Language Frictions in Consumer Credit

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Frictions in Consumer Credit Markets

Households make financial decisions affected by various frictions

- Costly search in auto loan markets
- Inaction when having refinancing opportunities
- Unaware of total borrowing costs of payday lending

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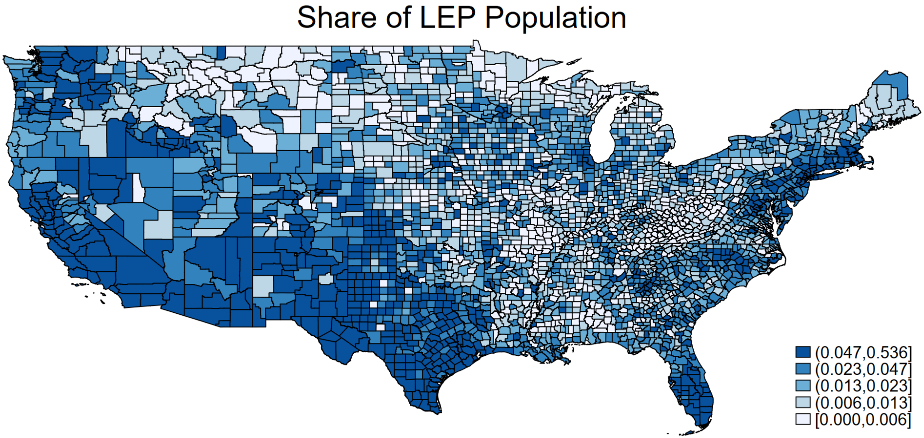
One fundamental yet often overlooked friction: language frictions

- Language barriers faced by limited English proficient (LEP) consumers
- LEP definition in the Census: speaking English less than "very well"

Over 25M LEP People in the US



Primary languages: Spanish (64%), Chinese, Korean, Vietnamese, Tagalog, Russian

This Paper

Question: How do language frictions affect household financial decisions?

- Do language frictions affect access to credit?
- How do language frictions affect the price of credit?
- Does reducing language frictions affect the quality of credit?

This Paper

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Setting: the U.S. mortgage market

- Mortgage balances accounted for 68% of total household debt in 2019 (FRBNY, 20)
- Hard to understand: disclosures (11th grade) vs. reading ability (8th grade)(GAO, 06)
- Regulators support access to credit for LEP borrowers (FHFA, 17)

This Paper

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Setting: the U.S. mortgage market

Solve the data challenge: survey + machine learning

- Data challenge: observe people's English proficiency
- Survey data: National Survey of Mortgage Originations (NSMO)
- Apply machine learning to predict LEP status

Natural Experiment: FHFA Language Access Plan

Identification Challenge: isolate the role of language from other factors

- Unobservables: financial literacy, cultural assimilation

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Federal Housing Finance Agency (FHFA) Language Access Plan

- Lenders used to face compliance risks (e.g., fair lending risks)
- FHFA provides an online centralized collection of translated mortgage documents
- Phased rollout: Spanish translations in 2018, followed by Chinese translations in 2019

Main Findings

Describe the distinct experiences of LEP borrowers:

- Before application: know less about the mortgage market
  $\approx$ 60% of the differences between borrowers with a college degree and those without

Main Findings

Describe the distinct experiences of LEP borrowers:

- Before application: know less about the mortgage market
- During application: encounter more problems
  5 pp more likely to redo mortgage paperwork

Main Findings

Describe the distinct experiences of LEP borrowers:

- Before application: know less about the mortgage market
- During application: encounter more problems
- After application: less familiar with their own mortgage contracts
  $\approx$ 2X more likely to be unsure if their own mortgage is an ARM

Main Findings

Describe the distinct experiences of LEP borrowers:

- Before application: know less about the mortgage market
- During application: encounter more problems
- After application: less familiar with their own mortgage contracts
- Mortgage outcomes: higher interest rate, same delinquency rate

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Estimate the effect of reducing language frictions:

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Estimate the effect of reducing language frictions:

- Access to credit (intensive): streamlined application process
  the probability of redoing paperwork $\downarrow$ 42%

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Estimate the effect of reducing language frictions:

- Access to credit (intensive): streamlined application process
- Access to credit (extensive): increased availability of credit
  mortgage application denial rate $\downarrow$ 16 pp

Main Findings

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Estimate the effect of reducing language frictions:

- Access to credit (intensive): streamlined application process
- Access to credit (extensive): increased availability of credit
- Price of credit: lower borrowing costs: at least 5 bps lower interest rates
  One possible channel: more borrower search

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Bottom line: a cost-effective way to create a more inclusive and sound mortgage market

Related Literature

- **Frictions in consumer credit markets**
  - Madrian & Shea, 01; Puri & Robinson, 07; Woodward & Hall, 12; Agarwal & Mazumder, 13; Lusardi & Tufano, 15; Stango & Zinman, 16; Argyle et al., 23
  - Document language frictions as a fundamental source of price dispersion
- **Real effects of government interventions in credit markets**
  - Bhutta, 11; Campbell et al., 11; Posner & Weyl, 13; Agarwal et al., 15; Célerier & Matray, 19; DeFusco et al., 20; Kielty et al., 21
  - Study a cost-effective policy targeting at an overlooked but nontrivial group
- **Effects of English ability**
  - McManus et al., 83; Tainer, 88; Chiswick, 91; Zavodny, 00; Dustmann & Fabbri, 03; Bleakley & Chin, 10; Guven & Islam, 15
  - Estimate the effects on financial decisions

Outline

- **Data**
- **Descriptive Profile of LEP Borrowers**
- **Effect of Reducing Language Frictions**
    - Empirical Design
    - Results
        - Intensive margin
        - Extensive margin
- **Conclusion**

Data

Data Sources

National Survey of Mortgage Originations (NSMO) 2013-19

- Demographic characteristics
- Perceptions and experiences
- Contract and performance variables
- LEP status at the individual level

Assigning LEP Status in NSMO

13. How important were each of the following in choosing the lender/broker you used for the mortgage you took out?

	Important	Not Important
Having an established banking relationship	☐	☐
Having a local office or branch nearby	☐	☐
Used previously to get a mortgage	☑	☐
Lender/broker is a personal friend or relative	☐	☐
Lender/broker operates online	☐	☐
Recommendation from a friend/ relative/co-worker	☐	☐
Recommendation from a real estate agent/home builder	☐	☐
Reputation of the lender/broker	☐	☐
Spoke my primary language, which is not English	☑	☐

About 10% are LEP borrowers

Trend

Data Sources

National Survey of Mortgage Originations (NSMO) 2013-19

- Demographic characteristics
- Perceptions and experiences in the mortgage market
- Contract and performance variables
- LEP status at the individual level

Home Mortgage Disclosure Act (HMDA) 2011-2019

- County-level outcomes: application denial rate, origination volume

Data Sources

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- Demographic characteristics
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Home Mortgage Disclosure Act (HMDA) 2011-2019

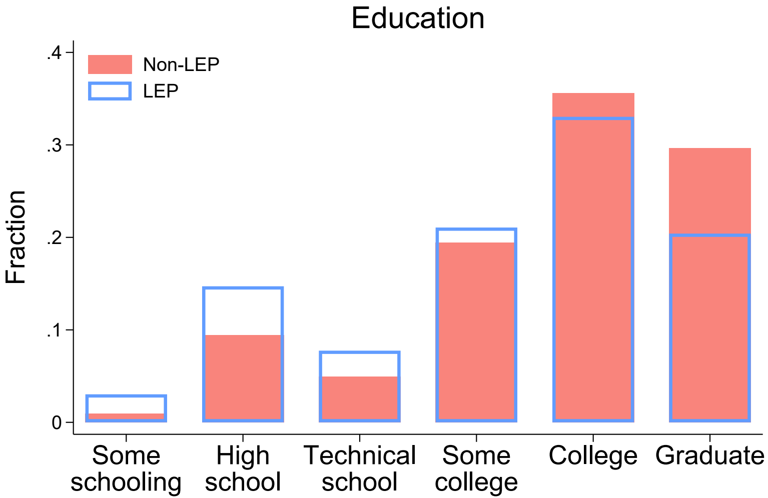
- County-level outcomes: application denial rate, origination volume

American Community Survey (ACS) 2011-2019

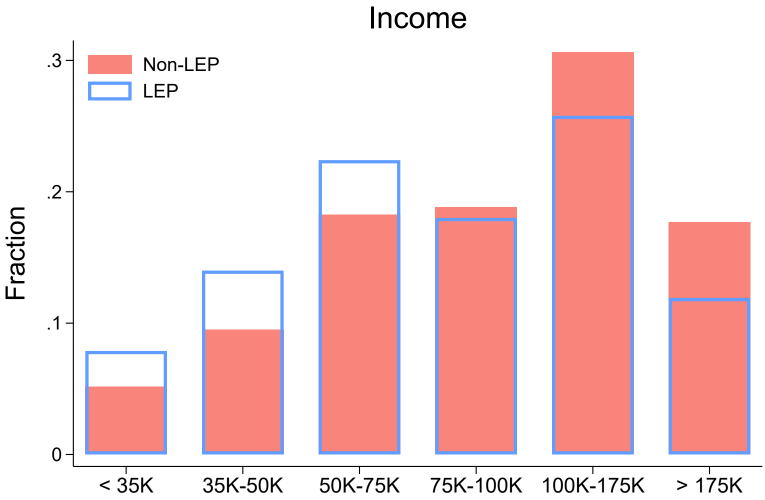
- LEP share at the county level
- County-level characteristics: population, median income, racial composition

Descriptive Analysis

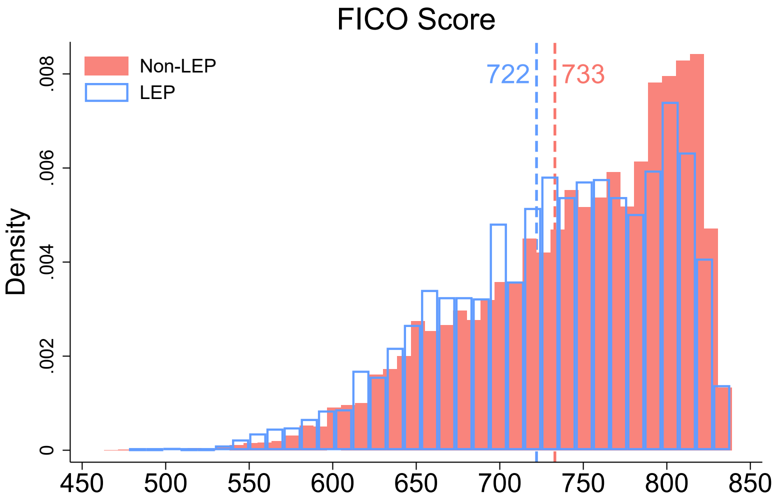
Demographic Differences: Education



Demographic Differences: Income

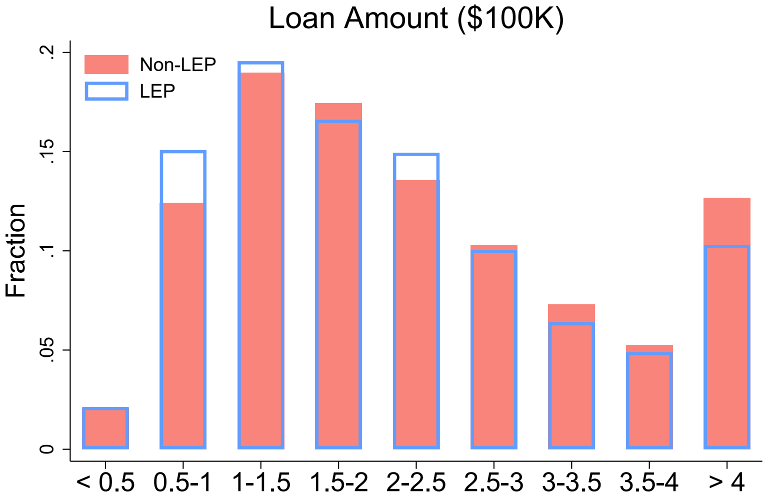


Demographic Differences: Credit Score

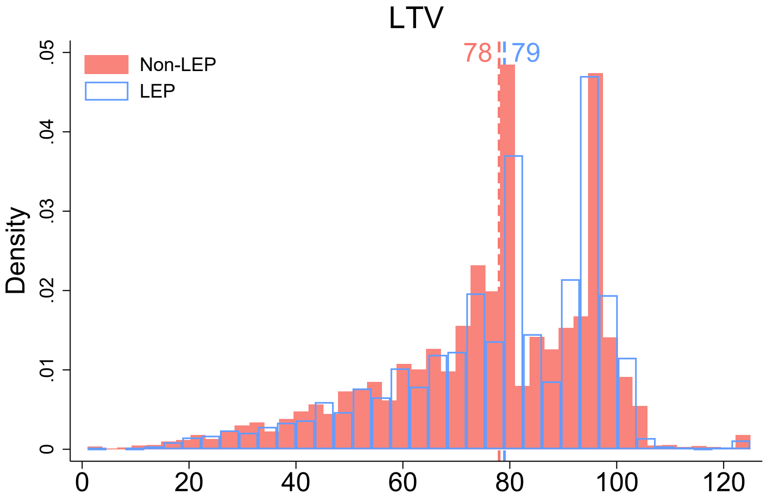


▸ Summary Statistics

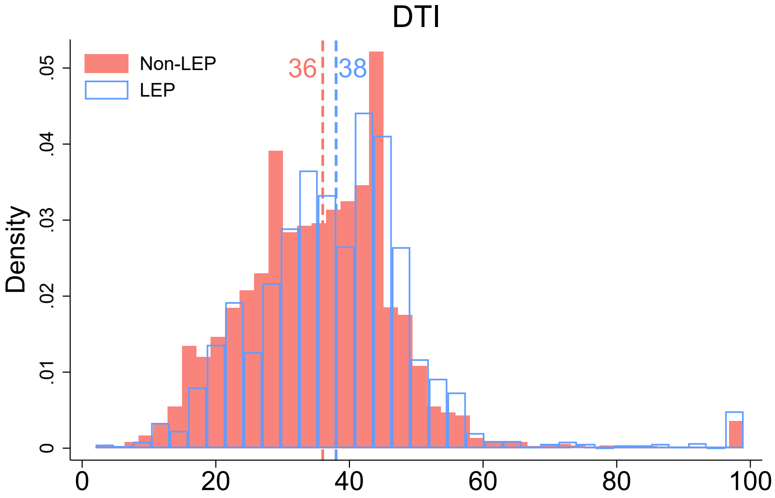
Mortgage Differences: Loan Size



Mortgage Differences: Loan-to-Value Ratio



Mortgage Differences: Debt-to-Income Ratio



Summary Statistics

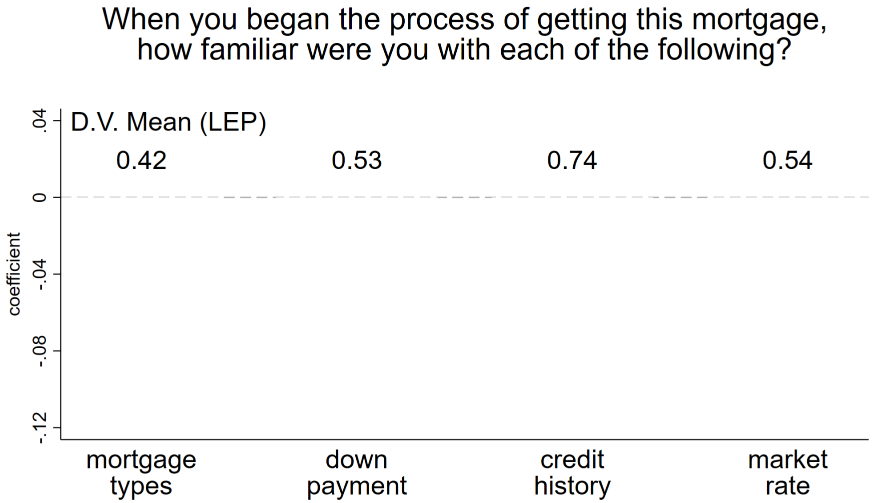
Descriptive Analysis

$$y_{it} = \alpha + \beta LEP_i + \gamma X_i + \delta_t + \epsilon_{it} \quad (1)$$

- y_{it}: outcome of mortgage i originated at time t
- LEP_i: borrower i's LEP status
- X_i: loan/borrower characteristics (e.g., race, ethnicity, income, and education)
- δ_t: quarter of origination fixed effects

▸ Regression Table

LEP Borrowers Know Less about the Mortgage Market



▸ Hispanic ▸ College ▸ Income ▸ Broker

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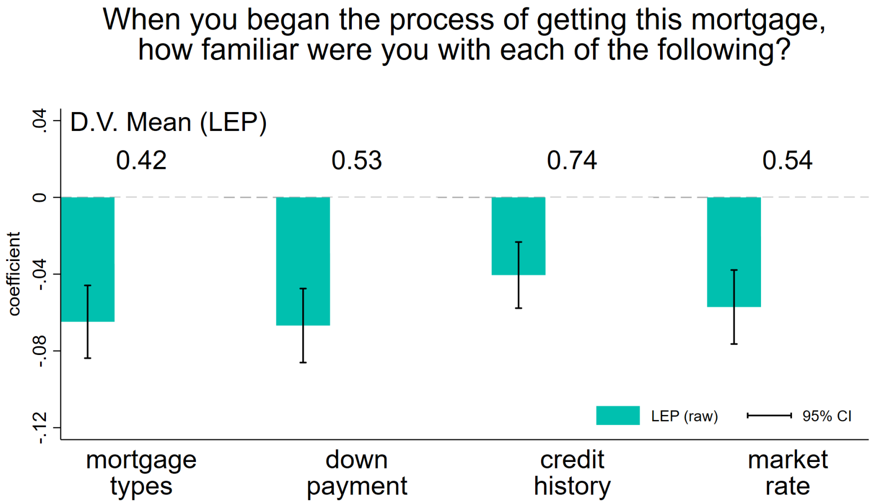

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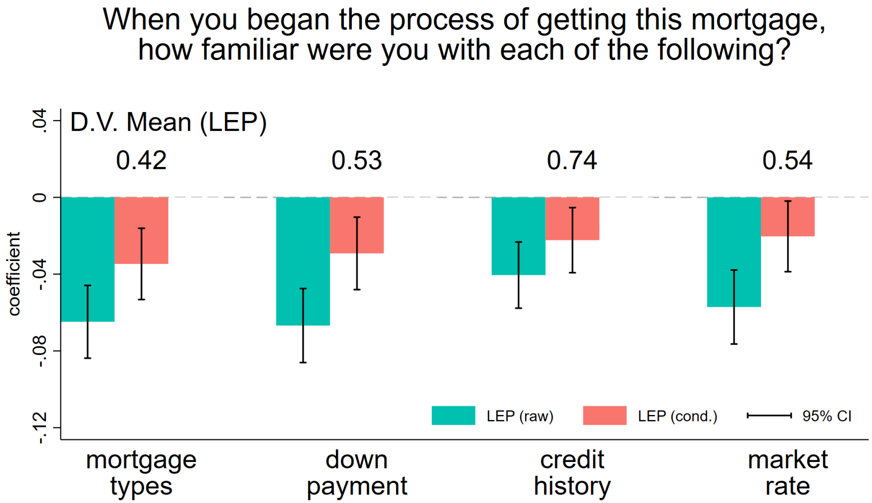

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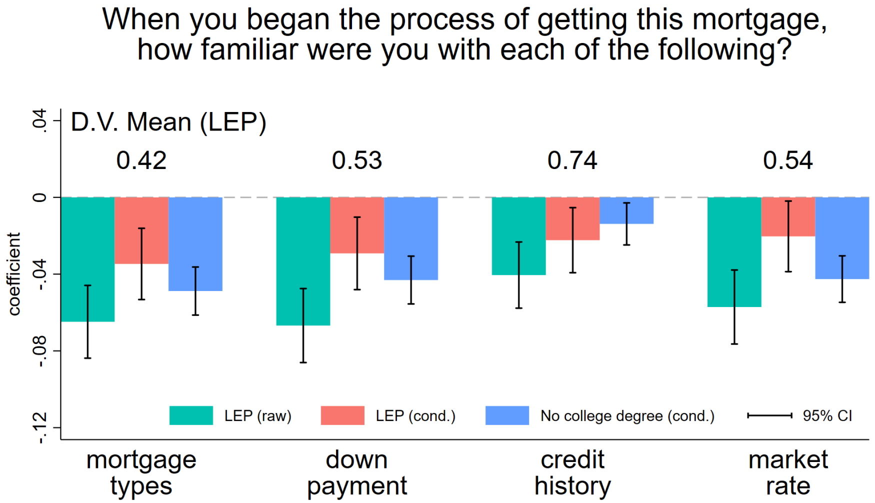

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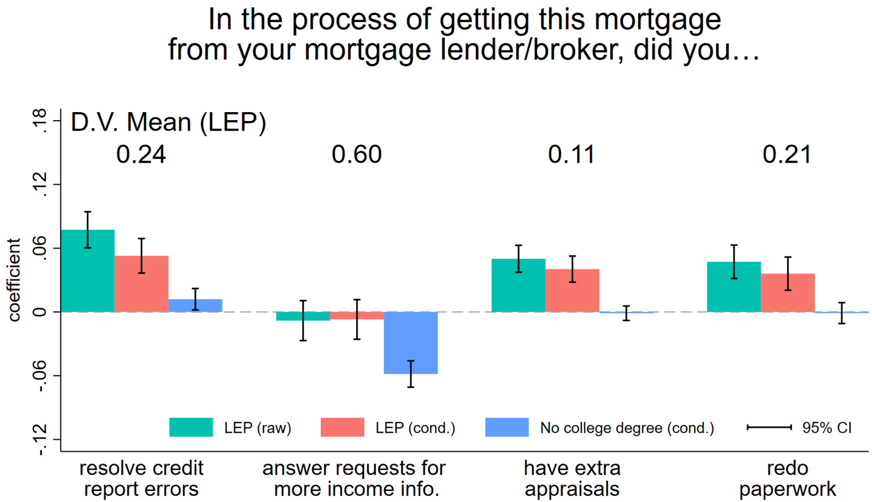
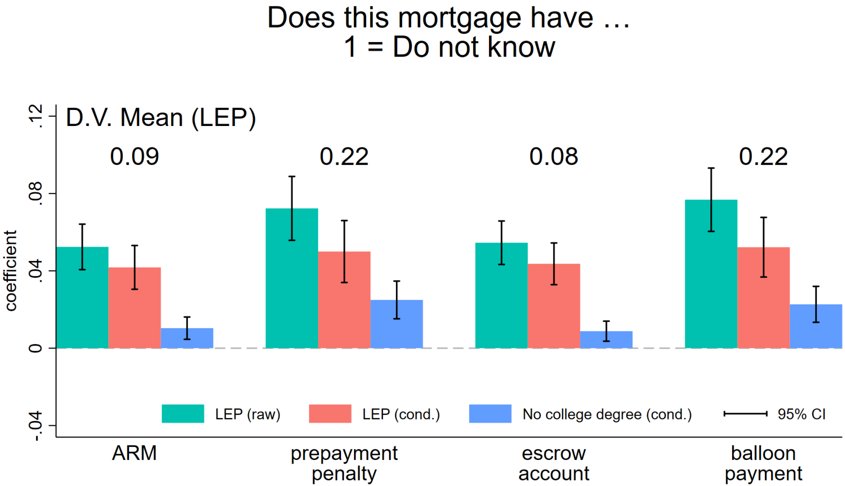
LEP Borrowers Encounter More Problems



▸ Hispanic ▸ College ▸ Income ▸ Broker

LEP Borrowers Are Less Familiar with Their Own Mortgage Contracts



▸ Hispanic ▸ College ▸ Income ▸ Broker

LEP Borrowers Search Less

Dependent variable	Number of lenders		Why apply to multiple lenders?		
	seriously considered (1)	applied to (2)	find better loan terms (3)	concern over qualification (4)	learn information (5)
LEP	-0.065***	-0.024**	0.016	0.105***	0.075***
	(0.015)	(0.012)	(0.017)	(0.020)	(0.021)
LEP mean	1.643	1.296	0.821	0.407	0.425
Non-LEP mean	1.719	1.303	0.822	0.270	0.319
Observations	37,720	37,720	8,569	8,569	8,569
Quarter FEs	✓	✓	✓	✓	✓
Tract type FEs	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓
Risk FEs	✓	✓	✓	✓	✓
Loan controls	✓	✓	✓	✓	✓

▸ Demographic coefficients

LEP Borrowers Have Different Search Incentives

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Loan controls	✓	✓	✓	✓	✓

▸ Demographic coefficients

LEP Borrowers Pay Higher Interest Rates

Dependent variable		Interest Rate		
	(1)	(2)	(3)	(4)
LEP	0.032***	0.029***	0.029***	0.021**
	(0.010)	(0.010)	(0.010)	(0.010)
Observations	37,720	37,720	37,720	37,720
Quarter FEs	✓	✓	✓	✓
Tract type FEs	✓	✓	✓	✓
Risk FEs	✓	✓	✓	✓
Loan controls	✓	✓	✓	✓
Race and ethnicity		✓	✓	✓
Gender			✓	✓
Education				✓

Demographic coefficients Mortgage types

LEP Borrowers Are Not Riskier

Dependent variable	90-Day Delinquency			
	(1)	(2)	(3)	(4)
LEP	0.003	0.002	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)
Observations	37,720	37,720	37,720	37,720
Quarter FEs	✓	✓	✓	✓
Tract type FEs	✓	✓	✓	✓
Risk FEs	✓	✓	✓	✓
Loan controls	✓	✓	✓	✓
Race and ethnicity		✓	✓	✓
Gender			✓	✓
Education				✓

▸ Demographic coefficients ▸ Mortgage types

Main Results: Descriptive Evidence

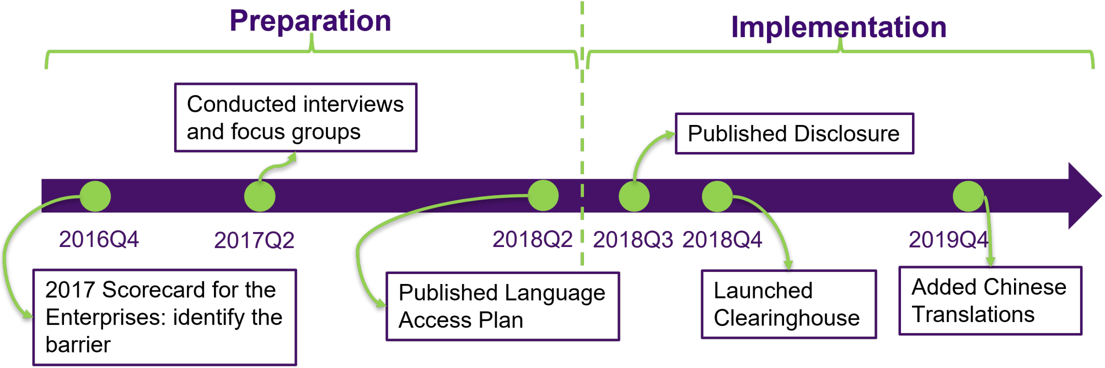
LEP borrowers have very different experiences:

- Before application: more concerned about qualification and less sophisticated
- During application: contact fewer lenders and encounter more problems
- After application: less familiar with their own mortgage contracts
- Mortgage outcomes: pay higher interest rates but have the same delinquency rate

Next: Estimate the effect of reducing language frictions more rigorously

Empirical Design

Empirical Design: FHFA Language Access Plan



Disclosure (2018)

English

Notice to Borrowers about Language

Your mortgage loan transaction is likely to be conducted in English. The information you receive and the official documents you will sign will likely be in English.

We want you to understand the transaction. Translations may be available to complement the English language documents. These documents are to help you understand the transaction. Your lender or servicer may not be able to provide you with translation services or translated documents.

Language assistance and resources may also be available through housing counseling agencies approved by the U.S. Department of Housing and Urban Development (HUD). You can find a list of HUD-approved housing counseling agencies at www.hud.gov/counseling.

1. Select "housing counseling agency" near you, then select your state.
2. To locate housing counseling agencies in your area that speak your language, select "Click here to narrow your search" and select a language.
3. Or, call HUD at 800-569-4287 for help in finding a counselor.

Information about housing counselors is also available at www.consumerfinance.gov/find-a-housing-counselor.

Espanol

Aviso para los prestatarios sobre el idioma

Es probable que la transacción de su préstamo hipotecario se lleve a cabo en inglés. La información que reciba y los documentos oficiales que firme probablemente estarán en inglés.

Queremos que entienda la transacción. Es posible que haya servicios de traducción disponibles para complementar los documentos que están en inglés. El objetivo de estos documentos es ayudarlo a entender la transacción. Es posible que su prestamista o su proveedor de servicio no puedan proporcionarle servicios de traducción ni los documentos traducidos.

Es posible que también haya recursos y asistencia de idioma disponibles a través de agencias de asesoramiento sobre vivienda aprobadas por el Departamento de Vivienda y Desarrollo Urbano de los Estados Unidos (U.S. Department of Housing and Urban Development, HUD). Puede encontrar una lista de agencias de asesoramiento sobre vivienda aprobadas por el HUD en www.hud.gov/counseling.

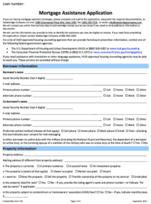
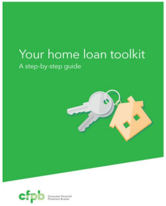
1. Seleccione una agencia de asesoramiento sobre vivienda cercana a su domicilio haciendo clic en "housing counseling agency" (agencia de asesoramiento sobre vivienda); luego, elija su estado.
2. Para encontrar agencias de asesoramiento sobre vivienda en su área en las que se hable su idioma, seleccione "Click here to narrow your search" (Haga clic aquí para limitar la búsqueda) y elija un idioma.
3. O bien llame al HUD al 800-569-4287 para que lo ayuden a encontrar a un asesor.

También puede obtener información sobre asesores de vivienda en www.consumerfinance.gov/find-a-housing-counselor.

"We designed this disclosure to alleviate lenders' concerns." —A policy expert at FHFA

Mortgage Translation Clearinghouse (2018)

FREQUENTLY USED MORTGAGE DOCUMENTS

Uniform Residential Loan Application (Fannie Mae 1003/Freddie Mac 065)	Mortgage Assistance Application (Fannie Mae/Freddie Mac Form 710)	Your Home Loan Toolkit (The Bureau of Consumer Financial Protection)
		
View in English View in Spanish / Español	View in English View in Spanish / Español	View in English View in Spanish / Español

Search by Document Name, Description, Keywords or Form # | Enter Document Name, Description, Keywords, Form #

Search | Reset

5.5% of the total web traffic on the FHFA website in late 2019 ▸ Google Trends

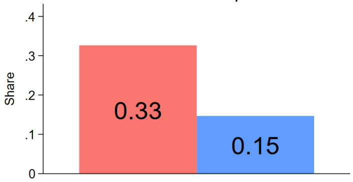
Triple-Difference Illustration

Dependent variable: $\mathbb{1}$(redo paperwork)

H_0: the decrease is smaller than 5 pp

Panel A. LEP & Hispanic (Treated)

p-value: 0.001



Panel B. Non-LEP & Hispanic (Control)

Panel C. LEP & Non-Hispanic (Control)

Panel D. Non-LEP & Non-Hispanic (Control)

Triple-Difference Illustration

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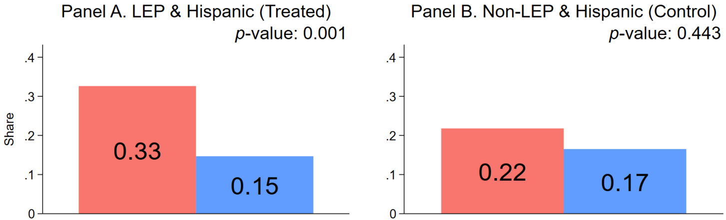

Panel C. LEP & Non-Hispanic (Control)

Panel D. Non-LEP & Non-Hispanic (Control)

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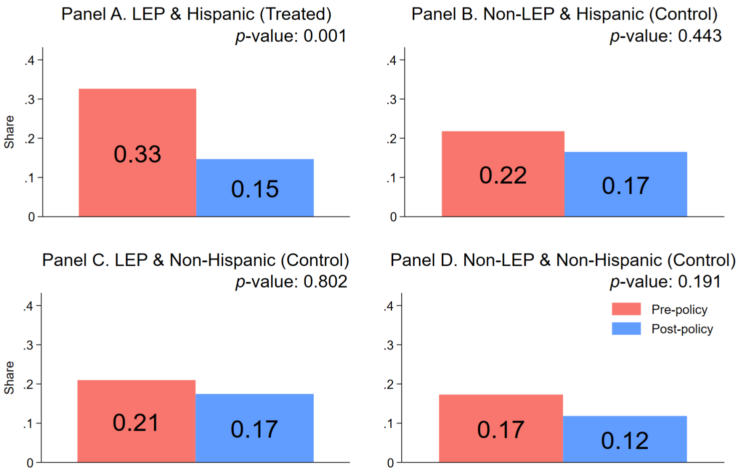


Triple-Difference Specification

$$\begin{aligned} y_{it} = \alpha + \beta_0 LEP_i + \beta_1 Hispanic_i + \beta_2 LEP_i \times Hispanic_i + \beta_3 LEP_i \times Post_t \\ + \beta_4 Hispanic_i \times Post_t + \beta_5 LEP_i \times Hispanic_i \times Post_t + \gamma X_{it} + \delta_t + \epsilon_{it}. \end{aligned} \quad (2)$$

- $Post_t = 1$ if mortgage i was originated after June 2018
- $Hispanic_i = 1$ if borrower i is Hispanic
- $X_{it} = Controls_i \times Post_t$
- Drop Asian borrowers (Chinese translations added in 2019)

Empirical Results: Intensive Margin

During the Application Process: Better Experience

Dependent variable	$\mathbb{1}$(encounter ... in the application process)			
	Resolve credit report errors (1)	Request more income info. (2)	Have more appraisals (3)	Redo paperwork (4)
LEP × Hispanic × Post	-0.163***	-0.162**	-0.125***	-0.137**
	(0.060)	(0.071)	(0.048)	(0.054)
Pre-policy treated mean	0.339	0.642	0.218	0.326
Observations	35,553	35,553	35,553	35,553
Quarter FEs	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓
Post × Tract type FEs	✓	✓	✓	✓
Post × Risk FEs	✓	✓	✓	✓
Post × Loan controls	✓	✓	✓	✓

Pre-policy: 33% of LEP Hispanic borrowers redid paperwork $\Longrightarrow$ 42% $\downarrow$

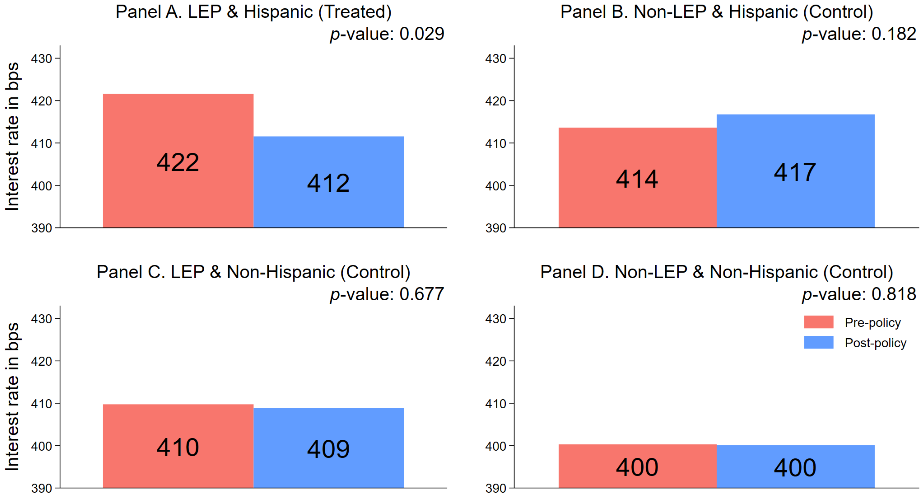
After the Application Process: More Familiar with Mortgage Contracts

Dependent variable	$\mathbb{1}$(do not know if my own mortgage has ...)			
	Adjustable rate (1)	Prepayment penalty (2)	Escrow account (3)	Balloon payment (4)
LEP $\times$ Hispanic $\times$ Post	-0.083*	0.025	-0.069	-0.164***
	(0.047)	(0.063)	(0.048)	(0.057)
Pre-policy treated mean	0.109	0.296	0.206	0.380
Observations	35,553	35,553	35,553	35,553
Quarter FEs	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓
Post $\times$ Tract type FEs	✓	✓	✓	✓
Post $\times$ Risk FEs	✓	✓	✓	✓
Post $\times$ Loan controls	✓	✓	✓	✓

Pre-policy: 38% of LEP Hispanic borrowers didn't know balloon payments $\Longrightarrow$ 42% $\downarrow$

Effect on Mortgage Rate: Graphical Evidence

H_0: pre- and post-policy average interest rates are the same



Price of Credit: Decreased Interest Rate

Sample	All	Purchase	Refinance	First-time borrowers	Repeat borrowers
	(1)	(2)	(3)	(4)	(5)
	Outcome: Interest Rate				
LEP $\times$ Hispanic $\times$ Post	-0.149**	-0.165*	-0.082	-0.221*	-0.145
	(0.074)	(0.096)	(0.121)	(0.125)	(0.093)
Observations	35,553	18,118	15,977	6,739	28,807
Quarter FEs	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓
Post $\times$ Tract type FEs	✓	✓	✓	✓	✓
Post $\times$ Risk FEs	✓	✓	✓	✓	✓
Post $\times$ Loan controls	✓	✓	✓	✓	✓

Mortgage rate $\downarrow$ by 15 bps $\Longrightarrow$ \$22 per month for an average borrower
$\Longrightarrow$ NPV \$1770 for the average duration

Heterogeneous Effects: By Loan Purpose

Sample	All	Purchase	Refinance	First-time borrowers	Repeat borrowers
	(1)	(2)	(3)	(4)	(5)
	Outcome: Interest Rate				
LEP × Hispanic × Post	-0.149**	-0.165*	-0.082	-0.221*	-0.145
	(0.074)	(0.096)	(0.121)	(0.125)	(0.093)
Observations	35,553	18,118	15,977	6,739	28,807
Quarter FEs	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓
Post × Tract type FEs	✓	✓	✓	✓	✓
Post × Risk FEs	✓	✓	✓	✓	✓
Post × Loan controls	✓	✓	✓	✓	✓

Mortgage purpose as a proxy of borrower experience

Heterogeneous Effects: By Borrowing History

Sample	All	Purchase	Refinance	First-time borrowers	Repeat borrowers
	(1)	(2)	(3)	(4)	(5)
	Outcome: Interest Rate				
LEP $\times$ Hispanic $\times$ Post	-0.149**	-0.165*	-0.082	-0.221*	-0.145
	(0.074)	(0.096)	(0.121)	(0.125)	(0.093)
Observations	35,553	18,118	15,977	6,739	28,807
Quarter FEs	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓
Post $\times$ Tract type FEs	✓	✓	✓	✓	✓
Post $\times$ Risk FEs	✓	✓	✓	✓	✓
Post $\times$ Loan controls	✓	✓	✓	✓	✓

Borrowing history as a proxy of borrower experience

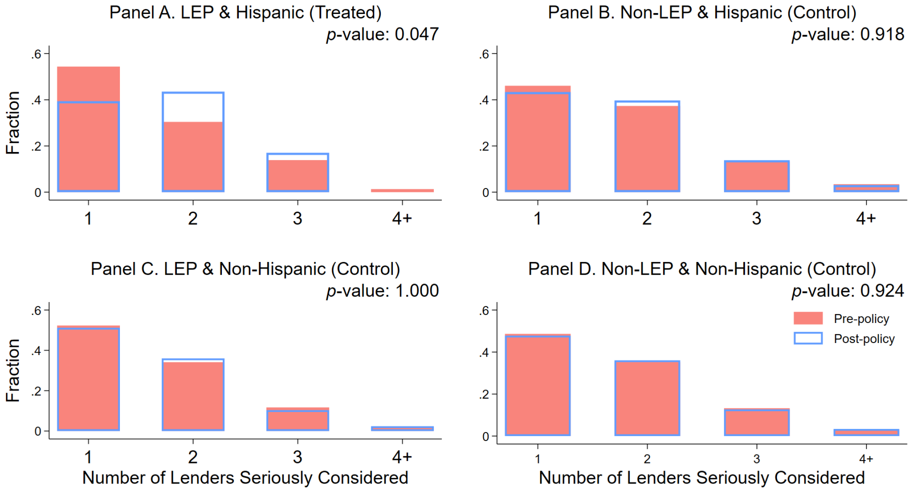
Mechanism of the Price Effect: Financial Literacy?

Dependent variable	$\mathbb{1}$(familiar with ...)			
	Mortgage types (1)	Down payment (2)	Credit history (3)	Market rate (4)
LEP $\times$ Hispanic $\times$ Post	-0.043 (0.068)	-0.054 (0.070)	-0.038 (0.067)	0.007 (0.067)
Pre-policy treated mean	0.319	0.425	0.706	0.421
Observations	35,553	35,553	35,553	35,553
Quarter FEs	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓
Post $\times$ Tract type FEs	✓	✓	✓	✓
Post $\times$ Risk FEs	✓	✓	✓	✓
Post $\times$ Loan controls	✓	✓	✓	✓

Probably No. Consistent with the design of the FHFA policy

Mechanism of the Price Effect: Borrower Search

H_0: pre- and post-policy distributions are the same



Inducing LEP Borrowers to Search More

Dependent variable	Search intensity		Why apply to multiple lenders?		
	$\mathbb{1}$(consider multi. lenders) (1)	# lenders considered (2)	find better loan terms (3)	concern over qualification (4)	learn information (5)
LEP × Hispanic × Post	0.162**	0.202*	0.058	-0.154	-0.269**
	(0.073)	(0.112)	(0.097)	(0.125)	(0.135)
Pre-policy treated mean	0.456	1.622	0.852	0.565	0.595
Observations	35,553	35,553	8,001	8,001	8,001
Quarter FEs	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓
Post × Tract type FEs	✓	✓	✓	✓	✓
Post × Risk FEs	✓	✓	✓	✓	✓
Post × Loan controls	✓	✓	✓	✓	✓

Pre-policy: 46% of LEP Hispanic borrowers considered multiple lenders $\Longrightarrow$ 35% $\uparrow$

▸ Lenders

No Need to Search for Learning

Dependent variable	Search intensity		Why apply to multiple lenders?		
	$\mathbb{1}$(consider multi. lenders)	# lenders considered	find better loan terms	concern over qualification	learn information
	(1)	(2)	(3)	(4)	(5)
LEP × Hispanic × Post	0.162**	0.202*	0.058	-0.154	-0.269**
	(0.073)	(0.112)	(0.097)	(0.125)	(0.135)
Pre-policy treated mean	0.456	1.622	0.852	0.565	0.595
Observations	35,553	35,553	8,001	8,001	8,001
Quarter FEs	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓
Post × Tract type FEs	✓	✓	✓	✓	✓
Post × Risk FEs	✓	✓	✓	✓	✓
Post × Loan controls	✓	✓	✓	✓	✓

Pre-policy: 60% of LEP Hispanic borrowers searched for learning $\Longrightarrow$ 45% $\downarrow$

Minimal Effect on Performance

Sample	All	Purchase	Refinance	First-time borrowers	Repeat borrowers
	(1)	(2)	(3)	(4)	(5)
	Outcome: 90-Day Delinquency				
LEP $\times$ Hispanic $\times$ Post	-0.016	-0.022	-0.022	-0.009	-0.012
	(0.015)	(0.020)	(0.024)	(0.029)	(0.017)
Observations	35,553	18,118	15,977	6,739	28,807
Quarter FEs	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓
Post $\times$ Tract type FEs	✓	✓	✓	✓	✓
Post $\times$ Risk FEs	✓	✓	✓	✓	✓
Post $\times$ Loan controls	✓	✓	✓	✓	✓

Robustness Checks: Using NSMO

Choices of control group

- Drop mortgages originated after the addition of Chinese translations ▸ DDD Chinese
- Compare LEP and non-LEP in the sample of Hispanic people ▸ DID Hispanic
- Compare Hispanic and non-Hispanic in the sample of LEP people ▸ DID LEP
- Compare LEP Hispanic and non-Asian borrowers ▸ DID Plot

Placebo tests

- Perturb $Post_t$ ▸ Post Table
- Perturb $Hispanic_i$ ▸ Hispanic Table
- Perturb LEP_i ▸ LEP Figure

Further Robustness Checks: Using HMDA+

Data limitations of NSMO

- No lender or location information
- No up-front costs (Bhutta and Hizmo, 2020)

  $\Longrightarrow$ Detailed information in HMDA

Further Robustness Checks: Using HMDA^{+}

Data limitations of NSMO

A new loan-level data: HMDA^{+}

- Merge HMDA with Fannie Mae, Freddie Mac, and Ginnie Mae data
- Cover $\approx$ 50% of HMDA 2015-2019 ▸ Matching
- Include borrower, lender, property, mortgage contract, mortgage performance information

Further Robustness Checks: Using HMDA$^+$

Data limitations of NSMO

A new loan-level data: HMDA$^+$

Same data challenge: No LEP status in HMDA$^+$

- Use machine learning (ML) to solve a binary classification problem
- Training sample: purchase mortgage holders in micro-level ACS ▸ Details
- 99% accuracy in the test sample ▸ Performance

Further Robustness Checks: Using HMDA$^+$

Data limitations of NSMO

A new loan-level data: HMDA$^+$

Same data challenge: No LEP status in HMDA$^+$

Recover the lower bound of the average treatment effect on the treated (ATT)

- Misclassification brought by ML ▸ Setup
- Use ML performance to bound measurement error ▸ Assumptions
- Underestimation: ATT $\geq$ 1.39 $\times$ θ_{DDD}

Lower Bound of the Effect on Mortgage Rate

Sample	Purchase	First-time borrowers	Repeat borrowers	Channel: retail	Channel: broker
	(1)	(2)	(3)	(4)	(5)
	Outcome: Interest Rate				
LEP $\times$ Hispanic $\times$ Post	-0.035***	-0.052***	-0.004	-0.041***	-0.023*
	(0.009)	(0.011)	(0.012)	(0.011)	(0.013)
Observations	3,877,813	1,680,325	2,196,946	2,513,026	1,364,024
Month FEs	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓
Post $\times$ County FEs	✓	✓	✓	✓	✓
Post $\times$ Risk FEs	✓	✓	✓	✓	✓
Post $\times$ Lender FEs	✓	✓	✓	✓	✓
Post $\times$ Loan controls	✓	✓	✓	✓	✓

Lower Bound of the Effect on Mortgage Rate

Sample	Purchase (1)	First-time borrowers (2)	Repeat borrowers (3)	Channel: retail (4)	Channel: broker (5)
	Outcome: Interest Rate				
LEP × Hispanic × Post	-0.035***	-0.052***	-0.004	-0.041***	-0.023*
	(0.009)	(0.011)	(0.012)	(0.011)	(0.013)
Implied lower bound	-0.049	-0.072	-0.006	-0.057	-0.032
Observations	3,877,813	1,680,325	2,196,946	2,513,026	1,364,024
Month FEs	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓
Post × County FEs	✓	✓	✓	✓	✓
Post × Risk FEs	✓	✓	✓	✓	✓
Post × Lender FEs	✓	✓	✓	✓	✓
Post × Loan controls	✓	✓	✓	✓	✓

Interest rate ↓ by at least 5 bps

Lender Response

Little Effect on Up-Front Costs

Sample	Purchase (1)	First-time borrowers (2)	Repeat borrowers (3)	Channel: retail (4)	Channel: broker (5)
	Outcome: Discount Points (% of Loan Amount)				
LEP $\times$ Hispanic $\times$ Post	0.006	0.035	-0.052*	0.004	0.035
	(0.018)	(0.023)	(0.031)	(0.025)	(0.025)
Implied lower bound	0.008	0.049	-0.072	0.006	0.049
Observations	1,713,458	780,230	932,503	1,095,149	617,429
Month FEs	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓
Post $\times$ County FEs	✓	✓	✓	✓	✓
Post $\times$ Risk FEs	✓	✓	✓	✓	✓
Post $\times$ Lender FEs	✓	✓	✓	✓	✓
Post $\times$ Loan controls	✓	✓	✓	✓	✓

0.049% of loan amount to buy points $\Longrightarrow$ 1.2 bps $<$ 7.2 bps

No Deterioration of Mortgage Performance

Sample	Purchase (1)	First-time borrowers (2)	Repeat borrowers (3)	Channel: retail (4)	Channel: broker (5)
	Outcome: 90-Day Delinquency				
LEP $\times$ Hispanic $\times$ Post	-0.013	-0.013	-0.008	-0.014	-0.012
	(0.008)	(0.012)	(0.011)	(0.011)	(0.012)
Implied lower bound	-0.018	-0.018	-0.011	-0.019	-0.017
Observations	3,877,813	1,680,325	2,196,946	2,513,026	1,364,024
Month FEs	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓
Post $\times$ County FEs	✓	✓	✓	✓	✓
Post $\times$ Risk FEs	✓	✓	✓	✓	✓
Post $\times$ Lender FEs	✓	✓	✓	✓	✓
Post $\times$ Loan controls	✓	✓	✓	✓	✓

Main Results: Effect of Reducing Language Frictions

Effect on access to credit?

- Intensive margin: a streamlined application process

Effect on the price of credit?

- Lower borrowing costs
- One possible channel: more borrower search

Effect on the quality of credit?

- Minimal effect on mortgage delinquency rate

Next: What is the effect on extensive margin access to credit?

Empirical Results: Extensive Margin

LEP Consumers Excluded From the Mortgage Market?

Complement the triple-difference analysis

- Estimate the effect on credit access on the extensive margin
  $\Longrightarrow$ Data: County-level HMDA
- Incorporate the effect of providing Chinese translations
  $\Longrightarrow$ Regression: Difference-in-Differences

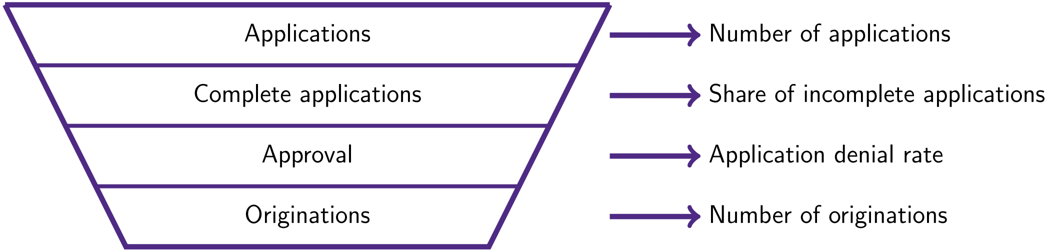
Difference-in-Differences Design

$$Y_{ct} = \alpha + \beta D_{ct} + \gamma X_{ct} + \delta_c + \delta_{st} + \epsilon_{ct} \tag{3}$$

- Y_{ct}: outcome of county c in year t
- $$\mathrm{D}_{ct} = \begin{cases} 0, \quad \text{if} \quad t \leq 2017 \\ \text{Hispanic LEP share}_c, \quad \text{if} \quad t = 2018 \\ \text{Hispanic LEP share}_c + \text{Chinese LEP share}_c, \quad \text{if} \quad t = 2019 \end{cases}$$
- X_{ct}: control variables at the county-year level
- δ_c and δ_{st}: county and state-year fixed effects

Effect on Credit Access on the Extensive Margin

- Data: HMDA 2011-19
- Sample: conventional purchase loans
- Outcomes: aggregate at the county $\times$ year level



Expanded Access to Credit

Dependent variable	# Applications (10K) (1)	Share of incomplete app. (2)	Denial rate (3)	# Originations (10K) (4)
LEP share × Post	0.121**	-0.062***	-0.155***	0.089**
	(0.060)	(0.022)	(0.041)	(0.044)
Sample mean	0.090	0.117	0.175	0.067
Observations	25,225	25,225	25,225	25,225
County FEs	✓	✓	✓	✓
Year × State FEs	✓	✓	✓	✓
Additional controls	✓	✓	✓	✓

Application incomplete and denial rate ↓ by 6 pp and 16 pp

Robustness checks: Refinance TWFE Heterogeneous Placebo Table Placebo Figure

More Applications and Originations

Dependent variable	# Applications (10K) (1)	Share of incomplete app. (2)	Denial rate (3)	# Originations (10K) (4)
LEP share × Post	0.121**	-0.062***	-0.155***	0.089**
	(0.060)	(0.022)	(0.041)	(0.044)
Sample mean	0.090	0.117	0.175	0.067
Observations	25,225	25,225	25,225	25,225
County FEs	✓	✓	✓	✓
Year × State FEs	✓	✓	✓	✓
Additional controls	✓	✓	✓	✓

4 pp ↑ in the local share of LEP people ⟹ + 48 applications and 36 originations

Robustness checks: ▸ Refinance ▸ TWFE Heterogeneous ▸ Placebo Table ▸ Placebo Figure

Interpreting the Magnitude

- Number of applications before the policy shock ($t = 0$):

$$APP_0 = D_{LEP} \times \underbrace{LEP \times POP}_{\text{LEP Population}} + D_{NLEP} \times \underbrace{(1 - LEP) \times POP}_{\text{Non-LEP Population}}$$

  - D_{LEP} and D_{NLEP}: pre-policy demand from LEP and non-LEP people
  - LEP: LEP share
  - POP: population

Interpreting the Magnitude

- Number of applications after the policy shock ($t = 1$):

$$APP_0 = D_{LEP} \times LEP \times POP + D_{NLEP} \times (1 - LEP) \times POP$$

$$APP_1 = (D_{LEP} + \Delta) \times LEP \times POP + D_{NLEP} \times (1 - LEP) \times POP$$

  - D_{LEP} and D_{NLEP}: pre-policy demand from LEP and non-LEP people
  - LEP: LEP share
  - POP: population
  - Δ: policy effect on LEP borrowers

Interpreting the Magnitude

- Number of applications at $t = 0, 1$:

$$APP_0 = D_{LEP} \times LEP \times POP + D_{NLEP} \times (1 - LEP) \times POP$$

$$APP_1 = (D_{LEP} + \Delta) \times LEP \times POP + D_{NLEP} \times (1 - LEP) \times POP$$

- DID coefficient β identifies:

$$\frac{\partial(APP_1 - APP_0)}{\partial LEP} = \Delta \times POP$$

Interpreting the Magnitude

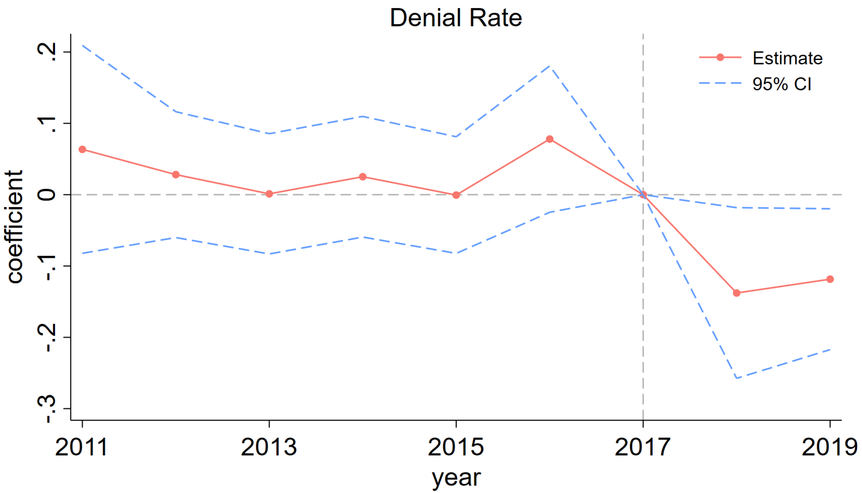
- Number of applications at $t = 0, 1$:

$$APP_0 = D_{LEP} \times LEP \times POP + D_{NLEP} \times (1 - LEP) \times POP$$

$$APP_1 = (D_{LEP} + \Delta) \times LEP \times POP + D_{NLEP} \times (1 - LEP) \times POP$$

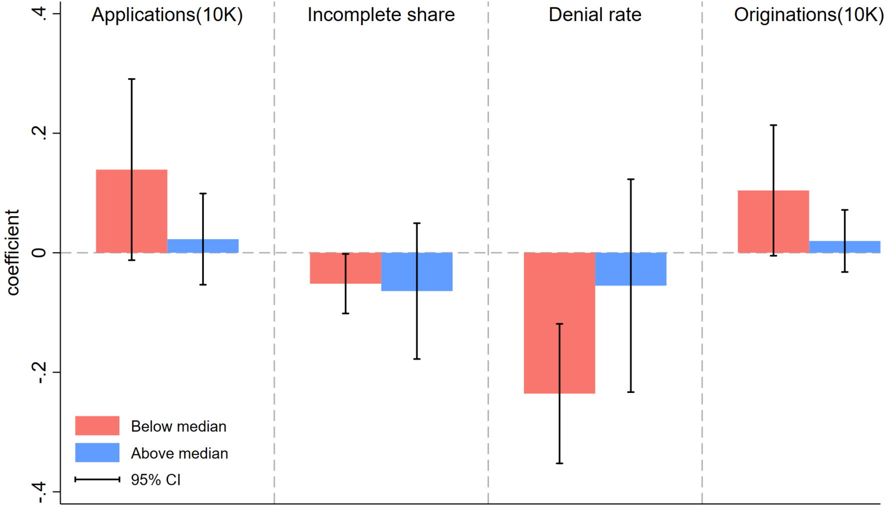
- DID coefficient β identifies $\Delta \times POP$
- **LEP people's propensity to apply for a mortgage $\uparrow$ by 1.1 pp**
- **LEP people's probability to get a mortgage $\uparrow$ by 0.8 pp**

Flexible Difference-in-Differences Estimates



Other Outcomes

Heterogeneous Effects: By Social Capital



▸ By Racial Composition ▸ By Lender Competition

Positive Effect on Ex-Ante Mortgage Risk

- Data: GSE single-family loan-level data (3-digit ZIP code × month)

Sample	All (1)	Purchase (2)	Refinance (3)	First-time borrowers (4)	Repeat borrowers (5)
	Outcome: Average FICO Scores				
LEP share × Post	7.744***	8.846***	7.065***	8.986***	6.883***
	(1.702)	(1.060)	(1.694)	(2.394)	(1.777)
Sample mean	747.626	750.533	742.704	740.392	749.510
Observations	52,435	52,088	52,160	51,234	52,382
ZIP3 code FEs	✓	✓	✓	✓	✓
Month FEs	✓	✓	✓	✓	✓
Additional controls	✓	✓	✓	✓	✓

Inclusion of creditworthy LEP borrowers

▸ FICO Dist. ▸ Unconditional

Main Results: Effect of Reducing Language Frictions

Effect on access to credit?

- Intensive margin: streamlined application process
- Extensive margin: lower denial rate and more originations

Effect on the price of credit?

- Lower borrowing costs ▸ DID
- One possible channel: more borrower search

Effect on the quality of credit?

- Minimal effect on mortgage delinquency rate ▸ DID
- Improvement in ex-ante mortgage risk

Conclusion

Studies an important type of frictions in the mortgage market: language frictions

- Document descriptive differences between LEP and non-LEP borrowers
- Estimate the causal effect on outcomes throughout the origination life cycle

Conclusion

Studies an important type of frictions in the mortgage market: language frictions

- Document descriptive differences between LEP and non-LEP borrowers
- Estimate the causal effect on outcomes throughout the origination life cycle

Offers clear policy implications

- Reduce compliance risks for financial institutions
- An effective and responsible integration of LEP consumers
- A cost-effective policy

In the News (JAN 13, 2021)

NOTICE

Statement Regarding the Provision of Financial Products and Services to Consumers with Limited English Proficiency

The Bureau of Consumer Financial Protection (Bureau) is issuing this Statement Regarding the Provision of Financial Products and Services to Consumers with Limited English Proficiency (Statement) to encourage financial institutions to better serve consumers with limited English proficiency (LEP) and to provide principles and guidelines to assist financial institutions in complying with the Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank Act), the Equal Credit Opportunity Act (ECOA), and other applicable laws.

CFPB provided principles and guidelines in complying with applicable laws

Thank You!

Feedback and comments are much appreciated:

chao.liu1@kellogg.northwestern.edu

Using Machine Learning to Predict LEP Status

- **Challenge 1:** Need a large and labeled borrower sample for training
- **Solution 1:** Micro-level American Community Survey (ACS) 2015-19
  - Adult household heads
  - Homeowners with mortgages
  - Moved to current residence in the last 12 months

$\Longrightarrow$ Prediction sample only includes purchase loans

Back

Using Machine Learning to Predict LEP Status

- **Challenge 1:** Need a large and labeled borrower sample for training
- **Solution 1:** Micro-level American Community Survey (ACS) 2015-19

- **Challenge 2:** Useful features not available in HMDA^{+}
- **Solution 2:** Gender, race, ethnicity, income, state-year FEs

- **Challenge 3:** Imbalanced classification
- **Solution 3:** XGBoost

Back

Machine Learning Performance: Precision

Model (1)	Class (2)	Precision (3)	Recall (4)	Accuracy (5)
Panel A. Full sample				
Logit	Non-LEP	0.952	0.999	0.952
	LEP	0.542	0.005	
XGBoost	Non-LEP	0.989	0.995	0.985
	LEP	0.886	0.787	
Panel B. Hispanics sample				
Logit	Non-LEP	0.786	0.997	0.785
	LEP	0.657	0.023	
XGBoost	Non-LEP	0.954	0.969	0.939
	LEP	0.882	0.831	

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

Back

Machine Learning Performance: Recall

Model (1)	Class (2)	Precision (3)	Recall (4)	Accuracy (5)
Panel A. Full sample				
Logit	Non-LEP	0.952	0.999	0.952
	LEP	0.542	0.005	
XGBoost	Non-LEP	0.989	0.995	0.985
	LEP	0.886	0.787	
Panel B. Hispanics sample				
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	LEP	0.657	0.023	
XGBoost	Non-LEP	0.954	0.969	0.939
	LEP	0.882	0.831	

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

Back

Triple-Difference Model with Misclassification

A canonical triple-difference model

- P: post-policy period
- L: LEP status in data
- H: Hispanic ethnicity
- Misclassification: $\rho = 1$ if $L \neq L^*$, where L^*: true LEP status
- D: treatment status $\Longrightarrow D = 1$ if $L^* = 1$ and $H = 1$
- $Y_t(D)$: potential outcome at time t when the treatment status is D
- $\text{ATT} = \mathbb{E}[Y_1(1) - Y_1(0) \mid L^* = 1, H = 1]$

Back

From DDD to ATT

- **Assumption 1:** Parallel trends between the misclassified treatment status (L)
- **Assumption 2:** Non-differential Misclassification: $\rho \perp\!\!\!\perp (Y_1(1), Y_1(0)) \mid L^*, H$
- **Proposition 1:**
  If Assumptions 1 and 2 hold, the triple-difference estimator can be written as:

$$\theta_{DDD} = \text{ATT}[\underbrace{\mathbb{P}(\rho = 0 \mid L = 1, H = 1) + \mathbb{P}(\rho = 0 \mid L = 0, H = 1)}_{\text{Precision in the prediction sample of Hispanic borrowers}} - 1]$$

Back

Recovering Lower Bound of ATT

Confusion matrix in the prediction sample of Hispanic borrowers

		Data 0	Data 1	
Prediction	0	TN=381,634-y+x	FN=y-x	381,634
	1	FP=49,857-x	TP=x	49,857
		431,491-y	y	

$$\textbf{Precision Rate} = \mathbb{P}(\rho = 0 \mid L = 1, H = 1) + \mathbb{P}(\rho = 0 \mid L = 0, H = 1)$$
$$= \frac{x}{49857} + \frac{381634 - y + x}{381634}$$

Back

Recovering Lower Bound of ATT

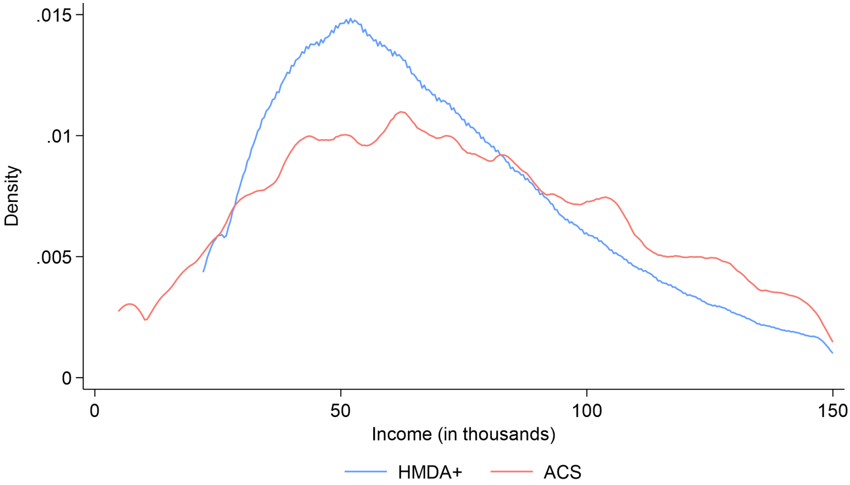
Confusion matrix in the prediction sample of Hispanic borrowers

		Data 0	Data 1	
Prediction	0	TN=381,634-y+x	FN=y-x	381,634
	1	FP=49,857-x	TP=x	49,857
		431,491-y	y	

- **Assumption 3 (on y):** $\mathbb{P}(\text{LEP} \mid \text{Hispanic})$ is higher in the training sample

Back

Income Distribution of Hispanic Households



▸ Back

Recovering Lower Bound of ATT

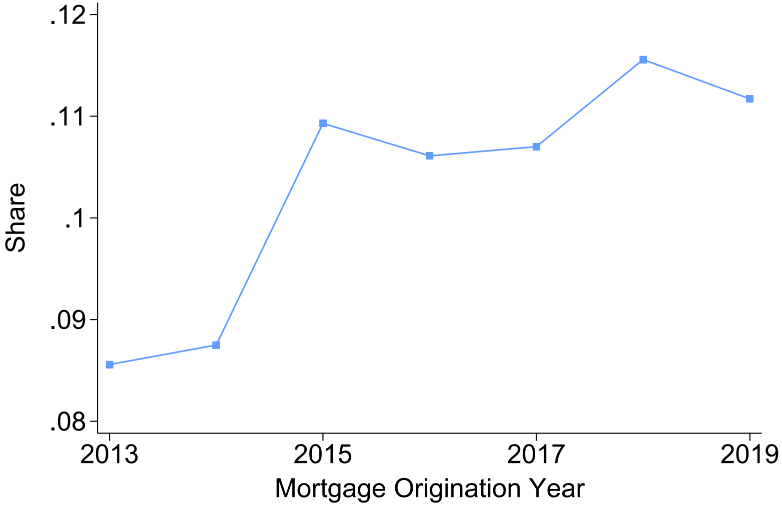
Confusion matrix in the prediction sample of Hispanic borrowers

		Data: 0	Data: 1	
Prediction	0	TN=381,634-y+x	FN=y-x	381,634
	1	FP=49,857-x	TP=x	49,857
		431,491-y	y	

- **Assumption 3 (on y):** $\mathbb{P}(\text{LEP} \mid \text{Hispanic})$ is higher in the training sample
- **Assumption 4 (on x):** The machine learning model performs better in the test sample
- **ATT $\geq$ 1.39 $\times$ θ_{DDD}**

Back

Growth in LEP Borrower Share



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Summary Statistics of NSMO: Demographic Characteristics

Sample	All borrowers (1)	LEP (2)	Non-LEP (3)
Female	0.435	0.454	0.432
	(0.496)	(0.498)	(0.495)
Married	0.666	0.644	0.669
	(0.472)	(0.479)	(0.471)
Age	46.214	46.487	46.182
	(13.854)	(13.817)	(13.858)
College education	0.645	0.534	0.658
	(0.479)	(0.499)	(0.475)
Income<$50K	0.151	0.218	0.143
	(0.358)	(0.413)	(0.350)
FICO score	732.164	722.015	733.330
	(65.924)	(66.552)	(65.752)
Observations	37,720	3,793	33,927

Back

Summary Statistics of NSMO: Mortgage Characteristics

Sample	All borrowers	LEP	Non-LEP
	(1)	(2)	(3)
Conventional loan	0.735	0.670	0.742
	(0.441)	(0.470)	(0.437)
Loan amount<\$200K	0.510	0.530	0.507
	(0.500)	(0.499)	(0.500)
Loan to value ratio	78.070	79.230	77.937
	(19.462)	(19.285)	(19.478)
Debt to income ratio	36.193	38.396	35.940
	(12.273)	(12.952)	(12.167)
Interest rate	4.029	4.090	4.022
	(0.678)	(0.669)	(0.678)
90-day delinquency	0.015	0.020	0.014
	(0.121)	(0.141)	(0.119)
Observations	37,720	3,793	33,927

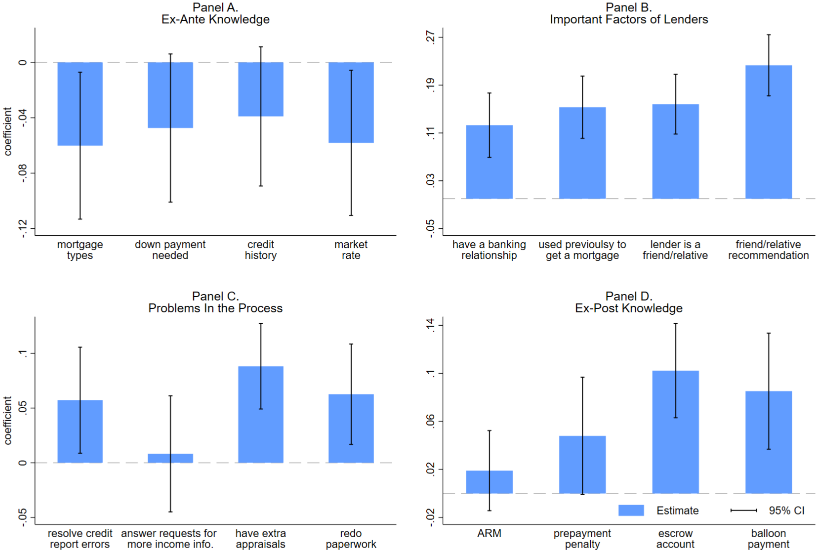
Back

Differences in Concern about Qualification

Dependent variable	$\mathbb{1}$(concern about qualifying for a mortgage)				
	(1)	(2)	(3)	(4)	(5)
LEP	0.102***	0.100***	0.064***	0.058***	0.059***
	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)
D.V. mean (LEP)			0.243		
Observations	37,720	37,720	37,720	37,720	37,720
Quarter FEs		✓	✓	✓	✓
Tract type FEs		✓	✓	✓	✓
Race and ethnicity			✓	✓	✓
Gender			✓	✓	✓
Education			✓	✓	✓
Additional demo. controls			✓	✓	✓
Risk FEs (FICO $\times$ LTV)				✓	✓
Loan controls					✓

Significant difference conditional on a long list of potential confounders Back

Descriptive Differences: Hispanic Borrowers



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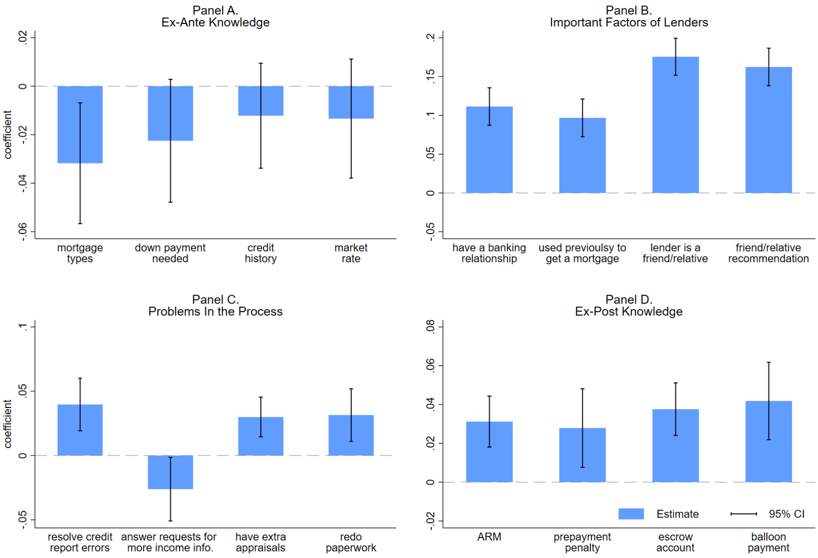
Descriptive Differences: College Graduates



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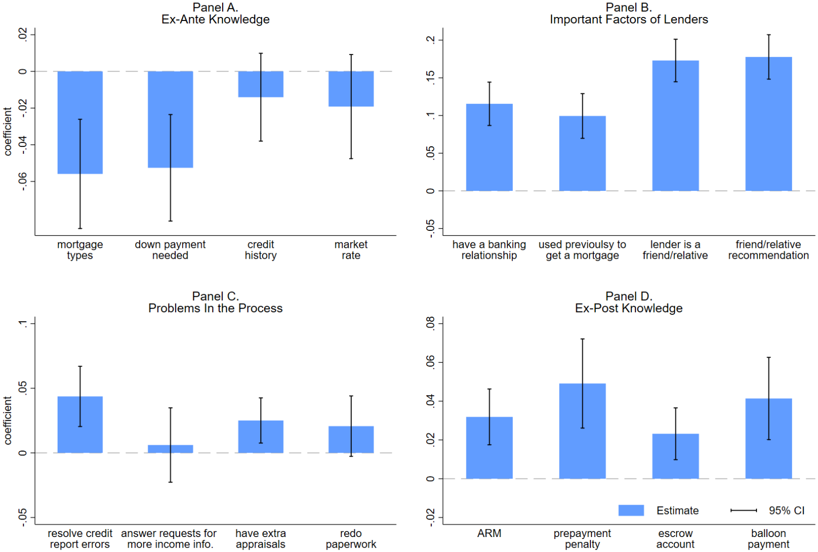
Descriptive Differences: High Income Borrowers



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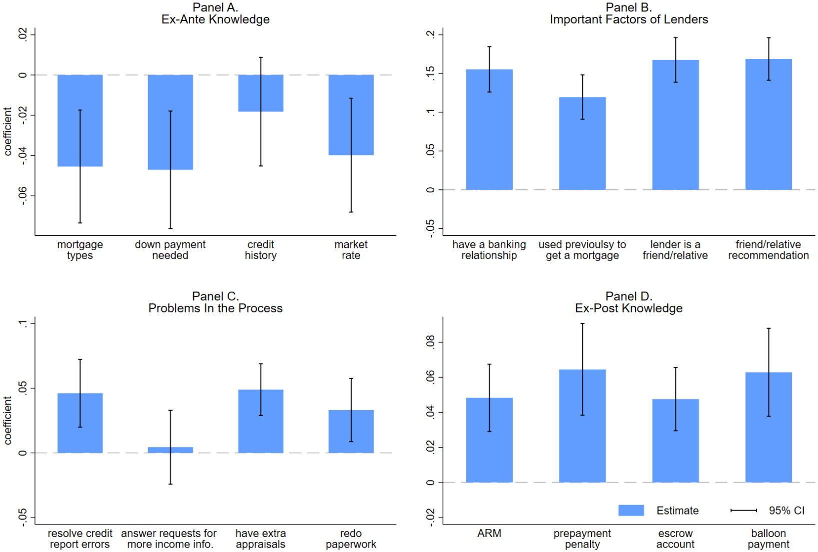
Descriptive Differences: Through Brokers



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Demographic Characteristics and Search Behavior

Dependent variable	Number of lenders		Why apply to multiple lenders?		
	seriously considered	applied to	find better loan terms	concern over qualification	learn information
	(1)	(2)	(3)	(4)	(5)
LEP	-0.065***	-0.024**	0.016	0.105***	0.075***
	(0.015)	(0.012)	(0.017)	(0.020)	(0.021)
Hispanic	0.049***	0.065***	0.012	0.043**	0.098***
	(0.018)	(0.015)	(0.016)	(0.019)	(0.021)
Asian	0.110***	0.058***	0.005	0.117***	0.133***
	(0.021)	(0.017)	(0.017)	(0.022)	(0.024)
Black	0.110***	0.116***	0.007	0.006	0.041*
	(0.021)	(0.017)	(0.018)	(0.021)	(0.022)
Observations	37,720	37,720	8,569	8,569	8,569
Quarter FEs	✓	✓	✓	✓	✓
Tract type FEs	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓
Risk FEs	✓	✓	✓	✓	✓
Loan controls	✓	✓	✓	✓	✓

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Demographic Characteristics and Interest Rate

Dependent variable	Interest rate				
	(1)	(2)	(3)	(4)	(5)
LEP	0.032***				0.029***
	(0.010)				(0.010)
Hispanic		0.047***			0.044***
		(0.011)			(0.011)
Asian			-0.097***		-0.093***
			(0.012)		(0.012)
Black				0.045***	0.044***
				(0.014)	(0.014)
Observations	37,720	37,720	37,720	37,720	37,720
Quarter FEs	✓	✓	✓	✓	✓
Tract type FEs	✓	✓	✓	✓	✓
Risk FEs	✓	✓	✓	✓	✓
Loan controls	✓	✓	✓	✓	✓

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LEP Status, Interest Rate, and 90-Day Delinquency

Sample	All	Purchase	Refinance	First-time borrowers	Repeat borrowers
	(1)	(2)	(3)	(4)	(5)
	Panel A. Interest rate				
LEP	0.032***	0.027**	0.034**	0.038*	0.028***
	(0.010)	(0.014)	(0.013)	(0.021)	(0.010)
	Panel B. 90-Day delinquency				
LEP	0.003	0.005	0.0002	0.005	0.001
	(0.003)	(0.004)	(0.004)	(0.007)	(0.003)
Observations	37,720	19,268	16,937	7,338	30,382
Quarter FEs	✓	✓	✓	✓	✓
Tract type FEs	✓	✓	✓	✓	✓
Risk FEs	✓	✓	✓	✓	✓
Loan controls	✓	✓	✓	✓	✓

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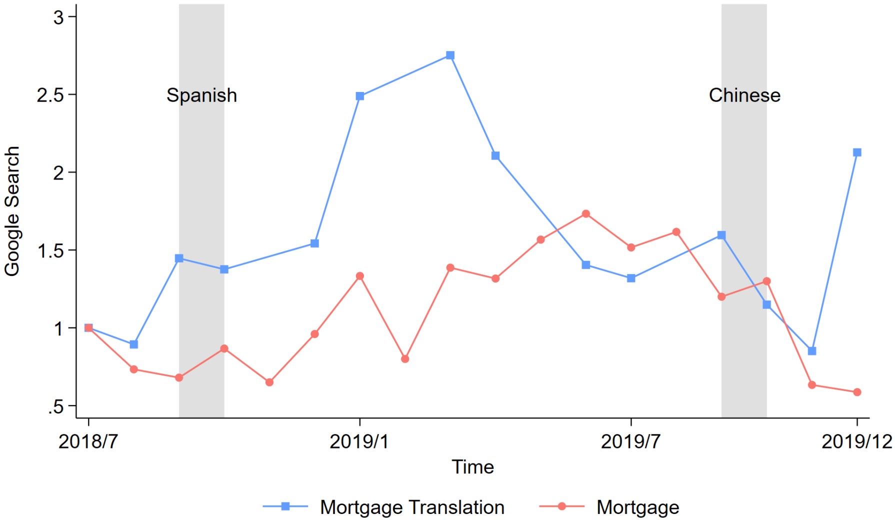
Google Trends: “Mortgage Translation” and “Mortgage”



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Effect on Lender Competition

Dependent variable	Number of Lenders		HHI	
	application	origination	application	origination
	(1)	(2)	(3)	(4)
	Panel A. Markets of Hispanic and Asian borrowers			
LEP share $\times$ Post	17.759*	21.983**	-0.120*	-0.263**
	(9.809)	(9.270)	(0.070)	(0.102)
	Panel B. Markets of all borrowers			
LEP share $\times$ Post	-24.805	-17.327	-0.001	-0.055*
	(16.586)	(14.581)	(0.024)	(0.030)
Observations	25,225	25,225	25,225	25,225
County FEs	✓	✓	✓	✓
Year $\times$ State FEs	✓	✓	✓	✓
Additional controls	✓	✓	✓	✓

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Drop Mortgages Originated after June 2019

Dependent variable	Redo paperwork (1)	Balloon payment (2)	Interest rate (3)	$\mathbb{1}$(consider multi. lenders) (4)
LEP $\times$ Hispanic $\times$ Post	-0.148** (0.064)	-0.208*** (0.067)	-0.091 (0.088)	0.143 (0.088)
Observations	34,871	34,871	34,871	34,871
Quarter FEs	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓
Post $\times$ Tract type FEs	✓	✓	✓	✓
Post $\times$ Risk FEs	✓	✓	✓	✓
Post $\times$ Loan controls	✓	✓	✓	✓

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Choice of Control Groups: Difference-in-Differences

Dependent variable	Redo paperwork (1)	Balloon payment (2)	Interest rate (3)	$\mathbb{1}$(consider multi. lenders) (4)
	Panel A. Sample of Hispanic borrowers			
LEP × Post	-0.117**	-0.133**	-0.106*	0.128*
	(0.054)	(0.054)	(0.064)	(0.070)
Observations	2,933	2,933	2,933	2,933
	Panel B. Sample of LEP borrowers			
Hispanic × Post	-0.157***	-0.135***	-0.095	0.174***
	(0.051)	(0.051)	(0.066)	(0.066)
Observations	3,485	3,485	3,484	3,485
Quarter FEs	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓
Post × Tract type FEs	✓	✓	✓	✓
Post × Risk FEs	✓	✓	✓	✓
Post × Loan controls	✓	✓	✓	✓

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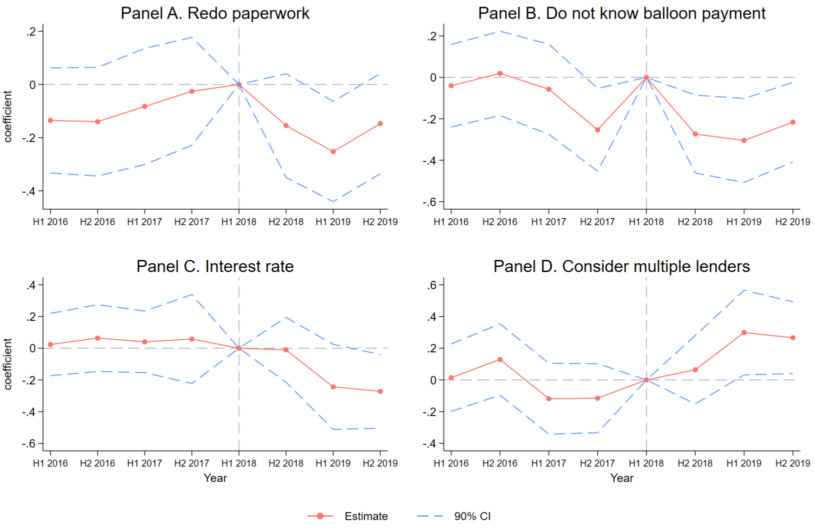
Flexible Difference-in-Differences Estimates



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Falsification Tests

Dependent variable	Redo paperwork (1)	Balloon payment (2)	Interest rate (3)	$\mathbb{1}$(consider multi. lenders) (4)
	Panel A. Change $Post_t$			
LEP × Hispanic × Post	-0.064	0.038	0.069	-0.027
	(0.060)	(0.060)	(0.064)	(0.067)
Observations	30,645	30,645	30,645	30,645
	Panel B. Change $Hispanic_i$			
LEP × Asian × Post	-0.044	0.032	0.005	0.022
	(0.061)	(0.086)	(0.089)	(0.097)
Observations	34,748	34,748	34,748	34,748
Quarter FEs	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓
Post × Tract type FEs	✓	✓	✓	✓
Post × Risk FEs	✓	✓	✓	✓
Post × Loan controls	✓	✓	✓	✓

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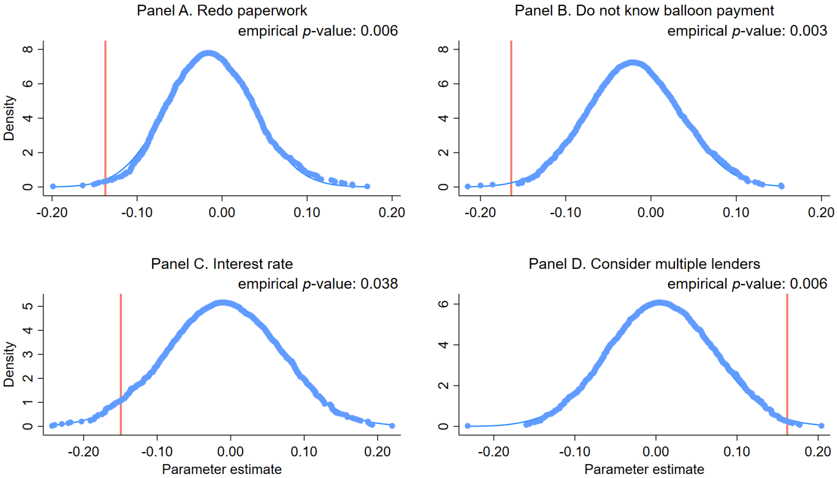
Random Assigned LEP Status



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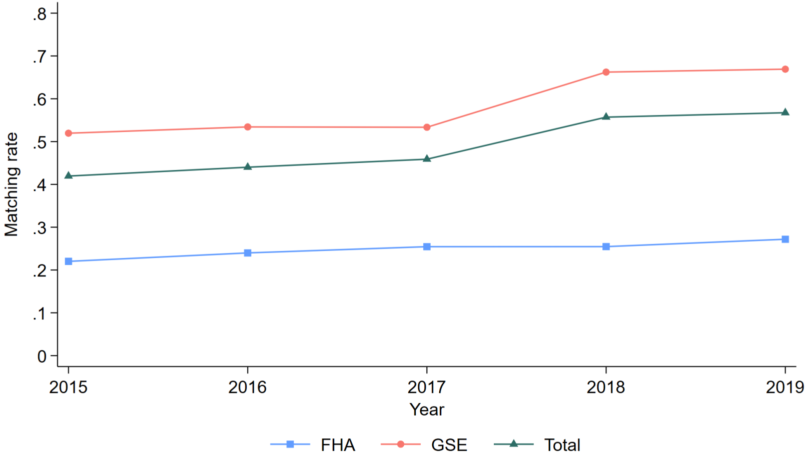
HMDA^{+} Matching Rate



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Control For Lender Response

Sample	Purchase (1)	First-time borrowers (2)	Repeat borrowers (3)	Channel: retail (4)	Channel: broker (5)
	Outcome: Interest Rate				
LEP $\times$ Hispanic $\times$ Post	-0.034*** (0.008)	-0.046*** (0.011)	-0.004 (0.012)	-0.043*** (0.011)	-0.017 (0.012)
Observations	3,779,493	1,616,120	2,111,259	2,428,526	1,325,020
Month FEs	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓
Post $\times$ Lender $\times$ County FEs	✓	✓	✓	✓	✓
Post $\times$ Risk FEs	✓	✓	✓	✓	✓
Post $\times$ Loan controls	✓	✓	✓	✓	✓

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Conventional Refinance Loans

Dependent variable	# Applications (10K) (1)	Share of incomplete app. (2)	Denial rate (3)	# Originations (10K) (4)
LEP share × Post	-0.445*	0.002	0.020	-0.211
	(0.240)	(0.020)	(0.026)	(0.145)
Observations	25,253	25,253	25,253	25,253
County FEs	✓	✓	✓	✓
Year × State FEs	✓	✓	✓	✓
Additional controls	✓	✓	✓	✓

Back

TWFE Estimation with Heterogeneous Treatment Effects

Dependent variable	# Applications (10K) (1)	Share of incomplete app. (2)	Denial rate (3)	# Originations (10K) (4)
D_{ct}	0.201***	-0.686**	-1.118***	0.065***
	(0.037)	(0.277)	(0.320)	(0.022)
No. of switchers	1,902	1,902	1,902	1,902
County FEs	✓	✓	✓	✓
Year $\times$ State FEs	✓	✓	✓	✓
Additional controls	✓	✓	✓	✓

Explanation Back

Heterogeneous Effects on Credit Access: By LEP Share

Dependent variable	# Applications (10K) (1)	Share of incomplete app. (2)	Denial rate (3)	# Originations (10K) (4)
	Panel A. Low LEP share			
LEP share × Post	1.507***	-1.349***	-3.781***	0.998***
	(0.321)	(0.380)	(1.260)	(0.227)
Observations	12,607	12,607	12,607	12,607
	Panel B. High LEP share			
LEP share × Post	0.081	-0.038*	-0.094*	0.063
	(0.054)	(0.020)	(0.048)	(0.040)
Observations	12,478	12,478	12,478	12,478
County FEs	✓	✓	✓	✓
Year × State FEs	✓	✓	✓	✓
Additional controls	✓	✓	✓	✓

Back

Falsification Tests

Dependent variable	# Applications (10K) (1)	Share of incomplete app. (2)	Denial rate (3)	# Originations (10K) (4)
	Panel A. Change $Post_t$			
LEP share × Post	0.011	0.015	-0.013	0.015
	(0.061)	(0.037)	(0.034)	(0.048)
Observations	19,623	19,623	19,623	19,623
	Panel B. Asian borrowers			
LEP share × Post	0.018	-0.039	-0.067*	0.016
	(0.014)	(0.038)	(0.037)	(0.012)
Observations	12,936	12,936	12,936	12,936
County FEs	✓	✓	✓	✓
Year × State FEs	✓	✓	✓	✓
Additional controls	✓	✓	✓	✓

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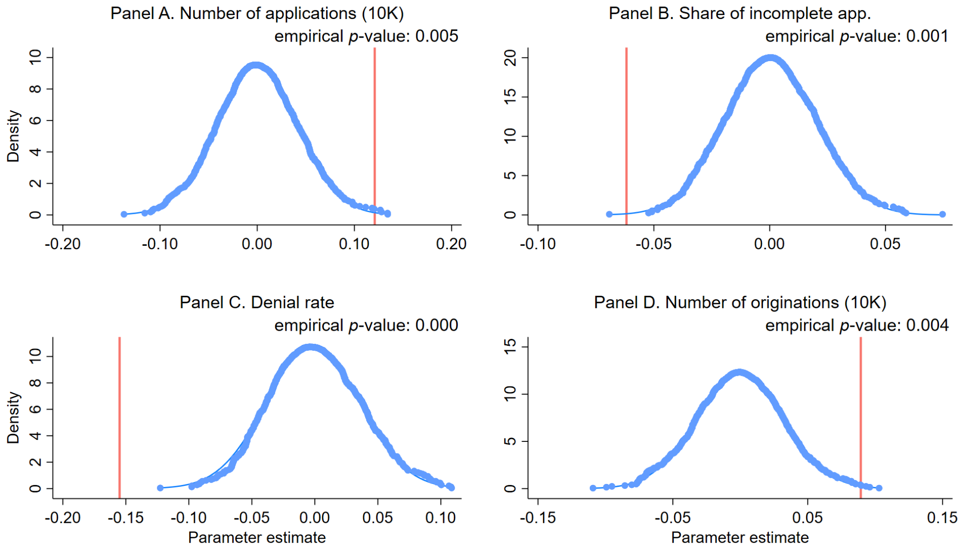
Random Assigned LEP Share



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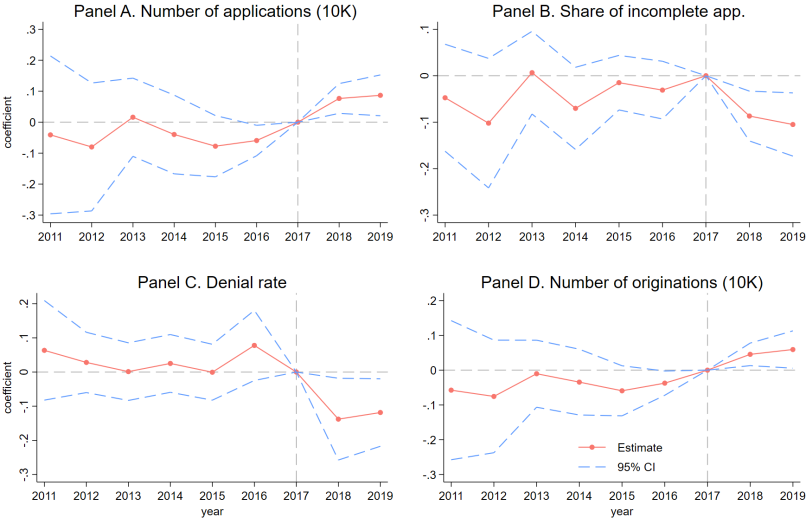
Flexible Difference-in-Differences Estimates



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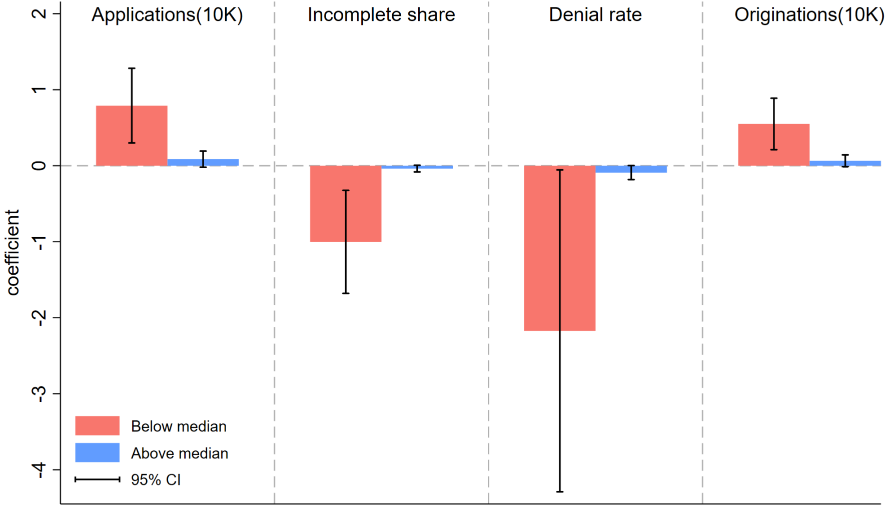
Heterogeneous Effects on Credit Access: By Racial Composition



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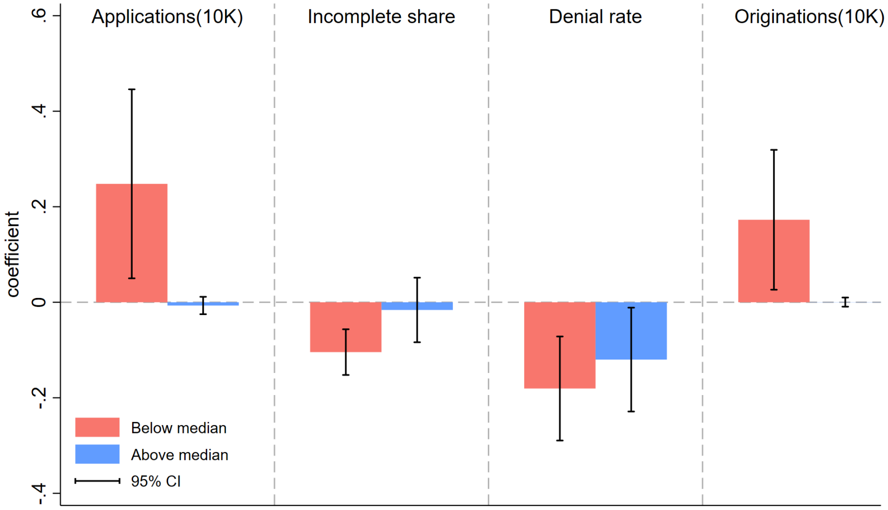
Heterogeneous Effects on Credit Access: By Lender Competition



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Effect on Mortgage Rate of GSE Loans

Outcome: conditional mortgage rate

- regress raw outcomes on loan characteristics
- average residuals at the 3-digit ZIP code level at a monthly frequency

Sample	All (1)	Purchase (2)	Refinance (3)	First-time borrowers (4)	Repeat borrowers (5)	Channel: retail (6)	Channel: broker (7)
	Outcome: Average Conditional Interest Rate						
LEP share × Post	-0.127**	-0.154***	-0.115	-0.152*	-0.120*	-0.108**	-0.044
	(0.060)	(0.053)	(0.100)	(0.078)	(0.069)	(0.053)	(0.079)
Observations	52,435	52,088	52,160	51,234	52,382	52,341	44,854
ZIP3 code FEs	✓	✓	✓	✓	✓	✓	✓
Month FEs	✓	✓	✓	✓	✓	✓	✓
Additional controls	✓	✓	✓	✓	✓	✓	✓

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Effect on Ex-Post Mortgage Risk of GSE Loans

Outcome: conditional 90-day delinquency rate

- regress raw outcomes on loan characteristics
- average residuals at the 3-digit ZIP code level at a monthly frequency

Sample	All	Purchase	Refinance	First-time borrowers	Repeat borrowers	Channel: retail	Channel: broker
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Outcome: Average Conditional 90-Day Delinquency Rate						
LEP share × Post	0.021	0.029	0.018	0.039	0.016	0.015	0.011
	(0.016)	(0.020)	(0.016)	(0.024)	(0.014)	(0.018)	(0.029)
Observations	52,435	52,088	52,160	51,234	52,382	52,341	44,854
ZIP3 code FEs	✓	✓	✓	✓	✓	✓	✓
Month FEs	✓	✓	✓	✓	✓	✓	✓
Additional controls	✓	✓	✓	✓	✓	✓	✓

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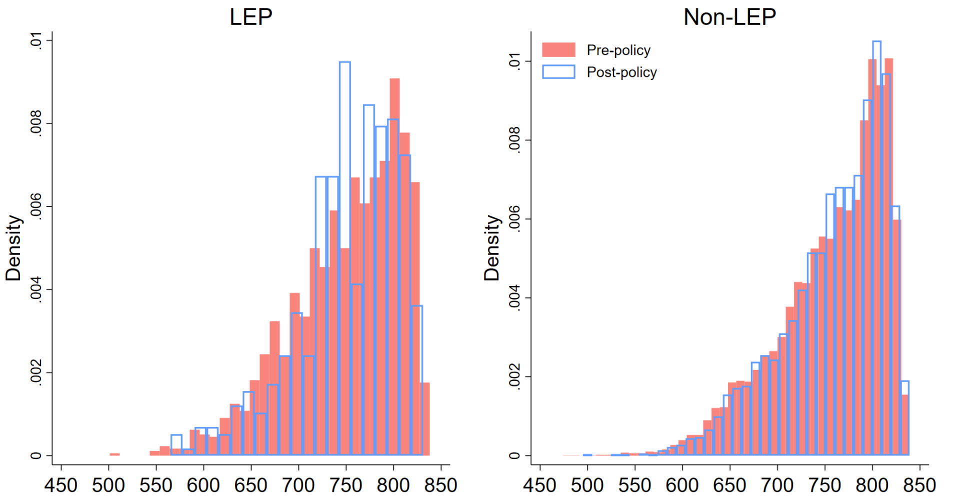
Distribution of FICO Scores (NSMO)



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Effect on Unconditional Mortgage Performance

Outcome: unconditional delinquency rate

- Source: National Mortgage Database (NMDB)
- Calculation: $\dfrac{\#\text{mortgages with missed payments}}{\#\text{ outstanding mortgages}}$

Dependent variable	90–day delinquency rate (1)	30-89 delinquency rate (2)
LEP share $\times$ Post	-0.193 (0.587)	-0.502 (0.303)
Observations	33,624	33,624
County fixed effects	Yes	Yes
Month fixed effects	Yes	Yes
Additional controls	Yes	Yes

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