Financial Skills and Search in the Mortgage Market

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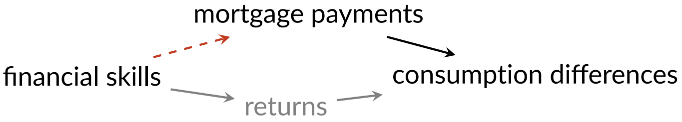
Current Landscape

So far: Financial skills $\rightarrow$ differences in returns $\xrightarrow{\text{model}}$ wealth inequality

This paper:

Highlights FinLit gaps in mortgage uptake and refinancing.



Mortgages in the U.S.:

- Lending is faster, with relaxed credit score limits
- Payments are fixed over 30 years

Role of financial education:

1. Pre-origination: shapes better outcomes
2. Rate changes: eases payment challenges

The paper in a nutshell

Data and stylized facts

- mortgages in the SCF
- stochastic record linkage $\rightarrow$ new U.S. mortgage data set

    1. mortgage registry and survey data on mortgage shopping experience (**NSMO**)
    2. household survey with FinLit questions **objective score** (**SCF**)

- financially unskilled secure mortgages at 33 b.p. higher rates

    $\rightarrow$ **unskilled search less**

    $\rightarrow$ skilled refinance more

    $\rightarrow$ skill gap persists with mortgage brokers (Woodward & Hall, 2012)

The paper in a nutshell

Micro-founded mortgage search model

- causal interpretation: costly search for mortgage options, costs $\sim$ data patterns,
  $\rightarrow$ can accommodate different types of loans
- skills and savings $\rightarrow$ differences in returns

Policy experiments

1. **accessible mortgages** (10% decrease in average search costs)
   - increases mortgage uptake among financially unskilled, reduces inequality
   - **0.19% increase in delinquency rate**
2. **financial education** – targeted policy
   - skilled new homeowners secure lower rates

   financial education has a stronger effects with accessible mortgages
3. Mortgage rate decrease
   - incentivize refinancing, but less effective for mortgage take-up
   - **increases inequality**

Related literature

Data analysis

Two Data Sets

Survey of Consumer Finances

- wealth, demographics, financial literacy
- self-reported data on **mortgages, shopping behavior and priorities**

National Survey of Mortgage Originations

- demographics
- mortgage registry data
- survey on **shopping experience**

NSMO+

- stochastic record linkage using education, gender, race, occ., family status, income, assets
  Details Shares R^2
- mortgage registry with objective financial literacy and contract specifics
- loan performance history

borrower_i

joint characteristics
with interdependencies

fin_skill_i

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

NSMO+ (2014-2021) and SCF (2016-2022)

Financial skills, search, and mortgage rates in the data

SCF Findings

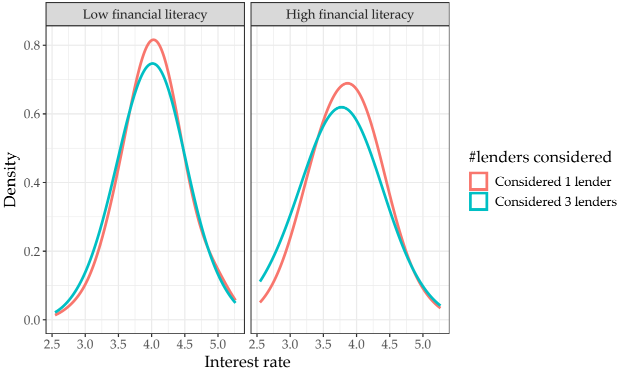
1. Financial skills vary by age ▸ Polynomial data fit
   → 5-10 years after refinancing, skills persist ▸ Estimates
2. Skilled borrowers lock in lower mortgage rates
   → Spend more time searching for credit ▸ Estimates
   → 21 b.p. lower rates ▸ Estimates

NSMO+ Findings

1. Search effort is effective for skilled borrowers - up to 33 b.p. lower rates ▸ Mortgage rates
   → Mortgage brokers serve as substitutes, showing a similar correlation pattern
2. As mortgages become more accessible, financial skills have a greater impact ▸ Marginal effects plot
3. Three years later, unskilled borrowers are 7 p.p. more likely to become delinquent ▸ Heatmap

Quantifying effective search ‣ Estimates ‣ Differences

- high-skilled search more ‣ Ordered logit



- $f_{\text{low}}, f_{\text{high}}$ and $\$100,000$ loan - difference is at least $\$450$ per year ($\$13,650$ over 30 years)
- all else fixed, considering lower # of lenders adds $\$125$ per year, translates to $\$3,750$ over 30 years

The model

Mortgage search framework - HA model in continuous time

Ingredients

- **endogenous financial skills and search intensity**

  $\rightarrow$ data: financial skills vary with age

- **heterogeneous search costs and expense shocks**

  $\rightarrow$ data: financially skilled search effectively and repay on time

Results

- steady state distribution of assets, mortgage debt, and skills

  $\rightarrow$ data: financially skilled secure lower rates

- **mortgage repayment $\implies$ consumption and saving choice**

Model setup

- agents face productivity shocks z, consume and save

  $\xrightarrow{\text{data}}$ invest in skills i, face cognitive costs $c^i(i,z) \rightarrow \dot{f} = \frac{\mu}{\eta}(if)^\eta - \delta f$

- can adjust housing costs **by sampling from a pool of mortgage offers** $\Phi(r)$

  $\xrightarrow{\text{data}}$ search for options with intensity s, face search cost $c^m(s, \mathbf{f})$

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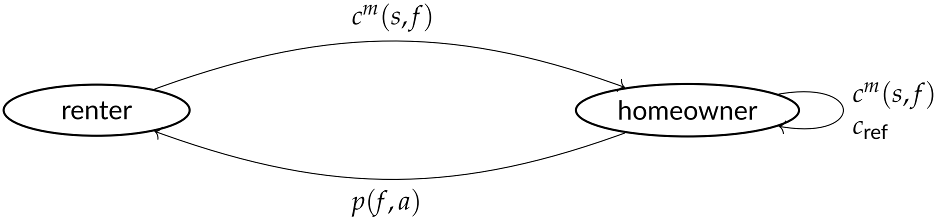
Search and skills correlations

- **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 $\stackrel{\text{data}}{\rightarrow}$ probability $p(f,a) \rightarrow$ lose the house

Delinquency and skills

- **renters** pay the rental rate κ
  - can search for a mortgage, face additional search costs ϕ

Model outline



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

Homeowner's problem

Kolmogorov Forward Equations

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

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

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

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

subject to

$$\dot{a} = Ra + wz - Mr - c,$$

$$\dot{f} = \frac{\mu}{\eta}(\boldsymbol{i}f)^\eta - \delta f.$$

Renter's problem

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

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

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Expense shock

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

Functional forms

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Mortgage search cost

mortgage accessibility

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financial education

Expense shock

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

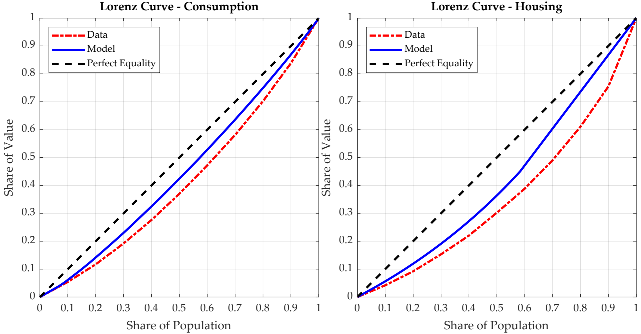
The economy in the steady state

Baseline parameter values

Definition	Symbol	Estimate	Source/Target		
Panel A. Externally set					
Discount factor	ρ	0.05	Moll, Rachel, and Restrepo (2022)		
CRRA parameter	σ	2	Laibson, Maxted, and Moll (2021)		
Investment cost elasticity	γ_i	0.5	Kapička and Neira (2019)		
Return	R	0.02	standard		
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, Hansen, and Heckman (1999)		
Depreciation	δ	0.07	Lusardi, Michaud, and Mitchell (2017)		
Panel B. Externally estimated					
Slope	μ	0.2	SCF, lifecycle profile		
Parameters	p_0, p_f, p_a	-2.12,-0.56,-0.81	SCF, late payments		
Panel C. Internally estimated				Model	Data
Investment cost scaling	i_0	927.28	Average financial skills - R	0.69	0.67
Renting cost	κ	0.27	Homeownership rate	0.58	0.59
Search cost elasticity	γ_s	2.15	Average financial skills - HO	0.71	0.73
Search cost - skill parameter	γ^f	0.40	correlation between f and s	-0.06	0.03
Search cost scaling	c_0	4.37	Average mtg. rate all	0.0390	0.0400
Search friction	ϕ	0.99	Average mtg. rate f.o.	0.0416	0.0408
Mtg. offer distribution parameter	β	3.28	Average mtg. rate - ref.	0.0350	0.0386
Mtg. offer distribution parameter	α	3.34	Standard deviation mtg. rate	0.0082	0.0073

Non-targeted moments ▸ Calibration

- non-durable consumption inequality patterns (BLS data, 2019.)



	Gini_c	$\frac{\mathbb{P}_{\text{ref}}(s\|f^H)}{\mathbb{P}_{\text{ref}}(s\|f^L)}$	$\frac{\text{mtg pay}}{\text{rent pay}}$	$\mathbb{P}(\text{del}\|f^L) - \mathbb{P}(\text{del}\|f^H)$
Model	0.12	20-25%	0.51	3.7 p.p.
Data	0.18	6-11%	0.49	7 p.p.

▸ Mortgage rate dispersion ▸ Consumption levels

Consumption growth

- current models (Jappelli & Padula, 2013; Lusardi et al., 2017): $c \uparrow f$ and $\Delta c \uparrow f$
  no pattern in the data (Bhutta et al., 2023; Dinkova et al., 2021)

  Our model

  - simplify $\phi = 1, p = const.$

$$\frac{\dot{c}}{c} = \frac{1}{\sigma}\Bigg[\underbrace{R - \rho}_{\text{impatience}} \underbrace{-\lambda s \left(\int_{\underline{r}}^{r} \left(1 - \frac{u'(c(f,a,r'))}{u'(c(f,a,r))}\right) d\Phi(r') \right)}_{\text{expected mtg rate change (2)}} \underbrace{+p \left(\frac{u'(c(f,a,\kappa))}{u'(c(f,a,r))} - 1 \right)}_{\text{expense shock (3)}} \Bigg]$$

  - search $s \rightarrow$ likelihood to refinance $\mathbb{P}_{\text{ref}}(s) = 1 - \exp(-\lambda s)$
  - financially skilled
    1. dissave and rely on future search (2)
    2. save out of precaution (3)

Elasticity of search and the Refinancing Channel

Direct link between refinancing, mortgage accessibility and financial skills

- **Search Cost Elasticity:** changes in search costs driven by financial skills
- **Mortgage Value Component:** the gain related to current mortgage contract

The overall elasticity is given by:

$$\frac{\partial s^H}{\partial f} \cdot \frac{f}{s} = \gamma_s \cdot \gamma_f \cdot \frac{f}{1+f} + \gamma_s \cdot \underbrace{\frac{f \cdot \frac{\partial}{\partial f} \int_{\underline{r}}^{r} V^H(f,a,z,r') - V^H(f,a,z,r')\, \mathrm{d}\Phi(r')}{\int_{\underline{r}}^{r} V^H(f,a,z,r') - V^H(f,a,z,r')\, \mathrm{d}\Phi(r')}}_{\text{Old rate, assets, and other observables}}$$

Policy experiments

Overview

- mortgage accessibility (γ_s)
    - digitization in the mortgage mkt. $\rightarrow$ getting more with less search
    - $\uparrow 0.43\%$ skills, $\uparrow 0.19\%$ delinquency rate

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  - mortgage uptake $\uparrow$, **3% drop in delinquencies**

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  why?$\rightarrow$ **amplification from the easier search incentive**

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  why?$\rightarrow$ **amplification from the easier search incentive**
- low rates benefit current homeowners
  - increase in refinancing, small effect on homeownership (i.e., inequality)

Increase in mortgage accessibility

→ **10% lower search cost; get more out of a small search**

- mortgage take-up increases
  - → **small incentive to accumulate skills**
  - → **relative increase in mortgage delinquencies**

Measure	Accessibility	Fin. edu	Fin. edu + Accessibility
average search renters	$\nearrow$ 3.68%		
average search homeowners	$\nearrow$ 7.18%		
consumption Gini	$\searrow$ 0.20%		
assets Gini	$\searrow$ 0.24%		
share of homeowners	$\nearrow$ 1.63%		
average financial skills	$\nearrow$ 0.43%		
average delinquency rate	$\nearrow$ 0.19%		

Financial education for renters

- targeted using easier access γ_i
  $\rightarrow$ decreases search costs **implicitly**

Measure	Accessibility	Fin. edu	Fin. edu + Accessibility
average search renters	$\nearrow$ 3.68%	$\nearrow$ 2.71%	
average search homeowners	$\nearrow$ 7.18%	$\nearrow$ 6.75%	
consumption Gini	$\searrow$ 0.20%	$\searrow$ 0.24%	
assets Gini	$\searrow$ 0.24%	$\searrow$ 0.12%	
share of homeowners	$\nearrow$ 1.63%	$\nearrow$ 2.56%	
average financial skills	$\nearrow$ 0.43%	$\nearrow$ 11.45%	
average delinquency rate	$\nearrow$ 0.19%	$\searrow$ 3.12%	

Financial education with accessible mortgages

- easier search works as an additional incentive, no adverse effects on delinquencies
- **non-linear effects** Breakdown

Measure	Accessibility	Fin. edu	Fin. edu + Accessibility
average search renters	$\nearrow$ 3.68%	$\nearrow$ 2.71%	$\nearrow$ 6.48%
average search homeowners	$\nearrow$ 7.18%	$\nearrow$ 6.75%	$\nearrow$ 14.22%
consumption Gini	$\searrow$ 0.20%	$\searrow$ 0.24%	$\searrow$ 0.44%
assets Gini	$\searrow$ 0.24%	$\searrow$ 0.12%	$\searrow$ 0.34%
share of homeowners	$\nearrow$ 1.63%	$\nearrow$ 2.56%	$\nearrow$ 4.19%
average financial skills	$\nearrow$ 0.43%	$\nearrow$ 11.45%	$\nearrow$ 12%
average delinquency rate	$\nearrow$ 0.19%	$\searrow$ 3.12%	$\searrow$ 2.93%

Downward shift in r Upward shift in r

Conclusion

New U.S. data findings

$\rightarrow$ correlation between skills, search and mortgage rates
$\rightarrow$ skills persist with financial decision making

Novel search framework

- endogenous financial skills and search intensity $\Longrightarrow$ mortgage rate dispersion
- **suitable for different types of credit**

Policy experiments

1. targeted FinEdu accomodates digital advancements and easier access to credit
2. lower mortgage rates benefit current homeowners

Relevant literature I

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Related literature - two streams

1. **Financial skills and behavior**

- financial literacy and portfolio choice, loan repayment (Bhutta, Blair, & Dettling, 2023; Gathergood & Weber, 2017; Lusardi, 2019) ▸ Experiments

  → objective financial literacy, search effort and mortgage repayment

- financial planning changes over time, not explained with individual risk (Agarwal, Driscoll, Gabaix, & Laibson, 2007, 2008), induces wealth heterogeneity (Lusardi, Michaud, & Mitchell, 2017)

- sophistication disparities in the mortgage market (Bhutta, Fuster, & Hizmo, 2020; Guiso, Pozzi, Tsoy, Gambacorta, & Mistrulli, 2022; Keys, Pope, & Pope, 2016)

  → endogenous financial skills **and** search $\overset{\text{model}}{\Longrightarrow}$ mortgage rate

Policy interventions small-scale and targeted (Attanasio et al., 2019) or large scale in schools (Lusardi, 2019; Lusardi et al., 2010)

Related literature - two streams

2. **Mortgage choice models**

- lending models with hidden information (Agarwal, Driscoll, & Laibson, 2013, 2020; Campbell, 2013)
- non-bank lenders - mortgage rate dispersion due to unobserved (Bartlett, Morse, Stanton, & Wallace, 2022; Fuster, Plosser, Schnabl, & Vickery, 2019; Kaiser, Lusardi, Menkhoff, & Urban, 2022)
  - → web apps and personal input - full information search framework
  - → model experiment - increase in mortgage accessibility
- fear of rejection induces search effort (Agarwal, Grigsby, Hortaçsu, Matvos, Seru, & Yao, 2020)
  - → number of lenders considered - cognitive search cost

Back

Empirics

- least skilled end up overpaying compared to financially savvy, effort varies with mortgage knowledge (Bhutta, Fuster, & Hizmo, 2020)
- homeowners make mistakes, do not refinance ($11,500, $19,000) (Keys, Pope, & Pope, 2016; Malliaris, Rettl, & Singh, 2022)
- rising number of non-bank lenders -lower FICO, low down-payment, FinTech algo pricing dispersion (Bartlett, Morse, Stanton, & Wallace, 2022; Fuster, Plosser, Schnabl, & Vickery, 2019; Kaiser, Lusardi, Menkhoff, & Urban, 2022)

Experiments

- (Attanasio, Bird, Cardona-Sosa, & Lavado, 2019; Carpena, Cole, Shapiro, & Zia, 2019) positive effects of financial education on savings and debt management

Back

Bayesian Record Linkage

- two observations: $i \in$ NSMO = $\mathcal{A}$, $j \in$ SCF = $\mathcal{B}$
- matching on K observables (vector $v_{\text{SCF}}, v_{\text{NSMO}}$) while accounting for inter-dependence
- a match $M_{i,j} = m \overset{\text{i.i.d}}{\sim} B(\lambda)$, with similarities $\gamma_k(i,j)|M_{i,j} \overset{\cancel{\text{indep.}}}{\sim}$ Discrete$(\pi_{k,m})$, $k = 1, \ldots K$
- $\gamma^k_{i,j} \in 0, \ldots, L-1$ degree of similarity, measured by L_2 across the set
- θ_m parametrizes correlations between characteristics $1, \ldots K$ for $\gamma(i,j) \in K \times L$
- likelihood

$$\mathcal{L}(\lambda, \theta|\gamma) = \prod_{i=1}^{N_{\mathcal{A}}} \prod_{j=1}^{N_{\mathcal{B}}} \left\{ \sum_{m=0}^{1} \lambda^m (1-\lambda)^{(1-m)} \pi(i,j,;\theta_m) \right\}$$

$$\pi_m(i,j) = \mathbb{P}(\gamma(i,j)|M_{i,j} = m, \theta_m), \quad m \in \{0,1\}$$

- complete log-likelihood

$$\log \mathcal{L}(\lambda, ,|\gamma) = \sum_{i=1}^{N_{\mathcal{A}}} \sum_{j=1}^{N_{\mathcal{B}}} \{M_{i,j} \log \lambda + (1-M_{i,j}) \log(1-\lambda) + M_{i,j} \log \pi(i,j;\theta_0) + (1-M_{i,j}) \log \pi(i,j;\theta_0)\}$$

Back

Bayesian Record Linkage

- two step E-M algorithm
- once we have $\hat{\lambda}$, $\hat{\pi}_m$, we are able to get back and evaluate posterior match probabilities
- $$\varepsilon_{i,j} = \frac{\lambda \pi_1(i,j;\theta_1)}{\lambda \pi_1(i,j;\theta_1) + (1-\lambda)\pi_0(i,j;\theta_0)}$$
- $\varepsilon_{i,j}$ define the distribution of financial literacy for $i \in$ NSMO across all potential matches in the SCF
- linear estimates $\rightarrow$ $\text{fin\_lit}_j^{NSMO} = \frac{\sum_{j=1}^{N_{\mathcal{B}}} \text{fin\_lit}_j^{\text{SCF}} \varepsilon_{i,j}}{\sum_{j=1}^{N_{\mathcal{B}}} \varepsilon_{i,j}}$

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%]

Back

Decomposition of R^2

	Decomposition of R^2:	
	Financial literacy	
	All households	Homeowners
Have financial assets	0.0215	0.0202
Income	0.0308	0.0289
Race	0.0160	0.0172
Sex	0.0124	0.0123
Age group	0.0062	0.0071
Employment	0.0021	0.0019
Education	0.0522	0.0568
Have retirement plan	0.0088	0.0061
Have kids	0.0032	0.0026
Asset group	0.0420	0.0421
R^2	0.1952	0.1952

Back

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

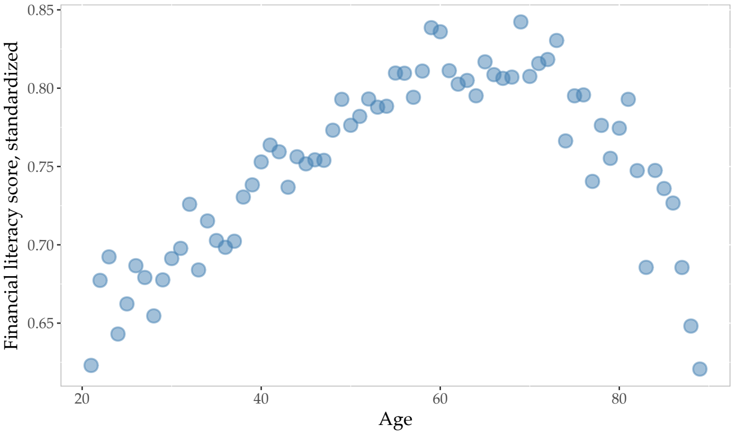
- likelihood function estimator adjusted for weights is asymptotically normal

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

Back

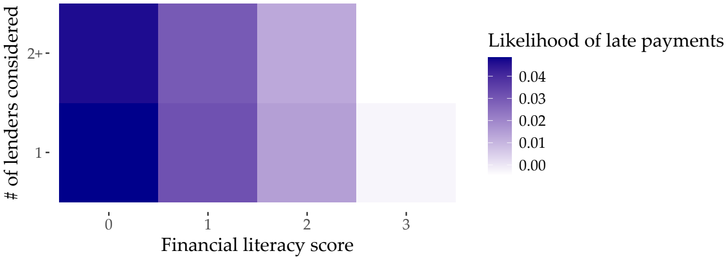
1. Suppose you had $100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow?
    - More than $102**
    - Exactly $102
    - Less than $102
    - Do not know
    - Refuse to answer
2. Imagine that 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

Financial literacy score, age-group fit



◂ Back

Likelihood of late payments



Uses the NSMO+ sample of all mortgages. Controls include loan amount, credit score, PTI, education, race, gender, and age.

Back

FinLit following refinancing

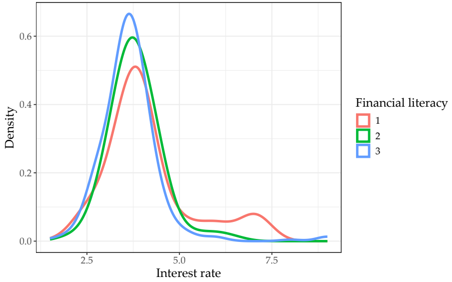
	FinLit score
AgeR	0.0004***
	(0.0001)
Education: High-school	0.069***
	(0.008)
College	0.148***
	(0.008)
Post-college	0.166***
	(0.009)
Female	−0.055***
	(0.004)
Refinanced	0.010***
	(0.004)
$5 <$ yrs passed since origination < 10	−0.024***
	(0.005)
$10 <$ yrs passed since origination	−0.024***
	(0.005)
Refinanced: $5 <$ yrs since < 10	0.029***
	(0.008)
Refinanced: $10 <$ yrs since	0.010
	(0.010)
Constant	0.571***
	(0.013)
Observations	26,620
R^2	0.145
Adjusted R^2	0.144
Residual Std. Error	37.642 (df = 26599)
F Statistic	224.647*** (df = 20; 26599)
Note: Survey weights.	*p<0.1; **p<0.05; ***p<0.01

SCF subsample of mortgage owners with a mortgage on their primary residence. Education, gender, refinanced, and time passed since origination are represented as dummy variables, with "no high school", "male", "no", "less than 5 yrs passed since origination" as base categories. FinLit score is a standardized score on a 0-1 scale, and controls include income, asset, and year FE.

Back

	Mortgage rate
Financial skills	0.283***
	(0.073)
Moderate search for credit	−0.038
	(0.072)
Great deal of search for credit	0.160**
	(0.065)
Financial skills:Moderate search	−0.047
	(0.089)
Financial skills:Great deal of search	−0.382***
	(0.080)
AgeR	0.0004
	(0.001)
Female	−0.005
	(0.021)
Alaskan, Native and other	0.018
	(0.036)
African-American	0.221***
	(0.024)
Hispanic or Latino	0.178***
	(0.025)
Asian	−0.024
	(0.045)
Refinanced (YES)	−0.157***
	(0.016)
Sponsorship(YES)	−0.073***
	(0.015)
Balloon payment (YES)	0.299***
	(0.054)
Constant	4.114***
	(0.092)
Observations	19,329
R^2	0.220
Adjusted R^2	0.218
Residual Std. Error	148.288 (df = 19278)
F Statistic	108.763*** (df = 50; 19278)
Note:	*p<0.1; **p<0.05; ***p<0.01

SCF households with fixed-rate mortgages originated after 2012. Financial skills are defined as the standardized FinLit score, and search effort is a three-level measure, based on self-reported time spent in search for credit. Gender, race, and education are dummy variables with "male", "Caucasian", and "no high school" as base categories. Base categories for sponsorship, balloon payments are "no". Estimates control for income, education, the sum of financial and non-financial assets, the total amount borrowed, LTV, term, property type, refinanced, mortgage origination year, and survey wave effects.

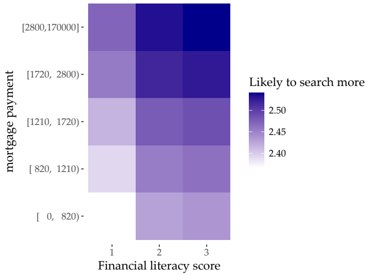


Unconditional mortgage rate distribution for mortgages originated in 2016.

Back

Skilled borrowers search more

Ordered logit model



Homeowners.

Renters.

- bottom row, search out of fear of denial (also in NSMO+)
- otherwise, time spent in the search for credit increases with skills

Back

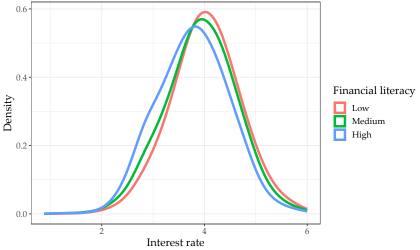
	Dependent variable:	
	time spent in search for credit	
	(homeowners)	(renters)
AgeR	−0.003***	−0.005***
	(0.0003)	(0.0003)
FinLit score 2	0.061***	0.024**
	(0.014)	(0.012)
FinLit score 3	0.070***	0.115***
	(0.014)	(0.014)
Female	0.018	0.098***
	(0.017)	(0.013)
Separated	−0.061***	−0.052***
	(0.017)	(0.016)
Never Married	−0.075***	−0.055***
	(0.019)	(0.014)
Education: High school	0.143***	0.218***
	(0.024)	(0.015)
College	0.150***	0.302***
	(0.024)	(0.018)
Post college	0.167***	0.286***
	(0.025)	(0.023)
Constant	2.142***	1.957***
	(0.039)	(0.026)
Observations	26,478	25,920
R^2	0.031	0.078
Adjusted R^2	0.030	0.077
Residual Std. Error	110.062 (df = 26452)	125.853 (df = 25894)
F Statistic	33.714*** (df = 25; 26452)	87.280*** (df = 25; 25894)
Note:		*p<0.1; **p<0.05; ***p<0.01

Estimates use SCF subsamples of mortgage owners (left) and renters (right). FinLit score, gender, marital status, and education are represented as dummy variables, with "FinLit score 1", "Married/Co-Living", "Male", and "No high-school" as baselines. Controls include income, asset level, current monthly mortgage and rent payments, and year FE.

Back

	Mortgage rate	
	(First origination)	(All mortgages)
Considered 2 lenders	−0.444*	−0.342**
	(0.228)	(0.152)
Considered 3+ lenders	0.907***	0.310
	(0.293)	(0.199)
Financial skills	−0.321	−0.303*
	(0.243)	(0.156)
Considered 2 lenders × Fin. skills	0.520*	0.396**
	(0.298)	(0.198)
Considered 3+ lenders × Fin. skills	−1.252***	−0.469*
	(0.381)	(0.259)
Age	0.011	0.054***
	(0.014)	(0.009)
Metro area: LMI tract	0.058***	0.032***
	(0.018)	(0.012)
Non-metro area	−0.008	0.012
	(0.019)	(0.013)
Married	0.003	0.009
	(0.016)	(0.011)
Female	0.019	0.022***
	(0.013)	(0.008)
Race: Black or African-American	0.017	0.022
	(0.029)	(0.018)
Asian	−0.045*	−0.035*
	(0.027)	(0.018)
Other (including Hispanic)	0.035	0.031
	(0.034)	(0.023)
Credit score	−0.226***	−0.225***
	(0.015)	(0.009)
Constant	5.265***	5.022***
	(0.202)	(0.129)
Observations	12,052	26,624
R^2	0.341	0.396
Adjusted R^2	0.338	0.395
Residual Std. Error	23.862 (df = 12003)	22.951 (df = 26574)
F Statistic	129.290*** (df = 48; 12003)	355.970*** (df = 49; 26574)
Note:		*p<0.1; **p<0.05; ***p<0.01

Uses NSMO+ subsamples of first origination mortgages and pooled mortgages (including refinancing) for borrowers who went directly to the lender. Controls include income, education, time-fixed effects, number of borrowers, loan amount, loan type, loan term, government-sponsored enterprise, LTV, and a refinancing dummy.

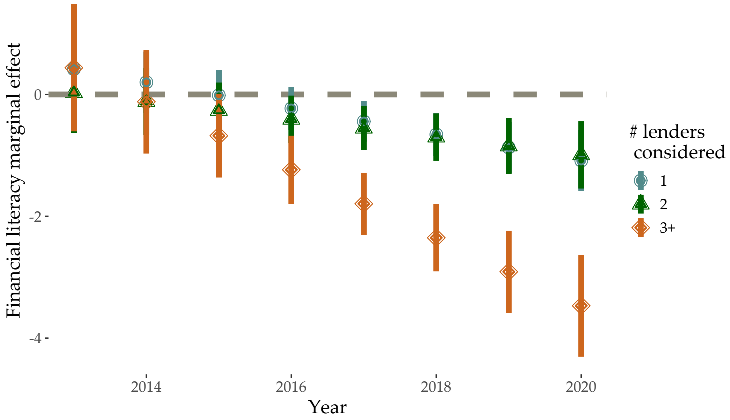


Back

Financial skills effect over the years

Back

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



Uses the NSMO+ of all mortgages. Controls include socio-economic characteristics, number of borrowers, loan amount, type and term, LTV, credit score, sponsorships, metropolitan area dummy.

Predicted average mortgage rates

- financially savvy that search more end up with $\approx$ 18 b.p. lower rates
- search hints at fear of denial, average increase of 39.b.p.

		Average mortgage rate
Low literacy	Consider 1 lender	3.97
	Consider 3 lenders	4.36
High literacy	Consider 1 lender	3.89
	Consider 3 lenders	3.71

Table: Linear regression model predictions.

Back

	Number of lenders considered	
	(All origination)	(Refinancing)
Age	-0.043^{***}	-0.020^{**}
	(0.005)	(0.008)
Credit score	0.009^{*}	0.005
	(0.005)	(0.007)
Married	0.021^{***}	0.014
	(0.006)	(0.010)
Female	-0.058^{***}	-0.077^{***}
	(0.005)	(0.007)
Race: Black or African-American	0.065^{***}	0.046^{***}
	(0.011)	(0.015)
Asian	0.059^{***}	0.059^{***}
	(0.010)	(0.014)
Other (including Hispanic)	0.065^{***}	0.089^{***}
	(0.014)	(0.020)
Financial Skills	0.398^{***}	0.341^{***}
	(0.074)	(0.106)
Education: some college or technical school	0.056^{***}	0.053^{***}
	(0.009)	(0.013)
College graduate	0.089^{***}	0.077^{***}
	(0.009)	(0.013)
Post-college graduate	0.106^{***}	0.088^{***}
	(0.010)	(0.014)
Constant	0.105	0.116
	(0.064)	(0.092)
Observations	43,094	21,625
R^2	0.024	0.025
Adjusted R^2	0.023	0.023
Residual Std. Error	17.837 (df = 43049)	17.675 (df = 21580)
F Statistic	23.837^{***} (df = 44; 43049)	12.720^{***} (df = 44; 21580)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Controlled for income, time effects, government-sponsored enterprise, term, LTV, borrower number, loan type, and metropolitan area.

Back

Renter's problem

Kolmogorov Forward Equation

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

subject to

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

Back

HJB equations

Renters

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

such that

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

Back

HJB equations, cont'd

Homeowners

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

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

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

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

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

KFE - homeowners

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

$$0 = \underbrace{-\frac{\partial g^H(f,a,z_i,r)}{\partial f}\dot{f} - \frac{\partial g^H(f,a,z_i,r)}{\partial a}\dot{a}}_{\text{outflow due to } f \text{ and } a \text{ accumulation}} - \underbrace{\big(p(f,a) + \lambda s \Phi(r)\big) g^H(f,a,z_i,r)}_{\text{outflow due to fin. shock and refinancing}} +$$

$$+ \underbrace{\lambda \int_{r}^{\bar{r}} s^H(f,a,z_i,r') g^H(f,a,z_i,r') d\Phi(r')}_{\text{inflow of borrowers who searched more}} + \underbrace{\lambda \phi s^R(f,a,z_i) g^R(f,a,z_i)}_{\text{inflow of new home owners}} +$$

$$+ \underbrace{\omega_i \big(g^H(f,a,z_{-i},r) - g^H(f,a,z_i,r)\big)}_{\text{net flow from change in productivity}}.$$

Back

KFE - renters

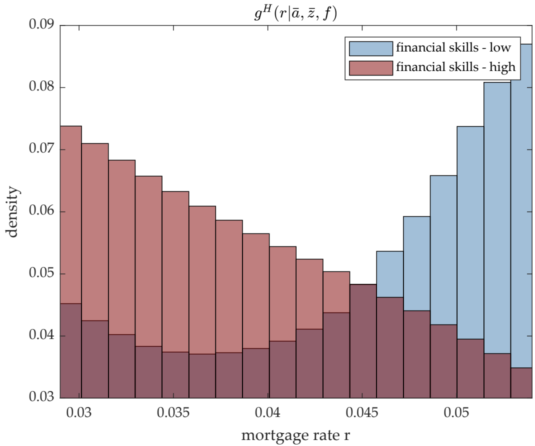
$g^R(f,a,z_i)$ stationary distribution renters with skills f, assets a, productivity z_i

$$0 = -\frac{\partial g^R(f,a,z_i)}{\partial f}\dot{f} - \frac{\partial g^R(f,a,z_i)}{\partial a}\dot{a} + \underbrace{p(f,a)\int_{\underline{r}}^{\overline{r}} g^H(f,a,z_i,r')d\Phi(r')}_{\text{inflow of homeowners after the fin. shock}} +$$

$$- \underbrace{\lambda\phi s^R(f,a,z_i)g^R(f,a,z_i)}_{\text{outflow due to mortgage take-up}} + \underbrace{\omega_i\left(g^R(f,a,z_{-i}) - g^R(f,a,z_i)\right)}_{\text{net flow from change in productivity}}.$$

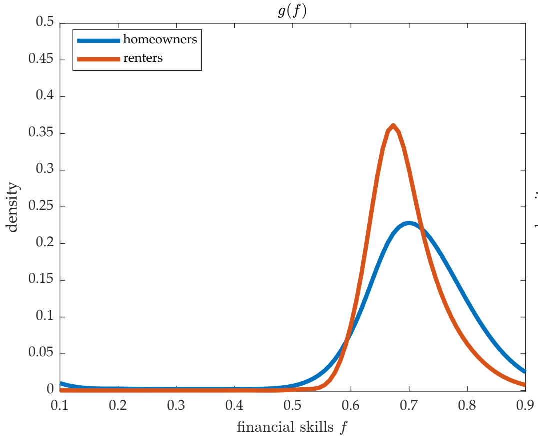
Back

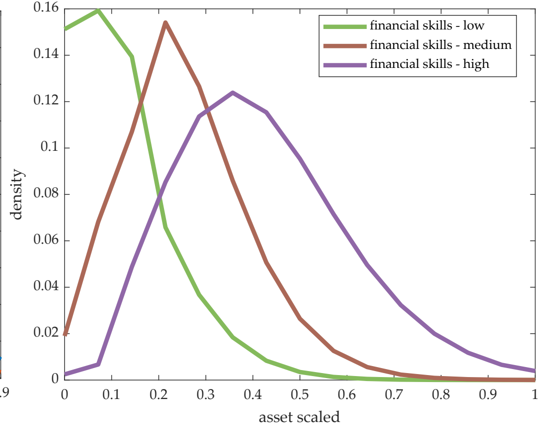
Mortgage rate dispersion in the steady state



▸ Skill dispersion ◂ Back

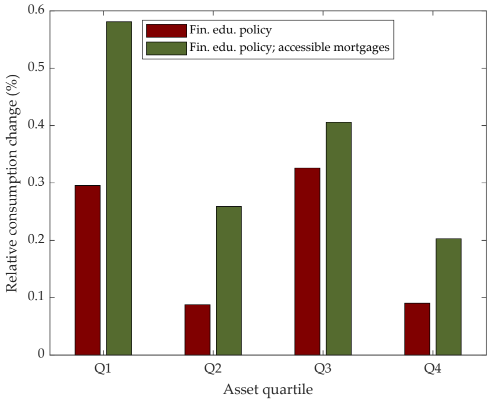
Skill differences and asset distribution



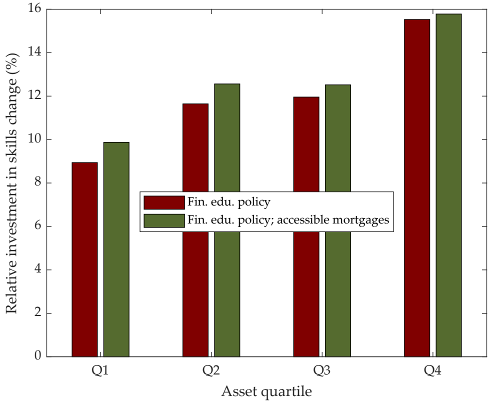


Back

Zooming in on the mortgage course effect



Relative change in consumption.

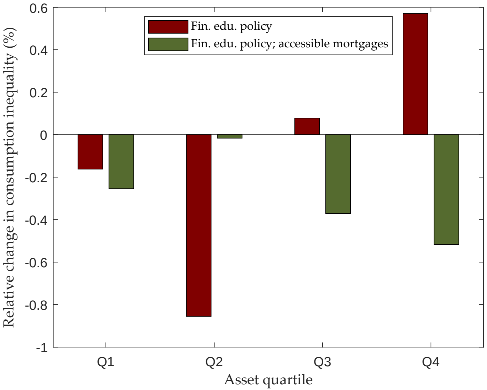


Relative change in fin. skill investment.

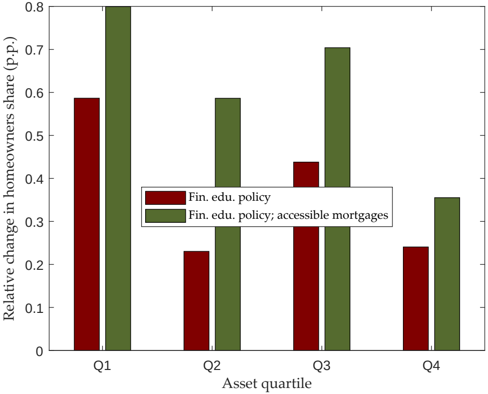
- consumption inequality decreases throughout ▸ Breakdown

◂ Back

Consumption changes due to mortgage take up



Change in consumption inequality.



Homeownership rate changes.

Back

Exogenous changes in mortgage repayments

- down/upward shift in the mean offer rate e.g., payment deductions Distribution shifts
  - $\rightarrow$ 5 b.p. downward shift benefits fin. skilled homeowners - high refinancing activity (McKay & Wolf, 2023)
  - $\rightarrow$ small effect for consumption inequality

Measure	relative change
average search renters	$\nearrow 3.4\%$
average search homeowners	$\nearrow 12.3\%$
consumption Gini	$\searrow 0.22\%$
assets Gini	$\searrow 0.2\%$
average financial skills	$\nearrow 1.1\%$
average delinquency rate	$\searrow 0.17\%$

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Upward shift in mortgage repayments

- 5 b.p. upward shift
  $\rightarrow$ lower skill investment incentives

Measure	relative change
average search renters	$\searrow$ 3.3%
average search homeowners	$\searrow$ 11.6%
consumption Gini	$\nearrow$ 0.22%
assets Gini	$\nearrow$ 0.19%
average financial skills	$\searrow$ 1.2%
average delinquency rate	$\nearrow$ 0.23%

- disincentivizes skill accumulation
- drop in mortgage attainment (0.6%)

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