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Borrower Self-Selection, Underwriting Costs, and Subprime Mortgage Credit Supply

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In the U.S., households participate in two very different types of credit markets. Personal lending is characterized by continuous risk-based pricing in which lenders offer households a continuous distribution of borrowing possibilities based on estimates of their creditworthiness. This contrasts sharply with mortgage markets where lenders specialize in specific risk categories of borrowers and mortgage supply is stepwise linear. The contrast between continuous lending for personal loans and discrete lending by specialized lenders for mortgage credit has led to concerns regarding the efficiency and equity of mortgage lending.

This paper sheds both theoretical and empirical light on the differences in the two credit markets. The theory section demonstrates why, in a perfectly competitive credit market where all lenders have the same underwriting technology, mortgage credit supply curves are stepwise linear and lenders specialize in prime or subprime lending. The empirical section

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then provides evidence that borrowers are being effectively sorted based on risk characteristics by the market.

1. Introduction

This paper is motivated by two stylized facts that distinguish the market for personal credit from the mortgage credit market. First, there are fundamental differences in the credit supply function between personal loan markets and mortgage markets. U.S. households face a continuous supply of personal credit from lenders. That is, individual lenders offer personal loans and revolving credit at rates that reflect the continuous distribution of consumer credit risk in the market. In contrast, mortgage credit is split into "prime" and "subprime" markets in which lenders specialize and the effective credit supply function is stepwise linear. The more or less continuous pricing of credit in personal loan markets contrasts with mortgage markets where price increases as a step function of credit risk. Within each step of these mortgage markets, there is substantial cross subsidy between the best and worst risks.

For example, IndyMac Bank provides borrowers with a menu of risk classifications (level 1 through level 5) to choose from. Level 1, the least risky classification, charges a 1.875 percentage point premium over the quoted prime mortgage rate of 5.875. The interest rate premium for 30-year, fixed-rate owner-occupied mortgages increases to 2.25, 2.75, 3.875, and 5.125 percentage points for the subsequent levels 2 through 5.[1]

A second stylized fact contrasting personal loan markets and mortgage markets concerns the relation between credit risk and rejection rates. In personal loan markets, rejection rates are higher for low-risk, low interest rate credit. In contrast, rejection rates in mortgage markets are much higher for subprime lenders than for prime lenders. For instance, the U.S. Department of Housing and Urban Development (HUD) reports that the rejection rate for subprime mortgage applications was 33 percent while for prime applications, the rejection rate dropped to 9.1 percent (see Scheessele (2003)).[2] Thus, in personal loan markets rejection rates vary inversely with interest rates and in mortgage markets rejection rates vary directly with interest rates.

These differences in operation between personal credit and mortgage credit markets are likely sufficient to raise concerns about the role of subprime lending. Concerns have been heightened because, based on simplistic and flawed Home Mortgage Disclosure Act (HMDA) measures, the subprime market appears to be growing dramatically to almost 9 percent of the total mortgage market, 10.9 percent of refinances, and 4.9 percent of home purchase originations.

In view of this concern, two natural questions arise. First, is there a reason to expect, a priori, that the separation of prime and subprime lenders and positive association between interest and rejection rates arise naturally in an efficient mortgage market? Second, does it appear that consumers are sorted into conventional A, FHA, and subprime mortgage categories based on characteristics that can be related to credit risk—(i.e., does the interaction of mortgage markets and borrowers look like risk-based pricing even if that pricing is based on a few discrete categories rather than a continuum)? In order to answer the first question, we formulate a simple competitive model of the mortgage market in which A lenders, which could include FHA and conventional lenders, are well established and ask when, if, and how B lenders can enter. Can B lenders successfully compete by offering a mortgage product that is very close to their A rivals or not? To answer the second question, we estimate a model of mortgage choice using a full set of applicant characteristics including credit score, which is likely to play a crucial role, to determine how well we can account for the separation of applicants into conventional A, FHA, and subprime mortgages.

2. A model of underwriting cost, self-selection, and subprime mortgage credit supply

We begin with a highly stylized statement of the lender's problem in a world with only BA^ lenders who underwrite each applicant and reject all those identified as high risk. The determinants of mortgage credit supply are identified and, given that higher risks are rejected, credit rationing arises by assumption.[3] Then we allow type "B" lenders who are willing to consider higher risks than the A lenders to enter the market. We determine the conditions under which these lenders are able to enter and earn normal profit. Specifically, we ask how closely they are able to compete with the A lenders, (i.e., can the Bs target borrowers with risks just greater than those targeted by the A lenders, or must entry occur at a discrete distance)? In previous work on consumer credit, Oreska (1983) demonstrates that a group of specialized lenders has an advantage over a general-purpose lender.

We find that, for plausible values of the parameters, and given substantial principal borrowed and underwriting costs in mortgage lending, entry occurs at discrete intervals and that the supply of credit to subprime borrowers is not continuous.

2.1. A market with only type A lenders

Assume that mortgage credit is provided by a large number of perfectly competitive, zero profit lenders operating under constant returns to scale, risk neutrality, and common information sets. These assumptions assure that our results do not arise from the technology of production or market organization. The mortgage contract is highly stylized. Loans are for one period with a balloon payment equal to one plus the interest rate due at the end of one period. For borrowers accepted in the A market, a payment of I_A is due in one year. In cases of default, the entire payment of principal and interest is lost.

Applicants are only differentiated by the default probability which equals D_i for applicant i. Given that all loans are offered under the same terms, there is no possibility for negotiation between borrower and lender. In contrast to the reality of mortgage markets, loan terms are exogenous. Applicants know both D_i and the probability of acceptance, α_A, at A lenders. D_i ranges from 0 to Δ, a constant value strictly less than one. Applicants are uniformly distributed on this interval. Without loss of generality, we can scale the number of applicants to equal 1. As noted above, the loan size is also set equal to unity and we further assume that there is no association between D_i and loan size. Lenders gain information about the D_i of an applicant by exerting underwriting effort. The cost of underwriting is constant for all applicants and equal to U, of which β is the fraction paid by the applicant in the form of an application fee, so that $(1 - \beta)U$ is the cost borne by the lender for each applicant. We impose upon the model the stylized fact that application fees cover a fraction, far less than half, of average underwriting cost.

Lenders have maximum acceptable default probability (D) equal to Θ for the A market. They accept all applicants whose D_i, where i indicates the individual applicant, is estimated, after underwriting, to be less than or equal to Θ. For applicants with D_i less than or equal to Θ acceptance is certain, $\alpha = 1$, regardless of the amount of underwriting (there is no type II underwriting error). For those with D_i strictly greater than Θ, the probability of acceptance in the A market is given by $\alpha_A = \Gamma\Theta/D_i$, where Γ is a between zero and unity, and the maximum value of D_i is Δ so that α is bounded from below by $\Gamma\Theta/\Delta$. Note this implies that, for a given U, the rejection rate rises with D_i.

Borrower self-selection is a crucial element of the model. Given that applicants know, Θ, α_A (based on their knowledge of U), and I_A, it could be that some high-risk applicants, (i.e., those with D_i close to D), would not apply at A lenders. We ignore this possibility in this version of the model. But, when a new entrant, the B market lender, with a cutoff risk level φ strictly greater than Θ tries to enter the market, we assume that high-risk borrowers will be aware of the terms offered by this lender and self-select accordingly. In actual practice the rejection of qualified applicants is an issue of concern to lenders, but does not alter our fundamental results.

It is useful to begin to solve the problem of a type A lender by writing the expected profit the firm receives from any individual applicant, i, as:

$$\pi_i = \alpha_A(\Theta, D_i; U)[I_A - I - D_i] - (1 - \beta)U \quad (1)$$

where α_A is the acceptance probability; $I_A - I$ is the interest spread over cost on A mortgages; D_i is expected default probability which is equal to expected loss because the loan amount is normalized to 1; and the final term is the portion of underwriting cost borne by the lender. Note that competition and constant returns drive π_i to zero for the average loan, but not for every loan.

Overall profit of the A lender, maximized at zero, is the integral over all applicants.

$$\pi_A = 0 = \int_0^\Delta \pi_i \, dD_i = \int_0^\Theta \pi_i \, dD_i + \int_\Theta^\Delta \pi_i \, dD_i \quad (2)$$

As shown in equation (2), it is useful to partition applicants into two groups. The first group includes applicants who are always accepted ($D_i \leq \Theta$, $\alpha = 1$) and the second group includes applicants who are accepted a fraction of the time depending on how much the underwriting standards are violated ($D_i > \Theta$, α_A is a decreasing function of D_i and increasing in Θ). This will prove very convenient throughout our analysis.

Substituting equation (1) into (2), solving for π_A, taking definite integrals, evaluating, and collecting terms gives:

$$0 = I_A[\Theta - \Gamma\Theta(\ln\Theta - \ln\Delta)] - I[\Theta - \Gamma\Theta(\ln\Theta - \ln\Delta)] \\ -\Theta\left[\left(\frac{\Theta}{2}\right) + \Gamma(\Delta - \Theta)\right] - \Delta(1-\beta)U \qquad (3)$$

Solving for I_A that yields normal profit to A lenders, we find:

$$I_A = I + \left\{\Theta\left[\left(\frac{\Theta}{2} + \Gamma(\Delta - \Theta)\right] + \Delta(1-\beta)U\right\} / \{\Theta + \Gamma\Theta[\ln\Delta/\Theta]\right\} \qquad (4)$$

Credit supply implied by equation (4) has an intuitive explanation. I_A equals cost of capital plus a markup to cover two costs of A lending. The first term, which can be written $\left\{\Theta\left[\left(\frac{\Theta}{2}\right) + \Gamma(\Delta - \Theta)\right]\right\} / \{\Theta + \Gamma[\ln\Delta/\Theta]\}$, reflects expected credit losses due to default. The numerator is positive and increasing in Δ, and is also positive and increasing in Θ whenever Γ is less than 1/2. The denominator is also positive, recalling that $\Delta/\Theta > 1 > \Delta > \Theta > 0$ and increasing in Δ while the effect of Θ on the denominator is ambiguous. The second term simply reflects the cost burden of underwriting which depends on the fraction of all applicants accepted and hence should rise with Δ and fall with Θ. These two effects reveal the lender's problem. Raising Θ has two opposite effects on costs. Increasing Θ raises expected default losses but it also lowers the fraction of applicants rejected and hence lowers the expected cost of underwriting applications.

It is also instructive to consider what happens to I_A if applicants self-select so that no one with $D_i > \Theta$ applies. In this case, π_A depends only on the integral of profit over the 0 to Θ interval and the second integral is dropped. The result is:

$$I_A = I + \frac{\Theta}{2} + (1-\beta)U \qquad (5)$$

The intuition of equation (5) is even more straightforward. Required interest is equal to cost of funds, I, plus average default loss $\frac{\Theta}{2}$, plus application cost when there are no rejections.

2.2. Entrance of B lenders in the presence of incumbent A lenders

As noted above, the B lender has the same constant returns to scale technology as lender A and entry by B lenders will drive their economic profit to zero, as it does in the A market. The only characteristic that differentiates a B lender from an A lender is the target risk level of applicants. B lenders will tolerate default risk of φ strictly greater than Θ. Applicants recognize this difference in lending standards, and all those D_I with strictly greater than Θ will apply at B. This assumption is favorable to the entrant, implying that all applicants switch from A to B when they perceive a higher probability of rejection at A than B, regardless of the higher cost of borrowing. However, this is a justifiable assumption given that the goal here is to analyze credit supply by B under conditions most favorable to the entrant.[4] We now proceed to characterize the nature of the credit supply by such lenders assuming that A lenders are passive.

Analysis of B lenders begins by writing expected profit from applicant i as:

$$\pi_i = \alpha_B(\varphi, D_i; U)[I_B - I - D_i] - (1-\beta)U \quad (6)$$

where α_B is the acceptance probability; $I_B - I$ is the interest spread over cost on B mortgages; D_i is expected default probability (which is again set equal to expected loss because the loan amount is normalized to 1); and the final term is the fraction of underwriting cost borne by the lender. Note that competition and constant returns drive to zero.

The overall profit of the B lender, maximized at zero, is the integral over all applicants, who in this case range from Θ to Δ.

$$\pi_B = 0 = \int_\Theta^\Delta \pi_i dD_i = \int_\Theta^\varphi \pi_i dD_i + \int_\varphi^\Delta \pi_i dD_i \quad (7)$$

As before, it is useful to partition applicants into two groups—those who meet the underwriting requirements and those who do not. Those who meet the underwriting requirements are defined as: $0 < \Theta < D_i \leq \varphi$ and $\alpha = 1$. Those who violate the underwriting standards are defined as: $D_i > \varphi$ and α_B is a decreasing function of D_i and an increasing function of φ.

Substituting equation (6) into (7), taking the definite integrals, evaluating, and collecting terms we have:

$$0 = \mathrm{I_B}\left\{\varphi\left[1+\Gamma\left(\ln\frac{\Delta}{\varphi}\right)\right]-\Theta\right\}-\mathrm{I}\left\{\varphi\left[1+\Gamma\left(\ln\frac{\Delta}{\varphi}\right)\right]-\Theta\right\}$$
$$-\left[\frac{\varphi^2-\Theta^2}{2}-\Gamma\varphi^2+\Gamma\varphi\Delta\right]-(\Delta-\Theta)(1-\beta)\mathrm{U} \qquad (8)$$

Solving for the value of IB that yields normal profit to B lenders, we find:

$$\mathrm{I_B} = \mathrm{I} + \frac{\left\{\left[\frac{\varphi^2-\Theta^2}{2}-\Gamma\varphi(\Delta-\varphi)\right]+(\Delta-\Theta)(1-\beta)\mathrm{U}\right\}}{\left\{\varphi\left[1+\Gamma\left(\ln\frac{\Delta}{\varphi}\right)\right]-\Theta\right\}} \qquad (9)$$

$\mathrm{I_B}$ must cover the cost of funds I, the cost of expected default losses $\left[\frac{\varphi^2-\Theta^2}{2}-\ \Gamma\varphi(\Delta-\varphi)\right]/\{\varphi[1+\Gamma(\ln\Delta/\varphi)]-\Theta\}$, and the cost of underwriting $\{(\Delta - \Theta)(1 - \beta)\mathrm{U}\}/\{\varphi[1 + \Gamma(\ln\Delta/\varphi)] - \Theta\}$. Comparing the value $\mathrm{I_B}$ implied by equation (9) when $\varphi = \Theta$, with $\mathrm{I_A}$ given by equation (4), we find that B lenders will not be able to attract low-risk applicants away from A lenders, because $\mathrm{I_A}$ is strictly less than $\mathrm{I_B}$.

Less intuitive is the effect of φ on the supply price of credit, $\mathrm{I_B}$, by B lenders. Note that, in the relevant range, the denominator of the expression involving default and underwriting costs is monotonically increasing in φ. The effect of φ on the numerator is ambiguous, but, simulation results shown in Figure 1 indicate that using plausible values of the parameters, over a significant range of $\Delta > \varphi > \Theta$ that $\frac{d\mathrm{I_B}}{d\varphi} < 0$. Thus the supply price of credit from B lenders falls when those lenders adopt more lenient lending criteria! The reason for this counterintuitive result is that the increase in the cost of expected default losses as φ rises is overcome by the fall in the average underwriting cost. Average underwriting cost falls as φ rises because the fraction of applicants accepted increases while total underwriting cost remains constant. Total underwriting cost is constant because all potential borrowers will apply regardless of the interest rate charged by the B lenders. This can be seen in Figure 2, which graphs the values of the average underwriting cost and the average default cost, as well as the total average cost of lending. Competition forces B lenders to set their credit limit, φ, at the point that minimizes the average cost of lending and the interest rate charged to borrowers.

As long as $\frac{dI_B}{d\varphi} < 0$, competitive forces will make B lenders continue to raise φ (i.e., lower underwriting criteria). This leads to our central result, B lenders will serve a market that is separated in credit risk from that served by A lenders by a significant gap in creditworthiness. We could extend this argument further and include a C lender with similar results. In such a model, the final market equilibrium would consist of a discrete number of credit alternatives separated by significant gaps in creditworthiness. Based on this argument, we conclude that the observed gap between prime and subprime lenders and the discrete nature of mortgage credit supply is not inconsistent with a perfectly competitive mortgage market.

Furthermore, our results also generate the second stylized fact separating personal loan and mortgage lending. Rejection rates are an increasing function of credit risk in our model because the significant cost of rejection for mortgage credit, including both the borrower's share of underwriting cost and transactions costs of failing to achieve financing, cause high-risk applicants to self-select away from prime lenders. The distinct separation of lenders into A and B categories facilitates this self-selection and leaves prime lenders with lower rejection rates.

Why is there a contrast between mortgage credit and credit cards, which provide risk-based pricing more or less continuously? The credit limit on credit cards serves to limit risk and allows borrowers to establish creditworthiness while limiting potential loss. Such credit limits are not appropriate for mortgage lending and are particularly problematic for consumers who are often seeking cash-out refinancing.

3. Credit history, mortgage, and demographic data

Table 1 provides descriptions, mean, minimum, maximum, and the standard deviation of each variable. Due to data availability, the data are limited to home purchase mortgages only and do not include refinances or cash-out refinances. The data in this study came from four sources. First is the F42 database of the Federal Housing Administration (FHA), which contains detailed loan information and household characteristics for FHA loans, but no credit history. Second is a real estate transaction database from Experian, which has detailed loan information and household identifiers (e.g., address of the property, amount of the loan, value of the property, loan-to-value (LTV) ratio, and type of loan), but no information on household characteristics. It contains a census of conventional loans in each county covered by Experian. This database was built from property transfer records at the local level. The third source is the individual borrower's credit history from Experian. This credit history was matched to FHA and conventional loans by name, Social Security number, and property address, with all identifying information subsequently deleted. The fourth source is HMDA data that were matched by loan amount, census tract, and lender identification to conventional Experian loans, to provide income and racial characteristics of households securing conventional loans.

To separate the subprime and prime conventional loans, a list[5] of subprime lenders that report to HMDA created by the Office of Policy, Development, and Research (PD&R) in HUD (see Scheessele (1998)) was used. This list was created from trade publications; therefore, it may not include all subprime lenders that report to HMDA. In addition, not all subprime lenders report to HMDA. Finally, the list is unable to separate prime from subprime lending by HMDA reporters that traditionally originate both types of loans.

The sample includes fixed-rate loans originated between February 1996 and July 1996, excluding loans for multifamily properties, refinancing, non-owner occupancy, and loans made to investors. The loans were matched by Experian to credit history files archived on March 31, 1996, by address, name, and Social Security number. This date was chosen to ensure that the credit data did not include information on the new mortgage, but were as current as possible. Observations with missing or obvious data coding errors were excluded.[6] A stratified sampling scheme varied sampling rates inversely with the FHA market share in each metropolitan statistical area (MSA). In subsequent statistical analysis, the effects of the sample stratification were offset by weighting each observation inversely to its sampling probability. Specifically, conventional loans were sampled at one-third of the FHA sampling rate.

3.1. Down payment, income, and credit history

Because FHA lending standards require very low down payments and even insure mortgages with negative equity once insurance premiums have been financed, we would expect mean FHA LTVs to be very high. Therefore, it is not surprising that Table 2 shows that the average down payment for subprime loans was 16.2 percent—well above the FHA average of 5.7 percent. In addition, prime borrowers have better payment-to-income ratios (PTIs) and Fair Isaac Corporation (FICO) credit scores. Note that subprime borrowers lie between FHA and prime borrowers, on average, in terms of LTV, PTI, and credit scores.

While FHA serves borrowers who are wealth constrained, as shown in Table 2, the borrowers using subprime lenders appear to be more diverse and not as easily characterized. The answer might lie in the ability of the subprime lender to use discretion and unique lending programs that may not require that the borrower's income be verified or that ignore the standard ratios (LTV or PTI) normally used in the underwriting process. Although a borrower who does not provide documentation supporting a steady income stream might not qualify for prime or FHA financing, this does not imply that the borrower has little wealth or a poor credit history.

4. Econometric specification and results

The choice model is estimated for a sample of 48,105 households that purchased homes in 39 MSAs from February through July 1996. Because it can be argued that LTV and mortgage choice are jointly determined, LTV is estimated using instrumental variables. The predicted LTVs are then used to generate any variables that are affected by LTV.[7]

4.1. Specification

The following specification, taken from Hendershott et al. (1997) and Gabriel and Rosenthal (1991), is used to estimate the conditional prime, FHA, subprime choice model:

$$C_j = \beta_0 + \beta_1 F_j + \beta_2 \Theta_j + \beta_3 D_j + \beta_4 L_j + \varepsilon_j \quad (10)$$

where F_j is a matrix of financial-monetary variables; Θ_j is a matrix of credit history variables; D_j is a matrix of demographic variables; L_j is a matrix of location-specific variables; and ε_j is a normally distributed error term. These matrixes are discussed in turn below, and Table 1 provides summary statistics for each explanatory variable as well as a brief description and the sources of data.

4.2. Financial-monetary variables

One consideration for the homebuyer is the relative cost of the mortgage. We focus on the costs to the homebuyer that are derived from differences in mortgage insurance rates and interest rates. For each buyer, we construct the present discounted value of interest and mortgage insurance payments for each mortgage option. For mortgage insurance fees, we assume payments stop when equity reaches 20 percent and that mortgage payments are made on time with no house-price appreciation. The borrower's credit is graded using the system reported by the Sub-Prime Funding Corp.'s *Underwriting Manual*. We rely on credit history variables such as late payment rates on revolving, installment, and mortgage credit as well as indicators of judgments, liens, or bankruptcy. In this fashion, we estimate what the best available interest rate would be from a subprime lender. Using estimates of interest rate spreads generated by Wall Street firms (see Weicher (1997)) and the Mortgage Guaranty Insurance Corporation survey of credit terms and interest rates (see Steinbach (1998)), rates are increased over prime rates by 200 basis points for B-rated borrowers, 300 basis points for C-rated borrowers, and 500 basis points for D-rated borrowers. Because we estimate that more than 95 percent of FHA borrowers financed the upfront mortgage insurance premiums in 1996, we assume this is true for everyone when calculating the cost of an FHA-insured mortgage. To measure the relative cost of prime mortgage insurance versus FHA insurance (P_c/P_f), we create the ratio of the present discounted value of the insurance fees. To measure the relative costs of FHA mortgage financing and subprime mortgage financing, we create a ratio of the discounted interest costs for FHA mortgage financing to the discounted interest costs of subprime mortgage financing (P_f/P_s). The specification uses these ratios to test the importance of relative prices in the mortgage choice framework.

A measure of the permanent income (y_j) of the individual is estimated from the cross section of homebuyers and follows the basic method used by Zorn (1993). A simple model of current income provides parameter estimates for age variables that are used to estimate a stream of income through the age 65. This stream is discounted at the rate of 7 percent and transformed into an annuity (a coupon bond) that matures when the individual is 65 years old. The annuity provides the estimated value of the individual's permanent income.[8]

The amount of debt (d_j) is created from the credit history data and is defined as the sum of current revolving debt and non-real estate installment loans. It is expected that increases in the non-real estate debt burden will make it more difficult for borrowers to qualify for the lower cost mortgage.

The value constraint (v_j) indicates if the household can purchase the desired amount of housing or if the household is constrained by income and/or down payment constraints. In spirit, we follow the approach of Haurin (1991) and Hendershott et al. (1997).

The utility maximizing amount of housing that a household would like to own, in the absence of any mortgage financing constraints, is determined by maximizing a utility function subject to a budget constraint. This ignores the income and wealth constraints imposed by lending standards. Following Pennington-Cross and Nichols (2000), to determine the unconstrained demand, we estimate a reduced-form, house-price equation over unconstrained homeowners, defined as households who purchase a home with down payments greater than or equal to 30 percent of the value of the home, PTIs of less than 20 percent, and FICO scores above 700. Using the estimated non-constrained coefficients, the desired house price is calculated for all remaining homeowners. If the estimated house price is greater than the actual house price, the homeowner is defined as value constrained (v_j = 1)

4.3. Credit history variables

A variety of credit measures are tested. The FICO score (f_j), one of the more common aggregate credit measures available, is used as a summary variable in the analysis.

Using Freddie Mac's Gold Measure Worksheet, we create the following more detailed credit history variables:

- any_j is 1 if the borrower has any delinquencies or derogatory information ever or if fewer than five credit lines have ever been open, otherwise any_j is 0;
- rev_j is 1 if the borrower does not have a revolving credit line or if total revolving balance is greater than $500, otherwise rev_j is 0;
- few_j is 1 if the borrower has fewer than three credit lines open ever, otherwise few_j is 0;
- del_j is 0, 1, 2, 3, or 4 if the borrower has respectively 0-10, 11-15, 16-40, 41-60, or > 60 percent of credit lines ever 30 days delinquent or worse;
- pub_j is 1 if there are any public record items (e.g., bankruptcy) on the credit report, otherwise pub_j is 0; and
- inq_j is the number of inquiries in the past six months divided by 2.

All of these variables have been designed so that positive values indicate worse credit history and are expected to increase the probability of selecting FHA or subprime financing.

4.4. Demographic characteristic variables

Demographic characteristics are represented by dummy variables indicating borrower race (African-American b_j, Indian i_j, Asian a_j, Hispanic h_j) and marital status (m_j). A spatial segregation version of the Gini coefficient (g_j) is also included to measure the extent of racial segregation in each MSA. A zero value indicates complete racial integration of the group, while a value of 100 indicates complete segregation of the racial group.

4.5. Location variables

A variety of location variables are used to describe the type of market in which the loan was made. Variables used to describe the housing market include a dummy variable indicating that the purchase is made in an "underserved" census tract (uns_j), as defined by HUD; the one-year percent change in Freddie Mac's reported repeat sales, home-price index (Δp_j); and the standard deviation of Δp_j for the last 10 years ($\sigma\Delta p_j$). Variables from the U.S. Bureau of Labor Statistics reflect the condition of the local labor market and are the average unemployment rate (u_j) for the last five years for the MSA and the change in the unemployment rate in the last year (Δu_j). Other variables measuring area housing cost and the FHA loan limit include a dummy variable indicating whether HUD defined the MSA as a high-cost area (hc_j) and the ratio of FHA's loan limit divided by DRI's estimate of the median house price for the MSA ($11/hp_j$). Indicators of increased risk associated with a location may increase the probability that a borrower will use FHA or subprime financing.

4.6. Estimation

Two sets of results are reported. Table 3 provides the estimated coefficients from the multinomial logit estimation and Table 4 provides the ordered logit results. The general specification is as follows:

$$C_j = \beta_0 + \beta_1 F_j + \beta_2 \Theta_j + \beta_3 D_j + \beta_4 L_j + \varepsilon_j \quad (11)$$

where F_j is a matrix of financial-monetary variables; Θ_j is a matrix of credit history variables; D_j is a matrix of demographic variables; L_j is a matrix of location-specific variables; and ε_j is a normally distributed error term as discussed above. For each of the estimation techniques (multinomial and ordered), two specifications are reported—one with the FICO score and the other with more detailed credit history.

Table 4 shows that ordering is statistically valid (as indicated by the *mu* of index), but the multinomial approach has better explanatory power. The log of likelihood is provided as a relative goodness-of-fit measure, and *t*-statistics indicate the significance of each parameter estimate with critical values of approximately 1.95 and 1.65 for the 5 percent and 10 percent levels, respectively. Tables 5 and 6 provide estimated marginal effects of the explanatory variables calculated at their means. All results discussed refer to the multinomial specification with FICO scores, unless otherwise noted.

Financial costs play an important and varied role in the choice of prime, FHA, and subprime mortgage financing. For instance, homebuyers who are value-constrained are more likely to use FHA than prime and subprime financing. Borrowers with higher permanent income are more likely to use prime financing, while borrowers carrying a lot of non-real estate debt are more likely to use FHA and subprime financing. But for all measures, the magnitude of the responses is always substantially higher for FHA and conventional choices. For instance, Figure 3 shows that as the amount of non-real estate debt increases from the mean of $10,842 to $48,000, the probability of selecting prime financing drops from 80 percent to 56 percent, while the probability of selecting FHA increases from 18 percent to 42 percent, and subprime decreases from 1.77 percent to 1.50 percent.

As the cost of conventional mortgage insurance increases relative to FHA mortgage insurance, borrowers tend to switch to FHA-insured mortgages. This result is consistent for both the multinomial and ordered logit models. But the result is not so consistent for the relative cost of FHA and subprime lending.

The ordered logit estimation finds the expected result that, as the interest cost of FHA financing increases relative to subprime, borrowers are more likely to use subprime financing and less likely to use FHA financing. But the multinomial estimates find the opposite result. In addition, when the full array of credit history indicators is included, the relative cost of FHA and subprime is no longer statistically significant. This may indicate measurement problems in the subprime price variation or that some households that use subprime lenders cannot respond to prices because they are being constrained by unobserved aspects of their credit history or other non-price rationing mechanisms.

While Figure 3 shows that the amount of non-real estate debt can more than double the probability of using FHA, the changes in credit score dwarf this effect. Figure 4 shows that a decrease in a borrower's FICO score—from a mean of 693 to 406, the lowest recorded score—increases the probability of choosing FHA from 20 percent to 68 percent. Over the same range, the probability of using prime financing decreases from 78 percent to 28 percent, and increases for subprime—from 1.77 percent to 3.10 percent.

The detailed credit history variables show that FHA is a more likely choice for borrowers with poor credit, no matter how their credit history is tarnished. In contrast, the impact of credit history is more varied on the use of subprime lending. Only two of the six indicators of credit history have the anticipated sign and significance. For instance, if the borrower has ever had any delinquencies the probability of using subprime decreases. But, the results for the FICO credit score and indicators of the level of delinquency and public record items are very similar for both FHA and subprime mortgage selection. In fact, borrowers who are more than 30 days late on 60 percent or more of their loans are more than twice as likely to use FHA or subprime financing, as compared with those who are at least 30 days delinquent on less than 10 percent of their loans.

The borrower demographic results indicate that (even after controlling for borrower income, debt, and credit history), racial groups behave differently. For instance, African-Americans, Indians, and Hispanics are more likely to use FHA and subprime financing than Whites. In contrast, Asians are less likely to use FHA, but more likely to use subprime financing than Whites.

Location plays a role in mortgage choice. In general, prime financing is more likely when house prices are increasing or when the unemployment rate is decreasing in the MSA. In contrast, while the choice of prime and FHA financing is unresponsive to the volatility of house prices ( ), the probability of choosing subprime financing increases from 1.77 percent to 2.9 percent when the volatility is increased from the mean of 2.3 percent to the maximum of 5.8 percent.

In locations considered high cost, the probability of choosing FHA is 6 percent higher. In addition, in areas where FHA sets the loan limit so that a large portion of the market is eligible for FHA mortgages, the probability of using FHA also increases. This is true despite the fact that this study includes only loans that are FHA eligible (i.e., loans under the FHA loan limit). These results support the hypothesis that, when the FHA market is defined as only the bottom part of the market, it may have difficulty generating enough business for lenders to overcome the fixed costs of learning and staying up with FHA programs and/or that it may be difficult to find homes that meet

FHA's habitability requirements in the lowest priced portion of the market.

5. Conclusions

Unlike other forms of credit, such as credit cards, risk-based pricing has not provided a smooth continuum of mortgage costs. Instead, the mortgage market is segmented into discrete risk classifications. Furthermore, rejection rates vary directly with interest rates in the mortgage market and inversely in the personal loan market. The theoretical model in this paper demonstrates that the discrete levels of mortgage credit supply and the positive relationship between interest and rejection rates arise from a separating equilibrium in the mortgage market. This separation does not rely on technology (returns to scale) or market power, but the simple observation that processing an application through the underwriting process is costly, and is only partially covered by the application fee. When a subprime lender tries to locate too close (in credit risk space) to prime lenders, the application costs overwhelm credit losses to the point where it is less costly to lower credit standards and accept a higher proportion of applicants. Equilibrium requires that the subprime lender move a substantial distance from prime lenders, thus leading to a discrete and segmented mortgage market.

The econometric results show that the use of prime, FHA, and subprime lending is related to indicators of creditworthiness. For instance, credit history plays an important role in the selection of prime, FHA, or subprime mortgage financing. Other measures of credit risk, such as income, non-real estate debt, and value constraints are also very important determinants of FHA use, but play a smaller role in determining the use of subprime financing.

Sensitivity tests show that no one indicator can make subprime a likely choice for any household. For subprime to be a likely choice requires that all of a household's risk indicators must be very negative. It also may be very difficult to identify the characteristics that make subprime lending a viable option to borrowers because not all underwriting criteria are captured in the estimation, and the sample of subprime loans is quite small. For instance, subprime lenders can make loans to people who do not want to document their income or source of down payment. But our results do indicate that a homebuyer is more likely to use subprime lending when risk indicators such as credit history and location are worse. Future research on subprime loan choice would benefit if loans could be characterized based on the total cost borne by the applicant, or borrower, instead of a simple lender classification.

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Notes

1. Downloaded from Indymacbank.com on 11/19/02 for 30-year, fixed-rate owner-occupied mortgages.

2. HUD creates a list of subprime specialists that is used to define loans as prime or subprime. These figures must be viewed with some skepticism because reporting to HMDA has changed over time (mortgage bankers especially) and acquisitions of subprime lenders by depositories in the 1990s transformed them into mortgage banking subsidiaries. These factors are likely to lead to an over-statement of subprime growth and make it very difficult to accurately measure the size of the subprime market. In addition, it is clear that the HMDA approach does not include all subprime loans. For instance, in 1995 the Inside Mortgage Finance estimate of subprime market share, using the dollar value of loans, is almost 7 percentage points higher than the HMDA estimates in 1995. By 1998, this spread had decreased to just over one point. This may indicate changing reporting in HMDA, changing methodology by Inside Mortgage Finance, or the changing market structure of subprime lending.

3. In this paper, risk is defined solely from the perspective of credit risk due to default. The value of a mortgage is determined by the expected cash flow from the instrument and variance of the expected cash flow. Therefore, prepayments of mortgages also affect the value of a mortgage whether the prepayment is due to changes in interest rates or other mobility issues. See Pennington-Cross (2003) for a discussion of the prepayment characteristics of subprime mortgages.

4. There are typically two sets of underwriting costs. The first set of costs, which has fairly low marginal costs, includes the costs of automated underwriting. The second set of costs, which is labor and time intensive, is the process of verifying income, assets, employment, and the physical state of the property.

5. Office of Policy, Development, and Research (PD&R) in the United States Department of Housing and Urban Development (HUD).

6. Incomplete data was defined as having missing values for one or more of the key variables used in the analysis: mortgage amount; property value; date of closing for the mortgage; interest rate; term of the mortgage; indicator for a first-time home buyer; purpose of the loan; and the name, Social Security number, income, and assets of the borrower. Some variables were not missing data, but instead contained data entry errors (e.g., LTVs greater than 300 percent or income of $20). The following set of conditions was used to identify any observations containing obvious data errors: FICO scores greater than 850 or less than 360; LTV greater than 110 percent or less than 20 percent; annual income of borrower greater than $1,000,000 or less than $1,000; age of borrower less than 18; and a loan amount less than $5,000.

7. See Pennington-Cross and Nichols (2000) for details of the estimation technique.

8. Since we do not have data on assets, income is estimated up to retirement age or 65 years of age and it is assumed that there is no par or face value payment at term (i.e., no retirement savings). A log-log form is used. See Pennington-Cross and Nichols for more details.

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Appendix

Appendix 1. Matching experian real estate transaction to HMDA data

Two key variables—race and income of borrower—were added to the Experian non-FHA home-purchase information by finding the corresponding mortgages in the Home Mortgage Disclosure Act (HMDA) database.

The Experian database includes all non-FHA home-purchase mortgages made during the months of February 1996 through July 1996. HMDA and Experian use different sets of lender codes, so a crosswalk of HMDA and Experian lender codes is created. Lender codes (HMDA and Experian) were considered to be equivalent for a pair of lenders when, at least five times in a single county, a single loan in the Experian file for a given lender code and a single loan in the HMDA file for a given lender code had the same loan amount within the same census tract. After this process, Experian loans that had multiple matches with HMDA were visually inspected (sorted by ZIP Code of lender and name of lender) to identify loans with the equivalent lender names. This crosswalk between HMDA and Experian lender codes was then used to match HMDA and Experian loan records. A loan was considered matched if it was the only loan that had the same loan amount and the same lender within a census tract.

Appendix 2. Calculation of user cost measure

The user cost of ownership is defined as follows:

$$UC_j = (1 - t_{y,j})(r_j + t_{p,s}) - \pi^e_m + \delta \quad (12)$$

where t_y is the marginal income tax rate; r is the nominal mortgage rate (FHA rate is available on sample records and national average for the month of origination is used for conventional loans); t_p is the marginal property tax rate; π^e is the expected inflation in housing prices which is assumed to be myopic; δ is the economic depreciation rate which is defined as $g * d$; g is the structure-land ratio which is assumed to be 0.83; d is the depreciation rate, which is assumed to be 0.017 following Linneman and Wachter (1989); and s, m, and j indicate that the variable is geographically defined at the state, MSA, and individual level, respectively.

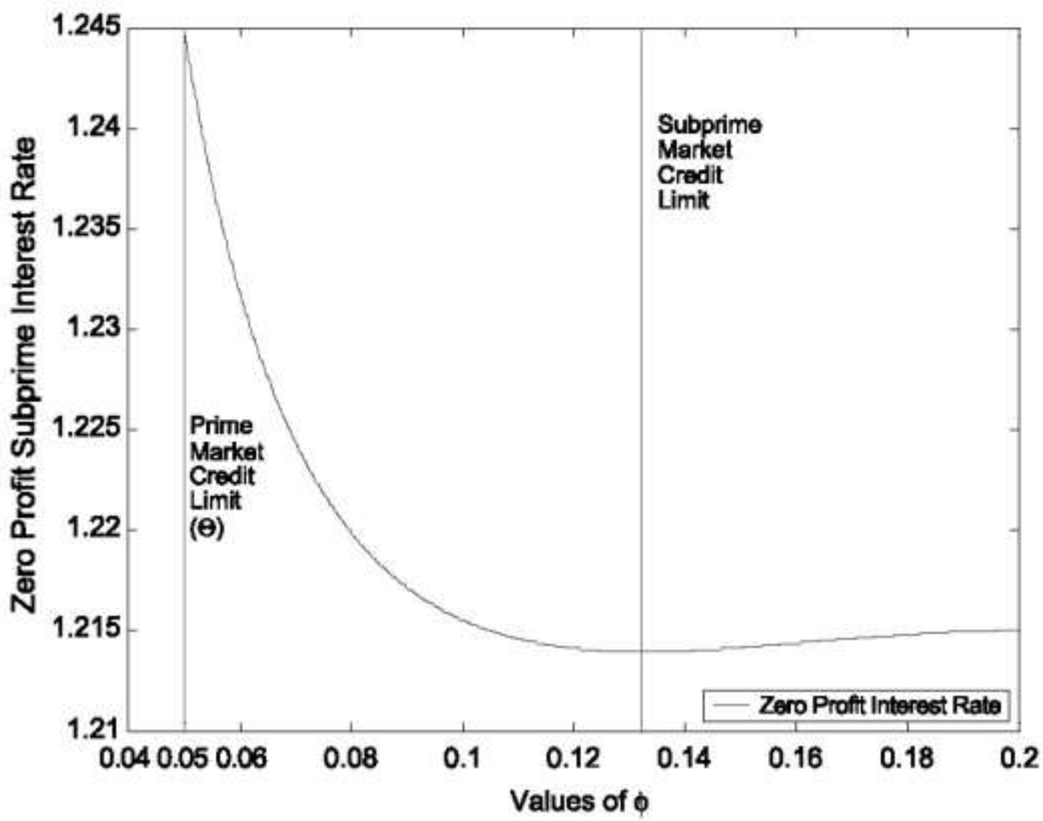
For FHA borrowers, the marginal income tax rate (t_y) is estimated based on the characteristics of each individual. Each borrower is assigned to one of three filing status categories—married, single, or head of household. All married persons are assumed to file jointly; non-married persons with dependents are assumed to file as head of household; and non-married persons with no dependents are assumed to file as single. Income levels are reduced by the deductions allowed by filing status, number of dependents, mortgage interest payments, and the estimated amount of state taxes paid. State taxes are based on the same information as federal taxes and the tax schedule of the state of residence. Total itemized deductions are defined as the sum of the interest rate deduction and state taxes. The federal taxable income is calculated using the minimum of itemized or standard deductions. In addition, a deduction of $10,000 is applied to all retirees (age greater than or equal to 65) to account for the non-taxable portion of Social Security benefits. Once the total federal taxable income is defined, the marginal tax rate is calculated using the appropriate schedule for the filing status of the borrower.

To estimate the marginal income tax rate of individuals buying non-FHA homes, we use the Current Population Survey (CPS)-reported federal tax rate average by income class groups for homeowners. Property tax rates ( ) are created at the state level for the last year available (1994), using state and local property tax revenues and estimates of the total valuation of property:

$$t_{p,s} = T_s/(KH_s * PH_s) \quad (13)$$

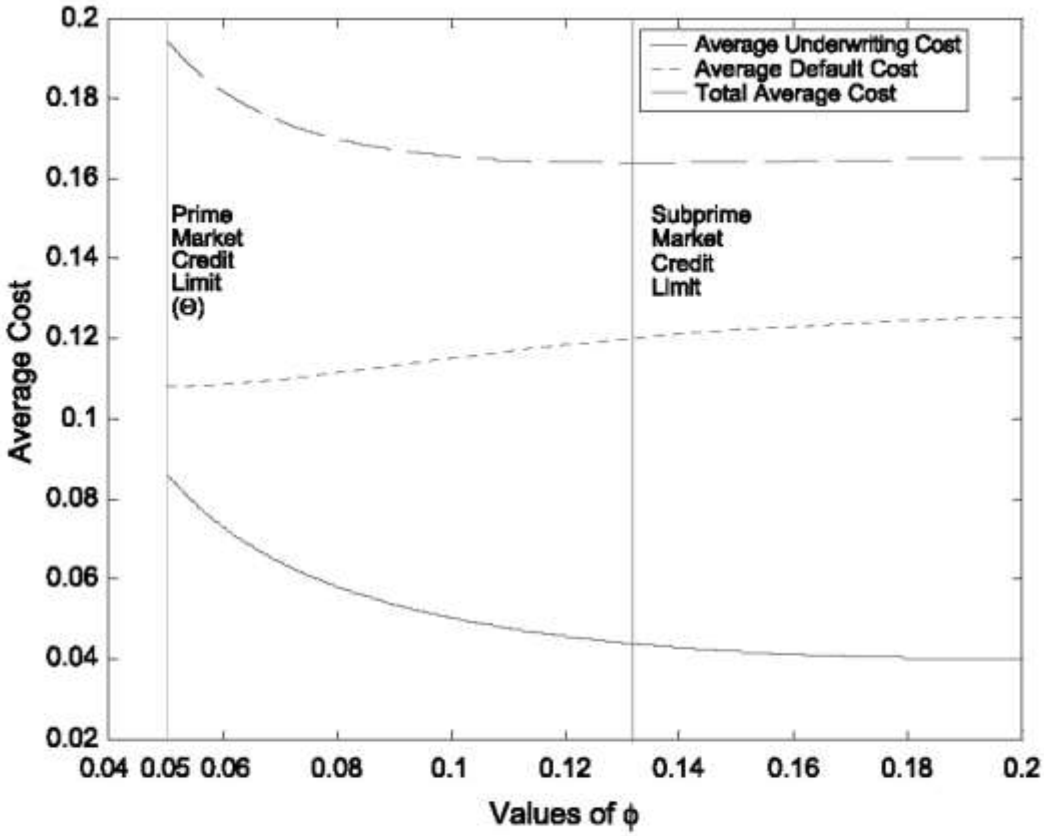
where T_s is the property tax revenue for the state and local governments; KH_s is the number of existing houses; PH_s is the median price of existing homes; and *s* is the state. Data on tax revenue are collected by DRI and are available from the U.S. Department of Commerce, Bureau of the Census, Government Finances. The number of existing homes is collected from DRI and is available from the U.S. Department of Commerce, Bureau of the Census. Median house prices were estimated by DRI and are derived from the Federal Housing Finance Board *Mortgage Interest Rate Survey* and median prices released by the National Association of Realtors.

Figure 1: Market Segmentation



The following parameters are used to create the stimulations in Figure 1 and 2: Δ = 0.2; Θ = 0.05; Γ = 1; b = 0.2; U = 0.05; and I = 1.05.

Figure 2: Average Cost Curves



The following parameters are used to create the stimulations in Figure 1 and 2: $\Delta = 0.2$; $\Theta = 0.05$; $\Gamma = 1$; $b = 0.2$; $U = 0.05$; and $I = 1.05$.

Figure 3: Mortgage Choice and Non-real Estate Debt

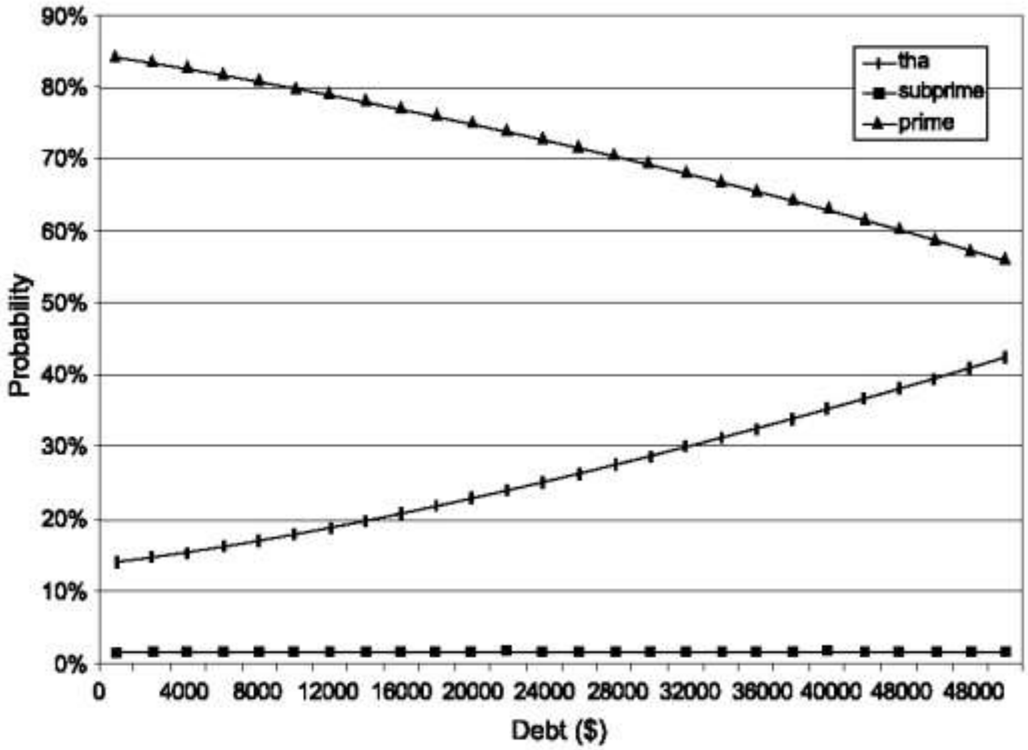


Figure 4: Mortgage Choice and FICO Score

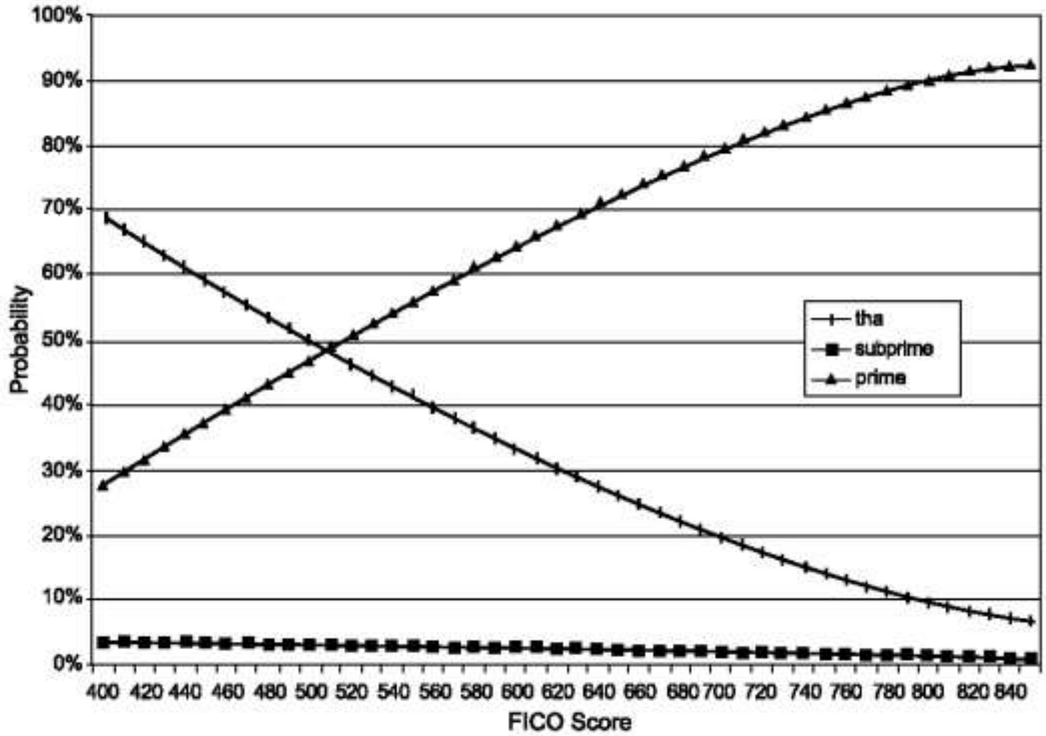


Table 1: Data Description

Variable	*Description*	*Source*	*Mean*	*Minimum*	*Maximum*	*Standard deviation*
Financial-monetary						
$(p_c/p_f)_j$	Relative cost of prime to FHA mortgage insurance	1,2	0.605	0.000	17.24	0.53
$(p_f/p_s)_j$	Relative cost of FHA to subprime interest	1,2	0.986	0.703	1.00	0.04
y_j	Permanent income ($10,000s)	1,2[a]	4.977	0.101	95.72	3.02
d_j	Debt ($10,000s)	2	1.084	0.000	34.66	1.37
v_j	Value constraint	1,2[a]	0.691	0.000	1.00	0.46
Credit history						
f_j	Summary credit score—FICO (10s)	2	69.341	40.600	82.60	7.10
any_j	Any delinquencies	2	0.428	0.000	1.00	0.49
rev_j	Revolving credit > $500 or = 0	2	0.772	0.000	1.00	0.42
few_j	Fewer than 3 credit lines open	2	0.057	0.000	1.00	0.23
del_j	Delinquency step variable 0 to 4	2	0.927	0.000	4.00	1.32
pub_j	Any public records	2	0.103	0.000	1.00	0.30
inq_j	Number of inquiries	2	0.673	0.000	13.00	0.81
Demographics						
b_j	African-American	1	0.100	0.000	1.00	0.30
i_j	Indian	1	0.004	0.000	1.00	0.07
a_j	Asian	1	0.041	0.000	1.00	0.20
h_j	Hispanic	1	0.123	0.000	1.00	0.33
g_j	Gini coefficient	3	0.459	0.146	0.75	0.16
m_j	Married	1	0.540	0.000	1.00	0.50
Location						
uns_j	Underserved census tract	4	0.369	0.000	1.00	0.48
Δp_j	Percent change in house price	5	0.017	−0.053	0.09	0.03
$\sigma\Delta p_j$	Standard deviation in Δp_j for the last 10 years	5	0.023	0.007	0.06	0.01
u_j	Average unemployment rate last 6 years	6	5.805	2.600	14.58	1.85
Δu_j	One year change in the unemployment rate	6	−0.453	−1.700	0.90	0.60
hc_j	High cost area	4	0.447	0.000	1.00	0.50
ll/hp_j	FHA loan limit/median house price	4,7	1.039	0.609	1.32	0.16

Notes: Explanation of Source: 1 = loan level data from the Experian transaction database as matched to HMDA and FHA's F42 database; 2 = Experian credit history reports; 3 = United States Census Bureau; 4 = general HUD sources; 5 = Freddie Mac; 6 = United States Bureau of Labor Statistics; 7 = Standard and Poor's DRI; [a] Value derived from auxiliary regression results.

Table 2: Mean Ratios and Scores by Mortgage Choice

Mortgage choice	*LTV*	*PTI*	*FICO*
Prime	0.813	0.173	717.2
FHA	0.943	0.199	664.8
Subprime	0.828	0.189	668.8

Table 3: Multinomial Logit Model of Mortgage Choice

		Specification I				*Specification II*			
		FHA		*Subprime*		*FHA*		*Subprime*	
	Variable	*Parameter*	*t-statistic*	*Parameter*	*t-statistic*	*Parameter*	*t-statistic*	*Parameter*	*t-statistic*
	Constant	−13.445	−36.9	−4.356	−5.0	−2.966	−9.5	1.578	2.1
Relative cost	$(p_s/p_f)_j$	0.875	28.0	0.371	4.4	0.765	23.5	0.154	1.7
	$(p_f/p_s)_j$	8.375	25.6	0.312	0.4	4.662	16.5	−1.347	−2.1
Income	y_j	−0.142	−20.9	−0.024	−1.8	−0.144	−21.5	−0.025	−1.9
Debt	d_j	0.387	37.0	0.119	3.9	0.301	31.7	0.054	1.9
Value	v_j	0.735	24.9	0.009	0.7	0.703	24.2	0.006	0.1
Credit	f_j					−0.079	−35.6	−0.057	−9.2
	any_j	0.557	17.6	−0.280	−3.0				
	rev_j	0.659	19.1	−0.151	−1.9				
	few_j	0.341	6.3	0.113	0.7				
	del_j	0.301	25.7	0.264	7.9				
	pub_j	0.787	17.8	0.758	7.0				
	inq_j	0.047	3.1	−0.033	−0.8				
Demographics	b_j	0.452	10.8	0.604	5.4	0.444	10.8	0.541	4.9
	i_j	0.454	2.7	0.778	2.1	0.370	2.2	0.796	2.2
	a_j	−0.370	−5.0	0.610	5.1	−0.456	−6.2	0.485	4.1
	h_j	0.659	17.5	0.198	1.9	0.621	16.8	0.105	1.0
	g_j	−0.510	−5.0	0.524	1.7	0.638	6.3	0.399	1.3
	m_j	0.687	25.6	0.041	0.6	0.702	26.5	0.082	1.2
Location	ums_j	0.296	10.7	0.015	0.2	0.291	10.7	0.005	0.1
	Δp_j	−1.637	2.2	−3.720	−1.6	−1.857	−2.5	−4.032	−1.7
	$\sigma\Delta p_j$	−0.468	−0.3	16.578	3.6	−2.017	−1.3	14.394	3.1
	u_j	0.020	2.0	0.044	2.0	0.021	2.1	0.040	1.8
	Δu_j	0.224	7.1	−0.395	−4.2	0.227	7.4	−0.387	−4.1
	be_j	0.362	11.3	0.019	0.2	0.419	13.4	0.046	0.5
	ll/hp_j	1.389	14.9	−1.203	−5.4	1.480	16.2	−1.096	−4.9
Summary statistics	Log of likelihood	−24,331				−24,929			
	Observations	48,105				48,105			

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Table 4: Ordered Logit Model of Mortgage Choice

		Specification I		*Specification II*	
	Variable	*Parameter*	*t-statistic*	*Parameter*	*t-statistic*
	Constant	−10.971	−56.9	−1.591	−9.2
Relative cost	$(p_c/p_f)_j$	0.791	50.1	0.671	40.0
	$(p_f/p_s)_j$	6.725	44.6	3.588	27.3
Income	y_j	−0.120	−42.3	−0.123	−43.8
Debt	d_j	0.327	84.4	0.258	68.1
Value	v_j	0.615	41.5	0.590	39.8
Credit	f_j			−0.074	−65.7
	any_j	0.435	28.7		
	rev_j	0.531	31.8		
	few_j	0.285	11.0		
	del_j	0.277	48.5		
	pub_j	0.729	38.0		
	inq_j	0.033	4.8		
Demographics	b_j	0.456	24.4	0.443	24.1
	i_j	0.490	7.0	0.422	6.4
	a_j	−0.135	−5.1	−0.230	−8.8
	h_j	0.547	32.1	0.506	30.1
	g_j	−0.339	−3.7	−0.471	−5.2
	m_j	0.575	43.7	0.598	46.0
Location	uns_j	0.261	19.0	0.257	19.0
	Δp_j	−1.727	−2.5	−1.965	−2.9
	$\sigma\Delta p_j$	1.642	1.3	−0.004	0.0
	u_j	0.023	2.5	0.023	2.5
	Δu_j	0.129	3.5	0.137	3.8
	hc_j	0.275	10.1	0.331	12.3
	ll/hp_j	0.905	13.9	1.008	15.7
Summary statistics	*mu* of index	3.230	86.7	3.178	86.1
	Log of likelihood	−25,520		−25,649	
	Observations	48,105			

Table 5: Marginal Probabilities: Specification I

		Multinomial logit			*Ordered logit*		
	Variable	*Conventional*	*FHA*	*Subprime*	*Conventional*	*FHA*	*Subprime*
	Constant	1.879	−1.842	−0.036	1.713	−1.611	−0.102
Relative cost	$(p_c/p_f)_j$	−0.123	0.120	0.004	−0.124	0.116	0.007
	$(p_f/p_s)_j$	−1.136	1.155	−0.019	−1.050	0.987	0.063
Income	y_j	0.020	−0.020	0.000	0.019	−0.018	−0.001
Debt	d_j	−0.054	0.053	0.001	−0.051	0.048	0.003
Value	v_j	−0.100	0.101	−0.001	−0.096	0.090	0.006
Credit	f_j						
	any_j	−0.071	0.078	−0.006	−0.068	0.064	0.004
	rev_j	−0.087	0.091	−0.005	−0.083	0.078	0.005
	few_j	−0.048	0.047	0.001	−0.045	0.042	0.003
	del_j	−0.044	0.041	0.004	−0.043	0.041	0.003
	pub_j	−0.117	0.106	0.011	−0.114	0.107	0.007
	inq_j	−0.006	0.007	−0.001	−0.005	0.005	0.000
Demographics	b_j	−0.070	0.061	0.009	−0.071	0.067	0.004
	i_j	−0.072	0.060	0.012	−0.077	0.072	0.005
	a_j	0.041	−0.053	0.012	0.021	−0.020	−0.001
	h_j	−0.092	0.090	0.002	−0.085	0.080	0.005
	g_j	0.061	−0.072	0.011	0.053	−0.050	−0.003
	m_j	−0.093	0.095	−0.001	−0.090	0.084	0.005
Location	uns_j	−0.040	0.041	−0.001	−0.041	0.038	0.002
	Δp_j	0.275	−0.215	−0.060	0.270	−0.254	−0.016
	$\sigma\Delta p_j$	−0.176	−0.113	0.289	−0.256	0.241	0.015
	u_j	−0.003	0.003	0.001	−0.004	0.003	0.000
	Δu_j	−0.025	0.032	−0.008	−0.020	0.019	0.001
	hc_j	−0.049	0.050	−0.001	−0.043	0.040	0.003
	ll/hp_j	−0.170	0.195	−0.025	−0.141	0.133	0.008

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Table 6: Marginal Probabilities: Specification II

		Multinomial logit			*Ordered logit*		
	Variable	*Conventional*	*FHA*	*Subprime*	*Conventional*	*FHA*	*Subprime*
	Constant	0.390	−0.426	0.036	0.252	−0.236	−0.016
Relative cost	$(p_c/p_f)_j$	−0.109	0.108	0.000	−0.106	0.100	0.007
	$(p_f/p_s)_j$	−0.629	0.667	−0.038	−0.569	0.533	0.036
Income	y_j	0.020	−0.020	0.000	0.020	−0.018	−0.001
Debt	d_j	−0.043	0.043	0.000	−0.041	0.038	0.003
Value	v_j	−0.098	0.100	−0.002	−0.094	0.088	0.006
Credit	f_j	0.012	−0.011	−0.001	0.012	−0.011	−0.001
Demographics	b_j	−0.070	0.062	0.008	−0.070	0.066	0.005
	i_j	−0.063	0.050	0.013	−0.067	0.063	0.004
	a_j	0.056	−0.066	0.010	0.037	−0.034	−0.002
	h_j	−0.088	0.088	0.000	−0.080	0.075	0.005
	g_j	0.083	−0.092	0.009	0.075	−0.070	−0.005
	m_j	−0.099	0.099	−0.001	−0.095	0.089	0.006
Location	uns_j	−0.041	0.041	−0.001	0.041	0.038	0.003
	Δp_j	0.316	−0.252	−0.064	0.311	−0.292	−0.020
	$\sigma\Delta p_j$	0.074	−0.330	0.256	0.001	−0.001	0.000
	u_j	−0.003	0.003	0.001	−0.004	0.003	0.000
	Δu_j	−0.026	0.033	−0.007	−0.022	0.020	0.001
	hc_j	−0.059	0.059	0.000	−0.053	0.049	0.003
	ll/hp_j	−0.190	0.214	−0.024	−0.160	0.150	0.010