### Language Frictions in Consumer Credit

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### Motivation

#### 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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Households make financial decisions affected by various frictions

One fundamental yet often overlooked friction: language frictions

- Language barriers faced by borrowers with limited English proficiency (LEP)
- Nearly one in ten working age adults in the US is LEP



#### 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?

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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)

- Question: How do language frictions affect household financial decisions?
- Setting: the U.S. mortgage market
- Data challenge: who are LEP borrowers?
  - Survey data: National Survey of Mortgage Originations (NSMO)
  - Apply machine learning to predict LEP status
- $\implies$  Document significant descriptive differences

- Question: How do language frictions affect household financial decisions?
- Setting: the U.S. mortgage market
- Data challenge: who are LEP borrowers?
- Identification challenge: isolate the role of language
  - Natural experiment: phased rollout of translated mortgage documents by FHFA
  - Triple-difference: LEP  $\times$  Hispanic  $\times$  Post
- $\implies$  Estimate the causal effect of language frictions

- Question: How do language frictions affect household financial decisions?
- Setting: the U.S. mortgage market
- Data challenge: who are LEP borrowers?
- Identification challenge: isolate the role of language
- Preview of results: reducing language frictions leads to
  - Better application experience
  - Lower borrowing costs
  - Expanded access to conventional loans
  - No deterioration of mortgage performance

#### National Survey of Mortgage Originations (NSMO) 2013-19

- Demographic characteristics
- Perceptions and experiences in the mortgage market (survey response)
- Contract and performance variables (administrative sources)
- LEP status at the individual level

Data

### Assigning LEP Status in the Survey

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

		Not
1	Important	Important
Having an established banking relationship		
Having a local office or branch nearby	у 🗌	
Used previously to get a mortgage	$\mathbf{\nabla}$	
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	$\checkmark$	

About 10% are LEP borrowers

#### Data

### Data Sources

### National Survey of Mortgage Originations (NSMO) 2013-19

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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

# Stylized Facts about LEP Borrowers: Mortgage Application

• Before application: know less about the mortgage market

 $\,\approx\,60\%$  of the differences between borrowers with a college degree and those without

When you began the process of getting this mortgage, how familiar were you with each of the following?



### Stylized Facts about LEP Borrowers: Mortgage Application

- Before application: know less about the mortgage market  $\approx 60\%$  of the differences between borrowers with a college degree and those without
- During application: encounter more problems 5 pp more likely to redo mortgage paperwork

### Stylized Facts about LEP Borrowers: Mortgage Application

- Before application: know less about the mortgage market  $\approx 60\%$  of the differences between borrowers with a college degree and those without
- During application: encounter more problems 5 pp more likely to redo mortgage paperwork
- After application: less familiar with their own mortgage contracts  $\approx 2X$  more likely to be unsure if their own mortgage is an ARM

# Stylized Facts about LEP Borrowers: Mortgage Outcomes



# Stylized Facts about LEP Borrowers: Mortgage Outcomes



# Policy Shock: 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, Chinese translations in 2019



Causal Effect

Google Trends: "Mortgage Translation" and "Mortgage"



# Empirical Strategy: Triple-Difference

Dependent variable: 1(redo paperwork)



#### $H_0$ : the decrease is smaller than 5 pp

### Causal Effect of Language Frictions on the Intensive Margin

#### Effect on access to credit (intensive)?

• Encounter fewer problems: redo mortgage paperwork  $\downarrow$  14 pp

# Effect on Mortgage Rate: Graphical Evidence

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









### Causal Effect of Language Frictions on the Intensive Margin

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#### Effect on the price of credit?

• Lower interest rates:  $\downarrow$  13 bps, save \$19 per month and \$1600 after 8 years

# One Potential Mechanism of the Price Effect: Borrower Search

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









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### Effect on the quality of credit?

• Minimal effect on mortgage delinquency rate

#### Data limitations of the survey data

- No lender or location information
- No up-front costs (e.g., discount points)

Data limitations of the survey data

Address these concerns in three steps:

- 1. A loan-level data set: HMDA<sup>+</sup>
  - Merge HMDA with Fannie Mae, Freddie Mac, and Ginnie Mae data
  - Include borrower, lender, property, mortgage contract, mortgage performance information

- Data limitations of the survey data
- Address these concerns in three steps:
- 1. A loan-level data set: HMDA<sup>+</sup>
- 2. Use machine learning to predict LEP status in HMDA<sup>+</sup>
  - Solve a binary classification problem
  - Training sample: micro-level American Community Survey
  - 99% accuracy in the test sample

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- Address these concerns in three steps:
- 1. A loan-level data set: HMDA<sup>+</sup>
- 2. Use machine learning to predict LEP status in HMDA<sup>+</sup>
- 3. Run triple-difference regressions in HMDA<sup>+</sup>
  - Misclassification brought by  $\mathsf{ML}\to\mathsf{Attenuation}$  bias if  $\mathsf{ML}$  performance is not too bad
  - Use ML performance to bound measurement error
  - Recover the lower bound of the average treatment effect on the treated (ATT)

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Revisit the price effect

- Interest rate decreases by at least 5 bps
- Lower total borrowing costs (interest rate  $\downarrow$  + net discount points  $\rightarrow$ )

# LEP Consumers Excluded From the Mortgage Market?

#### Estimate the effect on credit access on the extensive margin

- Data: county-level HMDA
- Sample: conventional purchase loans
- Regression: difference-in-differences

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

c, s, t: county c, state s, year t  

$$D_{ct} = \begin{cases} 0, & \text{if } t \leq 2017 \\ \text{Hispanic LEP share}_{c}, & \text{if } t = 2018 \\ \text{Hispanic LEP share}_{c} + \text{Chinese LEP share}_{c}, & \text{if } t = 2019 \end{cases}$$

### Causal Effect of Language Frictions on the Extensive Margin

Dependent variable	# Applications (10K) (1)	Share of incomplete app. (2) (3)		# Originations (10K) (4)
LEP share $ imes$ Post	0.124**	-0.052**	-0.105**	0.092**
	(0.058)	(0.023)	(0.042)	(0.042)
Sample mean	0.083	0.117	0.177	0.061
Observations	27,605	27,605	27,605	27,605
County FEs	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
Year $ imes$ State FEs	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
Additional controls	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$

Application incomplete and denial rate  $\downarrow$  by 5 pp and 11 pp

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4 pp  $\uparrow$  in the local share of LEP people  $\implies$  + 50 applications and 37 originations

Causal Effect

### Flexible Difference-in-Differences Estimates



Estimate – 95% CI

### Real Effect on Homeownership?

Dependent variable	# Conventional	# FHA	# All	Homeownership
	(1)	(2)	(3)	(4)
LEP share $\times$ Post	0.089**	-0.047	<mark>0.025</mark>	-0.029
	(0.044)	(0.030)	(0.046)	(0.028)
Observations	25,224	25,224	25,224	25,224
County FEs	Yes	Yes	Yes	Yes
Year × State FEs	Yes	Yes	Yes	Yes

Substitution between conventional and FHA loans  $\implies$  no increase in total purchase loan originations

### Conclusion

#### Main takeaway: Reducing language frictions can lead to

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### **Policy implications**

- Reduce compliance risks for financial institutions
- A cost-effective policy
- More work is needed to improve homeownership