Difference in means: 70 bps
Placebo test: no difference w/o discontinuity

Kernel Density

Spread to Lowest Available Rate

635 ≤ FICO ≤ 639

640 ≤ FICO ≤ 644
Is there selection around interest-rate discontinuities?

- 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 Loan Amount
Balance checks: Application DTI

![Graph showing the relationship between FICO Score Relative to Threshold and Average DTI. The graph includes a polynomial fit of order 4. Sample average within bin is also shown.]
Balance checks: Applicant Age

![Graph showing the relationship between FICO Score Relative to Threshold and Average Age. The graph includes the following elements:

- Sample average within bin:
- Polynomial fit of order 4]
Balance checks: Applicant Ethnicity

![Graph showing the average probability of white applicants across different FICO score thresholds. The graph includes a polynomial fit of order 4 and indicates sample average within bin.](image-url)
Balance checks: Applicant Gender

![Graph showing the average probability of Pr(male) for FICO scores relative to a threshold. The graph includes a polynomial fit of order 4, with sample average within bin markers.](image-url)
No bunching in running variable: Application Counts

McCrary Test of the Number of Applications
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Why don’t borrowers on LHS find better available rates?

- SCF indicates that many borrowers self-report doing very little shopping around for a loan

- 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)

- 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)
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
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 ≡ 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 ≡ 1(<10 lenders within 20 minute drive)
Indirect measure of search varies with search costs

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

- 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>
<th>Difference (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Discontinuity</td>
<td>0.097</td>
<td>-0.003</td>
<td>0.116</td>
<td>-0.12</td>
</tr>
<tr>
<td>Coefficient</td>
<td>[4.56]</td>
<td>[-0.06]</td>
<td>[4.90]</td>
<td>[-2.26]</td>
</tr>
<tr>
<td>Quarter FE</td>
<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>Number of Observations</td>
<td>19,784</td>
<td>3,822</td>
<td>16,088</td>
<td></td>
</tr>
</tbody>
</table>

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

• Robust to varying definition of high search cost area
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 diff-in-diffs around branch closings or by including Zip8 FEs
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>1.083</td>
<td>1.104</td>
<td>-.021</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>(.317)</td>
<td>(.352)</td>
<td>[-5.90]</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>10,846</td>
<td>75,837</td>
<td></td>
</tr>
</tbody>
</table>

• Data coverage makes this a lower bound
  ○ with uniform 1% coverage, difference of 2.1 applications.
• n.b., in Stahl equilibrium, all shoppers buy from first seller they query.
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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
## Real Effects: Loan Choice Impacts Real Consumption

<table>
<thead>
<tr>
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<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Purchase Price</td>
<td>715.41***</td>
<td>1,143.86***</td>
<td>0.03***</td>
<td>6.53***</td>
</tr>
<tr>
<td>Loan Amount</td>
<td>[8.55]</td>
<td>[10.31]</td>
<td>[3.92]</td>
<td>[4.97]</td>
</tr>
<tr>
<td>LTV</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Monthly Payment</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Discontinuity Coefficient</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Commuting Zone FE</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
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<td>Quarter FE</td>
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<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>N</td>
<td>274,029</td>
<td>274,029</td>
<td>274,029</td>
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</tr>
</tbody>
</table>
### Evidence on Substitution Patterns

<table>
<thead>
<tr>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Purchase Price</td>
<td>Purchase Price</td>
<td>Car Age (months)</td>
</tr>
<tr>
<td><strong>Discontinuity Coefficient</strong></td>
<td>647.42***</td>
<td>47.02</td>
</tr>
<tr>
<td></td>
<td>[6.41]</td>
<td>[0.79]</td>
</tr>
<tr>
<td>Commuting Zone FE</td>
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<td>✓</td>
</tr>
<tr>
<td>Quarter FE</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Make-Model FE</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>Year-Make-Model FE</td>
<td></td>
<td>✓</td>
</tr>
<tr>
<td><strong>Number of Observations</strong></td>
<td>247,493</td>
<td>247,485</td>
</tr>
</tbody>
</table>

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

1. Exclusivity of credit unions
2. Measurement error in interest rates
3. Digital search
4. Risk-based pricing on other dimensions
5. Lender price discrimination
6. Steering by car dealers to lenders
7. Dealer price discrimination
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Costly search inhibits monetary policy transmission

- Pushing on a string: need consumers to be able to find lower $r$ to pull
- Do search frictions affect pass-through of $\Delta$ Treasury rates?
- Estimate how link between relevant risk-free rate and originated rates is attenuated by search frictions
Costly search inhibits monetary policy transmission

- Pushing on a string: need consumers to be able to find lower $r$ to pull
- Do search frictions affect pass-through of $\Delta$ Treasury rates?
- Estimate how link between relevant risk-free rate and originated rates is attenuated by search frictions

$$r_{it} = \beta_1 Treas5_t + \beta_2 Treas5_t \cdot HighSearchCost_i + \beta_3 HighSearchCost_i$$

$$+ X'_i \gamma + \xi_{FICO(i)} + \alpha_{cz(i)} + \delta_t + \varepsilon_{it}$$
12-17% less pass-through of interest rates

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5-year Treasury</td>
<td>0.56</td>
<td></td>
<td>0.53</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[13.99]</td>
<td>[14.73]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5-year Treasury ×</td>
<td>-.019</td>
<td>-0.032</td>
<td>-0.03</td>
<td>-0.042</td>
</tr>
<tr>
<td>1(High Search Cost Area)</td>
<td>[-2.99]</td>
<td>[-5.36]</td>
<td>[-5.36]</td>
<td>[-7.69]</td>
</tr>
<tr>
<td>1(High Search Cost Area)</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>[8.74]</td>
<td>[10.18]</td>
<td>[12.50]</td>
<td>[13.86]</td>
</tr>
<tr>
<td>Commuting Zone FEs</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>FICO Bin FEs</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Month FEs</td>
<td>✓</td>
<td></td>
<td></td>
<td>✓</td>
</tr>
<tr>
<td>Loan-level Controls</td>
<td></td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Observations</td>
<td>2,529,362</td>
<td>2,529,362</td>
<td>2,529,362</td>
<td>2,529,362</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.59</td>
<td>0.61</td>
<td>0.76</td>
<td>0.78</td>
</tr>
</tbody>
</table>
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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• Provided direct evidence that search costs influence search behavior
• Transmission of interest rates to durables inhibited by search frictions
• Search costs ⇒ finance less, buy 3 months older, $700 less car
• Costly-search fueled markups affect consumer welfare through both extensive and intensive margins
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 715 (vs. 695 for US borrowers)
Pricing Discontinuities Largest for low FICO's
Robustness to varying definition of high search cost
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 Sample</th>
<th>High</th>
<th>Low</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Discontinuity Coefficient</td>
<td>0.025</td>
<td>.11</td>
<td>-0.084</td>
</tr>
<tr>
<td></td>
<td>[0.68]</td>
<td>[4.52]</td>
<td>[-1.84]</td>
</tr>
</tbody>
</table>

- Commuting Zone FE: ✓ ✓
- Quarter FE: ✓ ✓
- Number of Observations: 4,102 15,678

Robust t-stats in brackets clustered by normalized FICO score.
### 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></th>
<th>Levels</th>
<th>Differences</th>
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</thead>
<tbody>
<tr>
<td>High Search Cost Area</td>
<td>0.11</td>
<td>[2.97]</td>
</tr>
<tr>
<td>ΔHigh Search Cost Area</td>
<td></td>
<td>0.03</td>
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<tr>
<td>FICO</td>
<td>-0.0004</td>
<td>[-1.48]</td>
</tr>
<tr>
<td>ΔFICO</td>
<td></td>
<td>-0.0002</td>
</tr>
<tr>
<td>Geographic Fixed Effects</td>
<td>Zip9</td>
<td>CZ</td>
</tr>
<tr>
<td>Time Fixed Effects</td>
<td>Quarter</td>
<td>Quarter Pair</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>608</td>
<td>29,321</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.60</td>
<td>0.05</td>
</tr>
</tbody>
</table>

Robust t-stats clustered by time.
## Takeup Zip8 FEs

<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>-0.04</td>
<td>.12</td>
<td>-0.17</td>
</tr>
<tr>
<td></td>
<td>[-0.53]</td>
<td>[3.13]</td>
<td>[-1.95]</td>
</tr>
</tbody>
</table>

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>8-digit Zipcode 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>4,070</td>
<td>18,433</td>
<td></td>
</tr>
</tbody>
</table>

→ Borrowers in areas that are 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></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>
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</tbody>
</table>