Financial Skills and Search in the Mortgage Market *

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Abstract

This paper develops a microfounded model of mortgage choice in which households optimally trade off search effort against cognitive costs, allowing financial sophistication to shape both the intensity of search and mortgage terms. Using the Survey of Consumer Finances and the National Survey of Mortgage Originations, we document substantial heterogeneity in search behavior: more sophisticated households contact more lenders, refinance more frequently, and secure persistently lower interest rates, yielding average savings of up to $13,000 over a standard 30-year mortgage. We use these empirical moments to discipline a structural search model, which shows that reducing frictions lowers borrowing costs but does little to induce skill accumulation. Renters face the highest cognitive barriers to entering mortgage markets and gain little from lower rates, widening consumption gaps relative to homeowners. Policy simulations indicate that targeted financial education improves mortgage take-up and refinancing among low-skill households, reducing payment disparities and long-run inequality.
Keywords: mortgage refinancing, mortgage search, financial skills, financial education, consumption inequality
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1 Introduction

For most U.S. households, buying a home is their most significant—and often only—financial investment. Yet the growing number of mortgage products and lenders has made both selection and refinancing increasingly time-consuming and cognitively demanding. In the Survey of Consumer Expectations, 15% of households cite the time and effort required as a reason to avoid applying for loans, while 65% cite fear of rejection, often without fully understanding the alternatives available to them. These patterns suggest that what appear to be suboptimal mortgage choices may instead reflect rational responses to cognitive search costs, which contribute to persistent differences in borrowing outcomes and consumption inequality.

While a growing empirical literature documents associations between financial sophistication and mortgage rates, refinancing behavior, and delinquency risk (Keys et al., 2016; Bhutta et al., 2020; Coen et al., 2023), the mechanisms and their quantitative relevance remain unclear. This paper begins by documenting a set of new stylized facts linking financial literacy to mortgage search behavior and loan performance. These patterns motivate a structural framework in which cognitive search costs—shaped by financial skills—drive heterogeneity in borrower behavior and mortgage outcomes. Our model quantifies how differences in financial literacy translate into persistent disparities in borrowing costs and help explain broader patterns of consumption inequality. Understanding this mechanism is especially important in light of recent observations (Schnabel, 2025; Lusardi, 2019) emphasizing that the effectiveness of monetary policy depends on households' ability to assess and act on credit opportunities—an ability that, as we show, is closely linked to how much individuals search and how effectively they navigate the mortgage market.

Building on a set of stylized facts, our structural model quantifies long-term, financial skill-driven differences in consumption stemming from mortgage choices and household budgeting. We focus on the cognitive frictions borrowers face when navigating mortgage options—distinct from the approval frictions emphasized in Agarwal et al. (2024)—by modeling financial literacy as a key determinant of search effort and decision quality. While their analysis highlights application costs and lender-specific approval processes, we center on the cognitive effort required to compare offers and make informed borrowing decisions. Our framework incorporates both financial literacy and cognitive search costs—the utility costs of evaluating mortgage offers—to assess how financial

skills shape mortgage uptake, refinancing, and delinquency. It extends beyond mortgages to short-term debt and captures heterogeneous returns to financial literacy, offering a broader view of how financial capability contributes to long-run inequality (Lusardi et al., 2017; Jappelli and Padula, 2013).

The model builds on empirical facts from two complementary datasets: the Survey of Consumer Finances (SCF) and a newly constructed extension of the National Survey of Mortgage Originations (NSMO). To connect financial literacy with mortgage search behavior, we use probabilistic record linkage (Enamorado et al., 2019) to impute literacy scores in NSMO, based on predictive relationships estimated from the SCF. The imputation leverages a common set of demographic and financial variables across the two surveys and targets standard literacy questions on compounding, inflation, and diversification (Lusardi and Mitchell, 2014). The resulting dataset, NSMO+, augments loan-level data with predicted financial literacy, allowing us to study how decision-making skills relate to borrower behavior and outcomes.

The NSMO+ dataset enables us to examine the relationship between financial literacy, mortgage search, and loan performance. While Bhutta et al. (2020) show that mortgage-specific knowledge predicts interest rates, we take a broader view: we treat financial literacy as an evolving form of economic decision-making skill that influences borrower search behavior and long-run financial outcomes. The imputed literacy score serves as a proxy for accumulated financial knowledge at a given point in time—shaping not only the intensity and effectiveness of search, but also repayment behavior and budgeting capacity. While these relationships are correlational, they are consistent with a mechanism in which financial literacy and cognitive search costs jointly shape mortgage outcomes. These empirical patterns guide the structure of our model, which formalizes how financial skills accumulate endogenously and affect mortgage decisions and long-term repayment behavior.

Our empirical analysis yields four key patterns that inform the assumptions of our model. First, financial literacy is positively associated with prior refinancing activity: households that refinanced up to a decade ago consistently exhibit higher levels of financial skill. Second, more literate borrowers consider a wider set of lenders and are more likely to switch lenders when refinancing. Third, search intensity is strongly predictive of loan terms—borrowers who search more obtain mortgage rates that are, on average, 33 basis points lower, even after controlling for observables including

income. For a $100,000 loan, this translates to cumulative overpayment losses of at least $13,000 for less financially skilled households. Fourth, financially literate borrowers are 7 percentage points less likely to become delinquent, conditional on credit scores and payment-to-income ratios.

The residual mortgage rate gap in our estimates reflects more than credit conditions—it captures the effectiveness of search itself. Financially sophisticated borrowers are more likely to switch lenders and secure better terms, while less literate households often rely on advisors, who provide only partial compensation for underlying skill gaps. Even among advisor users, financially literate households search more and obtain lower rates. Between 2013 and 2022, the marginal benefit of search—conditional on financial literacy—has grown: skilled borrowers increasingly translate effort into rate reductions, widening cost disparities across households. In the absence of full lifecycle data, our model isolates this mechanism, quantifying how differences in financial sophistication—distinct from credit constraints—shape borrowing costs and contribute to long-run consumption inequality.

Given the long-term stability of U.S. homeownership rates and the significant role of government-sponsored enterprises such as Fannie Mae and Freddie Mac, which standardize and absorb much of the risk, our model focuses on demand-side heterogeneity while treating the supply side as exogenous. Households choose how much to consume, save, and invest in their financial skills. To manage their non-durable consumption, they can adjust their housing costs by searching for a new mortgage or refinancing an existing one on a standard-sized house. During this process, households face a distribution of mortgage rates and must decide how extensively to search, which incurs cognitive costs. [1]

Following the set of microfoundations, both cognitive costs and the individual likelihood of delinquency are decreasing in the level of skills. Borrowers recognize the connection between search costs and financial skills, leading them to invest in financial literacy as they optimize their housing costs. This behavior aligns with observed increases in search intensity during periods of low interest rates (Bhutta et al., 2020), and our evidence in the SCF on sustained skill level even 10 years after refinancing. While income shocks motivate liquid saving, lower housing costs and delinquency payments incentivize endogenous skill accumulation more so for financially skilled

[1] Our survey data shows that respondents prioritize the mortgage rate (97.5%) and monthly repayment (86%) when making their mortgage choice, suggesting that households simplify the decision-making process by focusing on these key numbers.

borrowers. These factors explain the differences in mortgage lock-in rates between segments (first-time homebuyers vs. current homeowners refinancing) and within each segment and the subsequent impact on consumption inequality.

Our model generates a novel set of implications on how financial skills shape refinancing activity and consumption growth. First, we show that refinancing depends not only on borrower-specific characteristics—such as mortgage rates, wealth, and income—but also on search elasticity, which is influenced by mortgage accessibility and financial skills. Both factors can be shaped by policy, highlighting the interaction between financial education initiatives and monetary policy in driving refinancing decisions and broader economic outcomes.

The second key implication concerns consumption growth. Financial skills affect consumption through two opposing channels: expectations of lower future rates, which encourage spending, and precautionary motives driven by delinquency risk, which encourage saving. This tension results in an ambiguous net effect, consistent with empirical findings (Dinkova et al., 2021). While financially savvy borrowers benefit from lower repayment costs, they may still prioritize savings to ensure financial stability.

Calibrated to U.S. data, our counterfactuals reveal that policies promoting financial skill accumulation enhance search intensity and improve mortgage outcomes. We also examine how the rise of online lending and digital advertising interacts with financial literacy incentives. While easier mortgage search lowers housing costs and reduces consumption inequality, it does not necessarily promote skill accumulation. Moreover, easier search reduces search costs but increases the average delinquency rate by 0.19%. Our findings suggest that this unintended consequence can be mitigated through policies aimed at improving financial sophistication, especially for renters transitioning to homeownership.

Finally, we leverage the search-skill elasticity to examine how mortgage rate declines affect consumption inequality. While financially savvy homeowners refinance to take advantage of lower rates, both financially unskilled renters and homeowners are left behind. For renters in particular, the cognitive costs of searching for and understanding mortgage options often outweigh the benefits of lower rates, deepening the consumption disparity between homeowners and renters. Since easier search and mortgage accessibility do not incentivize financial skill accumulation, our results on mortgage refinancing underscore that, now more than ever, improving financial literacy

is essential to strengthening the refinancing channel of monetary policy.

2 Related Literature

The relationship between financial sophistication and investment behavior is well established (Calvet et al., 2009; Lusardi and Mitchell, 2014), with empirical evidence linking financial skills to greater wealth accumulation (Lusardi et al., 2017; Bhutta et al., 2020; van Rooij et al., 2011). Motivated by evidence on learning dynamics in saving and investment behavior (Agarwal et al., 2007), a growing literature models the endogenous accumulation of financial skill. This research highlights the role of active investing in household finance and directly links financial sophistication to investment returns, introducing a new dimension of heterogeneity (Lusardi et al., 2017; Jappelli and Padula, 2013; **?**). While much of the existing literature focuses on stock participation and portfolio adjustments driven by financial skill, we focus on the predominant investment for most U.S. households—mortgage take-up and homeownership.

In contrast to Lusardi et al. (2017), who model how financial knowledge improves long-run wealth accumulation through better portfolio returns, we focus on how financial capability shapes behavior in the mortgage market—where decisions are infrequent but high-stakes. Rather than optimizing over investment returns, households in our model use financial skill to reduce cognitive search frictions when choosing mortgage products. We document empirical relationships between financial literacy and refinancing, contract terms, and delinquency, and use these to discipline a structural model in which endogenous financial skill accumulation shapes debt outcomes and rate dispersion, even among observably similar borrowers.

Although sophistication is often proxied by observable interactions, its dynamics and the role of learning have primarily been examined through models incorporating behavioral biases, including inattention (Andersen et al., 2020; Berger et al., 2024), self-control (Schlafmann, 2020), and present-bias (Maxted et al., 2024). We contribute to this literature by introducing endogenous financial skills, directly measurable using the "Big Three" questions proposed in seminal papers (Lusardi et al., 2010; Lusardi, 2019), establishing microfoundations that explicitly associate financial sophistication to mortgage search behavior and overall budgeting.

Empirical evidence shows that search plays a significant role in mortgage price dispersion, par-

ticularly through lender market power (Woodward and Hall, 2012; Agarwal et al., 2024; Allen et al., 2014, 2019). Search behavior is influenced by credit scores (Agarwal et al., 2024) and advertising (Gurun et al., 2016), with previous studies showing that increased search can lower mortgage rates, even when credit scores are fixed (Damen and Buyst, 2017; Bhutta et al., 2022; Malliaris et al., 2022; Coen et al., 2023). We contribute by showing that search intensity and financial skills are positively associated with better mortgage terms after controlling for credit scores. Our model introduces skill-dependent cognitive search costs, linking financial literacy to borrowers' ability to improve mortgage outcomes.

A common feature in models of search in the credit market is the assumption of i.i.d. search costs, which require search behavior to interact with observable borrower characteristics or biases, which generate heterogeneity in credit rates. While Agarwal et al. (2024) focuses on how lender screening interacts with credit scores and search, and Alexandrov and Koulayev (2018) introduces interest rate beliefs that dampen search intensity, we emphasize the role of search intensity subject to cognitive frictions, particularly among borrowers with similar observable characteristics. This approach allows us to take a first step in evaluating long-term effects of policy interventions aimed at reducing cognitive frictions, particularly as financial skills decline with age (Mazzonna and Peracchi, 2024).

Beyond the role of financial skill interventions, our model also speaks to the ease of information acquisition in the era of online bank lending. The widespread use of no-contact evaluation has been shown to reduce mortgage rate dispersion (Fuster et al., 2019; Zhou, 2022), thereby promoting competition in the mortgage market. U.S. fair pricing laws allow lenders to use other borrowers' observables to assess risk, and as a result, proxies for borrowers' mortgage knowledge—such as county-based branch densities and sophistication—still contribute to significant dispersion in mortgage pricing (Bartlett et al., 2022). With increased mortgage access and government sponsorships, the effectiveness of the mortgage channel of monetary policy is significantly influenced by borrowers' financial sophistication. Our counterfactual analysis provides a new take on mortgage rate decreases effects on inequality (Beraja et al., 2019), by showing that rate cuts disproportionately benefit the financially skilled within pools of otherwise similar borrowers.

When combined with targeted financial skill interventions, reductions in mortgage rates can have a more significant impact, even in the presence of borrowing constraints. Exler et al. (2024)

demonstrate that financial education can significantly increase welfare in models where lenders conduct screening. In our context, financial education reduces search costs and indirectly enhances household liquidity by lowering mortgage repayments.

The structure of the paper is as follows. Section 3 documents empirical facts relating individual financial skills, search behavior and mortgage attainment. Section 4 introduces the mortgage search model and Section 5 describes its calibration. Model results, counterfactuals and conclusions are presented in Section 6 and Section 7, respectively.

3 Data Analysis and Stylized Facts

Our mortgage search framework draws on two complementary data sources. First, we use the Survey of Consumer Finances (SCF) to analyze household-level mortgage decisions, including refinancing and lender switching, alongside a standardized measure of financial literacy (2016, 2019, 2022 waves). This enables us to document how observed literacy relates to mortgage behavior.

Second, we enrich a representative mortgage registry sample (NSMO) by imputing financial literacy scores using Bayesian record linkage (Enamorado et al., 2019). The resulting dataset (NSMO+) links detailed mortgage terms and shopping behavior to a latent measure of financial sophistication, proxied by literacy scores inferred from shared borrower characteristics (e.g., income, education, age). We interpret these scores not as direct measures, but as proxies for broader financial capability, reflecting persistent differences in household decision-making.

We take the set of mortgage borrowers as given due to data limitations but allow for endogenous selection into homeownership in our structural model. SCF evidence supports this margin: housing costs are generally lower than rents across much of the income distribution.

Together, these datasets reveal four empirical patterns that motivate our model:

1. Financial literacy peaks around age 55 and is higher among borrowers who previously refinanced.

2. Higher literacy is associated with greater search effort and more frequent lender switching.

3. Literacy and search effort together correlate with lower mortgage rates, conditional on observables.

4. Financially literate households are less likely to experience mortgage delinquency.

These patterns suggest that financial literacy evolves over time (Lusardi et al., 2017) and is systematically associated with differences in mortgage choices and outcomes. While prior work models skill accumulation in the context of saving and investment, we extend this framework to the mortgage market—where financial decisions are infrequent but have long-lasting implications. More financially capable households tend to search more intensively and obtain better terms, consistent with lower cognitive costs of search. This motivates our framework, where financial literacy evolves over the life cycle and enters as a key determinant of search frictions in mortgage choice.

3.1 The Survey of Consumer Finances (2016-2022)

We use data from the 2016, 2019, and 2022 waves of the Survey of Consumer Finances (SCF) to study patterns in financial literacy and its relationship to mortgage-related behaviors. The SCF provides detailed cross-sectional data on household balance sheets and includes a standardized, objective financial literacy measure based on the "Big Three" questions[2] (Lusardi et al., 2010, 2017). These scores offer a more reliable proxy for financial capability than perceived knowledge (Bhutta et al., 2022). We focus on a less explored module of the SCF that covers mortgage choice and refinancing behavior.

Although the SCF includes only self-reported mortgage contracts specifics, it allows us to document how financial literacy varies across households and over time, and to relate these patterns to self-reported refinancing and mortgage shopping activity. Our analysis focuses on households with first mortgages on primary residences, conditioning on origination year, LTV, term, and refinancing status. Retrospective information enables us to approximate loan and family characteristics at the time of origination for a subset of households[3].

While the SCF highlights key patterns in credit search, financial literacy, and its distribution across households and over time, our core empirical analysis relies on administrative mortgage registry data from NSMO+. These data provide precise loan-level information—including origination rates, terms, and borrower profiles—allowing us to systematically examine how interest

[2] See Appendix A.1 for question text and summary statistics.

[3] Loan-to-value ratios are inferred from home values and purchase prices; family structure from marriage year and children's ages.

rate variation and mortgage outcomes associate with financial skills, credit search, and refinancing behavior.

3.1.1 Variation in Financial Literacy Scores

We first focus on the variation in financial literacy scores across the sample. Table 1 shows that an extensive set of personal characteristics accounts for at most 20 percent of the financial literacy score variation among homeowners and renters. While the motive to increase literacy might partially explain the missing variation, little is understood about the incentives. Lusardi et al. (2017), **?** and Jappelli and Padula (2013) focus on the return heterogeneity, and we motivate the incentive through mortgage takeup, as for a majority of U.S households, this decision is the only financial investment they will make[4].

	Decomposition of R^2:	
	Financial literacy	
	All households	Homeowners
Age	0.014	0.008
Race	0.087	0.083
Gender	0.0160	0.051
Work status	0.008	0.005
Marital status	0.036	0.026
Education	0.266	0.237
Parent education	0.062	0.083
Income	0.167	0.167
Assets	0.296	0.304
R^2	0.18	0.158

Table 1: **Financial literacy and variance decomposition.** The left column uses the whole SCF sample, whereas the right column focuses on homeowners. The score is standardized, and race, gender, work and marital status, education, and parent education are categorized. Income combines labor and income from business and social security, and assets include liquid (including checking and saving accounts, stocks, bonds, and mutual funds) and quasi-liquid retirement accounts, current and future pension benefits, life insurance value, and nonfinancial assets, including vehicles, non-residential properties adjusted for mortgages, and other.

Going beyond the variation in individual characteristics and their power to explain differences in financial literacy, we exploit respondents' age differences and timing of mortgage origination to

[4]We also extend our model to capture the return-based incentive for endogenous financial skill accumulation.

show patterns in financial skill accumulation, particular to mortgage uptake.

Figure 1 suggests that financial literacy increases over the lifecycle, peaks at around the age of 55, and depreciates towards retirement and old age. Using the score and the mortgage origination year, we also show that financial literacy depreciates more slowly for borrowers who have refinanced (represented by the significant positive coefficient in Table 2), suggesting that these borrowers keep up with their budgeting over time.

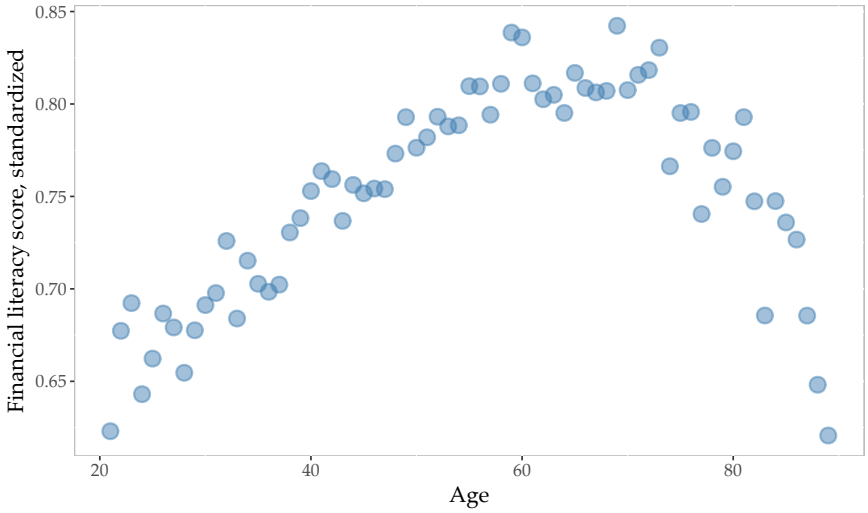


Figure 1: **Average financial literacy score by age groups.** Averages estimated using the SCF waves 2016, 2019, and 2022. The financial literacy score is standardized and based on the respondents' age. Averages are computed using survey weights.

Although we cannot disentangle learning effects from the active effort to accumulate financial skills using the data, we set a direction that we argue to be more plausible. First, Table 2 shows that skills depreciate over time for people who have not refinanced more than for those who did, suggesting that refinancing is an incentive to accumulate skills to decide the better mortgage option. As shown in Figure 1, the learning effect decreases over time and skills depreciate, but less so after an active financial decision, such as mortgage refinancing. These two findings round up our empirical Fact 1.

3.1.2 Financial Literacy and Shopping Behavior

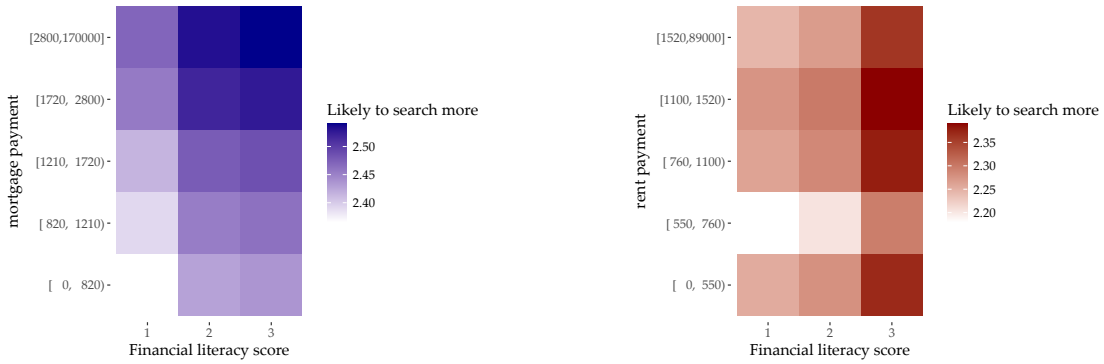
The key mechanism in our model operates through credit or mortgage search. We motivate our assumptions along two measures of search, both of which are self-reported, however are contained

	Financial skills (0-1)
Age	0.001***
	(0.0001)
Education: High-School	0.101***
	(0.007)
Bachelor	0.203***
	(0.007)
Post-Bacc	0.239***
	(0.007)
Female	−0.087***
	(0.005)
Refinanced (YES)	0.023***
	(0.004)
< 5 years passed since orig. < 10	−0.030***
	(0.005)
< 10 years passed since orig.	−0.023***
	(0.006)
Refinanced < 5 years < 10 since	0.034***
	(0.007)
Refinanced > 10 years ago	−0.0004
	(0.008)
Constant	0.607***
	(0.009)
Observations	29,404
R^2	0.116
Adjusted R^2	0.115
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 2: **Years passed since refinancing and financial literacy.** Estimates use the SCF subsample of mortgage owners with a mortgage on their primary residence. Education, gender, refinanced, and time passed since origination are represented as dummy variables, with "no high school", "male", "no", "less than 5 yrs passed since origination" as base categories. FinLit score is a standardized score on a 0-1 scale, and controls include income, asset, and year FE.

in two different data sources and point in the same direction.

The SCF asks respondents to evaluate the time spent searching for credit on a scale of 1-10. Our findings suggest that the time spent searching for credit is positively associated with financial literacy, regardless of individual housing status. Using the same empirical estimates, Figure 2 shows that the likelihood of searching increases with financial skills, and with the size of the housing payment costs. This represents our first line of evidence for systemic variation in search efforts and financial literacy.



(a) Time spent in searching for credit, homeowners.

(b) Time spent searching for credit, renters.

Figure 2: **The variation in time spent shopping for credit across homeowners and renters.** Predictions obtained using the linear models in Table 11, for average homeowner and renter in the respective SCF subsample. Increase in likelihood of doing "Great deal of time spent shopping for credit", conditional on housing status, is depicted with a change in color saturation. For homeowners, we plot the likelihood of high amount of time spent for shopping depending on financial literacy score (x-axis) and mortgage payment quintile (y-axis). For renters, we plot likelihood of high amount of time spent for shopping depending on financial literacy score (x-axis) and rent amount quintile (y-axis).

We also exploit the information on switching between lenders for borrowers who have refinanced. Our estimates in Table 3 show that financially savvy borrowers are 72% more likely to have switched between lenders, suggesting yet another way in which financial literacy, through search generates beneficial changes to current mortgage terms, backing up our empirical Fact 2.

3.1.3 Financial Skills, Search, and Mortgage Rates in the SCF

We have shown that financial literacy evolves over the lifecycle, and is influenced by homeownership and refinancing activity. Moreover, financially savvy borrowers spend more time in credit search and are more likely to switch lenders. These patterns suggest that search behavior varies systematically with financial literacy. To explore this relationship, we first link financial skills,

	Switched to a new lender upon refinancing (YES)
AgeR	0.001***
	(0.0004)
Education: high-school	0.0002
	(0.026)
College	−0.001
	(0.026)
Post-college	−0.068**
	(0.027)
FinLit score 2	0.148***
	(0.016)
FinLit score 3	0.133***
	(0.016)
Constant	0.365***
	(0.056)
Observations	11,424
Pseudo R^2	0.026
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 3: **Financially savvy borrowers more often switch lenders when refinancing.** Estimates use the SCF subsample of mortgage borrowers with mortgages on their primary residence, who have refinanced their mortgage in the past. Education and financial literacy scores are represented with dummy variables with "No high school" and "1" as base categories. Controls include mortgage origination year, loan amount, asset and income categories, and year FE.

search effort, and mortgage rates using retrospective self-reports in the SCF. Specifically, we infer family structure from self-reported marriage and children data and identify first-time mortgage borrowers by cross-referencing home purchase value and origination year.

While these estimates offer suggestive evidence, they cannot fully capture borrowers' financial positions at the time of origination. Therefore, our analysis with the SCF serves as a complement to the more detailed estimates we will present using the registry data in subsequent sections. At first glance in Figure 3, among first-time borrowers, financially savvy ones pay at lower interest rates.

To align observables with mortgage origination timing and motivate our registry-based analysis, we focus on a subsample of first-time mortgage borrowers, incorporating loan-to-value (LTV) ratios measured at origination. We estimate the following regression of reported mortgage rates on borrower characteristics and loan details:

$$\text{mtg_rate}_i = \alpha + \beta_m \mathbb{M}_i + \beta_x \mathbb{X}_i + \beta^{\text{f}} \text{FinLit_score}_i \times \text{search amount}_i + \varepsilon_i,$$

where the financial literacy score is standardized on the [0,1] scale, and credit search is captured via categorical indicators. Mortgage characteristics $\mathbb{M}_i$ include origination year, mortgage

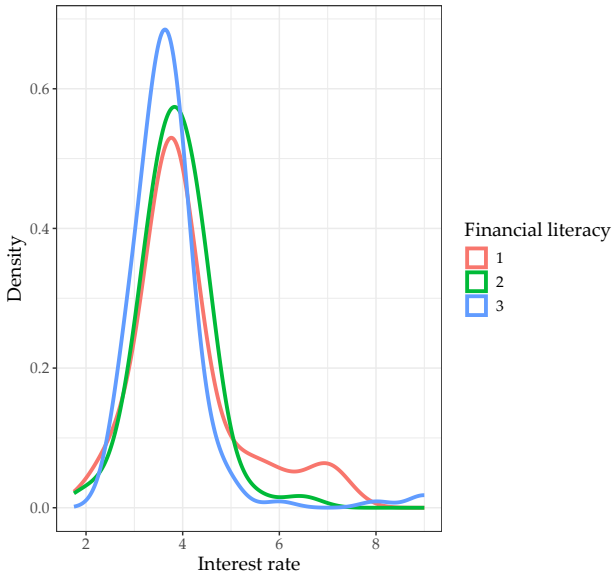


Figure 3: **Mortgage rate distribution across financial skills.** Kernel density estimation uses the SCF subsample of mortgages originated in 2016 among first-time borrowers. Bandwidth choice is obtained using Silverman's method, with an adjustment factor 2.5. Financial literacy category "1" denotes respondents who answered at most one question correctly, category "2" represents two questions answered correctly, and "3" denotes those borrowers with a full score.

insurance, balloon payments, and bank vs. non-bank originator indicators. Regression results, reported in Table 10 in the appendix, suggest that, controlling for loan and borrower characteristics, financially skilled borrowers who engage in more intensive credit search secure approximately 18 b.p. lower rates[5].

We now turn to the registry data, which enable us to observe granular borrower and loan characteristics at the time of origination, including credit scores (FICO) and shopping behavior and experience related to the contract in the registry.

3.2 Bridging Self-Reported and Registry Data: The NSMO+

While the SCF provides granular financial literacy data, its self-reported mortgage information lacks the precision of registry-based sources. To bridge this gap, we merge the SCF with the National Survey of Mortgage Originations (NSMO), which offers detailed mortgage-level data, including the number of borrowers, origination year, loan term and amount, mortgage insurance,

[5]These estimates control for demographic factors—including race, education, and marital status—which are known to contribute to disparities in mortgage pricing and refinancing outcomes (Bhutta et al., 2020; Keys et al., 2016; Andersen et al., 2020). We also control for post-origination income and wealth, which are the most granular financial indicators available in the SCF.

balloon payment, sponsorship type, metropolitan and low-to-moderate income tract identifiers, LTV, credit score, and payment-to-income ratio, as well as loan-based borrower search behavior and loan performance history. Our findings further motivate Fact 2 - Fact 4, while isolating the contract characteristics at a sufficiently granular level.

3.2.1 Mortgage Data Extension

We employ the Bayesian Record Linkage method (BRL), as described in (Enamorado et al., 2019), to probabilistically match SCF and NSMO observations based on shared characteristics such as gender, race, age, income, family size, and participation in the stock market and retirement accounts. This stochastic approach allows us to control for the uncertainty of the match, making it a more suitable choice for imputation than deterministic matching, particularly in cases where datasets lack overlap. While the quality of the match may decrease when overlap is limited, the BRL method offers a more flexible approach to estimating financial literacy for NSMO borrowers. We motivate our choice of shared characteristics by looking at the variance decomposition of the financial literacy score in the SCF, shown in Table 1, and compare sample shares across these characteristics in Table 14.

The BRL method incorporates match probabilities between observations, which reduces imputation bias while maintaining the consistency of our estimators[6]. This makes our approach not only robust but also practical, leveraging widely accessible data for effective analysis. Further methodological details can be found in Section B of the Appendix.

The resulting NSMO+ dataset combines key borrower and contract characteristics—such as credit scores, loan-to-value ratios, and mortgage sponsorship—that are essential for lenders when determining loan terms. By controlling for these factors, we isolate the effects of financial skills and search behavior on mortgage rate outcomes, focusing on demand-side dynamics.

3.2.2 NSMO+ Data Findings

Using NSMO+, we measure search behavior by the number of lenders considered *prior to applying for a loan*. While the number of formal applications bunches at one, this measure varies across the

[6] Additionally, the publicly available BRL implementation has demonstrated solid out-of-sample performance in voting predictions (Enamorado et al., 2019).

sample, as shown in Figure 10. Using the novel search measure, we find that financially skilled borrowers consider more lenders, supporting Fact 2. Moreover, the interaction between financial skill and search behavior negatively correlates with mortgage rates, reinforcing Fact 3. Finally, we quantify the financial losses from insufficient search and limited financial skills by quantifying the losses in mortgage payments over the loan term.

3.2.3 Shopping Behavior and Mortgage Search Priorities

Apart from asking about their shopping behavior in the mortgage search process, the NSMO+ survey asks the borrowers about their priorities in their mortgage search process. Specifically, the survey asks respondents to assign importance to each of the mortgage specifics listed on a scale of "Not important at all" to "Very important". Table 4 lists the importance of each mortgage characteristic, showing that borrowers reduce the complexity of the mortgage product by focusing their attention on the interest rate and monthly payment. Our framework closely follows this finding and separates mortgages based on their interest rates.

Question	Important
Lower interest rate	97.5%
Lower annual percentage rate	87%
Low closing fees	83%
Lower downpayment	57%
Lower monthly payment	79%
Fixed interest rate	89%
30-year term	59%
No mortgage insurance	56%

Table 4: **Borrower's priorities in the search process.** The table represents the percentage of borrowers who marked each of the mortgage specifics as "very important" when answering the question: "How important were each of the following in determining the mortgage you took out?". Responses are based on responses among borrowers with mortgages originated from 2015 onward.

Our search proxy, defined by the number of lenders considered, is a discrete variable ranging from "One lender" to "More than three lenders." We regress this measure on a set of borrower characteristics and mortgage contract details (as shown in Table 15 in the appendix), and find that financially skilled borrowers are more 4 p.p. more likely to consider multiple lenders during their search, regardless of the loan amount, number of borrowers, or credit score.

3.2.4 Effective Search

Parallel to our SCF data estimates, we regress the mortgage rate on a set of contract and borrower characteristics and focus on the interaction between search effort and financial skills. Note that mortgage origination years correspond to the subsample in the SCF. Also, the NSMO+ dataset enables us to differentiate between mortgages originated for distinct purposes, including refinancing.

$$\text{mtg_rate}_i = \alpha + \beta_m \mathbb{M}_i + \beta_x \mathbb{X}_i + \beta^{\text{f}} \text{FinLit_score}_i \times \text{number of lenders considered}_i + \varepsilon_i, \qquad (1)$$

where $\mathbb{M}_i$ represents mortgage contract characteristics, such as origination year, loan term, loan amount, type, loan-to-value ratio (LTV), geographic factors (e.g., urban versus rural location, low-to-moderate income tracts), jumbo loan status, number of borrowers, and government sponsorship. Borrower characteristics ($\mathbb{X}_i$) include demographic and socioeconomic variables: gender, age, race, education, income category, and marital status. Results of the estimation are presented in Table 16 in Section C of the Appendix.

We find that financially unskilled borrowers who considered fewer lenders faced mortgage rates 33 basis points higher[7]. To quantify this gap, we calculate predicted rates for a $100,000 loan using the regression model in Equation 1. Figure 4 illustrates the predicted rates by financial skill and search intensity, showing a clear distribution shift. This supports our hypothesis that financially savvy borrowers, who engage with multiple lenders, secure more favorable rates.

To quantify borrower's losses from mortgage overpayments over the loan term, we compute the payment streams over a 30-year term for predicted interest rates, employing the net present value formula:

$$\text{Payment}_r = 100,000 \frac{r(1+r)^{30}}{(1+r)^{30}-1}.$$

Predicted interest rates are presented in Table 17 in Section C of the Appendix. Our calculations show that financially unskilled borrowers pay $455 more annually compared to their skilled counterparts, amounting to $13,650 over the mortgage term. Accounting for differences in search effort adds another $125 per year, or $3,750 over 30 years. In total, borrowers who lack financial skills

[7] The same effect is observed among refinancing mortgages, with an 18 basis point gap.

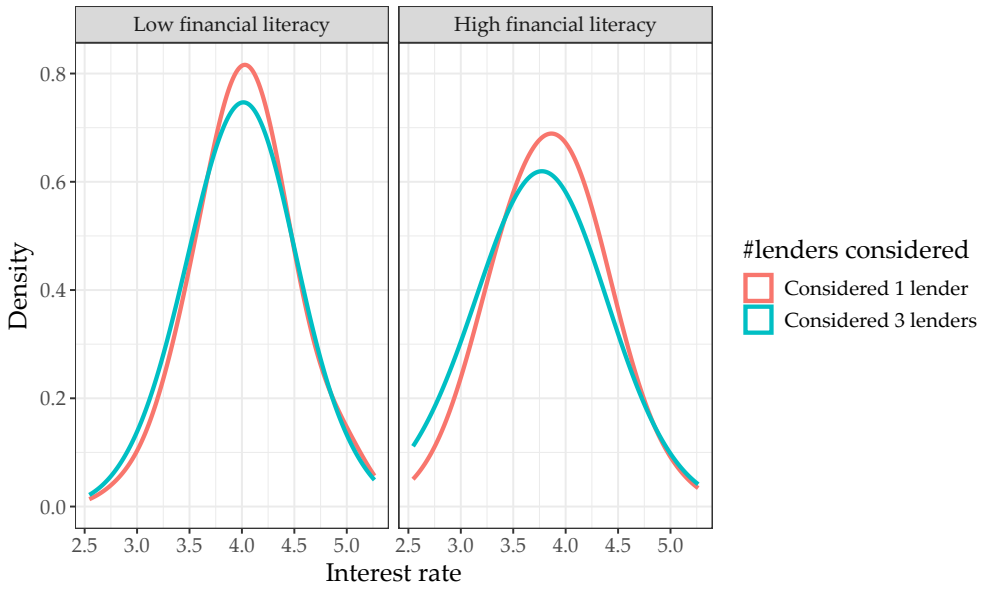


Figure 4: **Predicted mortgage rates by financial skills and search intensity.** Predictions are derived from the regression model in Equation 1, with coefficients detailed in Table 16 in Section C of the Appendix. Panels present predicted rates for borrowers in the bottom and top terciles of financial skill, considering one lender and three or more lenders, respectively.

and conduct limited searches incur losses exceeding $17,400 over the life of the loan. This estimate likely represents a lower bound: it excludes the potential benefits of refinancing, which financially skilled borrowers are more likely to undertake, and does not incorporate discounting into the calculations.

Cost of Hiring a Mortgage Broker Financial skill differences explain a part of the mortgage rate variation and can produce significant differences in consumption over the life of the mortgage loan. One of the policies aimed at mitigating this difference would be promoting mortgage broker takeups, which does not seem to alleviate the problem and creates differences in rates based on broker choice (Woodward and Hall, 2012). We corroborate this finding using the NSMO+ sample and show financially skilled borrowers refrain from taking up a broker, potentially due to the charge-up on the interest rate. Moreover, even if savvy borrowers decide to opt for a broker, they consider multiple brokers and still end up with better terms. We analyze and explain our findings in detail in Section C.5 of the Appendix.

3.2.5 Financial skills and Mortgage Delinquency

We motivate our empirical Fact 4 by leveraging the individual mortgage performance score in the NSMO+, which follows loans over time after the origination, until their closure or bankruptcy. This score captures various stages of delinquency, ranging from one month to over three months, as well as instances of bankruptcy. We regress the future loan performance score on a set of borrower characteristics, including the payment-to-income ratio, credit score, and financial literacy. Our findings indicate that higher financial skills are associated with a lower likelihood of mortgage delinquency. Specifically, financially skilled borrowers are 7 percentage points less likely to fall behind on payments. The results of this linear probability model are presented in Table 19 in the Appendix.

The predictions from our linear probability model, illustrated in Figure 5, suggest that a one-unit increase in financial literacy reduces the probability of delinquency by 35% - 58%, depending on the borrower's level of financial skills and the number of lenders considered. These results highlight the importance of financial literacy in shaping mortgage performance and mortgage repayment behavior, independent of credit score and payment-to-income ratio.



Figure 5: **Likelihood of Late Payments Across Financial Skill Levels and Search Effort.** Model predictions based on the NSMO+ sample are shown, controlling for loan amount, payment-to-income ratio, loan-to-value ratio, credit score, and age at origination. The x-axis represents the level of financial skills, while the y-axis depicts the number of lenders considered.

4 The Mortgage Search Model

In the absence of linked consumption and mortgage data, our model provides a first step in quantifying how financial sophistication affects consumption inequality through long-term debt. Our model captures the interaction between skill investment and depreciation in the context of housing adjustments. Early in life, housing status changes drive financial skill accumulation, while over time, reduced lock-in effects and rising wealth diminish the returns to further investment, leading to skill depreciation. This pattern aligns with the observed peak in financial literacy during working life, particularly following mortgage refinancing (Fact 1).

Before explicitly linking consumption and mortgage repayments, we outline key assumptions that shape individual housing adjustments: financial skill accumulation, cognitive search costs, and mortgage performance, following (Fact 1)-(Fact 4).

4.1 Financial Skills Accumulation

Agents accumulate financial skills (f) by investing effort $(i \geq 0)$which lowers mortgage search costs and improves access to favorable rates. Skill accumulation follows:

$$\dot{f} = \frac{\mu}{\eta}(if)^{\eta} - \delta f, \tag{2}$$

where μ scales the investment efficiency, η governs the return to effort, and δ represents depreciation. The utility cost of skill investment is:

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

where i_0 scales costs, γ_i determines the investment elasticity, and productivity z reduces the cognitive burden of acquiring knowledge.

4.2 Mortgage Refinancing - Decision and Options

Homeowners manage their housing costs and liquidity through two principal mechanisms: savings accumulation and mortgage refinancing. In each period, they must decide whether to refinance their existing mortgage, anticipating potential future expense shocks. The amount of search

effort for refinancing options determines the number of mortgage offers received. These offers are drawn from an exogenous distribution Φ, which represents the heterogeneity of the available mortgage rates in the market. The utility cost of searching for mortgage offers is modeled as:

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

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

We explicitly model the interaction between search and skills by including the denominator $(1+f)^{\gamma_f}$. Financial skills reduce the cognitive burden of search, lowering the costs required to secure favorable mortgage terms. The parameters γ_s and γ_f jointly shape individual refinancing behavior, as more financially skilled agents face lower costs to secure favorable mortgage terms.

4.2.1 Expense Shock

Homeowners face unforeseen expense shocks, such as medical emergencies, job losses, or changes in marital status, despite their efforts to manage housing costs. These shocks can lead to a transition from homeownership to renting and effectively increase housing costs. The probability of experiencing such a shock depends on financial skills f and accumulated assets a, and is modeled by the following logistic function:

$$p(f, a) = \frac{\exp(p_0 + p_f f + p_a a)}{1 + \exp(p_0 + p_f f + p_a a)}. \tag{3}$$

Although these shocks impose significant financial and utility costs, they are calibrated to reflect the average delinquency rate in the U.S., making them rare events.

4.3 The Agent's Problem

Agents recognize the benefits of investing in financial skills and searching for housing cost adjustments, with decisions extending beyond mortgage repayments to the allocation of consumption and savings. Denoting the housing state with $\theta_t \in \{\text{ho}, \text{rent}\}$ (homeownership and renting), the

general formulation of the agent's problem is:

$$\max_{\{c_t,s_t,i_t\}} \mathbb{E}_0 \int_0^\infty e^{-\rho t}[u(c_t,i_t,s_t) - c^f(i_t,z_t) - c^m(s_t,f_t)]_{\theta_t} dt, \text{ s.t.} \tag{4}$$

$$\begin{aligned}
&\dot{a}_t = Ra_t + wz_t - \mathbf{1}_{\{\theta_t=\text{ho}\}} Mr_t - \mathbf{1}_{\{\theta_t=\text{rent}\}}\kappa - c_t,\\
&\dot{f}_t = \frac{\mu}{\eta}(i_t f_t)^\eta - \delta f_t,\\
&ho \to rent \quad \text{with intensity} \quad p(f,a),\\
&z_t \in \{z_L, z_H\} \text{ is a Poisson process with intensities } \omega_1 \text{ and } \omega_2,\\
&a_t \geq 0,
\end{aligned}$$

where ρ is a discount rate, R is the rate of return on savings, M is the mortgage amount, and r_t is the obtained mortgage rate for homeowners.

4.3.1 Value Functions

The recursive problem form consists of Hamilton-Jacobi-Bellman (HJB) equations, housing type-flow dynamics, and boundary constraints, differentiated between renters and homeowners. Transitions between homeownership and renting are influenced by the distribution of financial skills and assets among agents, as well as prevailing mortgage rates[8].

For renters, the optimization problem involves incurring a fixed rental cost κ, saving through liquid assets a_t, and investing in financial skills f_t. Renters face search frictions, particularly before their first mortgage origination, where they incur additional costs denoted by ϕ. Dropping the time subscript for clarity, the HJB equation for renters is given by:

$$\rho V^R(f,a,z) = \max_{\{c,s,i\}} \Big\{ u(c) - c^f(i,z) - c^m(s,f) + \frac{\partial V^R}{\partial f}(f,a,z)\dot{f} + \frac{\partial V^R}{\partial a}(f,a,z)\dot{a} \tag{5}$$

$$+ \lambda\phi s(f,a,z) \int_{\underline{r}}^{\overline{r}} \max\{V^H(f,a,z,r') - V^R(f,a,z), 0\} d\Phi(r') \tag{6}$$

$$+ \sum_{z'} \omega(z,z')(V^R(f,a,z') - V^R(f,a,z)) \Big\} \tag{7}$$

[8]Detailed derivations of the value functions for renters and homeowners are in Appendix D.

subject to

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

For homeowners, the optimization problem incorporates mortgage repayment obligations and the option to refinance. The HJB equation for homeowners is expressed as:

$$\rho V^H(f,a,z,r) = \max_{\{c,s,i\}} \Big\{ u(c) - c^f(i,z) - c^m(s,f) + \frac{\partial V^H}{\partial f}(f,a,z,r)\dot{f} + \frac{\partial V^H}{\partial a}(f,a,z,r)\dot{a} \tag{8}$$

$$+ \lambda s(f,a,z,r) \int_{\underline{r}}^{\overline{r}} \max\{V^H(f, a - c_{\text{ref}}, z, r') - V^H(f,a,z,r), 0\} d\Phi(r') \tag{9}$$

$$+ \sum_{z'} \omega(z,z')(V^H(f,a,z',r) - V^H(f,a,z,r)) \tag{10}$$

$$+ p(f,a)(V^R(f,a,z) - V^H(f,a,z,r)) \Big\} \tag{11}$$

subject to

$$\dot{a} = Ra + wz - Mr - c,$$
$$\dot{f} = \frac{\mu}{\eta}(if)^{\eta} - \delta f,$$
$$a_t \geq 0.$$

Each term in the Hamilton-Jacobi-Bellman (HJB) equations represents a distinct economic trade-off. For renters, the first equation captures the net utility derived from consumption, skill investments, and search efforts. The second reflects the option value of transitioning to homeownership, contingent on the availability of mortgage offers, while the third accounts for external productivity shocks that influence income.

In the homeowner's equation, the second term quantifies the potential gains from refinancing, the third captures the effects of productivity shocks, and the final term represents the option value

of returning to renting due to financial distress or adverse events.

The boundary condition $a \geq 0$ introduces an additional constraint in the continuous-time setting, requiring that the marginal utility of consumption, $u'(c)$, aligns with the shadow value of liquid assets. This is formalized as $u'(c) \leq \partial V^H(f, 0, z, r)/\partial a$. Consumption, financial skill investment, and search effort policies satisfy first-order conditions, with solutions adhering to Kolmogorov Forward Equations to ensure consistency in agent flows between housing tenure states[9].

4.4 Housing Tenure, Refinancing, and Consumption Dynamics

This section examines the key analytical results of the model, focusing on housing tenure choices, mortgage take-up, and refinancing behavior. Our model considers borrowers with similar characteristics in average-sized U.S. homes, emphasizing how differences in financial skills and search ability lead to variations in mortgage rates, which in turn shape consumption patterns.

4.4.1 Mortgage Reservation Rate and Housing Tenure Choice

First, we focus on the homeownership choice and define the mortgage reservation rate $\tilde{r}(f, a)$ as the maximum interest rate for which the renter is indifferent between renting and homeownership, so $V^R(f, a) = V^H(f, a, \tilde{r}(f, a))$. This rate depends on financial skills (f), assets (a), and the rental cost (κ). In the presence of exogenous search frictions ϕ, the reservation rate captures the tradeoff between going through a cognitive process and lower housing repayment:

Proposition 4.1. *The reservation mortgage rate varies with skills and assets $\tilde{r}(f, a)$ and satisfies:*

$$
\begin{aligned}
&-c^m(s(f, a, \tilde{r}(f, a))) + c^m(s(f, a, \kappa)) + u'(c(f, a, \tilde{r}(f, a)))\big[\kappa - \tilde{r}(f, a)M\big] + \\
&+\lambda\big[s(f, a, \tilde{r}(f, a)) - \phi s(f, a, \kappa)\big] \int \max\{V^H(f, a, r') - V^H(f, a, \tilde{r}(f, a)), 0\} d\Phi(r') = 0. \qquad (12)
\end{aligned}
$$

In the absence of exogenous search frictions $(\phi = 1, c_{ref} = 0)$, the reservation rate align with rental costs:

$$\tilde{r}(f, a)M = \kappa.$$

Equation 12 highlights the core mechanism at the extensive margin – financially skilled renters

[9] Kolmogorov Forward Equations are defined in the Appendix.

face lower search costs and are more likely to transition to homeownership relative to their unskilled counterparts, irrespective of the mortgage rate they are facing.

4.5 Financial skills and consumption dynamics

Eliminating external borrowing frictions ($\phi = 1, c_{\text{ref}} = 0$) and simplifying $p(f, a) = p$ allows us to examine consumption dynamics among homeowners. Standard wealth accumulation models predict a positive correlation between financial literacy and consumption growth, as greater financial sophistication leads to better investment decisions and higher returns. However, our framework introduces two additional channels that fundamentally alter this relationship: (i) expected mortgage rates, which disproportionately affect high-rate borrowers who actively search for refinancing opportunities, and (ii) precautionary savings in response to expense shocks, which shape household consumption paths in ways not captured by traditional models.

Proposition 4.2. *In the absence of external search frictions, variations in consumption growth are driven by three key factors: patience, expected future mortgage rates, and precautionary savings in response to expense shocks.*

$$\frac{\dot{c}}{c} = \frac{1}{\sigma}\left[R - \rho - \lambda s\left(\int_{\underline{r}}^{r}\left(1 - \frac{u'(c(f,a,r'))}{u'(c(f,a,r))}\right)d\Phi(r')\right) + p\left(\frac{u'(c(f,a,\kappa))}{u'(c(f,a,r))} - 1\right)\right] \tag{13}$$

While patience is a standard determinant of consumption growth, our framework highlights two additional mechanisms. First, expected mortgage rates disproportionately impact high-rate borrowers who actively search for refinancing, linking financial literacy to consumption through mortgage decisions. Without search, this channel vanishes.

Second, precautionary savings play a key role. Households anticipating expense shocks save more, and declining mortgage rates amplify this behavior by increasing future refinancing opportunities. This mechanism aligns with evidence that wealthier borrowers exhibit stronger precautionary savings (Mian et al., 2020).

These forces make the relationship between financial literacy and consumption growth non-monotonic—a result consistent with SCF data on expense preparedness (Bhutta et al., 2022) and Dutch evidence on financial skills and consumption growth (Dinkova et al., 2021).

4.5.1 The Strength of the Refinancing Channel

Our model highlights how search cost elasticity shapes the refinancing response to monetary policy, operating through the intensive margin of mortgage adjustments. Unlike standard models where refinancing depends solely on rate incentives, we show that financial sophistication drives systematic heterogeneity in search behavior, even among observationally similar borrowers.

Proposition 4.3. *The elasticity of search with respect to financial skills is:*

$$\frac{\partial s^H}{\partial f} \cdot \frac{f}{s} = \gamma_s \cdot \gamma_f \cdot \frac{f}{1+f} + \gamma_s \cdot \underbrace{\frac{f \cdot \frac{\partial}{\partial f} \int_{\underline{r}}^{r} \left[V^H(f,a,z,r') - V^H(f,a,z,r') \right] d\Phi(r')}{\int_{\underline{r}}^{r} \left[V^H(f,a,z,r') - V^H(f,a,z,r') \right] d\Phi(r')}}_{\textit{Influence of prior rate, assets, etc.}} \tag{14}$$

The elasticity of search costs with respect to financial skills makes refinancing, through search, more responsive. Moreover, their interaction with prior mortgage conditions explains why otherwise similar borrowers display sharply different refinancing behavior, often explained with inattention (Andersen et al., 2020; Berger et al., 2024). In this context, financial education policies aimed at improving understanding of mortgage processes (i.e., increasing γ_f) could strengthen the refinancing channel of monetary policy[10].

5 Quantification

We solve the model using the finite difference method from Achdou et al. (2022). First, we estimate a set of parameters using the SCF data. In the second step, we minimize the distance between the empirical moments and their model counterparts, targeting homeownership rates, mortgage rate differences between first-time borrowers and refinancers, and the correlation between financial skills and search effort. We validate the model by comparing its predictions with Bureau of Labor Statistics consumption data in Garner et al. (2024) and housing cost shares in the SCF.

[10] The stochastic relationship between offer rate Φ and lock-in rate distribution G, derived in section E of the Appendix, underscores the positive effects of search on attained mortgage rates.

5.1 Parametrization

The model is parameterized annually, using a combination of exogenous parameters derived from empirical data and insights from the existing literature.

5.1.1 External Parameters

We set the CRRA utility parameter to $\sigma = 2$ (Maxted et al., 2024), the time preference rate to $\rho = 0.05$ (Moll et al., 2022), and the risk-free rate to $R = 0.02$ (Achdou et al., 2022). Individual productivity follows a two-state Poisson process with $z \in \{0.74, 1.26\}$ and intensities $\omega_1 = \omega_2 = \frac{1}{3}$, as in (Guerrieri and Lorenzoni, 2017), with wages normalized to 1. The elasticity of financial skill investment, γ_i, is set to 0.5, consistent with human capital model in (Kapička and Neira, 2019). Lastly, the refinancing cost is assumed to be 5% of the mortgage size, in line with industry estimates from Fannie Mae and Freddie Mac[11].

5.1.2 Financial Skills Parameters

Financial skill accumulation follows the flow equation (2), akin to the human capital models in (Lusardi et al., 2017), (Lusardi et al., 2020), and (Browning et al., 1999). The elasticity of financial skill investment, η, is set to $\frac{1}{2}$ (Browning et al., 1999), and the depreciation rate, δ, is set to 0.07, following (Lusardi et al., 2017). The slope parameter, μ, is estimated from the variation in financial skills by age using SCF data.

5.1.3 Expense Shock Probability

The probability of expense shocks is modeled as a function of homeowners' assets and financial skills, $p(f, a)$, by the logistic function in Equation (3). We estimate this logistic model using SCF data on late payments for a subsample of homeowners with mortgages on their primary residences, alongside their liquid asset holdings. Specifically, we consider liquid assets, including cash, prepaid cards, checking and savings accounts, money market funds, stocks, and mutual fund investments, to align with the asset liquidity structure in the model. The dependent variable is a binary

[11] Freddie Mac reports average refinancing costs between 2% and 6% of the loan principal https://myhome.freddiemac.com/refinancing/costs-of-refinancing

indicator for debt delinquencies exceeding 60 days. Our estimates control for mortgage size and house value, consistent with the assumptions of our model, and are listed in Table 5.

5.1.4 Mortgage Specifications

The mortgage amount is standardized at four times the average borrower's income[12]. Mortgage rate offers are exogenous and are assumed to follow a beta distribution parameterized by scale and shape. This specification enables us to calibrate the distribution of lock-in rates using data from NSMO+. Our calibration strategy involves varying the shape and scale parameters of the offer distribution, as the equilibrium distribution of accepted mortgage rates is determined endogenously, as formally derived in Appendix E.

5.1.5 Internally Calibrated Parameters

The remaining parameters are calibrated internally using the simulated method of moments (SMM), targeting moments that are salient in our framework. The target moments are described in the calibration table, Table 5. As is standard with SMM, certain moments are more informative for specific parameters, though the relationship is not strictly one-to-one. We discuss the informativeness of these moments throughout this section.

The offer rate follows a beta distribution with shape parameters $\beta = 3.2772$ and $\alpha = 3.3435$, calibrated to match the endogenous locked-in mortgage rate with its counterpart in the NSMO+. The rental cost parameter, $\kappa = 0.2673$, is informed by the SCF homeownership rate and reflects higher monthly payments for renters, consistent with SCF data showing that rent, on average, accounts for twice the share of income as mortgage payments (see Table 12 in the Appendix).

The mean and standard deviation of financial skills inform the elasticity of search effort, $\gamma_s = 2.1523$, and the scaling parameter for the investment cost function, $i_0 = 927.2781$, are calibrated from the financial skills moments in the SCF. The correlation between search activity and financial skills informs the elasticity of search costs with respect to financial sophistication, γ_f. Additionally, the disparity in average mortgage rates between first-time origination and refinancing facilitates the calibration of the scaling and search friction parameters, $c_0 = 4.3748$ and $\phi = 0.99$, respectively. The

[12]This is usually prescribed by institutional lenders, implied by the 28% rule of income allocated to mortgage payments.

targeted moments and the corresponding parameter values that minimize the distance between model outcomes and data are summarized in Panel C of Table 5.

Table 5: **Model parameter values.** Source: Model, SCF, and NSMO. Externally set parameters reflect values usually used and estimated in the literature. Externally estimated parameters of the financial skill accumulation function and parameters of the expense shock probability are estimated using the SCF dataset as explained in the main text. The targets for internally calibrated parameters are based on SCF data estimates (average financial skills for homeowners and renters, homeownership rate, and correlation between financial skills and shopping time) and NSMO data estimates (average mortgage rate at origination, upon refinancing, pulled together, and standard deviation of pulled mortgage rates).

Definition	Symbol	Estimate	Source/Target		
Panel A. Externally set					
Discount factor	ρ	0.05	Moll et al. (2022)		
CRRA parameter	σ	2	Maxted et al. (2024)		
Investment cost elasticity	γ_i	0.5	Kapička and Neira (2019)		
Return	R	0.02	standard		
Refinancing Cost	c_{ref}	0.21	Freddie Mac (5% of the mortgage size)		
Intensities	ω_1, ω_2	$\frac{1}{3}, \frac{1}{3}$	Guerrieri and Lorenzoni (2017)		
Curvature f	η	0.5	Browning et al. (1999)		
Depreciation	δ	0.07	Lusardi et al. (2017)		
Panel B. Externally estimated					
Slope	μ	0.2	SCF, lifecycle profile		
Parameters	p_0, p_f, p_a	-2.12,-0.56,-0.81	SCF, late payments		
Panel C. Internally estimated				Model	Data
Investment cost scaling	i_0	927.28	Average financial skills - R	0.69	0.67
Renting cost	κ	0.27	Homeownership rate	0.58	0.59
Search cost elasticity	γ_s	2.15	Average financial skills - HO	0.71	0.73
Search cost - skill parameter	γ^f	0.40	correlation between f and s	-0.06	0.03
Search cost scaling	c_0	4.37	Average mtg. rate all	0.0390	0.0400
Search friction	ϕ	0.99	Average mtg. rate f.o.	0.0416	0.0408
Mtg. offer distribution parameter	β	3.28	Average mtg. rate - ref.	0.0350	0.0386
Mtg. offer distribution parameter	α	3.34	Standard deviation mtg. rate	0.0082	0.0073

5.2 Model Fit

To validate the model, we compare key inequality measures—driven by differences in search effort, financial skills, and assets—to empirical data. We use Bureau of Labor Statistics (BLS) reports (Garner et al., 2022, 2024), documenting U.S. household consumption, to compare non-durable and housing consumption inequality both graphically (via Lorenz curves) and quantitatively (using Gini coefficients). We also assess model-implied housing cost differences between renters and homeowners, as well as refinancing rate differences by financial skill level, comparing them to SCF data. Model validity checks are presented in Table 6.

The model's consumption Gini coefficient ($\text{Gini}_c^{\text{model}} = 0.12$) slightly understates inequality compared to the BLS data ($\text{Gini}_c^{\text{BLS}} = 0.16$), as confirmed by the Lorenz curve comparison in Figure 6. This discrepancy arises because the model generates mortgage repayments from a similar pool of borrowers, thus understating inequality relative to U.S. averages (Garner et al., 2022, 2024).

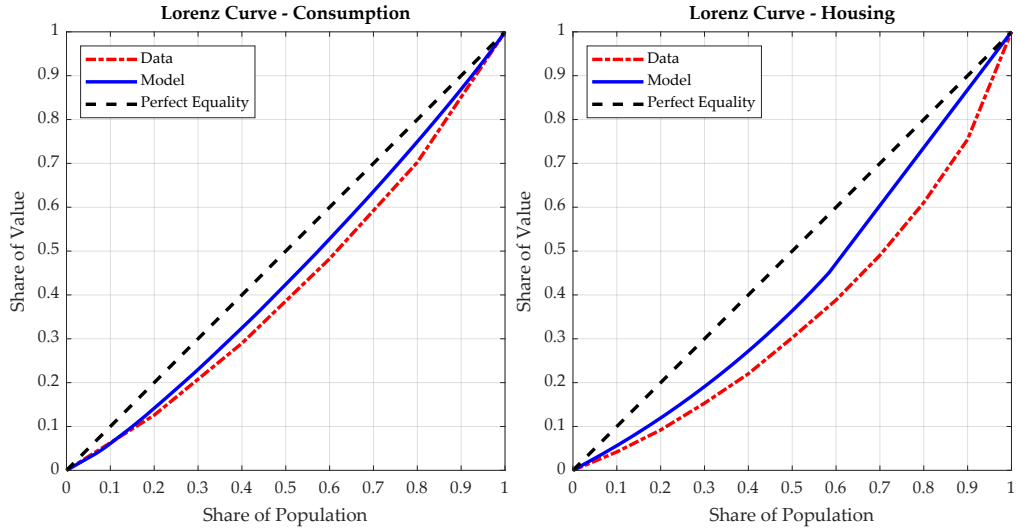


Figure 6: **Lorenz Curves, non-durable consumption (left) and housing consumption (right).** Lorenz curves are based on model simulations calibrated with values from Table 5, with data counterparts from the BLS. The left panel compares Lorenz curves for consumption, and the right panel compares Lorenz curves for housing consumption.

Beyond standard inequality measures, the model aligns with financial skill-driven differences in housing costs, refinancing, and delinquency rates observed in the SCF (see Table 6).

First, our framework maps search intensity into refinancing rates using the relationship $\mathbb{P}_{ref}(s) = 1 - \exp(-\lambda s)$, and in equilibrium, slightly overstates refinancing activity among financially skilled homeowners (Table 6). Second, the model understates financial skill-related differences in delin-

quency, primarily due to the simplifying assumption that delinquency and default are equivalent in the model. However, 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. Lastly, the model replicates key heterogeneity moments, predicting a 13.4% hand-to-mouth share (close to 14.2% in Kaplan and Violante (2022)) and substantial asset inequality, with a Gini coefficient of $G^a\text{model} = 0.41$. These results reflect disparities in asset holdings, assuming all agents are mortgage-eligible and require a mortgage to own a home.

	Gini$_c$	$\frac{\mathbb{P}\text{ref}(s\|f^H)}{\mathbb{P}_{\text{ref}}(s\|f^L)}$	$\frac{\text{mtg pay}}{\text{rent pay}}$	$\mathbb{P}(\text{del}\|f^L) - \mathbb{P}(\text{del}\|f^H)$	HtM share
Model	0.12	20-25%	0.51	3.7 p.p.	13.4%
Data	0.16	6-11%	0.49	7 p.p.	14.2%

Table 6: **Non-targeted model-implied moments and empirical counterparts.** Gini$_c$ is obtained from (Garner et al., 2022), and HtM share uses (Kaplan and Violante, 2022). The rest of data moments use the SCF, where delinquency differences are estimated among a subsample of homeowners with mortgages on their primary residences.

5.3 Model Extensions and Assumption Relaxation

In previous models linking financial literacy to inequality, returns are typically assumed to vary based on financial skills. We build on this by introducing heterogeneous, skill-dependent returns into our framework, following the work of Jappelli and Padula (2013) and Lusardi et al. (2017). Additionally, we relax the assumption that default probabilities depend on financial skills, $p(f, a)$, and instead model delinquency as dependent only on asset holdings.

The return function, which provides an incentive for skill accumulation, is specified as:

$$R(f) = \alpha_r f^{\beta_r} + \gamma_r, \quad \alpha_r, \beta_r \geq 0, \text{ with } \gamma_r = 0.02$$

Delinquency, on the other hand, depends solely on asset levels and is given by:

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

We re-estimate the parameters p_0 and p_a using late payments from the SCF data. After calibrating the model and conducting model validation exercise as with the benchmark, we find that the

extended model yields a similar level of inequality. Since our focus remains on mortgage take-up and refinancing, we use the benchmark model for counterfactual analysis. Details of this extension are provided in Section G.3 of the Appendix.

6 Policy Implications

6.1 Policy Exercises

Our mortgage search framework generates plausible levels of consumption inequality, driven by heterogeneity in repayment behavior and asset holdings. Leveraging insights from studies on mortgage price differentiation due to search behavior and financial sophistication (Fuster et al., 2019; Bartlett et al., 2022), we conduct counterfactual exercises to explore how financial literacy and search intensity interact, particularly among renters and homeowners.

Unlike the majority of financial education interventions aimed at high-school students (Lusardi et al., 2010; Lusardi and Mitchell, 2014), our exercises focus on enhancing financial skills among renters prior to mortgage take-up. Given the significance for homeowner's financial implications, the timing of such interventions is crucial[13].

The last set of counterfactual assesses the impact of exogenous shifts in mortgage rates, focusing on how financial literacy influences the refinancing channel. By incorporating skill heterogeneity, our framework offers a clearer understanding of how interest rate adjustments differentially affect borrowers, enabling more targeted and effective monetary policy.

6.1.1 Financial Education

We model a financial education policy targeting renters, designed to enhance financial skill accumulation by reducing the cost elasticity of skill investment by 5%. This modest reduction corresponds to a 0.04% decrease in average work time, equivalent to a 65-minute financial education course for renters[14]. The policy primarily targets younger households prior to homeownership and encompasses broader financial decision-making beyond mortgage literacy.

[13]The meta-analysis in (Kaiser and Menkhoff, 2017) suggests heterogeneous effects of financial education, likely influenced by the timing of interventions.

[14]This calculation assumes a 40-hour workweek across 52 working weeks per year, accounting for the disutility of time relative to the utility derived from annual income.

By improving financial skills, the policy lowers the probability of financial shocks, leading to better mortgage performance and reduced distress unrelated to housing. The intervention results in a 2.56% increase in homeownership, driven by a 2.71% rise in renters' search intensity. These new homeowners benefit from lower housing costs compared to rental rates, facilitating increased consumption and savings, which in turn reduces both consumption and asset inequality (first column in Table 7). Furthermore, improved financial skills reduce delinquency rates by 3.12%, highlighting significant welfare gains from the policy.

6.1.2 Mortgage accessibility and complementarity of financial education

Our second exercise simulates the entry of non-bank mortgage lenders into the U.S. mortgage market, which has substantially increased mortgage accessibility[15]. In this counterfactual, we reduce the search cost elasticity parameter, representing a decrease in the average search cost by 2.5% for renters and 5% for homeowners, effectively lowering the effort required to access a larger pool of mortgage offers.

The second column in Table 7 depicts the relative changes between the benchmark model and the higher-accessibility counterfactual. Lower search costs lead to a 7.18% increase in homeowners' search intensity and a 3.68% increase among renters. This reduces housing costs and subsequent consumption inequality by 0.2%. However, the influx of less financially skilled borrowers into the market increases average delinquency rates by 0.19%, as these individuals remain vulnerable to financial shocks. Furthermore, easier search does not incentivize skill accumulation, resulting in only a marginal increase 0.43% in average skills (middle column in Table 7).

To address the adverse effect of easier search on mortgage delinquency, we examine the complementary role of financial education. Introducing education alongside reduced search costs incentivizes skill accumulation, particularly at the bottom of the asset distribution, as depicted in top right panel of Figure 7. On the aggregate, financial skills increase by an additional 0.1 percentage points, ultimately reaching 12% (right column in Table 7). More importantly, delinquency rates decrease by 2.93%, countering the adverse effects of low-skilled borrowers entering the market. Consumption increases mostly at the bottom of the asset distribution (top left panel in Figure 7),

[15] (Zhou, 2022) documents that market expansion coincided with a rising share of mortgage offers for home purchases and refinancing. Similarly, (Fuster et al., 2019) finds that FinTech lenders improved loan processing speeds by 20% without adding costs to applicants.

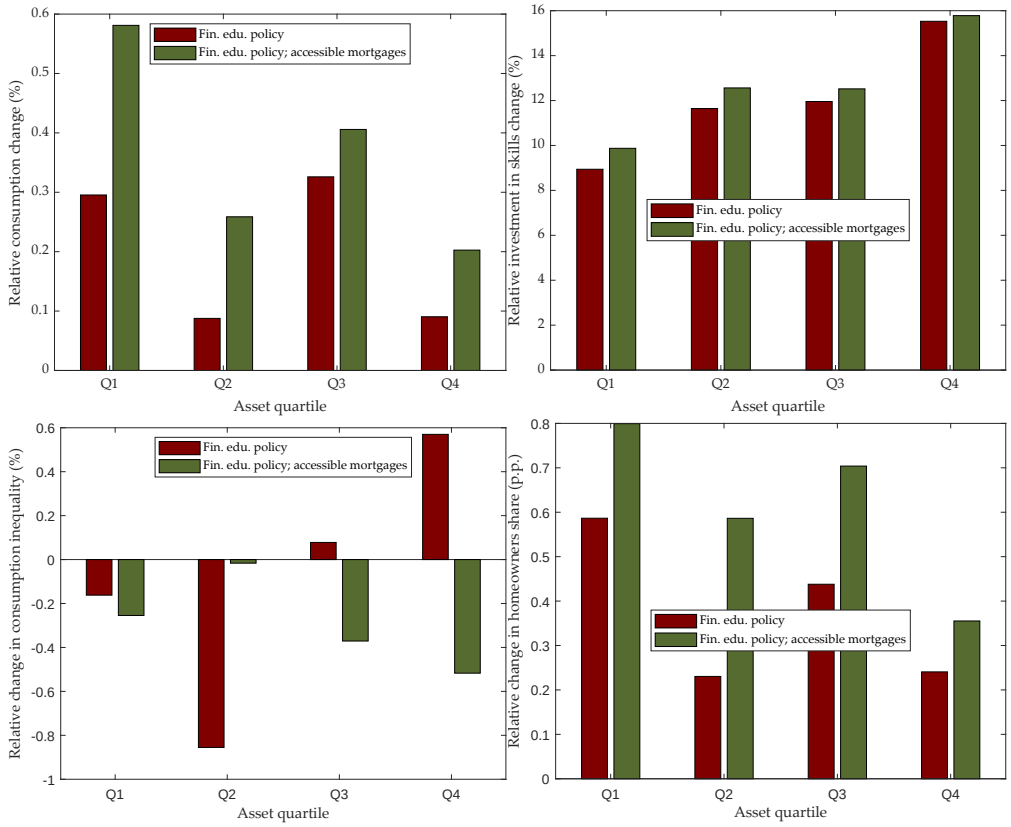
and produces a fall inequality across the asset distribution (bottom left panel in Figure 7).

Our findings produce a nonlinear effect of education policy, depending on the mortgage accessibility. While the quantification relies on many assumptions, the main message is... that while expanded mortgage accessibility improves affordability and equality in housing costs, integrating financial education policies mitigates the risk of delinquency and deepens the reduction in consumption inequality. This underscores the importance of pairing financial education with policies that broaden mortgage access.

Table 7: **Policy implications.** Steady state differences are based on simulations for model calibrated according to values from Table 5 (benchmark economy). First column - financial education course policy, second column - more accessible mortgage environment, and third column - financial education in more accessible environment, outline relative changes in comparison to our benchmark economy.

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

Figure 7: **Policy effects breakdown.** Steady state differences are based on simulations for model calibrated according to values from Table 5 (benchmark economy). Top left - consumption, top right - investment, bottom left - consumption inequality, and bottom right - homeownership share relative differences for financial education course policy and financial education in more accessible environment, relative to our benchmark economy. In each panel differences for two policies relative to benchmark economy are presented over asset quartiles.



6.2 Exogenous Shifts in Mortgage Rates

Our last set of counterfactuals quantifies the effects of exogenous mortgage rate changes on inequality, focusing on the refinancing channel and its dependence on financial skill levels. Without explicitly modeling the supply side (Cota and Šterc, 2023), we simulate a 5 basis point shift in the mean mortgage offer rate while maintaining the calibrated spread of the baseline Beta distribution.

A downward shift in rates significantly increases homeowners' search intensity by 12.3%, as they capitalize on lower housing costs through refinancing, while renters' search effort rises modestly by 3.4%. Despite reduced housing costs, renters remain constrained by search costs and limited financial skills, resulting in only marginal reductions in consumption and asset inequality (0.22% and 0.2%, respectively) and a 0.17% decline in delinquency rates.

In contrast, an upward shift reduces homeowners' search intensity by 11.6% and renters' by

3.3%, increasing inequality. Consumption and asset Gini coefficients rise (0.22% and 0.19%, respectively), while delinquency rates increase by 0.23%. Across both scenarios, financial skill accumulation remains low, with renters particularly disadvantaged.

These findings, summarized in Table 8, underscore how rate changes primarily benefit (or burden) homeowners, and reinforce disparities among homeowners and renters. Policies targeting renters' financial skills could enhance access to mortgage and later refinancing opportunities and strengthen the refinancing channel of monetary policy.

Table 8: **Shift in the offer rate distribution.** Steady state differences are based a model calibrated according to values from Table 5. Table compares relative steady state differences between our benchmark model and the model with downward shift in the offer distribution (left column), and upward shift (right column). Both downward and upward shift are represented with a 5 b.p. change in the mean, while keeping the spread from the baseline economy.

Measure	relative change	
	downward shift	upward shift
average search renters	↗ 3.4%	↘ 3.3%
average search homeowners	↗ 12.3%	↘ 11.6%
consumption Gini	↘ 0.22%	↗ 0.22%
assets Gini	↘ 0.2%	↗ 0.19%
average financial skills	↗ 1.1%	↘ 1.2%
average delinquency rate	↘ 0.17%	↗ 0.23%

7 Conclusion

In this paper, we examine the role of financial literacy in mortgage choice, a major investment decision for US households. As mortgage products become increasingly complex, financially illiterate households face challenges in selecting and refinancing, leading to significant disparities in mortgage rates among similar borrowers. Given the long-term nature of mortgages, these rate differences translate into substantial variations in budgeting and consumption.

Using two complementary datasets—the Survey of Consumer Finances and the National Survey of Mortgage Originations—we document a novel set of stylized facts linking financial literacy and search behavior to mortgage outcomes. Specifically, our findings highlight search effort as the mechanism through which financial literacy influences mortgage interest rates. We also show that active refinancing correlates with persistently high financial skills. By merging the SCF with detailed mortgage contract data, we find that financially unskilled households, who tend to consider

fewer lenders, overpay by an average of $13,000 on a $100,000 loan. These households are also less likely to refinance, suggesting that our estimates capture only the lower bound of their financial losses.

To quantify the impact of financial skills on mortgage repayments and consumption inequality, we develop a mortgage search framework that integrates endogenous financial literacy, wealth accumulation, and mortgage selection. Building on our set of stylized facts, we introduce micro-founded cognitive search frictions that vary with financial skills. This approach takes a first step in estimating the long-term effects of disparities in debt repayment on consumption inequality. Through counterfactual analyses, we evaluate the effects of financial education, digital advancements, and interest rate changes.

First, we show that policies promoting financial skills among renters mitigate the adverse effects of accessible mortgages on delinquency rates. When mortgage access improves, financially unskilled renters gain an additional incentive to invest in skills, leading to greater endogenous accumulation. Second, we examine the refinancing channel of monetary policy, showing that lower mortgage rates primarily benefit financially savvy homeowners who refinance, while renters facing cognitive search frictions gain less. As a result, mortgage rate reductions have a limited effect on reducing consumption inequality among similar borrowers.

Finally, while our analysis focuses on household demand-side heterogeneity, we abstract from supply-side dynamics. Future research could incorporate borrower-lender bargaining and strategic pricing decisions to explore the role of heterogeneity in credit search and its broader implications for aggregate inequality.

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A SCF data analysis

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, coupled with self-reported statistics on individual mortgages. Our analysis focuses on a SCF subset with a "financial literacy score," from the 2016 and 2019 waves, and includes 60,125 responses. We use the data on mortgages, self-assessed search behavior, and financial literacy to provide an additional check for the key empirical evidence mentioned in the main part of the paper, so to not depend on the stochastic record linkage.

A.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

We examine the average financial literacy score over the lifecycle to motivate investment in financial skills in the model. Figure 1 shows a hump-shaped profile of average financial literacy scores by age groups suggestive of accumulation and depreciation of financial literacy over the lifecycle.



Figure 8: **Financial literacy distribution by education level.** Uses SCF waves 2016 and 2019. Each light green bar presents relative frequency of number of correctly answered questions (from zero to three) conditional on highest degree of education obtained: high school degree (left chart), technical school degree (mid-left chart), college degree (mid-right chart), and post-college degree (right chart).

Next, we look at household characteristics and to which extent they explain financial literacy, and show how the characteristics account for a small part of the variation in financial literacy score. While Figure 8 shows that financial literacy correlates with education, variance decomposition of the standardized score outlined in Table 1 shows that there is more than 80% of unexplained variance, even after including a large set of controls. Interestingly, among homeowners, observables seem to explain less of the variation, suggesting an endogenous shift governed by the home purchase. Particularly, we include age, race, gender, work and marital status, own and parent's education, financial and nonfinancial assets categories, and income categories.

We next formalize the empirical correlation between observables and the literacy score using

linear regression in Table 9. While most of the coefficients do not show significant differences, the race coefficient decreases and becomes insignificant for "African American" and "Latino", potentially due to the selection bias or the larger effect of SES characteristics on homeownership.

Table 9: **Financial literacy regression on observables.** The left column uses the whole SCF sample, and the right column uses the homeowners subsample with respective survey weights. Gender, marital status, education and parent education, and race are defined as dummy variables, with "male", "married/co-living", "no high school", and "Alaska Native, Indian and other" as base categories. Both regressions control for work status, income and asset categories explained in the text, however are not listed.

	Financial literacy score (standardized)	
	(all observations)	(homeowners)
Female	-0.060^{***}	-0.062^{***}
	(0.003)	(0.005)
Age	0.0004^{***}	0.0004^{***}
	(0.0001)	(0.0001)
Divorced/Separated	0.013^{***}	0.020^{***}
	(0.003)	(0.005)
Never Married	0.021^{***}	0.010^{*}
	(0.003)	(0.006)
Caucasian	0.026^{***}	0.043^{***}
	(0.005)	(0.007)
African-American	-0.033^{***}	-0.012
	(0.005)	(0.008)
Hispanic/Latino	-0.009^{*}	-0.003
	(0.005)	(0.008)
Asian	0.031^{***}	0.020^{*}
	(0.009)	(0.012)
High school	0.058^{***}	0.052^{***}
	(0.003)	(0.007)
College	0.131^{***}	0.127^{***}
	(0.004)	(0.007)
Post college	0.162^{***}	0.150^{***}
	(0.004)	(0.008)
Parent education: high school	0.006^{**}	0.015^{***}
	(0.003)	(0.005)
college	0.033^{***}	0.043^{***}
	(0.003)	(0.005)
Constant	0.514^{***}	0.534^{***}
	(0.007)	(0.013)
Observations	83,100	31,895
R^2	0.181	0.158
Adjusted R^2	0.181	0.157
Residual Std. Error	38.908 (df = 83074)	37.054 (df = 31869)
F Statistic	736.739^{***} (df = 25; 83074)	239.114^{***} (df = 25; 31869)

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

A.2 Mortgage Uptake, Refinancing and Financial Literacy

We leverage detailed survey responses in the SCF about individual mortgage uptake and experience to better understand the link between financial literacy, mortgage rates, refinancing and late payments, serving as microfoundations of our model. Mortgage characteristics and details are self-reported and therefore potentially noisy, so we adhere to the registry data coupled with

mortgage performance and explore the variation in mortgage rates in more detail. However, for exposition, we first outline the properties of mortgage rates in the SCF. Second, SCF allows us to focus on shopping behavior and refinancing and, by exploiting the variation in time passed since refinancing, observe the potential effect on financial literacy, while controlling for observables.

A.2.1 Mortgage rates

In the SCF survey, households report their current mortgage rate and give details on the principal residence. We take a subsample of first-time mortgage owners, and take out those with adjustable mortgage rates and who reported not to be in full ownership of their property or home. The remaining data consists of mortgage data provided by 11,965 households.

We regress their mortgage rate on a set of respondents' characteristics and specifics about their mortgage, such as mortgage term, origination year, and LTV ratio calculated using the total amount borrowed and the cost of the property upon purchase. Individual responses allow us to control for mortgage sponsorships and insurance, balloon payment schedules, the lending institution type indicator. Given that the information in the SCF data is self-reported and subsequently imputed, we use our findings as complementary to the registry data linked with the National Survey of Mortgage Originations analysis, with mortgages originated after 2012, **NSMO+**. To make the analysis parallel, we use the SCF subsample with mortgages of similar origination years.

For the exposition, we depict the unconditional distribution of mortgage rates for mortgages that originated in 2016, the most frequent year in our sample, with 1173 homeowners reported having taken up a first-time purchase mortgage. In this year, 49% homeowners report obtaining the mortgage with a commercial bank, and 49% obtaining one with a non-bank institution. Figure 9 shows that financially literate households get charged with lowest rates, irrespective of the lender reported.

Beyond the unconditional distribution of mortgage rates, we underline the suggestive evidence in Table 10 that illustrates the negative link of interaction between financial skills and search intensity with interest rates, indicating that financially literate borrowers effectively leverage their search efforts to secure better terms.

Predictions from our linear model suggest substantial benefits for financially literate borrowers who actively search for credit, resulting in a reduction of 18 b.p in mortgage rates relative to

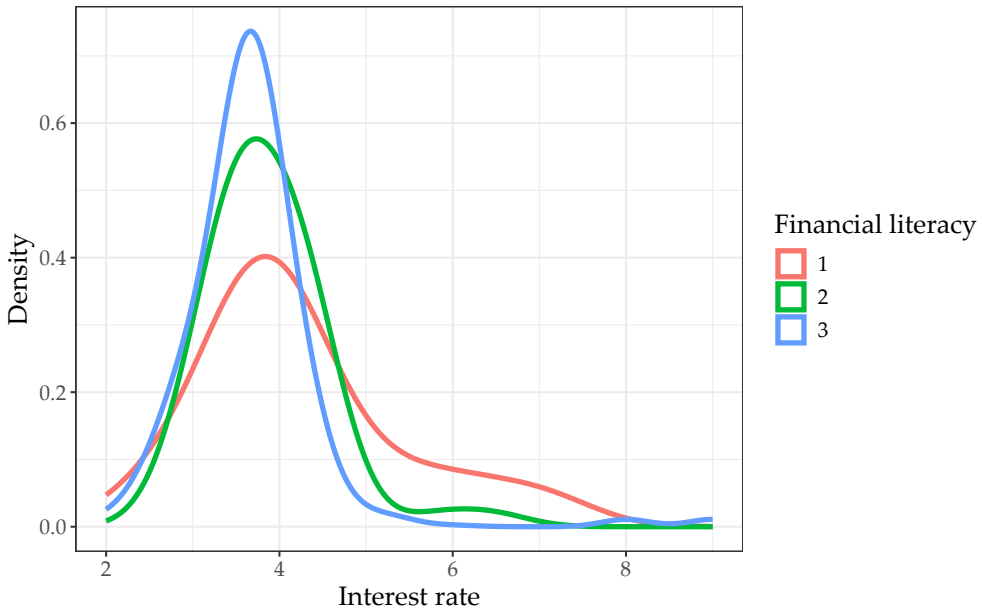


Figure 9: **Unconditional distribution of mortgage rates originated in 2016.** Kernel density estimation uses the SCF subsample of originations with non-banks, 577 observations. Bandwidth choice is obtained using Silverman's method, with adjustment factor 2.5. Financial literacy category "1" denotes respondents who answered at most one question correctly, category "2" represents two questions answered correctly, and "3" denotes those borrowers with a full score.

search-inactive financially unskilled counterparts. Using registry data, we show that, for financially unskilled borrowers, the relationship is non-linear and highlights the 'fear of denial' effect in mortgage applications, as documented in (Agarwal et al., 2024).

Table 10: **Mortgage rate, financial skills, and search - regression.** Estimates use the SCF sample households with fixed-rate, first-time mortgages originated. Financial skills are defined as the standardized FinLit score, and search effort is a three-level measure, based on self-reported time spent in search for credit. Education are dummy variables with "male", "Caucasian", and "no high school" as base categories. Base categories for mortgage insurance and balloon payments are "no". Estimates control for individual race, gender, total income, mortgage origination year, and survey wave effects.

	mortgage rate	
	(all first originstions)	(first originations starting 2012)
Fin. Skills	0.163	0.158
	(0.115)	(0.119)
Moderate search	0.089	0.082
	(0.110)	(0.116)
Great deal of search	0.081	0.120
	(0.100)	(0.105)
Fin. Skills: Moderate search	−0.148	−0.145
	(0.139)	(0.143)
Fin. Skills : Great deal of search	−0.378***	−0.412***
	(0.128)	(0.132)
Constant	3.812***	3.495***
	(0.318)	(0.154)
Age	0.002	0.002**
	(0.001)	(0.001)
Married	−0.042*	−0.097***
	(0.024)	(0.025)
Education: High-School	0.055	−0.154**
	(0.054)	(0.066)
Bachelor	−0.114**	−0.344***
	(0.056)	(0.068)
Post-Bacc	−0.094	−0.339***
	(0.059)	(0.070)
Loan term	0.022***	0.012***
	(0.002)	(0.002)
Mortgage insurance (YES)	0.185***	0.103***
	(0.026)	(0.025)
Balloon payment (YES)	0.364***	0.247**
	(0.089)	(0.098)
Non-Banks (YES)	0.045**	0.032
	(0.022)	(0.022)
Government, Nonprofits, and Other Institutions (YES)	0.235**	0.858***
	(0.097)	(0.114)
LTV	0.434***	0.357***
	(0.054)	(0.056)
Observations	11,965	8,487
R^2	0.234	0.176
Adjusted R^2	0.230	0.173
Note:		*p<0.1; **p<0.05; ***p<0.01

A.3 Credit shopping time

Besides the interaction between skills and search, our analysis of the variation in self-reported search effort motivates endogenous search in the mortgage search model. While the SCF asks about the usual approach to shopping for credit, the representative sample in the NSMO is followed with the survey on the household mortgage shopping experience specific to the mortgage in the registry. We exploit the equivalent measure in the NSMO, *the amount of lenders considered prior to applying for a mortgage*, and using the NSMO+, we show that our findings hold in both. Financially, skilled, better-educated, and wealthier households are more likely to spend a great deal of time when searching for credit.

We show that in both samples with different proxies for search intensity, financial skills positively correlate with the amount of search, suggesting that financially skilled borrowers may find it less difficult.

Table 11: **Variation in individual search for credit.** Estimates use SCF subsamples of mortgage owners (left) and renters (right). FinLit score, gender, marital status, and education are represented as dummy variables, with "FinLit score 1", "Married/Co-Living", "Male", and "No high-school" as baselines. Controls include income, asset level, current monthly mortgage and rent payments, and year FE.

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

We use the estimates in Table 11 to predict the likelihood of taking a great deal of time spent searching for credit. First, we note that 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 2, 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 2, right).

A.4 Rent and mortgage payments as shares of labor income

In calibrating the model, we target the rental rate κ using the share of homeowners in the SCF, resulting in κ reflecting rental costs that are approximately twice as large as mortgage payments. This outcome serves as an additional validation of our model's empirical robustness. Specifically, we compare the rental rate κ to the average mortgage payment as a share of individual income.

We focus on a subsample of SCF workers to analyze this relationship, examining how these differences manifest in average yearly housing costs.

Table 12 presents housing costs across financial literacy levels. The estimates are derived from the SCF subsample of workers under the age of 63, with group averages computed using survey weights.

Living arrangement	Financial literacy score			
	0	1	2	3
Homeowner	0.313	0.334	0.288	0.261
Renter	0.624	0.577	0.451	0.414

Table 12: **Housing costs across financial literacy levels.** The estimates use the SCF subsample of workers younger than 63 who have reported their monthly wages. All group averages are obtained using survey weights.

A.5 Homeownership choice and financial literacy

Our model assumes that the choice to become a homeowner 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 13 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, we control for labor market participation. The first two rows in the coefficient table 13 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 13: Binary regression estimates, homeownership choice, SCF data.

	Dependent variable:
	Owns a house or an apartment
Financial literacy score: medium	0.181***
	(0.031)
high	0.223***
	(0.033)
Education: some college or technical school	-0.020
	(0.030)
College degree	0.042
	(0.037)
Post-college degree	0.019
	(0.044)
Female	-0.016
	(0.037)
non-white	−0.586***
	(0.025)
Leverage ratio	-0.029***
	(0.003)
Willing to take risk	0.014
	(0.058)
Constant	−1.164***
	(0.071)
Pseudo R^2	0.277
Observations	40,071

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

B 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 14 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[16]. 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.

[16]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 14: 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%]

For each 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 $\gamma_k(i, j)|M_{i,j} \overset{\cancel{\text{indep.}}}{\sim}$ Discrete$(\pi_{k,m})$[17], $k = 1, \ldots K$ where $\pi_{kl},\ \ l \in \{0, \ldots, L_k - 1\}$ represents the probability of each agreement degree for the pair (i, j). The vector of probabilities is denoted with $\boldsymbol{\pi}_{km}$. Due to our assumption that allows for inter-dependence, θ_m parametrizes correlations between characteristics $1, \ldots K$ for $\gamma(i, j) \in K \times L$.

[17] We account for for inter-dependence between observable characteristics.

Overall, likelihood is defined with

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

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

and log-likelihood with:

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

We estimate the model 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}[18]:

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

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

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

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

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.

C NSMO+ estimates

C.1 Number of lenders considered

As an additional counterfactual exercise, to complement our SCF findings, 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 (15). 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 39.8 p.p. higher 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 15: **Variation in individual search for mortgage.** Estimates use NSMO+ subsamples of all mortgage contracts (left) and mortgage contracts upon refinancing (right). Marital status, gender, race, education, and loan amount modeled as dummy variables with base-categories: Single, Male, White, High school, and Less than $49,999$. Age and credit score are standardized. Controls include income category, time fixed effects, government-sponsored enterprise, term, LTV, borrower number, loan type, and metropolitan area.

	Number of lenders considered	
	(All origination)	(Refinancing)
Age	-0.043^{***}	-0.020^{**}
	(0.005)	(0.008)
Credit score	0.009^{*}	0.005
	(0.005)	(0.007)
Married	0.021^{***}	0.014
	(0.006)	(0.010)
Female	-0.058^{***}	-0.077^{***}
	(0.005)	(0.007)
Race: Black or African-American	0.065^{***}	0.046^{***}
	(0.011)	(0.015)
Asian	0.059^{***}	0.059^{***}
	(0.010)	(0.014)
Other (including Hispanic)	0.065^{***}	0.089^{***}
	(0.014)	(0.020)
Financial Skills	0.398^{***}	0.341^{***}
	(0.074)	(0.106)
Education: some college or technical school	0.056^{***}	0.053^{***}
	(0.009)	(0.013)
College graduate	0.089^{***}	0.077^{***}
	(0.009)	(0.013)
Post-college graduate	0.106^{***}	0.088^{***}
	(0.010)	(0.014)
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)
$\$150,000 - \$199,999$	0.048^{**}	0.154^{***}
	(0.020)	(0.029)
$\$200,000 - \$249,999$	0.067^{***}	0.152^{***}
	(0.020)	(0.030)
$\$250,000 - \$299,999$	0.072^{***}	0.167^{***}
	(0.021)	(0.031)
$\$300,000 - \$349,999$	0.072^{***}	0.180^{***}
	(0.021)	(0.032)
$\$350,000 - \$399,999$	0.088^{***}	0.182^{***}
	(0.022)	(0.033)
$\geq \$400,000$	0.100^{***}	0.176^{***}
	(0.021)	(0.031)
Constant	0.105	0.116
	(0.064)	(0.092)
Observations	43,094	21,625
R^2	0.024	0.025
Adjusted R^2	0.023	0.023
Residual Std. Error	17.837 (df = 43049)	17.675 (df = 21580)
F Statistic	23.837^{***} (df = 44; 43049)	12.720^{***} (df = 44; 21580)
Note:		*p<0.1; **p<0.05; ***p<0.01

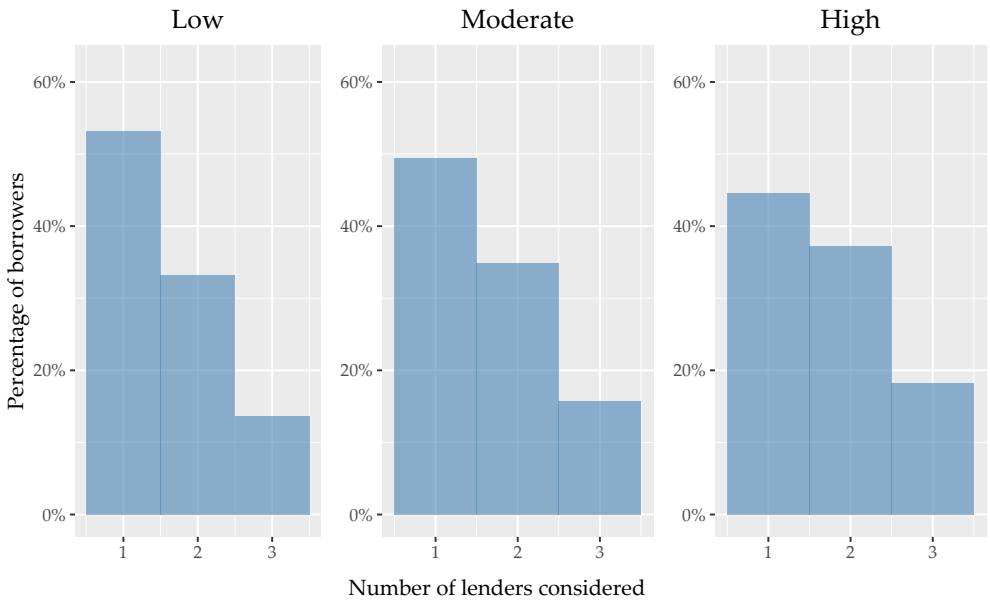


Figure 10: **The number of lenders considered at the time of loan origination** This figure plots relative frequency of number of lenders considered at the time of loan origination across financial skill level, left-to-right panel (Low, Moderate and High financial skills) using the NSMO+ dataset. In each panel represents relative frequency of considering one, two, and three or more lenders.

C.2 Mortgage rate regression

Based on our estimations, we predict the mortgage interest rate for a median borrower, while varying her financial skills and mortgage search effort. Table 17 outlines predicted interest rates.

Next, using the predictions, we plot a quantitative search plot. In addition, we do a triple interaction with the origination year and plot marginal effects.

	Mortgage rate	
	(First origination)	(All mortgages)
Considered two lenders	0.149	−0.025
	(0.161)	(0.112)
Considered three or more lenders	0.842***	0.393***
	(0.216)	(0.148)
Financial skills	−0.060	−0.073
	(0.171)	(0.114)
Considered two lenders × Fin. skills	−0.224	0.002
	(0.212)	(0.146)
Considered three or more lenders × Fin. skills	−1.172***	−0.573***
	(0.282)	(0.193)
Age	0.044***	0.063***
	(0.010)	(0.007)
Metro area: LMI tract	0.033**	0.022**
	(0.013)	(0.009)
Non-metro area	−0.018	0.002
	(0.015)	(0.010)
Married	0.010	0.007
	(0.011)	(0.008)
Female	0.032***	0.030***
	(0.009)	(0.006)
Race: Black or African-American	−0.015	0.002
	(0.020)	(0.013)
Asian	−0.025	−0.037***
	(0.020)	(0.013)
Other (including Hispanic)	0.062**	0.048***
	(0.025)	(0.017)
Income: $\$35,000 - \%50,000$	0.011	−0.040**
	(0.024)	(0.017)
$\$50,000 - \$75,000$	0.043*	−0.015
	(0.023)	(0.016)
$\$75,000 - \$100,000$	0.043*	−0.007
	(0.024)	(0.017)
$\$100,000 - \$175,000$	0.075***	0.009
	(0.025)	(0.017)
$\$175,000$ and more	0.074***	0.007
	(0.028)	(0.020)
Education: some college or technical school	−0.054***	−0.034***
	(0.017)	(0.011)
College graduate	−0.100***	−0.071***
	(0.017)	(0.011)
Post-college graduate	−0.125***	−0.090***
	(0.018)	(0.012)
Refinancing		−0.074***
		(0.007)
Credit score	−0.261***	−0.246***
	(0.010)	(0.007)
Constant	5.309***	4.993***
	(0.143)	(0.096)
Observations	21,469	43,094
R^2	0.369	0.440
Adjusted R^2	0.368	0.439
Residual Std. Error	23.651 (df = 21420)	22.323 (df = 43044)
F Statistic	261.448*** (df = 48; 21420)	689.454*** (df = 49; 43044)

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

Controlled for time effects, loan amount, loan type, government-sponsored enterprise, number of borrowers, term, and LTV.

Table 16: **Mortgage rate regression** controlling for loan and borrower characteristics. Estimates based on mortgages originated from 2013 to 2021. Left column represents only first-time originations, whereas the right includes mortgages that are refinanced. The number of lenders considered, metro area, gender, race, income, education, and refinancing indicator are represented as dummy variables with "considered one lender", metropolitan/urban area, single, male, Caucasian, below $35,000, high-school and first origination as base categories. The rest of the controls are LTV, loan amount and type categories, sponsorship dummy, number of borrowers, loan term, and year FE, and are not depicted in the table.

Table 17: **Predicted mortgage rates.** Tables shows linear regression model (from Table 16) based predicted mortgage rates conditional on financial skills level and number of lenders considered.

	Number of lenders considered		
	one	two	three or more
Financial skills =0	3.966453	3.941524	4.359803
Financial skills =$\frac{1}{2}$	3.929709	3.905587	4.036557
Financial skills =1	3.892966	3.869649	3.713311

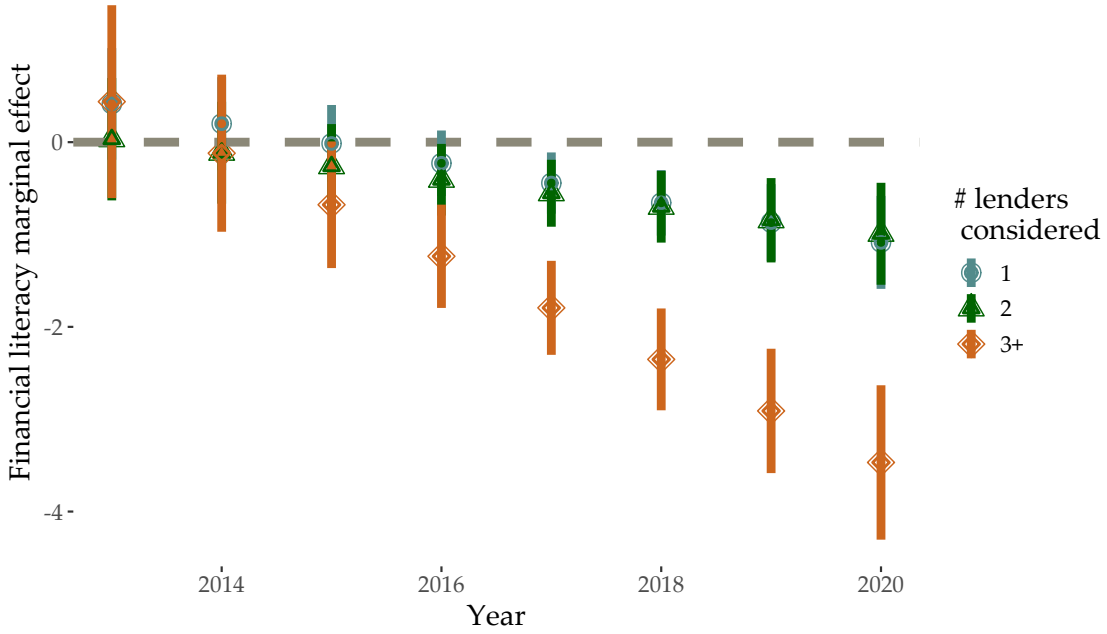


Figure 11: **Interaction of financial skills and search over time**. Financial skill coefficient in the mortgage rate regression, differences over the sample period. Source: merged NSMO+ data set, authors' calculations.

C.3 Additional month fixed effects

Table 18 presents estimates for regression model (1) from the main part of the text with additional month fixed effects. The results in Table 18 show that month fixed effects have a small effect on R^2 and almost no effect on the other coefficients of other variables compared to the results in Table 16.

	Mortgage rate	
	(First origination)	(All mortgages)
Considered two lenders	0.178	−0.010
	(0.161)	(0.111)
Considered three or more lenders	0.836***	0.392***
	(0.216)	(0.148)
Financial skills	−0.043	−0.072
	(0.171)	(0.114)
Considered two lenders × Fin.skills	−0.260	−0.015
	(0.211)	(0.145)
Considered three or more lenders × Fin.skills	−1.162***	−0.570***
	(0.282)	(0.192)
Age	0.044***	0.062***
	(0.010)	(0.007)
Metro area: LMI tract	0.035***	0.024***
	(0.013)	(0.009)
Non-metro area	−0.014	0.006
	(0.015)	(0.010)
Married	0.010	0.007
	(0.011)	(0.008)
Female	0.032***	0.031***
	(0.009)	(0.006)
Race: Black or African-American	−0.012	0.002
	(0.020)	(0.013)
Asian	−0.026	−0.038***
	(0.020)	(0.013)
Other (including Hispanic)	0.062**	0.049***
	(0.025)	(0.017)
Income: $\$35,000 - 50,000$	0.012	−0.041**
	(0.024)	(0.017)
$\$50,000 - 75,000$	0.043*	−0.016
	(0.023)	(0.016)
$\$75,000 - 100,000$	0.044*	−0.007
	(0.024)	(0.017)
$\$100,000 - 175,000$	0.073***	0.007
	(0.025)	(0.017)
$\$175,000$ and more	0.072**	0.007
	(0.028)	(0.020)
Education: some college or technical school	−0.053***	−0.035***
	(0.017)	(0.011)
College graduate	−0.101***	−0.072***
	(0.017)	(0.011)
Post-college graduate	−0.126***	−0.092***
	(0.018)	(0.012)
Refinancing		−0.077***
		(0.007)
	(0.038)	(0.026)
Credit score	−0.260***	−0.245***
	(0.010)	(0.007)
Constant	5.446***	5.097***
	(0.144)	(0.096)
Observations	21,469	43,094
R^2	0.374	0.444
Adjusted R^2	0.372	0.443
Residual Std. Error	23.579 (df = 21409)	22.242 (df = 43033)
F Statistic	216.409*** (df = 59; 21409)	572.540*** (df = 60; 43033)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 18: **Mortgages rate regression with additional time fixed effects.** Mortgage rate regression controlling for loan and borrower characteristics. Estimates based on mortgages originated from 2013 to 2021. Left column represents only first-time originations, whereas the right includes mortgages that are refinanced. The number of lenders considered, metro area, gender, race, income, education, and refinancing indicator are represented as dummy variables with "considered one lender", metropolitan/urban area, single, male, Caucasian, below $\$35,000$, high-school and first origination as base categories. The rest of the controls are LTV, loan amount and type categories, sponsorship dummy, number of borrowers, loan term, and year and month FE, and are not depicted in the table.

C.4 Late payments

In this section, we make a causal claim. We track mortgage performance until the end of the NSMO+ sample or closure. In tables, we regress the indicator of late payments on household's characteristics at the time of mortgage attainment.

	$\mathbb{P}$(late payment)
Financial skills	-0.072^{***}
	(0.013)
Multiple lenders considered	-0.002^{**}
	(0.001)
Female	0.002^{*}
	(0.001)
Education: some college or technical school	0.003^{*}
	(0.002)
college graduate	0.001
	(0.002)
post-college graduate	0.001
	(0.002)
Race: non-white	0.004^{***}
	(0.001)
Age	0.002^{*}
	(0.001)
Payment-to-income	0.004^{***}
	(0.001)
Credit score	-0.020^{***}
	(0.001)
Constant	0.072^{***}
	(0.010)
Observations	43,094
R^2	0.021
Adjusted R^2	0.021
Residual Std. Error	3.493 (df = 43072)
F Statistic	44.257^{***} (df = 21; 43072)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 19: **Late payments.** Table shows estimates of a linear probability model using NSMO+ sample. Controlling for time fixed effects. Base categories for dummy variables: Number of lenders considered, Gender, Education, and Race are: One lender considered, Male, High school, and White. Controls include loan amount and origination year fixed effects.

C.5 Cost of hiring a mortgage broker

In this section, we focus on pricing differences of financing through financial intermediary. More specifically, we look at question: *Which one of the following best describes how you applied for this mortgage?* The possible answers are

- Directly to a lender, such as a bank or credit union.
- Through a mortgage broker who works with multiple lenders to get you a loan.
- Through a builder who arranged financing.

Table 20: **Share of borrowers hiring an intermediary.** Tables shows relative frequency of across financial skills terciles (columns). Rows show relative frequency of how households applied for a mortgage contract: "Directly to a lender, such as a bank or credit union" (Direct), "Through a mortgage broker who works with multiple lenders to get you a loan" (Broker), and "Through a builder who arranged financing" (Builder).

	Financial skills tercile		
Search tool	Low	Moderate	High
Direct	0.5661	0.6155	0.6161
Broker	0.4169	0.3721	0.3739
Builder	0.0170	0.0124	0.0100

Table 21 summarizes the results of the analysis. From the table, in comparison to the main regression, we do not see major differences for other regressiors, nor in size, significance or sign. However, we see differences in pricing both at origination and while controlling for refinancing, differences coming from taking up a mortgage through intermediary such as a broker or a builder who arranged financing. Interestingly, both upon origination or when refinancing, the most expensive is the mortgage contract signed through a builder.

To quantify pricing in of mortgage brokers, we look at model prediction for an average borrower in the pool of all mortgages. The model predicts mortgage rate of 3.887% without hiring a mortgage broker and 3.974% with hiring a mortgage broker. From model-based mortgage rate predictions, we see that the interest rate for those who hired a mortgage broker on average is 8.8. b.p. higher than for those who went directly to the lender. More specifically, if we look at the smaller size mortgage loan of $\$100,000$ with median term of 30 years, these differences sum-up to more than $\$60$ per month on the the mortgage payment. In addition, over the mortgage term, these differences sum-up to more than $\$1,800$ overall.

Table 21: **Cost of hiring a mortgage broker.** Controls include time effects, loan amount, loan type, government-sponsored enterprise, number of borrowers, term, and LTV.

	Mortgage rate	
	(First origination)	(All mortgages)
Intermediary: Broker	0.151***	0.087***
	(0.009)	(0.006)
Builder	0.195***	0.171***
	(0.030)	(0.027)
Considered two lenders	0.114	−0.042
	(0.160)	(0.111)
Considered three or more lenders	0.814***	0.366**
	(0.216)	(0.148)
Financial skills	−0.057	−0.078
	(0.170)	(0.114)
Considered two lenders × Fin. skills	−0.171	0.026
	(0.211)	(0.146)
Considered three or more lenders × Fin. skills	−1.117***	−0.530***
	(0.281)	(0.193)
Age	0.037***	0.063***
	(0.010)	(0.007)
Metro area: LMI tract	0.032**	0.021**
	(0.013)	(0.009)
Non-metro area	−0.003	0.010
	(0.015)	(0.010)
Married	0.009	0.007
	(0.011)	(0.008)
Female	0.030***	0.030***
	(0.009)	(0.006)
Race: Black or African-American	−0.017	0.002
	(0.020)	(0.013)
Asian	−0.030	−0.043***
	(0.019)	(0.013)
Other (including Hispanic)	0.063**	0.047***
	(0.025)	(0.017)
Income: $\$35,000 - \%50,000$	0.010	−0.042**
	(0.024)	(0.017)
$\$50,000 - \$75,000$	0.041*	−0.016
	(0.023)	(0.016)
$\$75,000 - \$100,000$	0.044*	−0.007
	(0.024)	(0.017)
$\$100,000 - \$175,000$	0.076***	0.009
	(0.025)	(0.017)
$\$175,000$ and more	0.079***	0.010
	(0.028)	(0.020)
Education: some college or technical school	−0.053***	−0.034***
	(0.017)	(0.011)
College graduate	−0.096***	−0.069***
	(0.017)	(0.011)
Post-college graduate	−0.120***	−0.086***
	(0.018)	(0.012)
Refinancing		−0.065***
		(0.007)
Credit score	−0.250***	−0.242***
	(0.010)	(0.007)
Constant	5.237***	4.965***
	(0.143)	(0.096)
Observations	21,469	43,094
R^2	0.377	0.442
Adjusted R^2	0.376	0.442
Residual Std. Error	23.504 (df = 21418)	22.270 (df = 43042)
F Statistic	259.558*** (df = 50; 21418)	669.523*** (df = 51; 43042)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 22: **Mortgages obtained directly without hiring a financial intermediary.** Table shows estimates of a linear regression model for two NSMO+ subsamples, first origination mortgages and pulled mortgages (including refinancing) for borrowers who went directly to the lender. Controlling for time fixed effects, loan amount, loan type, government-sponsored enterprise,number of borrowers,term, and LTV.

	Mortgage rate	
	(First origination)	(All mortgages)
Considered two lenders	−0.444*	−0.342**
	(0.228)	(0.152)
Considered three or more lenders	0.907***	0.310
	(0.293)	(0.199)
Financial skills	−0.321	−0.303*
	(0.243)	(0.156)
Considered two lenders × Fin. skills	0.520*	0.396**
	(0.298)	(0.198)
Considered three or more lenders × Fin. skills	−1.252***	−0.469*
	(0.381)	(0.259)
Age	0.011	0.054***
	(0.014)	(0.009)
Metro area: LMI tract	0.058***	0.032***
	(0.018)	(0.012)
Non-metro area	−0.008	0.012
	(0.019)	(0.013)
Married	0.003	0.009
	(0.016)	(0.011)
Female	0.019	0.022***
	(0.013)	(0.008)
Race: Black or African-American	0.017	0.022
	(0.029)	(0.018)
Asian	−0.045*	−0.035*
	(0.027)	(0.018)
Other (including Hispanic)	0.035	0.031
	(0.034)	(0.023)
Income: $35,000-$50,000	0.090***	−0.028
	(0.033)	(0.022)
$50,000-$75,000	0.102***	−0.014
	(0.032)	(0.021)
$75,000-$100,000	0.126***	0.006
	(0.033)	(0.022)
$100,000-$175,000	0.145***	0.016
	(0.034)	(0.023)
$175,000 and more	0.164***	0.008
	(0.038)	(0.026)
Education: some college or technical school	−0.075***	−0.040***
	(0.024)	(0.015)
College graduate	−0.107***	−0.068***
	(0.024)	(0.015)
Post-college graduate	−0.127***	−0.087***
	(0.025)	(0.016)
Refinancing		−0.036***
		(0.009)
Credit score	−0.226***	−0.225***
	(0.015)	(0.009)
Constant	5.265***	5.022***
	(0.202)	(0.129)
Observations	12,052	26,624
R^2	0.341	0.396
Adjusted R^2	0.338	0.395
Residual Std. Error	23.862 (df = 12003)	22.951 (df = 26574)
F Statistic	129.290*** (df = 48; 12003)	355.970*** (df = 49; 26574)
Note:		*p<0.1; **p<0.05; ***p<0.01

D 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:

$$V^R(f,a,z) = \max_{\{i,s,c\}} \left\{ [u(c) - c^f(i,z) - c^m(s,f)]\Delta t + \frac{1}{1+\rho\Delta t}\mathbb{E}V^{R+} \right\}, \tag{15}$$

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

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

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

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

and rearranging yields

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

Multiplying the value function (15) with $(1+\rho\Delta t)$ and denoting $u_R = u(c) - c^f(i,f) - c^m(s,f)$ 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

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

and dividing by Δt to derive the limit:

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

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

$$\begin{aligned}\rho V^R(f,a,z) = \max_{\{c,s,i\}} \Big\{ & u_R + \frac{\partial V^R(f,a,z)}{\partial f}\dot{f} + \frac{\partial V^R(f,a,z)}{\partial a}\dot{a} && (16) \\ & + \phi\lambda s \int_{\underline{r}}^{\bar{r}} \max\left\{V^H(f,a,z,r') - V^R(f,a,z), 0\right\} d\Phi(r') && (17) \\ & + \sum_{z'} \omega(z,z')[V^R(f,a,z') - V^R(f,a,z)] \Big\}. && (18)\end{aligned}$$

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:

$$V^H(f,a,z,r) = \max_{\{i,s,c\}} \Big\{ \big[u(c) - c^f(i,z) - c^m(s,f)\big]\Delta t + \frac{1}{1+\rho\Delta t}\mathbb{E}V^{H+} \Big\}, \tag{19}$$

where $c^m(s,f)$ 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

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

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 (19) and multiply it by $(1+\rho\Delta t)$ and substitute

for $\mathbb{E}V^{H+}$ and $u_H = u(c) - c^m(s,f) - c^f(i,f)$, (19) 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

$$\rho V^H(f,a,z,r) = \max_{\{c,s,i\}} \Big\{ u_H(1+\rho\Delta t) \xrightarrow{\Delta t \to 0} u_H \tag{20}$$

$$+ \frac{V^H(f+\Delta f, a+\Delta a, z, r) - V^H(f,a,z,r)}{\Delta t} \xrightarrow{\Delta t \to 0} \frac{\partial V^H(f,a,z,r)}{\partial f}\dot{f} + \frac{\partial V^H(f,a,z,r)}{\partial a}\dot{a} \tag{21}$$

$$+ \lambda s \int_{\underline{r}}^{\bar{r}} \max\Big\{ V(f+\Delta f \xrightarrow{\Delta t \to 0} f, a+\Delta a - c_{\text{ref}} \xrightarrow{\Delta t \to 0} a - c_{\text{ref}}, z, r'), \tag{22}$$

$$V^H(f+\Delta f \xrightarrow{\Delta t \to 0} f, a+\Delta a \xrightarrow{\Delta t \to 0} a, z, r) \Big\} d\Phi(r') \tag{23}$$

$$+ p(f,a)[V^R(f+\Delta f \xrightarrow{\Delta t \to 0} f, a+\Delta a \xrightarrow{\Delta t \to 0} a, z) - \tag{24}$$

$$V^H(f+\Delta f \xrightarrow{\Delta t \to 0} f, a+\Delta a \xrightarrow{\Delta t \to 0} a, z, r)] \tag{25}$$

$$+ \sum_{z'} \omega(z,z')[V^H(f+\Delta f \xrightarrow{\Delta t \to 0} f, a+\Delta a \xrightarrow{\Delta t \to 0} a, z', r) - \tag{26}$$

$$V^H(f+\Delta f \xrightarrow{\Delta t \to 0} f, a+\Delta a \xrightarrow{\Delta t \to 0} a, z, r)] \tag{27}$$

$$+ \frac{\mathcal{O}(t)}{\Delta t} \xrightarrow{\Delta t \to 0} 0 \Big\}. \tag{28}$$

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 Δt and letting $\Delta t \to 0$. The renter's budget constraint translates to

$$\begin{aligned} a_{t+\Delta t} &= (1 + R\Delta t)a_t + \big[wz_t - \kappa - c_t\big]\Delta t \\ a_{t+\Delta t} - a_t &= \Delta t\big[Ra_t + wz_t - \kappa - c_t\big]/\Delta t \\ \frac{a_{t+\Delta t} - a_t}{\Delta t} &= Ra_t + wz_t - \kappa - c_t \xrightarrow{\Delta t \to 0} \dot{a} = Ra_t + wz_t - \kappa - c_t. \end{aligned} \tag{29}$$

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

$$\dot{a}^H = Ra_t^H + wz_t - rM - c_t^H. \tag{30}$$

The financial skill accumulation process satisfies

$$\begin{aligned} f_{t+\Delta t} &= (1 - \delta\Delta t)f_t + \frac{\mu}{\eta}(i_t f_t)^\eta \Delta t \\ f_{t+\Delta t} - f_t &= \big[\frac{\mu}{\eta}(i_t f_t)^\eta - \delta f_t\big]\Delta t / : \Delta t \\ \frac{f_{t+\Delta t} - f_t}{\Delta t} &= \big[\frac{\mu}{\eta}(i_t f_t)^\eta - \delta f_t\big] \\ \dot{f} &= \frac{\mu}{\eta}(i_t f_t)^\eta - \delta f_t. \end{aligned} \tag{31}$$

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 (18) under the budget constraint (29) and financial skill accumulation (31) 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 $c^f(i,f) = i_0 i^{\frac{1}{1+\gamma_i}} \frac{1}{1+z}$ yields

$$i^{\frac{1}{\gamma_i}-(\eta-1)} = \frac{\partial V^R}{\partial f}\mu f^\eta \frac{1+z}{i_0} \Big/ () \overline{\frac{1}{\gamma_i}-(\eta-1)}$$

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

and

$$\begin{aligned}
&[c] \;\; u'(c) = \frac{\partial V^R(f,a,z)}{\partial a} \\
&[s] \;\; \frac{c^m(s,f)}{\partial s} = \phi\lambda \int_{\underline{r}}^{\bar{r}} \max\Big\{V^H(f,a,z,r') - V^R(f,a,z), 0\Big\} d\Phi(r') \qquad (32)
\end{aligned}$$

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

$$s^* = \left[\phi\lambda \int_{\underline{r}}^{\bar{r}} \max\Big\{V^H(f,a,z,r') - V^R(f,a,z), 0\Big\} d\Phi(r') \frac{(1+f)^{\gamma_f}}{s_0}\right]^{\gamma_s}. \qquad (33)$$

Under (31) and the budget constraint (30), first order conditions for the homeowner's problem 28 include comparing values between staying at the current mortgage rate or refinancing

$$i_H^* = \left[\frac{\partial V^H(f,a,z,r)}{\partial f}\frac{\mu f^\eta(1+z)}{i_0}\right]^{\frac{1}{\frac{1}{\gamma_i}-(\eta-1)}} \qquad (34)$$

$$u'(c_H^*) = \frac{\partial V^H(f,a,z,r)}{\partial a} \qquad (35)$$

$$s_H^* = \left[\lambda \int_{\underline{r}}^{\bar{r}} \max\Big\{V^H(f,a-c_{\text{ref}},z,r') - V^H(f,a,z,r), 0\Big\} d\Phi(r') \frac{(1+f)^{\gamma_f}}{s_0}\right]^{\gamma_s}. \qquad (36)$$

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

which ultimately yields

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

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

$$
u'(c) \leq \frac{\partial V^H(f,0,z,r)}{\partial a} \tag{37}
$$

and

$$u'(c) \leq \frac{\partial V^R(f,0,z,r)}{\partial a} \tag{38}$$

for homeowners and renters, respectively.

D.1 Kolmogorov Forward Equations

Flow dynamics, characterized by Kolmogorov Forward Equations, are driven by both exogenous and endogenous factors. Exogenous shocks include expense shocks and productivity transitions, while endogenous changes arise from agents' search intensity and corresponding arrival rates of mortgage offers.

The distribution of homeowners, characterized by financial skills f, assets a, productivity $z_i, i \in \{L, H\}$,, and mortgage rate r satisfies the Kolmogorov Forward Equation:

$$\begin{aligned} 0 = &- \frac{\partial g^H(f,a,z_i,r)}{\partial f}\dot{f} - \frac{\partial g^H(f,a,z_i,r)}{\partial a}\dot{a} - \big(p(f,a) + \lambda s^H(f,a,z_i,r)\Phi(r)\big)g^H(f,a,z_i,r) + \\ &+ \lambda \int_r^{\bar{r}} s^H(f,a+c_{\text{ref}},z_i,r')g^H(f,a+c_{\text{ref}},z_i,r')d\Phi(r') + \lambda\phi s^R(f,a,z_i)g^R(f,a,z_i) + \\ &+ \omega_i(g^H(f,a,z_{-i},r) - g^H(f,a,z_i,r)). \end{aligned} \tag{39}$$

Similarly, the distribution of renters, defined by financial skills f, assets a, productivity $z_i, i \in \{L, H\}$, satisfies the following equatin:

$$\begin{aligned} 0 = &- \frac{\partial g^R(f,a,z_i)}{\partial f}\dot{f} - \frac{\partial g^R(f,a,z_i)}{\partial a}\dot{a} + p(f,a)\int_{\underline{r}}^{\bar{r}} g^H(f,a,z_i,r')d\Phi(r') + \\ &- \lambda\phi s^R(f,a,z_i)g^R(f,a,z_i) + \omega_i(g^R(f,a,z_{-i}) - g^R(f,a,z_i)). \end{aligned} \tag{40}$$

D.2 Stationary equilibrium properties

The exogenous interest rate distribution Φ, rental rate κ, and the interest rate on assets R define the stationary equilibrium of the model. The joint distribution of assets, skills, and housing costs arises endogenously, through individual search intensity and locked-in mortgage rates.

Under the assumption of heterogeneous lenders, characterized by a distribution of mortgage offers $\Phi(r)$, the equilibrium is defined by the following components:

- **Value Functions:** The value functions for renters, $V^R(f, a, z)$, and for homeowners, $V^H(f, a, z, r)$, as derived from equations (5) and (8), respectively.
- **Optimal Policy Functions:** Optimal choices for search intensity, financial skill investment, and consumption, which differ for renters and homeowners:
  - $\{s^H(f, a, z, r), i^H(f, a, z, r), c^H(f, a, z, r)\}$, for homeowners.
  - $\{s^R(f, a, z), i^R(f, a, z), c^R(f, a, z)\}$, for renters.
- **Agent Distributions:** The equilibrium distributions of homeowners, $g^H(f, a, z, r)$, and renters, $g^R(f, a, z)$, over financial skill levels f, assets a, productivity z, and mortgage rates r. These distributions satisfy the Kolmogorov Forward Equations (39) and (40).

In the next section, we outline several equilibrium properties of the model and revisit empirical findings relating to financial skill, search, and mortgage rate. deliver new insights for consumption differences within the search framework. For ease of exposition, we fix individual productivity and show how skills define consumption, search, and refinancing.

E 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

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

Proposition 4.1 states that: *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. (Proposition 4.1) 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

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

□

Proof. (Proposition 4.1) 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

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

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.

Proposition 4.2 states that: *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:*

$$
\frac{\dot{c}}{c} = \frac{1}{\sigma}\left[R - \rho - \lambda s\left(\int_{\underline{r}}^{r}\left(1 - \frac{u'(c(f,a,r'))}{u'(c(f,a,r))}\right)d\Phi(r')\right) + p\left(\frac{u'(c(f,a,\kappa))}{u'(c(f,a,r))} - 1\right)\right] \tag{41}
$$

Proof. (Proposition 4.2) When we exclude external frictions, using the fact that value is decreasing in r, homeowners' problem simplifies to

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

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

$$\begin{aligned}\rho\frac{\partial V^H(f,a,r)}{\partial a} = &\frac{\partial^2 V^H(f,a,r)}{\partial f \partial a}\dot{f} + \frac{\partial^2 V^H(f,a,r)}{\partial a^2}\dot{a} + \frac{\partial V^H(f,a,r)}{\partial a}R \\ &+ \lambda s \int_{\underline{r}}^{r} \frac{\partial V^H(f,a,r')}{\partial a} - \frac{\partial V^H(f,a,r)}{\partial a} d\Phi(r') + \\ &+ p\Big(\frac{\partial V^R(f,a,\kappa)}{\partial a} - \frac{\partial V^H(f,a,r)}{\partial a}\Big).\end{aligned} \tag{42}$$

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

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

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

$$\begin{aligned}d\frac{\partial V^H(f,a,r)}{\partial a} = &\frac{\partial^2 V^H(f,a,r)}{\partial a^2} da + \frac{\partial^2 V^H(f,a,r)}{\partial f \partial a} df + \\ &+ \Big[\frac{\partial V^H(f,a,\min\{\tilde{r} - r\})}{\partial a} - \frac{\partial V^H(f,a,r)}{\partial a}\Big] dq_{\lambda s} + \\ &+ \Big[\frac{\partial V^H(f,a,\frac{\kappa}{M})}{\partial a} - \frac{\partial V^H(f,a,r)}{\partial a}\Big] dq_p.\end{aligned} \tag{43}$$

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 (42) 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 (43). Thereby, equation (42) simplifies to

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

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

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

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

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

Finally, dividing by σ and rearranging yields final expression

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

□

E.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

$$(1-h)\lambda\Phi(\bar{r})\phi\sum_z \int_a \int_f s^R(f,a,z,\kappa)g(f,a,z,\kappa), \tag{44}$$

whereas homeowners return to renting in case of an expense shock

$$h\sum_{z}\int_{r}\int_{f}\int_{a}p(f,a)g(f,a,z,x)dadfdx. \tag{45}$$

Equalizing the two yields

$$(1-h)\lambda\Phi(\bar{r})\phi\sum_{z}\int_{a}\int_{f}s^{R}(f,a,z,\kappa)g(f,a,z,\kappa)=h\sum_{z}\int_{r}\int_{f}\int_{a}p(f,a)g(f,a,z,x)dadfdx \tag{46}$$

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:

$$(1-h)(1-\Phi(r))\lambda\phi\sum_{z}\int_{a}\int_{f}s^{R}(f,a,z,\kappa)g(f,a,z,\kappa)dfda, \tag{47}$$

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

$$h(1-G(r))\sum_{z}\int_{a}\int_{f}\int_{r}p(f,a)g(f,a,z,x)dxdfda+h\Phi(r)\lambda\int_{a}\int_{f}\int_{r}^{\bar{r}}s^{H}(f,a,z,x)g(f,a,z,x)dxdfda. \tag{48}$$

Equalizing the flows at mortgage rate r (expressions (47) and (48)), dividing with total outflow of homeowners (45), and using the expression (46), we get

$$1-\Phi(r)=1-G(r)+\frac{\Phi(r)\lambda\sum_{z}\int_{r}^{\bar{r}}\int_{a}\int_{f}s^{H}(f,a,z,x)g(f,a,z,x)dfdadx}{\sum_{z}\int_{r}\int_{f}\int_{a}p(f,a)g(f,a,z,x)dadfdx},$$

which implies

$$\frac{G(r)-\Phi(r)}{\Phi(r)}=\frac{\lambda\sum_{z}\int_{r}^{\bar{r}}\int_{a}\int_{f}s^{H}(f,a,z,x)g(f,a,z,x)dfdadx}{\sum_{z}\int_{r}\int_{f}\int_{a}p(f,a)g(f,a,z,x)dadfdx}>0, \tag{49}$$

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

$$G(r)=\Phi(r)\Big[1+\frac{\lambda\sum_{z}\int_{r}\int_{a}\int_{f}s^{H}(f,a,z,x)g(f,a,z,x)dfdadx}{\sum_{z}\int_{r}\int_{f}\int_{a}p(f,a)g(f,a,z,x)dadfdx}\Big], \tag{50}$$

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.

F 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 (5) and (8) 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 (39) and (40).

F.1 Homeowner's and renter's problem

As in Achdou et al. (2022), solving the (5) and (8) 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:

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

where the step differences $i+1$, i and $i-1$ approximate derivatives of the value function $\frac{\partial V}{\partial a}$ and $\frac{\partial V}{\partial f}$. 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 $[r_1, \ldots, r_s]$, 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 (37), 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

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

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

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

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

$$\frac{V^{l+1} - V^{l}}{\Delta} + \rho V^{l+1} = U^{l} + (A^{l} + B^{l} + \Lambda + P)V^{l+1} + \Omega^{l}(V^{l}), \tag{51}$$

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 (51) into a linear system that has a solution

$$V^{l+1} = \underbrace{\left((\frac{1}{\Delta} + \rho)I - A^{l} - B^{l} - \Lambda - P\right)^{-1}}_{\mathbb{C}} (U^{l} + \frac{1}{\Delta}V^{l} + \Omega_l), \tag{52}$$

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

F.2 Stationary distributions

The second part of the algorithm iterates on the discretized version of the KFE for homeowners (39) and renters (40), 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

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

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 $\text{vec}(s^H)$. 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 $r_1, \ldots, r_s$

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:

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

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

G Stationary equilibrium results

In this section, we present additional and more detailed results from our calibrated model.

G.1 Individual decisions in the equilibrium

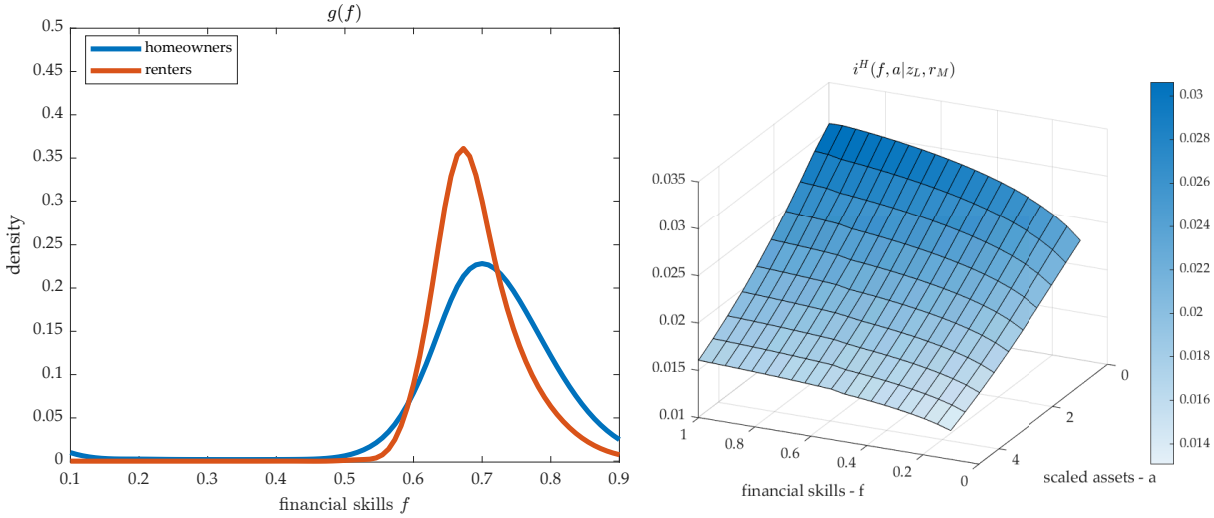
Because our paper introduces a novel dimension in mortgage payment heterogeneity, our primary focus is to examine individual policy variations between low- and high-skilled borrowers. Incentives for mortgage take-up differ significantly across these two groups, contingent on their respective skill levels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

In line with the non-monotonic age averages observed in financial literacy scores from the SCF (Figure 1) and the panel data on financial behavior Agarwal et al. (2007), the right panel of Figure 12 depicts a pattern with differences in slope of investment in skills contigent on current skill levels. Over time, as the level of skills increases, investment in skills begins to change its slope. Skills investment policy for renters 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). Due to differences

in investment in skills policies between renters and homeowners are reflected with differences in stationary distributions of financial skills in the equilibrium. The right panel of Figure 12 shows that renter have lower financial skills on average, which is further reinforced by refinancing activity. This turns us back to our estimates on time passed since refinancing effects in Table 2 in the SCF.

Figure 12: **Financial skills.** The left panel compares financial skills distribution for renters and homeowners. The right panel presents the individual policy functions as 3-dimensional surfaces across assets (x-axis) and financial skills (y-axis).



In Figures 12, we present the individual policy function of homeowners with low productivity and median mortgage payments as 3-dimensional surfaces. Moreover, the left panel compares equilibrium distributions of financial skills for homeowners and renters. These policy functions capture the behavior and characteristics of homeowners and renters as policy functions takes similar shape, however with different slope and size. Notably, both the slopes and relative relationships depicted in the figures closely align with our empirical data findings.

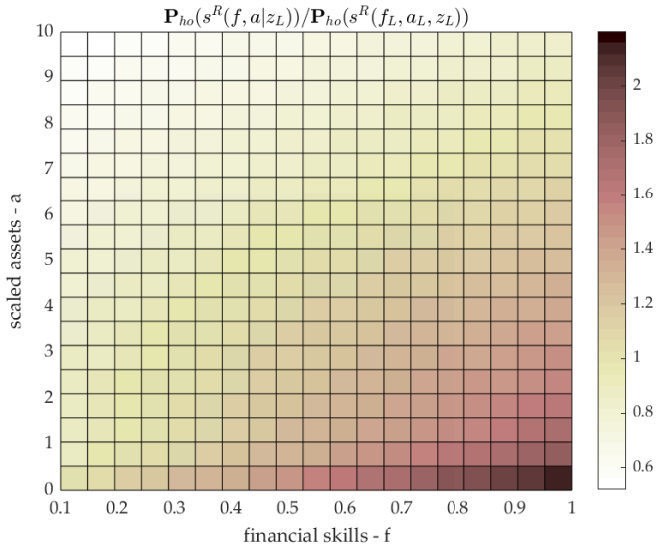
G.1.1 Endogenous search effort

Figure 13 depicts differences in search intensity and corresponding likelihood of a mortgage take up, across the financial skill-asset distribution.

G.1.2 Mortgage locked-in rate in the equilibrium

In equilibrium, the heterogeneity in locked-in mortgage rates contributes to consumption disparities. Figure 14 compares the conditional densities of locked-in mortgage rates for high- and low-

Figure 13: **Likelihood of mortgage take-up.** Likelihoods are depicted using a heatmap plot across assets (x-axis) and financial skills (y-axis). The values are presented in relative terms, i.e., relative to the probability of homeownership for an agent with lowest financial skills and lowest assets, with greater likelihood denoted in shades of red.



skilled borrowers. Unskilled borrowers tend to lock in at higher rates due to lower search effort, which restricts their access to mortgage offers. Conversely, financially savvy borrowers exert more search effort, drawing from a larger sample of offers (i.e., considering more lenders) and ultimately securing better rates. As a result, these financially savvy borrowers have more resources left after mortgage repayment compared to their unskilled counterparts.

The red histogram in Figure 14 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 (13)).

Figure 15 presents densities over assets and financial skills for renters and for homeowners with a average mortgage rate, in low productivity state. Additional precautions induces saving among the best-performing mortgage owners (shown in the right panel of Figure 15). 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

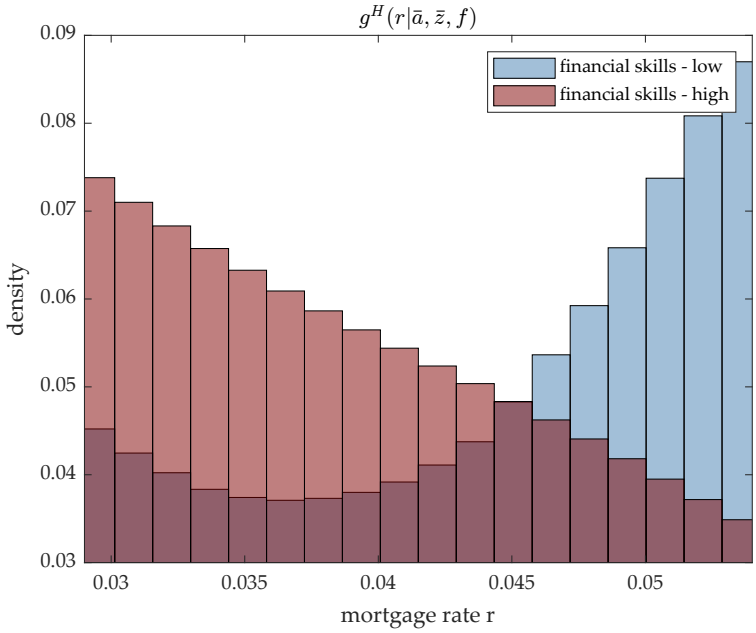


Figure 14: Mortgage rate density for low- and high-skilled borrowers, averaged over assets and productivity.

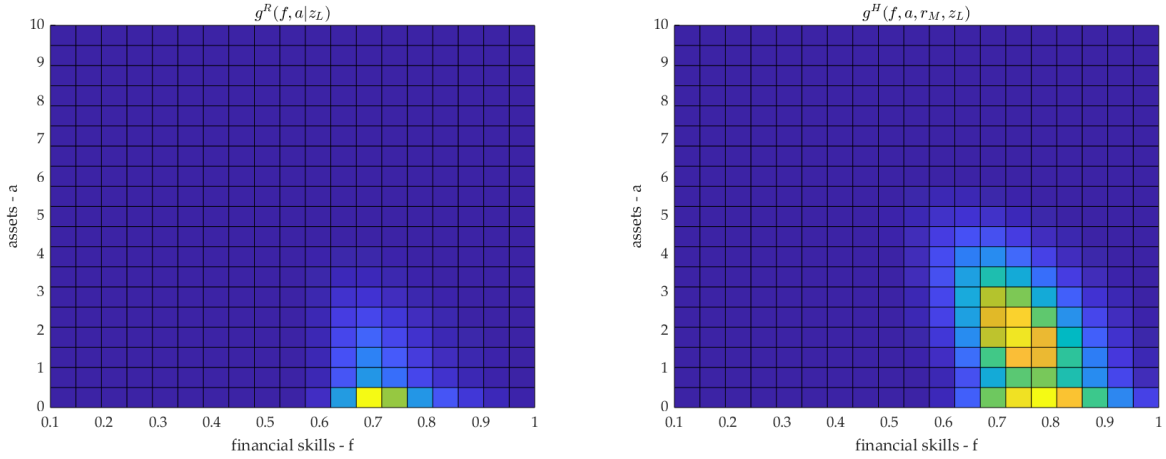
channel outlined in the equation (13). Because returning to renting is not as costly when compared to large mortgage payments, lower precautionary motives propagate savings inequality among homeowners. To this extent, model simulations show that the equilibrium consumption growth exhibits the precautionary 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 lower on average, 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 15). 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.

G.2 Expense shock probabilities

Figure 16 presents model implied expense shock probabilities over financial skills and assets.

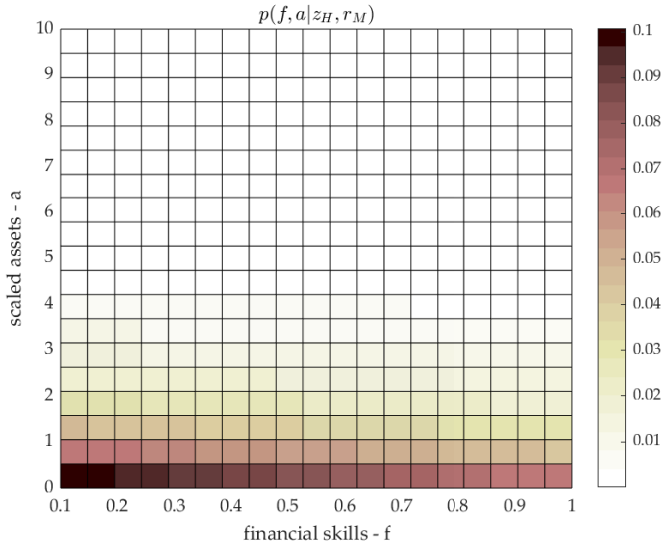
Figure 15: **Density over assets and skills** Model-implied steady state densities are based on a model calibrated according to values from Table 5. 3-dimensional distribution over assets and financial skills of agents in the economy is presented in form of a heat map with x-axis varying with financial skills and y-axis with asset to income ratio. The left panel presents distribution of low productive renters and the right one of low productive homeowners with low mortgage payments.



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

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

Figure 16: **Expense shock over assets and financial skills.** Model implied probabilities of a shock are based on steady state objects for a model calibrated according to values from Table 5. 3 dimensional surface over assets and financial skills od expense shock probabilities is presented in form of a heat map with x-axis varying with financial skills and y-axis with asset to income ratio, and color represents value of the expense probability for high productive agents with med-sized mortgage payments.



G.3 Model extensions and assumption relaxation

Our benchmark model assumes that the probability of delinquency depends on both financial skills and assets, providing an incentive to invest in financial literacy (in addition to refinancing) af-

ter acquiring a mortgage. In this extension, we relax this assumption by introducing a financial skill-dependent return as the primary incentive for skill investment, while allowing delinquency probability to depend solely on asset holdings.

Building on the work of Lusardi et al. (2017) and Jappelli and Padula (2013), we relax the assumption of exogenously fixed returns by allowing them to depend on financial skills. We abstract from participation costs associated with high-return investments, focusing on refinancing behavior and mortgage take-up. In this modified model, housing is treated as a fixed investment with a constant return, leading to lower monthly mortgage repayments.

The return on investment is now specified as:

$$R(f) = \alpha_r f^{\beta_r} + \gamma_r, \quad \alpha_r, \beta_r \geq 0, \tag{53}$$

where $\alpha_r = 0$ represents the baseline model. Equation (53) implies that all agents can invest in safe assets to receive a risk-free return, $R = \gamma_r$. However, investing in risky assets requires financial skills, and more financially literate agents earn higher returns, as $\frac{\partial R}{\partial f} \geq 0$. In addition, the probability of delinquency follows the same logistic form, but only depends on asset holdings,

$$p(a) = \frac{\exp(p_0 + p_a a)}{1 + \exp(p_0 + p_a a)}.$$

We re-estimate p_0 and p_a using late payments data in the SCF.

G.3.1 Model calibration

The set of externally set parameters coincides with the benchmark (depicted in Panel A of Table 5), except from delinquency probability parameters.

We set return parameters in equation 53 so that expected returns $\mathbb{E}[f] = 0.04$, and include γ_r to 0.02 as the low bound. We also set $\alpha_r = 0.02$ and $\beta_r = 0.1$, such that $\mathbb{E}[f] = 0.04$, and keep $\gamma^f = 0.25$ consistent with benchmark calibration. Table 23 summarizes internally calibrated values and compares model implied moments to its (SCF and NSMO+) data counterparts.

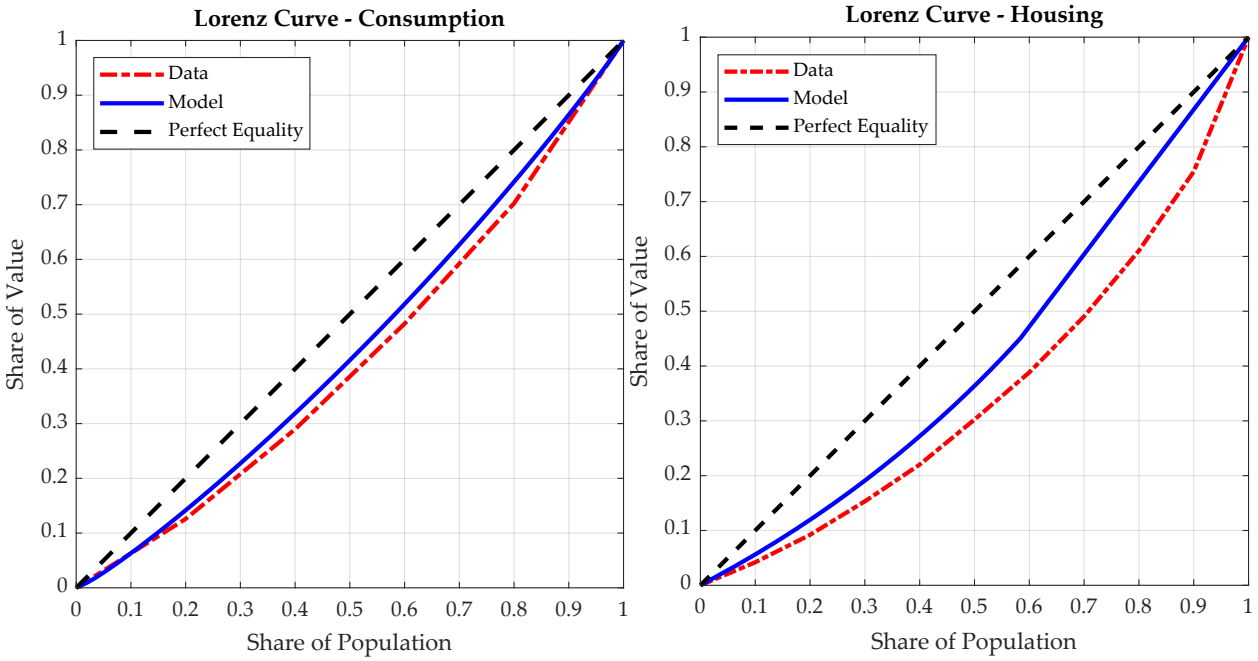
With regards to non-targeted moments, the model extension performs better in matching the refinancing rates compared to the SCF data, largely due to disincentive coming from return accu-

Table 23: Model parameter values. Source: Model, SCF, and NSMO+.

Definition	Symbol	Estimate	Source/Target		
Panel A. Externally set					
Panel B. Externally estimated					
Slope	μ	0.2	SCF, lifecycle profile		
Parameters	p_0, p_a	-2.48,-1.01	SCF, late payments		
Panel C. Internally estimated				Model	Data
Investment cost scaling	i_0	618	Average financial skills - R	0.6883	0.6689
Renting cost	κ	0.3003	Homeownership rate	0.5675	0.5904
Search cost elasticity	γ_s	2.9819	Average financial skills - HO	0.7122	0.7281
Search cost scaling	c_0	8.5322	Average mtg. rate all	0.0390	0.0400
Search friction	ϕ	0.99	Average mtg. rate f.o.	0.0417	0.0408
Mtg. offer distribution parameter	β	5.054	Average mtg. rate - ref.	0.0354	0.0386
Mtg. offer distribution parameter	α	5.2248	Standard deviation mtg. rate	0.0080	0.0073

mulation. Figure 17 compares model implied Lorenz curves, and suggests a closer fit to data in terms of non-durable consumption, whereas the Gini coefficients remain the same. The right panel of Figure 17 shows similar pattern of housing consumption inequality as our baseline model.

Figure 17: **Lorenz Curves.** Model implied Lorentz Curves are based on simulations for model calibrated accroding to values from Table 23 and data counterparts are based on the BLS data. The left panel compares Lorentz Curves for consumption and the right panel compares Lorentz Curves for housing consumption.



More specifically, extended version of our model implies 28% higher average likelihood of mortgage take-up for those at the top of financial skills distribution, close to our SCF estimate of 25%.

Table 25 summarizes policy experiments parallel to ones for baseline model from Table 7 in the main text.

	Gini$_c$	$\frac{\mathbb{P}\text{ref}(s\|f^H)}{\mathbb{P}_{\text{ref}}(s\|f^L)}$	$\frac{\text{mtg pay}}{\text{rent pay}}$	$\mathbb{P}(\text{del}\|f^L) - \mathbb{P}(\text{del}\|f^H)$	HtM share
Model	0.12	11-13%	0.52	3.7 p.p.	13.4%
Data	0.16	6-11%	0.49	7 p.p.	14.2%

Table 24: **Non-targeted model-implied moments and empirical counterparts.** Gini$_c$ is obtained from consumption data in (Garner et al., 2022), and HtM share uses (Kaplan and Violante, 2022). The rest of data moments use the SCF, where delinquency differences are estimated among a subsample of homeowners with mortgages on their primary residences.

Table 25: **Policy implications.** Steady state differences are based on simulations for model calibrated accroding to values from Table 23 (benchmark economy). First column - financial education course policy, second column - more accessible mortgage environment, and third column - financial education in more accessible environment, outline relative changes in comparison to our benchmark economy.

Measure	Fin. edu	Accessibility	Fin. edu + Accessibility
average search renters	$\searrow 0.4\%$	$\nearrow 6.93\%$	$\nearrow 6.53\%$
average search homeowners	$\nearrow 2.99\%$	$\nearrow 13.99\%$	$\nearrow 17.31\%$
consumption Gini	$\nearrow 0.11\%$	$\searrow 0.57\%$	$\searrow 0.39\%$
assets Gini	$\searrow 0.23\%$	$\searrow 0.96\%$	$\searrow 1.20\%$
share of homeowners	$\nearrow 0.82\%$	$\nearrow 3\%$	$\nearrow 3.83\%$
average financial skills	$\nearrow 8.54\%$	$\nearrow 0.16\%$	$\nearrow 8.95\%$
average delinquency rate	$\searrow 2.19\%$	$\nearrow 0.12\%$	$\searrow 2.07\%$