Financial Skills and Search in the Mortgage Market EEA-ESEM 2024

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Current Landscape

- financial skills \rightarrow returns heterogeneity $\stackrel{\mathsf{model}}{\rightarrow}$ consumption differences (extensive)
- this paper: financial skills $\stackrel{\text{data}}{\rightarrow}$ mortgage repayments $\stackrel{\text{model}}{\rightarrow}$ consumption differences (intensive)

Mortgages in the U.S.

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

Questions

Data

1. What is the role of financial skills in mortgage choice?

Model counterfactuals

- 2. How do financial skills affect consumption inequality?
- 3. How does mortgage accessibility affect the consumption gap?
- 4. How effective is financial education in reducing consumption inequality?

The paper in a nutshell

Data and stylized facts

Bayesian record linkage \rightarrow new U.S. mortgage data set

 financially unskilled secure mortgages at orange 13.4 b.p. higher rates unskilled borrowers search less (mechanism)

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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 ↓ 1.4% has a stronger effect with accessible mortgages



Data sets



- joint characteristics: Shares R²
 education, gender, age, race, occupation, marital status, kids income, owns asset, owns retirement plans
- stochastic record linkage → NSMO+ (* Details)
 new evidence on mortgage take-up and <u>objective financial literacy</u>

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: education, income, family characteristics, credit score, risk attitude, imputed financial literacy

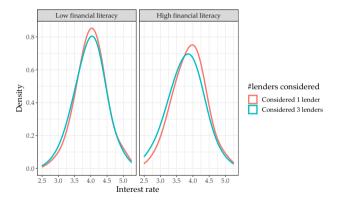
mortgage shopping behavior: number of lenders considered prior to applying

Findings

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

Quantifying effective search **Estimates PDifferences**

• high-skilled search more Ordered logit



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

Continuous time model with mortgage search

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

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

- current homeowners: mortgage $M \approx 4wz$ with a period repayment rM 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
- renters pay the rental rate κ can search for a mortgage, face additional search costs ϕ

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

$$\rho V^{H}(f, a, z, r) = \max_{\{c, s, i\}} \left\{ u(c) - c^{f}(i, z) - c^{m}(s, f) + \frac{\partial V^{H}}{\partial f}(f, a, z, r)\dot{f} + \frac{\partial V^{H}}{\partial a}(f, a, z, r)\dot{a} + \lambda s(f, a, z, r) \int_{r}^{r} \max\{V^{H}(f, a - c_{\text{ref}}, z, r') - V^{H}(f, a, z, r), 0\} d\Phi(r') \right\}$$

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subject to

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

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

Consumption growth

• current models with financial knowledge: c and $\Delta c \uparrow f$

Our model

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

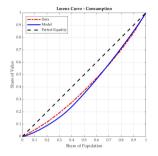
$$\frac{\dot{c}}{c} = \frac{1}{\sigma} \left[\underbrace{R - \rho}_{\text{impatience}} - \underbrace{\lambda s \left(\int_{\underline{r}}^{r} \left(1 - \frac{u'(c(f, a, r'))}{u'(c(f, a, r))} \right) d\Phi(r') \right)}_{\text{expected mrtg rate change (2)}} + p \underbrace{\left(\frac{u'(c(f, a, \kappa))}{u'(c(f,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

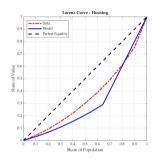
search $s \to \text{likelihood}$ to refinance $\mathbb{P}_{\mathsf{ref}}(s) = 1 - \mathsf{exp}(-\lambda s)$ financially skilled

- 1. dissave and rely on future search (2)
- 2. save due to low mortgage repayments (3)

Non-targeted moments • Calibration

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





	Model	Data
Gini _c	0.2	0.18
$\frac{\mathbb{P}_{ref}(s f^H)}{P_{ref}(s f^L)}$	30%	20-30%
$\frac{\overline{P_{ref}(s f^L)}}{\frac{\mathbb{P}(del f^L)}{\mathbb{P}(del f^H)}}$	39.5%	35-45%

Renters' financial education

- skill investment cost $c^f(i,z) = rac{i^{1+rac{1}{\gamma_i}}}{1+rac{1}{\gamma_i}} rac{1}{1+z}$
 - \rightarrow 90 minutes course in financial planning
 - → implicitly incentivizes search

Measure	Fin.edu.	Mrt. accessibility	both
average search renters	₹ 0.4%		
average search homeowners	-		
consumption gini	√ 1.4%		
assets gini	√ 1.5%		
share of homeowners	₹ 1.5%		
average financial skills	≥ 9%		
average delinquency rate	≥ 2.8%		

Increase in mortgage accessibility

• mrtg search cost
$$c^m(s,f) = \frac{s^{1+\frac{1}{\gamma_s}}}{1+\frac{1}{\gamma_s}} \frac{1}{(1+f)^{\gamma_f}}$$

- ad hoc reduction in search elasticity
 - \rightarrow 5% for renters and 10% for homeowners

Measure	Fin. edu.	Mrt. accessibility	both
average search renters	₹ 0.4%	<i>></i> 7.8%	
average search homeowners	-	₹ 16.8%	
consumption gini	√ 1.4%	√ 3%	
assets gini	√ 1.5%	≥ 2.3%	
share of homeowners	≯ 1.5%	₹ 3.3.%	
average financial skills	<i>></i> 7 9%	≯ 1.1%	
average delinquency rate	∕₂ 2.8%	₹ 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

 $ightarrow \uparrow 0.4\%$ in average skills ightharpoons Breakdown

Measure	Fin. edu.	Mrt. accessibility	both
average search renters	₹ 0.4%	≯ 7.8%	→ 0.3%
average search homeowners	-	₹ 16.8%	→ 2.7%
consumption gini	√ 1.4%	> 3%	$\searrow 1.5\%$
assets gini	√ 1.5%	≥ 2.3%	√ 1.3%
share of homeowners	≯ 1.5%	→ 3.3.%	$\nearrow 1.5\%$
average financial skills	<i>></i> 7 9%	$\nearrow 1.1\%$	→ 9.4%
average delinquency rate	≥ 2.8%	₹ 1.5%	√ 0.36%

► Downward shift in r

Conclusion

New U.S. data findings

- ightarrow mortgage rate correlates with financial skills and search effort search mechanism in mortgage attainment
- $\,\rightarrow\,$ long-term effect on mortgage repayments and consumption

Novel search framework

- ightarrow endogenous financial skills and search intensity \implies mortgage rate dispersion mortgage rate schedule across assets, productivity and skills
- → financial skills ⇒ consumption and saving choice

Model experiments

- → accessible mortgages accommodate financial education
- ightarrow lower mortgage rates benefit current homeowners ightarrow propagate inequality

Relevant literature I

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- Agarwal, S., Driscoll, J. C., Gabaix, X., & Laibson, D. (2008). Learning in the credit card market (tech. rep.). National Bureau of Economic Research.
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Relevant literature II

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Relevant literature III

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Relevant literature IV

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Related literature - two streams

1. Financial skills and behavior

- financial literacy and portfolio choice, loan repayment (Bhutta, Blair, & Dettling, 2021; 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)
 - ightarrow endogenous financial skills **and** search $\stackrel{\text{model}}{\Longrightarrow}$ mortgage rate

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



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



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, Fifield, & Imai, 2019)

borrower;

```
fin_skill;
```

 $0 \rightsquigarrow \omega_0$

 $1 \rightsquigarrow \omega_1$

 $2 \rightsquigarrow \omega_2$

 $3 \rightsquigarrow \omega_3$



Bayesian Record Linkage (Enamorado, Fifield, & Imai, 2019)

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

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

• match score defined on K observables via the agreement vector

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

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



NSMO and SCF data, population shares - observables

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



Decomposition of $\ensuremath{\mathsf{R}}^2$

		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	



Linear estimator

• fin. literacy score is a posterior-weighted average

$$\zeta_i^* = \sum_{j=1}^{N_{\mathsf{SCF}}} \zeta_{ij} \frac{Z_j}{\mathsf{fin}\,\mathsf{lit}\,\mathsf{in}\,\mathsf{SCF}} / \sum_{j=1}^{N_{\mathsf{SCF}}} \zeta_{ij}$$

• 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

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

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

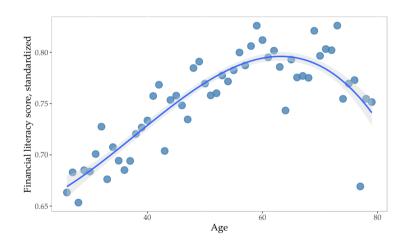
False**

Do not know

Refuse to answer

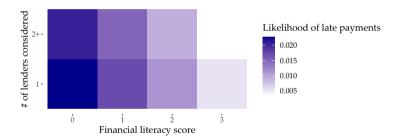


Financial literacy score, age-group fit





Likelihood of late payments



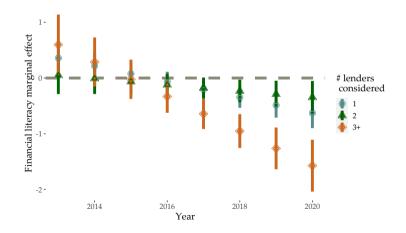
controlled for loan amount, credit score, PTI, education, race, gender, and age



Financial skills effects over the years

linear estimates

$$\mathsf{rate}_i = \alpha + \gamma_t + \beta X_i + \beta^m M_i + \beta^f \mathsf{fin_skills}_i + \beta^{\mathsf{eff}} \mathsf{fin_skills}_i \times \mathsf{num_cons}_i \times \gamma_t + \varepsilon_i$$



mortgage rate

(All mortgages)

(First origination)

0.034	-0.006
(0.087)	(0.062)
0.220*	0.125
(0.120)	(0.083)
0.017	-0.016
(0.088)	(0.060)
-0.072	-0.023
(0.113)	(0.080)
-0.354**	-0.220**
(0.153)	(0.106)
0.044***	0.062***
(0.010)	(0.007)
-0.054***	-0.033***
(0.017)	(0.011)
-0.105***	-0.071***
(0.017)	(0.012)
-0.131***	-0.090***
(0.019)	(0.012)
(/	-0.074***
	(0.007)
5.269***	4.955***
(0.099)	(0.066)
21,461	43,084
0.369	0.440
0.368	0.439
23.662 (df = 21412)	22.325 (df = 43034)
	689.013*** (df = 49; 43034)
	(0.087) 0.220° (0.120) 0.017 (0.088) -0.072 (0.113) -0.354** (0.153) 0.044*** (0.010) -0.054*** (0.017) -0.105*** (0.017) -0.131** (0.019) 5.269*** (0.099) 21,461 0.368 23.662 (df = 21412)

Note: Controlled for loan type, government-sponsored enterprise, loan amount, area number of borrowers, time effects, LTV, credit score, income, broker (yes/no), race and sex.

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

Predicted average mortgage rates

- financially savvy that search more end up with \approx 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: Linear regression model predictions.



	Dependent variable: # of lenders considered		
	Coefficient	SE	z score
(Intercept):1-2	-0.4515***	0.0947	-4.7665
(Intercept):2-3	-2.1960***	0.0950	-23.1239
Financial literacy	0.0444**	0.0216	2.0616
Age	-0.1603***	0.0143	-11.1923
Credit score	0.0515***	0.0146	3.5298
Female	-0.2904***	0.0141	-20.5282
Race: non-white	0.2426***	0.0198	12.2247
Income:			
\$35,000 - \$49,999	-0.0262	0.0379	-0.6922
\$50,000 - \$74,999	-0.0312	0.0356	-0.8767
\$75, 000 — \$99, 999	-0.0172	0.0364	-0.4734
\$100,000 - \$174,999	-0.0351	0.0362	-0.9685
\$175,000+	-0.0227	0.0401	-0.5659
Metropolitan area:			
Low-to-moderate income	-0.0176	0.0215	-0.8195
Non-metropolitan area	-0.0517*	0.0237	-2.1834
Loan Amount:			
\$100,000-\$199,999	0.0852***	0.0231	3.6859
\$200,000-\$299,999	0.1864***	0.0260	7.1664
\$300,000-\$399,999	0.2337***	0.0305	7.6579
> \$400,000	0.3157	0.0324***	9.7351
Education:			
some college	0.2657***	0.0249	10.6772
college	0.4228	0.0247***	17.1297
post-college	0.5302***	0.0264	20.0973
Observations			155,500

Note: controlled for year effects.

Table: Ordered logit with imputed financial literacy and weights.



p < 0.1; p < 0.05; p < 0.01

Renter's problem Nolmogorov Forward Equation

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

Renter's problem • Kolmogorov Forward Equation

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

Renter's problem • Kolmogorov Forward Equation

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

Renter's problem • Kolmogorov Forward Equation

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

subject to

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

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

Utility

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

Utility

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Mortgage search cost

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

Utility

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

Mortgage search cost

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

Fin. skill investment cost

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

Utility

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

Mortgage search cost

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

Fin. skill investment cost

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

Expense shock

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

HJB equations

Renters

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

such that

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

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



HJB equations, cont'd

Homeowners

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

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

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

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

subject to

$$\dot{a} = y(a,s) + wz - Mr - c,$$
 $\dot{f} = \frac{\mu}{\eta} (if)^{\eta} - \delta f,$
 $y(a,s) = 0$ with intensity $p(f,a)$.

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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

$$0 = -\frac{\partial g^H(f,a,z_i,r)}{\partial f}\dot{f} - \frac{\partial g^H(f,a,z_i,r)}{\partial a}\dot{a} - \left(p(f,a) + \lambda s\Phi(r)\right)g^H(f,a,z_i,r) + \\ \text{outflow due to } f \text{ and } a \text{ accumulation} \\ + \lambda \int_r^{\overline{r}} s^H(f,a,z_i,r')g^H(f,a,z_i,r')d\Phi(r') + \lambda \phi s^R(f,a,z_i)g^R(f,a,z_i) + \\ \text{inflow of borrowers who searched more} \\ + \omega_i \left(g^H(f,a,z_{-i},r) - g^H(f,a,z_i,r)\right). \\ \text{net flow from change in productivity}$$



KFF - renters

 $g^{R}(f, a, z_{i})$ stationary distribution renters with skills f, assets a, productivity z_{i}

$$0 = -\frac{\partial g^R(f,a,z_i)}{\partial f}\dot{f} - \frac{\partial g^R(f,a,z_i)}{\partial a}\dot{a} + p(f,a)\int_{\underline{r}}^{\overline{r}}g^H(f,a,z_i,r')d\Phi(r') + \inf_{\text{inflow of homeowners after the fin. shock}} - \lambda\phi s^R(f,a,z_i)g^R(f,a,z_i) + \omega_i(g^R(f,a,z_{-i}) - g^R(f,a,z_i)).$$
outflow due to mortgage take-up net flow from change in productivity

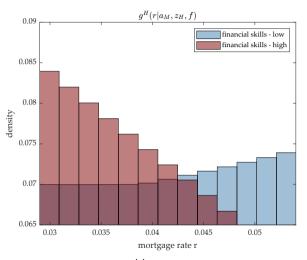
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Baseline parameter values

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	0.04	Moll, Rachel, and Restrepo (2022)		
Refinancing Cost	Cref	0.21	Freddie Mac (5% of the mortgage size)		
Intensities	ω_1, ω_2	$\frac{1}{3}$, $\frac{1}{3}$ 0.5	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	-1.08,-1.02,-7.65	SCF, late payments		
			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	<i>c</i> 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

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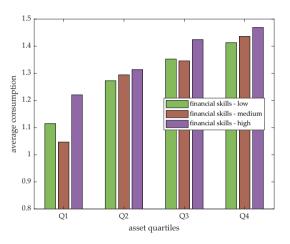
Mortgage rate across financial skills skills



• fin. unskilled borrowers search less $\stackrel{\mathsf{model}}{\to}$ secure higher mortgage rate (NSMO+ est.)



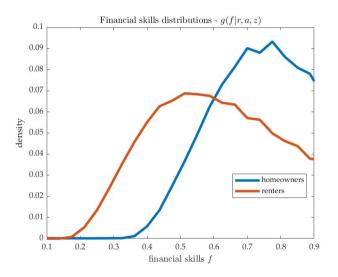
Consumption differences



- 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

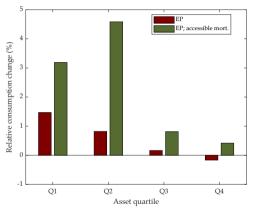


Skill dispersion in the steady state





Zooming in on the financial education effect



EP; accessible mort Relative investment in skills change (%) 10 01 O2 O3 Asset quartile

Relative change in consumption.

Relative change in fin. skill investment.



Exogenous changes in mortgage repayments

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

Measure	relative change
average search renters	₹ 1.4%
average search homeowners	<i>></i> 64.9%
consumption Gini	₹ 1.4%
assets Gini	$\nearrow 1.1\%$
average financial skills	₹ 0.1%



Upward shift in mortgage repayments

- 10 b.p. upward shift
 - → lower skill investment incentives

Measure	relative change
average search renters	∨ 0.7%
average search homeowners	√ 36.5%
consumption Gini	> 5.6%
assets Gini	√ 4.3%
average financial skills	√ 0.6%

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

