Financial Skills and Search in the Mortgage Market

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Motivation

"Well-informed consumers, who can serve as their own advocates, are one of the best lines of defense against the proliferation of financial products and services that are unsuitable, unnecessarily costly, or abusive." (Ben Bernanke, 2011)

Mortgages in the U.S.

- lending faster than ever, low credit score thresholds
- monthly repayments
  - $\rightarrow$ locked in over the 30 year span
  - $\rightarrow$ 70% of total debt repayments

Questions

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1. Are **financially unskilled** households **disadvantaged** in the mortgage market?
2. How do **financial skill differences** reflect in **consumption inequality**?
3. How effective is **financial education** in reducing consumption inequality?
4. How does **mortgage accessibility** affect the consumption gap?

Our paper in a nutshell

Empirical findings

- stochastic record linkage $\rightarrow$ new U.S. mortgage data set

1. financially unskilled secure mortgages at 13.4 b.p. higher rates

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Micro-founded mortgage search model

2. heterogeneous mortgage repayments generate consumption differences
3. accessible mortgages - 8% decrease in average search costs
    - promote mortgage take-up among financially unskilled
    - $\uparrow$ 1.5% in average delinquency
4. financial education - 90 min. course increases search effectiveness
    - new homeowners secure lower rates - consumption inequality $\downarrow$ 1.4%
    - **has a stronger effect with accessible mortgages**

Related literature - two streams

1. **Financial skills and behavior**

- financial literacy and portfolio choice, loan repayment (Gathergood and Weber, 2017; Bhutta et al., 2021; Lusardi, 2019) ▸ Experiments

  → objective financial literacy, search effort and mortgage repayment

- financial planning changes over time, not explained with individual risk (Agarwal et al., 2008, 2007), induces wealth heterogeneity (Lusardi et al., 2017)

- race, gender and education disparities in the mortgage interest rate (Bhutta et al., 2020; Keys et al., 2016)

  → endogenous financial skills $\Longrightarrow$ mortgage rate

Related literature - two streams

2. **Mortgage choice models**

- lending models with hidden information (Agarwal et al., 2013, 2020; Campbell, 2013)
- non-bank lenders - mortgage rate dispersion due to unobserved (Bartlett et al., 2022; Fuster et al., 2019; Kaiser et al., 2022)
  - → web apps and personal input - full information search framework
  - → model experiment - increase in mortgage accessibility
- fear of rejection induces search effort (Agarwal et al., 2020)
  - → number of lenders considered - cognitive search cost

Data analysis

Data sets

The Survey of Consumer Finances	The **N**ational **S**urvey of **M**ortgage **O**riginations
borrower's characteristics	
financial literacy ▸ Score def. refinancing mortgage amount	mortgage specifics search behavior

- **joint characteristics**: ▸ Shares
    - education, gender, age, race, occupation, marital status, kids
    - income, owns asset, owns retirement plans
- stochastic record linkage $\rightarrow$ **NSMO+** ▸ Details
    - new evidence on mortgage take-up and objective financial literacy

NSMO+ data (2014-2020)

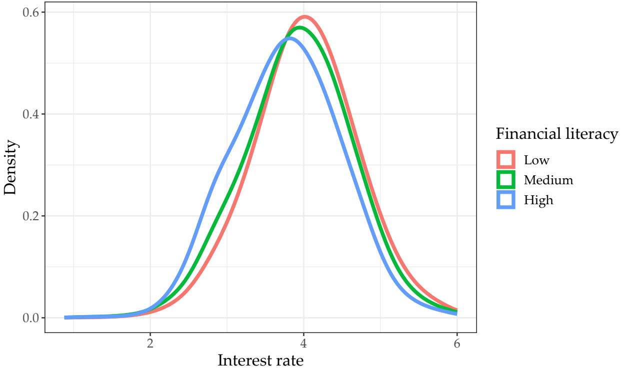
- mortgage registry data coupled with household survey on shopping experience
  - mortgage specifics: purpose, term, amount, interest rate, sponsorship, urban/rural
  - household characteristics: education, income category, family characteristics, credit score, risk attitude, **imputed financial literacy**
  - mortgage shopping behavior: number of lenders considered prior to applying

Findings

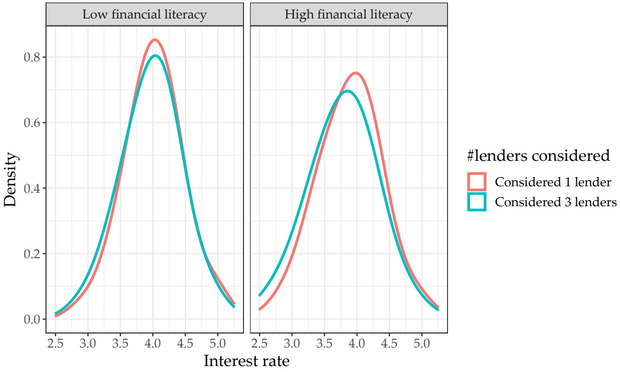
1. financial skills vary with age ▸ Polynomial data fit
2. 3 years after financially unskilled 35-45% more likely to become delinquent ▸ Regression
3. as mortgages become accessible, financial skills effect increases ▸ Marginal effects plot
4. search effort is effective with skilled borrowers - up to 13.4 b.p. lower rate

Mortgage rate differences by financial literacy

- keeping loan amount, credit score and origination year fixed



Quantifying effective search ▸ Estimates ▸ Differences



Predicted rates across skill levels and search effort.

- $f_{\text{low}}, f_{\text{high}}$ and \$100,000 loan - difference is at least \$6,693 over the mortgage term
- all else fixed, considering lower # of lenders adds \$2,636 on total mortgage payments

The model

Mortgage search framework - HA model in continuous time

- endogenous financial skills and search intensity
- heterogeneous search costs and expense shocks
  $\rightarrow$ data: financial skills vary with age
  $\rightarrow$ data: financially skilled search effectively and repay on time
- steady state distribution of mortgage rates, skills and search effort
  $\rightarrow$ data: financially skilled secure lower rates
- **mortgage repayment $\implies$ consumption and saving choice**

Model setup

- agents face productivity shocks, consume and save
- can adjust housing costs **by sampling from a pool of mortgage offers** $\Phi(r)$

$\overset{\text{data}}{\rightarrow}$ search for options with intensity s, face utility costs $c^m(s, \mathbf{f})$
$\overset{\text{data}}{\rightarrow}$ invest in skills i, face utility cost $c^i(i, z) \rightarrow \dot{f} = \frac{\mu}{\eta}(if)^\eta - \delta f$

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- **current homeowners:** mortgage M $\approx 4wz$ with a period repayment **r**M
  - can search for refinancing options to get a better rate
  - face expense shocks $\overset{\text{data}}{\to}$ probability $p(f, a)$ $\to$ lose the house
- **renters** pay the rental rate κ
  - can search for a mortgage, face additional search costs ϕ

Homeowner's problem

$$\rho V^H(f,a,z,r) = \max_{\{c,s,i\}} \Big\{ u(c) - c^f(i,z) - c^m(s,f) + \frac{\partial V^H}{\partial f}(f,a,z,r)\dot{f} + \frac{\partial V^H}{\partial a}(f,a,z,r)\dot{a}$$

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$$+ \lambda s(f,a,z,r) \int_{\underline{r}}^{\bar{r}} \max\{V^H(f,a-c_{\text{ref}},z,r') - V^H(f,a,z,r), 0\} d\Phi(r')$$

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$$+ \sum_{z'} \omega(z,z')\big(V^H(f,a,z',r) - V^H(f,a,z,r)\big)\Big]$$

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& + p(f,a)\big(V^R(f,a,z) - V^H(f,a,z,r)\big) \Bigg\}
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\end{aligned}
$$

subject to

$$
\begin{aligned}
\dot{a} &= Ra + wz - Mr - c, \\
\dot{f} &= \frac{\mu}{\eta}(if)^{\eta} - \delta f.
\end{aligned}
$$

Renter's problem

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subject to

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Functional forms

Utility

$$u(c) = \frac{c^{1-\sigma}}{1-\sigma}$$

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Mortgage search cost

$$c^m(s,f) = c_0 \frac{s^{1+\frac{1}{\gamma_s}}}{1+\frac{1}{\gamma_s}} \frac{1}{(1+f)^{\gamma_f}}, \quad \gamma_s \quad \text{search cost elasticity}$$

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Fin. skill investment cost

$$c^f(i,z) = i_0 \frac{i^{1+\frac{1}{\gamma_i}}}{1+\frac{1}{\gamma_i}} \frac{1}{1+z}, \quad \gamma_i \quad \text{investment cost elasticity}$$

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Expense shock

$$p(f,a) = \frac{\exp(p_0 + p_f f + p_a a)}{1+\exp(p_0 + p_f f + p_a a)},$$

The economy in the steady state

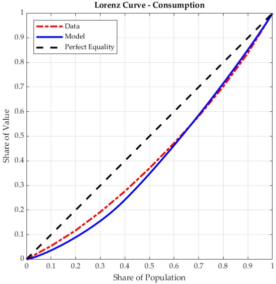
Baseline parameter values

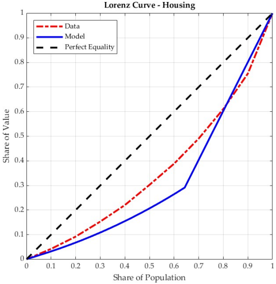
Definition	Symbol	Estimate	Source/Target	Model	Data
		Panel A. Externally set			
Discount factor	ρ	0.05	Moll et al. (2022)		
CRRA parameter	σ	2	Laibson et al. (2021)		
Investment cost elasticity	γ_i	0.5	Kapička and Neira (2019)		
Return	R	0.04	Moll et al. (2022)		
Refinancing Cost	c_{ref}	0.21	Freddie Mac (5% of the mortgage size)		
Intensities	ω_1, ω_2	$\frac{1}{3}, \frac{1}{3}$	Guerrieri and Lorenzoni (2017)		
Curvature f	η	0.5	Browning et al. (1999)		
Depreciation	δ	0.07	Lusardi et al. (2017)		
		Panel B. Externally estimated			
Slope	μ	0.2	SCF, lifecycle profile		
Parameters	p_0, p_f, p_a	-1.08,-1.02,-7.65	SCF, late payments		
		Panel C. Internally estimated		Model	Data
Search cost - skill parameter	γ_f	0.2977	Average financial skills - HO	0.7690	0.7654
Investment cost scaling	i_0	434.2084	Average financial skills - R	0.6270	0.6499
Renting cost	κ	0.7340	Homeownership rate	0.6432	0.64
Search cost elasticity	γ_s	1.7539	Standard deviation fin. skills	0.1868	0.3041
Search cost scaling	c_0	152.9484	Average mrt. rate all	0.0398	0.0400
Search friction	ϕ	0.8062	Average mrt. rate f.o.	0.0415	0.0408
Offer distribution parameter	β	6.0411	Average mrt. rate - ref.	0.0362	0.0386
Offer distribution parameter	α	6.0805	Standard deviation mrt. rate	0.0087	0.0073

Model Validity

Non-targeted moments

1. recreates consumption inequality patterns (BLS data, 2019.)

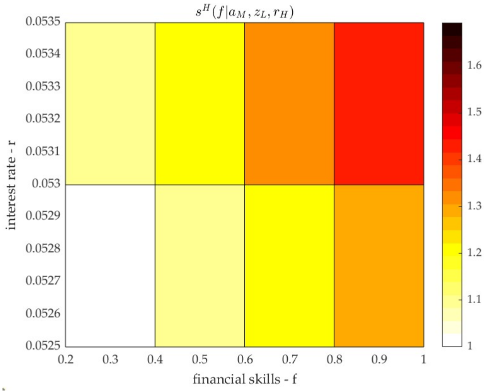




	Model	Data
Gini_c	0.2	0.18

Non-targeted moments

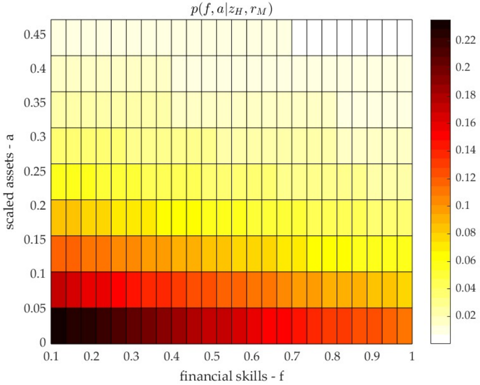
2. financially skilled search more and are likely to refinance
   - search $s \overset{\text{model}}{\rightarrow}$ likelihood to refinance $\mathbb{P}_{\text{ref}}(s) = 1 - \exp(-\lambda s)$



	Model	Data
$\mathbb{P}_{\text{ref}}(s \mid f^H)$	30%	20-30%

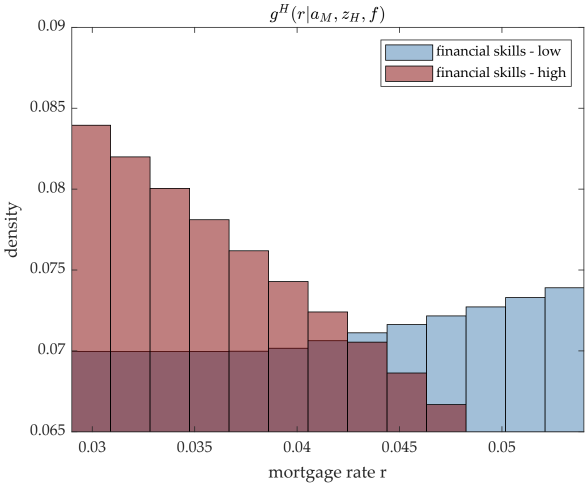
Delinquency rates in the steady state

3. financially unskilled are more likely to become delinquent



	Model	Data
$\mathbb{P}(\text{del}\|f^L)$	39.5%	35-45%

Mortgage rate across financial skills ▸ Skill disp.



- fin. skilled borrowers secure lower mortgage rates (NSMO+ est.)
- fin. unskilled borrowers search less $\overset{\text{model}}{\rightarrow}$ secure higher mortgage rate (NSMO+ est.)

Mortgage rate dispersion decomposed

- model rate decomposition across all dimensions of individual heterogeneity

$$\log(1+r) = \beta_0 + \beta_f f + \beta_a a + \beta_z z + \beta_s s + \beta_{f\times s}(f \times s) + \varepsilon$$

	explained variance share ω^2
Financial skills (f)	1.3073%
Assets (a)	0.3332%
Productivity: (z_H)	0.0486%
Search intensity (s)	55.8971%
Financial skills $\times$ search intensity ($f \times s$)	9.9925%

Table: Variance decomposition of the mortgage interest rate in the model equilibrium.

▸ Mortgage rate regression

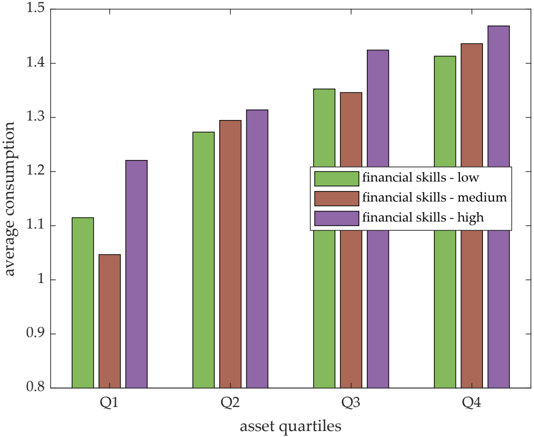
Consumption growth

Derive consumption differences

- simplify $\phi = 1, p = const$
- three components, not equally strong across the mortgage rate distribution

$$\frac{\dot{c}}{c} = \frac{1}{\sigma}\left[\underbrace{R-\rho}_{\text{impatience}} \underbrace{-\lambda s\left(\int_{\underline{r}}^{r}\left(1-\frac{u'(c(f,a,r'))}{u'(c(f,a,r))}\right)d\Phi(r')\right)}_{\text{exp mort rate change}} \underbrace{+p\left(\frac{u'(c(f,a,\kappa))}{u'(c(f,a,r))}-1\right)}_{\text{expense shock}}\right]$$

Consumption differences



- *standard* - average consumption increases by asset quartiles
- *new* - high-skilled spend less on mortgages, have more resources
- consumption dispersion two times larger among poor borrowers

Policy experiments

Overview

- financial education
  - 90 min course $\rightarrow$ smaller $c^f(i,z)$ for small investments
    $\rightarrow$ implicit decrease in search costs
  - $\uparrow$ 1.5% homeowners, $\uparrow$ 9% average skills
- mortgage accessibility
  - digitization in the mortgage mkt. $\rightarrow$ getting more with small s
  - $\uparrow$ 3.3% homeownership, $\uparrow$ 1.1% skills, $\uparrow$ 1.5% delinquency rate
- financial education has a stronger effect once mortgages are easily accessible
- low rates benefit current homeowners
  - increase in refinancing, no effect on homeownership
  - consumption inequality $\uparrow$ 1.4%

Renters' financial education

- reducing skill elasticity $\gamma_i \times 0.95$
  - $\rightarrow$ 90 minutes course in financial planning
  - $\rightarrow$ implicitly incentivizes search

Measure	Fin.edu.	Mrt. accessibility	both
average search renters	$\nearrow$ 0.4%		
average search homeowners	-		
consumption gini	$\searrow$ 1.4%		
assets gini	$\searrow$ 1.5%		
share of homeowners	$\nearrow$ 1.5%		
average financial skills	$\nearrow$ 9%		
average delinquency rate	$\searrow$ 2.8%		

Increase in mortgage accessibility

- *ad hoc* reduction in search elasticity
  $\rightarrow$ 5% for renters and 10% for homeowners
- you get more out of a small search
- mortgage take-up among financially unskilled
  $\rightarrow$ relative increase in mortgage delinquencies

Measure	Fin. edu.	Mrt. accessibility	both
average search renters	$\nearrow$ 0.4%	$\nearrow$ 7.8%	
average search homeowners	-	$\nearrow$ 16.8%	
consumption gini	$\searrow$ 1.4%	$\searrow$ 3%	
assets gini	$\searrow$ 1.5%	$\searrow$ 2.3%	
share of homeowners	$\nearrow$ 1.5%	$\nearrow$ 3.3.%	
average financial skills	$\nearrow$ 9%	$\nearrow$ 1.1%	
average delinquency rate	$\searrow$ 2.8%	$\nearrow$ 1.5%	

Financial education with accessible mortgages

- increase in better performing mortgages - drop in mtg. delinquencies

  $\overset{\text{data}}{\rightarrow}$ easier search reinforces skill accumulation

  $\rightarrow \uparrow 0.4\%$ in average skills Breakdown

Measure	Fin. edu.	Mrt. accessibility	both
average search renters	$\nearrow$ 0.4%	$\nearrow$ 7.8%	$\nearrow$ 0.3%
average search homeowners	-	$\nearrow$ 16.8%	$\nearrow$ 2.7%
consumption gini	$\searrow$ 1.4%	$\searrow$ 3%	$\searrow$ 1.5%
assets gini	$\searrow$ 1.5%	$\searrow$ 2.3%	$\searrow$ 1.3%
share of homeowners	$\nearrow$ 1.5%	$\nearrow$ 3.3.%	$\nearrow$ 1.5%
average financial skills	$\nearrow$ 9%	$\nearrow$ 1.1%	$\nearrow$ 9.4%
average delinquency rate	$\searrow$ 2.8%	$\nearrow$ 1.5%	$\searrow$ 0.36%

Downward shift in r   Upward shift in r

Conclusion

New U.S. data findings

→ mortgage rate varies with individual financial skills and search effort

→ long-term effect on mortgage repayments and consumption

Novel search framework

- endogenous financial skills and search intensity $\Longrightarrow$ mortgage rate dispersion
- mortgage rate schedule across assets, productivity and skills
- financial skills $\Longrightarrow$ consumption and saving choice

Model experiments

- accessible mortgages accommodate financial education

Future work

- move to GE with heterogeneous lenders and bargaining (Fair Price Lending)
- monetary policy; the strength of the refinancing channel based on fin. skill heterogeneity

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Empirics

- least skilled end up overpaying compared to financially savvy, effort varies with mortgage knowledge (Bhutta et al., 2020)
- homeowners make mistakes, do not refinance ($11,500, $19,000) (Keys et al., 2016; Malliaris et al., 2022)
- rising number of non-bank lenders -lower FICO, low down-payment, FinTech algo pricing dispersion (Fuster et al., 2019; Kaiser et al., 2022; Bartlett et al., 2022)

Experiments

- (Carpena et al., 2019; Attanasio et al., 2019) positive effects of financial education on savings and debt management

Back

Record linkage procedure

Probabilistic model

- Bayesian Record Linkage method merges on the set of joint characteristics
- estimates a distribution of financial skills for every borrower i
- reduces imputation bias (Enamorado et al., 2019)

borrower_i

fin_skill_i

$$0 \rightsquigarrow \omega_0$$
$$1 \rightsquigarrow \omega_1$$
$$2 \rightsquigarrow \omega_2$$
$$3 \rightsquigarrow \omega_3$$

Back

Bayesian Record Linkage (Enamorado et al., 2019)

- record pair (i, j), i in NSMO, j in SCF is a match with probability

$$M_{i,j} \sim \mathrm{B}(\lambda),$$

- match score defined on K observables via the agreement vector

$$\gamma_k(i,j)|M_{i,j} \overset{i.i.d}{\sim} \begin{pmatrix} 0 & 1 & \dots & L_k - 1 \\ \pi_{k0} & \pi_{k1} & \dots & \pi_{kL_k-1} \end{pmatrix},$$

- gender, race, age, family, education, income, occupation, assets ▸ Shares
- define the likelihood $\mathcal{L}_{\text{obs}}(\lambda, \pi)$, estimated using the Expectation Maximization algorithm
- coefficients $\hat{\lambda}$ and $\hat{\pi}$ define posterior match probabilities ζ_{ij} - use for inference ▸ Details

◂ Back

NSMO and SCF data, population shares - observables

	Data set	
	NSMO	SCF
income brackets	[6%, 9% , 18%, 19%, 30%, 18%]	[13%, 8%, 13% ,11%,20%, 35%]
education brackets	[1%, 10%, 5%, 20%, 35%, 29%]	[6%, 18%, 9%, 15%, 27%, 25%]
gender (Female,Male)	[44%, 55%]	[17%,83%]
age ($<$35,35-44,45-54,55-64,65-74,$>$=75)	[18%, 22%, 22%, 21%, 14% ,3%]	[8%, 14%, 20%, 26% , 20%, 12%]
race (Caucasian, African-American, other)	[84%, 6%, 10%]	[82%, 7%, 11%]
occupation (Employed, Self-employed, Retired/Student, Other)	[68%, 10%, 19% ,2%]	[47%, 26%, 25%, 2%]
has kids (Yes, No)	[64%, 36%]	[60% , 40%]
owns financial assets (Yes, No)	[57%, 43%]	[58% 42%]
retirement plan participation (Yes, No)	[86%, 14%]	[62%, 38%]

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Linear estimator

- fin. literacy score is a posterior-weighted average

$$\zeta_i^* = \sum_{j=1}^{N_{\text{SCF}}} \zeta_{ij} \underbrace{Z_j}_{\text{fin lit in SCF}} \Big/ \sum_{j=1}^{N_{\text{SCF}}} \zeta_{ij}$$

- $\text{rate}_i = \alpha + \beta\zeta_i^* + \eta^T X_i + \varepsilon_i$ estimated using ζ_i

Non-linear estimator

- every record pair enters as a separate observation

- likelihood function estimator adjusted for weights is asymptotically normal

$$\hat{\theta} = \arg\max_{\theta} \sum_{i=1}^{\mathcal{N}_A} \sum_{j=1}^{\mathcal{N}_B} \zeta_{ij}^* \mathbb{P}(Y_i | Z_i = Z_j, X_i)$$

Back

1. Suppose you had \$100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow?
    - More than \$102**
    - Exactly \$102
    - Less than \$102
    - Do not know
    - Refuse to answer
2. Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account?
    - More than today
    - Exactly the same
    - Less than today**
    - Do not know
    - Refuse to answer
3. Please tell me whether this statement is true or false. "Buying a single company's stock usually provides a safer return than a stock mutual fund."
    - True
    - False**
    - Do not know
    - Refuse to answer

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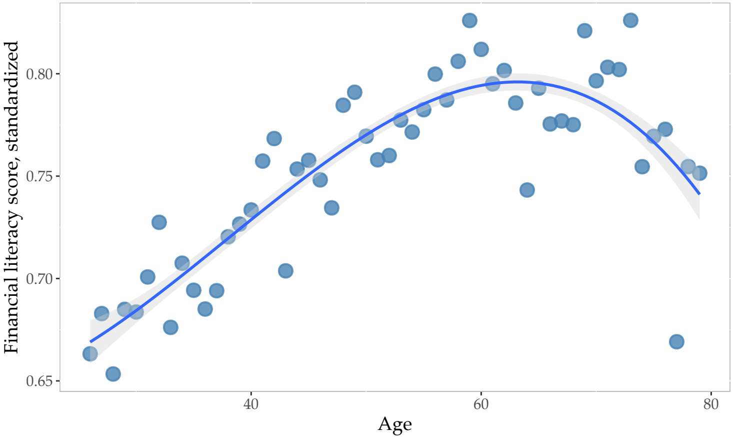
Financial literacy score, age-group fit



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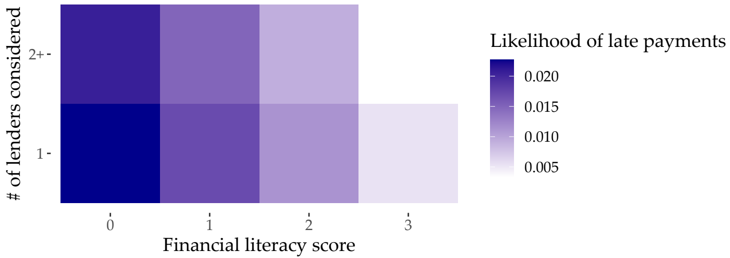
Likelihood of late payments



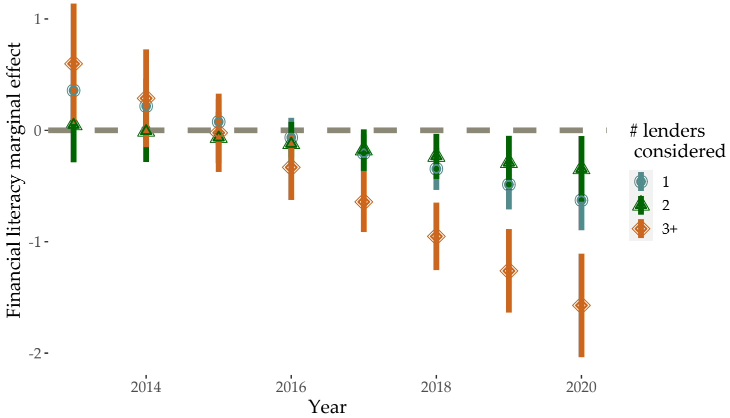
- controlled for loan amount, credit score, PTI, education, race, gender, and age

Back

Financial skills effects over the years

- linear estimates

$$\text{rate}_i = \alpha + \gamma_t + \beta X_i + \beta^m M_i + \beta^f \text{fin\_skills}_i + \beta^{\text{eff}} \text{fin\_skills}_i \times \text{num\_cons}_i + \varepsilon_i$$



Back

	mortgage rate	
	(First origination)	(All mortgages)
#lenders considered: two	0.034	−0.006
	(0.087)	(0.062)
#lenders considered: three	0.220*	0.125
	(0.120)	(0.083)
financial skills	0.017	−0.016
	(0.088)	(0.060)
considered 2 lenders× fin skills	−0.072	−0.023
	(0.113)	(0.080)
considered 3 lenders × fin skills	−0.354**	−0.220**
	(0.153)	(0.106)
age	0.044***	0.062***
	(0.010)	(0.007)
Education: high-school	−0.054***	−0.033***
	(0.017)	(0.011)
college graduate	−0.105***	−0.071***
	(0.017)	(0.012)
post-college graduate	−0.131***	−0.090***
	(0.019)	(0.012)
Refinancing		−0.074***
		(0.007)
Constant	5.269***	4.955***
	(0.099)	(0.066)
Observations	21,461	43,084
R^2	0.369	0.440
Adjusted R^2	0.368	0.439
Residual Std. Error	23.662 (df = 21412)	22.325 (df = 43034)
F Statistic	260.809*** (df = 48; 21412)	689.013*** (df = 49; 43034)

Note: Controlled for loan type, government-sponsored enterprise,loan amount, area number of borrowers, time effects, LTV, credit score, income, race and sex.

*p<0.1; **p<0.05; ***p<0.01

Back

Predicted average mortgage rates

- financially savvy that search more end up with ≈ 11 b.p. lower rates
- search is not as effective among low-skilled, get a decrease of 4.b.p. on average

		Average mortgage rate
Low literacy	Consider 1 lender	4.01
	Consider 3 lenders	3.97
High literacy	Consider 1 lender	3.89
	Consider 3 lenders	3.78

Table: Source: linear regression model predictions.

Back

HJB equations

Renters

$$\rho V^R(f,a,z) = \max_{\{c,s,i\}} \Big\{ u(c) - c^f(i,z) - c^m(s,f) + \frac{\partial V^R}{\partial f}(f,a,z)\dot{f} + \frac{\partial V^R}{\partial a}(f,a,z)\dot{a}$$
$$+ \lambda \phi s(f,a,z) \int_{\underline{r}}^{\bar{r}} \max\{V^H(f,a,z,r') - V^R(f,a,z), 0\} d\Phi(r')$$
$$+ \sum_{z'} \lambda(z,z')\big(V^R(f,a,z') - V^R(f,a,z)\big) \Big\}$$

such that

$$\dot{a} = Ra + wz - \kappa - c,$$
$$\dot{f} = \frac{\mu}{\eta}(if)^\eta - \delta f,$$

◂ Back

HJB equations, cont'd

Homeowners

$$\rho V^H(f,a,z,r) = \max_{\{c,s,i\}} \Big\{ u(c) - c^f(i,z) - c^m(s,f) + \frac{\partial V^H}{\partial f}(f,a,z,r)\dot{f} + \frac{\partial V^H}{\partial a}(f,a,z,r)\dot{a}$$

$$\lambda s(f,a,z,r)\int_{\underline{r}}^{\overline{r}} \max\{V^H(f,a,z,r') - V^H(f,a,z,r),0\} d\Phi(r')$$

$$+ \sum_{z'} \lambda(z,z')\big(V^H(f,a,z',r) - V^H(f,a,z,r)\big)]$$

$$+ p(f,a)\big(V^R(f,0,z) - V^H(f,a,z,r)\big)\Big\}$$

subject to

$$\dot{a} = y(a,s) + wz - Mr - c,$$

$$\dot{f} = \frac{\mu}{\eta}(if)^\eta - \delta f,$$

$$y(a,s) = 0 \text{ with intensity } p(f,a).$$

Back

Kolmogorov Forward Equations - homeowners

$g^H(f, a, z_i, r)$ stationary distribution of homeowners with skills f, assets a, productivity z_i and mortgage rate r

$$
\begin{aligned}
0 = & \underbrace{-\frac{\partial g^H(f,a,z_i,r)}{\partial f}\dot{f} - \frac{\partial g^H(f,a,z_i,r)}{\partial a}\dot{a}}_{\text{outflow due to } f \text{ and } a \text{ accumulation}} \underbrace{- \big(p(f,a) + \lambda s \Phi(r)\big) g^H(f,a,z_i,r)}_{\text{outflow due to fin. shock and refinancing}} + \\
& + \underbrace{\lambda \int_{\underline{r}}^{\bar{r}} s^H(f,a,z_i,r') g^H(f,a,z_i,r') d\Phi(r')}_{\text{inflow of borrowers who searched more}} + \underbrace{\lambda \phi s^R(f,a,z_i) g^R(f,a,z_i)}_{\text{inflow of new home owners}} + \\
& + \underbrace{\lambda_i \big(g^H(f,a,z_{-i},r) - g^H(f,a,z_i,r)\big)}_{\text{net flow from change in productivity}}.
\end{aligned}
$$

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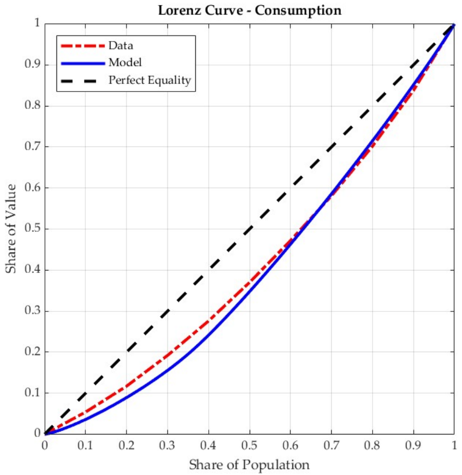
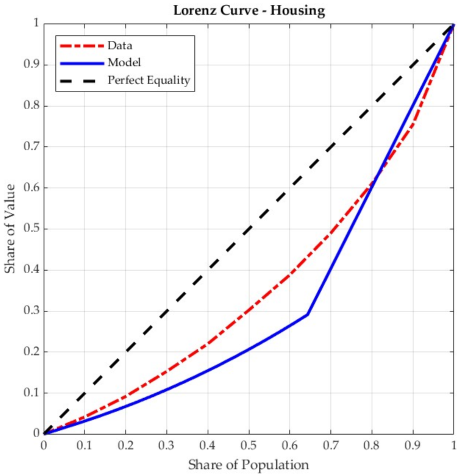
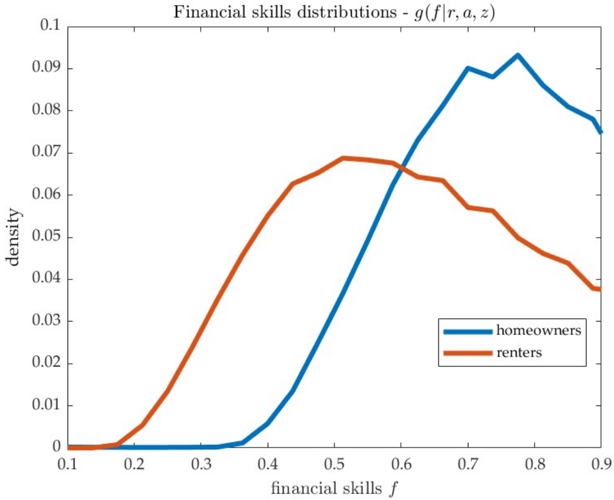
Model validity ◂ Back

- consumption inequality in equilibrium, compared to BLS consumption reports (2019)





Skill dispersion in the steady state



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Mortgage rate regression, steady state

	Dependent variable:
	mortgage interest rate $\log(1+r)$
Financial skills (f)	-0.0033^{***}
	(0.00024)
Assets (a)	0.0021^{***}
	(0.00030)
Productivity:	
(z_H)	0.0002^{***}
	(0.00009)
Search intensity (s)	0.0884^{***}
	(0.00097)
Financial skills $\times$ search intensity $(f \times s)$	-0.0600^{***}
	(0.00156)
Constant	0.0434^{***}
	(0.00018)
Observations	15,000
R^2	0.554
Adjusted R^2	0.554
Residual Std. Error	0.0052 (df = 15,000)
F Statistic	3732.06^{***} (df = 6; 15,000)
Note:	*p$<$0.1; **p$<$0.05; ***p$<$0.01

Base category productivity is z_L.
Observations weighted by the equilibrium stationary distribution.
Continuous variables are normalized.

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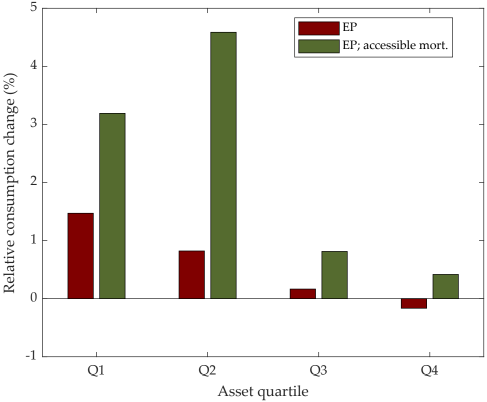
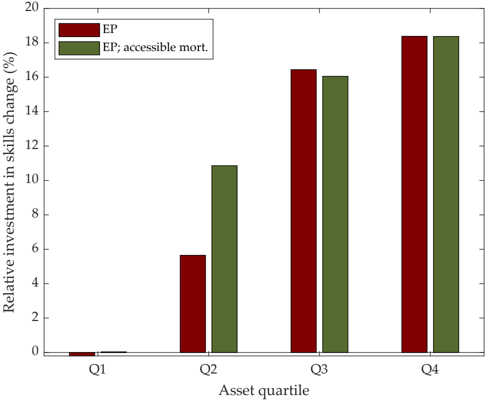
Zooming in on the financial education effect



Relative change in consumption.



Relative change in fin. skill investment.

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Exogenous changes in mortgage repayments

- down/upward shift in the mean offer rate e.g., payment deductions ▸ Distribution shifts
  - → 20 b.p. downward shift benefits fin. skilled homeowners - high refinancing activity (McKay and Wolf, 2023)
  - → increase in consumption inequality

Measure	relative change
average search renters	↗ 1.4%
average search homeowners	↗ 64.9%
consumption Gini	↗ 1.4%
assets Gini	↗ 1.1%
average financial skills	↗ 0.1%

◂ Back

Upward shift in mortgage repayments

- 10 b.p. upward shift
  - $\rightarrow$ lower skill investment incentives
  - $\rightarrow$ not sure

Measure	relative change
average search renters	$\searrow$ 0.7%
average search homeowners	$\searrow$ 36.5%
consumption Gini	$\searrow$ 5.6%
assets Gini	$\searrow$ 4.3%
average financial skills	$\searrow$ 0.6%

- disincentivizes skill accumulation
- drop in mortgage attainment
- housing costs across renters and homeowners are more similar

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