Working Paper Series 780
(ISSN 2788-0443)

Financial Skills and Search in the Mortgage Market

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CERGE-EI
Prague, May 2024

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April 8, 2024

Abstract

Are households with low financial skills disadvantaged in the mortgage market? Using stochastic record linking, we construct a unique U.S. dataset encompassing a rich set of mortgage details and borrowers' characteristics, including their objective financial literacy measure. We find that households with low financial literacy are up to 4% more likely to search less and lock in at 15-20 b.p. higher rates. Upon origination, unskilled borrowers face a 35-45% higher mortgage delinquency and end up with a 30% lower likelihood of refinancing. Overall, for a \$100,000 loan, the potential losses from low financial literacy are more than \$9,329 over the mortgage duration. To understand how financial education, more accessible mortgages, or mortgage rate changes affect households with low financial literacy, we formulate and calibrate a mortgage search model with heterogeneous search frictions and endogenous financial skills. Our model estimates show that search intensity and financial skill variations contribute to 55% and 10% of mortgage rate variations, respectively. We find that *i*) more accessible mortgages lead to a higher delinquency risk among low-skilled households, *ii*) financial education mitigates the adverse effects of increased accessibility, and *iii*) low mortgage rates favor high-skilled homeowners and, by reinforcing refinancing activity, deepen consumption differences across different financial skill levels.

Keywords: mortgage refinancing, mortgage search, financial skills, financial education, consumption inequality

J.E.L. classification: E21, G51, G53

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1 Introduction

The period of low interest rates spanning from 2010 to 2020 witnessed a notable rise in the mortgage market and the entry of non-bank lenders, leading to increased accessibility and speed in mortgage acquisition (McCafrey, 2021). This trend was marked by a significant shift towards non-banks, with non-bank lenders capturing 70% of the first-lien mortgage market in 2021 (Degerli and Wang, 2022). The entry of new lenders resulted in relaxed requirements for potential borrowers, including lowered credit score thresholds for mortgage approval (Cornelli et al., 2022). The combination of higher availability and reduced criteria enabled younger and less experienced borrowers to enter the housing market. County-level data in the U.S. reveals that differences in borrower search behavior and financial sophistication contribute to residual mortgage rate variations (Degerli and Wang, 2022). Consequently, the level of borrowers' financial skills and their search efforts introduce variability in consumption and saving decisions throughout the mortgage term.

This paper estimates the effect of financial skills and search behavior on mortgage rate acquisition and respective consumption patterns among U.S. households. We employ the stochastic record linkage method and generate a unique U.S. data set on mortgage attainment. Leveraging the rich set of borrower characteristics, we provide new evidence of the variation in mortgage shopping outcomes based on individual financial literacy levels. Our estimates lay out monetary losses resulting from ineffective search practices among financially inexperienced borrowers. Moreover, joint data patterns in mortgage rates, individual financial skills, and search effort motivate a novel mortgage search framework. The search framework, embedded within a heterogeneous agents model allows us to link differences in financial skills to consumption disparity via the mortgage repayment channel. In the model, pertaining to heterogeneous search costs, individual mortgage attainment depends on endogenous financial skills and search intensity.

Our framework generates empirically plausible disparities in non-durable consumption and aligns with refinancing and delinquency probabilities across borrower's financial skills. Subsequently, we use our model to conduct counterfactual analyses that underscore the potential impact of financial education on mortgage attainment and repayment regularity. We show that financial education mitigates the adverse effects of higher mortgage accessibility on less financially skilled homeowners. Finally, our findings reveal that low mortgage rates disproportionately favor highly skilled homeowners, leading to increased refinancing activity and perpetuating consumption disparities across different financial skill levels.

To assess the impact of financial skills and search behavior on individual mortgage performance, we combine our data estimates with quantitative modeling. First, we link two publicly available datasets, the National Survey of Mortgage Originations (NSMO) and the Survey of Consumer Finances (SCF). This way, within the new data set (NSMO+), we obtain the distribution of financial skill levels for every borrower in the NSMO, including detailed borrower and loan characteristics for each mortgage origination in the period 2014-2019. Data estimates show that after controlling for other borrower and loan characteristics, financial skills and search effort become increasingly prevalent in explaining the mortgage rate attainment in the U.S. Second, we introduce a micro-founded mortgage search framework and quantify the effect of individual financial skills on consumption inequality.

While the effect of skills and search effort varies across mortgage types, their interaction explains a portion of the variation in mortgage rates. Specifically, financially skilled borrowers who explore a broader array of lenders secure a 13.4 basis points lower mortgage rate, showing evidence of *effective search*. Mortgage rate disparities translate into compound losses from overpayments over the typical 30-year mortgage term, and potentially take up a sizable share of borrower's monthly expenses. For example, financially unskilled borrowers dealing with a $100,000 loan face at least $9,329 in overpayments over 30 years. The long-term impact of mortgage repayments disproportionately restricts the liquidity of financially unskilled borrowers, highlighting the importance of financial education.

Our estimates from the NSMO+ data set, coupled with our findings from the SCF data, comprise a set of stylized facts important for our structural model of mortgage rate attainment. First, financial skills vary with age and are subject to cognitive effects among older cohorts. Second, we show that financially unskilled applicants are 4% more likely to consider fewer lenders. Third, we find that otherwise similar borrowers end up with different mortgage rates, conditional on the extent of their search and financial skill level. The financial skill-based spread of 13.4 b.p. in mortgage rates generates sizable overpayments among financially unskilled borrowers. Lastly, we show that financial skills increasingly affect mortgage rates from 2014 to 2021, mirroring the uptick in lender investments in digital origination.

A more detailed analysis of mortgage rates show that the financial skill-based mortgage spread goes up to 20 b.p. Specifically, linear estimates show that, for a $100,000 loan, the mortgage spread of

13.4 b.p. translates to more than $9,329 of losses for low-skilled borrowers upon mortgage attainment. Two-thirds of the losses ($6,693) are accounted for by the differences in skill levels, with additional costs of $2,636 pertaining to low search effort. After observing the attainment pattern, we exploit the fact that NSMO+ tracks loans after their origination and argue that losses at origination create pressure on low-skilled borrower's liquidity. Namely, we find that, 3 years after the mortgage origination, financially unskilled borrowers face a 35-35% higher likelihood of late mortgage repayments. Added to our liquidity risk exposure estimates, we show that financially unskilled households exhibit a 30% lower likelihood of refinancing their mortgage.

Besides providing new evidence on mortgage shopping behavior, our paper links two publicly available data sets using the method that allows control over the imputation bias[1]. Our linking procedure implements the Bayesian Record Linkage (BRL) method to merge the NSMO and SCF. Using this method, we estimate the distribution of financial skill levels for each NSMO borrower based on their SCF matches. The objective measure of financial skills provides unique insights for individual mortgage attainment. In this regard, our findings surpass subjective perceptions of financial knowledge and risk aversion.

In the second part of our paper, we assess the impact of financial education on consumption inequality through the lens of our micro-founded mortgage search framework. This framework integrates endogenous financial skills and search effort as choices within the heterogeneous agents model. In the model, potential home buyers engage in costly search to secure a mortgage rate before purchasing a house. Meanwhile, existing mortgage holders face additional expenses related to refinancing if they opt for it. Search costs, consistent with observed data patterns, fluctuate and are contingent upon individual financial skill levels. Our model generates a mortgage rate schedule that leads to consumption disparities among borrowers with different financial skills.

Our paper provides a unique contribution to the existing literature through a novel structural framework that incorporates our key findings on heterogeneous search costs. In the model, agents invest in financial skills, which reduce the costs of searching for mortgages and affect subsequent mortgage performance. In the steady state, borrowers with higher financial skills actively search for mortgages, exploring a broader range of offers, and lock-in at lower mortgage rates. Conversely, financially unskilled borrowers are less inclined to participate in the mortgage search process. When

[1] The details on the method and applications in text linking can be found in (Enamorado et al., 2019).

they do engage, their limited search efforts result in random, higher mortgage rates, making the mental effort of search comparable to the advantages of renting. This insight sheds light on the crucial interplay between financial skills, search behavior, and mortgage outcomes.

We derive the equilibrium properties of individual consumption growth and show that financial skills, level of assets, and search intensity characterize consumption patterns through two novel channels. While expected changes in mortgage repayments incentivize dissaving, possible expense shocks induce saving, with the strongest effect on the financially savviest borrowers. The distribution of mortgage offers, in conjunction with individual search and skills, endogenously defines the lock-in mortgage rate distribution used for model calibration.

The model equilibrium specifies the mortgage repayment schedule across the joint distribution of financial skills and assets among otherwise similar borrowers (intensive margin). At the extensive margin, the model delivers differential housing costs that, together with savings choices, collectively describe consumption variation. We calibrate the model using a set of key data moments from NSMO+ and the SCF, and perform validity checks using non-durable consumption data from the external data set of the Bureau of Labor Statistics. Our model reproduces empirical patterns in mortgage rate attainment, with search effort and skills explaining 55% and 10% of the mortgage rate dispersion. Moreover, financially skilled homeowners employ search effort and are 30% more likely to refinance. On average, renters accumulate lower levels of skills, reflecting data patterns from the SCF.

We use the model and obtain key findings from our three model experiments. First, we show that financial education positively affects the average delinquency rate. Second, we show that accessible mortgages accommodate financial education, as flatter search costs feed back into financial skill accumulation incentives. Third, we emphasize the importance of heterogeneous search costs and show that low mortgage rates encourage refinancing among financially skilled homeowners, with insignificant effects on mortgage attainment for less-skilled renters.

First, we introduce financial education, which effectively reduces skill investment costs among low-skilled agents. We set up a policy test to appropriate a 90 minute course in financial planning for low skilled renters. In this environment, skills are 9% higher on average, which reinforces search intensity and mortgage take-up, leading to a 1.6% greater share of homeowners overall. As relatively more skilled renters enter the mortgage market, the average delinquency rate is 2.8% lower than the benchmark. Moreover, since investment costs flatten out across all agents, the consumption inequality is, relatively, 1.4% lower.

Our second experiment accommodates mortgage market advancements and increases mortgage availability, effectively decreasing search costs for all agents in the economy. Corresponding to empirical findings (Degerli and Wang, 2022), accessible mortgages reflect a relative increase in search intensity by 7.8% for renters and 16.9% for homeowners. In this regard, mortgage accessibility mainly works in favor of current homeowners. Also, we show that accessible mortgages expose households to delinquency due to small incentives for skill accumulation (with a relative increase by 1.1%). The relative increase in the delinquency rate is 1.7%.

The relative increase in the average delinquency rates reflects the adverse effect of increase in access to mortgages. We show that financial education has a stronger effect with highly accessible mortgages, and leads to relatively higher (0.4 p.p.) average financial skill level. In this regard, cheaper search reincentivizes skill accumulation. Easier search and skill investment produce a relatively more skilled pool of homeowners, who exhibit lower delinquency rates. In this regard, increases in mortgage availability accommodate financial education as effective in reducing consumption inequality by 1.5% and decreasing average delinquency rate by 2.7%.

Our third experiment compares two distinct mortgage rate levels and reflects policy changes, such as modifications in mortgage rate deductions. We introduce a left and right shift in the mean offer rate while keeping the rate dispersion fixed. We compare two scenarios: a low-mean rate scenario, marked by a 20 b.p. decrease in the average mortgage rate, and a high-mean rate scenario, characterized by a 10 b.p. increase in the average rate.

We show that the low-rate scenario benefits existing homeowners, leading to a 64.9% increase in refinancing activity. Therefore, homeowners secure lower mortgage rates and reduce their housing expenses. However, renters experience only a 1.4% increase in search activity, often ending up with higher rates or staying in rentals, thus widening consumption inequality by 1.4%. Lower mortgage rates, in this context, perpetuate the gap in consumption between renters and homeowners.

Conversely, the high-rate scenario exhibits a 36.5% decrease in search intensity among current homeowners. The increase in mortgage rates narrows the consumption disparity between renters and homeowners, leading to a 5.6% reduction in consumption inequality. Both scenarios underscore the crucial role of search intensity and the sensitivity of credit search to interest rates.

Although changes in the U.S. mortgage market have tightened the gap between mortgage rates among similar borrowers, they have needed to be more effective with low-skilled borrowers. Our model experiments offer compelling evidence suggesting that promoting investments in financial skills could be crucial in addressing these persistent disparities. With accessible mortgages and a better understanding of the mortgage process, attaining lower mortgage repayments reduces the exposure of financially unskilled households to liquidity constraints.

Lastly, within the pool of financially savvier households, the diminishing utility cost of searching for new mortgage options reinforces refinancing activity. This observation hints at the amplified potency of the refinancing channel of monetary policy. A richer set of sources of heterogeneity and careful outlining of the mortgage supply can give insights into mortgage market responses to financial education and monetary policy.

2 Related literature

This paper contributes to empirical and theoretical studies on mortgage undertaking and financial literacy effects in household finance, and leverages the current way U.S. households face mortgage process.

Following the structural changes in mortgage lending, the main focus has been put on consumer choice and search. The closest two papers to ours introduces hidden information or heterogeneity in rate beliefs, while keeping i.i.d costs of search. Whereas Agarwal et al. (2020) introduce a model with search and screening and reproduce "the searching for approval" mechanism, we leverage on FinTech algo pricing and assume perfect screening. Alexandrov and Koulayev (2018) incorporate a static framework with borrowers who hold beliefs about the interest rate dispersion, while we assume perfectly informed borrowers. In this respect, we complement Alexandrov and Koulayev (2018) in two ways. First, we add structure to search cost variation as opposed to taking an i.i.d. cost assumption. Second, we endogenize search costs as they depend on individual accumulation of financial skills. We add to the line of search models and go beyond the mortgage take-up, and include the choice to refinance.

The data availability during the low interest rate for the last ten years shifted focus on refinancing. Andersen et al. (2020) argue that search frictions induce failure to refinance, attributing search frictions to behavioral factors such as inattention. Keys et al. (2016) find that more than 20% of U.S.

borrowers did not refinance at the optimal time, when interest rates were low, and relate individual sub-optimality to procrastination and financial sophistication. Gerardi et al. (2023) and Agarwal et al. (2017) discuss race and age disparities in mortgage refinancing, and argue that sophistication may be the underlying source. Our data analysis complements Andersen et al. (2020) and Keys et al. (2016), and is supportive of the view in Gerardi et al. (2023), showing that financial skills increase search effectiveness and the likelihood of refinancing, further supporting our model's assumptions.

While standard measures like loan-to-value constraints and income uncertainty disincentivize home ownership (Paz-Pardo, 2023), recent studies argue that behavioral assumptions affect mortgage take-up and subsequent performance. While Schlafmann (2020) underscores the importance of self-control in mortgage undertaking, Bailey et al. (2018) focus on leverage choice pertaining to individual house price beliefs. Moreover, Exler et al. (2021) highlight the difference in income risk perception for default and consumer scoring. In this regard, our paper introduces individual financial sophistication and search intensity as additional drivers of heterogeneity in mortgage undertaking.

The empirical literature argues that financial literacy explains financial behavior in the credit market (Bhutta et al., 2020; Agarwal et al., 2016; Koszegi, 2014) and debt management (Bhutta et al., 2022; Van Rooij et al., 2011; Allgood and Walstad, 2016). Focusing on mortgage rate differences, Gerardi et al. (2023) find significant race differences in mortgage prices, pertaining to more than income and education differences. Closer to our data analysis, Bhutta et al. (2020) and Malliaris et al. (2022) show that a combination of search effort and mortgage process knowledge explains a part of the interest rate spread in the U.S. Damen and Buyst (2017) use a unique European website data and show that borrowers who shop more end up saving €7,078 over the mortgage term. We evaluate the effects of objective measure of financial literacy (Lusardi et al., 2010; Lusardi and Mitchell, 2014; Lusardi, 2019) and search effort jointly. Moreover, we introduce the interaction of the level of skills and search as a key ingredient in our analysis.

Finally, our novel approach to modeling mortgage search leverages on digital advancements in the era of increasing market share of non-bank lenders. Empirical studies show that these lenders most often operate online and frequently make use of FinTech algorithms for mortgage pricing. The no-contact evaluation reduces the mortgage rate dispersion (Fuster et al., 2019; Zhou, 2022), albeit not fully. The U.S. law of fair pricing allows lenders to utilize other borrower's observables to evaluate risks associated with the specific mortgage origination. In this regard, lenders are free to use any data that may inform about delinquency risk. Bartlett et al. (2022) show that county-based characteristics, including search effort and sophistication, add to the final mortgage price.

Adding to debt behavior literature, our model introduces endogenous financial skills accumulation, and captures skill depreciation (Agarwal et al., 2007). In their paper, Mazzonna and Peracchi (2023) show that cognitive decline significantly affects wealthier households who mispercieve their cognitive abilities. Jappelli and Padula (2017) relate consumption growth differences to financial sophistication through the model of sophistication-driven access to portfolio returns. To that end, financial education policy that targets households who cannot keep up with skills may have heterogeneous effects across older cohorts.

Our model experiments with financial education target renters who are about to take up a mortgage. In the model with lenders who score their consumers, financial education significantly increases welfare (Exler et al., 2021). In our context, financial education alleviates search costs and implicitly affects household's liquidity through lower mortgage repayments.

3 Data analysis and stylized facts

The empirical part of our paper stochastically merges two publicly available survey data sets, effectively defining a novel data set on U.S. mortgage originations. Leveraging on the robustness of stochastic imputations, we outlines the set of estimates that highlight the importance of financial skills and search behavior in mortgage attainment. Whereas most of our inference is correlational, novel data set provides causal explanation for mortgage performance a couple of years after the mortgage is originated. First, we introduce the SCF data and present three stylized facts important for our model assumptions. Next, we introduce the second data source (NSMO) and later proceed to present the findings of the novel U.S. dataset (NSMO+) generated using the stochastic merging method.

3.1 The Survey of Consumer Finances

The SCF, a triennial survey of randomly chosen U.S. households, captures data on investment, housing, and debt. These responses construct a comprehensive balance sheet for typical U.S. households, vital for empirical household finance studies. Our analysis focuses on a SCF subset with a ”financial literacy score,” from the 2016 and 2019 waves, comprising 60,125 responses. By incorporating data on credit search behavior and mortgage refinancing, akin to the NSMO data, we explore credit shopping patterns among 41,788 first-lien mortgage holders and renters, aligning with NSMO standards. The evidence on variation in individual financial literacy provide three key insights that form foundational assumptions for our mortgage search model.

3.1.1 Financial literacy

Financial literacy score is based on a set of three questions (*The Big Three*) that are shown to be efficient in comprehensively evaluating individual financial skills (Lusardi et al., 2010; Lusardi and Mitchell, 2014; Bhutta et al., 2022). The set of questions tests individual understanding of inflation, risk diversification and compounding:

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**/Exactly/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/Exactly/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

Unlike perceived financial knowledge, which signifies confidence, these objective scores provide insight into actual financial planning and behavior (Bhutta et al., 2022; Lusardi et al., 2010). To explore this, we employ a stochastic merging procedure, integrating mortgage data with the SCF. This approach allows us to discern collective patterns in *objective financial skills*, search effort, and mortgage rates among comparable borrowers.

First, we highlight essential household characteristics pertaining to financial literacy. Utilizing an ordered logistic model, we predict financial literacy scores based on borrower attributes. Table 1 presents personal attributes associated with financial literacy. Model-generated probabilities indicate that college graduates correctly respond to all financial literacy questions with a probability of 77%, while high-school graduates do so with a probability of 52%. Additionally, Figure 1 offers empirical evidence demonstrating a positive correlation between educational attainment and financial literacy.

Table 1: Ordered logistic model, personal characteristics correlating with financial literacy. Source: SCF, 2016-2019, authors' calculations.

	Dependent variable:
	Financial literacy score
Worker	0.041^{*}
	(0.025)
Married	0.111^{***}
	(0.024)
Non-white	-0.392^{***}
	(0.019)
Female	-0.474^{***}
	(0.025)
Education: High-school	0.211^{***}
	(0.031)
Some college	0.599^{***}
	(0.031)
College degree	1.123^{***}
	(0.033)
Income percentile: 20^{th} - 40^{th}	0.049^{*}
	(0.028)
40^{th} - 60^{th} 3	0.073^{**}
	(0.031)
60^{th} - 80^{th}	0.179^{***}
	(0.035)
80^{th} - 90^{th}	0.349^{***}
	(0.043)
90^{th} - 100^{th}	0.649^{***}
	(0.048)
Observations	60,125
Note: Controlling for age and asset amount.	*p<0.1; **p<0.05; ***p<0.01

Although education explains a considerable portion of the variation in financial literacy, as evident from the significant and substantial coefficients in Table 1, income, age, and race also play significant

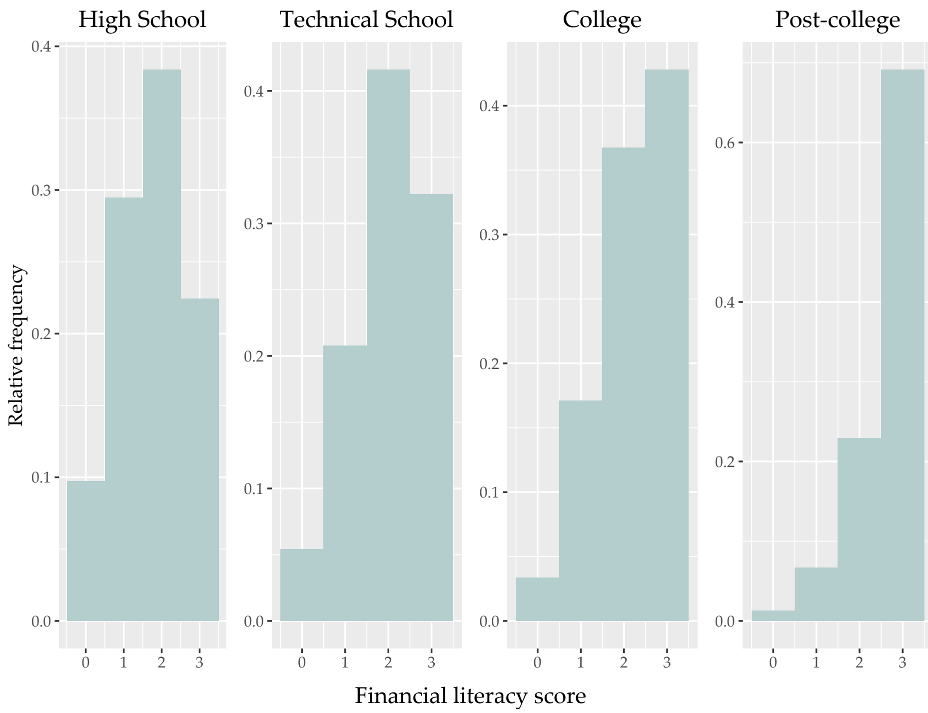

Figure 1: Financial literacy distribution by education level. Source: SCF, 2016-2019, authors' calculations.

roles. These factors highlight additional dimensions crucial for skills and, consequently, individual saving and borrowing behaviors. We consider financial skills as a dimension that encompasses these conventional explanatory variables, albeit imperfectly, due to the impacts of learning by doing and unexpected expense shocks, as discussed in studies such as Agarwal et al. (2007) and Lusardi and Mitchell (2014).

3.1.2 Stylized facts from the SCF

While the separation of financial literacy from other household characteristics falls beyond the scope of this paper, we present key data patterns shedding light on individual financial skills and their potential impacts on mortgage shopping behavior. These patterns define a set of three empirical facts important for our model assumptions and validity.

First, we document that financial skills vary with age. We apply a polynomial fit to the standardized skill score across age groups. Although Figure 2 can not account cohort effects, the hump-shaped fit corresponds to panel data estimates depicting skill variations over time (see Agarwal et al. (2007)

and Lusardi et al. (2010)). Indicative of a decline in consumer finance knowledge with approaching retirement, Figure 2 illustrates skill depreciation, corroborating findings from panel-data studies on financial sophistication.

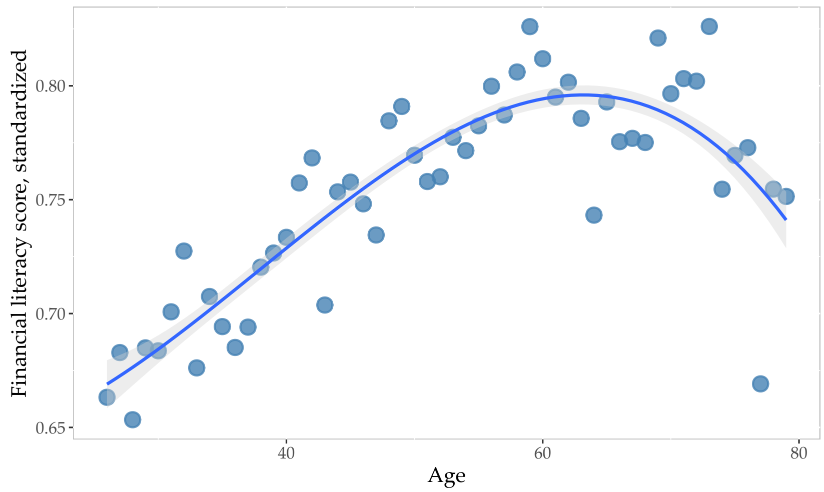

Figure 2: Average financial literacy by age groups, polynomial fit. Source: SCF 2016-2019, authors' calculations.

The second empirical fact underscores the positive correlation between refinancing probability and financial literacy. Our analysis reveals that the likelihood of mortgage refinancing increases with higher financial skills and mortgage payments, holding other characteristics constant. Variations in these probabilities are illustrated in the heatmap depicting predicted refinancing probabilities in Figure 3.

We evaluated the likelihood of mortgage refinancing among borrowers based on their self-reported search efforts in making borrowing decisions. With borrower attributes and mortgage size held constant, greater financial literacy, income, and effort imply a higher likelihood of mortgage refinancing (as illustrated in Table 20 in the Appendix). In contrast, Table 2 demonstrates that education does not significantly influence refinancing. Thus, financial skills emerge as a distinct dimension significantly impacting refinancing decisions within the SCF dataset.

Overall, coefficients in Table 2 imply that, across all income categories, financially savvy borrowers are 20%-30% more likely to refinance their mortgage.

Our third finding highlights a positive correlation between financial skills and the time households dedicate to credit shopping. Employing an ordered logistic model, we find that financially savvy

Table 2: Binary regression estimates, likelihood of refinancing. Source: SCF 2016-2019, authors' calculations.

	Dependent variable:
	Ever refinanced their mortgage
Financial literacy score: low	0.093
	(0.122)
medium	0.262**
	(0.116)
high	0.478***
	(0.115)
Search effort, borrowing: medium	0.055
	(0.056)
high	0.125**
	(0.058)
Education: high school	−0.106
	(0.081)
some college	−0.222***
	(0.081)
college degree	−0.089
	(0.080)
Female	0.103*
	(0.057)
non-white	−0.280***
	(0.037)
Mortgage size: \$83,000 - \$159,000	−0.170***
	(0.047)
\$159,001 - \$ 297,000	−0.360***
	(0.049)
\$ 297,001 - \$ 1,450,000	−0.394***
	(0.054)
Constant	−0.869***
	(0.175)
Observations	18,702
Note: Controlled for age, income, family structure and survey wave effects.	*p<0.1; **p<0.05; ***p<0.01

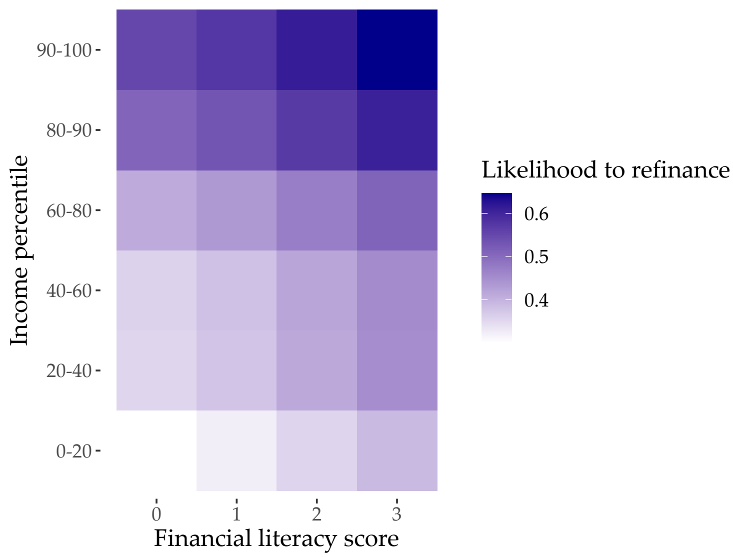

Figure 3: Mortgage refinance likelihood across income percentiles and financial literacy scores. Source: SCF 2016-2019, authors' calculations.

renters and homeowners invest a significant amount of time in credit shopping, regardless of their housing expenses. The coefficient estimates are detailed in Table 3, and Figure 4 illustrates a heatmap showing model-predicted probabilities of spending a considerable amount of time searching for credit among renters. Households with strong financial skills tend to allocate more time to exploring credit opportunities, with a 15% increase in the likelihood of spending additional time for mortgage owners and a 10% increase for renters. Furthermore, our estimates indicate that renters, on average, dedicate less time to search efforts, and their search intensity shows a more gradual growth with higher levels of financial skills[2].

In the SCF, an average homeowner has over 70% of their total monthly debt obligations dedicated to mortgage repayments. Consequently, the specifics of a mortgage contract significantly influence expenditure and savings patterns throughout their working years, deeply impacting available liquidity. In this context, we obtain a dataset that is comprehensive, encompassing detailed information on both the mortgage contract and household characteristics. Shifting our attention to mortgage data, we gain insights into individual mortgage shopping behavior. Individual shopping behavior, coupled with a standard set of observable factors, determines the mortgage interest rate, which frequently remains fixed over the mortgage term. Through our model, shopping behavior shapes spending and saving

[2]The heatmap of predicted probabilities for homeowners is available in Appendix C, Figure 27.

Table 3: Ordinal logistic regression, time spent shopping for credit. Source: SCF 2016-2019, authors' calculations.

	Low-to-great deal of spent in shopping for credit(1-3)	
	Homeowners	Renters
Low|Medium	-15.343^{***}	0.439^{***}
	(0.236)	(0.086)
Medium|Great	-18.042^{***}	-1.748^{***}
	(0.237)	(0.090)
Mort. payment per month: -$750-$1150	-0.017	
	(0.049)	
$1150-$1700	0.038	
	(0.053)	
$1700-$2700	0.0314	
	(0.060)	
$2700+	0.071^{***}	
	(0.056)	
Rent payment per month: $500-$690		-0.132^{**}
		(0.046)
$690-$920		-0.058
		(0.047)
$920-$1300		0.029
		(0.048)
$1300+		0.0385
		(0.052)
Education: HS	0.421^{***}	0.373^{***}
	(0.074)	(0.048)
some college	0.436^{***}	0.612^{***}
	(0.074)	(0.048)
college degree	0.437^{***}	0.565^{***}
	(0.075)	(0.053)
Wage percentile: 20-40	-0.0368	0.147^{**}
	(0.059)	(0.051)
40-60	-0.016	0.140^{*}
	(0.061)	(0.056)
60-80	-0.051	0.122^{*}
	(0.063)	(0.058)
80-100	-0.097	0.260^{***}
	(0.068)	(0.062)
Financial literacy: level 1	0.256	0.090
	(0.112)	(0.065)
level 2	0.400^{***}	0.161^{***}
	(0.106)	(0.062)
level 3	0.350^{***}	0.360^{***}
	(0.105)	(0.064)
Observations	22,178	19,610

Note: Controlled for gender, race, age, debt-to-income, risk attitudes, assets and survey wave effects. *p<0.1; **p<0.05; ***p<0.01

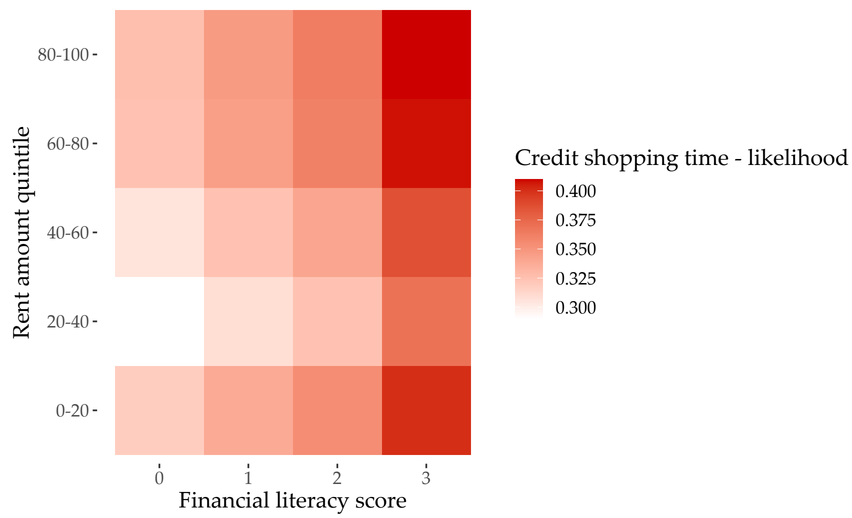

Figure 4: Great deal of time spent shopping for credit, ord. logit predictions, renters only. Source: SCF 2016-2019, authors' calculations.

patterns over the 30-year mortgage duration. To substantiate our assumptions regarding mortgage search, we base the majority of our model assumptions on our new U.S. data findings.

3.2 The National Survey of Mortgage Originations (NSMO)

Our novel data set leverages the amount of information within the NSMO. For a representative sample of U.S. population, NSMO connects mortgage registry data to the survey on mortgage acquisition experience, spanning mortgage originations from 2013 to 2021. This survey includes newly originated first-lien residential mortgages, covering both initial acquisitions and refinances. Important for our paper, the survey inquires about loan shopping behavior and the overall consumer experience during the mortgage process. All survey responses are matched with institutional lender data, providing specific details of the mortgage contract, including locked-in mortgage rates, government sponsorship, low-income area indicators, loan-to-value ratios (LTVs), borrower's payment-to-income ratio, credit score, education, and income. We limit the data to home purchases and refinancing, resulting in a survey sample of 43,094 mortgages, each weighted to ensure representativeness in our analysis.

Our focus revolves around borrowers' search behavior prior to the mortgage application. We use the question

- *How many different mortgage lenders/brokers did you seriously consider before choosing where to apply* *for this mortgage?*

The individual survey responses serve as a proxy variable for cognitive search effort. Instead of relying on the number of formal mortgage applications, we analyze the number of lenders considered. We argue that the response reveals the variation in the cognitive search effort **prior to the application process**.

While the majority of borrowers tend to submit formal applications to a single lender – resulting in over 35,000 mortgages being obtained from that chosen lender – the numbers of lenders seriously taken into account varies across the sample. We assert that, due to the expense associated with the application process, borrowers concerned about rejection are more likely to apply to multiple lenders, driven by fear of being declined. This phenomenon has been discussed in works such as Agarwal et al. (2020). Consequently, the number of lenders considered reveals shopping behavior that provides deeper insights into cognitive efforts invested into the attainment process. Important for our paper, approximately 70 percent of the survey respondents undergo the mortgage process without the use of a mortgage broker.

Furthermore, the number of lenders considered reflects the contemporary approach to mortgage exploration. Online applications typically compare various lenders and "recommend" the optimal choice, considering the borrower's credit score, income, and down payment options [3].

In Figure 5, we depict the raw data estimates to give a preview of search effort variation across different financial skill levels. Low-skilled borrowers predominantly concentrate on a single lender, while high-skilled borrowers frequently consider two, three, or more lenders. While our paper's foundation leverages financial skills data acquired through stochastic matching, the appendix demonstrates how locked-in mortgage rates fluctuate in relation to education and search effort. Leveraging the matched dataset, we introduce the concept of **effective search** among borrowers with higher skills and education. Thus, the rest of our analysis remains concentrated on financial skills.

After the mortgage origination, the NSMO tracks individual mortgage performance until loan closure. Conditional on averages in other borrower characteristics, our estimates underline financial skills and search behavior as being significant in predicting meeting payment due dates.

[3] For instance, a consumer can visit `https://www.bankrate.com/mortgages/mortgage-rates/` and input their current or desired mortgage amount to compare rates across lenders.

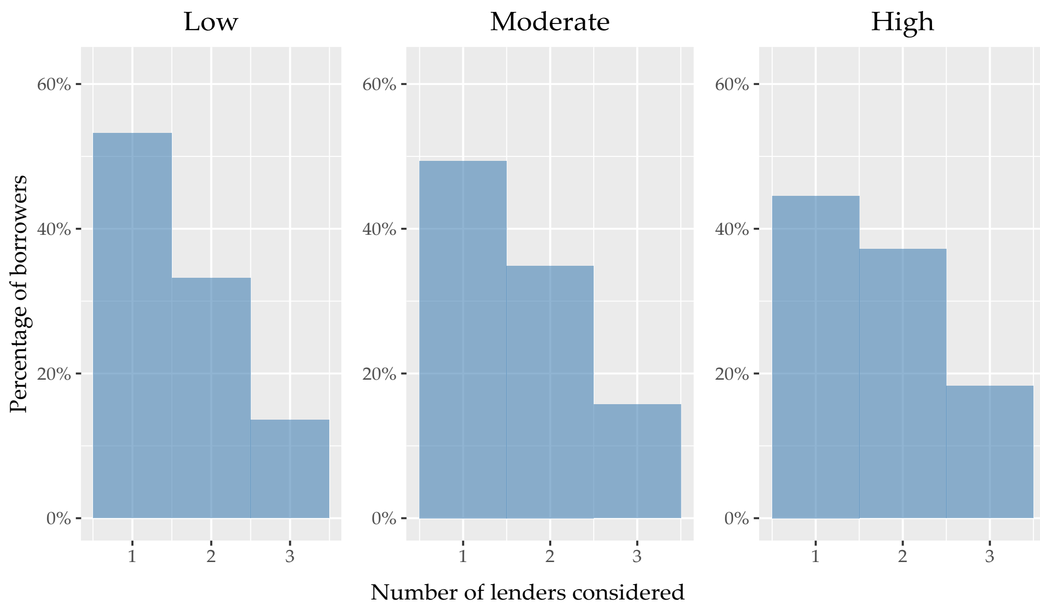

Figure 5: The number of lenders considered at the time of loan origination, across financial skill level, left-to-right panel. Source: NSMO+ data, authors' calculations.

3.3 Stochastic imputation, mortgage data extended (NSMO+)

Information regarding individual mortgages is limited within the SCF. Beyond mortgage payments and past refinancing behavior, data on a mortgage contract is unavailable. To overcome this limitation, we employ stochastic matching to integrate the two datasets. By doing so, we maximize the utility of publicly accessible information about mortgage contract specifics and individual skills, and account for the uncertainty inherent in the matching process.

Instead of imputing financial literacy scores deterministically, the BRL method estimates the distribution of financial skill level for every borrower in the NSMO. Based on the set of mutual observables, we obtain Bayesian weights for every match between NSMO and the SCF, and use them later for making in statistical inferences. This method has been analytically shown to reduce the biases in coefficient estimates in linear models and preserve asymptotic normality and consistency in non-linear estimation (Enamorado et al., 2019). We outline the BRL assumptions and likelihood formulation in section D of the Appendix.

Our paper is the first to link SCF and NSMO. Record matching allows us to estimate the financial skill distribution, for every NSMO borrower. While Bayesian weights control for the imputation-driven bias, details of the mortgage contract allow us to control our estimates for other borrowers and mortgage specifics. In this way, our estimates reflect potential sources od the mortgage rate dispersion among otherwise similar borrowers who apply for similar contracts. Table 4 outlines population shares in respective data sources. The selection of common observables we base our matches on are measures relevant to individual financial skills, including income, education, gender, age, race, occupation, family characteristics, and retirement plan and asset holdings. Once we have a borrower-specific skill distribution, our estimates separate skilled and unskilled borrowers who search more or less, keeping the lender's side of the contract fixed (term, amount, government sponsorship, origination year, etc.)

Table 4: Population shares in the respective sample. Source: NSMO 2013-2022 and SCF 2016-2019, authors' calculations.

	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 children (Yes, No)	[64%, 36%]	[60% , 40%]
owns financial assets (Yes, No)	[57%, 43%]	[58% 42%]
retirement plan participation (Yes, No)	[86%, 14%]	[62%, 38%]

NSMO+ data findings

In this section, we outline joint patterns in mortgage rates, individual search effort and financial skills, and discuss individual mortgage performance across skill levels. Initially, we discuss the importance of financial skills and their role in how much search effort is exerted prior to mortgage attainment. Next, we delve into the interplay between financial skills, search effort and mortgage rates, and introduce the concept of **effective** search among skilled borrowers. Lastly, we focus on repayment behavior heterogeneity across different skill levels. We return to our empirical estimates in the model's steady-state analysis, and align the model-driven patterns to our merged data findings.

3.3.1 Search, financial skills and locked-in mortgage rates

Using imputed financial skills, we find that financially savvy borrowers consider more lenders on average, and show that search effort variation patterns resemble the breakdown by education level (see Figure 24 in section B of the Appendix). Moreover, we find that savvy applicants search more effectively and generally secure lower mortgage rates in comparison to their comparable counterparts.

3.3.2 Search effort and financial skills

In our sample, we redefine the number of lenders considered and bin 3, 4 and $5+$ together, and represent it with $3+$. Our estimates show that while 60% of low-skilled borrowers focus on only one lender, and only 10% on three or more lenders, 58% of financially savvy borrowers consider multiple lenders (Table 5).

Table 5: Number of lenders considered across financial skills, weighted frequencies. Source: merged dataset, authors' calculations.

	Number of lenders considered		
	1	2	3+
Financial Literacy			
Low	58.48%	41.52%	0
High	41.37%	36.42%	22.21%

Next, we estimate a ordinal logistic model that assumes latent thresholds for every observation ij in the merged data set

$$\mathbb{P}(\text{num\_cons}_{ij} = k) = p_{ij,k} = \mathbb{P}\big(-\kappa_{k-1} < \beta X_i + \beta^f \text{fin\_skills}_j + u_{ij,k} < \kappa_k \big), \quad k \in \{1, 2, 3+\}.$$

We adjust our estimates with borrower-skill specific distributional weights that account for match uncertainty in the inflated set of 155,500 observations[4].

Table 6 depicts the explanatory power of each borrower characteristic. Important to our narrative, our estimates imply that financially skilled borrowers (top tercile) are 4% more likely to consider more

[4]We repeat the analysis with the linear probability model that does not require weights inclusion and obtain similar results

lenders i.e., search more. Moreover, we find that females and borrowers living in non-metropolitan areas are 30 and 5 percent less likely to consider multiple lenders. Additionally, education significantly affects search effort, as we find that college graduates and post-college borrowers are 40% and 50% more likely to search more, respectively.

	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. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 6: Ordered logit with imputed financial literacy and weights.

Search effort correlates negatively with low-to-moderate non-metropolitan areas, known as low-shopping areas, which are often subject to mortgage overpricing (Bartlett et al., 2022). Notably, the effect of financial skills is of the same magnitude as income or credit score, or the geo-location effect[5].

[5]In addition, our SCF analysis shows significant variation of credit search effort with financial literacy, with 20% higher likelihood for high-skilled borrowers to spend more time in loan shopping. The two findings together support our search model assumptions.

Abstracting from all standard observables leaves a significant residual effect of financial skills. However, the skills effect in our estimates remains conservative due to the nature of our merging process and strong correlations between skills and gender, income, education, etc. outlined in the SCF data analysis.

3.3.3 Residual mortgage rate dispersion and repayment costs heterogeneity

Next, we turn to the mortgage rate dispersion, controlled for mortgage specifics. We focus on differences in mortgage rates across individual financial skills and search effort.

Controlling for the loan amount, term (30 years), borrower's credit score (*"Very good" and "excellent"*) and the origination year (fixed to 2016), we compare the residual mortgage rate dispersion across different levels of financial skills. Even though these borrowers are comparable to mortgage lenders, financially savvy ones tend to lock in at lower rates. Figure 6 shows that the interest rate density for the savviest borrowers (denoted with the blue curve) has a lower mean, and is thicker towards lower interest rates. On the other hand, unskilled borrowers are more likely to end up with higher interest rates, as shown in Figure 6 with the red density graph.

Using the 2020 origination subsample, we show that, for a \$200,000 loan, the top tercile of financially skilled borrowers secured mortgages with a **20 percent lower spread in the mortgage rate distribution**, underscoring the larger variation in interest rates obtained by low-skilled borrowers. This pattern holds consistently over time, with the usual spread difference ranging between 15% and 20%.

Next, we regress the locked-in interest rate on a set of borrower characteristics X_i, mortgage contract specifics M_i and match-based financial skills fin_skills_i:

$$\text{rate}_i = \alpha + \beta X_i + \beta^m M_i + \beta^f \text{fin\_skills}_i + \gamma \text{fin\_skills}_i \times \text{num\_len}_i + \varepsilon_i,$$

and estimate the rate-based losses over the mortgage duration.

Table 7 displays coefficients for two sets of estimates, with the first column focusing solely on first originations. In both regressions, we account for mortgage specifics, including loan type, amount, term, sponsorships, number of underwriters, and loan-to-value ratios. Notably, both sets of estimates reveal an interaction between financial literacy and search effort, significantly contributing to the explanation for locked-in mortgage rates.

Table 7: Mortgage rate regression, controlling for loan and borrower characteristics. Source: merged data set, authors' calculations.

	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)
Metro area - LMI tract	0.033**	0.022**
	(0.013)	(0.009)
Non-metro area	−0.018	0.003
	(0.015)	(0.010)
Female	0.032***	0.030***
	(0.009)	(0.006)
African-American	−0.005	0.007
	(0.019)	(0.013)
Asian	−0.021	−0.036***
	(0.020)	(0.013)
Other (including hispanic)	0.069***	0.051***
	(0.025)	(0.017)
Income: $35,000-$50,000	0.007	−0.043**
	(0.024)	(0.017)
$50,000-$75,000	0.036	−0.018
	(0.023)	(0.016)
$75,000-$100,000	0.034	−0.011
	(0.024)	(0.017)
$100,000-$175,000	0.064***	0.004
	(0.024)	(0.017)
$175,000 and more	0.054**	−0.00004
	(0.027)	(0.019)
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)
Credit score	−0.263***	−0.247***
	(0.010)	(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, number of borrowers, time effects, LTV and term. *p<0.1; **p<0.05; ***p<0.01

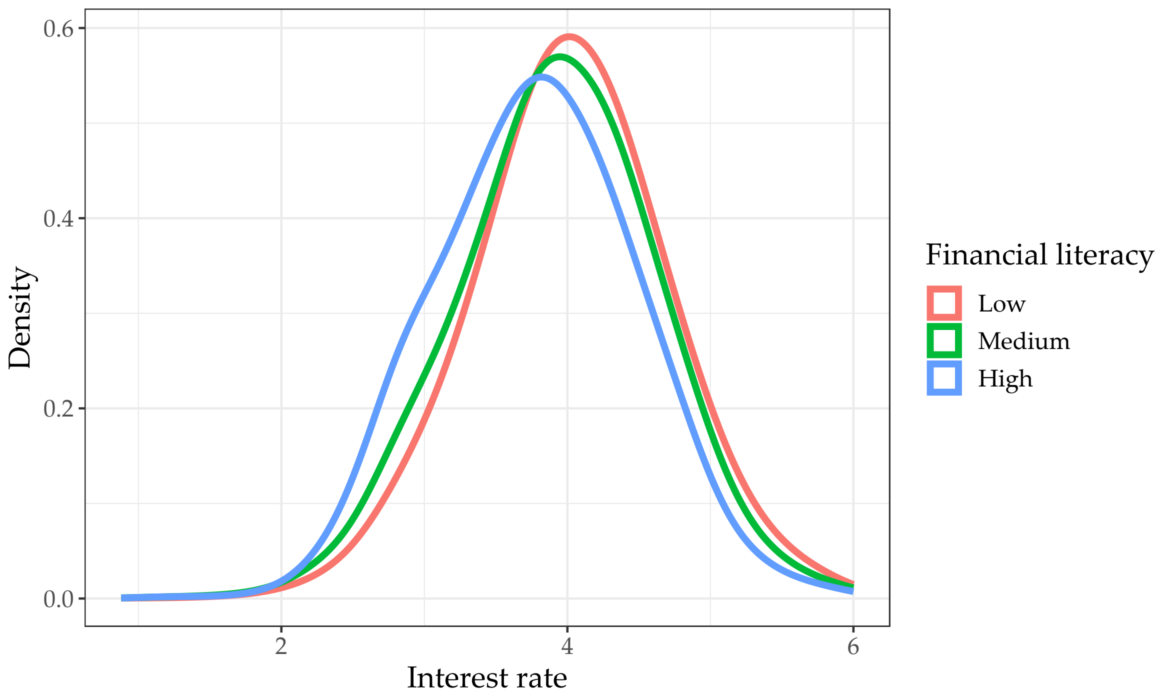

Figure 6: Residual mortgage rate across financial skills. Source: merged data set, authors' calculation.

Initially, our findings align with those of Agarwal et al. (2020), showing that fear of application rejection mechanically amplifies search efforts among first originations, ultimately leading to higher average rates. This is highlighted in Table 7, which reveals a significant and positive coefficient of 0.220 for search effort within the context of first originations. Upon interaction with skills, the intensity of search assumes the role of an informed mortgage search. Financially skilled borrowers who explore a wider range of lenders tend to secure lower mortgage rates. This translates to an average rate difference of 13.4 basis points (with a corresponding coefficient of 0.220-0.354=-0.134).

Our supplementary findings align with existing research employing loan-level data, underscoring that female and Hispanic borrowers often encounter higher mortgage rates. On the flip side, individuals with higher education enjoy, on average, a reduction of 13.1 basis points in rates during initial originations, though this effect decreases during refinancing. As we consider the intricate interplay among skills, gender, race, and education, our estimates concerning skill disparities present a cautious estimate of the minimum divergence in mortgage repayments, subsequently impacting differences in consumption after accounting for mortgage payments.

Nevertheless, when we analyze the variations in search effort and interest rate regressions, it becomes evident that the extent and effectiveness of search effort differs based on financial skills. This implies the likelihood of lower mortgage payments among financially skilled yet comparable borrowers.

3.3.4 Effective search

We emphasize the role of effective search and compare our predicted distributions of locked-in rates between borrowers who engage in extensive searches and those who consider one lender only. Figure 7 depicts mortgage rate distributions across two scenarios. Low-skilled borrowers that search more effectively do not gain from the search, as the mortgage rate distribution stays the same (left panel in Figure 7). In contrast, high-skilled borrowers who search more end up with lower rates (depicted by the blue curve in the right panel of Figure 7), rendering their search as effective. Our findings on search effectiveness, coupled with a significant and positive search coefficient in the interest rate regression (Table 7), align with the fear of rejection mechanism among low-income borrowers in Agarwal et al. (2020). Less financially savvy borrowers search more because they fear rejection. As a result, this does not significantly change their mortgage rates compared to those who put in less effort.

The disparities observed in lock-in rates during the origination phase ultimately translate into compounded losses over the entire mortgage term[6]. To illustrate, for a $\$100,000$ loan with a standard duration, an average borrower with high financial skills can secure a rate of approximately 3.8%, compared to 4.05% for those with lower financial skills. This sets the lower boundary for cumulative losses at $\$6,693$ over the mortgage term. Moreover, the additional impact of low search effort introduces more than $\$2,636$ in costs throughout the mortgage term. These estimates, though not accounting for other correlations among borrower characteristics, stand as conservative approximations for losses in the mortgage market, amounting to at least $\$9,329$. Notably, this represents a significant proportion of the losses derived from institutional data and subjective insights into the mortgage process (Bhutta et al., 2020). Given that mortgage repayments accounts for over 70% of monthly debt payments, addressing these losses is an imperative for bolstering liquidity for all households, especially those with lower incomes.

Figure 8 represents the year and financial skills interaction coefficient over the sample period. Rel-

[6]Over 75% of mortgages in our sample are 30 years fixed-rate mortgages.

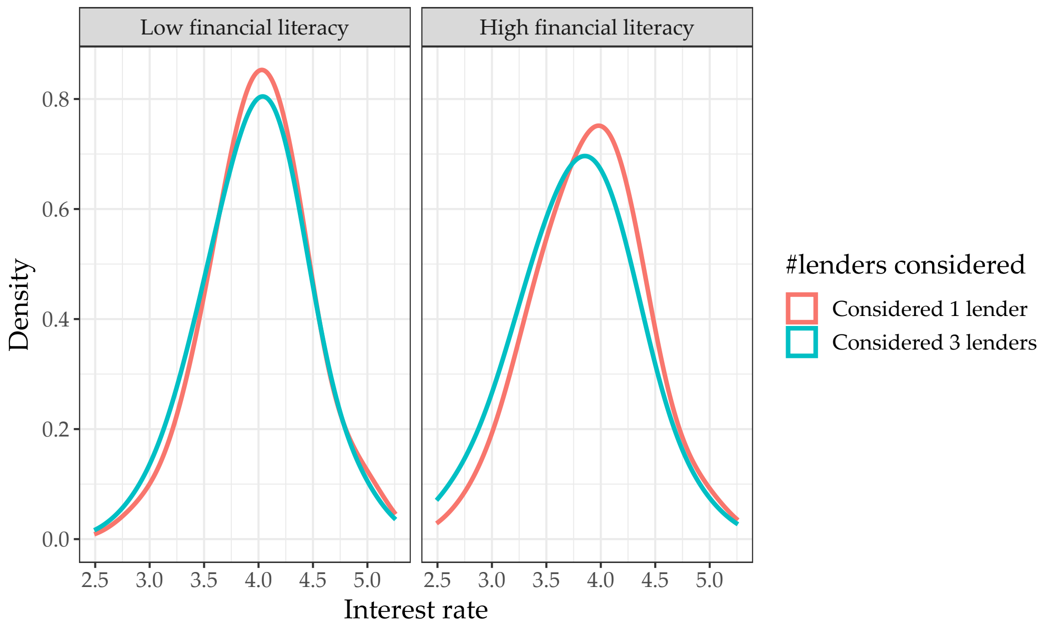

Figure 7: Mortgage rate dispersion; interaction of search effort and financial skills. High skilled borrowers who exert more search effort generally lock in at lower mortgage rates. Source: merged data set, authors' calculation.

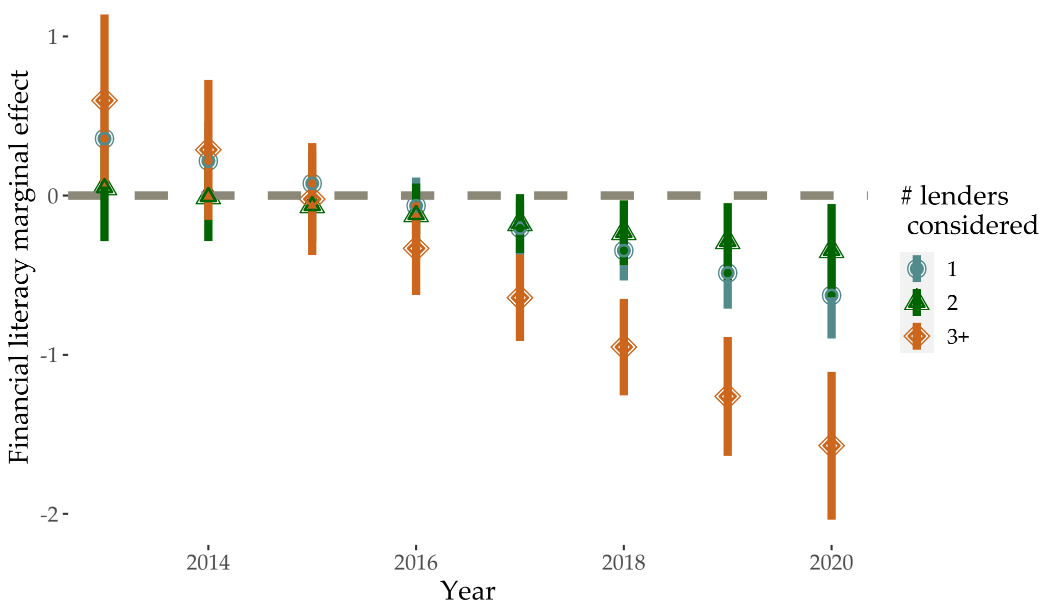

Figure 8: Financial skill coefficient in the mortgage rate regression, differences over the sample period. Source: merged data set, authors' calculations.

ative to the first year in the sample, 2013, later mortgage origination years show signs of increasing significance of both financial skills and search effort for mortgage rate attainment. Our sample period is marked by the steady increase in non-bank lenders share in the mortgage market. As these lenders turn to online advertising and borrowing (Bhattacharya et al., 2021), our findings are suggestive of increasing effects of skilled search effort amidst the mortgage options expansion.

3.3.5 Mortgage performance after origination

NSMO+ tracks the individual mortgage performance until the loan closure, with scores denoting missing repayment due dates up to and over 180 days, bankruptcy levels based on U.S. law, and regular payments made on time. Specifically, the data set separates scores for late payments up to 150 days, and the worst scores indicates mortgage payments later than 150 days and defaults.[7].

The sample size constrains our analysis of the default and late payment indicators, so we separate the score values for late payments and defaults from regular payments and define the indicator variable $\mathbf{1}_{\{\text{late payments or defaults}\}}$. We quantify the effect of individual financial skills and search effort at the time of origination using the linear probability model estimation that controls for other observables.

We model the probability as

$$\mathbb{P}(\text{late with payments}) = \alpha + \beta X_i + \beta^f \text{fin\_lit}_i + \beta^s \text{search\_effort}_i + \varepsilon_i,$$

where fin_lit_i is the average skill amount across all matches[8]. We regress the indicator on a set of borrower observables, mortgage characteristics, individual financial skills, and search effort at the time of origination.

We standardize all continuous regressors (age, credit score, payment-to-income ratio) and compare the size of the coefficients. Our estimates are presented in Table 8.

Table 8 conforms to the standard intuition regarding household characteristics prevalent for mortgage performance. While borrowers with greater payment-to-income ratio are more likely to be late, those with higher credit scores are more likely to meet their payment due dates. In line with Gerardi et al. (2023) and Bhutta et al. (2020), we find that non-white borrowers are more likely to be late with

[7] According to the Home Mortgage Disclosure Act data, delinquency rates are reliable indicators of mortgage default. https://www.consumerfinance.gov/data-research/mortgage-performance-trends/mortgages-30-89-days-delinquent/

[8] We perform a separate, score-based analysis that shows significance and a similar effect size.

payments. Importantly for our paper, financially skilled borrowers who exerted more effort are less likely to have been late on payments two years after mortgage origination.

Figure 9 plots default prediction differences across different skill and search levels. Specifically, our predictions state that financial unskilled face a 1.6 p.p. higher likelihood of being late with mortgage payments. Added to this, borrowers who considered one lender are 0.2 p.p. more likely to be late with payments, possibly because they secured their mortgages at higher rates. Put differently, getting one more question wrong in the financial literacy test corresponds to being 40%-50% more likely to not meet mortgage repayments dates three years after the origination.

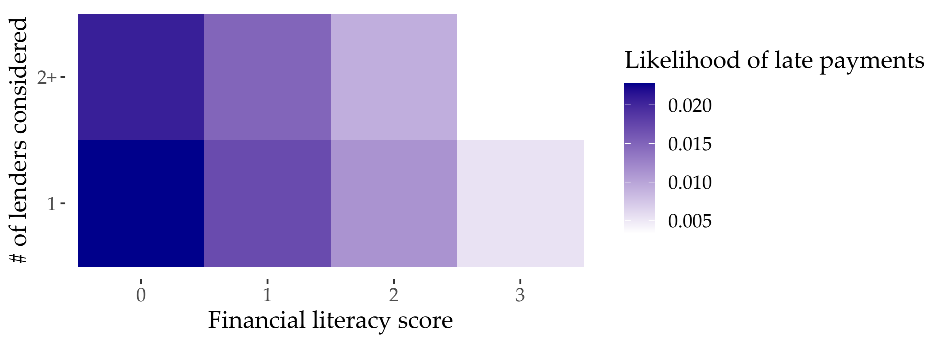

Figure 9: Likelihood of late payments across effort and financial skills. Source: Probability model predictions, merged data set, authors' calculation.

The patterns identified through our analysis of the SCF and NSMO+ serve as the foundation for a mortgage search model that accounts for the variation in search costs contingent on individual financial skills. We revisit each of these findings within the framework of our model setup and explore their implications in our analysis of the steady state.

Table 8: Late payment probability, linear model. *Source:* merged data set, authors' calculation.

	$\mathbb{P}(\textit{Late payment})$
Loan Amount: $100,000-$199,999	0.0001
	(0.002)
$200,000-$299,999	-0.004^{**}
	(0.002)
$300,000-$399,999	-0.004^{**}
	(0.002)
> $400,000	-0.005^{***}
	(0.002)
Financial literacy	-0.017^{**}
	(0.007)
Multiple lenders considered	-0.002^{**}
	(0.001)
Female	0.002^{*}
	(0.001)
Education: high-school	0.003
	(0.002)
college	-0.0001
	(0.002)
post-college	-0.0002
	(0.002)
Race: non-white	0.005^{***}
	(0.001)
Age	0.002^{*}
	(0.001)
Payment-to-income	0.005^{***}
	(0.001)
Credit Score	-0.020^{***}
	(0.001)
Constant	0.023^{***}
	(0.005)
Observations	43,084
Adjusted R^2	0.017
F Statistic	54.783^{***} (df = 14; 43069)
Note: all variables are standardized to preserve interpretability.	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

4 Empirically motivated mortgage search model

Following our data findings, we develop a mortgage search model with endogenous financial skill accumulation and heterogeneous search costs. In the model, search cost assumptions conform to search-skill variation patterns in the data. Accumulating financial skills requires costly investment and pertains to learning-by-doing effects.

4.1 Model setup

A continuum of risk-averse agents solves an infinite horizon problem in continuous time. Agents are heterogeneous with respect to initial financial skills $f_0 \sim \Gamma(f_0)$, labor productivity $z \in \{z_L, z_H\}$, and assets $a \sim \Gamma_a$. Upon income realization, agents pay their housing costs, consume c and save a. While renting, the agent continues to pay the rent cost κ. At any point, agents may take up or refinance their mortgage and adjust their housing costs to support their preferred level of consumption.

In our model, housing preferences correspond to willingness to invest in skills and put in search effort when acquiring a mortgage. In this regard, our model accounts for the cognitive complexity surrounding mortgage undertaking and introduces housing preferences through willingness to learn and search. The trade-off preceding the decision to own a home includes the possibility of facing a large expense shock once becoming a homeowner.

The change in housing status requires exerting search effort s that increases the number of mortgage offers the agent receives. In this way, the search effort corresponds to our data measure that uses the number of lenders considered as a search proxy. As the survey question focused on the consideration rather than formal application, out search costs are modeled as utility costs. The agent faces mortgage offers every period, corresponding to the current lender's web advertising practice in the U.S. On top of arrivals, the agent chooses search intensity that effectively increases the number of sample draws, rendering the mortgage arrival rate as endogenous.

The search cost depends on individual financial skills and thus changes over time. Conditional on searching, agents can take up a mortgage proportional to their income wz. We set the mortgage size to 4 times an agent's current income, capturing median-to-upper quartile mortgage amounts. The endogeneity of individual search intensity gives rise to the endogenous lock-in rate distribution G[9].

[9] We derive the expression for the lock-in rate distribution in the appendix (Expression 40).

The mean and the variance of the lock-in distribution act as calibration targets for the model solution.

Individual search intensity s, together with consumption and saving choices, comprises the set of individual policies that maximize expected future utility. Conditional on their optimal choice, borrowers "sort" into mortgage rates based on the number of offers drawn. After taking up a mortgage, homeowners face an expense shock that depends on their financial skills and assets. The expense shock represents any event that triggers losing a house, such as health, divorce, or other shock that prevents the owner from repaying their mortgage. These shocks are rare but serve as a reason to precaution among current homeowners. After the shock, the agent returns to renting and can undergo a relatively more costly mortgage take-up.

With the goal of decreasing their monthly repayments, homeowners may choose to refinance at any point in time. Refinancing carries an upfront cost c_{ref}, equivalent to 5% of the mortgage amount[10]. In addition, refinancing requires search effort, which corresponds to meeting more lenders. Our model assumes that the homeowner's primary goal is to attain the lower mortgage rate, corresponding to our survey analysis (87% of the NSMO respondents state a lower interest rate as the primary benefit from refinancing. In addition, 68% render lower monthly payments as their priority).

4.2 Financial skills accumulation

Our model closely follows standard assumption in human capital accumulation literature (Browning et al., 1999; Kapička and Neira, 2019). Agents invest in financial skills that depreciate with exogenous rate δ. Each period, agents decides to invest $i \geq 0$ in financial skills f, facing a utility cost $c^f(i, z)$. The choice i represents the share of current financial skills invested into the next period skill level. Utility costs depend on an agent's productivity and increases with the share i:

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

where γ_i is the elasticity of investment cost with respect to investment i, and i_0 is the scaling parameter. Attaining financial skills implies lower search costs, which, through the amount of sampling from mortgage offers, generates a better position in the mortgage market. Corresponding to the life cycle pattern (the fit in Figure (2)), financial skills depreciate at rate δ. Overall, choosing i yields utility cost

[10] According to Freddie Mac, refinancing costs range from 3-6% of the mortgage size. (Source: https://myhome.freddiemac.com/refinancing).

$c^f(i,z)$, adding to individual financial skills level according to

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

Similar to human capital literature, the curvature parameter η characterizes the returns to additional investment in financial skills. When choosing the optimal i, the agent includes the gains characterized by η and utility loss generated by the elasticity parameter γ_i.

4.3 Refinancing - decision and options

Homeowners face expense shocks and ensure liquidity through savings accumulation and mortgage refinancing. On a period basis, the agent chooses to refinance a mortgage or become a homeowner to ensure lower housing payments. Refinancing a mortgage or selecting into homeownership requires exerting search effort that effectively increases the amount of mortgages drawn from the exogenous distribution Φ. Search costs enter the utility, and are explicitly modeled as

$$c^m(s,f) = c_0 \frac{s^{1+\frac{1}{\gamma_s}}}{1+\frac{1}{\gamma_s}} \frac{1}{(1+f)^{\gamma_f}}, \quad \frac{1}{\gamma_s}, \gamma_f > 0,$$

where m stands for mortgage. The coefficient γ_s represents the search cost elasticity with respect to search effort s, c_0 is the scaling parameter, and γ_f characterizes the effect of individual financial skills on the mortgage search process.

4.3.1 Expense shock

Expense shocks proxy for a homeowner's poor financial management and loosing a house. The probability of facing a financial shock $p(f,a)$ decreases with the level of financial skills and assets. $p(f,a)$ serves as an additional incentive to accumulate financial skills or save. When the shock hits, homeowners lose their house and switch to renting with cost κ. The lender gets the house, and therefore does not reflect the default in mortgage pricing later on. Later, we externally estimate parameters of the logistic probability model that captures the dependence on individual financial skills and assets.

4.4 The agent's problem

Denoting the housing state with $\theta_t \in \{\text{ho}, \text{ren}\}$, the most general formulation for the agent's problem is

$$\max_{\{c_t, s_t, i_t\}} \mathbb{E}_0 \int_0^\infty e^{-\rho t}[u(c_t, i_t, s_t) - c^f(i_t, z_t) - c^m(s_t, f_t)]_{\theta_t} dt, \text{ s.t.}$$

$$\dot{a}_t = Ra_t + wz_t - \mathbf{1}_{\{\theta_t=\text{ho}\}} Mr_t - \mathbf{1}_{\{\theta_t=\text{ren}\}}\kappa - c_t,$$

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

$$h \to r \quad \text{with intensity} \quad p(f, a),$$

z_t is a Poisson process with intensities ω_1 and ω_2,

$$a_t \geq 0.$$

Recursive formulation of the problem with respective first order conditions reveal the salient trade-offs for individual consumption and search choice.

4.4.1 Value functions

The recursive problem form consists of Hamilton-Jacobi-Bellman (HJB) equations, housing type-flow equations and boundary constraints, separately for renters and homeowners. The flow of homeownership at different mortgage rates combines the distributions of homeowners and renters across their financial skills and assets.

Renters pay fixed rent cost κ, save in liquid accounts a_t and accumulate financial skills f_t. They engage in costly searches to get mortgage options and may decide to move to a house. Prior to the first origination, renters face additional search frictions ϕ. Dropping the time subscript, the HJB equation for renters is

$$
\begin{aligned}
\rho V^R(f,a,z) = \max_{\{c,s,i\}} \Big\{ & u(c) - c^f(i,z) - c^m(s,f) + \frac{\partial V^R}{\partial f}(f,a,z)\dot{f} + \frac{\partial V^R}{\partial a}(f,a,z)\dot{a} \\
& + \lambda\phi s(f,a,z) \int_{\underline{r}}^{\overline{r}} \max\{V^H(f,a,z,r') - V^R(f,a,z), 0\} d\Phi(r') \\
& + \sum_{z'} \omega(z,z')\big(V^R(f,a,z') - V^R(f,a,z)\big) \Big\}
\end{aligned} \tag{1}
$$

subject to

$$
\begin{aligned}
\dot{a} &= Ra + wz - \kappa - c, \\
\dot{f} &= \frac{\mu}{\eta}(if)^\eta - \delta f, \\
a &\geq 0.
\end{aligned}
$$

The homeowner's problem is defined with

$$
\begin{aligned}
\rho V^H(f,a,z,r) = \max_{\{c,s,i\}} \Big\{ & u(c) - c^f(i,z) - c^m(s,f) + \frac{\partial V^H}{\partial f}(f,a,z,r)\dot{f} + \frac{\partial V^H}{\partial a}(f,a,z,r)\dot{a} \\
& + \lambda s(f,a,z,r) \int_{\underline{r}}^{\overline{r}} \max\{V^H(f,a-c_{\text{ref}},z,r') - V^H(f,a,z,r), 0\} d\Phi(r') \\
& + \sum_{z'} \omega(z,z')\big(V^H(f,a,z',r) - V^H(f,a,z,r)\big) \\
& + p(f,a)\big(V^R(f,a,z) - V^H(f,a,z,r)\big) \Big\}
\end{aligned} \tag{2}
$$

subject to

$$
\begin{aligned}
\dot{a} &= y(a,s) + wz - Mr - c, \\
\dot{f} &= \frac{\mu}{\eta}(if)^\eta - \delta f, \\
a_t &\geq 0.
\end{aligned}
$$

Every row in equation 2 represent possible transitions into different productivity or homeownership states.

The state constraint $a \geq 0$ gives rise to the *boundary constraint* in the continuous time setup. That is, the FOC $u'(c(a)) = V'^{R,H}(a)$ holds everywhere (Achdou et al., 2022), so we include the boundary condition for assets $u'(c) \leq \frac{\partial V^H(f,0,z,r)}{\partial a}$. Optimal search effort, financial skill investment, and consumption satisfy the set of first order and boundary conditions. Moreover, the policy functions are consistent with Kolmogorov Forward Equations, i.e., they respect flows in and out of the mortgage market.

4.5 Kolmogorov Forward Equations

Flow changes work through exogenous separations (financial shocks and jumps in productivity) or are endogenously driven by search intensity and mortgage offer arrival rates.

Therefore, the distribution of homeowners with financial skills f, assets a, productivity $z_i, i \in \{L,H\}$, who repay mortgage at rate r satisfies the Kolmogorov Forward Equation:

$$
\begin{aligned}
0 = &-\frac{\partial g^H(f,a,z_i,r)}{\partial f}\dot{f} - \frac{\partial g^H(f,a,z_i,r)}{\partial a}\dot{a} - \big(p(f,a) + \lambda s^H(f,a,z_i,r)\Phi(r)\big)g^H(f,a,z_i,r) + \\
&+ \lambda \int_{\underline{r}}^{\overline{r}} s^H(f,a+c_{\text{ref}},z_i,r')g^H(f,a+c_{\text{ref}},z_i,r')d\Phi(r') + \lambda\phi s^R(f,a,z_i)g^R(f,a,z_i) + \\
&+ \omega_i\big(g^H(f,a,z_{-i},r) - g^H(f,a,z_i,r)\big). \qquad (3)
\end{aligned}
$$

The distribution of renters with financial skills f, assets a, productivity $z_i, i \in \{L,H\}$, satisfies the Kolmogorov Forward Equation:

$$
\begin{aligned}
0 = &-\frac{\partial g^R(f,a,z_i)}{\partial f}\dot{f} - \frac{\partial g^R(f,a,z_i)}{\partial a}\dot{a} + p(f,a)\int_{\underline{r}}^{\overline{r}} g^H(f,a,z_i,r')d\Phi(r') + \\
&- \lambda\phi s^R(f,a,z_i)g^R(f,a,z_i) + \omega_i\big(g^R(f,a,z_{-i}) - g^R(f,a,z_i)\big). \qquad (4)
\end{aligned}
$$

4.6 Partial equilibrium properties

The exogenous interest rate distribution Φ, rental rate κ, and the interest rate on liquid deposits R define the partial equilibrium of the model. Joint distribution of assets, skills, and housing costs arises endogenously, through individual search intensity and locked-in mortgage rates. In this section, we refer to partial equilibrium as an equilibrium.

Assuming heterogeneous lenders (i.e., heterogeneous mortgage offers $\Phi(r)$), the equilibrium consists of values $V^R(f,a,z)$, $V^H(f,a,z,r)$ defined with equations (1) and (2), respectively, and optimal policies for search intensity, financial skill investment and consumption $s^H(f,a,z,r)$, $i^H(f,a,z,r)$, $c^H(f,a,z,r)$ for homeowners and $s^R(f,a,z,r)$, $i^R(f,a,z,r)$, and $c^R(f,a,z,r)$ for renters. Policy functions imply the distribution of homeowners $g^H(f,a,z,r)$ and renters $g^R(f,a,z)$ across financial skill level, assets, productivity and mortgage rates. These satisfy Kolmogorov Forward Equations (3) and (4). The object of our interest is the model fit across the (f,r) subspace, as we aim to capture the patterns in the data from our empirical analysis.

In the following sections, we present equilibrium properties for both the benchmark version and the simplified version of the model. The derivations and propositions presented in this context do not consider income uncertainty and instead focus on outlining model properties related to consumption and savings effects.

4.7 Mortgage reservation value

We define mortgage reservation rate $\tilde{r}(\cdot)$ as the rate that leaves renters indifferent between taking up a mortgage and remaining renters: $V^R(f,a) = V^H(f,a,\tilde{r}(f,a))$. In addition to the rental rate κ, search costs that depend on skills represent an additional value of being a renter. Therefore, the reservation value is pinned down by the rent-to-mortgage rate ratio, conditional on the level of skills and assets. Because the value function strictly decreases with the interest rate, the mortgage reservation rate represents the highest interest rate at which the renter is willing to borrow, and thus to transition into homeownership.

Proposition 4.1. *The reservation mortgage rate ($\tilde{r}(f,a)$) is heterogeneous across assets and financial skills, and is implicitly given with an equation*

$$\begin{aligned}
&-c^m(s(f,a,\tilde{r}(f,a))) + c^m(s(f,a,\kappa)) + u'(c(f,a,\tilde{r}(f,a)))\big[\kappa - \tilde{r}(f,a)M\big] \\
&\quad + \lambda\big[s(f,a,\tilde{r}(f,a)) - \phi s(f,a,\kappa)\big] \int \max\Big\{V^H(f,a,r') - V^H(f,a,\tilde{r}(f,a)), 0\Big\} d\Phi(r') = 0
\end{aligned}$$

Abstracting from additional frictions upon first-time mortgage origination (i.e., setting $\phi = 1$ and $c_{\text{ref}} = 0$) simplifies the reservation value equation. Particularly, there is no additional value in remaining a renter, other than paying rent costs κ. Therefore, across the asset-skill distribution, the reservation mortgage payment $\tilde{r}(f,a)$ corresponds to the rent price κ.

Corollary 4.1.1. *Abstracting from mortgage adjustment frictions ($\phi = 1, c_{ref} = 0$), the reservation interest rate $\tilde{r}(f,a)$ does not depend on assets or financial skills; it is constant across borrowers and corresponds to renting costs κ: $\tilde{r}(f,a)M = \kappa$.*

In this simplified setting, the reservation rate strategy reduces the complexity of the value function expression, and can be used to infer mortgage performance effects on consumption growth.

Corollary 4.1.2. *Excluding external search frictions, variations in consumption growth can be attributed to three factors: patience, expected future mortgage rates, and precautionary measures in response to expense shocks.*

$$\frac{\dot{c}}{c} = \frac{1}{\sigma}\left[R - \rho - \lambda s\left(\int_{\underline{r}}^{r}\left(1 - \frac{u'(c(f,a,r'))}{u'(c(f,a,r))}\right)d\Phi(r')\right) + p\left(\frac{u'(c(f,a,\kappa))}{u'(c(f,a,r))} - 1\right)\right] \tag{5}$$

Expression (31) disentangles three channels that influence consumption growth. The initial segment represents the conventional impact of impatience, while the second term reflects the effect of expected mortgage rate attainment. This effect is especially significant for high-mortgage rate payers, as they primarily depend on their search efforts without emphasizing savings. Considering states of skills and assets that dictate the level of search effort, borrowers possess knowledge of the offer rate distribution, and thus rely on future search outcomes. However, in the absence of any effort exerted by a borrower, expected future mortgage rates do not influence consumption growth.

The third segment in equation (31) corresponds to the precautionary effect triggered by the possibility of an expense shock. Precautionary motives diminish as the mortgage rate decreases. When mortgage conditions are favorable, the loss of a house carries significant negative consequences. In this regard, the model captures the increasing propensity to save along the percentiles of the asset distribution, as documented in Mian et al. (2020).

5 Quantification

In our approach to a quantitative solution, we utilize the finite difference method for continuous time models, following the methodology described in Achdou et al. (2022). While certain model parameters can be directly obtained from the merged dataset described in the empirical section of the paper, we categorize them into *exogenously set* parameters and *calibrated* parameters. The calibration targets involve essential data moments that capture distinctions in homeownership and mortgage rates for first-time borrowers and upon refinancing. When we target data averages and medians, we evaluate the model's ability to match the rate-skill-assets distribution. Specifically, we establish the validity of the model using consumption and housing expenditure inequality measures.

We describe the two steps in model calibration and outline the simulated patterns relevant to our data findings.

5.1 Parametrization

The model is parameterized at the annual level. The first set of parameters is exogeneous and combines our data estimates with literature standards.

5.1.1 External parameters

Utility is CRRA and the coefficient of risk aversion is set to the standard in the literature $\sigma = 2$. The time preference rate is set to $\rho = 0.05$, and the risk-free rate is $R = 0.04$ (Achdou et al., 2022). Individual productivity follows a Poisson process with transition rates estimated in Guerrieri and Lorenzoni (2017), $z \in \{0.8, 1.3\}$ with intensities $\omega_1 = \omega_2 = \frac{1}{3}$. Wage rates are normalized to 1, leaving wage equal to productivity. We follow the human capital investment model in Kapička and Neira (2019), and set the elasticity of investment in financial skills $\gamma_i = 0.5$. Lastly, we set the monetary refinancing cost c_{ref} to equal 5% of the mortgage size.

5.1.2 Financial skills parameters

We assume that financial skill accumulation satisfies the flow equation:

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

We follow seminal papers by Lusardi et al. (2017), Lusardi et al. (2020), and Browning et al. (1999), and fix $\eta = \frac{1}{2}$, and $\delta = 0.7$. Next, we estimate the slope parameter μ using the SCF data on financial skills. Parameters η and δ correspond to human capital elasticity and depreciation estimates, respectively.

5.1.3 Expense shock probability

In our model, individual expense shocks translate into delinquency and default. We assume that shock probability depends on homeowners' assets and financial skills, $p(f,a)$, and approximate the functional form as

$$p(f,a) = \frac{\exp(p_0 + p_f f + p_a a)}{1 + \exp(p_0 + p_f f + p_a a)}. \tag{6}$$

We estimate the coefficients using the SCF data on late payments among homeowners with a mortgage on their primary residences. Corresponding to the assets in the model, the assets in the SCF include only liquid assets[11]. We re-scale these assets to match the grid bounds in the numerical implementation. The dependent variable is an indicator of over 60 days debt delinquencies. Our estimates control for mortgage size and house value, and thus pertain to the model assumptions.

According to our estimates, financial skills and assets correlate negatively with the likelihood of late debt payments, and the coefficients estimates are $p_0 = -1.08$, $p_f = -1.016$, and $p_a = -7.649$.

5.1.4 Mortgage specifications

The mortgage amount follows the standard and corresponds to 4 times the average borrower's income. The lenders are heterogeneous in their mortgage rate offers, which we assume are beta-distributed. In the equilibrium, the accepted mortgage rate distribution is endogenous and stochastically dominated by the exogeneous offer rate distribution (analytical proof (40) appears in the Appendix).

5.1.5 Internally calibrated parameters

The rest of the parameters are internally calibrated using the simulated method of moments with moment targets that are salient for model performance. Target moments are weighted equally and comprised of the share of homeowners, normalized average financial skills, standard deviation of financial skills, and NSMO-based sample mean and standard deviation of mortgage rates attained, separately for first origination and upon refinancing. Although all parameters are calibrated jointly, we discuss below which moment aims to pin down which specific parameter.

We assume that the offer rate is beta-distributed and calibrate the two shape parameters $\beta = 6.0411$ and $\alpha = 6.0805$ to match the moments of the (endogenous) locked-in mortgage rate. The rental cost

[11]Specifically, we include cash and prepaid cards, checking and savings accounts, directly held money market funds and stocks, and the value of mutual funds investment.

$\kappa = 0.7340$ is informed by the homeownership rate in the SCF sample and yields higher monthly payments on housing for renters, which is consistent with the data[12]. The elasticity of search effort $\gamma_s = 1.7539$ and scaling parameter of the investment cost function $i_0 = 434.2084$ are pinned down by the sample moments of financial skills in the SCF data. The difference between average rates under refinancing and first origination pins down the scaling and search friction parameter $c_0 = 152.9484$, and $\phi = 0.8062$, respectively. In the equilibrium, renters search less than homeowners, aligning with SCF credit search estimates.

We report the targeted moments and the parameter values that minimize the distance between the moments in the data and in the model in Panel C of Table 9.

Table 9: Model parameter values. Source: Model, SCF, and NSMO.

	Definition	Symbol	Estimate	Source/Target		
	Panel A. Externally set					
(dis-)utility	Discount factor	ρ	0.05	Standard		
	CRRA parameter	σ	2	Standard		
	Investment cost elasticity	γ_i	0.5	Kapička and Neira (2019)		
assets	Return	R	0.04	Standard		
	Refinancing Cost	c_{ref}	0.21	Freddie Mac (5% of the mortgage size)		
productivity	Intensities	ω_1, ω_2	$\frac{1}{3}, \frac{1}{3}$	Guerrieri and Lorenzoni (2017)		
skill accumulation	Curvature f	η	0.5	Browning et al. (1999)		
	Depreciation	δ	0.07	Lusardi et al. (2017)		
	Panel B. Externally estimated					
skill accumulation	Slope	μ	0.2	SCF, lifecycle profile		
housing shock	Parameters	p_0, p_f, p_a	-1.08,-1.02,-7.65	SCF, late payments		
	Panel C. Internally estimated				Model	Data
dis-utility	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

[12]Using the SCF data, we compare monthly rent and mortgage payments as income shares across financial skills. Rent shares are twice as high on average. (Table 21 in the Appendix.)

5.2 Model fit

We validate the model fit using graphic and qualitative measures of consumption inequality in the data. Specifically, we use the Gini coefficient and Lorenz Curve as two relevant measures for comparing model-implied consumption and housing expenditures to data counterparts. For this purpose, we use the 2019 Bureau of Labor Statistic report (Garner et al., 2022) on consumption disparity across different types of goods.

We compare our model-implied consumption net of housing costs to the non-durable goods consumption reported in Garner et al. (2022). The Gini coefficient from our model simulations $G_{\text{model}} = 0.2$ matches the data Gini coefficient $G_{\text{BLS}} = 0.18$. We also compare Lorenz Curves from model simulations to the data. The left panel in Figure 10 shows that our model performs well, not only in fitting the area below the perfect equality curve, but in fitting the curve itself.

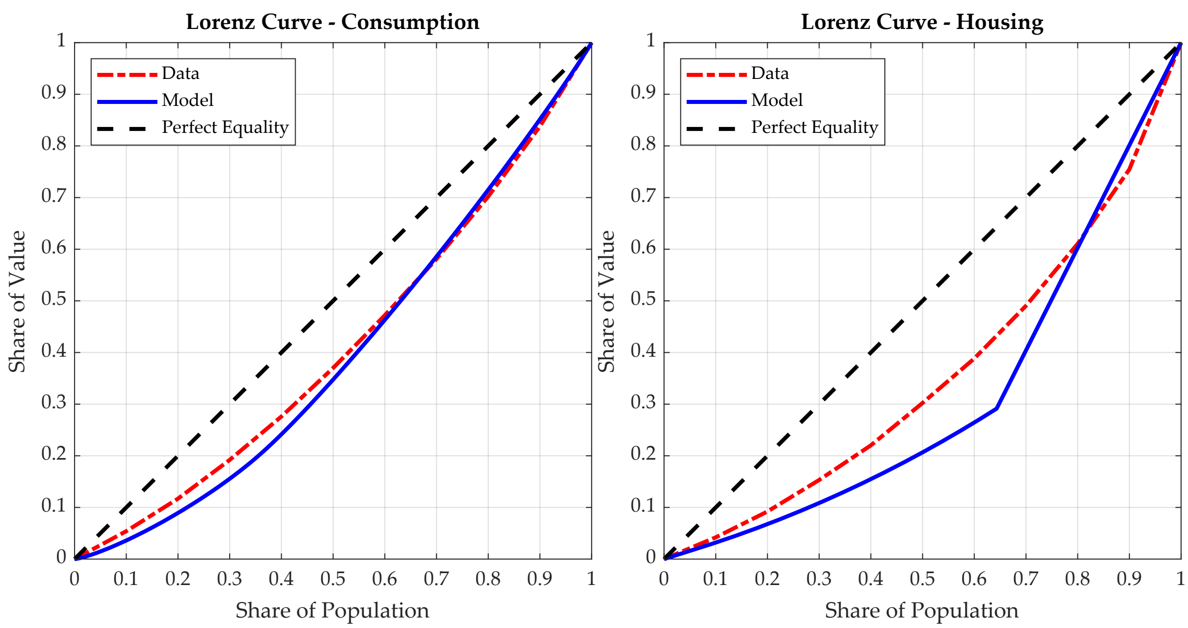

Figure 10: Lorenz Curves for consumption (left) and housing consumption (right) compared to the BLS data.

In addition, we compare total housing costs (including household expenditures on housing and utilities) from Garner et al. (2022) to the total individual housing cost in our model simulations. Depending on the homeownership state, housing costs in our model correspond to either rental rates or mortgage repayments.

In our simulation, the Gini coefficient of housing costs equals 0.37, slightly overstating the data counterpart value 0.29. The right panel in Figure 10 shows that our model understates housing costs for homeowners (the Lorenz Curve in this case does not overlap completely with data implied Lorenz Curve, though, they are close), potentially pertaining to fixed rental rates. Given that we test our model with policies that potentially reduce heterogeneity in individual liquidity (either through consumption or savings) we rely on the good performance of our model in matching non-durable consumption inequality.

6 Skill-based consumption differences

Because our paper introduces a novel dimension in mortgage payment heterogeneity, our primary focus is to examine individual policy variations between low- and high-skilled borrowers. Incentives for mortgage take-up differ significantly across these two groups, contingent on their respective skill levels and asset holdings. Through the lens of our model, these differences translate to consumption disparities.

Our analysis of consumption inequality begins by aligning equilibrium patterns within our model with key data insights from the SCF and our new dataset. Firstly, our model highlights a correlation between skills and choices, and accurately predicts adjustments in housing costs at mortgage initiation and refinancing stages. Specifically, the model demonstrates a positive link between mortgage initiation and financial skills, leading to renters having lower average skill levels, as shown in Figure 11.

Skilled homeowners in the model are more likely to explore refinancing options and to attain lower mortgage rates on average, as depicted in Figure 15. We also identify a slight negative correlation between individual search behavior and asset holdings, as seen in Figures 16 and 13. Borrowers further from the liquidity constraint are more inclined to forego the advantages of lower mortgage payments.

The second set of model patterns directly relates to housing cost heterogeneity, leading to consumption differences across assets and skills. Skilled borrowers are more inclined to take up a mortgage and refinance soon, resulting in relatively lower shares of their savings being allocated to durable consumption. As a result, the model successfully delivers non-durable consumption inequality that aligns with the observed data, as already outlined in the Lorenz curve comparison in Figure 10.

The third set of model performance evidence pertains to our assumption on skill investment choice.

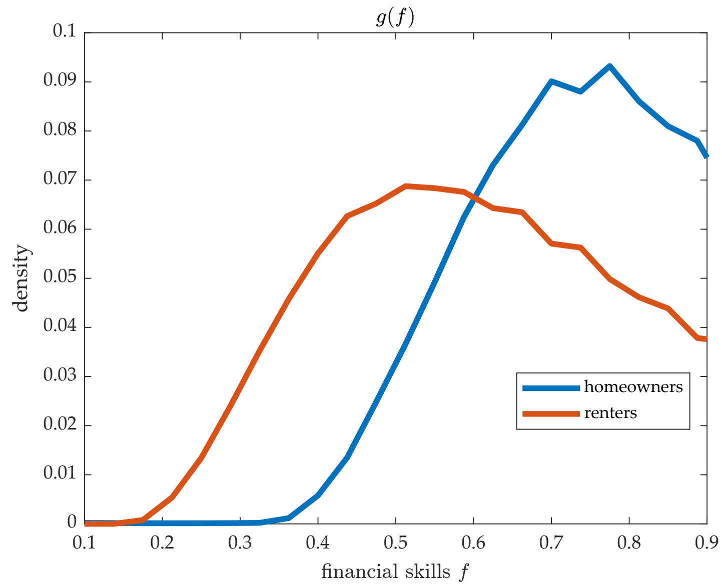

Figure 11: Differences in skill distribution between renters and homeowners.

In the equilibrium, the investment choice exhibits a hump-shaped pattern with respect to the skill level. As shown in Figure 12, an average homeowner invests in skills until a certain skill level. This behavior corresponds to another key pattern we observe in the SCF data (as depicted in Figure 2) - the hump-shaped life-cycle path of individual skills, evident in the SCF data analysis. When interpreted through the lens of our model, skill investment is not as prominent as the homeowner attains a lower interest rate.

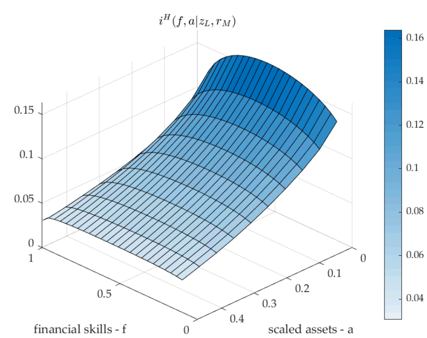

Figure 12: Investment in skill as a function of individual assets and skill level, for the low productive homeowner with an average mortgage rate.

6.1 Mortgage take-up across the skill distribution

Figure 13 presents the variation of search intensity among renters. The heatmap plot illustrates that as financial skills improve, there is an increase in search effort. This trend aligns with the SCF data findings regarding factors that influence homeownership (the estimates from the probabilistic regression model are provided in Table 22). Within the model, individuals within the second tercile of the skill distribution are 17% more likely to opt for a mortgage than are low-skilled renters. Moreover, those in the top tercile of the skill distribution have a 70% higher likelihood of transitioning into homeownership. In contrast, individuals with lower financial skills tend to continue as renters, which affects their available resources and results in reduced consumption.

Conversely, the search intensity plot shows that wealthier renters tend to search less and are more willing to forgo the benefits of lower mortgage payments[13].

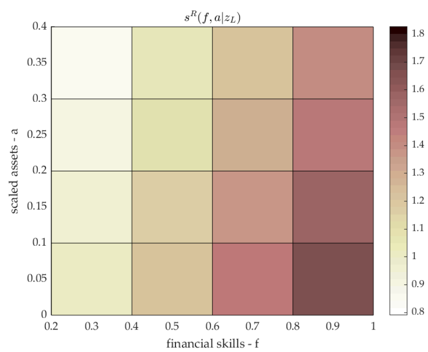

Figure 13: Likelihood to mortgage take-up across financial skills and current mortgage rates for low productive agents and average assets. Likelihood is depicted relative to the least financially skilled.

6.2 Mortgage rate differences among homeowners

In the model, housing cost heterogeneity among homeowners boils down to mortgage payment differences. Figure 14 depicts differences in locked-in mortgage rates between low- and high- skilled borrowers. Low-skilled borrowers search less and borrow at rates as-good-as random, pertaining to the exogenous random draw (represented with a purple histogram in Figure 14). On the other hand, high-skilled borrowers sample more from the offer rate distribution, ultimately landing at better rates

[13]Comparing monthly housing ratios among similar households in the SCF data reveals higher rental rates in comparison to mortgage payments. Admittedly, our model may overstate the rent-to-mortgage payment ratio

(the green histogram in Figure 14). Our model successfully generates a mortgage rate dispersion that decreases as financial skills increase, which aligns with the findings from our NSMO data[14].

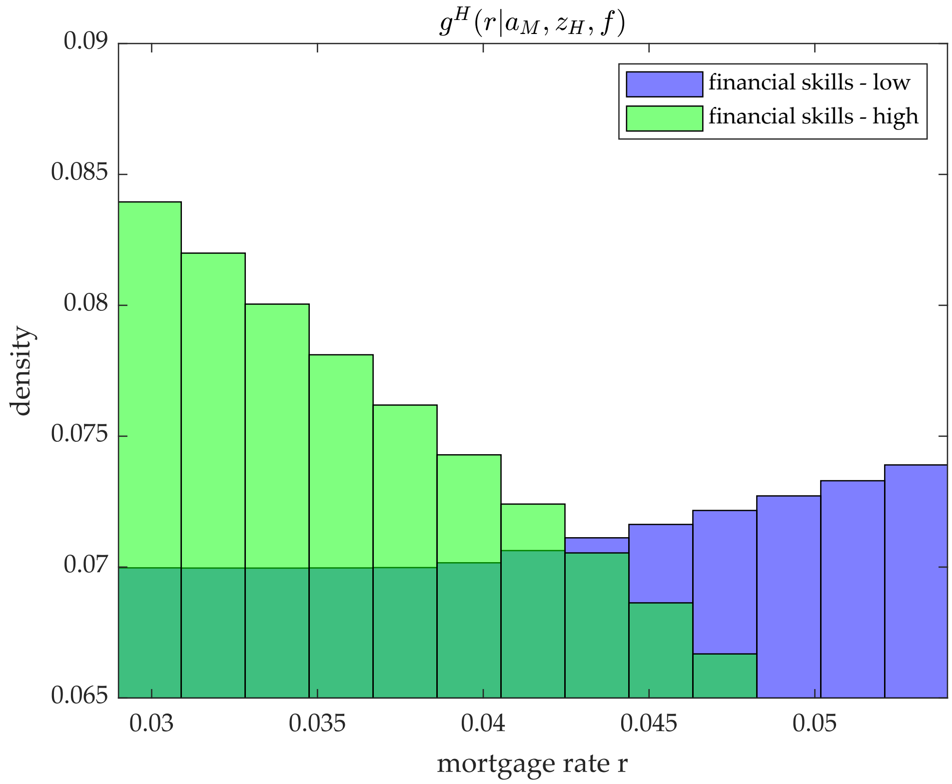

Figure 14: Distribution of low- and high-skilled homeowners across mortgage rates.

In our model, refinancing matches one-to-one with search intensity. That is, we evaluate the expression

$$\mathbb{P}_{\text{ref}}(s) = 1 - \exp(-\lambda s),$$

corresponding to individual refinancing probability. Among homeowners, refinancing activity depends on individual assets and current mortgage rates. Figure 15 shows that search intensity (i.e., refinancing activity) increases with financial skills and mortgage rates, consistent with the evidence from the SCF (regression Table 20 of the Appendix). Our model's predictions indicate that high-skilled borrowers are 30% more likely to search for and refinance their mortgages. Additionally, housing costs contribute to a 10% increase in the overall likelihood of refinancing, which aligns with the

[14]Our novel dataset shows a consistently positive spread differences between the top and bottom skill terciles throughout the sample duration.

prediction differences observed in the SCF data (Figure 3).

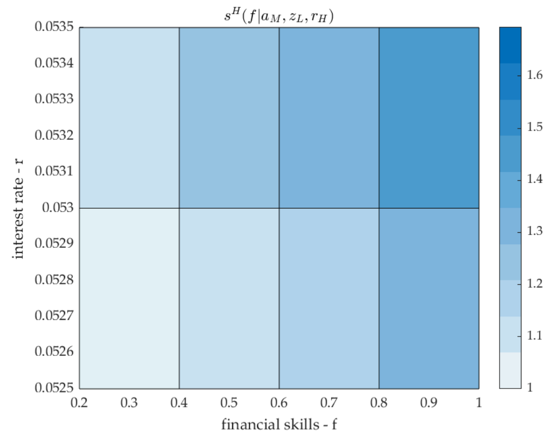

Figure 15: Likelihood to refinance across financial skills and current mortgage rates for low productive agents and average assets. Likelihood depicted relative to the least financially skilled.

Focusing on variation in refinancing activity across the asset-skill distribution, we observe a decrease in search for refinancing options as asset holdings increase 16. Wealthier homeowners are less constrained by housing costs, and are less willing to forego refinancing opportunities.

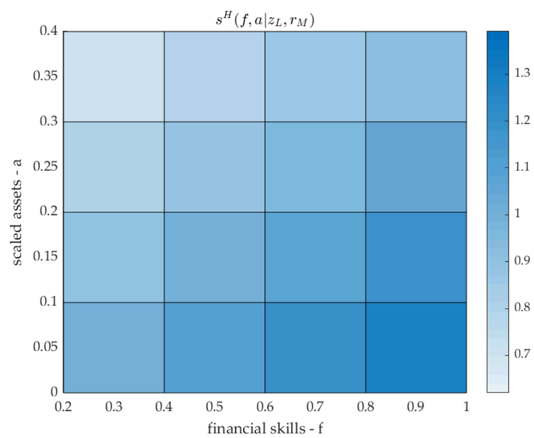

Figure 16: Likelihood to refinance across financial skills and assets for low productive borrowers with an average mortgage rate. Likelihood is depicted relative to the least financially skilled.

6.2.1 Mortgage rate dispersion decomposed

To gain a more comprehensive understanding of mortgage rate dispersion in the model, we perform a variance decomposition across all dimensions of agent heterogeneity. First, we regress the mortgage rate on individual skills, assets, search intensity, and productivity to evaluate the model's performance recreating the correlation signs we observe in our novel dataset. Next, we decompose the variance in the mortgage rate to identify the contributions of each dimension of heterogeneity.

Rather than regressing the resulting interest rate, we regress a linear transformation $\log(1+r)$ on sources of individual heterogeneity, namely assets a, productivity z, search intensity s and financial skills f. To make these estimates parallel to the merged data estimates, we account for the interaction term between search intensity and skill level. We estimate the regression equation

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

using the calibrated model, and we use weights derived from the steady-state distribution of the model. Keeping in mind that our model considers fairly similar borrowers in search of a basic mortgage product, the mortgage rate variation aligns with that in our data analysis, represented by yearly average rates for fixed loan amounts, as shown in Figure 6.

Table 10: The regression results for calibrated model weighted by the steady state distribution.

	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 × 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 for better interpretability.

The linear regression estimates presented in Table 10 show that our model outcome aligns with the interest rate regression we obtain from the merged dataset, with coefficients that are consistent with those outlined in Table 7. Specifically, individual productivity (income) has a positive correlation with the mortgage rate, while skill and search show correlations with opposite signs: skills correlate negatively (regr. coefficient -0.0033), and search effort correlates positively (with a regr. coefficient 0.0884).

Given that financially skilled borrowers face lower search costs, they tend to refinance more frequently, and to lock in at lower mortgage rates. This corresponds to the negative correlation we observe, and to a regression coefficient of -0.0033. Moreover, borrowers with greater wealth might be less motivated to refinance often, as indicated by the modest yet positive asset regression coefficient (0.0021). The main regression Table 7 supports this, showing a positive coefficient for total borrower income. Accordingly, in the model, individuals with higher productivity and wealth are less susceptible to mortgage repayment effects.

Most importantly, the regression estimates show that our model performs well in capturing the *effective search* phenomenon discussed in the empirical part of our study. Notably, there is a positive correlation between search intensity and individual lock-in rate (with a coefficient estimate 0.0884), indicative of the efforts made by individuals with lower skill levels to secure mortgages, even at the cost of accepting higher rates. In contrast, skilled borrowers search more effectively, meet more lenders, and tend to lock in lower mortgage rates. This distinction is quantified by the coefficient estimate of -0.0600. Consequently, our model effectively captures and reproduces the significant patterns governing individual mortgage rate attainment.

As mortgage rate dispersion in the model corresponds to the data-driven dispersion, which accounts for mortgage controls (represented with density plot in Figure 7, for example), model-based variance decomposition depicts the strength of each of the heterogeneity dimensions in explaining mortgage rate attainment.

Table 11 shows that most of the difference in rate attainment lies in search effort heterogeneity, at 55% and 10% of the variance, respectively. Search intensity accounts for the relatively higher rates among the financially unskilled who aim to secure any type of mortgage (positive slope β_s in regression Table 10) and lower rates among financially savvy borrowers who search for refinancing (negative interaction coefficient $\beta_{f\times s}$). Skills alone explain 1.3% of the variation, corresponding to small

Table 11: Mortgage rate variance decomposition across all sources of heterogeneity in the mortgage search model.

	explained variance share
Financial skills (f)	1.2877%
Assets (a)	0.3291%
Productivity: (z_H)	0.0480%
Search intensity (s)	55.2445%
Financial skills $\times$ search intensity ($f \times s$)	9.8865%

and significant regression estimates in the data. Overall, the model-implied link between search effort and levels of financial skill further reinforces the effective search mechanism, which plays a key role in explaining the residual dispersion of mortgage rates in our data analysis.

6.3 Delinquency rate

We assume that expense shock probability (i.e., the delinquency rate) decreases with individual skills and assets (depicted by equation (6) in the model setup). The average borrower in the economy faces an expense shock probability of 0.02, matching the low number of delinquencies we retrieve from the SCF data. Our model is successful in matching the elasticity of an expense shock to individual financial skills level. Specifically, the model solution suggests that, averaged across assets, getting one more question wrong in the financial literacy tests corresponds to being 39.5% more likely to face expense shocks. Overall, the model prediction of expense shock probability aligns well with our NSMO+ data estimates 9.

6.4 Consumption differences across skills

Our analytical findings reveal that homeowners who repay their mortgages at the best rates exhibit the strongest precautionary motive in response to the positive probability of an expense shock, thereby influencing their consumption growth (31). In line with this, individuals who search the most and secure the best mortgage rates (as is evident from the likelihood comparison in Figure 15) are highly skilled borrowers with strong precautionary motives due to possible expense shocks. Figure 18 showcases consumption differences across financial skills levels, within each asset quartile. Consistent with our analytical results, these consumption disparities decrease as assets increase, signaling the impact

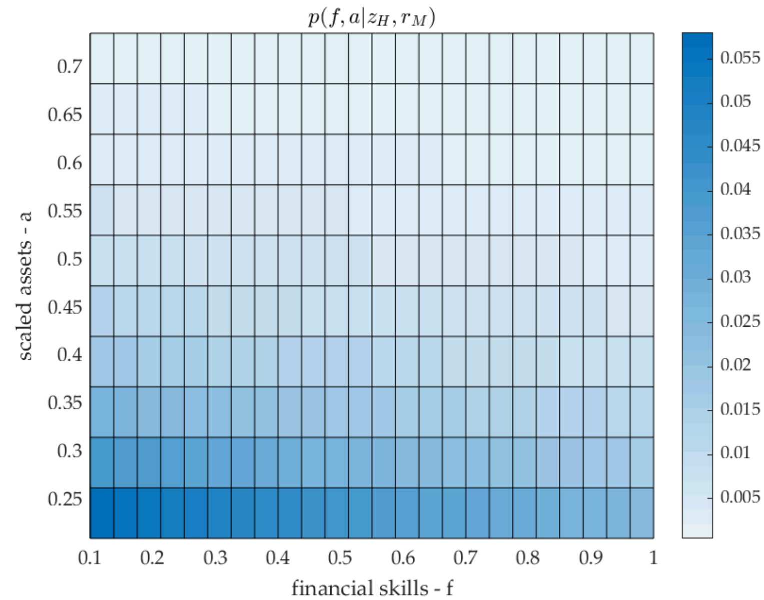

Figure 17: Probability of shock for high productive agents with med-sized mortgage payments.

of precaution among wealthier borrowers.

The most significant skill-based difference in consumption appears at the bottom of the asset distribution, primarily due to the heterogeneity in housing costs (illustrated by the leftmost bar plot in Figure 18). Specifically, financially savvy individuals at the lower end of the asset distribution are more likely to take up mortgages and face lower housing costs, leading to notable consumption disparities.

Ultimately, variation in liquidity among otherwise equal borrowers depends on their search and skill investment choices, speaking to a line of evidence in liquidity differences between financially skilled and unskilled borrowers (Bhutta et al., 2020, 2022; Agarwal et al., 2007). Because these agents are otherwise similar, their effort in adjusting housing costs directly translates to inequality in non-durable consumption and saving opportunities. To mitigate these differences, we render our model as a fitting laboratory for introducing financial education policy. We incorporate relevant changes in U.S. mortgage attainment over the past ten years, and observe differences in search incentives for different values of mortgage servicing costs.

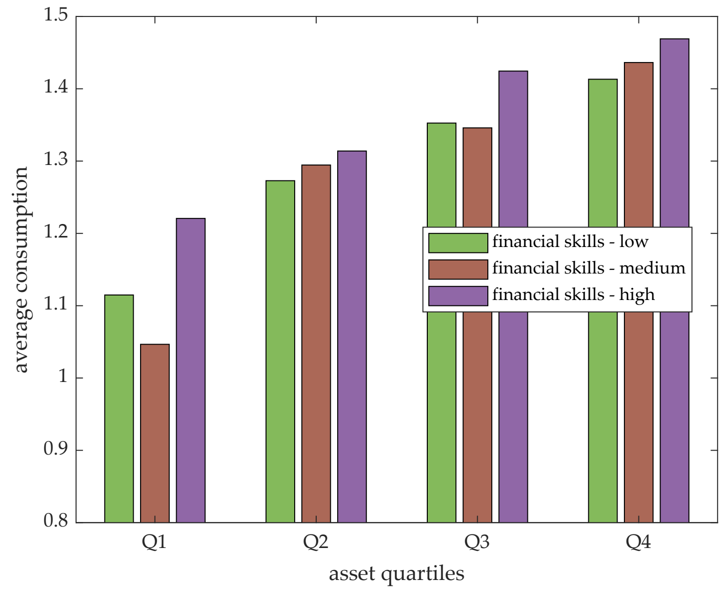

Figure 18: Skill-based consumption differences, within each asset quartile.

7 Policy implications

In this section, we first tackle the adverse effects of skills on liquidity among similar borrowers, and introduce financial education as a potential remedy in our model. Second, we conduct a counterfactual excercise with more accessible mortgages, mirroring increasing entry of non-bank lenders into the market. When mortgages are easily attainable, search is cheaper, and the incentives to accumulate skills are relatively lower. Therefore, the skill-based gap between mortgage rates becomes even more prominent.

While both mortgage attainability and financial education policy enhance arrival rates of mortgages, financial education does so through stimulating individual search intensity. Moreover, education-driven increases in average skills implies a decrease in delinquency rates. On the other hand, the extension of our second experiment suggests that increased mortgage accessibility is more accommodating for financial education policy. With accessible mortgages, lower search and skill investment costs jointly reinforce skills accumulation incentives. Given that loan-level data studies indicate persistence of mortgage price differentiation based on search behavior and financial sophistication (Fuster et al., 2019; Bartlett et al., 2022), our policy tests call for an extension beyond a partial equilibrium setting.

In our last exercise, we investigate the difference in mortgage take-up and refinancing for two different interest rate levels. Our findings reinforce model validity, even when we move away from data used for calibration purposes. We find that the low mortgage rate environment benefits homeowners because they engage in refinancing more often. There is also a small increase in total homeownership, corresponding to the steeper increase in refinancing during the low interest rate period at the onset of the COVID pandemic in the U.S.[15]. In the high-rate environment, homeowners tend to remain at their initial lock-in rates, while renters do not exhibit a significant change in mortgage take-up. To that extent, the high-rate environment depicts lower consumption disparity due to decreases in the gap between rental and housing costs.

7.1 Introducing financial education

We introduce a financial education policy by changing the quality of financial education for renters, through a decrease in investment cost elasticity. Reducing the cost elasticity by 5% effectively reduces the average work time by 0.01%. We interpret financial education as a course for renters that takes 90 minutes out of their working hours[16]. This policy targets young households before their home purchase, and is comprised of more than mortgage undertaking courses. In the model, financial skills affect individual financial shock probability, so higher investments contribute to mortgage performance that is affected by financial distress not related to the mortgage.

Overall, homeownership rate increases by 1.5%, owing to an increase in average search intensity among renters (by 0.4%, Table 12). New homeowners lock in at higher mortgage rates that still imply lower housing costs than the rental rate, thereby consuming and saving more, propagating a decrease in consumption and assets inequality. Moreover, higher financial skills reduce the average delinquency rate by 2.8%, substantiating the increase in welfare.

Table 12: Introducing financial education with renters, source: model simulations.

Measure	relative change
average search renters	$\nearrow 0.4\%$
consumption Gini	$\searrow 1.4\%$
assets Gini	$\searrow 1.3\%$
share of homeowners	$\nearrow 1.6\%$
average financial skills	$\nearrow 9\%$
average delinquency rate	$\searrow 2.8$

[15] https://libertystreeteconomics.newyorkfed.org/2023/05/the-great-pandemic-mortgage-refinance-boom/
[16] We calculate this cost based on a standard working week of 40 hours without any time off.

7.2 Increase in mortgage accessibility

Our second exercise mirrors the entrance of non-bank mortgage lenders in the U.S. mortgage market. In this counterfactual, we reduce the search cost elasticity parameter that directly affects the search effort needed to obtain a larger sample from the pool of mortgage offers.

Table 13 outlines the relative difference between the benchmark and higher accessibility counterfactual. The first line in Table 13 shows that the average search of homeowners increases by 16.9%, whereas renters search 7.8% more intensively. Taking up a mortgage lowers housing costs, and together with intensified refinancing, decreases consumption inequality by 3% (Table 13). As less savvy borrowers become homeowners, they are exposed to financial shock, implying an increase in average delinquencies by 1.7%. Lower search costs do not incentivize skills accumulation, and skills increase only by 1.1% (Table 13).

Table 13: Increase in mortgage accessibility, source: model simulations.

Measure	relative change
average search renters	$\nearrow$ 7.8%
average search homeowners	$\nearrow$ 16.9%
consumption Gini	$\searrow$ 3%
assets Gini	$\searrow$ 2.4%
share of homeowners	$\nearrow$ 3.3%
average financial skills	$\nearrow$ 1.1%
average delinquency rate	$\nearrow$ 1.7%.

Search cost reduction does not instigate financial skill accumulation. We show that introducing financial education helps to mitigate the increase in delinquency rates that results from highly attainable mortgages. Table 14 compares the resulting relative change between the accessible benchmark with and without financial education. Introducing education incentivizes skill accumulation, increasing average skills by 0.3 p.p. more than in the benchmark education exercise, ultimately averaging at 9.3% (Table 14, right column). Moreover, delinquency rates decrease by 2.7%, weakening the effect of low-skilled homeowners entering the market (Table 14, right column, last row). In this regard, financial education decreases current and potential future consumption disparity among otherwise similar borrowers. Our analysis suggests that the current increases in mortgage availability in the U.S. represents a solid ground for introducing financial education policies.

Table 14: Financial education policy with accessible mortgages. Source: model simulations.

Measure	Accessibility	Fin. education, competitive benchmark
average search renters	$\nearrow$ 7.8%	$\nearrow$ 0.4%
average search homeowners	$\nearrow$ 16.9%	$\nearrow$ 2.6%
consumption Gini	$\searrow$ 3%	$\searrow$ 1.5%
assets Gini	$\searrow$ 2.4%	$\searrow$ 1.3%
share of homeowners	$\nearrow$ 3.3.%	$\nearrow$ 1.5%
average financial skills	$\nearrow$ 1.1%	$\nearrow$ 9.3%
average delinquency rate	$\nearrow$ 1.7%	$\searrow$ 2.7%

7.3 Exogenous change in the mortgage repayment level - implications for inequality

In our third experiment, we contrast the baseline steady-state with two distinct mortgage rate scenarios in terms of their effects on consumption inequality patterns. Without an explicit representation of the supply side (a topic we investigate in a separate paper), we introduce external shifts in the average mortgage repayment, representing mortgage policies that affect all borrowers equally. We leverage the adaptability inherent in the Beta distribution, assuming both a downward and an upward shift in the mean offer rate.

To derive parameters for the new Beta distribution, we maintain the calibrated model's offer distribution spread and compute parameters that align with the new mean. In the initial case, we compare the baseline with a lower average rate scenario, signifying a leftward shift (as shown in Figure 19). Quantitatively, this corresponds to a decrease of 20 basis points in the mean of the offer distribution. The parameters for the new offer distribution, characterized by the lowered mean when we retain the same spread as the baseline offer distribution, are $\alpha^{low-i.r.} = 5.1016$ and $\beta^{low-i.r.} = 6.7629$.

Table 15: Comparison of the baseline with a downward shift in the offer rate. Source: model simulations.

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

Table 15 showcases the relative differences in key model metrics, encompassing search intensity by homeowners and renters, Gini coefficients, and financial skills. In the low-rate scenario, a signifi-

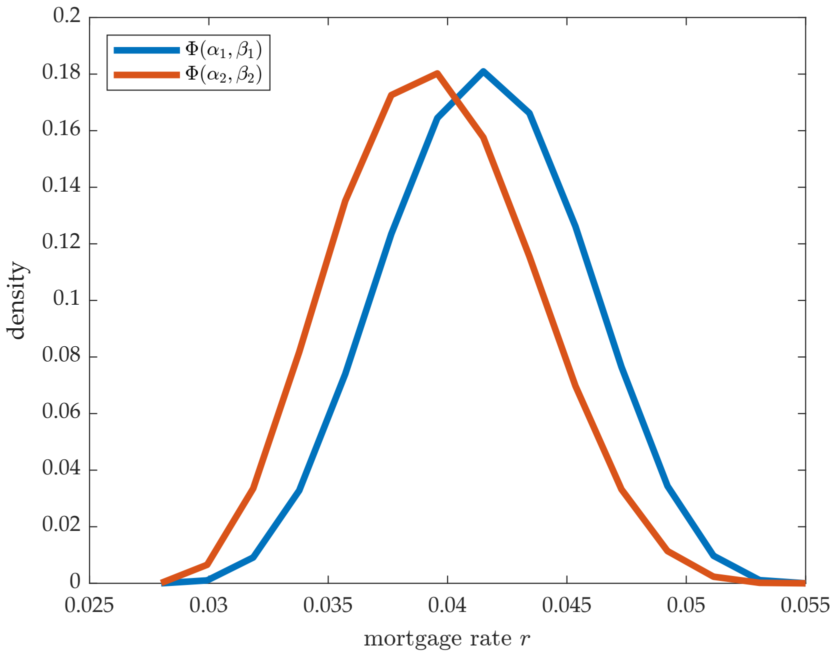

Figure 19: Original and left-shifted distribution of the offer rate.

cant variance arises in homeowners' search intensity, reaching 60% higher than the benchmark value. Homeowners opt to forgo search costs and capitalize on the advantages of securing lower rates that lead to reduced housing expenses. In contrast, renters do not engage in skill accumulation due to the persistence of search costs. Ultimately, the downward shift in mortgage payments is linked primarily to existing homeowners, exacerbating the disparity in consumption levels between renters and homeowners. This outcome is reflected in the relative difference of 1.4% and 1.1% in the consumption and asset Gini coefficients, respectively. Across all measures of comparison, lower mortgage payments perpetuate skill-based inequality.[17].

Table 16: Comparison of the baseline equilibrium with the equilibrium with a higher mean of the offer distribution. Source: model simulations.

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	$\searrow 0.6\%$

[17] Admittedly, without modeling the general equilibrium effects, we keep the rental rate fixed.

Next, we compare our benchmark with an exogenous upward shift, and implement an average offer rate 10 b.p higher than the baseline. Table 16 presents relative differences in our model metrics. As housing costs flatten out across the skill distribution, consumption inequality falls relatively lower in relation to the benchmark (-5.6% depicted in the Table 16). Search disincentives kick in mostly among homeowners, depicted by the relative fall in search intensity of more than 36%. Similar to the downward shift, renters' search effort does not change significantly (-0.7% depicted in Table 16).

Figure 20 presents the difference in non-durable consumption inequality. We compare Lorenz Curves for non-durable consumption across baseline, upward, and downward shift scenarios. Higher mortgage payments bring skill-based housing cost differences closer together, flattening non-durable consumption across households (depicted with a red curve in Figure 20). On the other hand, a lower repayment scenario yields an outward shift from perfect equality, (depicted with a green curve in Figure 20), which reflects the advantages of current homeowners. In this scenario, the low incentives for financial skills accumulation speaks to low-skilled mortgage take-up.

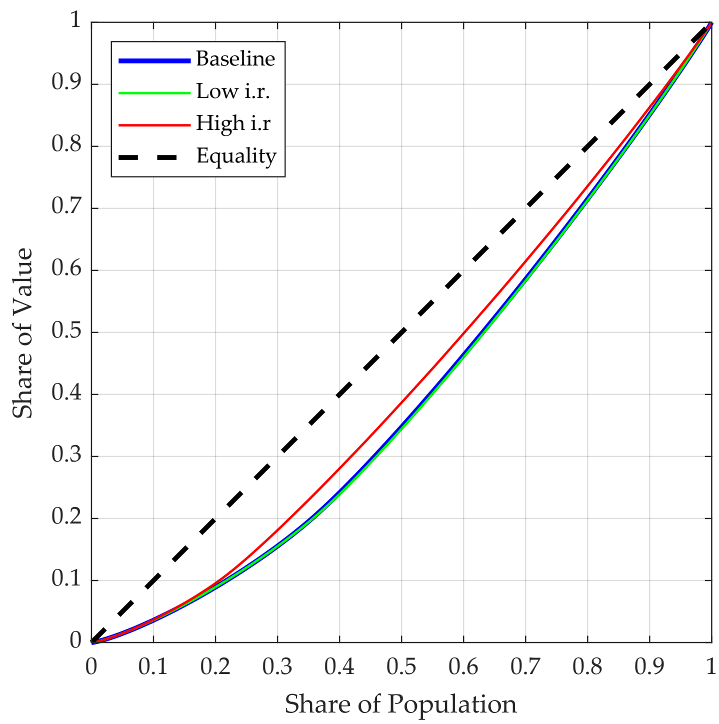

Figure 20: Lorenz Curves comparison between baseline and the exogenous upward and downward shift in the offer rate. Source: model simulations.

8 Conclusions

In the past decade, the surge in mortgage accessibility driven by the entry of non-bank lenders has decreased mortgage rate dispersion among comparable borrowers. Nevertheless, disparities linked to individuals' loan shopping behavior and financial skill levels have remained persistent. Our paper quantifies the effect of individual financial skills and search effort in shaping mortgage repayment variation, giving rise to consumption inequality across households.

We implement a two-step approach that leverages new empirical estimates that underscore the presence of variation in mortgage search cost contingent on individual skill level. In our first step, we employ the Bayesian Record Linkage method to retrieve a unique dataset that encompasses individual mortgage specifics along with an objective metric of borrowers' financial literacy. Our new data analysis allows us to gauge the potential of individual search behavior and financial literacy levels to explain residual mortgage dispersion between comparable borrowers in search of similar mortgages. Along these lines, our paper sheds new insights on the importance of individual financial skills for mortgage repayments and corresponding effects on long-term consumption heterogeneity.

Our back-of-the-envelope calculations suggest that, for $100,000 loan, financially unskilled borrowers end up overpaying approximately $10,000 throughout the mortgage term, compared to their savvy counterparts. Added to this, we argue that financial skills-related losses persist over the mortgage duration. Specifically, we find a notable increase of 35% - 45% higher likelihood in mortgage delinquency rates among unskilled borrowers, suggesting additional losses in delinquency fees. Moreover, with a decrease of up to 30% in the likelihood of refinancing, financially unskilled households often face persistent over-payment costs. Our set of new findings underscores the importance of financial skills as a dimension of household heterogeneity, one closely linked to borrowers' financial flexibility and consumption patterns.

Our second step implements a continuous-time heterogeneous agents model with a micro-founded mortgage search framework. Within this framework, agents accumulate financial skills and exert effort endogenously during the mortgage acquisition process. Exerting effort delivers utility costs that systematically vary with financial skill level. Current borrowers can engage in a costly search and refinance their mortgages to lower their mortgage repayments. In the steady state, individual consumption growth depends on individual skills and assets, and is shaped by expected future mortgage rates and the need for precautionary savings for unexpected expenses. The steady state distinguishes between renters and homeowners, defining the joint distribution of mortgage rates, assets, skills, and productivity within the borrower group. Validity tests confirm the model's accuracy in reproducing consumption inequality using out-of-sample consumption data. The model indicates that search behavior and skills significantly contribute to determining mortgage rates among comparable borrowers, explaining 55% and 10% of the lock-in rate variation.

We employ our model as a controlled environment and conduct a series of three experiments: introducing financial education, enhancing mortgage availability, and comparing various mean mortgage rate scenarios. Our first experiment uses the baseline framework, and shows that financial education stimulates skill accumulation and results in a modest relative increase in search effort among renters, ultimately yielding an elevated homeownership rate. New homeowners exhibit higher financial proficiency; they allocate fewer resources to mortgage servicing, and thereby contribute to decreased consumption inequality and a lower delinquency rate.

Our second test introduces increased mortgage availability, reflecting digital advancements in the U.S. mortgage market. We show that financial education reinforces skill accumulation and decreases the delinquency rate, mitigating the adverse effects of mortgage take-up among low-skilled borrowers. Mortgage accessibility effectively flattens out search costs across the skill distribution, showing negligible effects on skill accumulation. New mortgage owners are less financially savvy, and thus are more likely to face expense shocks, ultimately leading to higher delinquency rates. We show that, with increased availability, financial education delivers a relatively higher skill level. In this regard, financial education accommodates growing trends in credit availability.

In our final experiment, we contrast two mean mortgage rate scenarios, holding the dispersion of mortgage offers constant. This approach accommodates the external shift in mean mortgage rates, encompassing mortgage relief policies that reduce payments for all existing borrowers. The scenario with lower rates benefits current homeowners, thereby intensifying the divergence in consumption levels between homeowners and renters. Within this context, the persistent presence of search costs leads to renters continuing to rent, forfeiting the advantages of comparatively lower mortgage payments. With lower mean rates, skill-based differences reflected in mortgage take-up yield relatively higher consumption inequality. In contrast, the high-rate scenario closes the gap between rental and mortgage repayments, decreasing consumption inequality.

Backed by our current findings, our ongoing work includes the model extension to general equilibrium. A richer set of sources of household heterogeneity and careful outline of the mortgage supply can yield insights into market responses to financial education and monetary policy.

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A Motivating Findings From SCE

Motivating findings based on the data from the U.S. Survey of Consumer Expectations. Figure 21 shows that the largest mass of non-informed households is from the lowest income group. Moreover, the figure shows that the mass of non-informed households decreases with higher income. Figure 22 shows that households from the lowest income group have the highest debt to income ratios. In addition, Figure 23 shows that the largest shares of highest debt to income ratios are in the lowest part of the income distribution. The findings from these figures imply that most exposed households are those that are the least informed about credit possibilities.

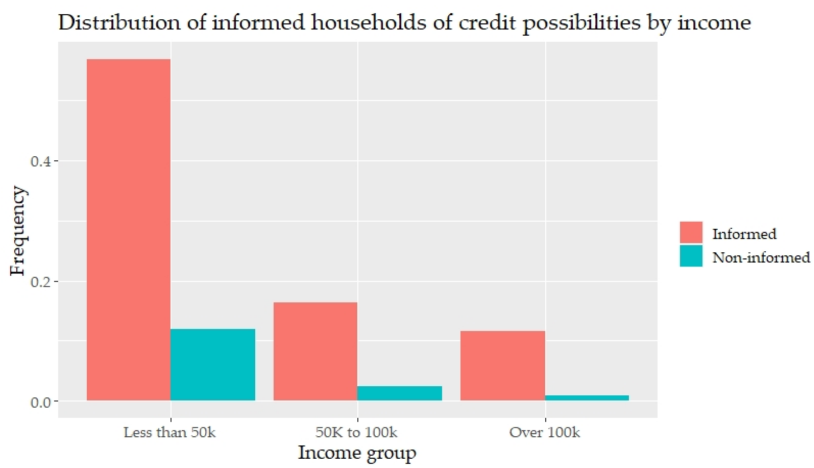


Figure 21: Share of non-informed households by income group. Source: SCE, authors' calculation.

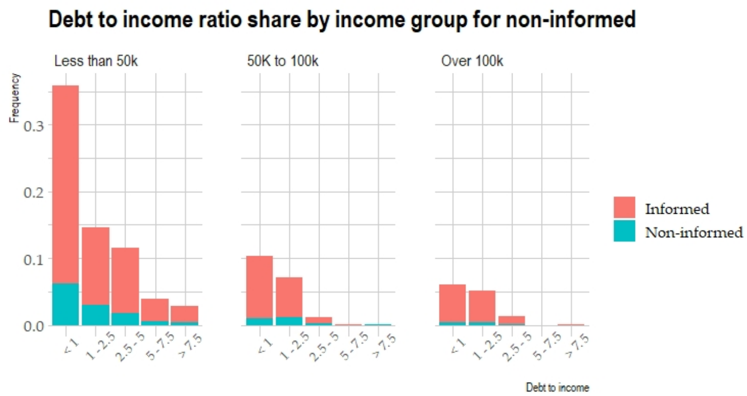


Figure 22: Share of non-informed households for each debt to income level over the income distribution. Source: SCE, authors' calculation.

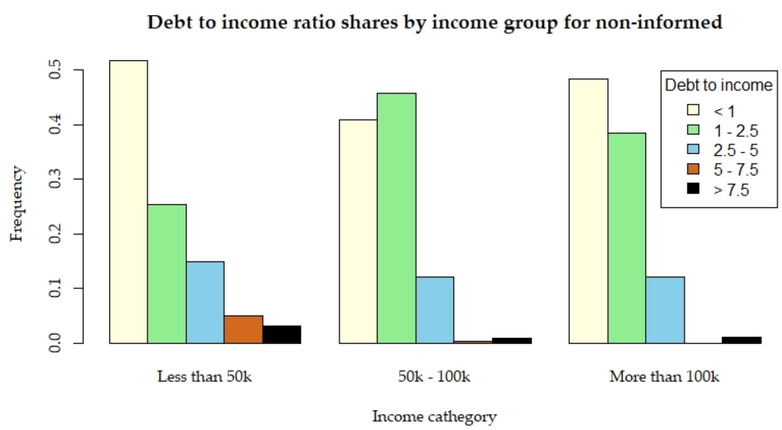


Figure 23: Debt to income ratio distributions for each income group. Source: SCE, authors' calculation.

B The NSMO (2013-2020) analysis

The data on mortgages in the NSMO data range from 2013 to 2021, and tracks mortgages originated during the 2013-2020 period. Households were chosen at random to report the specifics of their mortgage contracts, reasons, and experiences. Details about mortgage origination, combined with demographic characteristics, allow us to estimate the effect of borrowers' characteristics on the acquired mortgage interest rate, controlling for mortgage specifics. First, we consider respondents' attitudes toward the mortgage market and their beliefs about the appropriateness of their lender selection. Second, we quantify the correlation between education and search effort variation and the mortgage rate attained at origination. Third, we extrapolate financial literacy from the Survey of Consumer Finances to find a link between financial skills and the interest rate obtained after mortgage is locked in.[18]

Interestingly, almost 70% of the borrowers believe that they would be getting the same interest rate regardless of their choice of lender. 86% initiated the contact with the lender themselves. While searching for options, 48% consider only one lender/mortgage broker. Consequently, 77% apply to only one lender. However, the number of lenders considered varies with education level (Figure **??**). Borrowers who apply to multiple lenders usually do so in search of better contract terms.

When refinancing, 88% of borrowers found lower interest rates as a important reason to start the process. Moreover, 75% of these borrowers rendered lower monthly payments as equally important. In our paper, the search model conforms to the trade-offs of a homeowner, and assigns lower repayments as the benefit. Figure 24 shows that almost 60 percent of high-skilled borrowers consider two or more lenders (the right histogram), which holds for lower percentage of low-skilled borrowers (the left histogram). In the paper, we show that financial skills remain significant for search effort, and that one standard deviation increase in skill leads to a four percent increase in the probability of considering more lenders.

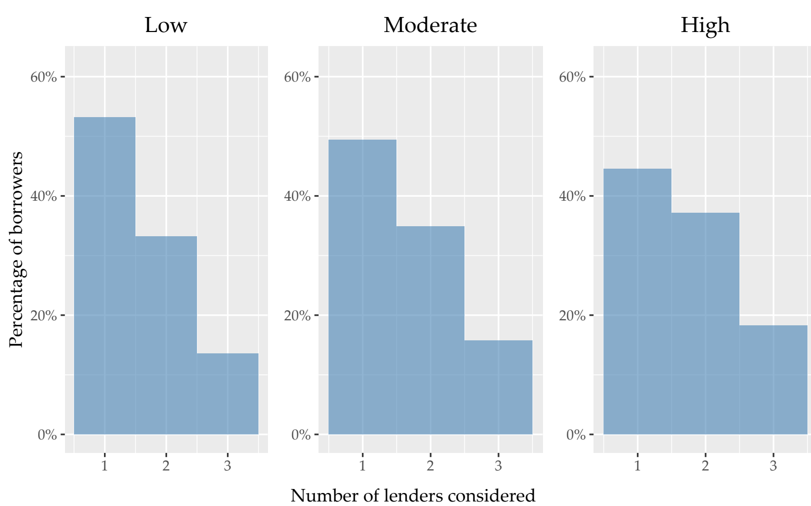


Figure 24: Number of lenders considered by financial skills tercile. Source: merged data set, authors' calculations.

[18]Because we are the first to match the NSMO and the SCF to impute financial literacy scores in the NSMO, the imputation details are in the main part of the paper.

Our latter findings suggest that education and effort simultaneously affect the mortgage interest rate. Using NSMO data only, we control for individual and loan characteristics to support our findings in the merged data set, as financial literacy exhibits strong, but not perfect correlation with education.

B.1 Mortgage rate regressions

Mortgage interest rates are comprised of two components: PMMS determined by the borrower's characteristics[19] and the rate spread assigned to each borrower at origination. Combining the two yields the mortgage interest rate, which is the dependent variable in the analysis.

Because nearly half of all reported mortgages are for refinancing, we estimate the linear regression separately. Both estimations control for loan-sponsorship types, guarantor enterprises (Fannie Mae, Freddie Mac, or Federal Home Loan Bank), loan amount, metropolitan (low-to-moderate) area, time effects, and the number of borrowers. The rate under refinance estimates control for non cash-out loans.

The variation in search efficacy with education is represented by interaction coefficients. Controlling for other demographic factors, we find that highly educated borrowers who shop around for loans get significantly lower interest rates. Given that we employ a novel measure that includes both cognitive and effort costs, our estimates account for a unprecedented part of the interest rate dispersion (Table 17, highlighted). All interaction coefficients are statistically significant and pass difference tests.

Model predictions allow us to calculate the present value of the difference in mortgage payments over the duration of a mortgage. We think of the payment difference as the additional costs low-educated and low-shopping behavior borrowers pay. For a 30-year loan at $200,000, high-school graduates pay on average at the 4.43% rate, whereas post-college graduates get 4.26%. The mortgage spread implies $9900 mortgage payment difference over the duration of the mortgage. Keeping education fixed, search effort induces the mortgage spread of 8 b.p. and implies an additional $7500 in mortgage payments, on top of education differences. These estimates serve as a lower bound for mortgage payment losses in the market, as they abstract from additional correlations that substantiate search effort or mortgage process knowledge.

Our predicted rate plots (Figure 25) show that searches are most effective for highly educated

[19] Freddie Mac's Primary Mortgage Market Survey® (PMMS®) surveys lenders each week on rates and points for their most popular 30-year fixed-rate, 15-year fixed-rate and other mortgage products.

borrowers, as the predicted interest rate density moves to the left. On the other hand, those low-educated borrowers who search more do so due to the fear of rejection. All plots show that controlling for other characteristics still leaves the residual spread that borrowers face, based on their education.

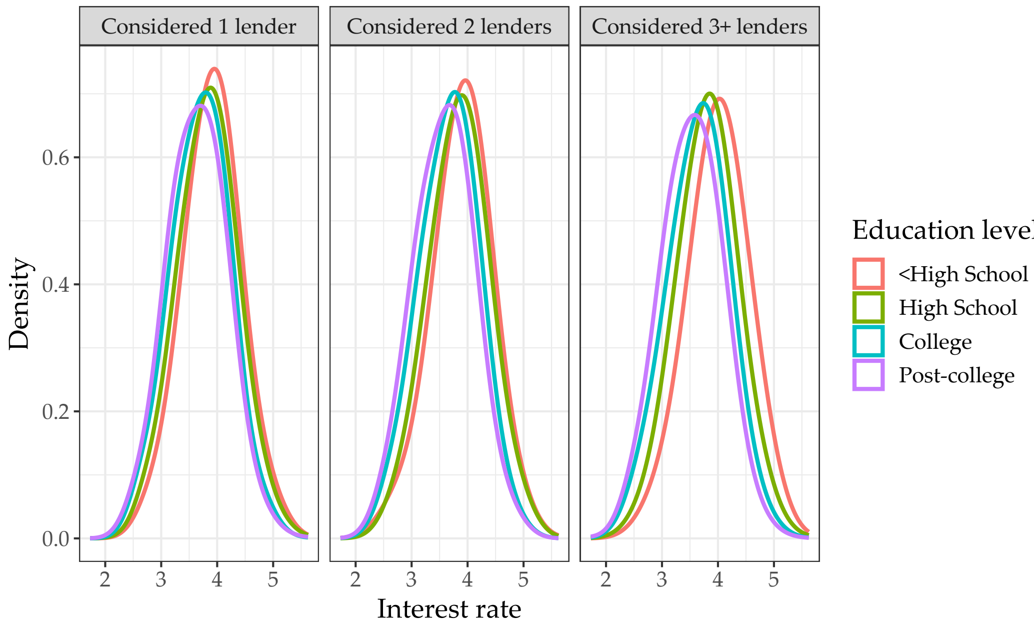


Figure 25: Predicted interest rate by education type. Each plot represents a separate case for the number of lenders considered in the mortgage process. Regression predictions, NSMO.

B.2 Education effects in mortgage search

Because the mortgage interest rate varies with search effort, we investigate borrower characteristics that affect the amount of search borrowers are willing to take on. Controlling for loan characteristics, ordered logistic model estimates show that college and post-college graduates are 50% and 65% more likely to search more (Table 18). On the other hand, women and financially inexperienced search less. Both of these characteristics are highly correlated with financial literacy in the SCF data and this strand of literature (Lusardi et al., 2010; Lusardi and Mitchell, 2014; Lusardi, 2019).

B.3 What agents are most likely to default on mortgage

The NSMO dataset allows us to track mortgage performance after origination. In the main part of the paper, we show that financially skilled borrowers are 50% more likely to meet the due date of their

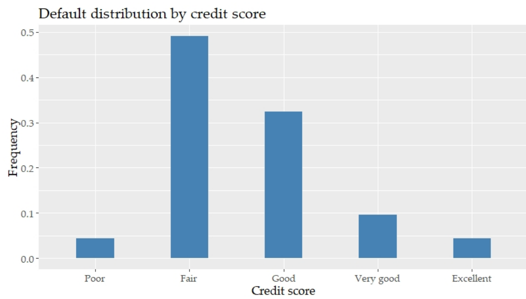
Table 17: Interest rate upon origination and under refinancing, explanatory characteristics, NSMO data.

	mortgage rate	
	(first origination)	(under refinancing)
Age	0.043***	0.076***
	(0.010)	(0.010)
Female	0.033***	0.033***
	(0.009)	(0.008)
Race: African-American	−0.005	0.026
	(0.019)	(0.018)
Asian	−0.020	−0.049***
	(0.020)	(0.017)
Other	0.068***	0.012
	(0.025)	(0.023)
Income: $30,000 - $50,000	0.008	−0.107***
	(0.024)	(0.024)
$50,000 - $75,000	0.034	−0.082***
	(0.023)	(0.022)
$75,000 - $100,000	0.031	−0.064***
	(0.024)	(0.023)
$100,000 - $175,000	0.061**	−0.063***
	(0.024)	(0.023)
$175,000 or more	0.050*	−0.063**
	(0.026)	(0.025)
Credit Score	−0.264***	−0.218***
	(0.010)	(0.009)
Loan term	0.024***	0.036***
	(0.001)	(0.001)
Loan-to-Value ratio	0.004***	0.004***
	(0.0004)	(0.0003)
Number of lenders considered: 2 lenders	0.038	−0.014
	(0.030)	(0.027)
3 lenders or more	0.115**	0.053
	(0.047)	(0.038)
Education: Some college	−0.037*	−0.001
	(0.022)	(0.019)
college degree	−0.066***	−0.024
	(0.021)	(0.019)
post-college degree	−0.079***	−0.011
	(0.023)	(0.020)
Interaction: some college; considered 2	−0.028	0.005
	(0.036)	(0.033)
some college; considered 3 or more	−0.130**	−0.102**
	(0.055)	(0.045)
college degree; considered 2	−0.076**	−0.011
	(0.034)	(0.031)
college degree; considered 3 or more	−0.177***	−0.088**
	(0.051)	(0.042)
post-college degree; considered 2	−0.085**	−0.053*
	(0.035)	(0.032)
post-college degree;considered 3 or more	−0.234***	−0.131***
	(0.052)	(0.043)
Constant	5.256***	4.578***
	(0.081)	(0.070)
Observations	21,469	21,625
R^2	0.370	0.466
Residual Std. Error	23.650 (df = 21417)	20.678 (df = 21572)
F Statistic	246.159*** (df = 51; 21417)	362.082*** (df = 52; 21572)
Note: Other regressors are stated in the text.		*p<0.1; **p<0.05; ***p<0.01

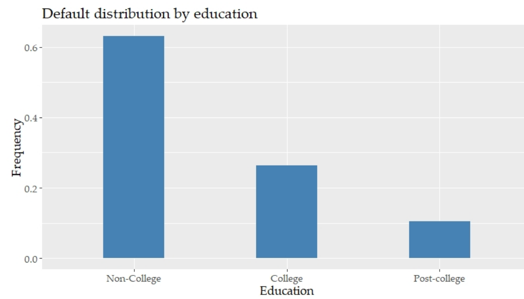
Table 18: Ordered logistic regression results

	Dependent variable:	
	Number of lenders considered	
	(all originations)	(under refinancing)
Income: \$35,000-\$50,000	-0.018	-0.013
	(0.053)	(0.077)
\$50,000-\$75,0000	-0.024	-0.034
	(0.050)	(0.071)
\$75,000-\$100,000	-0.024	-0.070
	(0.051)	(0.073)
\$100,000-\$175,000	-0.054	-0.157^{**}
	(0.051)	(0.074)
\$175,000 or more	-0.090	-0.162^{**}
	(0.056)	(0.081)
Education: some college	0.267^{***}	0.263^{***}
	(0.035)	(0.049)
college degree	0.408^{***}	0.383^{***}
	(0.035)	(0.048)
post-college degree	0.501^{***}	0.431^{***}
	(0.036)	(0.051)
Female	-0.279^{***}	-0.336^{***}
	(0.019)	(0.027)
Age	-0.177^{***}	-0.040
	(0.019)	(0.030)
Have stocks	-0.097^{***}	-0.103^{***}
	(0.020)	(0.029)
Metro area, low-to-moderate income tract	0.007	-0.036
	(0.029)	(0.041)
Non-metro area	-0.053^{*}	-0.071
	(0.032)	(0.046)
Observations	43,094	21,625
Note: Controlled for time and loan amount effects.		*p<0.1; **p<0.05; ***p<0.01

mortgage payments. Here, we show that low-educated borrowers default more often (Figure 26b).



(a) Default by credit score.



(b) Default by education.

Figure 26: Share of households that default by credit score and education. Source: NSMO, authors' calculation.

The distributions in Figure 26 shows that households that default on a mortgage and face bankruptcy are associated with lower credit scores and lower education. The only exception is those with the lowest credit scores, but household mortgage requests with "Poor" credit score are usually denied.

C SCF data analysis

We use the Bayesian Record Linkage algorithm to impute the financial literacy score from the SCF data into the NSMO data. To begin, we examine the average financial literacy score over the lifecycle to motivate investment in and accumulation of financial skills in the model. Figure 2 shows increasing average financial literacy scores by age groups.

The first model estimates outline correlations between financial literacy and household characteristics. Our predicted probabilities of the ordered logistic model (Table 19) suggest that high-income level households are 12% more likely to be fully financially skilled, keeping other characteristics fixed. Though education explains the largest part of financial literacy, income-based differences relate to financial skills needed to understand the mortgage refinancing process.

Table 19: Financial Literacy Score, relation to observables. Source: SCF data.

	Dependent variable:
	Financial literacy score
Worker	0.041^{*}
	(0.025)
Married	0.111^{***}
	(0.024)
Non-white	-0.392^{***}
	(0.019)
Female	-0.474^{***}
	(0.025)
Education: High-school	0.211^{***}
	(0.031)
Some college	0.599^{***}
	(0.031)
College degree	1.123^{***}
	(0.033)
Income percentile: 20^{th} - 40^{th}	0.049^{*}
	(0.028)
40^{th} - 60^{th} 3	0.073^{**}
	(0.031)
60^{th} - 80^{th}	0.179^{***}
	(0.035)
80^{th} - 90^{th}	0.349^{***}
	(0.043)
90^{th} - 100^{th}	0.649^{***}
	(0.048)
Observations	60,125
Note: Controlling for age and asset amount.	*p<0.1; **p<0.05; ***p<0.01

Next, we restrict the SCF sample to borrowers who hold a mortgage on their primary residence and estimate a binary regression model to evaluate their likelihood of refinancing. The estimates pinpoint vital characteristics that explain a household's effort in shopping for credit.

Controlling for income and mortgage size, we find significant and large effects of financial literacy - a high financial literacy score relates to a 60% higher likelihood of refinancing. In contrast, education effects are insignificant (Table 20). Our analysis supports Lusardi (2019) and highlights the relevance of the financial knowledge margin in the decision to refinance.

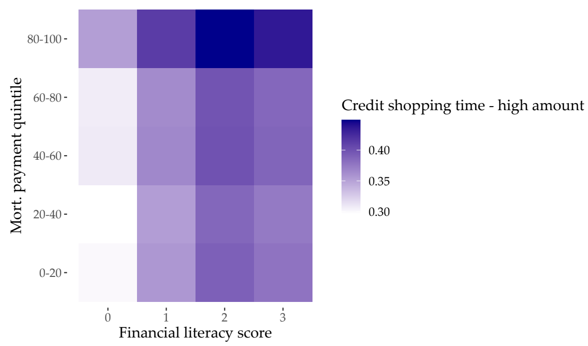
Using the question about the amount of shopping time allocated to borrowing options, we proxy borrower's search effort and find a 12% higher likelihood of refinancing by borrowers who allocate time to exploring borrowing options (Table 20). Further, keeping other characteristics fixed, financial knowledge and search effort positively correlate with the decision to refinance. As a result, the mortgage search model with financial skills investment and search effort disentangles the two dimensions relevant to the decision to refinance.

Our estimates on credit shopping behavior emphasize financial skills as an important dimension of heterogeneity (Table 3). While mortgage owners shop more on average, separate analyses for mortgage owners and renters reaches the same conclusion; controlling for individual characteristics, including age, income, and education, financially savvy borrowers spend more time searching for credit.

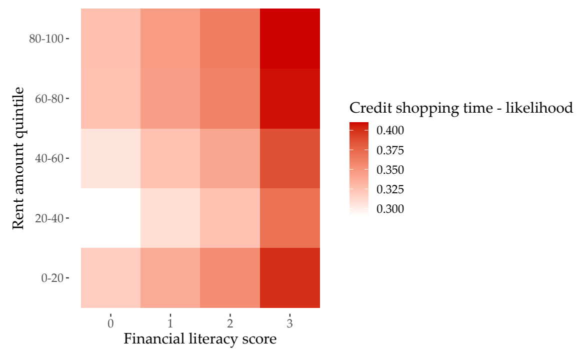
Keeping other characteristic fixed at the mean of each subsample, we plot the likelihood change over financial literacy level and monthly housing expenses. Homeowners are more likely to spend a lot more time shopping for credit than renters. Specifically, financially savvy homeowners are up to 15 p.p. more likely to allocate more time to credit shopping than low-skilled homeowners (Figure 27, left). The difference in likelihood decreases with the size of their mortgage payment. In contrast, renters allocate their time to credit shopping independently of their rent amount, and financially skilled are 10.p.p. more likely to spend a great deal of time in searching for credit (Figure 27, right).

Table 20: Binary regression estimates, likelihood to refinance, SCF data.

	Dependent variable:
	Ever refinanced their mortgage
Financial literacy score: low	0.099
	(0.104)
medium	0.252^{***}
	(0.098)
high	0.400^{***}
	(0.098)
Search effort, borrowing: medium	0.055
	(0.050)
high	0.110^{**}
	(0.052)
Female	0.075
	(0.049)
non-white	-0.247^{***}
	(0.034)
Mortgage size: \$83,000 - \$159,000	-0.148^{***}
	(0.042)
\$159,001 - \$ 297,000	-0.285^{***}
	(0.044)
\$ 297,001 - \$ 1,450,000	-0.304^{***}
	(0.050)
Liquid savings: $\leq$ \$4,500	0.145^{***}
	(0.049)
\$4,500 - \$21,000	- 0.045
	(0.050)
$\geq$\$21,000	-0.017
	(0.051)
Income percentile group: 20^{th}-40^{th}	0.242^{***}
	(0.083)
40^{th}-60^{th}	0.260^{***}
	(0.079)
60^{th}-80^{th}	0.482^{***}
	(0.079)
80^{th}-90^{th}	0.874^{***}
	(0.084)
top 10	1.047^{***}
	(0.085)
Constant	-0.961^{***}
	(0.145)
Observations	22,178
Note: Controlled for age, family structure, education, and survey wave effects.	*p<0.1; **p<0.05; ***p<0.01



(a) Likelihood variation, homeowners.



(b) Likelihood variation, renters.

Figure 27: Great deal of time spent shopping for credit, SCF data. Ord.logit predictions.

C.1 Rent and mortgage payments as shares of labor income

In the model calibration, we inform the rental rate κ with the share of homeowners in the SCF. When compared to an average mortgage monthly payment, rental payments are twice as high. The averages from the SCF data are computed for the subsample of workers up to age 55 with wage income higher than yearly amount of retirement benefits. Sample averages show that monthly rental payments are up to two times higher than monthly mortgage payments.

Living arrangement	Financial literacy score			
	0	1	2	3
Homeowner	0.140	0.139	0.142	0.129
Renter	0.257	0.241	0.233	0.222

Table 21: First row: monthly mortgage payment as a share of income - homeowners, second row: monthly rent as a share of income; renters. SCF data, worker subsample.

C.2 Homeownership choice and financial literacy

Our model assumes that the homeownership choice depends on individual assets, financial skills, and productivity. As a result, the model's equilibrium generates a positive correlation between mortgage take-up and financial skills, which aligns with the similar positive association we observe in the SCF data. Table 22 presents estimates from the logistic regression, where we regress the choice to rent or own against a set of observable characteristics, including skills, assets, and wage income. To maintain consistency with our model, the estimates are derived from a subsample of workers. The first two rows in the coefficient table 22 show that the likelihood of owning a home increases with skills, with age and wage income showing the same direction. Importantly, education is non-significant and varies in the direction of the correlation. The SCF data reinstate the salience of individual skills in financial behavior and choice.

Table 22: Binary regression estimates, homeownership choice, SCF data.

	Dependent variable:
	Owns a house or an apartment
Financial literacy score: medium	0.170^{***}
	(0.038)
high	0.146^{***}
	(0.039)
Education: high-school	0.067
	(0.052)
some college	-0.051
	(0.052)
college	-0.039
	(0.056)
Married	-0.852^{***}
	(0.042)
Female	0.176^{***}
	(0.044)
non-white	-0.536^{***}
	(0.029)
Leverage ratio	-0.029^{***}
	(0.003)
Willing to take risk	0.009
	(0.063)
Wage income quartile: $ 25,800 -$58,200	0.235^{***}
	(0.041)
$58,200 - $117,000	0.778^{***}
	(0.047)
≥$117,000	1.143^{***}
	(0.061)
Constant	-1.112^{***}
	(0.064)
Observations	40,071

Note: Controlled for age, family structure, occupation category, liquid savings amount, and survey wave effects. *p<0.1; **p<0.05; ***p<0.01

D Bayesian Record Linkage method (BRL)

Recently developed in Enamorado et al. (2019), Bayesian Record Linkage (BRL) is a probabilistic approach designed to match census data. Unlike deterministic methods such as mean-imputation and cluster-based algorithms commonly used in standard imputation, BRL leverages probabilistic techniques to account for the uncertainty inherent in the merging process. The advantages of employing BRL in this context include its scalability to handle large datasets and its ability to facilitate post-merge analyses through the utilization of match-specific posterior weights.

In the context of Bayesian Record Linkage (BRL), the matching process assigns posterior probabilities of a match for each record pair (i, j), where i represents the records from the NSMO data ($i \in \mathcal{A}$), and j corresponds to the SCF dataset ($j \in \mathcal{B}$). The BRL method employs pairwise comparisons for each distinct record pair (i, j) and computes the probability of a match based on the presence of a specific set of common observables denoted as K. The selection of these common observables focuses on factors generally considered relevant for assessing individual financial skills, including income, education, gender, age, race, occupation, family characteristics, retirement plan, and asset holdings. Table 23 shows the population shares in SCF and NSMO for every common observable used in the matching process. To ensure consistency in the matching procedure, we impose certain restrictions on the SCF sample. Specifically, we only include homeowners who hold a first lien mortgage, while we make no restrictions to the NSMO sample.

For each of $card(\mathcal{A}) \times card(\mathcal{B})$ distinct observations, BRL defines an agreement vector $\gamma(i, j)$ of length K. The k-th element $\gamma_k(i, j)$ represents the degree of agreement corresponding to the k-th observable in the set of mutual observables[20]. Following Enamorado et al. (2019), for a given observable k, we assume the agreement degree to be discrete, with a maximum $L_k - 1$.

Based on variable k (for example, income category), $\gamma_k(i, j) = 0$ represents a no-match, whereas agreement level $\gamma_k(i, j) = L_k - 1$ corresponds to a perfect match for a pair of records (i, j). Therefore, two records from SCF and NSMO may be matching in education brackets, but may differ in income levels, leading to a lower degree of agreement. The BRL takes every agreement degree into account and evaluates the posterior probability conditional on all agreement degrees for the pair. For each

[20] Income brackets are not listed for compactness; we group income in the SCF according to brackets in the NSMO data: (<\$35,000,\$35,000-\$50,000,\$50,000-\$75,000,\$75,000-\$100,000,\$100,000-\$175,000, >\$175,000). Similarly, we take the highest education grade data in the SCF and group them according to education brackets in the NSMO: (Some schooling, High-school graduate, Technical School, Some College, College degree, Post-college degree).

Table 23: Population shares in the respective samples. Source: NSMO 2013-2022 and SCF 2016-2019, authors' calculations.

	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%]

observation in the NSMO, we obtain the distribution of matches across the SCF sample.

BRL builds on the Fellegi-Sunter model (Fellegi and Sunter, 1969): $M_{i,j}$ denotes a latent mixing variable that shows whether distinct records pair (i, j) form a match or not. That is, M_{ij} is Bernoulli-distributed

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

and k-based agreement level $\gamma_k(i, j)$ has a discrete distribution

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

where $\pi_{kl},\ \ l \in \{0, \dots, L_k - 1\}$ represents the probability of each agreement degree for the pair (i, j). The vector of probabilities is denoted with $\boldsymbol{\pi}_{km}$.

Record matching probabilities imply the observed-data likelihood $\mathcal{L}_{\text{obs}}$, that we estimate later using the Expectation-Maximization algorithm (suggested by Enamorado et al. (2019)). Using the matched records from the NSMO and SCF data, we apply the Bayesian posteriors $\epsilon_{i,j} = \mathbb{P}(M_{ij} = 1|\gamma(i, j))$

as weights for statistical inference when we use the (imputed) financial literacy score. This way, we incorporate the match procedure uncertainty and avoid biases that emerge in standard deterministic methods.

Bayes rule implies the probability of a match which defines the post-merge weight

$$\begin{aligned}\varepsilon_{ij} &= \mathbb{P}(M_{ij} = 1 \mid \gamma(i,j)) \\ &= \frac{\lambda \prod_{k=1}^{K} (\prod_{l=0}^{L_k-1} \boldsymbol{\pi}_{k1l}^{\mathbf{1}\{\gamma_k(i,j)=l\}})}{\sum_{m=0}^{1} \lambda^m (1-\lambda)^{1-m} \prod_{k=0}^{K} (\prod_{l=0}^{L_k-1} \boldsymbol{\pi}_{kml}^{\mathbf{1}\{\gamma_k(i,j)=l\}})},\end{aligned}$$

that we use later for statistical inference. Financial literacy for the borrower i, $\bar{Z}_i$ is the sum of literacy scores of the respective record matches in the SCF Z_j, with corresponding weights ε_{ij}[21]:

$$\bar{Z}_i = \frac{\sum_{j=1}^{N_{\mathcal{B}}} \varepsilon_{ij} Z_j}{\sum_{j=1}^{N_{\mathcal{B}}} \varepsilon_{ij}}.$$

Post-merge analysis includes $\bar{Z}_i$ as the independent variable in linear model estimates.

Non-linear models, such as the ordered logistic and binary regression models we use for inference, need to be adjusted with the posterior weight. Therefore, the maximum likelihood function includes all the record pair matches with the corresponding Bayesian weight. With the assumption $Y_i|X_i, Z_i^* \overset{indep.}{\sim} P_\theta(Y_i|X_i, Z_i^*)$, the ML estimator

$$\hat{\theta} = \sum_{i=1}^{\mathcal{N}_A} \sum_{j=1}^{\mathcal{N}_B} \varepsilon_{ij}^* \log P_\theta(Y_i|X_i, Z = Z_j^*), \quad \varepsilon_{ij}^* = \frac{\varepsilon_{ij}}{\sum_{j=1}^{\mathcal{N}_B} \varepsilon_{ij}}$$

is consistent and asymptotically normal, and hence follows standard rules of significance tests. We use these theoretical results derived in Enamorado et al. (2019), and implement our estimators that ensure solid statistical properties.

[21] Our merging procedure uses the standardized literacy score.

D.1 Number of lenders considered

For every record pair (i, j) with a corresponding match weight ε^*_{ij}, the likelihood of number of lenders considered num_cons is characterized using the borrower's observables $(X_i, \text{fin\_skills}_i)$

$$\mathbb{P}(\text{num\_cons}_{ij} = k) = p_{ij,k} = \mathbb{P}\big(-\kappa_{k-1} < \beta X_i + \beta^f \text{fin\_skills}_j + u_{ij,k} < \kappa_k \big), \quad k \in \{1, 2, 3+\},$$

with κ_{k-1} and κ_k representing latent thresholds that define the search effort level. The logistic model assumes

$$p_{ij,k} = \frac{1}{1 + \exp\big(-\kappa_k + \beta X_i + \beta^f \text{fin\_skills}_i \big)} - \frac{1}{1 + \exp\big(-\kappa_{k-1} + \beta X_i + \beta^f \text{fin\_skills}_i \big)},$$

which pins down the log-likelihood adjusted by the posterior match weight

$$\ln L = \sum_{i=1}^{\mathcal{N}_A} \sum_{j=1}^{\mathcal{N}_B} \varepsilon^*_{ij} \sum_{k=1}^{3+} \mathbf{1}_{\{\text{num\_cons}_{ij} = k\}} \ln(p_{ij,k} | X_i, \text{fin\_skills}_j).$$

D.2 Additional NSMO+ estimates

As an additional counterfactual exercise, we estimate linear probability model where the dependent variable is number of lenders considered with our new NSMO+ dataset. We estimate the model when number of lenders considered equals one versus more than one. Estimates are presented Table (24). The results imply strong positive correlation between higher financial skills and probability of considering more than one lender when searching for a mortgage. In particular, model predicts that an average borrower who answered zero questions correctly has a probability of considering more than one lender equal to 0.381. On the other hand, for an average financially savvy borrower who answered all questions correctly, our linear probability model predicts 0.546 probability of considering more than one lender. The model predicts similar probabilities of considering more than one lender for average borrowers who upon refinancing the mortgage.

Table 24: Linear probability model for number of lenders considered one vs. more. Source: NSMO+, own calculation.

	Lenders considered	
	All origination	Refinancing
Age	-0.042^{***}	-0.019^{**}
	(0.005)	(0.008)
Credit Score	0.009^{*}	0.005
	(0.005)	(0.007)
Married	0.020^{***}	0.014
	(0.006)	(0.010)
Female	-0.058^{***}	-0.076^{***}
	(0.005)	(0.007)
Race: Black or African-American	0.055^{***}	0.038^{**}
	(0.011)	(0.015)
Asian	0.055^{***}	0.055^{***}
	(0.010)	(0.014)
other (including hispanic)	0.059^{***}	0.083^{***}
	(0.014)	(0.020)
Financial Literacy	0.164^{***}	0.166^{***}
	(0.038)	(0.056)
Education: high school	0.056^{***}	0.052^{***}
	(0.009)	(0.013)
college graduate	0.090^{***}	0.075^{***}
	(0.009)	(0.013)
post-college graduate	0.107^{***}	0.086^{***}
	(0.010)	(0.014)
Loan amount: $50,000 - $99,999	0.019	0.066^{**}
	(0.019)	(0.029)
$100,000 - $149,999	0.037^{*}	0.130^{***}
	(0.019)	(0.029)
$150,000 -$199,999	0.047^{**}	0.154^{***}
	(0.020)	(0.029)
$200,000 - $249,999	0.066^{***}	0.152^{***}
	(0.020)	(0.030)
$250,000 to $299,999	0.071^{***}	0.167^{***}
	(0.021)	(0.031)
$300,000 -$349,999	0.071^{***}	0.180^{***}
	(0.021)	(0.032)
$350,000 - $399,999	0.088^{***}	0.182^{***}
	(0.022)	(0.033)
≥$400,000	0.099^{***}	0.176^{***}
	(0.021)	(0.031)
Constant	0.271^{***}	0.246^{***}
	(0.047)	(0.068)
Observations	43,084	21,623
R^2	0.024	0.025
Adjusted R^2	0.023	0.023
Residual Std. Error	17.837 (df = 43039)	17.676 (df = 21578)
F Statistic	23.681^{***} (df = 44; 43039)	12.666^{***} (df = 44; 21578)

Note: *p<0.1; **p<0.05; ***p<0.01

Controlled for: Loan type, Year, Government Sponsored Enterprise, Term, LTV, Number of borrowers, and Income.

E Bellman Equation Derivation

This section outlines the agent's problem in discrete time with period size equal to Δt, generalizes into continuous time, and derives first order conditions of the homeowner's and renter's problem.

Let V^R and V^H represent the renter's and homeowner's value, respectively. Each period, the renter faces a productivity shock, invests in financial skills, accumulates assets, and may choose to take up a mortgage and, if yes, decides how much to search. If the renter chooses to take up a mortgage, they become homeowners, obtaining value V^H. State variables of the renter's problem are financial skills f, liquid assets a, and productivity z:

$$V^R(f,a,z) = \max_{\{i,s,c\}} \left\{ \big[u(c) - c^f(i,z) - c^s(s,f)\big]\Delta t + \frac{1}{1+\rho\Delta t}\mathbb{E}V^{R+} \right\}, \tag{7}$$

where $c^s(s,f)$ represents the cost of searching for a mortgage and $\mathbb{E}V^{R+}$ is the expected next period value, comprised of three transitions:

$$\begin{aligned}\mathbb{E}V^{R+} = &\underbrace{\Big(1 - \lambda s\phi\Delta t - \Delta t\sum_{z'}\omega(z,z')\Big)V^R(f+\Delta f, a+\Delta a, z)}_{\text{no change in } z\text{, no mortgage offers}} \\ &+ \underbrace{\phi\lambda s\Delta t\int_{\underline{r}}^{\bar{r}} \max\Big\{V^H(f+\Delta f, a+\Delta a, z, r'), V^R(f+\Delta f, a+\Delta a, z)\Big\} d\Phi(r')}_{\text{renter searches for an offer, decides based on the interest rate offered}} \\ &+ \underbrace{\Delta t\sum_{z'}\omega(z,z')V^R(f+\Delta f, a+\delta a, z')}_{\text{gets a productivity shock, does not search}} + \mathcal{O}(t),\end{aligned}$$

where the decision to become a homeowner depends on the search intensity s, the mortgage interest rate r, accumulated assets $a + \Delta t$ and skills $f + \Delta f$.

Using

$$-\lambda s\phi\Delta t V^R(f+\Delta f, a+\Delta a, z) = -\lambda s\phi\Delta t V^R(f+\Delta f, a+\Delta a, z)\underbrace{\int_{\underline{r}}^{\bar{r}} d\Phi(r')}_{=1}$$

and

$$\max\Big\{V^H, V^R\Big\} - V^R = \max\Big\{V^H - V^R, 0\Big\}$$

and rearranging yields

$$\begin{aligned}\mathbb{E}V^{R+} &= V^R(f+\Delta f, a+\Delta a, z) + \phi\lambda s\Delta t\int_{\underline{r}}^{\bar{r}} \max\Big\{V^H(f+\Delta f, a+\Delta a, r') - V^R(f+\Delta f, a+\Delta a, z), 0\Big\} d\Phi(r') \\ &= \Delta t \sum_{z'} \omega(z,z')\big[V^R(f+\Delta f, a+\Delta a, z') - V^R(f+\Delta f, a+\Delta a, z)\big] + \mathcal{O}(t).\end{aligned}$$

Multiplying the value function 7 with $(1+\rho\Delta t)$ and denoting $u_R = u(c) - c^f(i,f) - c^s(s,f)$ yields

$$V^R(f,a,z)(1+\rho\Delta t) = \max_{\{i,s,c\}}\Big\{u_R\Delta t + \mathbb{E}V^{R+}\Big\}.$$

Plugging in for $\mathbb{E}V^{R+}$ and rearranging yields

$$\begin{aligned}\rho\Delta t V^R(f,a,z) = \max_{\{i,s,c\}}\Big\{ & u_R(1+\rho\Delta t)\Delta t + V^R(f+\Delta f, a+\Delta a, z) \\ & + \phi\lambda s\Delta t\int_{\underline{r}}^{\bar{r}} \max\Big\{V^H(f+\Delta f, a+\Delta a, z, r') - V^R(f+\Delta f, a+\Delta a, z), 0\Big\} d\Phi(r') \\ & + \Delta t \sum_{z'} \omega(z,z')\big[V^R(f+\Delta f, a+\Delta a, z') - V^R(f+\Delta f, a+\Delta a, z)\big] + \mathcal{O}(t)\Big\},\end{aligned}$$

and dividing by Δt to derive the limit:

$$\begin{aligned}\rho V^R(f,a,z) = \max_{\{c,s,i\}}\Big\{ & u_R(1+\rho\Delta t) + \frac{V^R(f+\Delta f, a+\Delta a, z) - V^R(f,a,z)}{\Delta t} \\ & + \phi\lambda s\int_{\underline{r}}^{\bar{r}} \max\big\{V^H(f,a,z,r') - V^R(f,a,z), 0\big\} d\Phi(r') \\ & + \sum_{z'} \omega(z,z')\big[V^R(f,a,z') - V^R(f,a,z)\big] + \frac{\mathcal{O}(t)}{\Delta t}\Big\}.\end{aligned}$$

Finally, we let $\Delta t \to 0$ and obtain the continuous version of the renter's Bellman equation:

$$\rho V^R(f,a,z) = \max_{\{c,s,i\}}\Big\{ u_R + \frac{\partial V^R(f,a,z)}{\partial f}\dot{f} + \frac{\partial V^R(f,a,z)}{\partial a}\dot{a} \tag{8}$$

$$+ \phi\lambda s\int_{\underline{r}}^{\bar{r}} \max\big\{V^H(f,a,z,r') - V^R(f,a,z), 0\big\} d\Phi(r') \tag{9}$$

$$+ \sum_{z'} \omega(z,z')\big[V^R(f,a,z') - V^R(f,a,z)\big]\Big\}. \tag{10}$$

Deriving the continuous version of the Bellman equation for the homeowner follows the same approach. However, initial (discrete) value functions are different because:

1. Homeowners may search for refinancing options to ensure their liquidity

2. Homeowners may face financial shocks, after which they lose their house and become renters.

As for the renter's value function derivation, we start from the value function in discrete time:

$$V^H(f,a,z,r) = \max_{\{i,s,c\}} \left\{ \left[u(c) - c^f(i,z) - c^s(s,f)\right]\Delta t + \frac{1}{1+\rho\Delta t}\mathbb{E}V^{H+} \right\}, \tag{11}$$

where $c^s(s,f)$ represent the cost of searching for refinancing opportunities. Similar to the renter's case, the continuation value $\mathbb{E}V^{H+}$ for the homeowner $V^H(f,a,z,r)$ is comprised of disjoint transition possibilities

$$\begin{aligned}
\mathbb{E}V^{H+} =& \underbrace{\big(1 - \lambda s\Delta t - p(f,a)\Delta t - \sum_{z'}\omega(z,z')\big)V^H(f+\Delta f, a+\Delta a, z, r)}_{\text{no refinancing, no change in productivity}} \\
&+ \underbrace{\lambda s\Delta t \int_{\underline{r}}^{\bar{r}} \max\Big\{V^H(f+\Delta f, a+\Delta a - c_{\text{ref}}, z, r'), V^H(f+\Delta f, a+\Delta a, z, r)\Big\}d\Phi(r')}_{\text{searches for refinancing options and refinances if it yields higher value}} \\
&+ \underbrace{p(f,a)\Delta t V^R(f+\Delta f, a+\Delta a, z)}_{\text{loses the house, goes back to renting}} \\
&+ \Delta t \sum_{z'}\omega(z,z')V^H(f+\Delta f, a+\Delta a, z) + \mathcal{O}(t).
\end{aligned}$$

Rearranging the expression implies

$$\begin{aligned}
\mathbb{E}V^{H+} =& V^H(f+\Delta f, a+\Delta a, z, r) \\
&+ \lambda s\Delta t \int_{\underline{r}}^{\bar{r}} \max\Big\{V^H(f+\Delta f, a+\Delta a - c_{\text{ref}}, z, r') - V^H(f+\Delta f, a+\Delta a, z, r), 0\Big\}d\Phi(r') \\
&+ \Delta t p(f,a)\big[V^R(f+\Delta f, a+\Delta a, z) - V^H(f+\Delta f, a+\Delta a, z, r)\big] \\
&+ \Delta t \sum_{z'}\omega(z,z')\big[V^H(f+\Delta f, a+\Delta a, z', r) - V^H(f+\Delta f, a+\Delta a, z, r)\big] + \mathcal{O}(t),
\end{aligned}$$

and if we go back to the discrete value function (11) and multiply it by $(1+\rho\Delta t)$ and substitute for

$\mathbb{E}V^{H+}$ and $u_H = u(c) - c^s(s,f) - c^f(i,f)$, (11) boils down to

$$\begin{aligned}\rho\Delta t V^H(f,a,z,r) = \max_{\{c,s,i\}} \Big\{ & u_H(1+\rho\Delta t) + V^H(f+\Delta f, a+\Delta a, z, r) - V^H(f,a,z,r) \\ & + \lambda s \Delta t \int_{\underline{r}}^{\bar{r}} \max\Big\{ V^H(f+\Delta f, a+\Delta a - c_{\text{ref}}, z, r') - V^H(f+\Delta f, a+\Delta a, z, r), 0 \Big\} d\Phi(r') \\ & + \Delta t p(f,a)\big[V^R(f+\Delta f, a+\Delta a, z) - V^H(f+\Delta f, a+\Delta a, z, r)\big] \\ & + \Delta t \sum_{z'} \omega(z,z')\big[V^H(f+\Delta f, a+\Delta a, z', r) - V^H(f+\Delta f, a+\Delta a, z, r)\big] + \mathcal{O}(t) \Big\},\end{aligned}$$

dividing by Δt and letting $\Delta t \to 0$ yields

$$\rho V^H(f,a,z,r) = \max_{\{c,s,i\}} \Big\{ u_H(1+\rho\Delta t) \xrightarrow{\Delta t\to 0} u_H \tag{12}$$

$$+ \frac{V^H(f+\Delta f, a+\Delta a, z, r) - V^H(f,a,z,r)}{\Delta t} \xrightarrow{\Delta t\to 0} \frac{\partial V^H(f,a,z,r)}{\partial f}\dot{f} + \frac{\partial V^H(f,a,z,r)}{\partial a}\dot{a} \tag{13}$$

$$+ \lambda s \int_{\underline{r}}^{\bar{r}} \max\Big\{ V(f+\Delta f \xrightarrow{\Delta t\to 0} f, a+\Delta a - c_{\text{ref}} \xrightarrow{\Delta t\to 0} a - c_{\text{ref}}, z, r'), \tag{14}$$

$$V^H(f+\Delta f \xrightarrow{\Delta t\to 0} f, a+\Delta a \xrightarrow{\Delta t\to 0} a, z, r) \Big\} d\Phi(r') \tag{15}$$

$$+ p(f,a)\big[V^R(f+\Delta f \xrightarrow{\Delta t\to 0} f, a+\Delta a \xrightarrow{\Delta t\to 0} a, z) - \tag{16}$$

$$V^H(f+\Delta f \xrightarrow{\Delta t\to 0} f, a+\Delta a \xrightarrow{\Delta t\to 0} a, z, r)\big] \tag{17}$$

$$+ \sum_{z'} \omega(z,z')\big[V^H(f+\Delta f \xrightarrow{\Delta t\to 0} f, a+\Delta a \xrightarrow{\Delta t\to 0} a, z', r) - \tag{18}$$

$$V^H(f+\Delta f \xrightarrow{\Delta t\to 0} f, a+\Delta a \xrightarrow{\Delta t\to 0} a, z, r)\big] \tag{19}$$

$$+ \frac{\mathcal{O}(t)}{\Delta t} \xrightarrow{\Delta t\to 0} 0 \Big\}. \tag{20}$$

In the final step we derive the continuous version of the budget constraint and financial skill accumulation. Again, we start from the discrete version and build up towards the expression suitable for division by $\varDelta t$ and letting $\varDelta t \to 0$. The renter's budget constraint translates to

$$\begin{aligned} a_{t+\varDelta t} &= (1 + R\varDelta t)a_t + \big[wz_t - \kappa - c_t\big]\varDelta t \\ a_{t+\varDelta t} - a_t &= \varDelta t\big[Ra_t + wz_t - \kappa - c_t\big]/\varDelta t \\ \frac{a_{t+\varDelta t} - a_t}{\varDelta t} &= Ra_t + wz_t - \kappa - c_t \xrightarrow{\varDelta t \to 0} \dot{a} = Ra_t + wz_t - \kappa - c_t. \end{aligned} \tag{21}$$

The homeowner's budget constraint differs due to the mortgage repayment and boils down to

$$\dot{a}^H = Ra_t^H + wz_t - rM - c_t^H. \tag{22}$$

The financial skill accumulation process satisfies

$$\begin{aligned} f_{t+\varDelta t} &= (1 - \delta\varDelta t)f_t + \frac{\mu}{\eta}(i_t f_t)^\eta \varDelta t \\ f_{t+\varDelta t} - f_t &= \big[\frac{\mu}{\eta}(i_t f_t)^\eta - \delta f_t\big]\varDelta t / : \varDelta t \\ \frac{f_{t+\varDelta t} - f_t}{\varDelta t} &= \big[\frac{\mu}{\eta}(i_t f_t)^\eta - \delta f_t\big] \\ \dot{f} &= \frac{\mu}{\eta}(i_t f_t)^\eta - \delta f_t. \end{aligned} \tag{23}$$

First order conditions

The full version of the continuous time problem permits us to take first order conditions to infer more about the search intensity and consumption elasticity in the model.

The renter's problem (10) under the budget constraint (21) and financial skill accumulation (23) satisfies

$$[i] \quad \frac{\partial c^f(i,f)}{\partial i} = \frac{\partial V^R(f,a,z)}{\partial f}\mu(if)^{\eta-1}f = \frac{V^R(f,a,z)}{\partial f}\mu f^\eta i^{\eta-1},$$

which after plugging in for $c^f(i,f) = i_0 i^{\overline{1+\gamma_i}} \frac{1}{1+f}$ yields

$$
\begin{aligned}
i^{\frac{1}{\gamma_i}-(\eta-1)} &= \frac{\partial V^R}{\partial f}\mu f^\eta \frac{1+z}{i_0} \Big/ ()^{\frac{1}{\frac{1}{\gamma_i}-(\eta-1)}} \\
i^* &= \left[\frac{\partial V^R(f,a,z)}{\partial f}\frac{\mu f^\eta(1+z)}{i_0}\right]^{\frac{1}{\frac{1}{\gamma_i}-(\eta-1)}}
\end{aligned}
$$

and

$$
\begin{aligned}
&[c] \;\; u'(c) = \frac{\partial V^R(f,a,z)}{\partial a} \\
&[s] \;\; \frac{c^s(s,f)}{\partial s} = \phi\lambda \int_{\underline{r}}^{\bar{r}} \max\Big\{V^H(f,a,z,r') - V^R(f,a,z), 0\Big\} d\Phi(r')
\end{aligned} \tag{24}
$$

where substituting for $c^s(s,f) = s_0 s^{1+\frac{1}{\gamma_s}} \frac{1}{1+f}$ yields

$$
s^* = \left[\phi\lambda \int_{\underline{r}}^{\bar{r}} \max\Big\{V^H(f,a,z,r') - V^R(f,a,z), 0\Big\} d\Phi(r') \frac{1+f}{s_0}\right]^{\gamma_s}. \tag{25}
$$

Under (23) and the budget constraint (22), first order conditions for the homeowner's problem 20 include comparing values between staying at the current mortgage rate or refinancing

$$
i_H^* = \left[\frac{\partial V^H(f,a,z,r)}{\partial f}\frac{\mu f^\eta(1+z)}{i_0}\right]^{\frac{1}{\frac{1}{\gamma_i}-(\eta-1)}} \tag{26}
$$

$$
u'(c_H^*) = \frac{\partial V^H(f,a,z,r)}{\partial a} \tag{27}
$$

$$
s_H^* = \left[\lambda \int_{\underline{r}}^{\bar{r}} \max\Big\{V^H(f,a-c_{\text{ref}},z,r') - V^H(f,a,z,r), 0\Big\} d\Phi(r') \frac{1+f}{s_0}\right]^{\gamma_s}. \tag{28}
$$

$$
\begin{aligned}
\text{[renter]} \quad \frac{\partial c(s,f)^m}{\partial s} &= \lambda\phi \int_{\underline{r}}^{\overline{r}} \max\{V^H(f,a,z,r') - V^R(f,a,z), 0\} d\Phi(r'), \\
\frac{\partial c(i,z)^f}{\partial i} &= \frac{\partial V^R(f,a,z)}{\partial f} \frac{\partial \dot{f}}{\partial i}, \\
u'(c) &= \frac{\partial V^R(f,a,z)}{\partial a}, \\
\text{[homeowner]} \quad \frac{\partial c(s,f)^m}{\partial s} &= \lambda \int_{\underline{r}}^{\overline{r}} \max\{V^H(f,a - c_{\text{ref}}, z, r') - V^H(f,a,z,r), 0\} d\Phi(r'), \\
\frac{\partial c(i,z)^f}{\partial i} &= \frac{\partial V^H(f,a,z,r)}{\partial f} \frac{\partial \dot{f}}{\partial i}, \\
u'(c) &= \frac{\partial V^H(f,a,z,r)}{\partial a}
\end{aligned}
$$

which ultimately yields

$$
\begin{aligned}
\text{[renter]} \quad s &= \left(\frac{1+f}{c_0} \lambda\phi \int_{\underline{r}}^{\overline{r}} \max\{V^H(f,a,z,r') - V^R(f,a,z), 0\} d\Phi(r') \right)^{\gamma_s}, \\
i &= \left(\frac{1+z}{i_0} \frac{\partial V^R(f,a,z)}{\partial f} \mu f^\eta \right)^{\frac{1}{\frac{1}{\gamma_i} - (\eta - 1)}} \\
c &= \left(\frac{\partial V^R(f,a,z)}{\partial a} \right)^{-\frac{1}{\sigma}}, \\
\text{[homeowner]} \quad s &= \left(\frac{1+f}{c_0} \lambda \int_{\underline{r}}^{\overline{r}} \max\{V^H(f,a - c_{\text{ref}}, z, r') - V^H(f,a,z,r), 0\} d\Phi(r') \right)^{\gamma_s}, \\
i &= \left(\frac{1+z}{i_0} \frac{\partial V^H(f,a,z,r)}{\partial f} \mu f^\eta \right)^{\frac{1}{\frac{1}{\gamma_i} - (\eta - 1)}} \\
c &= \left(\frac{\partial V^H(f,a,z,r)}{\partial a} \right)^{-\frac{1}{\sigma}}.
\end{aligned}
$$

Boundary Conditions

Both the renter's and homeowner's problems are subject to the budget constraint $a_t \geq 0$. The constraint, using the derived first order conditions, translates to boundary conditions

$$u'(c) \leq \frac{\partial V^H(f,0,z,r)}{\partial a} \tag{29}$$

and

$$u'(c) \leq \frac{\partial V^R(f,0,z,r)}{\partial a} \tag{30}$$

for homeowners and renters, respectively.

F Analytical results from the model

Similar to standard search models, we characterize the reservation wage across assets and financial skills. The reservation mortgage rate is either constant across assets and skills, or is implicitly given as a function of these two. Throughout this section, we assume deterministic productivity and no monetary refinancing costs (i.e., $c_{\text{ref}} = 0$).

Interest rate strategy

In a frictionless model, the arrival rate of mortgage offers is the same across homeownership rates. In this instance, the reservation rate does not depend on assets or financial skills, and always corresponds to the mortgage payment.

Fixing productivity and denoting the reservation interest rate with $\tilde{r}$, the characterizing equality is

$$V^H(f,a,\tilde{r}) = V^R(f,a,\kappa).$$

Theorem F.1. *If the mortgage market does not differentiate between first time home-buyers and homeowners ($\phi = 1$), the reservation interest rate does not depend on assets or financial skills, and corresponds to the costs of renting $\tilde{r}(f,a)M = \kappa$.*

Proof. The reservation mortgage rate $\tilde{r}(f,a)$ satisfies $V^H(f,a,\tilde{r}(f,a)) = V^R(f,a,\kappa)$. Because the value function V^H strictly decreases with the interest rate (budget constraint effect), the equation for $V^H(f,a,r)$ simplifies to

$$\begin{aligned}\rho V^H(f,a,\tilde{r}(f,a)) &= u(c(f,a,\tilde{r}(f,a))) - c^m(s(f,a,\tilde{r}(f,a))) - c^f(i(f,a,\tilde{r}(f,a)))\\ &+ \frac{\partial V^H(f,a,\tilde{r}(f,a))}{\partial f}\left[\frac{\mu}{\eta}(i(f,a,\tilde{r}(f,a)))^\eta - \delta f\right]\\ &+ \frac{\partial V^H(f,a,\tilde{r}(f,a))}{\partial a}\left[Ra + w - \tilde{r}(f,a)M - c(f,a,\tilde{r}(f,a))\right]\\ &+ \lambda s(f,a,\tilde{r}(f,a))\int_{\underline{r}}^{\bar{r}} \max\left\{V^H(f,a,r') - V^H(f,a,\tilde{r}(f,a)), 0\right\} d\Phi(r')\\ &+ p\left[V^R(f,a,\kappa) - V^H(f,a,\tilde{r}(f,a))\right],\end{aligned}$$

while the renters value is

$$\begin{aligned}\rho V^R(f,a,\kappa) &= u(c(f,a,\kappa)) - c^m(s(f,a,\kappa)) - c^f(i(f,a,\kappa))\\ &+ \frac{\partial V^R(f,a,\kappa)}{\partial f}\left[\frac{\mu}{\eta}(i(f,a,\kappa))^\eta - \delta f\right]\\ &+ \frac{\partial V^R(f,a,\kappa)}{\partial a}\left[Ra + w - \kappa - c(f,a,\kappa)\right]\\ &+ \lambda s(f,a,\kappa)\int_{\underline{r}}^{\bar{r}} \max\left\{V^H(f,a,r') - V^R(f,a,\kappa), 0\right\} d\Phi(r')\end{aligned}$$

Using the characterizing equation for the reservation rate and going into FOCs $\dfrac{\partial V^H(f,a,\tilde{r}(f,a))}{\partial a} = \dfrac{\partial V^R(f,a,\kappa)}{\partial a} = u'(c)$ implies equal policy functions. Therefore, subtracting one value from the other yields

$$u'(c(f,a,\tilde{r}(f,a)))\left[\kappa - \tilde{r}(f,a)M\right] = 0 \implies \tilde{r}(f,a)M = \kappa.$$

$\square$

The assumption $\phi = 1$ has a bite when used to infer policy function equalities. Plugging back $\phi < 1$ yields heterogeneity in reservation rates, across financial skills and assets. In that case, subtracting $\rho V^R(f,a,\kappa)$ from $\rho V^H(f,a,\tilde{r}(f,a))$ yields

$$
\begin{aligned}
&- c^m(s(f,a,\tilde{r}(f,a))) + c^m(f,a,\kappa) + \\
&+ \lambda\Big[s(f,a,\tilde{r}(f,a)) - s(f,a,\kappa)\Big]\int_{\bar{r}}^{\tilde{r}(f,a)} (V^H(f,a,r') - V^R(f,a,\kappa))d\Phi(r') \\
&+ u'(c(f,a,\tilde{r}(f,a)))\big[\kappa - \tilde{r}(f,a)M\big] = 0,
\end{aligned}
$$

the implicit equation that characterizes the reservation rate $\tilde{r} = r(f,a)$.

Without assuming initial frictions at the mortgage market ($\phi = 1$) significantly reduces complexity when we infer the effect of mortgage performance on consumption growth. Optimal consumption growth in periods between mortgage refinancing elicits the effect of mortgage offer arrival rates and expense shocks. Whereas the expected change in debt repayment has the greatest effect on the highest-paying mortgage borrowers, the possibility of an expense shock has the strongest effect on borrowers with the lowest interest rates. For them, the next period value decreases all the way to rent payment.

Corollary F.1.1. *Excluding external search frictions, variations in consumption growth can be attributed to three factors: patience, expected future mortgage rates, and precautionary measures in response to expense shocks.*

$$
\frac{\dot{c}}{c} = \frac{1}{\sigma}\left[R - \rho - \lambda s\left(\int_{\underline{r}}^{r}\left(1 - \frac{u'(c(f,a,r'))}{u'(c(f,a,r))}\right)d\Phi(r')\right) + p\left(\frac{u'(c(f,a,\kappa))}{u'(c(f,a,r))} - 1\right)\right] \tag{31}
$$

Proof. When we exclude external frictions, using the fact that value is decreasing in r, homeowners' problem simplifies to

$$
\begin{aligned}
\rho V^H(f,a,r) = \max_{\{c,s,i\}}\Bigg\{&u(c) - c^f(i) - c^m(s,f) + \frac{\partial V^H(f,a,r)}{\partial f}\dot{f} + \frac{\partial V^H(f,a,r)}{\partial a}\dot{a} + \\
&+ \lambda s\int_{\underline{r}}^{r} V^H(f,a,r') - V^H(f,a,r)d\Phi(r') + p\Big(V^R(f,a,\kappa) - V^H(f,a,r)\Big)\Bigg\}.
\end{aligned}
$$

In the first step of the proof, we apply the envelope theorem to homeowners' problem with respect to assets (a) and obtain

$$\begin{aligned}\rho\frac{\partial V^H(f,a,r)}{\partial a} &= \frac{\partial^2 V^H(f,a,r)}{\partial f \partial a}\dot{f} + \frac{\partial^2 V^H(f,a,r)}{\partial a^2}\dot{a} + \frac{\partial V^H(f,a,r)}{\partial a}R \\ &+ \lambda s \int_{\underline{r}}^{r} \frac{\partial V^H(f,a,r')}{\partial a} - \frac{\partial V^H(f,a,r)}{\partial a} d\Phi(r') + \\ &+ p\bigg(\frac{\partial V^R(f,a,\kappa)}{\partial a} - \frac{\partial V^H(f,a,r)}{\partial a}\bigg).\end{aligned} \tag{32}$$

In the second step of the proof, we derive total derivative of $\frac{\partial V^H(f,a,r)}{\partial a}$. Possible changes can come from changes in assets da, changes in financial skills df, and changes in housing costs dr. Housing costs can change either due to refinancing $dq_{\lambda s}$ or due to financial shock, and transition to renting dq_p. Thus, we can summarize these changes with

$$dr = \min\{\tilde{r} - r, 0\}dq_{\lambda s} + \bigg(\frac{\kappa}{M} - r\bigg)dq_p.$$

Using changes mentioned above, total derivative of $\frac{\partial V^H(f,a,r)}{\partial a}$ satisfies

$$\begin{aligned}d\frac{\partial V^H(f,a,r)}{\partial a} &= \frac{\partial^2 V^H(f,a,r)}{\partial a^2}da + \frac{\partial^2 V^H(f,a,r)}{\partial f \partial a}df + \\ &+ \bigg[\frac{\partial V^H(f,a,\min\{\tilde{r}-r\})}{\partial a} - \frac{\partial V^H(f,a,r)}{\partial a}\bigg]dq_{\lambda s} + \\ &+ \bigg[\frac{\partial V^H(f,a,\frac{\kappa}{M})}{\partial a} - \frac{\partial V^H(f,a,r)}{\partial a}\bigg]dq_p.\end{aligned} \tag{33}$$

We focus on the case in which homeowners do not receive good enough refinancing offer and do not face financial shock, thus $dq_{\lambda s} = dq_p = 0$.

Next, we multiply equation (32) with dt and substitute for $\frac{\partial^2 V^H(f,a,r)}{\partial a^2}da + \frac{\partial^2 V^H(f,a,r)}{\partial f \partial a}df$ with the expression from equation (33). Thereby, equation (32) simplifies to

$$\begin{aligned}\rho\frac{\partial V^H(f,a,r)}{\partial a}dt &= d\frac{\partial V^H(f,a,r)}{\partial a} + \frac{\partial V^H(f,a,r)}{\partial a}Rdt \\ &+ \lambda s \int_{\underline{r}}^{r} \frac{\partial V^H(f,a,r')}{\partial a} - \frac{\partial V^H(f,a,r)}{\partial a} d\Phi(r')dt \\ &+ p\bigg(\frac{\partial V^R(f,a,\kappa)}{\partial a} - \frac{\partial V^H(f,a,r)}{\partial a}\bigg)dt.\end{aligned}$$

To further simplify, we use first order condition identities:

$$\frac{\partial V^H(f,a,r)}{\partial a} = u'(c(f,a,r)), \quad d\frac{\partial V^H(f,a,r)}{\partial a} = u''(c(f,a,r))dc$$

for homeowners, and

$$\frac{\partial V^R(f,a,\kappa)}{\partial a} = u(c(f,a,\kappa)),$$

for renters. Applying these identities yields the following expression

$$\rho u'(c(f,a,r))dt = u''(c(f,a,r))dc + u'(c(f,a,r))Rdt+ \\ + \lambda s \int_{\underline{r}}^{r} \big(u'(c(f,a,r')) - u'(c(f,a,r))\big) d\Phi(r')dt + p\Big(u'(c(f,a,\kappa)) - u'(c(f,a,r))\Big).$$

We divide this expression by $u'(c(f,a,r))dt$, we use CRRA property $\sigma = -\frac{u''(c)c}{u'(c)}$ and derivative notation $\frac{dc}{dt} = \dot{c}$, to obtain

$$\rho = -\sigma\frac{\dot{c}}{c} + R - \lambda s \int_{\underline{r}}^{r} \left(1 - \frac{u'(c(f,a,r'))}{u'(c(f,a,r))}\right) d\Phi(r') + p\left(\frac{u'(c(f,a,\kappa))}{u'(c(f,a,r))} - 1\right).$$

Finally, dividing by σ and rearranging yields final expression

$$\frac{\dot{c}}{c} = \frac{1}{\sigma}\left[R - \rho - \lambda s \int_{\underline{r}}^{r} \left(1 - \frac{u'(c(f,a,r'))}{u'(f,a,r)}\right) d\Phi(r') + p\left(\frac{u'(c(f,a,\kappa))}{u'(c(f,a,r))} - 1\right)\right].$$

□

F.1 Mortgage rate distributions

The *ad hoc* assumption on mortgage rate offer distribution $\Phi(r)$ dictates a structure for the endogeneous accepted rate distribution. Utilizing the equlibrium flows between mortgage and rental markets, we derive the expression for the accepted rate distribution $G(r)$. Let h denotes the measure of homeowners in the equilibrium.

The flow of renters becoming homeowners is given with

$$(1-h)\lambda\Phi(\bar{r})\phi \sum_{z} \int_{a} \int_{f} s^R(f,a,z,\kappa) g(f,a,z,\kappa), \tag{34}$$

whereas homeowners return to renting in case of an expense shock

$$h\sum_z\int_r\int_f\int_a p(f,a)g(f,a,z,x)dadf\,dx. \tag{35}$$

Equalizing the two yields

$$(1-h)\lambda\Phi(\bar{r})\phi\sum_z\int_a\int_f s^R(f,a,z,\kappa)g(f,a,z,\kappa) = h\sum_z\int_r\int_f\int_a p(f,a)g(f,a,z,x)dadf\,dx \tag{36}$$

For a mortgage rate r or higher, the flow to homeownership is governed only by renters, as homeowner's utility decreases with higher interest rates:

$$(1-h)(1-\Phi(r))\lambda\phi\sum_z\int_a\int_f s^R(f,a,z,\kappa)g(f,a,z,\kappa)df\,da, \tag{37}$$

whereas the outflow of homeowners occurs exogeneously due to the expense shock or endogeneously through mortgage refinancing

$$h(1-G(r))\sum_z\int_a\int_f\int_r p(f,a)g(f,a,z,x)dxdf\,da + h\Phi(r)\lambda\int_a\int_f\int_r^{\bar{r}} s^H(f,a,z,x)g(f,a,z,x)dxdf\,da. \tag{38}$$

Equalizing the flows at mortgage rate r (expressions (37) and (38)), dividing with total outflow of homeowners (35), and using the expression (36), we get

$$1-\Phi(r) = 1-G(r) + \frac{\Phi(r)\lambda\sum_z\int_r^{\bar{r}}\int_a\int_f s^H(f,a,z,x)g(f,a,z,x)df\,dadx}{\sum_z\int_r\int_f\int_a p(f,a)g(f,a,z,x)dadf\,dx},$$

which implies

$$\frac{G(r)-\Phi(r)}{\Phi(r)} = \frac{\lambda\sum_z\int_r^{\bar{r}}\int_a\int_f s^H(f,a,z,x)g(f,a,z,x)df\,dadx}{\sum_z\int_r\int_f\int_a p(f,a)g(f,a,z,x)dadf\,dx} > 0, \tag{39}$$

which implies that Φ first-order stochastically dominates G. Moreover, we rearrange

$$G(r) = \Phi(r)\left[1+\frac{\lambda\sum_z\int_r\int_a\int_f s^H(f,a,z,x)g(f,a,z,x)df\,dadx}{\sum_z\int_r\int_f\int_a p(f,a)g(f,a,z,x)dadf\,dx}\right], \tag{40}$$

which yields

$$\int_{\underline{r}}^{\bar{r}} (G(r) - \Phi(r))dr \geq 0,$$

so Φ second-order stochastically dominates G. The mean of Φ is as least as high as the mean of G, eliciting positive effects of search effort.

G Numerical solution method

Our numerical computation of the continuous time problem follows the method in Achdou et al. (2022). Individuals' decisions define a joint distribution of wealth, individual productivity, and housing type choice (represented by mortgage repayments). The exogenous grid for the mortgage rate, HJB equations (1) and (2) with corresponding first order conditions characterize agent's choice, conditional on owning a home. For a given productivity level, individual choices aggregate to a distribution of homeowners and renters that satisfy the Kolmogorov Forward Equation (3) and (4).

G.1 Homeowner's and renter's problem

As in Achdou et al. (2022), solving the (1) and (2) includes using the finite difference method for a joint grid on assets, financial skill level, productivity, and mortgage rates. The finite difference method includes assigning grids $[a_1, a_2, \ldots, a_n]$ and $[f_1, f_2, \ldots, f_m]$ with respective steps Δa and Δf to solve the discretized homeowner's and renter's problem. The grid is four-dimensional: - i runs through the asset grid, j denotes the financial knowledge grid point, k separates between two productivity states and r denotes the mortgage rate grid element $[r_1, \ldots, r_s]$. At each point in the grid, the discretized HJB equation is:

$$\begin{aligned}
\rho V^H_{i,j,k,r} = u(c^H_{i,j,k}) - c^f_{i,j,k,r} - c^m_{i,j,k,r} &+ \frac{V^H_{i+1,j,k,r} - V^H_{i,j,k,r}}{\Delta a}[\dot{a}_{i,j,k,r}]^+ + \frac{V^H_{i,j,k,r} - V^H_{i-1,j,k,r}}{\Delta a}[\dot{a}_{i,j,k,r}]^- \\
&+ \frac{V^H_{i,j+1,k,r} - V^H_{i,j,k,r}}{\Delta f}[\dot{f}_{i,j,k,r}]^+ + \frac{V^H_{i,j,k,r} - V^H_{i-1,j,k,r}}{\Delta f}[\dot{f}_{i,j,k,r}]^- \\
&+ \lambda s^H_{i,j,k,r} \sum_{r'=r_1}^{r_s} \max\left\{V^H_{i,j,k,r'} - V^H_{i,j,k,r}, 0\right\} d\Delta_r \\
&+ \omega(k,k')[V^H_{i,j,k',r} - V^H_{i,j,k,r}] + p[V^R_{i,j,k} - V^H_{i,j,k,r}],
\end{aligned}$$

where the step differences $i+1$, i and $i-1$ approximate derivatives of the value function $\dfrac{\partial V}{\partial a}$ and $\dfrac{\partial V}{\partial f}$. Choosing between the forward and backward differencing ensures convergence to the unique HJB solution (Achdou et al., 2022). The individual choice of mortgage refinancing necessitates going through all possible mortgage options (i.e., mortgage rates). Numerically, the integral breaks down to the average value over the mortgage rate grid $[r_1, \dots, r_s]$, at every iteration.

$\dot{a}_{i,j,k,r}$ are calculated using the upwind scheme described in Achdou et al. (2022) and separate two cases - whenever the corresponding state variable (assets) exhibits a positive or a negative drift.

That is, using the FOC for the homeowner, we separate consumption for a positive or a negative drift in assets. Denote the consumption with respective difference as

$$\begin{aligned} u'(c^{Hb}_{i,j,k,r}) &= {}_aV^{Hb}_{i,j,k,r} \\ u'(c^{Hf}_{i,j,k,r}) &= {}_aV^{Hf}_{i,j,k,r}. \end{aligned}$$

Plugging into the budget constraint of the homeowner yields

$$\begin{aligned} \dot{a}^{Hb}_{i,j,k,r} &= Ra^{i,j,k,r} + wz_{i,j,k,r} - Mr^m_{i,j,k,r} - c^{Hb}_{i,j,k,r} \\ \dot{a}^{Hf}_{i,j,k,r} &= Ra^{i,j,k,r} + wz_{i,j,k,r} - Mr^m_{i,j,k,r} - c^{Hf}_{i,j,k,r}. \end{aligned}$$

Now, setting

$$c^H_{i,j,k,r} = \mathbf{1}_{\{\dot{a}^{Hf}_{i,j,k,r}>0\}} c^{Hf}_{i,j,k,r} + \mathbf{1}_{\{\dot{a}^{Hb}_{i,j,k,r}<0\}} c^{Hb}_{i,j,k,r} + \mathbf{1}_{\{\dot{a}^{Hf}_{i,j,k,r}<0<\dot{a}^{Hb}_{i,j,k,r}\}} c^0_{i,j,k,r}$$

and denoting corresponding assets as $\dot{a}^H_{i,j,k,r} = Ra^{i,j,k,r} + wz_{i,j,k,r} - Mr^m_{i,j,k,r} - c^H_{i,j,k,r}$ ensures convergence to the unique solution of the HJB equation. Moreover, the boundary condition given with the equation (29), corresponding to $a \geq 0$ constraint is enforced by setting

$${}_aV^{H,b}_{1,j,k,r} = u'(wz_{1,j,k,r} - Mr^m_{1,j,k,r}).$$

Similarly, the upwind scheme and FOC with respect to financial skills investment separate between two types of investment, depending on a drift in financial skills

$$i^{Hb}_{i,j,k,r} = \left(\frac{1+z_{i,j,k,r}}{i_0} V^{Hb}_{i,j,k,r} \mu f^{\eta}_{i,j,k,r}\right)^{\dfrac{1}{\frac{1}{\gamma_1}-(\eta-1)}}$$

$$i^{Hf}_{i,j,k,r} = \left(\frac{1+z_{i,j,k,r}}{i_0} V^{Hf}_{i,j,k,r} \mu f^{\eta}_{i,j,k,r}\right)^{\dfrac{1}{\frac{1}{\gamma_1}-(\eta-1)}},$$

which then imply the corresponding financial skill investment costs $c^f(i^{Hf}_{i,j,k,r}, z_{i,j,k,r})$. The solution defines the grid for financial skills between 0 and 1, and the bounds are enforced with reflections in the corners

$$_fV^{H,b}_{1,j,k,r} = {}_fV^{H,b}_{2,j,k,r} \quad \text{and} \quad {}_fV^{H,f}_{i,m,k,r} = {}_fV^{H,f}_{i,m-1,k,r}.$$

Lastly, the HJB solution satisfies the FOC for search intensity that

$$s^H_{i,j,k,r} = \left(\frac{1+f_{i,j,k,r}}{c_0} \lambda \sum_{r'=r_1}^{r_s} \max\left\{V^H_{i,j,k,r'} - V^H_{i,j,k,r}, 0\right\} d\Delta_r\right)^{\gamma_s},$$

which defines the costs endured when searching for better mortgage options $c^m(s^H_{i,j,k,r}, f^H_{i,j,k,r})$.

Thus, our algorithm uses the current value function iteration to compute the integral over possible mortgage offers, simply by averaging out over all grid points for the mortgage interest rate.

The value function iteration generated by the upwind scheme is

$$\begin{aligned}
\frac{V^{H,l+1}_{i,j,r,k} - V^{H,l}_{i,j,r,k}}{\Delta} + \rho V^{H,l+1}_{i,j,k,r} &= U(c^H_{i,j,k,r}) + \frac{{}_aV^{Hb,l+1}}{\Delta a}[\dot{a}^{Hb}_{i,j,k,r}] + \frac{{}_aV^{Hf,l+1}}{\Delta a}[\dot{a}^{Hf}_{i,j,k,r}] \\
&+ \frac{{}_fV^{Hb,l+1}}{\Delta f}[\dot{f}^{Hb}_{i,j,k,r}] \frac{{}_fV^{Hf,l+1}}{\Delta f}[\dot{f}^{Hf,l+1}_{i,j,k,r}] \\
&+ \lambda s^H_{i,j,k,r} \sum_{r'=r_1}^{r_s} \max\{V^{H,l}_{i,j,k,r'} - V^{H,l}_{i,j,k,r}, 0\} d\Delta_r \\
&+ \omega(k,k)'[V^{H,l+1}_{i,j,k',r} - V^{H,l+1}_{i,j,k,r}] + p[V^{R,l+1}_{i,j,k} - V^{H,l+1}_{i,j,k,r}],
\end{aligned}$$

and due to the finite sum calculation in each iteration, it does not allow for a compact expression. However, the value function update $V^{H,l+1}$ boils down to solving a linear system of equations, similar to (Achdou et al., 2022). The value function for the renter V^R is discretized analogously.

Value functions for the homeowner and the renter V^H and V^R are four-dimensional matrices. When stacked together, V satisfies the set of equations, written compactly as

$$\frac{V^{l+1} - V^l}{\Delta} + \rho V^{l+1} = U^l + (A^l + B^l + \Lambda + P)V^{l+1} + \Omega^l(V^l), \tag{41}$$

where dimensions correspond to joint grid points in a column vector $\dim V^l = \dim V^{l+1} = \dim U^l = N_a \times N_f \times N_z \times N_r$. Matrix A^l contains asset changes $\dot{a}^{Hb,Hf}$ and $\dot{a}^{Rb,Rf}$, whereas changes in financial skills comprise B^l. Analogously to the literature, Λ depicts productivity changes and P the stochastic transition from homeownership to renting.

Lastly, Ω^l is a $\max$ function that takes the current value and compares it to the new value along the r dimension. Our algorithm pre-computes $\Omega_l = \Omega^l(V^l)$ and and transforms (41) into a linear system that has a solution

$$V^{l+1} = \underbrace{\left((\frac{1}{\Delta} + \rho)I - A^l - B^l - \Lambda - P\right)^{-1}}_{\mathbb{C}}(U^l + \frac{1}{\Delta}V^l + \Omega_l), \tag{42}$$

given that the matrix $\mathbb{C}$ is not ill-conditioned.

G.2 Stationary distributions

The second part of the algorithm iterates on the discretized version of the KFE for homeowners (3) and renters (4), respectively. As KFEs include integration, we use Kronecker product matrix multiplication to include the integrals and ultimately obtain a linear system of equations. Our discretized version of the KFE for homeowners states

$$\begin{aligned}
0 = &- \frac{{}_f g^{Hb}_{i,j,k,r}}{\Delta_f}[\dot{f}_{i,j,k,r}]^- - \frac{{}_f g^{Hf}_{i,j,k,r}}{\Delta_f}[\dot{f}_{i,j,k,r}]^+ \\
&- \frac{{}_a g^{Hb}_{i,j,k,r}}{\Delta_a}[\dot{a}_{i,j,k,r}]^- - \frac{{}_a g^{Hf}_{i,j,k,r}}{\Delta_a}[\dot{a}_{i,j,k,r}]^+ \\
&- (p + \lambda s^H_{i,j,k,r}\Phi(r))g^H_{i,j,k,r} + \lambda \sum_{r'=r_1}^{r_s} s^H_{i,j,k,r'} g^H_{i,j,k,r'} d\Delta_r \\
&+ \lambda\phi s^R_{i,j,k} g^R_{i,j,k} + \omega(k,k')(g^H_{i,j,k',r} - g^H_{i,j,k,r}),
\end{aligned}$$

and for the renter takes the form

$$
\begin{aligned}
0 = &- \frac{{}_a g^{Rb}_{i,j,k}}{\varDelta_a}[\dot{a}_{i,j,k,r}]^- - \frac{{}_a g^{Rf}_{i,j,k}}{\varDelta_a}[\dot{a}_{i,j,k,r}]^+ \\
&- \frac{{}_f g^{Rb}_{i,j,k}}{\varDelta_f}[\dot{f}_{i,j,k}]^- - \frac{{}_f g^{Rf}_{i,j,k}}{\varDelta_f}[\dot{f}_{i,j,k}]^+ \\
&+ p \sum_{r'=r_1}^{r_s} g^H_{i,j,k,r'} \varDelta_r - \lambda \phi s^R_{i,j,k} g^R_{i,j,k} \\
&+ \omega(k,k')(g^R_{i,j,k'} - g^R_{i,j,k}).
\end{aligned}
$$

The two equations together can be denoted in a more compact way, stacking two distributions (homeowners and renters) on top of each other. Compact notation reduces the system to a homogeneous linear system of equations.

While other components are simple to denote as linear operators, we construct the operator that produces the sum over all mortgage rates for each of the state variables as a Kronecker product of a sparse matrix τ that contains ones along the corresponding dimension and a matrix $\mathbb{S}^H$, which is constructed from a vectorized policy matrix vec(s^H). That is, we obtain $\sum_{r'=r_1}^{r_s} s^H_{i,j,k,r'} g^H_{i,j,k,r'}$ with $\tau \mathbb{S}^H g$. In the discretized version of KFE for the renter we do the same thing, and define a matrix that extracts the distribution of homewoners along the mortgage rate dimension, $g^H_{i,j,k,r}$, for $r_1, \dots, r_s$ and multiply the matrix τ with the vectorized policy matrix vec(s^H).

Using a similar argument for the renter's KFE equation, the stacked distribution g satisfies:

$$
(A + B - P + \varLambda + \mathbb{S}^H)g = 0,
$$

with an additional equation that ensures that stacked g is in fact a distribution and integrates to one.

G.3 Individual decisions in the equilibrium

In Figures 28 and 29, we present the individual policy functions as 3-dimensional surfaces. These policy functions capture the behavior and characteristics of homeowners and renters. Notably, both the slopes and relative relationships depicted in the figures closely align with our empirical data findings.

In line with the non-monotonic age averages observed in financial literacy scores from the SCF

(Figure 2 in the main text) and the panel data findings presented in Agarwal et al. (2007), the left panel of Figure 28 displays a non-monotonic pattern of investment in skills concerning current skill levels. Over time, as the level of skills increases, investment in skills begins to decrease. The right panel of Figure 28 matches the variation in search effort shown in our data findings - search effort increases with skill level and mortgage repayment amount, conforming to our estimates from the NSMO (Table 20) and SCF data (Figure 27).

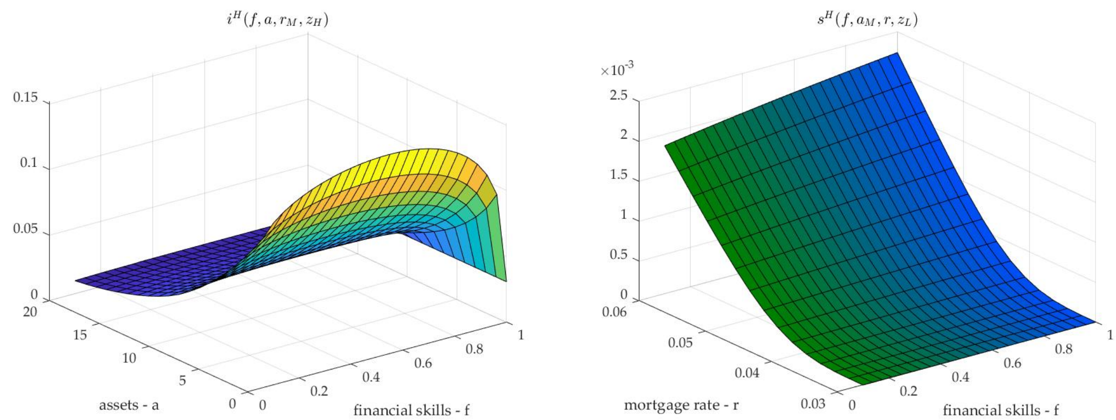


Figure 28: Investment (left) and search effort (right) policy functions for low productive homeowners over mortgage rates and financial skills, averaged over assets.

Skills investment policy for renters (left panel in Figure 29) resembles that of homeowners in term of its shape, but is lower in the level pertaining to the lack of learning-by-doing effects (Agarwal et al., 2007). Moreover, renter search intensity increases with skills, conforming to our SCF data findings (see Figure 4). Individual search and investment policies generate housing cost heterogeneity through mortgage take-up and refinancing, both of which we analyze in depth in our main text.

G.4 Locked-in rate in the equilibrium

In the equilibrium, the heterogeneity in locked in interest rates dictates consumption disparity net of housing costs. Figure 30 compares conditional densities of locked in mortgage rates between high and low skilled borrowers. In the equilibrium, unskilled borrowers lock-in at almost random rates, due to less sampling from the mortgage offer distribution (Figure 30). In the data, this translates to considering only one lender. Financially savvy borrowers exert more search effort, draw from a larger sample of mortgage offers (which we interpret as considering more lenders), and ultimately

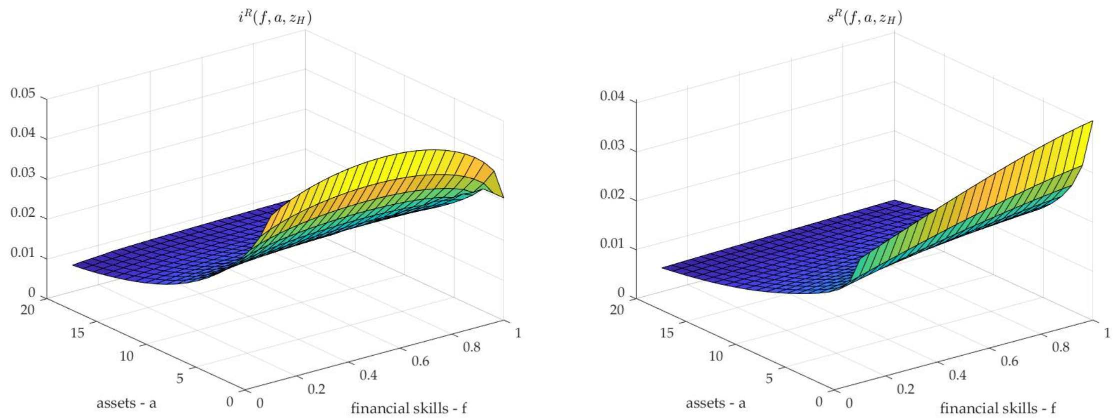


Figure 29: Renter's policy function for investment (left) and search effort (right) over assets and financial skills.

achieve better rates. In comparison with unskilled borrowers, the financially savvy end up with more resources net of mortgage repayment.

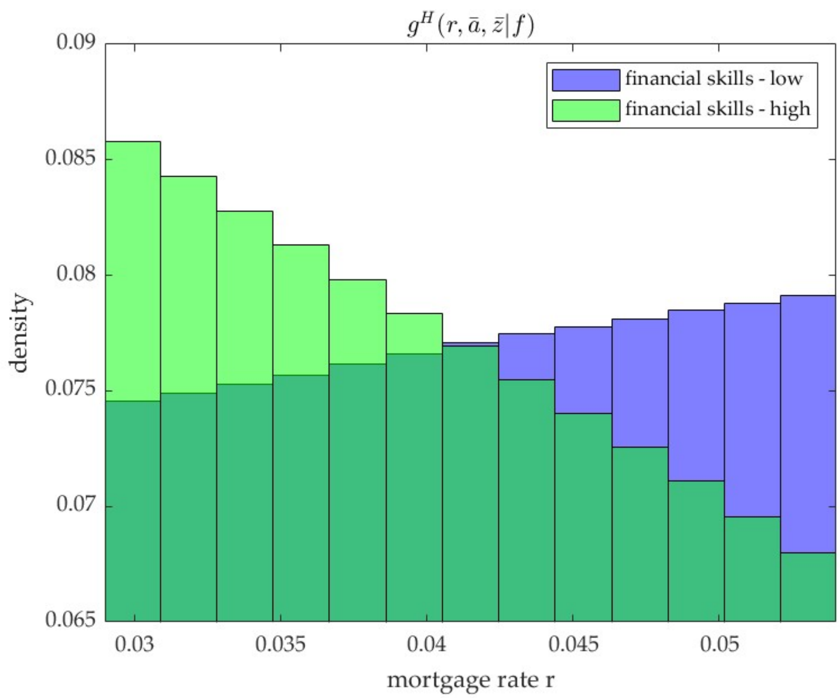
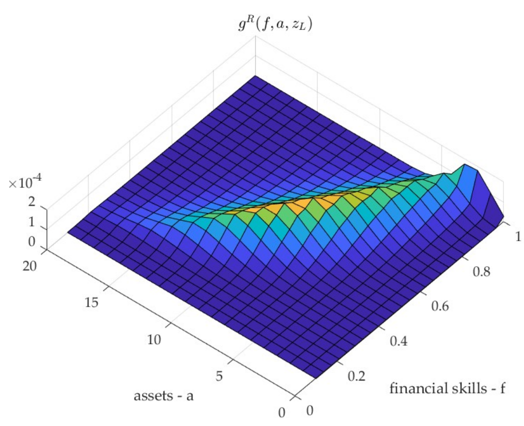


Figure 30: Mortgage rate density, for low- and high- skilled borrowers, averaged over assets and productivity.

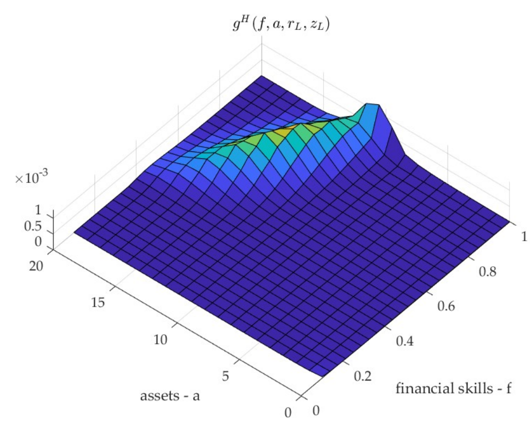
The green histogram in Figure 31 highlights the search intensity among savvy homeowners. Due to their search efforts, high-skilled borrowers bunch at the lowest rates, and adjust their consumption due to precautionary motives caused by the possibility of an expense shock (states in the consumption growth equation (31)). Additional precautions induces saving among the best-performing mortgage owners (shown in the right panel of Figure 31). In this regard, saving policy conforms to higher savings rates among wealthy homeowners found in Mian et al. (2020).

On the other hand, high-rate payers continue to invest in their financial skills so as to reduce their future mortgage rates, exhibiting the dissaving effect of the expected mortgage rate change channel outlined in the equation (31). Because returning to renting is not as costly when compared to large mortgage payments, lower precautionary motives propagate savings inequality among homeowners. To this extent, model simulations show that the equilibrium consumption growth exhibits the precautionary channel in the less simple setting with endogenous default rates. In addition, the model generates stationary distributions that capture the disincentive for homeowners with substantial assets from refinancing, simply because the mortgage payment does not affect their liquidity.

On the renter's side, assets are more dispersed, as a majority of renters accumulate skills to enter the mortgage market and face lower housing costs (the joint assets-skill density for renter is shown in the left panel in Figure 31). The model suggests that the wealthy renter exhibits low incentives to accumulate additional skills and prefers to remain a renter, regardless of paying higher housing costs. For wealthy renters, a costly search has a significant effect.



(a) $g^R(f, a, z_L)$; renters.



(b) $g^H(f, a, r_L, z_L)$; homeowners.

Figure 31: Density over assets and skills, low productive renters (left) and low productive homeowners with low mortgage payments (right).

Abstrakt

Jsou domácnosti s nízkými finančními dovednostmi na hypotečním trhu znevýhodněny? Pomocí stochastického propojování záznamů vytváříme unikátní soubor dat v USA, který zahrnuje bohatý soubor podrobností o hypotékách a charakteristikách dlužníků, včetně jejich objektivní míry finanční gramotnosti. Zjistili jsme, že u držitelů domů s nízkou finanční gramotností je až o 4 % vyšší pravděpodobnost, že budou hledat méně a uzavírat hypotéky za sazby vyšší o 15 až 20 bazických bodů. Při sjednání hypotéky čelí nekvalifikovaní dlužníci o 35-45 % vyšší delikvenci a nakonec mají o 30 % nižší pravděpodobnost refinancování. Celkově u úvěru ve výši 100 000 USD činí potenciální ztráty způsobené nízkou finanční gramotností více než 9 329 USD za dobu trvání hypotéky. Abychom pochopili, jak finanční vzdělávání, dostupnější hypotéky nebo změny hypotečních sazeb ovlivňují domácnosti s nízkou finanční gramotností, formulujeme a kalibrujeme model vyhledávání hypotéky s heterogenními frikcemi při vyhledávání a endogenními finančními dovednostmi. Odhady našeho modelu ukazují, že intenzita vyhledávání a rozdílných finančních dovedností přispívají k 55 %, resp. 10 % ropzdílu v hypotečních sazbách. Zjistili jsme, že i) dostupnější hypotéky vedou k vyššímu riziku delikvence u domácností s nízkou kvalifikací, ii) finanční vzdělání zmírňuje nepříznivé účinky zvýšené dostupnosti a iii) nízké hypoteční sazby zvýhodňují majitele domů s vysokou kvalifikací a posílením refinanční aktivity prohlubují rozdíly ve spotřebě mezi různými úrovněmi finančních dovedností.

Working Paper Series
ISSN 2788-0443

Individual researchers, as well as the on-line version of the CERGE-EI Working Papers (including their dissemination) were supported from institutional support RVO 67985998 from Economics Institute of the CAS, v. v. i.

Specific research support and/or other grants the researchers/publications benefited from are acknowledged at the beginning of the Paper.

Published by
Charles University, Center for Economic Research and Graduate Education (CERGE)
and
Economics Institute of the CAS, v. v. i. (EI)
CERGE-EI, Politických vězňů 7, 111 21 Prague 1, tel.: +420 224 005 153, Czech Republic.
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Editor: Byeongju Jeong

The paper is available online at https://www.cerge-ei.cz/working-papers/.

ISBN 978-80-7343-587-5 (Univerzita Karlova, Centrum pro ekonomický výzkum a doktorské studium)