How Does Credit Score Rationing Shape the Housing Market?

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Abstract

We build a quantitative heterogeneous agents macro-housing model with endogenously and dynamically evolving credit scores based on households' earnings and decision-making behavior regarding portfolio choices and debt repayment. Utilizing this model, we conduct counterfactual analyses to examine the consequences of implementing a minimum credit score requirement in the mortgage loan market, a practice that has become prevalent since the 2008 Great Recession. We obtain the result as follows. The minimum credit score threshold decreases the mortgage default risk, which reduces average mortgage rates. Also, the threshold decreases the average Loan-to-Value ratio and the fraction of mortgage owners. Intriguingly, when the threshold is set at the subprime credit score level, the rate of homeownership increases by approximately 5 percentage points. Our counterfactual experiments and econometric analyses reveal that the 5 percentage point increase in homeownership is equally influenced by two key factors: i) credit scores motivation, which encourages households to pursue ownership in anticipation of the positive effects of ownership on creditworthiness; and ii) the availability of affordable mortgage rates, facilitated by reduced default behavior in a economy with minimum credit score requirement. From a distributional perspective, for households in the lower-income bracket, the rate of homeownership remains largely static, as these households have higher likelihood of credit rationing due to strong relation between income and credit score, which are endogenously derived in the model economy.

JEL classification: E21,E30,E40,E51

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1 Introduction

The role of credit conditions in shaping housing market dynamics has been studied in existing structural housing-macro literature (Dong, Liu, Wang, and Zha, 2022; Favilukis, Ludvigson, and Van Nieuwerburgh, 2017; Garriga and Hedlund, 2020; Garriga, Manuelli, and Peralta-Alva, 2019; Greenwald, 2018; Guren, Krishnamurthy, and McQuade, 2021; Justiniano, Primiceri, and Tambalotti, 2019). These studies generally contend that changes in credit conditions—largely shaped by lenders imposing borrowing constraints like maximum loan-to-value ratios and maximum debt-to-income ratios—significantly affect housing market dynamics.

This paper extends this line of inquiry by specifically exploring an under-examined borrowing constraint: *minimum credit scores requirement*. Specifically, in this study, we quantitatively explored the long-run aggregate and distributional effects of minimum credit score requirements on key housing metrics such as default rates, homeownership rates, mortgage rate, the number of mortgage originations, price-to-rent ratios, and average loan-to-value ratios. The questions are especially pertinent at present, as highlighted by Laufer and Paciorek (2022), which discovered that minimum credit score requirements have become increasingly prevalent in the mortgage market following the 2008 Great Recession[1].

Our research examines the role that credit scores play in influencing household portfolio choices, especially in the context of the housing market. In particular, the prediction of the minimum credit score's impact on home purchasing is not simple. While, ceteris paribus, tightening borrowing constraints like loan-to-value and debt-to-income ratios generally discourages homeownership, the effect of minimum credit score requirements is twofold. On one hand, it restricts access to mortgages for those with lower credit scores, thus limiting their home purchasing options. Conversely, these constraints can motivate

[1]While the data scope of their study extends from 2005 to 2012, we have further verified the continuity of these lenders' rule changes up to 2019, as detailed in Appendix A.

individuals to pursue homeownership. Not only is owning a home a positive indicator for credit ratings on its own, but when combined with responsibly managed mortgage debt, it can significantly elevate one's credit score. This enhanced score can open up future borrowing opportunities, further underscoring the benefits of homeownership. This interplay between restriction and encouragement complicates our understanding of how this lending policy affects housing demand and, subsequently, the price-to-rent ratio.

Additionally, other facets of our research, such as the impact of minimum credit score requirements on default rates, the number of mortgage originations, and average loan-to-value ratios, may appear more predictable. With simple intuition, one could argue that a minimum credit score requirement encourages individuals to adopt more sound borrowing behavior. However, these areas have not been quantitatively studied in depth, leaving them still shrouded in uncertainty.

In response, by employing a quantitative heterogeneous agent macro-housing model with endogenously and dynamically evolving credit score, we discover that the effects of minimum credit score requirement. We found that the requirement contributes to higher homeownership rates while also promoting a stable mortgage market with lower default rate and lower average loan-to-value ratio in the long run without exogenous change in loan-to-value ratio.

In detail, we construct a heterogeneous agent housing-macro model that incorporates several features, including short-term defaultable mortgages with endogenous mortgage pricing, the decision between renting and owning a home, idiosyncratic earning shocks, and an endogenously evolving credit score based on existing housing macroeconomic literature and quantitative theory of credit score in Chatterjee, Corbae, Dempsey, and Ríos-Rull (2020) .We provide a more detailed explanation of the model in section 2 and, especially, the credit score construction process in Section 2.3.1.

Using the model, to assess the effect of the minimum credit score requirement on housing market, we do counterfactual experiment. In our baseline model, we introduce a minimum credit score threshold by disallowing borrowing for households whose credit score falls below this threshold. To comprehensively comprehend the impact of this minimum credit score requirement, we derive an alternative steady state—referred to as the counterfactual—where no credit score-related constraint is enforced. By comparing these two economies, we can effectively evaluate the implications of the minimum credit score threshold.

The summarized outcomes of the highlighted results are as follows. Firstly, the elimination of the minimum credit score threshold leads to an increase in mortgage default rates, driven by a reduction in the cost of default. Conversely, when a minimum credit score requirement is in effect, the probability of households opting for default decreases. This tendency arises from the consideration that defaulting elevates the risk of their credit score dropping below the designated threshold. Consequently, this situation impedes them from acquiring a mortgage until their credit score recovers and surpasses the threshold. This additional cost of default caused by the minimum credit score requirement makes default rate lower in the economy with the requirement. Secondly, the absence of a minimum credit score requirement translates into higher mortgage rates due to the heightened default risk. This risk directly influences the cost of mortgages for lenders, thereby affecting the model's mortgage rates. Thirdly, surprisingly, the removal of the credit score requirement induces more households to favor renting over homeownership, leading to a decline in the homeownership rate. Specifically, when we set the threshold as lower 24% of credit score, the homewoernship rate increase in around 5 percent point compared to that of economy with our minimum credit score requirement. Our empirical evaluations show that the 5% rise in homeownership is driven equally by two pivotal elements: 1) the incentivizing role of credit scores, specifically the anticipated credit advantages that come with homeownership; and 2) the availability of more affordable mortgage rates, which are facilitated by reduced default risk as a result of minimum credit score thresholds.

While the aggregate level of homeownership increases when credit score rationing is implemented, this effect is not uniform across all income groups. Specifically, lower-income households do not experience higher rates of homeownership in the presence of minimum credit score thresholds. This is primarily due to their higher likelihood of facing credit rationing, stemming from the strong correlation between income and credit score. As a result, the aforementioned factors that generally encourage homeownership are nullified for households in lower income brackets.

This paper relates to three groups of studies. First, this paper complements the stream of research aimed at identifying the causal effect of the credit accessibility on housing market outcomes throught reduced form analysis(Barakova, Bostic, Calem, and Wachter, 2003; Barakova, Calem, and Wachter, 2014; Laufer and Paciorek, 2022; Rosenthal, 2002). Specifically, Barakova et al. (2003) provide the estimation that bad credit history predicts lower homeownership. In line with this, this paper drives the negative relationship between credit score and homeownership rate endogenously. Laufer and Paciorek (2022) is strongly connected to this paper. Based on the estimation results capturing the effect of credit access availability on the probability of originating new mortgage loans, they performed a simple counterfactual experiment, which predicted that eliminating the minimum credit score threshold causes a 7% increase in the number of mortgages originated from 2011 to 2014. Although the size of the effect between Laufer and Paciorek (2022) and this paper cannot be compared due to different research periods and frameworks, the direction of the effect of minimum credit score threshold on the number of mortgages originated is the same.

In contrast to existing literature, which predominantly focuses on how individual behavior adapts to fixed conditions of credit score, we account for the dynamic evolution of credit score distribution. This approach enables us to closely examine the long-run equilibrium effects stemming from the interaction between the pursuit of a higher credit score and housing market variables.

Second, this paper is related to a large stream of literature on consumer debt and default from the perspective of the heterogeneous agent macro model[2]. Chatterjee et al. (2020) is a seminal study incorporating credit score into the model class to examine how households' unsecured debt market behavior changes when the reputation can be tracked via credit score. To bring their framework into the secured debt market, we explain how the minimum credit score threshold in the mortgage market shapes the housing market.

Third, this work adds a new angle into the papers that examine the effect of changes in credit condition on housing market outcome using quantitative housing macro models.(Garriga and Hedlund, 2020; Garriga, Manuelli, and Peralta-Alva, 2019; Greenwald, 2018; Guren, Krishnamurthy, and McQuade, 2021; Justiniano, Primiceri, and Tambalotti, 2019; Kaplan, Mitman, and Violante, 2020; Kiyotaki, Michaelides, and Nikolov, 2011; Landvoigt, Piazzesi, and Schneider, 2015). These studies are primarily motivated by the housing market boom and bust during the 2000s. The shared purpose of those papers is to construct a macro housing model with features of a realistic mortgage market to examine the effect of variation of credit conditions on housing market outcomes such as house price and homeownership rate. The credit score is not a critical underwriting condition to constrain households' borrowing at that time and is abstracted in this model class. Our model introduces the process of generating endogenous credit scores into the macro-housing model to address the changed circumstances in the mortgage market that we mention above.

The rest of the paper is organized as follows. In section 2, we explain the model and equilibrium concept. Then, in section 3, we describe the calibration process. In Section 4, we demonstrate the validity of our model as a tool for assessing credit rationing rules. In Section 5, we evaluate the impact of minimum credit score thresholds on key variables in the housing market.

[2]For a recent survey, see Exler and Tertilt (2020)

2 Model

2.1 Outline

Our model advances the current state of macro-housing literature by incorporating elements from the credit score model discussed in Chatterjee et al. (2020). Consistent with existing research, our framework features a range of actors, including households, financial intermediaries, final goods producers, and the residential construction sector. A distinguishing aspect of our model is the inclusion of two types of time discount rates within households, considered private information. Also, unlike traditional models that typically include only banks as financial intermediaries, our model also incorporates a role for credit rating firms in shaping the distribution of credit scores.

Households in the model make choices about homeownership versus renting, and saving versus borrowing. Borrowing is exclusively mortgage-based and subject to two constraints: loan-to-value rates and a minimum credit score threshold. Indebted households can either repay or default on their loans. Those who default incur administrative costs and suffer from a diminished credit history, thereby potentially reducing their lifetime utility by constraining their future borrowing ability. Defaulting households are also temporarily barred from the housing market.

Financial intermediaries consist of both banks and credit rating firms. Banks offer mortgage loans based on a competitive mortgage pricing function, where the expected return is zero, factoring in default rates. Credit rating firms calculate the probability of each household being of a high type based on observable behaviors. They then rank households according to these probabilities, and this ranking serves as the basis for credit score constraints.

The model also includes a representative final goods producer that uses labor as its only input factor and a representative residential construction firm that converts final goods into residential construction without any frictions. Households with excess housing assets relative to their residential needs can rent these out, with rental rates determined in equilibrium.

To facilitate the use of a Bayesian updating process for generating credit scores, our model incorporates a discrete choice framework with preference shocks following a Type 1 Extreme Value distribution. This design choice ensures that all decision variables within the model are discrete. One advantage of employing a discrete choice model is its intrinsic property that allows for non-zero choice probabilities across all state-space. This feature is particularly beneficial as it enables these non-zero probabilities to serve as the marginal probabilities in the Bayes rule.

2.2 Household

2.2.1 Household environment

Demographic The economy consists of a continuum of infinitely lived heterogeneous households. We assume that there are two types of households with different time discount rates, denoted by β^H and β^L, where $\beta^H > \beta^L$. The time preference is private information and not a fixed value, but rather persistent over time. The dynamic evolution of this preference rate is governed by the law of motion denoted as $\mathcal{L}(\beta'|\beta)$. The concept of time is discretized and denoted by t.

Preferences Individual households, labeled as i, assess their utility using a utility function characterized by constant relative risk aversion. Specifically, the utility function is given by:

$$U^i(c_t, h_t) = \frac{\left[(1-\phi)c_t^{1-v} + \phi h_t^{1-v}\right]^{\frac{1-\gamma}{1-v}} - 1}{1-\gamma} \tag{1}$$

In this equation, the variables are defined as follows: c_t represents non-durable consumption, where $c_t > 0$; h_t represents consumption related to housing services, with $h_t > 0$. The term $\frac{1}{\gamma}$ denotes the intertemporal elasticity of substitution. The elasticity of substitution between the non-durable consumption good and housing service is represented by $\frac{1}{\nu}$. The parameter ϕ represents a preference weight that captures the relative importance of housing services compared to non-durable consumption in the individual's utility assessment.

Endowment Households supply one unit of labor inelastically during each time period. The individual labor income endowment resulting from providing one unit of labor for household i is represented as $Z_t z_t^i$, where Z_t represents the aggregate productivity in period t, and z_t^i represents the idiosyncratic productivity of household i during that period.

In each period, the idiosyncratic productivity z_t^i is exogenously determined through a stationary finite state Markov process denoted as $\pi(z_{t+1}|z_t)$. To facilitate analysis, the productivity process is discretized into N_z points, resulting in $z_t \in \{z_1, z_2, z_3, ..., z_{N_z}\}$.

Financial Position Within the model economy, there exists a single financial good referred to as a_t. The financial good has a one-period duration. Households choose a_{t+1} from a finite set A, where $A = \{a_1, a_2, ..., 0, ..., a_{N_a}\}$, during each time period. Households intending to borrow, denoted by choosing $a_{t+1} < 0$, must satisfy two constraints.

i) A maximum loan-to-value limit: Borrowers are subject to a constraint determined by the value of the housing they possess, which acts as collateral for the loan. Since the model does not accommodate unsecured debt, negative financial asset positions can be interpreted as mortgage debt. Equation (2) outlines the loan-to-value constraint, where the maximum loan-to-value ratio is denoted by η. Here, g represents the housing asset and $p_{g,t}$ denotes the house price in period t.

$$a_{t+1} > -\eta \cdot p_{g,t} \cdot g_{t+1} \tag{2}$$

ii) Minimum credit score threshold: Households must possess a credit score, φ^H that is not lower than a specified threshold δ in order to secure a mortgage loan. The construction of the credit score is detailed in Section 1.2.1.

$$\varphi^H \geq \Delta \tag{3}$$

Equation (3) introduces a novel borrowing constraint that previous literature has not considered.

Households that carry debt ($a_t < 0$) have the option to avoid repayment by defaulting on their debt. Defaulting, however, incurs an administration cost denoted as κ. Furthermore, during the period of default, individuals who default face restricted access to the owner-occupied housing market. They are unable to purchase a house and can only access housing services through renting.

Housing In each time period, households make decisions regarding the amount of housing to own, denoted as g_{t+1}, and the quantity of housing services to consume, denoted as h_t. To facilitate analysis, we discretize the housing assets into N_g points, resulting in g belonging to the set $G = \{g_1, g_2, ..., g_{N_g}\}$, where $g_1 = 0$ and $g_{N_g} > 0$ for $N_g > 1$. Also, housing service for every period should be non-zero, $h_t > 0$. In each time period, households make decisions regarding the amount of housing to own, denoted as g_{t+1}, and the quantity of housing services to consume, denoted as h_t. To facilitate analysis, we discretize the housing assets into N_g points, resulting in g belonging to the set $G = \{g_1, g_2, ..., g_{N_g}\}$, where $g_1 = 0$ and $g_{N_g} > 0$ for $N_g > 1$. Also, housing service for every period should be non-zero, $h_t > 0$. In the model, h_t is the only continuous choice variable. It is determined by the optimal consumption ratio between consumption and housing services, as described by the CRRA utility function in Euation (1) using remaining budget after considering optimal choices for future housing g^*_{t+1} and assets a^*_{t+1}. The prices for housing assets and rental rate for housing services are represented as $p_{g,t}$ and $p_{r,t}$ respectively. The prices for housing assets and rental rate for housing services are represented as $p_{g,t}$ and $p_{r,t}$ respectively.

If households do not own a home ($g_{t+1} = g_1 = 0$), they are classified as renters. In this context, households consume housing services, represented as h_t, by engaging in a rental agreement at a unit rental rate of $p_{r,t}$. The duration of this rental contract is one model period. To summarize, in order to consume housing service, h_t during period t, a household pays $h_t p_{r,t}$. In the subsequent period $t+1$, the household must decide whether to purchase a home or enter into another rental agreement.

If households purchase their own homes, indicating that $g_{t+1} > 0$, several different cases may arise as outlined below. When households utilize all their housing assets for their residential needs ($g_{t+1} = h_t$), they are classified as pure owners. On the other hand, if a household's housing assets exceed their housing service consumption ($g_{t+1} > h_t$), they become landlords, renting out $g_{t+1} - h_t$ to renters while also being owners themselves. In cases where a household's housing service consumption surpasses their housing assets ($g_{t+1} < h_t$), they create a demand for housing services equal to $h_t - g_{t+1}$. Note that these households who are partially renting to fulfill their housing needs are considered as owner in this model.

Lastly, the owners are responsible for bearing the depreciation cost of their housing assets, which is equal to δg_{t+1}.

Feasible choices The set of feasible choices for a given household i is denoted by $\mathcal{F}^i$. Households can be categorized into two groups based on their financial status in the previous period: borrowers, who had a negative asset balance $a_t < 0$, and savers, who had a non-negative asset balance $a_t \geq 0$.

The first part of Equation (4) describes the choices available to borrowers. These households have two options: either repay their existing mortgage debt ($D = 0$) or default on their mortgage ($D = 1$). For those who opt to repay ($D = 0$), if their credit score φ^H is higher than a minimum threshold Δ, they can either borrow further, subject to loan-to-value constraints, or rent without any restrictions. If their credit score is below this threshold, they are not eligible for borrowing via mortgage debt. For those who default ($D = 1$), as mentioned, the household faces a penalty: it is barred from accessing the owner-occupied housing market and can only rent. Consequently, these households are not eligible to borrow, given that the only form of borrowing in this context is through mortgage debt.

The second part of Equation (4) describes the choices available to savers, defined as households with a non-negative asset balance $a_t \geq 0$. The feasible set of choices for savers $\mathcal{F}^i$ is identical to that of borrowers who choose to repay their mortgage debt ($D = 0$).

$$
\begin{aligned}
a_t < 0 \quad & \begin{cases} D_t = 0: & \begin{cases} \varphi_t^H \geq \Delta: & \mathcal{F} = \{(g_k, a_k) \mid a_k > -\eta \cdot p_{g,t} \cdot g_{t+1}\}, \\ \varphi_t^H < \Delta: & \mathcal{F} = \{(g_k, a_k) \mid a_k \geq 0\} \end{cases} \\ D_t = 1: & \mathcal{F} = \{(g_k, a_k) \mid g_k = g_1, a_k \geq 0\} \end{cases} \\
a_t \geq 0 \quad & \begin{cases} \varphi_t^H \geq \Delta: & \mathcal{F} = \{(g_k, a_k) \mid a_k > -\eta \cdot p_{g,t} \cdot g_{t+1}\}, \\ \varphi_t^H < \Delta: & \mathcal{F} = \{(g_k, a_k) \mid a_k \geq 0\} \end{cases}
\end{aligned}
\tag{4}
$$

2.2.2 Households' decision problem

Timeline The decision problem of households is based on the following time line.

1. At any period t, households arrive period t with housing asset, g_t, financial position, a_t and credit score φ_t^H. The process of getting credit score is explained in section 2.3.1

2. Households take as given the mortgage price schedule, $p_m(D_t, g_{t+1}, a_{t+1} | g_t, a_t, \varphi_t^H, z_t)$,

the credit score updating process $\varphi^H_{t+1}(D_t, g_{t+1}, a_{t+1}|g_t, a_t, \varphi^H_t, z_t)$, risk free rate, p_a, house price $p_{h,t}$, and rental rate $p_{r,t}$. These are summarized in $\mathcal{Q}_t$.

3. By the first order stationary Markov process $\pi(z_t|z_{t-1})$, households get idiosyncratic labor productivity for current period, $z_t \in \{z_1, z_2, ..., z_{Nz}\}$.

4. Household i receives additively separable preference shock across all feasible combination of choices, which is a vector, $\varepsilon^i_t = (\varepsilon^i_1, \varepsilon^i_2, ...\varepsilon^i_n..., \varepsilon^i_{N^{i,\varepsilon}})$, where ε^i_n is preference shock for the choice bundle, $(g_{t+1}, a_{t+1}, D_t) \in \mathcal{F}^i$ indexed by n, $n \in \{1, 2, ..., N^{i,\varepsilon}\}$. $N^{i,\varepsilon}$ is the number of feasible combinations of choice variables of household i. All preference shocks are independently and identically distributed following a standard type-1 extreme value distribution, and its cumulative distribution function is given Equation (5).

$$\Lambda(\varepsilon^i_n) = exp\Big(-exp\Big(-\varepsilon^i_n\Big)\Big) \tag{5}$$

Household problem Household i, characterized by state variables such as type, β_t, financial asset a_t, housing asset g_t, and credit score φ^H, enters period t. At the beginning of period t, two shocks are realized simultaneously: an idiosyncratic productivity shock, z_t, and a preference shock, ε_t. Taking these shocks into account, the household makes decisions regarding its housing asset g_{t+1}, financial asset a_{t+1}, and the discrete choice of default D_t if she is indebted ($a_t < 0$) in order to maximize lifetime utility.

In adopting a discrete choice model, our objective is to determine the choice probability of a particular choice bundle, which is included in the feasible choice set given the state variables and productivity shock. Equations (6) through (9) outline the process to obtain this choice probability, as summarized in Equation (10).

Equation (6) represents the value function, denoted as $\hat{V}$, which quantifies the maximized lifetime utility given the state variables, income shock, and preference shock. This equation captures the household's underline decision making process. However, for the feasibility, tracking all the preference shock is a huge burden to compute and our interest is not on how the preference shock affect optimal choices we don't need to track the preference shock. To this end, we introduce Equation (7), which represents the value of a specific choice bundle, (D_t, g_{t+1}, a_{t+1}), while excluding the current period's preference shock, but implicitly considering preference shock at continuation value, W.

$$\begin{aligned}
&\widehat{V^i}(\varepsilon_t, \beta_t, g_t, a_t, \varphi_t^H, z_t|\mathcal{Q}_t) \\
&\qquad = \max_{(g_{t+1}, a_{t+1}, D_t)\in F^i} V^i(D_t, g_{t+1}, a_{t+1}||\beta_t, g_t, a_t, \varphi_t^H, z_t|\mathcal{Q}_t) + \varepsilon_t^i(g_{t+1}, a_{t+1}, D_t)
\end{aligned} \tag{6}$$

$$\begin{aligned}
&V^i(D_t, g_{t+1}, a_{t+1}||\beta_t, g_t, a_t, \varphi_t^H, z_t|\mathcal{Q}_t) \\
&\qquad = U(c_t, h_t) + \beta_t \sum_{\beta_{t+1}} \sum_{\epsilon_{t+1}} \mathcal{L}(\beta_{t+1}|\beta_t)\pi(\epsilon_{t+1}|\epsilon_t) W^i(\beta_{t+1}, g_{t+1}, a_{t+1}, \varphi_{t+1}^H, z_{t+1}|\mathcal{Q}_{t+1})
\end{aligned} \tag{7}$$

The last part of Equation (7) includes a continuation value, denoted as W. Although the continuation value should take into account the preference shock occurring in the next period, the type-1 extreme value distribution allows us to calculate W without considering this shock, as demonstrated in Equation (8).

$$\begin{aligned}
&W^i = \int \hat{V}(\varepsilon_t, \beta_t, g_t, a_t, \varphi_t^H, z_t|\mathcal{Q}_t) d\Lambda(\epsilon_t) = log(\sum_k exp^{V^k/\alpha}) \\
&V^k = V(D_t = D_l, g_{t+1} = g_m, a_{t+1} = a_n||g_t, a_t, \varphi_t^H, z_t|\mathcal{Q}), \quad \{D_l, g_m, a_n\} \in \mathcal{F}^i
\end{aligned} \tag{8}$$

Budget Constraint

$$\text{(a)} \quad a_t < 0, \quad D_t = 0 \tag{9}$$

$$c_t + p_{h,t}g_{t+1} + p_{r,t}h_t - a_t = Z_t z_t + p_{m,t}(-a_{t+1}) + p_{r,t}g_{t+1} + (1-\delta)p_{h,t}g_t,$$

$$-a' < (1-\theta)p_h g_{t+1},$$

$$\varphi^H \geq \Delta \quad \text{if} \quad a_{t+1} < 0$$

$$\text{(b)} \quad a_t < 0, \quad D_t = 1$$

$$c_t + p_{r,t}h_t + a_{t+1} + \kappa = Z_t z_t$$

$$\text{(c)} \quad a_t \geq 0$$

$$c_t + p_{h,t}g_{t+1} + p_{r,t}h_t - a_t = Z_t z_t + p_{m,t}(-a_{t+1}) + p_{r,t}g_{t+1} + (1-\delta)p_{h,t}g_t,$$

$$-a' < (1-\theta)p_h g_{t+1},$$

$$\varphi^h \geq \Delta \quad \text{if} \quad a_{t+1} < 0$$

The budget constraint can be segmented into three distinct cases, delineated as (a), (b), and (c). These cases are presented in Equation (9). The first two cases pertain to indebted households, while the last case is for savers. Case (a) involves indebted households that choose to repay their debt, and case (b) involves those that opt to default on their mortgage.

In case (a), households have already repaid their debt a_t. They can either purchase a house with a new mortgage when their credit score φ is greater than the minimum credit score Δ, or become homeowners without taking on new debt, in which case $a_{t+1} > 0$ and $g_{t+1} > 0$. Alternatively, they can choose to rent by setting $g_{t+1} = 0$.

In case (b), the households are in default, so their only option for housing is to rent. They must also pay a constant administrative fee κ.

In case (c), the budget constraint for households without debt is described. In this case, the budget constraint is exactly the same as that for indebted households who do not default.

Choice probability By the property of type-1 extreme value distribution, the probability of choosing g_{t+1}, a_{t+1}, D_t for household i can be written in closed form as follows:

$$P^i(D_t = D_l, g_{t+1} = g_m, a_{t+1} = a_n | \beta^\iota, g_t, a_t, \varphi_t^H, z_t) \\ = \frac{e^{V^k/\alpha}}{\sum e^{V^k/\alpha} + \sum e^{V^o/\alpha}} \tag{10}$$

$$\begin{aligned} \text{where} \quad & V^k = V(D_t = D_l, g_{t+1} = g_m, a_{t+1} = a_n \mid\mid g_t, a_t, \varphi_t^H, z_t \mid \mathcal{Q}), \\ & V^o = V(D_t = D_e, g_{t+1} = g_s, a_{t+1} = a_j \mid\mid g_t, a_t, \varphi_t^H, z_t \mid \mathcal{Q}), \\ & (D_{l(e)}, g_{m(s)}, a_{n(j)}) \in \mathcal{F}^i, \\ & e, s, j \quad \text{are any arbitrary number satisfying} \quad \{D_l, g_m, a_n\} \neq \{D_e, G_s, a_j\} \end{aligned}$$

2.3 Financial intermediaries

2.3.1 Credit rating firm

Bayesian updating of type score Following the approach outlined in Chatterjee et al. (2020), we assume that financial intermediaries possess extensive data on household behavior across every points in their state space. They use this information to try to infer the hidden types of households.

$$\begin{aligned}
&\varphi^H_{t+1}(D_t, g_{t+1}, a_{t+1}|g_t, a_t, \varphi^H_t, z_t) \qquad (11)\\
&= \mathcal{L}(\beta^H|\beta^H)\frac{\varphi^H_t P(D_t, g_{t+1}, a_{t+1}|\beta^H, g_t, a_t, \varphi^H_t, z_t)}{\sum_{k\in L,H}\varphi^k_t P(D_t, g_{t+1}, a_{t+1}|\beta^k, g_t, a_t, \varphi^H_t, z_t)}\\
&+ \mathcal{L}(\beta^H|\beta^L)\frac{(1-\varphi^H_t) P(D_t, g_{t+1}, a_{t+1}|\beta^L, g_t, a_t, \varphi^H_t, z_t)}{\sum_{k\in L,H}\varphi^k_t P(D_t, g_{t+1}, a_{t+1}|\beta^k, g_t, a_t, \varphi^H_t, z_t)}
\end{aligned}$$

Equation (11) describes the Bayesian updating process for φ^H_{t+1}, which represents the probability that a household is of the high type. To estimate φ^H_{t+1} for households making the optimal choices D_t, g_{t+1}, a_{t+1} under the state variables $g_t, a_t, \varphi^H_t, z_t$, Bayesian updating is employed.

The right-hand side (RHS) of Equation (11) consists of two terms. The first term calculates the probability that households are of the high type at period t, while the second term calculates the probability for the low type. We account for these two terms because the individual's time discount rate varies over time. By taking a weighted average of these two terms, using the law of motion for β, denoted as $\mathcal{L}(\beta^H|\beta^H)$, $\mathcal{L}(\beta^H|\beta^L)$, we can compute φ^H_{t+1}.

More specifically, the denominator of the first term on the RHS of Equation (11) represents the marginal probability of selecting D_t, g_{t+1}, a_{t+1} under the given state variables. The numerator of the term is the conditional probability that patient households will choose D_t, g_{t+1}, a_{t+1} given these state variables. By applying Bayes' rule, the posterior probability, φ^H_{t+1}, is obtained as a result of the calculations in Equation (11).

Credit score: in the model vs. the data The Consumer Financial Protection Bureau (CFPB) defines a credit score as 'a prediction of your credit behavior, such as how likely you are to pay back a loan on time, based on information from your credit reports.' These reports include information on credit utilization and repayment history. Since the true process for determining credit scores is not publicly available, we use φ^H, the probability of being the high (patient) type, as a model definition of a credit score.[3] This probability serves as a proxy for default risk.

To understand why φ^H is a good proxy, consider that, all else being equal, high-type households are more likely to repay a given loan than low-type households. This is partly because some penalties associated with default, such as temporary exclusion from future borrowing due to lower credit score, could occur in the future.

Another reason φ^H is a useful proxy for empirical credit scores is that it incorporates accumulated information from Bayesian updates across all periods. This aligns with the second aspect of credit scores, which is that they reflect a household's credit history.

2.3.2 Banks

Choice probability of default Using the choice probability of Equation (8), probability of default, P^D, at period $t+1$ who choose g_{t+1}, a_{t+1} under the given state variables, g_t ,a_t, φ_t, can be calculated as follows:

$$\begin{aligned} &P^D(g_{t+1}, a_{t+1}|g_t, a_t, \varphi_t^H, z_t) \\ &\qquad = \sum_{z_t} \pi(z_{t+1}|z_t) \sum_{\substack{k\in\{H,L\},\\ g_{t+2},\\ a_{t+2}}} \varphi_{t+1}^k P(D_{t+1}=1, g_{t+2}, a_{t+2}|\beta^k, g_{t+1}, a_{t+1}, \varphi_{t+1}^H, z_{t+1}) \end{aligned} \tag{12}$$

Mortgage pricing The mortgage price, p_m, is determined in a competitive mortgage market where banks' expected return on unit mortgage lending is zero.

[3] Chatterjee et al. (2020) define credit scores as the probability of default for a certain loan size, considering factors like income and time discount rate. We diverge from this approach and use φ^H as a proxy for credit scores because the mortgage debt market has less variation in default risk, making it a more suitable candidate for our research objective—to assess the effect of minimum credit score thresholds in the mortgage market.

$$
\begin{aligned}
&a_{t+1} p_m(D_t, g_{t+1}, a_{t+1} | g_t, a_t, \varphi_t^H, z_t) \\
&\quad = \frac{1}{(1 + r_a + r_w)} \Big[\big\{ 1 - P^D(g_{t+1}, a_{t+1} | g_t, a_t, \varphi_t^H, z_t) \big\} a_{t+1} \\
&\qquad + P^D(g_{t+1}, a_{t+1} | g_t, a_t, \varphi_t^H, z_t) \min\big\{ -a_{t+1}, g_{t+1}(1 - \delta - \gamma) \big\} \Big]
\end{aligned} \tag{13}
$$

The mortgage price, $p_m(D_t, g_{t+1}, a_{t+1}|g_t, a_t, \varphi_t^H, z_t)$, is influenced by households' current observable portfolio (a_t, g_t), current productivity shock (z_t), optimal choices (a_{t+1}, g_{t+1}), and credit score (φ_t^H).

The first term on the right side of Equation (12) represents the discount rate, where r_a is the risk-free rate, and r_w is the intermediation wedge per unit of mortgage issued. Consequently, $r_a + r_w$ constitutes the cost per unit of mortgage issued for banks. Banks discount their expected returns by this rate.

The term $P^D(g_{t+1}, a_{t+1}|g_t, a_t, \varphi_t^H, z_t)$ captures the probability of choosing to default on the mortgage debt a_{t+1} in the next period for households currently in the state $(g_t, a_t, \varphi_t^H, z_t)$ and choosing (g_{t+1}, a_{t+1}).

When households repay their entire mortgage debt, the expected return for the bank is $(1 - P^D)a_{t+1}$. If households default, the bank can liquidate the collateral housing asset g_{t+1}. Given the presence of preference shocks, households may choose to default even when they are not strictly underwater on their mortgage. Therefore, the expected return upon default can be defined as $P^D \min(-a_{t+1}, g_{t+1}(1 - \delta - \gamma))$.[4]

For saving, when $a_{t+1} > 0$, a single competitive unit price $p_a = \frac{1}{1+r_a}$ is applied. Here, r_a is the risk-free rate, determined in competitive international financial markets. In this framework, a household that saves $p_a a_{t+1}$ in period t will repay a_{t+1} in the next period.

[4]The depreciation rate of REO (Real Estate Owned) is higher than that for normal housing assets. γ denotes this additional rate of depreciation. Consequently, in the baseline model, there is no case where $a_{t+1} < g_{t+1}(1 - \delta - \gamma)$.

2.4 Production

2.4.1 Final good production

A representative producer supplies a non-durable consumption good, denoted as c, at a competitive price $p_{c,t}$. We use c as the numeraire good, setting $p_{c,t} = 1$. In this economy, labor, represented as N_t, serves as the sole input for the production of the non-durable consumption good. We denote the total output for this good as Y_t. Equation (12) describes the production function for the non-durable consumption good.

The technology for producing this non-durable consumption good exhibits constant returns to scale. We introduce $\mathcal{Z}_t$ to represent an aggregate efficiency term.

$$Y_t = \mathcal{Z}_t N_t \tag{14}$$

$$\max_{N_t} \quad Y_t - w_t N_t \tag{15}$$

As a result of solving the profit maximization problem of Equation (13), $w_t = \mathcal{Z}_t$

2.4.2 Residential construction sector

Following (Jeske, Krueger, and Mitman, 2011), we assume perfectly elastic supply of housing at exogenously fixed house price, $p_{h,t} = 1$, but the rent, $P_{r,t}$, is endogenously determined in the model. A representative constructor supplies perfectly divisible housing stock, I^h.

Consumption good is the only one input factor for production. C_h is the consumption good for an input of housing production. The representative builder operates a technology transfer consumption good to housing stock one-for-one, so total housing investment, I_h, is always equal to C_h.

$$\max_{s.t \quad I^h = C^h} \quad I_t^h - C_t^h \tag{16}$$

2.5 Equilibrium

In this section, we formalize the concept of a stationary Recursive Competitive Equilibrium for the baseline economy.

Definition Given the minimum credit score threshold Δ and house price $p_h = 1$, **a stationary Recursive Competitive Equilibrium** includes rent price p_r, mortgage pricing function p_m, a type scoring function ψ, a choice probability function P, policy function for the consumption and housing consumption $c, h,$ and a steady-state distribution Φ such that:

1) $P(D, g, a'|\beta, g, a, \varphi^H, z)$ satisfies Equation (8).

2) $\varphi_{t+1}(D, g', a'|g, a, \varphi^H, z)$ satisfies Equation (9).

3) $p_m(D, g, a'|g, a, \varphi^H, z)$ satisfies Equation (11).

4) The rental market clears

$$\int g' \times \sum_{a'} \sum_{D} P(D, g', a'|\beta, g, a, \varphi^H, z) d\Phi \tag{17}$$
$$= \int h(D, g, a'|\beta, g, a, \varphi^H, z) \times P(D, g, a'|\beta, g, a, \varphi^H, z) d\Phi$$

5) Final Goods Market Clearing Condition:

$$
\begin{aligned}
Y = & \int c(D, g, a' | \beta, g, a, \varphi^H, z) \times P(D, g, a' | \beta, g, a, \varphi^H, z) d\Phi \\
& + \int p_b a' \times \sum_{g'} \sum_{D} P(D, g', a' | \beta, g, a, \varphi^H, z) d\Phi \\
& - \int \sum_{g'} \sum_{D} [a' p_m(D, g', a' | g, a, \varphi^H, z) P(D, g', a' | \beta, g, a, \varphi^H, z)] d\Phi \\
& + C_h
\end{aligned} \tag{18}
$$

where Y is total output:

$$
Y = \int z d\Phi \tag{19}
$$

and C_h is given by:

$$
\begin{aligned}
C_h = \delta_n & \int g' \times \sum_{a'} P(D = 0, g', a' | \beta, g, a, \varphi^H, z) d\Phi \\
& + (\delta_n + \delta_f) \int g' \times \sum_{a'} P(D = 1, g', a' | \beta, g, a, \varphi^H, z) d\Phi
\end{aligned} \tag{20}
$$

By fulfilling these conditions, we establish the a Stationary Recursive Competitive Equilibrium in the baseline economy. The equilibrium we define here is solved by computational algorithm explained an Appendix B.

3 Calibration

3.1 External calibration

In our model, we externally calibrate nine key parameters, drawing upon widely accepted values or empirical evidence from the literature. These parameters are displayed in Table 1. We use estimates of Piazzesi, Schneider, and Tuzel (2007) to calibrate $1/\nu$, the elasticity of substitution between non-durable consumption c_t and housing service h_t. For

Table 1: Calibration of Externally Calibrated Parameters in Baseline Model

Parameter	Value	Interpretation
Externally Calibrated Parameters		
Households		
γ	2	Risk aversion
$1/\nu$	1.25	Elasticity of substitution
ρ	0.98	Autocorrelation of earning
σ_ϵ	0.3	S.D of earning shock
ϕ	0.15	Preference weight for housing
$\mathcal{L}(\beta^{H(L)} \vert \beta^{H(L)})$	0.987	Law of motion for time discount rate
$\Phi(\beta^H) : \Phi(\beta^L)$	$0.5 : 0.5$	Population ratio between types
Housing		
g_2, g_3	(2, 5)	Housing asset/median income P25 and P75
δ_n	0.015	Deprecation rate
δ_f	0.22	Depreciation rate(foreclosure)
Mortgage		
κ	0.02	Foreclosure cost
Δ	0.42	Minimum credit score threshold
η	1.07	Maximum loan-to-value ratio
Bank		
r_b	0.0235	Risk free rate
Productivity		
Z_t	1	Aggregate productivity

Note: The figures in this table are annualized for relevant time periods. One unit of the final good in the model corresponds to the median household income.

the risk aversion parameter γ, we use 2, which implies a value of 0.5 for the elasticity of intertemporal substitution. This calibration is based on the fact that the estimates of elasticity of intertemporal substitution using micro data are around 0.5(Runkle (1991),Attanasio and Weber (1995)). Taste for housing service, ϕ, ranges from 0.16 to 0.14 across the literature(Jeske, Krueger, and Mitman, 2011; Kaplan, Mitman, and Violante, 2020). They choose the value by calculating average share of residential cost in total consumer expenditure using National Income and Product Accounts(NIPA). We pick middle of the range, 0.15.

For the household income process, we follow Storesletten, Telmer, and Yaron (2004). To be specific, we set ρ, persistence of income to $0.$ and its variance, σ_ϵ to 0.3.

We choose depreciation rate, δ_n of 1.5% following(Kaplan, Mitman, and Violante, 2020). For the depreciation rate for the foreclosure property, we use 22%, following Jeske, Krueger, and Mitman (2011).

The risk free rate, r_a is 0.0235, which is the average market yields on US Treasury securities at 10-year constant maturity of 2013. Lastly, we set pecuniary default cost 2% of median income following Chatterjee et al. (2020).

In our model, we exogenously calibrate two key parameters related to the time discount rate: the population share of each household type (high-type and low-type), and the law of motion governing the time discount rate. The calibration of the population share is informed by a paper that estimates time discount rates using 2013 U.S. data (Bradford, Courtemanche, Heutel, McAlvanah, and Ruhm, 2017). Although this paper does not offer a complete distribution of discount rates, it does provide critical summary statistics like the mean, median, and various quantiles in their Table 1. Based on these statistics, we infer that the distribution of discount rates is approximately symmetrical, justifying our choice of an even population share between the two household types. Additionally, we also set the law of motion for the time discount rate at 0.985, following the findings of

Chatterjee et al. (2020).[5]

We calibrate the minimum credit score threshold $\Delta = 0.42$, $\Phi(\varphi^H < \Delta) = 0.24$. In Appendix A, we detail the process by which we selected 0.24 as the credit score threshold. It means we limit households to borrow when their credit score is located in below 24% in overall credit score distribution.

3.2 Internal calibration

We carried out the internal calibration of three key parameters simultaneously. The initial part of this calibration focuses on setting the values for β^H and β^L. These two parameters are calibrated to match the homeownership rate and default risk observed in the model with their respective counterparts in the data. Following this, we adjust r_w, the mortgage origination wedge, to align the average mortgage rate produced by the baseline model with the observed average mortgage rate in the data. The results of this internal calibration are presented in Table 2.

For calibrating the homeownership rate, we rely on data from the 2013 Survey of Consumer Finance (SCF), which reports a rate of 67.1$\%$. To calibrate the mortgage origination wedge, r_w, we use the average 30-year mortgage rate as calculated by Freddie Mac. Finally, for the data point related to the default rate, we refer to the number of completed foreclosure sales as reported in the Foreclosure Prevention and Refinance Report for the year 2023.

[5] Although the law of motion derived in their study is context-specific, its role in our model is introducing a small degree of uncertainty by allowing a tiny fraction of households to change their type, thereby disrupting perfect learning for credit rating firm about the hidden type. We tested various values in close proximity to the Chatterjee et al. (2020) estimate and found that this parameter is not quantitatively significant within that range.

Table 2: Calibration of Internally Calibrated Parameters in Baseline Model

Parameter	Value	Interpretation	Target	Data	Model
Internally Calibrated Parameters					
Discount rate					
β^H	0.8891	Time discount rate for patient type	Homeownership rate	67.1	67.9
β^L	0.8441	Time discount rate for impatient type	Default rate	0.54	0.58
Mortgage					
r_w	0.02	Mortgage origination wedge	Avg. 30 yrs mortgage rate	4.48	4.42

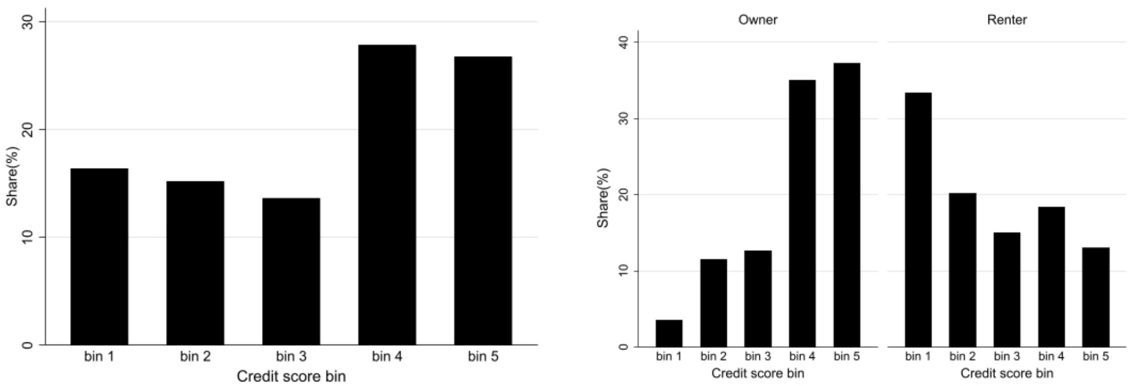
Note: The figures in this table are annualized for relevant time periods.

4 Model Fit

In this section, we delve into the multifaceted components of our baseline model. Specifically, we investigate how the model articulates relationships between credit scores and key variables such as default rate, income, and homeownership rate. By comparing these results with existing data or empirical studies, we substantiate the model's reliable integration of credit score mechanisms. This aspect serves as a pivotal dimension of model fit in our research. The reason for this is that the core mechanisms of the model are significantly influenced by how credit score thresholds shape the dynamic interplay between household decision-making and credit ratings. Hence, for the model to serve effectively as a testing ground for policy experiments concerning minimum credit score thresholds, it is crucial that it accurately captures the characteristics of credit scores.

4.1 Distribution of credit score by tenure

The panel (a) of Figure 1 displays the distribution of credit scores based on data from the 2014 Survey of Consumer Expectations (SCE). While the survey does not provide specific credit scores, it does categorize households into different credit score bins. These bins are defined as follows: Bin 1 includes scores below 620; Bin 2 ranges from 620 to 679; Bin 3 spans from 680 to 719; Bin 4 covers the range of 720 to 759; and Bin 5 consists of scores greater than 760. In the distribution, Bin 1 accounts for 15.12%, Bin 2 for 12.29%, Bin 3 for 13.83%, Bin 4 for 27.25%, and Bin 5 for 31.52%.



(a) Overall

(b) By tenure

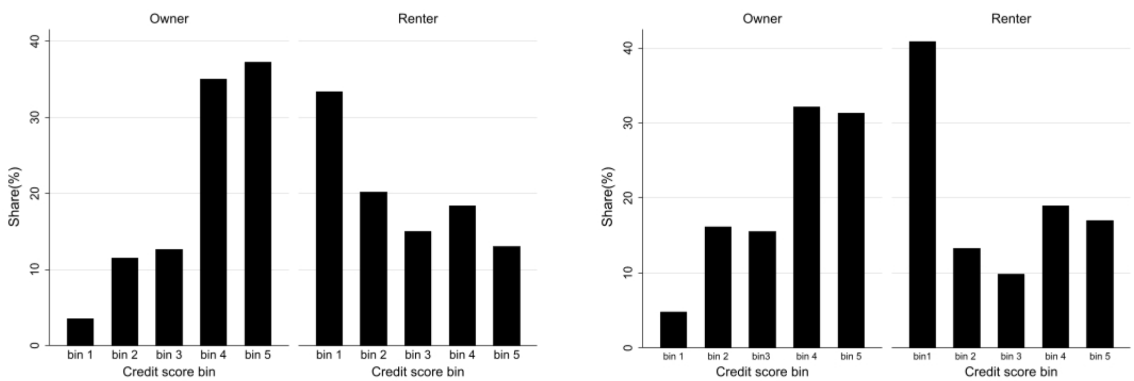
Figure 1: Credit Score Distributions from the Survey of Consumer Expectation

Note: In panel (a), each bin does not represent a uniform share, reflecting the survey's defined categories: bin 1 (<620), bin 2 (620-679), bin 3 (680-719), bin 4 (720-759), and bin 5 (>760). The respective shares for these bins are 15.12%, 12.29%, 13.83%, 27.25%, and 31.52%. Based on definition of Bin in the panel (a), the panel (b) show the credit score distribution by tenure. The Data source: 2014 Survey of Consumer Expectation, NYFED.

In panel (b) of Figure 1, households are categorized according to their housing status as either owners or renters. There are significant disparities in the distribution of credit scores between the two tenure groups—homeowners and renters—as evidenced by Figure 1. In the left side of panel (b), which depicts the homeowners' credit score distribution, we observe a tendency for the fraction of households in each credit score bin to increase as the credit score rises. Specifically, bins 1, 2, and 3 account for approximately 6%, 8%, and 13% of homeowners, respectively. In contrast, bin 4 comprises about 30% of the homeowner population, while bin 5 accounts for about 40%.

The right side of panel (b) in Figure 1 focuses on the credit score distribution among renters. Here, the fraction of households generally decreases from bin 1 to bin 3. About 34% of renter households fall into bin 1, while 20% are in bin 2. Bin 3 accounts for 15% of the renter population. The population of bins 4 and 5 each have populations that is close to that of bin 3. These disparities are not a unique phenomenon observed only in the 2014 SCE. We found similar patterns in the extensive data spanning from the 2015 to 2020 SCE, as documented in Figures C1 to C6 in Appendix C.

The novel contribution of this paper lies in examining the distribution of credit scores by tenure choices. Through our data analysis, we find that households with lower credit scores predominantly opt for renting over homeownership. This observation suggests that creditworthiness plays a non-trivial role in the decision-making process surrounding tenure choice.



(a) SCE 2014 (b) Baseline Model

Figure 2: Credit Score Distributions from the Baseline Model, Credit Score Rationing Economy

Note: The panel (a) is same figure of panel(b) in Figure 1. The panel (b) presents the distribution of credit scores, segmented by tenure choices. This data is generated from our baseline model, which incorporates credit score rationing that disallows mortgage loans for the lowest 24% of credit scores. Bins are constructed based on the percentages according to the 2014 Survey of Consumer Expectations. Specifically, bin 1 includes credit scores in the lowest 15.12% of the distribution; bin 2 includes scores in the next 12.29%; bin 3 represents the next 13.83%; bin 4 includes the next 27.25%; and the remaining scores are in bin 5. This non-linearity of bin distribution might cause the non-monotonic property of distribution and to test this we construct credit score bin with uniform distribution and this explained in Figure C7 in Appendix C. The left panel represents owner ($g_{t+1} > 0$) and right panel shows the distribution for the renter ($g_{t+1} = 0$).

Figure 2 compares the credit score distribution by tenure choices from the SCE 2014 and the baseline model. The panel (a) of Figure 2 is exactly same to the panel (b) of

Figure 1. The left side of panel (b) of Figure 2 shows the credit score distribution of the homeowner. Overall, the baseline model reproduces the main property of the data: the higher the fraction, the higher the credit score well.

The right side of panel (b) in Figure 2 shows the credit score distribution of renters from the baseline model. The model looks valid in that it reproduces the main characteristic of the data: the largest group of renters is credit bin 1. Furthermore, the fact that this distribution is not a targeted moment makes the validation of the model more credible.

Note that the credit score bin were created according to the distribution outlined in the 2014 Survey of Consumer Expectations. Specifically, we allocate households whose credit scores, φ^H that fall in the lowest 15.12% of the overall range to Bin 1. Bin 2 accounts for the subsequent 12.29% of scores, followed by bin 3, which represents the next 13.83%. Bin 4 then contains the next 27.25% of scores, while all remaining scores are grouped into bin 5. This results in a non-linear distribution of credit scores as depicted in Figure 2 since the credit score bin in SCE is not uniform distribution as panel (a) of Figure 1 shows. We create another credit score bin evenly distributed across the credit score bin and the result are provided in Figure C7 panel (a) in Appendix.

4.2 Determinant of loan performance: credit score and loan-to-value ratio

Figure 3 describes the default rate by credit score bin. As we stated in the calibration section, we targeted the default rate of 2013, and the model generating default rate is about 0.5%. In Figure 3, we provide the default rate for each credit score bin. There is a negative relationship between the credit score group and the default rate.

We set up a simple probit model where we regressed the binary default choice on the ranking of the credit score. We establish a ranking system consisting of 100 levels, where a higher rank corresponds to a higher credit score. According to Table 3, the marginal effect of credit score ranking on default risk is evident. Moving up one rank reduces the default

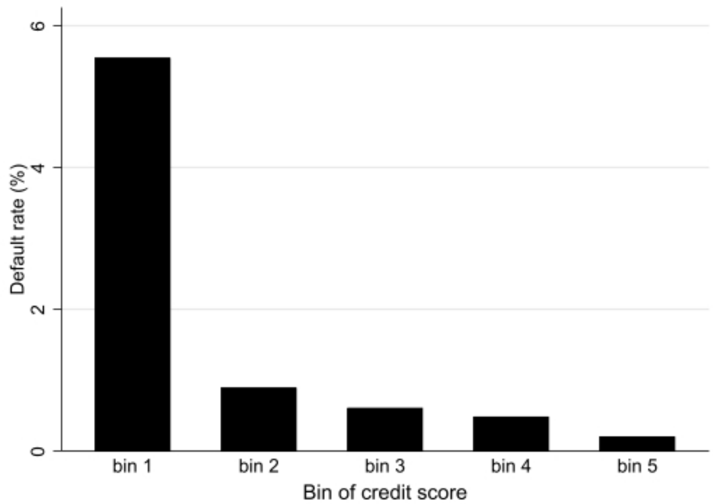


Figure 3: Default Rate on Mortgages by Credit Bin for Indebted Households

Note: This graph displays the default rate on mortgages, conditional on indebted households, segmented by credit bins. The credit bins are based on the 2014 SCF data. The default rate is calculated as the ratio of households choosing to default ($D_t = 1$) to those with negative financial asset ($a_t < 0$) within each credit bin. The data is generated using a baseline model that implements credit score rationing.

risk by approximately 0.052 percentage points. This increase is significant, amounting to nearly 10% of the average default rate. Consequently, the impact of a single step increase in ranking is non-negligible.

The relationship between credit score and default rate, as determined by the baseline model, aligns with empirical studies that investigate the factors affecting loan performance.(Davis, Larson, Oliner, and Smith, 2019; Fout, Li, Palim, and Pan, 2020; Haughwout, Peach, and Tracy, 2008; Lam, Dunsky, and Kelly, 2013). Furthermore, the papers concur that a higher loan-to-value ratio drives higher default risk. Table 4 shows how loan-to-value and credit score jointly affect the default rate. The default rate strictly increases in the loan-to-value ratio and decreases in the credit score bin. The default rate jumps in the range where the loan-to-value ratio is $\geq 90\%$, and this result is consistent with the simulated default risk of Davis et al. (2019) and Lam, Dunsky, and Kelly (2013).

Variable	Model dy/dx
Dependent variable: default=1, repay=0	
Credit score ranking	$-0.05211\%^{***}$
	(0.00)

Table 3: Probit Regression Results for the Likelihood of Default from the Baseline model

Note: The table presents the results of a probit regression model examining the likelihood of mortgage default. The dependent variable is coded as 1 for default and 0 for repayment. The model dy/dx represents the marginal effect of the credit score ranking on the probability of default. The data is generated from the baseline model where we implement credit score rationing. The values in the parentheses are p-values. The notation "***" indicates statistical significance at the 99% confidence level.

	Credit Score Bin					
Loan-to-Value(%)	1	2	3	4	5	Total
-60	4.92	0.52	0.32	0.23	0.11	0.31
61-71	5.89	0.87	0.52	0.40	0.20	0.51
71-75	5.98	1.21	0.72	0.50	0.23	0.62
76-80	7.03	1.61	1.01	0.70	0.48	0.90
81-85	7.77	1.80	1.23	0.88	0.54	1.10
86-90	8.45	2.29	1.62	1.31	0.92	1.60
91-	15.2	15.3	15.1	14.5	8.56	14.9
Total	6.04	0.90	0.62	0.49	0.024	0.58

Table 4: Default rate by credit score bin and loan-to-value ratio from the Baseline Model. Unit $\%$.

Note: This table summarizes default rate across different credit score bins and loan-to-value ratio. Each cell represents the percentage of loans defaulting in a given loan-to-value category and credit score bin. The 'Total' row and column provide the overall default rate across all credit score bins for each loan-to-value category and vice versa. The data generated from the baseline model where we implement credit score rationing.

4.3 Income and credit score

There is empirical evidence that credit score and income are correlated.(Albanesi, DeGiorgi, and Nosal, 2022; Beer and Li, 2018). To investigate whether the model replicates the same relationship between the variables, we performed a simple regression analysis. In this regression, the dependent variable is the credit score, denoted by φ_t^H. The independent variables are the financial asset a_{t+1}, housing asset g_{t+1}, productivity shock z_t,

Variable	Coefficient
Dependent variable: Credit score, t , $[0.013, 0.987]$	
Financial asset	0.042^{***}
	(0.00)
Housing asset	0.036^{***}
	(0.00)
Earning	0.042^{***}
	(0.00)
Credit score, $t-1$	0.973^{***}
	(0.00)
Financial asset, $t-1$	-0.021^{***}
	(0.00)
Housing asset, $t-1$	-0.022^{***}
	(0.00)
Cons	-0.108^{***}
	(0.00)
Number of obs	13,637,826
R-squared	0.91

Table 5: Determinants of Credit Score From the Baseline Model

Note: This table reports the determinants of credit score, using a data from the baseline model where the credit score rationing is implemented. We regress credit score(φ^H) on choice of financial asset(a_{t+1}), choice of housing asset(g_{t+1}), productivity(earning) shock(z_t), lagged value of same variables($\varphi^H_{t-1}, a_t, g_t$). The dependent variable is the credit score at time t, ranging from a minimum value of $\varphi^H = 0.013$ to a maximum value of $\varphi^H = 0.987$, which is generated in equilibrium. The values in the parentheses are p-values. The notation "***" indicates statistical significance at the 99% confidence level.

Variable	Model dy/dx	SCE 2014 dy/dx
Dependent variable: owner=1, renter=0		
Credit score bin	0.107***	0.145***
	(0.00)	(0.00)

Table 6: Probit Regression Results for the Likelihood of Homeownership: Model Vs Data

Note: The table presents the marginal effects of credit score bins on the likelihood of being a homeowner, as calculated from a probit regression model. The column Model dy/dx presents results from our baseline model, while SCE 2014 dy/dx shows the results based on data from the 2014 Survey of Consumer Expectations. The dependent variable is a binary outcome indicating homeownership status: owner=1, renter=0. The values in the parentheses are p-values. The notation "***" indicates statistical significance at the 99% confidence level.

lagged credit score φ_{t-1}, lagged housing asset g_t, lagged financial asset $a_t)$

It is important to note that in this analysis, we do not employ credit score rankings. Instead, we use raw credit scores, which range from a minimum value of 0.013 to a maximum value of 0.987.

According to Table 5, there is a correlation between income and credit score, denoted as φ^H, with a value of 0.042 in the baseline model. Based on this information, we can infer that when all other factors are held constant, an increase in income equivalent to the average income results in a four-step increase in the ranking within the 100-level ranking system.

4.4 Homeownership rate

Table 6 illustrates that a one-step increase in the credit score bin is associated with an approximate 10 percentage point increase in the probability of being a homeowner, as observed in the model. This result is consistent with the findings of a similar regression analysis using SCE 2014 data.

5 The assessment of the minimum credit score threshold

In this section, we conduct a counterfactual experiment to examine the impact of removing the minimum credit score threshold. Starting with the same calibration as the baseline model, we generate a new steady-state—referred to as the counterfactual—by solely eliminating this threshold. By comparing these two steady states, one with and one without the credit score constraint, we aim to evaluate its influence on key housing market variables. These include homeownership rates, rent-to-price ratios, mortgage default rates, average loan-to-value ratios, the number of mortgage origination, and average mortgage rates. Additionally, this experiment allows us to explore distributional aspects. For example, we address how the credit score constraint shapes the typical credit score distribution across different tenure choices, as depicted in Figure 3. We also examine how the minimum credit score threshold alters the relationship between income and homeownership.

5.1 Aggregate effects of minimum credit score constraint

Table 7 offers a comparison of significant housing market moments between the baseline model and the counterfactual model.

First, removing the minimum credit score results in a significant increase in the default rate. Specifically, the default rate is almost 10 times higher when the threshold is removed. The choice to default is based on a comparison between the immediate benefits and immediate-to-long-term costs of defaulting. The benefit of defaulting is that the borrower is no longer burdened by loan payments. The cost of defaulting consists of two factors: i)losing the chance to buy the house, ii)decreased reputation, which causes ψ^H to decrease. Implementing a minimum credit score threshold does not affect this benefit. However, the cost of losing reputation might be higher in an economy with a minimum credit score threshold since it increases the defaulter's probability of locating under the minimum credit score threshold in the future. In other words, the minimum credit score threshold brings a more persistent negative effect to the default choice.

Surprisingly, removing the minimum credit score threshold decreases the homeownership rate by 5.1%. Two potential pathways could explain why implementing a credit score threshold in the mortgage market leads to an increase in homeownership rates, despite the conventional wisdom that additional credit constraints usually discourage households from purchasing homes: credit score path and mortgage rate path

First, the motivation provided by credit score criteria could play a role. In this model, high-type households are more likely to become homeowners because housing serves as an effective means of saving and smoothing consumption. Given that a credit score is defined as the probability of being a high-type household, homeowners are likely to achieve higher credit scores. This in turn benefits them by reducing the likelihood of being rationed in an economy that employs a credit score threshold. Second, reduced default behavior accompanies more affordable mortgages. In this model, mortgage rates are dependent on the expected default rate as described in Equation (13). As a result, lower default rates would drive down mortgage costs, ultimately boosting the homeownership rate.

However, quantitatively separating these two paths is challenging due to the interrelationship between mortgage rates, default risk, and minimum credit score requirements. To address this, we employ a two approach: first, we conduct empirical analysis using data from our model, and second, we carry out counterfactual analysis for further insights.

In the model, mortgage rates are determined by the following state variables: housing assets g_t, financial assets a_t, productivity z_t, and credit score φ_t. These rates are also influenced by the choice variables g_{t+1} and a_{t+1}, as described in Equation (13). Even when presented with the same state variables, households may make different choices—some opting for homeownership while others choose to rent. However, if they select the same housing size g_{t+1} and financial assets a_{t+1}, they could potentially face identical mortgage rates.

Using this property, we perform a simple Probit regression that examines how the likelihood of homeownership differs between the baseline and counterfactual scenarios conditional on possibly same mortgage rate. Specifically, we regress tenure choice (1 for homeowners and 0 for renters) on a dummy variable (1 for baseline and 0 for counterfactual), as well as on housing assets g_t, financial assets a_t, productivity z_t, and credit score φ_t. This indicates that among households who could qualify for the same mortgage rate, the likelihood of choosing homeownership is 2.65 percentage points higher in an economy with a minimum credit score requirement. We define this difference as attributable to the "credit score path." The remaining difference, calculated as $5.1\%p - 2.65\%p = 2.45\%p$, is attributed to the "mortgage path." We explain computational algorithm to find p_m^{new} in Appendix A.

Secondly, we aim to reassess whether the elevated mortgage rates in the counterfactual economy are the sole drivers behind the observed decline in homeownership rates. We focus specifically on the extent to which a change in mortgage rates, denoted as $p_m^{new} - p_m^{baseline}$, across all state spaces could account for a decline in homeownership rates equivalent to that observed in an economy without a minimum credit score requirement. Through our analysis, we find that when we adjust p_m^{new} such that $p_m^{new} = p_m \times 0.98$, and hold the policy functions of the baseline model constant, we arrive at the same homeownership rate as observed in the counterfactual economy. This compelled new mortgage rate is almost 2 percentage points higher than that in the baseline model. This indicates that the 0.5 percentage point difference in mortgage rates between the two economies is only partially responsible for the changes in homeownership rates, a conclusion consistent with our empirical findings.

Lastly, as expected, the removal of the minimum credit score requirement leads to a nearly 1.5-fold increase in both the average loan-to-value rate and the number of mortgage originations. This increase is likely attributable to reduced default costs, which in

	Baseline (%) (with threshold)	Counterfactual (%) (without threshold)
Default rate	0.58	5.29
Rent to price	9.38	10.1
Homeownership rate	67.9	62.8
Average mortgage rate	4.41	4.96
Avg. loan-to-value ratio of mortgage owner	41	62
Fraction of mortgage owners among homeowners	58	82

Table 7: Aggregate effects of rationing: moments baseline Vs counterfactual

turn encourage more extensive borrowing behavior.

5.2 Distributional analysis and strategic interaction

The distribution of credit score In section 4, we mention that the distributions of credit scores between owners and renters are distinguishable, and the baseline model reproduces this feature well. Figure 4 shows the distribution of credit scores with and without a minimum credit score threshold for both owners and renters. The non-colored bars are a histogram for the baseline model, and the colored bars are that for the counterfactual. By removing the minimum credit score threshold, the fraction of households with credit score bin 1 among renters decreases by about $20\%p$. In contrast, the fraction of households with credit score bin 1 among the homeowner increasesd by about $9\%p$; this result comes from the two channels. The first route is straightforward; someone should be located in bin 1 due to the ordinal property of credit score and removing the credit score constraint extends the budget constraint of most households that are located in bin 1, so the share of owners in bin 1 increases and that of renters decreases. The second channel is as follows; we find that the fraction of households with income class z_1 in bin 1 is 23.34% in the baseline model, and the fraction is 12.47% in the counterfactual. This means that the threshold increases the fraction of lower-income households in bin 1; as a result, it might affect the lower homeownership rate of bin 1 in the baseline model.

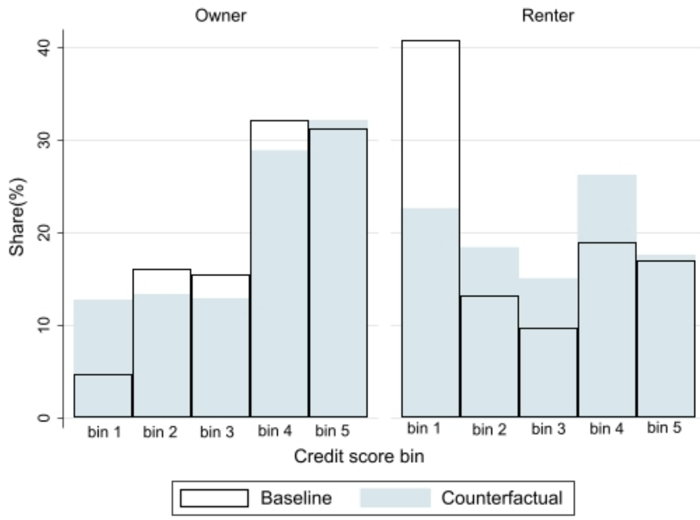


Figure 4: Change in the credit score distribution in response to removing the minimum credit score threshold.

Note: The white bars represent the distribution of credit scores in the baseline model, where constraints based on credit scores are implemented. The colored bars, on the other hand, depict the distribution in the counterfactual model, where no credit-score-related constraints are in place. The categorization of credit score bins is consistent with that outlined in Figure 2, following the definition of SCE 2014.

The distribution of homeownership rate Figure 5 shows how homeownership rates by income class changes in response to removing credit score constraints. The counterfactual homeownership rate for each income class decreases compared to the baseline due to the higher mortgage rate in the counterfactual. However, the homeownership rate of the lowest income class, z_1 does not change.

To empirically validate these findings, we conducted a simple probit regression to examine the impact of income on the probability of being credit-rationed. Specifically, we regressed a binary variable—where ’rationed’ is coded as 1 and ’unrationed’ as 0—on earnings. The results, presented in Table 8, show a negative relationship between income and the probability of being rationed. Specifically, an increase in income equivalent to the median income leads to a 2.6 percentage point decrease in the probability of being rationed, on average.

This result helps explain the underlying dynamics depicted in Figure 5. While the existence of a credit score threshold motivates more households to aspire to homeownership, those with lower incomes are less likely to realize this aspiration due to a higher probability of being credit-rationed. Therefore, despite the increased incentives for homeownership in a threshold economy, access to home loans remains inequitable, disproportionately affecting lower-income households.

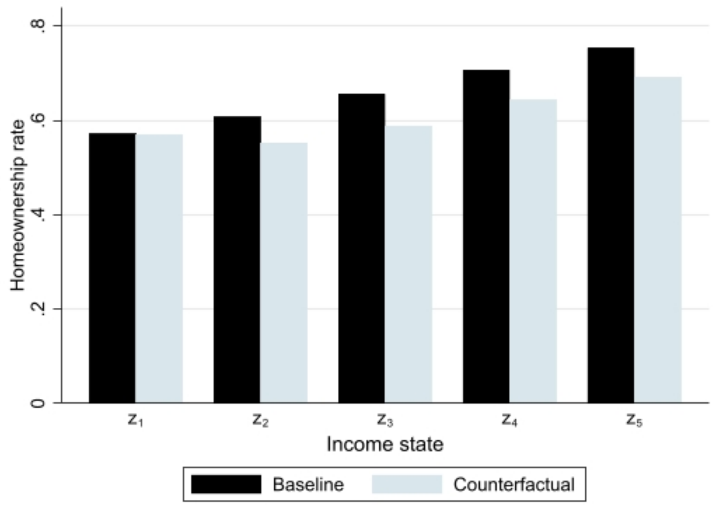


Figure 5: Homeownership rate by earning class, Baseline Vs Counterfactual

Note: The black bars display the homeownership rate by earning class(z_t) in the baseline model, where credit score rationing is applied. The colored bars represent the homeownership rate in the counterfactual model without such rationing.

Variable	**dy/dx**
Dependent variable: ration=1, non-ration=0	
Earning	-2.6% ***
	(0.00)

Table 8: Effects of Earning on Probability of Rationing from the Baseline Model

Note: This table, we investigate how earning levels affect the likelihood of being subject to credit rationing, based on the baseline model. The dy/dx column presents the marginal effect of earning on the probability of rationing. The median earning is normalized to 1 in this model. The values in the parentheses are p-values. The notation "***" indicates statistical significance at the 99% confidence level.

Strategic interaction An intriguing result of our study is that credit rationing intensifies signaling competition among households, leading to greater separation between the two types of households. This finding is supported by data presented in Table 9. In the counterfactual scenario, the ratio between the average φ^H values for patient and impatient households is close to one across all segments, indicating little differentiation between the two types. However, this ratio drops substantially in the baseline model, signifying that credit rationing fosters more intense signaling competition and, consequently, greater separation between the two household types.

Furthermore, the data show that this separation is not uniformly distributed across different housing status categories. Unlike in the counterfactual scenario, where the ratios are quite similar across all segments, the ratios in the baseline model increase as we move from renters to homeowners and even further among those homeowners with mortgages. This suggests that households aspiring to homeownership are willing to incur greater signaling costs, and this tendency is even more pronounced among those who take on mortgages. This behavior implies that the benefits of homeownership and mortgage financing are deemed to outweigh the signaling costs.

	Average φ^H of β^H / Average φ^H of β^L			
	Renter	Owner	Owner with mortgage	Total
Baseline	0.7	0.9	0.96	0.83
Counterfactual	0.94	0.95	0.94	0.92

Table 9: Comparing φ^H by type and model.

Note: In this table, we present the average credit score ratio between households with a high type of time discount rate β^H and those with a low type β^L. These ratios are displayed across both the baseline and counterfactual models, segmented by different housing statuses. The term "Renter" refers to households with zero housing assets ($g_{t+1} = 0$), "Owner" corresponds to households with positive housing assets ($g_{t+1} > 0$), and "Owner with Mortgage" describes households that not only have positive housing assets but also have negative financial assets, indicating a mortgage ($g_{t+1} > 0$ and $a_{t+1} < 0$).

6 Conclusion

This paper contributes to the literature by constructing a quantitative heterogeneous agent macro-housing model to examine the impact of minimum credit score thresholds in the mortgage market, especially in the post-2008 Great Recession landscape. Unlike previous macro-housing models, our framework uniquely generates an endogenous distribution of credit scores, allowing us to capture complex dynamics and interactions between credit availability and housing market outcomes.

Our key findings suggest that removing the minimum credit score threshold leads to higher mortgage default rates. This outcome arises because the threshold effectively increases the cost of defaulting: a defaulting household faces the risk of being excluded from the mortgage market in the future due to a lower credit score. Interestingly, the presence of the credit score threshold incentivizes households to transition from renting to owning. This is primarily because homeownership can positively impact a household's credit score and also because the threshold indirectly lowers mortgage rates by mitigating default risks. As a result, we observe a higher rent-to-price ratio in economies that do not enforce a credit score threshold.

Although average homeownership rate increases by introducing the threshold, this impact is not uniform across income groups. For lower-income households, the homeownership rate remains largely unaffected when the threshold is removed. This is because these households are more likely to be credit rationed due to the strong correlation between income and credit score, effectively nullifying the general incentives for homeownership offered by a minimum credit score threshold.

Moreover, the elimination of the credit score threshold leads to a higher average loan-to-value ratio and increases the proportion of mortgage-owning households.

These findings provide a understanding of how credit score requirements in mortgage markets shape housing outcomes, enriching the ongoing policy debates on financial regulation and housing affordability.

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A Appendix: Selecting minimum Credit Score Threshold

The changes in lenders' policy related to credit scores in both the conventional and unconventional mortgage markets can be summarized as the prevalence of a minimum credit score requirement in the mortgage industry. Laufer and Paciorek (2022) provide evidence on the prevalence of minimum credit scores, utilizing the Black Knight data set. Specifically, they observed a dramatic decline in the number of newly originated mortgages with FICO scores just below certain thresholds around subprime credit scores from 2008 to 2012. This pattern contrasts sharply with the period before the crisis, where the distribution of credit scores—including those in the lower, subprime range—was more continuous. They argue that the observation may serve as evidence of a minimum credit score threshold imposed by the credit supply side, as small changes in credit scores are unlikely to cause such significant shifts in mortgage demand. Extending the analysis of Laufer and Paciorek (2022) to a more recent period, we documentation the continued prevalence of the minimum credit score requirement in this section.

Using data from the National Survey of Mortgage Origination (NSMO), Figure A.1 illustrates the distribution of newly originated mortgages based on Vantage Score. The red line indicates the Vantage Score threshold we selected for the year 2013.

To identify the most appropriate minimum credit score threshold, we adopt a methodology similar to Laufer Laufer and Paciorek (2022). Specifically, we compute a ratio that captures the density variation in the Vantage Scores around each potential threshold. This ratio is calculated by dividing the density of scores that are 10 points below the potential threshold by the density of scores that are 10 points above it.

For example, to evaluate a Vantage Score of 600 as a potential threshold, we compute the density of credit scores at 590 and divide it by the density of scores at 610. A lower ratio suggests that any sharp decline in density within this 20-point interval could be attributed to supply-side factors, as the demand for mortgages is likely to remain relatively stable over such a minor range of credit scores.

These calculated ratios for each Vantage Score bin are presented in Table A1. A "Vantage Score band" refers to a 20-point range; for example, the 510 band includes mortgages with Vantage Scores between 500 and 520 (i.e., 510 - 10 and 510 + 10).

The data in Table A1 provide these calculations for each Vantage Score band. Notably, at higher Vantage Score ranges, the ratios are relatively high, suggesting a continuous distribution of scores. Based on these analyses, we selected our threshold using the following criterion: We chose the highest Vantage Score band where the corresponding ratio is lower than 0.5. Tables A1 through A7 present the calculations used to select the minimum credit score threshold. Figures A1 through A7 display the distribution of newly originated mortgages for each period, with a red line indicating the chosen minimum credit score threshold. Our analysis reveals that the threshold varies within a narrow range, specifically between scores of 550 and 610.

The primary objective of this section is to determine the minimum credit score threshold, denoted as Δ, for implementation in our model. Specifically, we aim to quantify the percentage of the lower distribution that is rationed in the market. This corresponds to finding X in the equation, $\Phi(\varphi^H < \Delta) = X$.

Unfortunately, we do not have comprehensive data on Vantage Scores, including those for renters; our dataset is limited to homeowners. Despite this limitation, we do have access to the distribution of FICO scores. Importantly, the thresholds we are considering largely fall within the subprime range, as defined by the VantageScore 3.0 White Paper. We can therefore approximate Δ by identifying it with a subprime FICO score, typically a score lower than 600, as defined by Calabria (2011).

Furthermore, we were able to determine that approximately 24% of the population had subprime FICO scores in 2013, based on information available on the FICO website[6]. With this information in hand, we selected Δ to satisfy $\Phi(\varphi^H \leq \Delta) = 0.24$, utilizing the computational algorithm described in Appendix B.

[6]https://www.fico.com/blogs/us-average-fico-score-hits-700-milestone-consumers

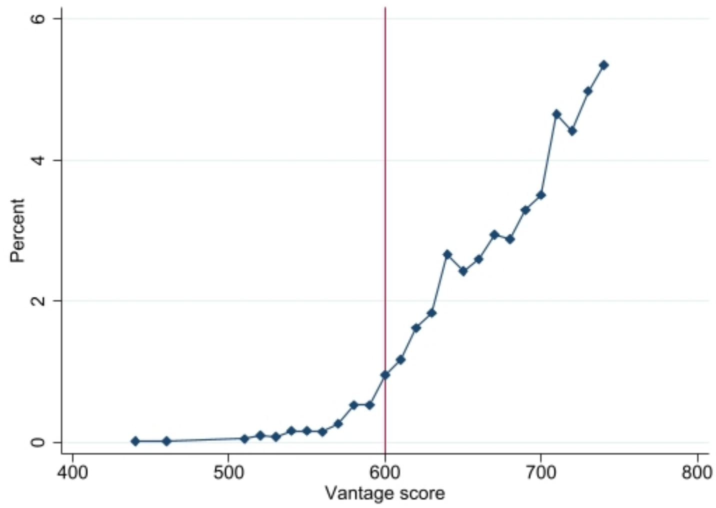


Figure A1: Mortgage density, 2013

Note: This figure plots the histogram of newly originated mortgage by 10 point Vantage Score. The red vertical line marks Vantage score 600.

Vantage score band	460	510	520	530	540	550	560	570	580	590	600	610	620	630	640
ratio	0.33	0.17	0.60	0.60	0.50	1.11	0.62	0.28	0.50	0.55	0.45	0.59	0.64	0.61	0.76

Vantage score band	650	660	670	680	690	700	710	720	730	740	750	760	770	780	790
ratio	1.03	0.83	0.90	0.89	0.82	0.71	0.79	0.93	0.83	0.93	0.96	0.97	0.78	0.75	0.87

Table A1: Discontinuity of mortgage density from 2013 National Survey of Mortgage Origination

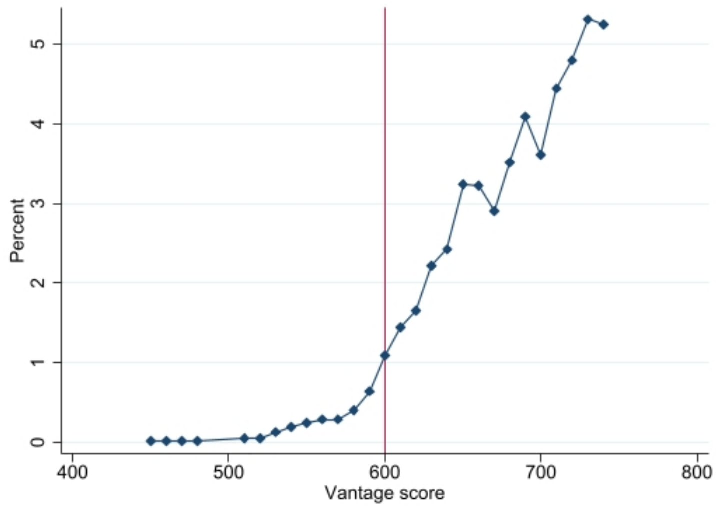


Figure A2: Mortgage density, 2014

Note: This figure plots the histogram of newly originated mortgage by 10 point Vantage Score. The red vertical line marks Vantage score 600

vantage_band	460	470	480	510	520	530	540	550	560	570	580	590	600	610	620	630
ratio_var	1.00	1.00	0.33	0.33	0.38	0.25	0.53	0.67	0.83	0.72	0.45	0.37	0.44	0.66	0.65	0.68

vantage_band	640	650	660	670	680	690	700	710	720	730	740	750	760	770	780	790
ratio_var	0.68	0.75	1.12	0.92	0.71	0.97	0.92	0.75	0.84	0.91	0.94	0.98	1.03	0.84	0.86	0.85

Table A2: Discontinuity of mortgage density from 2014 National Survey of Mortgage Origination

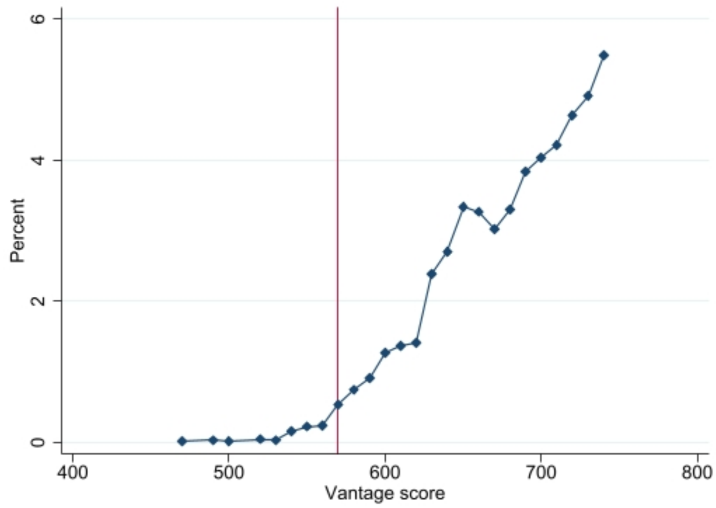


Figure A3: Mortgage density, 2015

Note: This figure plots the histogram of newly originated mortgage by 10 point Vantage Score. The red vertical line marks Vantage score 570.

Vantage score band	490	500	520	530	540	550	560	570	580	590	600	610	620	630	640	650
Ratio	1.00	0.67	0.50	0.30	0.14	0.67	0.42	0.33	0.59	0.59	0.67	0.90	0.57	0.52	0.72	0.83

Vantage score band	660	670	680	690	700	710	720	730	740	750	760	770	780	790	800	810
Ratio	1.10	0.99	0.79	0.82	0.91	0.87	0.86	0.85	0.90	1.02	1.02	0.91	0.78	0.81	0.98	1.94

Table A3: Discontinuity of mortgage density from 2015 National Survey of Mortgage Origination

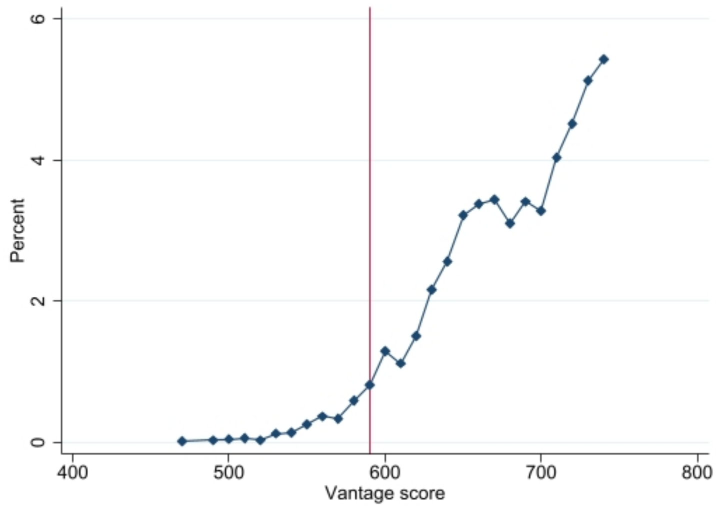


Figure A4: Mortgage density, 2016

Note: This figure plots the histogram of newly originated mortgage by 10 point Vantage Score. The red vertical line marks Vantage score 600, 620, 710, 780.

Vantage score band	490	500	510	520	530	540	550	560	570	580	590	600	610	620	630	640	650
Ratio	0.33	0.50	1.50	0.50	0.22	0.50	0.39	0.76	0.62	0.41	0.46	0.73	0.86	0.52	0.59	0.67	0.76

Vantage score band	660	670	680	690	700	710	720	730	740	750	760	770	780	790	800	810	820
Ratio	0.93	1.09	1.01	0.95	0.85	0.73	0.79	0.83	0.97	0.93	1.07	0.97	0.64	0.77	1.16	1.86	8.18

Table A4: Discontinuity of mortgage density from 2016 National Survey of Mortgage Origination

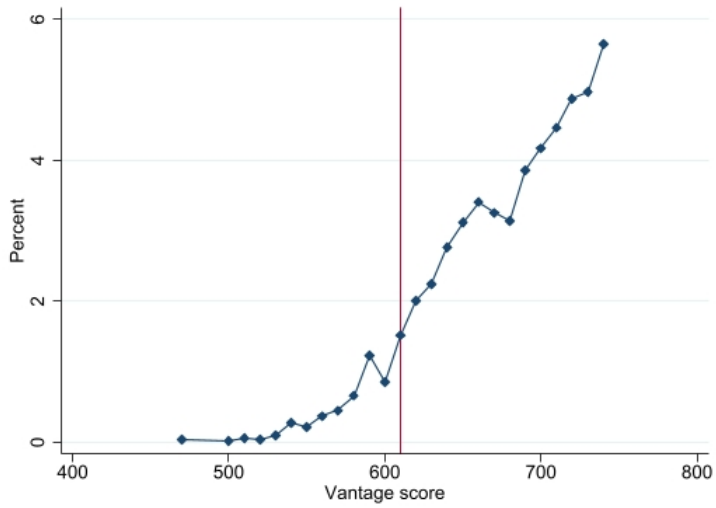


Figure A5: Mortgage density, 2017

Note: This figure plots the histogram of newly originated mortgage by 10 point Vantage Score. The red vertical line marks Vantage score 610.

Vantage score band	500	510	520	530	540	550	560	570	580	590	600	610	620	630	640	650
Ratio	0.67	0.50	0.60	0.14	0.45	0.74	0.48	0.56	0.37	0.77	0.81	0.43	0.68	0.73	0.72	0.81

Vantage score band	660	670	680	690	700	710	720	730	740	750	760	770	780	790	800	810
Ratio	0.96	1.09	0.84	0.75	0.86	0.86	0.90	0.86	0.97	1.04	1.00	1.04	0.87	0.70	0.93	1.70

Table A5: Discontinuity of mortgage density from 2017 National Survey of Mortgage Origination

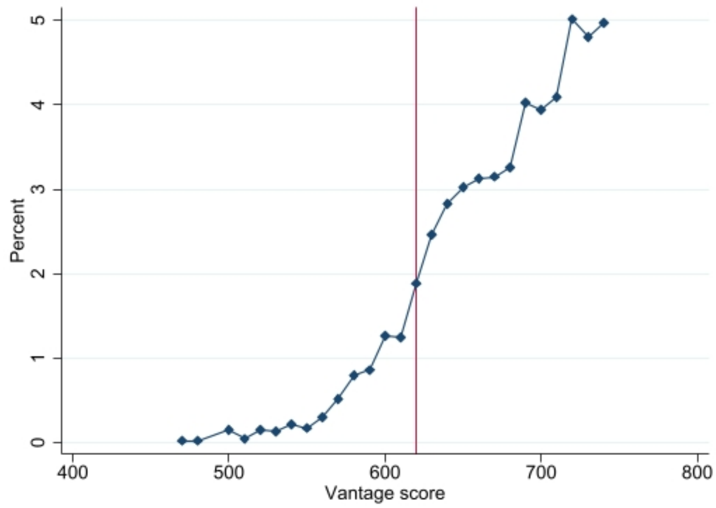


Figure A6: Mortgage density, 2018

Note: This figure plots the histogram of newly originated mortgage by 10 point Vantage Score. The red vertical line marks Vantage score 620.

Vantage score band	480	500	510	520	530	540	550	560	570	580	590	600	610	620	630	640	650
Ratio	0.14	0.50	1.00	0.33	0.70	0.75	0.71	0.33	0.38	0.60	0.63	0.69	0.67	0.50	0.67	0.82	0.90

Vantage score band	660	670	680	690	700	710	720	730	740	750	760	770	780	790	800	810	820
Ratio	0.96	0.96	0.78	0.83	0.98	0.79	0.85	1.01	0.86	0.89	1.14	0.96	0.69	0.87	1.05	1.77	5.54

Table A6: Discontinuity of mortgage density from 2018 National Survey of Mortgage Origination

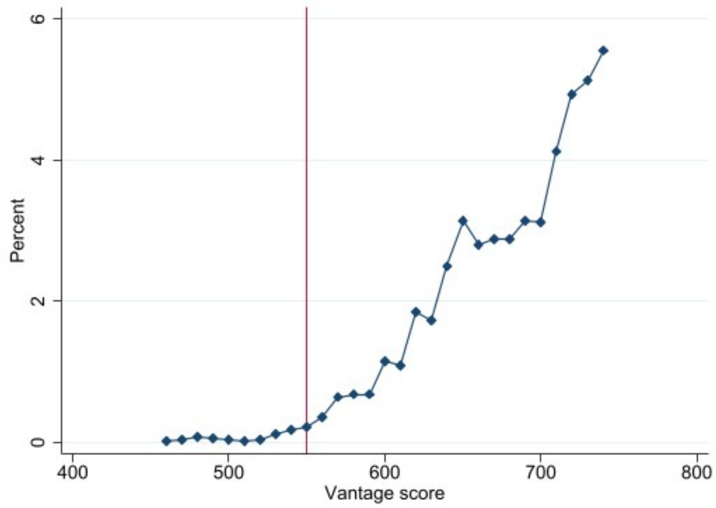


Figure A7: Mortgage density, 2019

Note: This figure plots the histogram of newly originated mortgage by 10 point Vantage Score. The red vertical line marks Vantage score 620.

Vantage score band	470	480	490	500	510	520	530	540	550	560	570	580	590	600	610	620	630	640
Ratio	0.25	0.67	2.00	3.00	1.00	0.17	0.22	0.55	0.50	0.34	0.53	0.94	0.60	0.63	0.62	0.63	0.74	0.55

Vantage score band	650	660	670	680	690	700	710	720	730	740	750	760	770	780	790	800	810	820
Ratio	0.89	1.09	0.97	0.92	0.92	0.76	0.63	0.80	0.89	0.87	0.94	1.03	0.86	0.79	0.93	1.05	1.85	6.84

Table A7: Discontinuity of mortgage density from 2019 National Survey of Mortgage Origination

B Appendix: Computational Algorithm

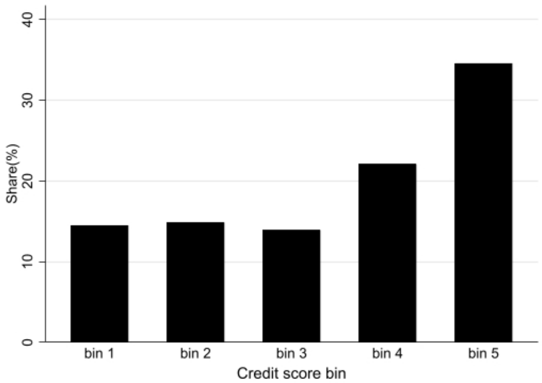
Algorithm 1: Find equilibrium rental rate, mortgage pricing function, credit scoring update function, and minimum credit score threshold.

```
Set initial guess for price-to-rent ratio, P_r;
    Set initial guess for the minimum credit score threshold Δ^0;
        Set initial guess for the mortgage price schedule, p_m^0, φ^0;
            Set initial guess for W^0;
                i. Solve Equation (5),(6) and get W^1;
                ii. If sup|W^0 − W^1| < tol then, exit the loop. Otherwise, set W^0 = W^1 and return to i;
            Find W;
        Calculate choice probabilities and using them find new mortgage pricing function, p_m^1 and law of
          motion of the credit score, φ^1. If sup|p_m^0 − p_m^1| < tol & sup|φ^0 − φ^1| < tol exit;
    If Φ(φ^H ≤ Δ^0) = 0.24 exit, otherwise update Δ^0 as Δ^1;
If rental market clearing condition in section 2.5 is satisfied then exit, otherwise update P^r;
```

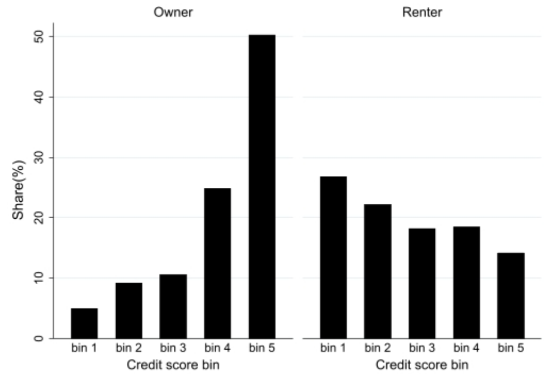
Algorithm 2: Determine the exogenous mortgage pricing function, p_m^{new}, to equalize the homeownership rate between the baseline and the counterfactual, given the law of motion of credit score and prices of the baseline except the mortgage pricing function, p_m.

```
Set initial guess for p_m^new as a fraction of p_m, p_m^new = ψ p_m;
    Set initial guess for W^0;
        i. Solve Equation (5),(6) and get W^1;
        ii. If sup|W^0 − W^1| < tol then exit the loop. Otherwise, set W^0 = W^1 and return to i;
    Find W;
Calculate homeowenership rate and if the homeowership rate is equal to that of counterfactual then exit.
  Otherwise, update ψ.
```

C Appendix: Additional graphs



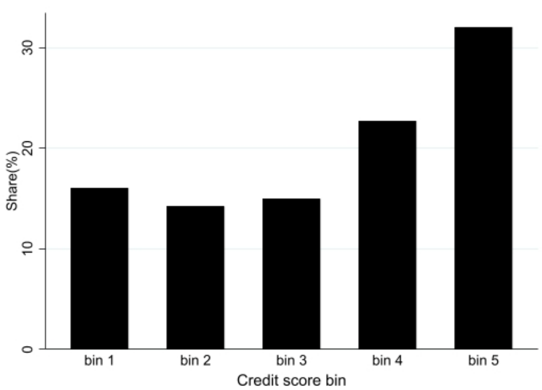
(a) Overall



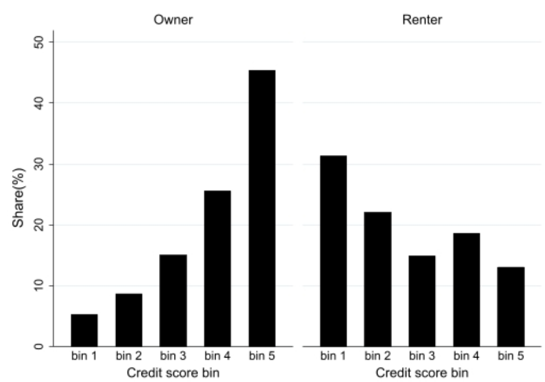
(b) By tenure

Figure C1: Credit Score Distributions from the Survey of Consumer Expectation 2015

Note: Each bin does not represent a uniform share, reflecting the survey's defined categories: bin 1 (<620), bin 2 (620-679), bin 3 (680-719), bin 4 (720-759), and bin 5 (>760). The respective shares for these bins are 15.12%, 12.29%, 13.83%, 27.25%, and 31.52% in left panel. Data source: 2015 Survey of Consumer Expectation, NYFED.



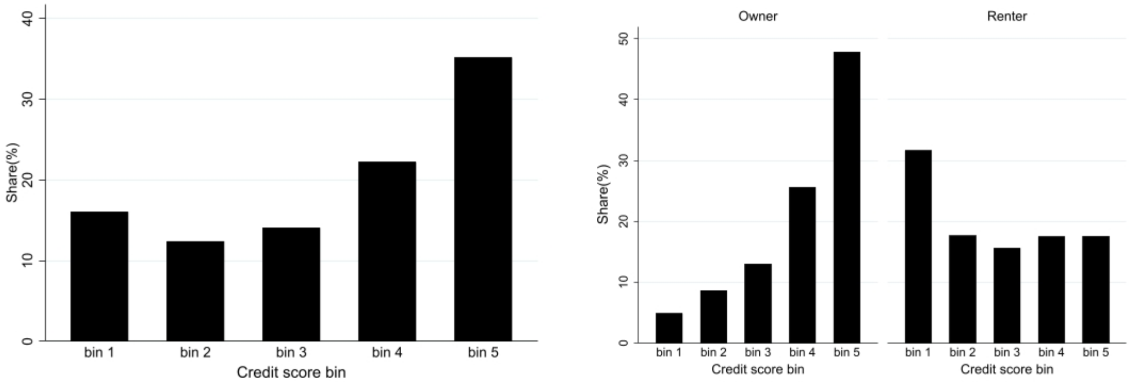
(a) Overall



(b) By tenure

Figure C2: Credit Score Distributions from the Survey of Consumer Expectation 2016

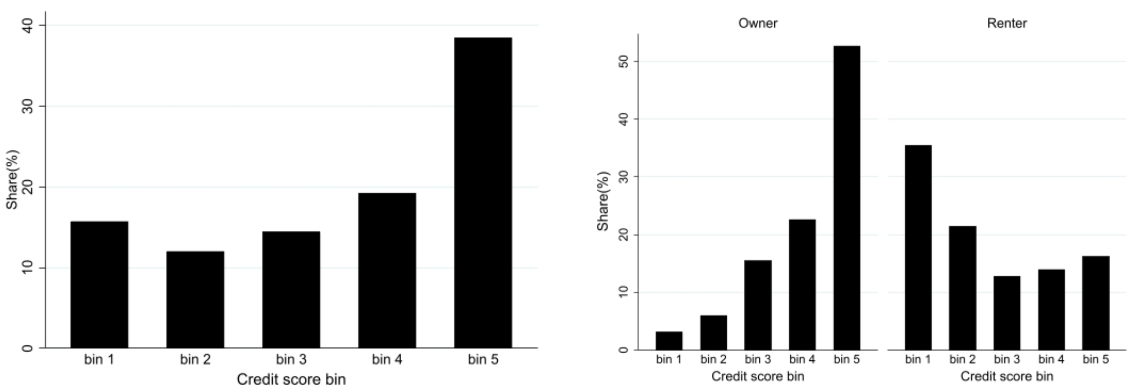
Note: Each bin does not represent a uniform share, reflecting the survey's defined categories: bin 1 (<620), bin 2 (620-679), bin 3 (680-719), bin 4 (720-759), and bin 5 (>760). The respective shares for these bins are 15.12%, 12.29%, 13.83%, 27.25%, and 31.52% in left panel. Data source: 2016 Survey of Consumer Expectation, NYFED.



(a) Overall (b) By tenure

Figure C3: Credit Score Distributions from the Survey of Consumer Expectation 2017

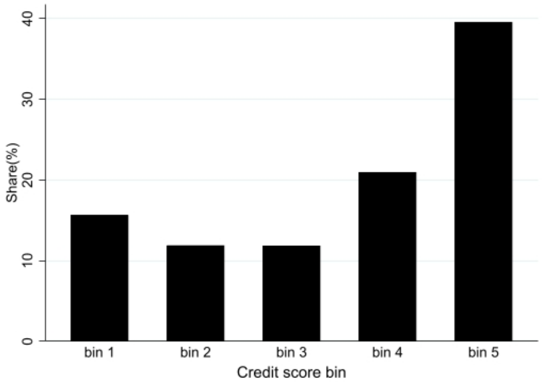
Note: Each bin does not represent a uniform share, reflecting the survey's defined categories: bin 1 (<620), bin 2 (620-679), bin 3 (680-719), bin 4 (720-759), and bin 5 (>760). The respective shares for these bins are 15.12%, 12.29%, 13.83%, 27.25%, and 31.52% in left panel. Data source: 2017 Survey of Consumer Expectation, NYFED.



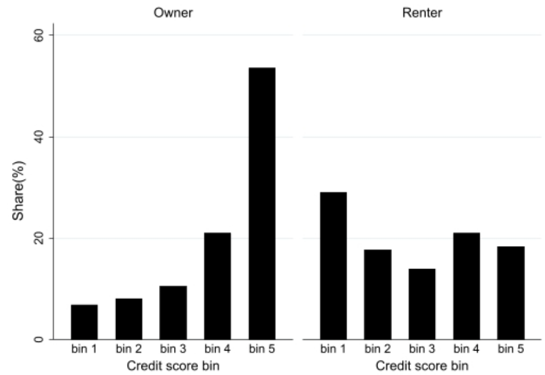
(a) Overall (b) By tenure

Figure C4: Credit Score Distributions from the Survey of Consumer Expectation 2018

Note: Each bin does not represent a uniform share, reflecting the survey's defined categories: bin 1 (<620), bin 2 (620-679), bin 3 (680-719), bin 4 (720-759), and bin 5 (>760). The respective shares for these bins are 15.12%, 12.29%, 13.83%, 27.25%, and 31.52% in left panel. Data source: 2018 Survey of Consumer Expectation, NYFED.



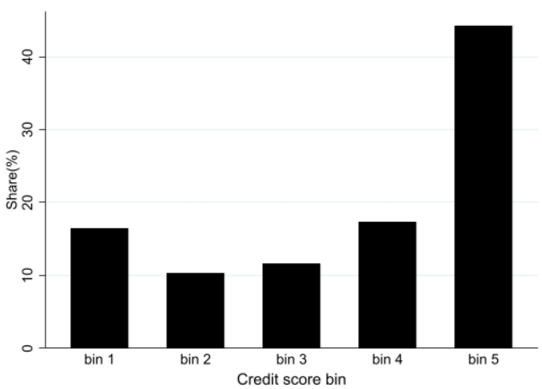
(a) Overall



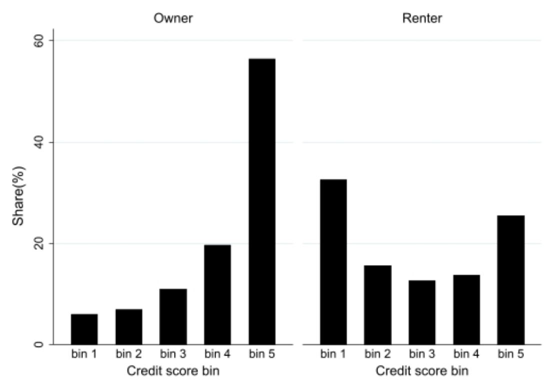
(b) By tenure

Figure C5: Credit Score Distributions from the Survey of Consumer Expectation 2019

Note: Each bin does not represent a uniform share, reflecting the survey's defined categories: bin 1 (<620), bin 2 (620-679), bin 3 (680-719), bin 4 (720-759), and bin 5 (>760). The respective shares for these bins are 15.12%, 12.29%, 13.83%, 27.25%, and 31.52% in left panel. Data source: 2019 Survey of Consumer Expectation, NYFED.



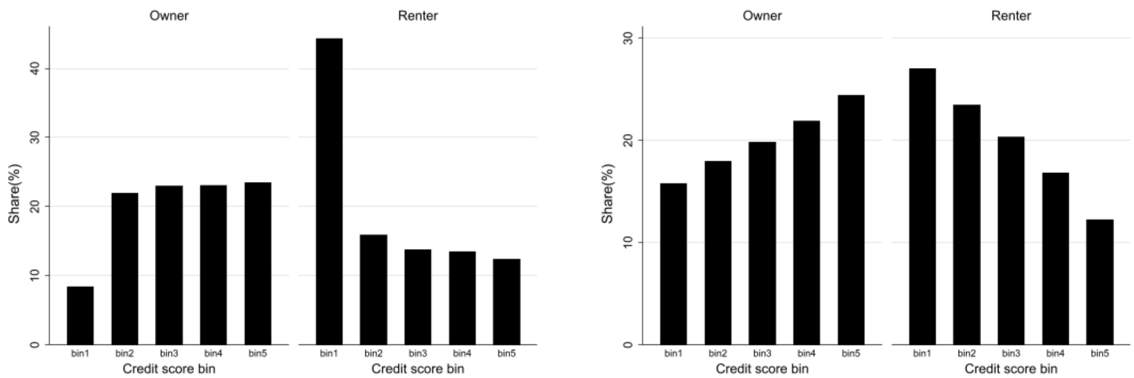
(a) Overall



(b) By tenure

Figure C6: Credit Score Distributions from the Survey of Consumer Expectation 2020

Note: Each bin does not represent a uniform share, reflecting the survey's defined categories: bin 1 (<620), bin 2 (620-679), bin 3 (680-719), bin 4 (720-759), and bin 5 (>760). The respective shares for these bins are 15.12%, 12.29%, 13.83%, 27.25%, and 31.52% in left panel. Data source: 2020 Survey of Consumer Expectation, NYFED.



(a) Baseline

(b) Conterfactual

Figure C7: Credit Score Distributions from the model with uniform distribution across credit score bin

Note: Each bin represents 20% of the population, with higher bins corresponding to higher credit scores. For example, bin 1 contains households that fall within the lowest 20% of the credit score variable φ^H, while bin 2 includes households in the next highest 20% tier.