The Age Gap in Mortgage Access*

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Abstract

This paper uses data on millions of single-borrower mortgage applications to study the relationship between applicant age and mortgage application outcomes. Conditional on a rich set of applicant, property, and loan characteristics, mortgage refinance applications submitted by older borrowers are associated with higher rejection probabilities. This pattern holds within lender and across loan types. Rejection probability increases smoothly with age and accelerates in old age. The acceleration is slower for female applicants. Inability to maintain properties may contribute as older applicants are more likely to be rejected for insufficient collateral. Lastly, using the loan-level pricing adjustment identification strategy, I find similar empirical relationships between borrower age and coupon rate on home purchase and refinance mortgages that were sold to Fannie Mae and Freddie Mac. Taken at face value, age appears to be an equally important correlate of mortgage application outcomes as race and ethnicity. Overall, the results suggest that older individuals systematically face higher barriers to mortgage access. Potential explanations are discussed.

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1 Introduction

Conditional on observable credit risk characteristics, do older individuals face higher barriers to credit access? If so, why might that be the case? As birth rates continue to fall and the Baby Boomer generation reaches retirement age, these questions are worth answering because aging is an increasingly important demographic issue for the United States. From a policy perspective, as the US population ages and the natural human lifespan increases, it is important to understand how aging affects an individual's ability to access credit because many individuals do and will spend a larger portion of their lives as senior citizens. In the academic literature, the relationship between age and access to credit has received little attention mainly due to data limitations.

This paper uses the 2018 to 2020 vintages of the anonymized Confidential Home Mortgage Disclosure Act (CHMDA) data, a representative data set of the US mortgage market that contains information on applicant age, to study the relationship between age and mortgage access.[1] The mortgage market is one of the largest retail credit markets in the United States and, therefore, serves as an ideal laboratory to study this empirical relationship. In the same spirit as the seminal work by Munnell et al. (1996), which uses, at the time, the state-of-the-art data set on mortgage application outcomes to study the relationship between applicants' race and mortgage access, this paper's main objective is to carefully estimate the conditional correlation between applicant age and two mortgage application outcomes: rejection probability and coupon rate.

This paper is divided into three parts. The first part uses a sample of rate-and-term mortgage refinance applications associated with a single applicant to study the conditional correlation between applicant age and rejection probability.[2] As described in greater detail below, I choose to focus on rate-and-term refinance loan applications because the statistical biases that are driven by unobservable differences between applicants who belong to different age groups are likely to be less severe among refinance mortgage applications than among home purchase mortgage applications.[3] Following several

[1]See Chapter V-9.1 of the FDIC Consumer Compliance Examination Manual. `https://www.fdic.gov/resources/supervision-and-examinations/consumer-compliance-examination-manual/documents/5/v-9-1.pdf`.

[2]The sample selection process follows CHMDA's classification of cash-out and simple refinance mortgages. Refer to Appendix A.1 for more details on the relevant definitions. The analyses conducted in this paper exclude lines of credit and reverse mortgages.

[3]Homeownership status is not disclosed in CHMDA. Homeownership status is strongly correlated with credit risk and age. Therefore, omitting this variable from a regression that studies that relationship between applicant age and rejection probability may introduce substantial bias to the estimated conditional correlation.

prominent papers in the literature (Munnell et al., 1996; Bayer et al., 2014; Bhutta and Hizmo, 2021), I run linear probability regressions where a mortgage application rejection indicator variable is regressed on age group indicator variables and a rich set of control variables that may be relevant to the underwriters' decision to extend credit. The age groups are 18 to 24, 25 to 29, 30 to 39, 40 to 49, 50 to 59, 60 to 69, and 70 or older. The first group is used as the reference group.

The first set of regressions reveals that, starting from the 25 to 29 age group, there is a monotonically increasing relationship between applicant age and probability of rejection. The economic magnitude is large. For example, applications associated with individuals who belong to the three oldest age groups are 2.4%, 3.5%, and 5.5%, respectively, more likely to be rejected than applications associated with individuals who are in the 18 to 24 age group. These estimates show large increases relative to the sample's unconditional rejection probability of 17.5%. This core result is surprising because older individuals are generally in better financial conditions than younger ones.[4] This baseline pattern cannot be explained by the way in which borrowers select lenders because the results are qualitatively and quantitatively similar when the regressions are estimated with lender by time fixed effects. Furthermore, the positive relationship also holds across loan types: conforming loans, government guaranteed loans, and nonconforming loans. Auxiliary analyses show that similar patterns also show up among cash-out refinance mortgage applications.

Since the literature on mortgage access has largely focused on the role of race and ethnicity (Ladd, 1998), it is worth comparing the size of the age coefficients to that of the coefficients on race and ethnicity variables. In line with estimates from the literature Bhutta and Hizmo (2021), the regression results show that applications associated with a Black or a Hispanic applicant are 2.6% and 1.6%, respectively, more likely to be rejected than applications associated with White applicants.[5] Compared to the aforementioned point estimates on the age group indicator variables, it is clear that an individual's age is a comparably important correlate of mortgage application outcomes as his or her race and ethnicity.

Exploiting the large number of observations, I document additional facts using *individual* age values. First, rejection probability increases smoothly with age. This result shows that the baseline

[4]Data from the SCF show that average annual income and average net worth tend to increase with age. Data from American Express show that average FICO score increases monotonically with age: from 662 for individuals in their twenties to 749 for individuals who are older than 59 years old. `https://www.americanexpress.com/en-us/credit-cards/credit-intel/credit-score-by-age-state/`.

[5]Disparities in lending outcomes across race and ethnic groups alone do not prove that lenders discriminate with respect to these characteristics. A fair lending review on each lender's activities is required to make such determination.

positive correlation between applicant age and rejection probability does not occur only at certain points (e.g., decade cut-offs) on the age spectrum. Second, increases in the probability of rejection accelerate in old age. Lastly, female applicants tend to face lower rejection probabilities than male applicants and the difference in rejection probability across the two groups grows larger in old age. As discussed in more detail below, these finer age value results are helpful in providing suggestive evidence for certain mechanisms that may be at play.

To shed some light on why underwriters are more likely to reject applications associated with older individuals, I regress indicator variables that equal one if the application was rejected for a certain reason on the same age group variables. I find that there is a monotonically increasing relationship between applicant age and the probability that his or her application is rejected because of "insufficient collateral." Generally, mortgage applications are rejected because of insufficient collateral when the appraised value of the property is too low, relative to the requested loan amount.[6] Taken at face value, the contribution of insufficient collateral is large. A simple quantification exercise shows that insufficient collateral can explain between 50% to 70% of the age effect on application rejection probability. This result suggests that inability to maintain one's property may be a contributing factor (Campbell et al., 2011).

The second part of the paper uses the loan-level pricing adjustment (LLPA) grid identification strategy (Bartlett et al., 2022) to study the relationship between borrower age and coupon rate on CHMDA originated home purchase and refinance mortgages that were bought by Fannie Mae or Freddie Mac. The identification strategy rests on the assumption that, if these mortgages were originated to be sold to these government sponsored enterprises (GSEs), then originators' loan pricing decisions should only depend on the fee structure that is given by the LLPA grid. Any excess differences in coupon rate across age groups can be attributed to factors unrelated to unobservable credit risk. In practice, this identification strategy is implemented by estimating a linear regression where coupon rate is regressed on demographic variables of interest and month by LLPA grid fixed effects.

The regression analysis reveals that there is a monotonically increasing relationship between borrower age and coupon rate from the 30 to 39 age group onward. The difference between the 30 to 39 and

[6] For rate-and-term mortgage refinance applications, lenders typically require that there is at least 20% equity left on the property. Therefore, if the property value dropped substantially between the time that the first mortgage was originated and the time that the refinance application was submitted, or the loan amount has grown relative to the property value due to, for example, features of the original mortgage such as negative amortization, then the application could be denied for "insufficient collateral."

70+ age group is 10 basis points (bps) for home purchase mortgages and 4 bps for refinance mortgages. The qualitative result survives the inclusion of lender by time fixed effects, which eliminates the concern that the result may be driven by differences in lender selection or differences in overhead cost of issuance across lenders. Lastly, the result cannot be explained by differences in points purchasing behavior across age groups because older borrowers in the sample bought *more* points than their younger counterparts, which means that, after accounting for points purchased, the age gap in coupon rate is even larger.

Taking advantage of the large number of observations, I explore the relationship between borrower age and coupon rate using individual age values. I find that, for both home purchase and refinance mortgages, coupon rates increase smoothly with age and the marginal increases accelerate in old age. Visually, plots of regression coefficient estimates suggest that, similarly to the rejection probability results, older female borrowers face slower marginal increases in coupon rates than male borrowers. However, the estimates are not sufficiently precise to be statistically significant.

In keeping with the literature on unequal mortgage access, I compare the coefficients on the age variables to those on the race and ethnicity variables. For the sample of home purchase mortgages, the indicator variable for Hispanic borrowers are consistently positive and statistically different from zero and range from 1 to 2 bps.[7] The same is not true for the refinance mortgage sample where the Hispanic indicator variable is rarely statistically different from zero. The coefficients on the Black borrower indicator variable are not consistent statistically different from zero in both samples. Bartlett et al. (2022) find that Hispanic and Black borrowers face 9 bps and 3 bps higher coupon rates for home purchase and refinance mortgages, respectively. Compared to these estimates, age seems to be an equally important determinant of mortgage coupon rate.

Taken together, results from the first two parts of the paper suggest that older individuals face higher barriers to mortgage access than younger individuals in the form of higher rejection probabilities and coupon rates, conditional on a rich set of observable characteristics. The final part of the paper discusses *potential* mechanisms that could drive the results. For the rejection probability results, the non-exhaustive list includes, but are not limited to, selection bias, age-related mortality risk, differential impacts from facially demographic-blind statistical underwriting models, and taste-based age discrimination. For the coupon rate results, the non-exhaustive list includes, but are not limited to, differences

[7] Disparities in lending outcomes across race and ethnic groups alone do not prove that lenders discriminate with respect to these characteristics. A fair lending review on each lender's activities is required to make such determinations.

in shopping behavior, market segmentation, competition, and taste-based age discrimination. The correlations presented in this paper should be interpreted as being driven by any combination of the listed mechanisms and any other mechanisms that I do not cover in the paper.

Since the findings broach the subject of fair lending, there are several important caveats to consider. First, the results presented in this paper are conditional correlations between age and mortgage application outcomes, which cannot be used to make a statement about whether lenders are *actually* using age to make lending decisions. A rigorous fair lending analysis of individual lenders' activities would be required to make such statements and is beyond the scope of this paper. Second, it follows that the results also cannot be used to make definitive statements about whether the lenders included in this study are behaving legally or illegally with respect to fair lending laws. Lastly, this paper does not aim to make a normative statement about whether older individuals *should* have easier access to credit. The paper's main goal is to present systematic empirical relationships between age and mortgage outcomes without making any welfare or normative statements.

This paper contributes to the literature on aging and credit access in several ways. First, using a large data set of mortgage applications that contains applicant age and a rich set of applicant, loan, and property characteristics, this paper is the first to systematically document stylized facts about the relationship between aging and mortgage access. I find that, conditional on a rich set of observable characteristics, older applicants for mortgage refinance systematically face higher rejection probabilities. Furthermore, using the LLPA grid identification strategy (Bartlett et al., 2022), I find that older borrowers face higher coupon rates on home purchase and refinance mortgages that were sold to the GSEs. The current paper's contribution pushes the literature forward because prior works generally studied small samples of applications and loans and did not find systematic relationships between age and credit access (Black et al., 1978; Dunson and Reed, 1991; Epley and Liano, 1999; Dietrich, 2005). In turn, this paper also contributes to the larger literature on the disparity in mortgage access across subgroups of the population (Ladd, 1998) by showing that age is an economically important correlate of such outcomes. As a practical matter to researchers in this field, when possible, borrower age should be included as a control variable when estimating this class of regressions.

The second contribution that this paper makes to the literature on aging and credit access is the empirical evidence that the aforementioned stylized facts, especially on rejection probabilities, appear to be consistent with, among others, the idea that lenders consider age-related mortality risk, which is tightly associated with prepayment, default, and recovery risks. I show that the positive correlation between age and rejection probability is larger for older and male applicants. These facts are consistent with the empirical fact that, all else equal, the probability of death within one year is higher for these subgroups. Taken together, this set of results suggests that, by nature, the age effect may manifest in many credit markets because mortality risk is priced. To my knowledge, no other paper in the finance literature has made this suggestion.

Perhaps most closely related to this paper is the work by Bayer et al. (2014), which used a fairly large sample of mortgages from metropolitan areas to study whether minority borrowers were more likely to receive high-cost mortgages. Although age was not the focus of the paper, borrower age appeared as an explanatory variable in the regressions and the results showed that older borrowers face higher interest rate spreads. The current paper improves our understanding of the relationship between aging and credit access beyond the findings in Bayer et al. (2014) by showing that older individuals systematically face higher barriers to mortgage access via both higher rejection rates and higher coupon rates. Lastly, this paper complements the work by Mayer and Moulton (2020), which studies the usage pattern of reverse mortgages and home equity among older homeowners, and the work by Dobbie et al. (2021), which finds that older borrowers face higher loan application rejection rates in the market for short-term consumer loans.

The remainder of the paper is organized as follows. Section 2 discusses relevant parts of the US fair lending laws. Section 3 describes the data set and samples that are used in the analyses. Section 4 outlines the regression specifications that I use to estimate the aforementioned conditional correlations. Section 5 presents the results. Section 6 lists the potential mechanisms that may explain the core empirical results. Section 7 discusses important caveats that the reader should keep in mind when thinking about the empirical results and Section 8 concludes.

2 Borrower Age Under Regulation B

Regulation B implements the Equal Credit Opportunity Act (ECOA), which aims to "promote the availability of credit to all creditworthy applicants without regard to race, color, religion, national origin, sex, marital status, or age... The regulation prohibits creditor practices that discriminate on the basis of any of these factors."[8] However, the law does not prohibit lenders from using age as part of a credit scoring system.

Under Regulation B, credit scoring systems are divided into two types: an empirically derived credit scoring system and a judgemental system. If using a judgemental credit scoring system, the "creditor may not decide whether to extend credit or set the terms and conditions of credit based on age or information related exclusively to age."[9] However, "[a]ge or age-related information may be considered only in evaluating other 'pertinent elements of creditworthiness' that are drawn from the particular facts and circumstances concerning the applicant."[10] The Official Staff Comment for 1002.6(b)(2)-3 gives several, but not exhaustive, examples. First, "[a] creditor may consider the applicant's occupation and length of time to retirement to ascertain whether the applicant's income (including retirement income) will support the extension of credit to its maturity." Second, "[a] creditor may consider the adequacy of any security offered when the term of the credit extension exceeds the life expectancy of the applicant and the cost of realizing on the collateral could exceed the applicant's equity." Lastly, "[a] creditor may consider the applicant's age to assess the significance of length of employment (a young applicant may have just entered the job market) or length of time at an address (an elderly applicant may recently have retired and moved from a long-term residence)."

In a similar vein, an empirically derived credit scoring system is also permitted to consider age to determine a pertinent element of creditworthiness. Section § 1002.11(b)(1)(iv) of Regulation B states that the federal regulation preempts state law that "[p]rohibits asking about or considering age in an empirically derived, demonstrably and statistically sound, credit scoring system to determine a pertinent element of creditworthiness, or to favor an elderly applicant."[11] The main takeaway from this discussion is that there *may* be systematic correlations between applicant age and mortgage application outcomes because, under certain circumstances, lenders *may* consider an applicant's age in connection with a relevant credit risk factor when making lending decisions.

[8] Regulation B Section § 1002.1.

[9] Official Staff Comment for 1002.6(b)(2)-3.

[10] Official Staff Comment for 1002.6(b)(2)-3.

[11] A lender may make lending decisions based on a system that combines an empirically derived system and a judgemental system. Per the Official Staff Comment for 1002.6(b)(2)-5, "[d]oing so will not negate the classification of the credit scoring component of the combined system as 'demonstrably and statistically sound.' While age could be used in the credit scoring portion, however, in the judgmental portion age may not be considered directly. It may be used only for the purpose of determining a pertinent element of creditworthiness." For the interested reader, additional details on considerations of borrower age under Regulation B are provided in the Appendix.

3 Data

3.1 Data Sources and Sample Description

This paper uses mortgage application data from the anonymized CHMDA data set that spans 2018 to 2020. Crucially, the new vintages contain applicant and co-applicant age in years. In addition, the post-2017 vintages contain a richer set of applicant, property, and loan characteristic variables, which is helpful in controlling for observable characteristics that may matter for lending decisions. More details on the control variables are presented in the next section and the Appendix.

The analyses presented below can be divided into two parts: rejection probability and coupon rate. For the rejection probability portion of the paper, I analyze rate-and-term refinance mortgage applications that are associated with a single borrower and a property that does not contain more than four housing units.[12] The focus on single-borrower applications stems from the need to know the borrower's age. The binding age is unclear when the application has two borrowers. The choice to focus on rate-and-term refinance applications is driven by the study's goal to estimate the conditional correlation between applicant age and rejection probability with as little selection bias as possible. In this respect, home purchase loan applications are problematic because I cannot observe whether, at the time of application, the borrower was a homeowner or not.

Homeownership status is potentially important for lending decisions because, from a credit risk perspective, homeowners are likely to have lower credit risk than renters. Data from the Survey of Consumer Finance (SCF) show that the median single homeowner's net worth is approximately $150,000 and his annual income is approximately $37,500. On the other hand, the median renter's net worth is approximately $3,800 and his annual income is approximately $22,500.[13] In addition, homeowners are more likely to have a longer credit histories because they hold at least one mortgage and are likely to differ from renters in difficult-to-observe characteristics such as financial sophistication, which may indirectly affect lending-decision-relevant variables. For example, Vestman (2019) finds that homeowners are more than twice as likely to participate in the stock market than renters. Focusing on rate-and-term

[12] I drop loans associated with a property that contains more than four housing units because the FHFA conforming loan limit data only provide information for properties with up to four housing units. `https://www.fhfa.gov/DataTools/Downloads/Pages/Conforming-Loan-Limit.aspx`.

[13] All numbers are presented in 2016 USD.

refinance applications eliminates some, but not all, concerns related to differences between homeowners and renters. The final sample contains approximately 5 million rate-and-term refinance applications.

Table A1 presents the distribution of mortgage application purposes (e.g., home purchase, rate-and-term refinance, and so on) across and within age groups. There are several key takeaways. First, the second column of Panel A shows that rate-and-term refinance applications make up 27% of the sample. Second, Panel B of Table A1 shows that older individuals make up a large proportion of the borrowers that applied for rate-and-term refinance. For example, borrowers who are older than 50 years old account for approximately 40% of the sample's rate-and-term refinance applications. These two points show that the sample of refinance applications that this paper focuses on still represents a fairly large portion of the overall mortgage market.

In the second part of the paper, I use the LLPA grid identification strategy from Bartlett et al. (2022) to study the relationship between borrower age and coupon rate on originated mortgages that were sold to the GSEs. In the same spirit as the sample selection procedure from Bartlett et al. (2022), I include originated conforming fixed-rate 30-year mortgages with credit scores between 620 and 850, LTV between 0.3 and 1.3, loan amount greater than or equal to $30,000.[14] Commercial loans, non-first lien loans, loans with balloon payment, interest-only loans, loans associated with second homes, loans associated with investment properties, loans associated with multi-family properties, loans associated with manufactured homes, and loans with uncommon amortizing features are excluded. The final sample contains approximately 1.7 million home purchase mortgages and 1.1 million refinance mortgages.[15] For this portion of the paper, I can study home purchase mortgages because, as discussed in more detail below, the LLPA identification strategy eliminates the concern that omitting homeownership status variable may bias the regression estimates.

[14] Acceptable credit scoring models are the Equifax Beacon, the Experian Fair Isaac, and TransUnion FICO. Source: B3-5.1-01, General Requirements for Credit Scores (10/05/2022) https://selling-guide.fanniemae.com/Selling-Guide/Origination-thru-Closing/Subpart-B3-Underwriting-Borrowers/Chapter-B3-5-Credit-Assessment/Section-B3-5-1-Credit-Scores/1032996841/B3-5-1-01-General-Requirements-for-Credit-Scores-08-05-2020.htm.

[15] Approximately 1 million home purchase and 0.65 million refinance mortgages were sold to Fannie Mae. I use this sample for the analyses that are presented in the main text. The rest were sold to Freddie Mac. I present results for this sample of mortgages in the Appendix as a robustness check.

3.2 Summary Statistics – Applicant Characteristics

Since this is the first paper to use a representative data set to study the relationship between age and mortgage access, it is worth summarizing the correlation between applicant age, applicant characteristics, and application characteristics. This section presents summary statistics on applicant characteristics from the main sample of rate-and-term refinance applications. The top panel of Table 1 presents average borrower characteristics by age group. The goal of this exercise is to show the way in which lending-decision-relevant variables vary across age groups. Using associated borrower ages, applications are sorted into the following age groups: 18 to 24, 25 to 29, 30 to 39, 40 to 49, 50 to 59, 60 to 69 and 70+.

Average credit scores tend to increase with age, which agrees with conventional wisdom; that is, older individuals should have higher credit scores than younger individuals because older individuals have longer credit histories. Data from American Express shows that average FICO score increases monotonically with age: from 662 for individuals in their twenties to 749 for individuals who are older than 59 years old.[16]

The distribution of average annual income across age groups is slightly different from that of the population of single homeowners. Data from the SCF show that average annual income, in 2016 USD, across the age groups are $33,000, $55,000, $59,000, $71,000, $76,000, $52,000, and $40,000, respectively. Comparing the two sets of numbers reveal that single homeowners in the sample tend to earn more than single homeowners in the SCF.

Average debt-to-income (DTI) ratios vary little across age groups. However, the small variation seems to suggest that older applicants in the sample have higher credit risk than younger ones. This dynamic is likely driven by the fact that average annual income in the sample peaks in the 40 to 49 age group. Average cumulative loan-to-value (CLTV) ratios decrease monotonically with age, which suggests that older applicants tend to take out smaller loans, relative to the collateral value, than their younger counterparts.

A unique feature of the post-2017 CHMDA data set is the information on Automated Underwriting System (AUS) recommendation. For many applications in the sample, I observe a recommendation by up to four different automatic underwriting systems, which could be one of the following: insufficient

[16] `https://www.americanexpress.com/en-us/credit-cards/credit-intel/credit-score-by-age-state/`.

information to make a recommendation, approve, or deny. AUS recommendations are useful because the AUS "observes" more information than the econometrician and so the AUS's recommendation is a measure of credit quality that captures more credit risk information beyond what the other variables in the CHMDA data set provide.[17]

I define the variable AUS Approved as an indicator variable that equals one if the application was approved by at least one AUS and zero otherwise. The final row of the top panel of Table 1 presents AUS approval rate across age groups. The results show that the AUS recommends approval less often for older applicants than for younger ones, which suggests older applicants have higher credit risk than younger ones or that older applicants are less likely to have sufficient information for the AUS to give a recommendation.[18]

3.3 Summary Statistics – Application Characteristics

The bottom panel of Table 1 presents the distribution of refinance application characteristics across age groups. The column titled "Row Total" presents the total number of applications that have the listed characteristics and the remaining columns present the proportion of this set of applications that belongs to each age group. Since older applicants are likely to be very different from younger applicants, at least from a life expectancy standpoint, individuals in different age groups are likely to select into different rate-and-term refinance products. This exercise sheds light on this sorting behavior. These summary statistics should be viewed as the result of a joint decision between borrowers and loan officers because the two parties typically work closely together throughout the application process (Bhutta et al., 2021).

The first set of characteristics presented is associated with loan term. Younger applicants tend to apply for loans that have longer maturities than older applicants. For example, applicants who are older than 59 years old make up more than 40% of applications that have maturities shorter than 15 years, while the same group make up only approximately 20% of loan applications with maturities of 30 years or longer.

[17]See Bhutta et al. (2021) for additional details on AUS information in CHMDA. See Fannie Mae's Single Family Selling Guide for more information on information that the AUS observes. `https://singlefamily.fanniemae.com/media/31886/display`.

[18]Insufficient information is also a helpful status to consider because mortgage applications do get rejected when certain information is missing or cannot be verified.

The next set of variables summarizes the type of property that applicants use as collateral. Younger applicants tend to borrow against their first homes, while older applicants are more likely to use their second or investment homes as collateral. This pattern is not surprising, given that older individuals have more time to own second and investment homes. Accordingly, older applicants are also more likely to use the loan for business purposes. Along the same line, older applicants are also more likely to own larger homes, indicated by the distribution of applications among the Total Units breakdown.

The third set of variables looks at the likelihood that the loan contains certain features. Overall, older individuals tend to sort into less common loan products such as loans with balloon payments, interest only loans, and loans with negative amortization features. The final set of variables captures the likelihood that the loan is guaranteed by a governmental agency. The only noticeable pattern is that older individuals are more likely to apply for mortgages that are guaranteed by the United States Department of Veterans Affairs (VA). Altogether, the summary statistics presented in sections 3.2 and 3.3 show that it is important to condition on observable borrower and loan characteristics in the regressions described below because these variables differ systematically across age groups.

4 Empirical Methodology

The goal of this paper is to study the empirical relationship between applicant age and several mortgage application outcomes: rejection probability and coupon rate. To this end, I use two empirical methodologies.

4.1 Application Rejection Regression Specification

Since the relationship between applicant age and rejection probability may not be linear, one way to estimate the conditional correlation between the two variables is to estimate the following ordinary least squares (OLS) regression equation:

$$Rejected_i = \alpha + \sum_{j}^{J} \beta_j \times \mathbb{1}(Age\,Group\,j)_i + \gamma' \mathbf{x_i} + Month \times Tract\,FE + \epsilon_i. \tag{1}$$

Following important papers in the mortgage access literature (Munnell et al., 1996; Bayer et al., 2014; Bhutta and Hizmo, 2021; Bartlett et al., 2022), I use OLS regressions for ease of interpretation. This regression specification conditions on observable characteristics that lenders may use to make lending decisions. i indexes loan applications. *Rejected* is an indicator variable that equals one if the application gets rejected and zero otherwise. I sort applications into the following age groups, indexed by j: 18 to 24, 25 to 29, 30 to 39, 40 to 49, 50 to 59, 60 to 69, 70 or older, and missing age. Applicant age enters into the equation as a set of indicator variables where the applicant's age determines which age group indicator variable equals one. Applications associated with individuals in the first age group are used as the reference group.

$\gamma' \mathbf{x_i}$ is a vector of applicant, loan, and property characteristics. The variables include sex, race, ethnicity, credit score, income, loan-to-value ratio, debt-to-income ratio, loan features, property types, lien status, and AUS approval. Additional details of these variables are provided in Appendix A.3. I include month by census tract fixed effects to difference out time-varying local macroeconomic effects and property location effects.[19] I include lender by year-quarter fixed effects to account for differences in each lender's time-varying business opportunities. Standard errors are clustered at the lender level because underwriting methods are assumed to be constant within lender.[20]

The regression specification outlined above allows me to study the conditional correlation between applicant's age and mortgage application outcomes among individuals who applied for rate-and-term mortgage refinance loans under very similar circumstances; that is, the applications were submitted to the same lender, in the same month, and are associated with properties located in the same census tract. Although I am able to control for a large set of observable characteristics, the β_j coefficients do not admit a causal interpretation because of several reasons. First, the estimates likely suffer from omitted variable bias because I do not observe many important variables that are likely to be correlated with age and mortgage application outcomes (e.g., mobility risk and many more) (Quigley and Weinberg, 1977; Myers et al., 1997; South and Crowder, 1998; Clapp et al., 2006).

Furthermore, selection bias potentially plays an important role in biasing the coefficient estimates.

[19] I use action (e.g., rejection decision) month to construct the month fixed effects for all rejection regressions. Application months are used for all coupon rate regressions because rates are locked based on the date of application. These choices do not materially affect the results.

[20] It is important to note that this regression is not an underwriting model. The regression includes certain variables (e.g., race, ethnicity, and sex) that lenders cannot use to make underwriting decisions and excludes other variables (e.g., wealth) that lenders do consider, but I cannot observe.

First, not every homeowner chooses to apply for a rate-and-term mortgage refinance loan. Second, lenders often discourage unqualified applicants from applying before they could submit an application and appear in the CHMDA data set. Lastly, the relatively young (18 to 29) and old (60+) applicants in the sample are likely to be very dissimilar to the median individual in their respective age groups. For example, the very young are likely to have uncommonly low credit risk because most young people do not have sufficient resources and credit history to apply for a mortgage. On the flip side, the very old are likely to have uncommonly high credit risk because, anecdotally, most would-be retirees and retirees do not like to carry debt into retirement and so this particular group of older individuals may be in financial distress, which I cannot observe.

Therefore, the sample of applications that I use to estimate the regressions is not a random sample and the selection mechanisms may be correlated with the relative differences in credit quality and, hence, mortgage application outcomes across age groups. Overall, due to the limitations outlined above, the estimation results from variants of equation 1 should be interpreted as a set of carefully estimated conditional correlations.[21]

4.2 LLPA Grid Regression Specification – Coupon Rate

The main empirical results presented by Bartlett et al. (2022) are conditional correlations between borrower's race and ethnicity and loan coupon rate that stem from sources beyond pricing adjustments for conforming mortgages that were sold to the GSEs. The argument is that, for loans that were sold to Fannie Mae and Freddie Mac, the sole determinant of the coupon rates is where the loans land in the LLPA grid, which determines the fee that originators have to pay the GSEs. Econometrically, this argument translates to that, if the econometrician includes LLPA grid fixed effects in the regression that estimates the relationship between coupon rate and borrower's race and ethnicity, then any differences in coupon rates across racial or ethnic groups can be attributed to factors unrelated to relevant credit risk, observed and unobserved.[22] These factors include differences in shopping behavior and taste-based

[21]Since, in the context of loan approval, it is difficult to randomly assign demographics (e.g., race and ethnicity) to estimate the causal effect that certain demographics have on lending decisions, it is common for researchers to estimate conditional correlations using the richest data sets available (Bayer et al., 2014; Bhutta et al., 2020; Bhutta and Hizmo, 2021; Bhutta et al., 2021).

[22]See Bartlett et al. (2020) and Bartlett et al. (2022) for a detailed discussion of the legal framework that justifies the interpretation of LLPA grid fixed effects regressions. The GSEs' price adjustment tables that are used to construct the LLPA grid fixed effects can be found in Appendix Figures A1 and A2. For mortgages that were originated and sold to

discrimination.

Following the same logic, I can use the OLS regression specification shown below to estimate the relationship between borrower age and coupon rate that is free from concerns of unobservable credit quality:

$$Coupon\,Rate_i = \alpha + \sum_{j}^{J} \delta_j \times \mathbb{1}(Age\,Group\,j)_i + \gamma' \mathbf{x_i} + Month \times LLPA\,Grid\,FE + \epsilon_i. \tag{2}$$

Following Bartlett et al. (2022), this regression equation is estimated using a sample of originated home purchase and refinance mortgages from CHMDA that were sold to either Fannie Mae or Freddie Mac.[23] The outcome variable *Rate* is the coupon rate on the loan. $\gamma' \mathbf{x_i}$ is a vector of demographic controls. If the identifying assumption described above holds, then δ_j is the estimate of the relationship between borrower age and coupon rate that is in excess of the LLPA grid. In some specifications, I include lender fixed effects to address the concern that differences in coupon rate across age groups could arise from differences in overhead cost of issuance across lenders. Differences in points purchasing behavior across age groups are addressed by adjusting the outcome variable to reflect the number of points that each borrower purchased. Lastly, as discussed in Bartlett et al. (2022), repayment and put-back risk is not a material concern in the post-2008 sample.

It is important to note that, if the stated identifying assumption does not hold, then the results from the LLPA grid regression would suffer from the same drawbacks that are listed in Section 4.1. One way that the identifying assumption could fail is that, for each mortgage that I include in the sample, the probability of sale is not equal to one. In this case, the lender may use its own underwriting model to determine the mortgage's coupon rate and this model can use information that captures unobservable credit risk beyond the LLPA grid and other variables that appear in the CHMDA data set.

the GSEs, all else equal, originators/lenders have an incentive to charge a coupon rate that is as high as possible because lenders' profit is a positive function of the coupon rate (Fuster et al., 2013).

[23] Refer to the data section for details on the sample selection procedure.

5 Results

In this section, I present the core regression results. I defer the discussion of potential mechanisms that may drive the results to Section 6.

5.1 Mortgage Application Rejection Probability Across Age Groups

I begin my empirical analysis of the relationship between applicant age and mortgage application outcomes by estimating variants of regression equation 1 where the rejection indicator variable is regressed on a vector of age group variables. Table 2 present the results. Column 1 presents the regression result from a specification where, along with the age group variables, I include the full set of control variables. There are several notable patterns. First, the results show that, relative to the 25 to 29 age group, there is a clear monotonically increasing relationship between applicant age and probability of rejection with the exception that the reference group, 18 to 24, has a slightly elevated rejection probability relative to the 25 to 29 age group. This result is surprising because, in the United States, credit score and wealth are positively correlated with age.[24] Second, the economic magnitude of these coefficients are large when compared to the unconditional probability of rejection of 17.5%. For example, the coefficients for the three oldest age groups indicate a 10% to 30% relative increase in rejection probability.

Column 2 presents regression results where I include lender by year-quarter fixed effects and I find that, although the coefficients are smaller, the qualitative results are largely robust, which means that the core empirical pattern is not entirely driven by differences in lender matching across age groups; that is, older individuals are not selecting to apply for mortgages with more stringent lenders. Appendix Table A2 presents regression results for the sample where I exclude applications from the year 2020. The results are qualitatively and quantitatively similar to those presented in Table 2, which suggests that the main results are not driven by the COVID-19 pandemic. Table A3 shows that the same qualitative pattern also shows up for cash-out refinance mortgage applications and is not driven by the COVID-19 pandemic.

[24] In 2019, average FICO scores for people in age groups 20 to 29, 30 to 39, 40 to 49, 50 to 59, and 60 or older are 662, 673, 684, 706, and 749, respectively. Data is gathered from https://www.americanexpress.com/en-us/credit-cards/credit-intel/credit-score-by-age-state/. The SCF shows that the average net worth of people in the same age groups are, in thousands of 2016 USD, \$137, \$280, \$593, \$995, and \$960, respectively. https://sda.berkeley.edu/sdaweb/analysis/?dataset=scfcomb.

As briefly discussed in the previous section and in greater detail in Section 6, the reference group, applicants aged 18 to 24 years old, is likely to be an odd group of individuals; that is, these applicants are likely to have exceptionally high credit quality to be able to apply for a mortgage refinance at such a young age. Therefore, the conditional rejection probability that they face may be much lower than that of a more representative young applicant. However, note that if I ignore the two youngest groups of applicants that are included in the regression and, instead, compare the 30 to 39 age group to the remaining older age groups, the core empirical pattern still hold.

Since the literature on the disparity in mortgage application outcomes (Ladd, 1998) largely focuses on race and ethnicity, it is worth comparing the coefficients on the age variables with those on the race and ethnicity variables. Across the two specifications, the coefficients on the three oldest age groups are generally larger than the coefficients on Black and Hispanic. This result suggests that, relative to race and ethnicity, applicant age is an equally important correlate of mortgage approval decision.[25]

Regression results shown in columns 3 and 4 explore whether, as in prior works in the literature, omitting age from this type of lending decision regression significantly affect the coefficients on race and sex indicator variables. In column 3, I omit age variables from the regression and, in column 4, I omit sex, race, and ethnicity variables from the regression. Comparing results in columns 2 through 4 reveals that such omissions do not significantly affect the coefficients on the included variables.

Table 3 presents regression results where I estimate equation 1 with lender by year-quarter fixed effects for each loan type. Columns 1 and 2 present the results for conforming loan applications. Although the sizes of the age group coefficients are smaller than those shown in Table 2, the qualitative conclusion that the conditional rejection probability increases with age holds. Columns 3 and 4 present the results for government guaranteed loans (e.g., VA, Federal Housing Administration (FHA), and USDA Farm Service Agency (FSA) loans) and find the same qualitative results. Columns 5 and 6 show the results for loans that are ineligible for the GSEs to buy. A loan is considered to be ineligible if the loan amount exceeds the Federal Housing Finance Agency's (FHFA) conforming loan limit or at least one AUS determines that the loan is ineligible for the GSEs to buy. For this sample of loans, I also find the same increasing relationship between age and rejection probability, although the coefficients are not always statistically different from zero due to the small sample sizes. Overall, the generally positive correlation between

[25] The size of the race and ethnicity coefficients are comparable to those estimated by recent works (Bhutta et al., 2021).

applicant age and rejection probability holds across loan types.

5.2 Age, Sex, and Mortgage Application Rejection

In this section, I make use of the large sample size to study the conditional correlation between age and probability of rejection at *each* age and by sex. I begin by estimating the following OLS regression equation using the main sample of refinance applications:

$$Rejected_i = \alpha + \sum_{j=30}^{89} \beta_j \times \mathbb{1}(Age\, j)_i + \gamma' \mathbf{x_i} + Month \times Tract\, FE + \epsilon_i. \tag{3}$$

This regression equation replaces the age group indicator variables with *individual* age indicator variables that range from 25 to 89. Using applications associated with applicants whose ages range from 18 to 24 as the reference group, this specification allows me to study the marginal difference in rejection probabilities at every single age between 25 and 89 years old.[26]

The top panel of Figure 1 presents the regression result. A visual inspection of the figure reveals several notable patterns. First, the marginal difference in rejection probability generally increases with age. In other words, the relationship between rejection probability and age is not a step function, which could also produce the results presented in Table 2. Second, the marginal increase in rejection probability accelerates around the age of 70; that is, a one year increase in age is associated with a larger increase in rejection probability for older applicants. I formally confirm the second observation by estimating variants of the following OLS regression equation:

$$Rejected_i = \alpha + \delta_1 \times Age_i + \delta_2 \times (Age_i \times 70+_i) + \gamma' \mathbf{x_i} + Month \times Tract\, FE + \epsilon_i. \tag{4}$$

Age_i is the applicant's age in years and $70+_i$ is an indicator variable that equals one if the applicant is older than 69 years old.[27] Table 4 presents the regression results. The sample size is smaller than that

[26] I exclude individuals who are older than 89 years old because there are too few observations to estimate the marginal difference by each age value.

[27] The standalone term $70+_i$ is included in the regression but omitted from the equation above and the regression outputs

of Table 2 because I drop applications that are associated with borrowers who have missing age values. The results in column 1 show that the coefficient on the interaction term is more than two times larger than the coefficient on Age_i. For younger applicants, on average, a one year increase in age is associated with a 0.1% increase in rejection probability. In contrast, for applicants who are older than 69 years old, a one year increase in age is associated with a 0.33% increase in rejection probability. Column 2 presents the results from a regression specification where I include lender by year-quarter fixed effects. The coefficient estimates are qualitatively and quantitatively similar.

Next, I investigate the correlation between rejection probability, age, and sex by estimating a variant of regression equation 3 where I interact an indicator variable that equals one for female applicants with each age indicator variable. The sample only includes loan applications where the applicant's sex can be identified as male or female.

The bottom panel of Figure 1 presents the regression result. The figure plots two curves. The first, formed by blue dots, plots the coefficients on the standalone age terms, which is the marginal change in rejection probability for male applicants. The second, formed by red dots, plots the coefficients on the interaction terms, which is marginal difference in rejection probability between male and female applicants at each age. There are several notable observations. First, generally, male applicants face higher rejection probabilities than female applicants. Second, female applicants also experience the age effect, although the increase in rejection probability tends to be slower. Third, the difference in rejection probabilities between male and female applicants becomes statistically different from zero around the age of 50 and continues to widen into old age. I formally confirm these observations by estimating variants of the following OLS regression equation:

$$\begin{aligned} Rejected_i = {} & \alpha + \theta_1 \times Age_i + \theta_2 \times (Age_i \times 70+_i) \\ & + \theta_3 \times (Age_i \times Female_i) + \theta_4 \times (Age_i \times 70+_i \times Female_i) \\ & + \gamma' \mathbf{x_i} + Month \times Tract\, FE + Lender\, FE \times YearQtr\, FE + \epsilon_i. \end{aligned} \tag{5}$$

$Female_i$ equals one if the application is associated with a female applicant.[28] The sample of anal-

for presentation purposes.

[28]Other necessary standalone (e.g., $Female_i$ and $70+_i$) and interaction (e.g., $Age_i \times Female_i$) terms are included in the regression but omitted from the equation and regression outputs for presentation purposes.

ysis excludes applications that are associated with applicants with unknown sex. The visual observation implies that θ_3 and θ_4 should be negative and statistically different from zero. Furthermore, the absolute value of θ_4 should be larger than the absolute value of θ_3. Columns 4 through 6 of Table 4 present the regression results, which are largely consistent with the observation.[29]

5.3 Underwriter's Reasons for Rejection

A natural question that comes to mind is why are older applicants more likely to be rejected than younger ones? In CHMDA, for each rejected application, the underwriter provides at least one explanation for the decision. This section explores the conditional correlation between applicant age and the stated reasons for rejection. To do so, I use the main sample of refinance applications to estimate variants of regression equation 1 where the dependent variable is an indicator variable that equals one for a certain rejection reason. For example, the first reason for rejection in the CHMDA data set is high DTI ratio. Therefore, the analogous outcome variable is an indicator variable that equals one if the application is rejected because its debt-to-income ratio is too high.

Table 5 presents the regression results.[30] The first rejection reason that seems to qualitatively match the baseline correlation between applicant age and application rejection probability is "insufficient collateral," shown in column 4. A rate-and-term refinance application is rejected for insufficient collateral because the homeowner does not have enough equity on his or her property to take out the desired loan amount. This scenario could occur if the homeowner's estimate of his property value was too optimistic or the property had experienced a substantial price decline since the time the original mortgage was originated.

One way to quantify the contribution that insufficient collateral makes to the baseline age effect result is to re-estimate the baseline age regression with a dependent variable that is equal to the original rejected indicator variable except for cases where the application was rejected because of insufficient collateral. With the new estimates in hand, I can quantify the contribution of insufficient collateral by comparing the age group coefficients from the new regression to those in the baseline results. The

[29] Post-estimation t-tests confirm that, across all three specifications, θ_4 is statistically different from θ_3.

[30] Values in the Average Outcome row do not add up to 17.5% because a single application could be rejected for multiple reasons.

first two columns of Table 6 presents the counterfactual rejection regression results for the quantification exercise for the insufficient collateral reason. The coefficients on the three oldest age groups, those that suffer the most from the age effect, are smaller than those that appear in Table 2. By comparing the coefficients on the 50 to 59 age group from column 2 of Tables 2 and 6, I find that insufficient collateral accounts for approximately 70% ($\frac{1.07-0.33}{1.07}$) of the age effect among applicants who belong to this age group. Repeating the calculation for the 60 to 69 and 70+ age groups reveal that insufficient collateral can explain between 50% to 70% of the age effect on application rejection.

The insufficient collateral result is consistent with the conjecture that older homeowners are less able to maintain the quality of their homes than younger homeowners (Campbell et al., 2011). Therefore, the value of their collateral may have dropped substantially between the time that they first bought the property and the time that they applied for refinancing. Other reasons for significant collateral value declines include selecting into houses that are more likely to experience functional obsolescence and buying houses at the wrong place and at the wrong time. Insufficient collateral could also result if the loan amount has grown relative to the property value. This event could occur if the original mortgage has a negative amortization feature or the borrower wishes to consolidate multiple mortgages into one.[31] The insufficient collateral result is also consistent with the selection bias explanation; that is, older homeowners in the sample are more likely to be in financial distress because they were forced to carry mortgage debt into retirement. Hence, insufficient funds lead to inadequate maintenance.

The second rejection reason that exhibits an increasing relationship between applicant age and probability of rejection is "other," which is shown in column 9. "Other" is the catch-all reason that underwriters supply when the application is rejected because of reasons other than the eight reasons that are shown in Table 5. It is possible that the "other" category is capturing the effect of age-related incapacity to contract. However, using the same quantification approach as before, I find that the "other" rejection reason can explain very little of the overall age effect on mortgage application rejection.

[31] A borrower who wishes to refinance a mortgage that has a negative amortization feature may be more likely to be rejected for insufficient collateral because, during the life of the first mortgage, the principal amount that needs to be refinanced has grown relative to the value of the property. And so, even if the property did not experience a large decline in value, its current collateral value may be insufficient to back the new loan. I do not observe information on the original mortgage and, therefore, cannot quantify the importance of this mechanism. Per Appendix A.1, it is possible that some lenders in the sample classify a refinance mortgage that consolidates multiple existing mortgages into one as a simple refinance. In this situation, the loan amount on the new mortgage would have increased substantially relative to the property value and so the borrower's application may be more likely to be rejected because of insufficient collateral.

5.4 Coupon Rate Across Age Groups

This section explores the relationship between borrower age and coupon rate on originated home purchase and refinance mortgages. Following Bartlett et al. (2022), I apply the LLPA grid identification strategy to the sample of selected loans that were originated and sold to Fannie Mae. For the interested readers, Table A4 presents average borrower characteristics by age group for the sample of mortgages that I analyze in this section. If the identifying assumption outlined in Section 4 holds, then variation in observable characteristics such as credit score, income, LTV, and DTI should not matter for coupon rates, once I condition on the LLPA grid.

Table 7 presents the regression results for home purchase loans. Several notable patterns emerge. First, much like the rejection probability results, the reference group has a slightly elevated conditional average coupon rate compared to borrowers in the 25 to 29 and 30 to 39 age groups. Second, starting from the 30 to 39 age group, there is a monotonically increasing relationship between borrower age and coupon rate. The economic magnitudes of the coefficients are not very large when compared to the sample's unconditional average of 391 basis points (bps). For example, 70+ borrowers pay, on average, 8.5 bps more than the reference group or 10 bps more than the 30 to 39 group. This marginal effect translates to approximately a 2% relative increase. The remaining columns of the table presents regression results where I include stricter sets of fixed effects. The generally positive relationship between borrower age and coupon rate is robust. Table 8 presents the results for refinance loans and finds the same qualitative patterns.

The results discussed above hold for loans that were sold to Freddie Mac. Freddie Mac loans need to be analyze separately because, as shown in Appendix Figures A1 and A2, the two GSEs use slightly different fee grids. Appendix Tables A7 and A8 present results for Freddie Mac loans and find the same qualitative conclusions. The COVID-19 pandemic also does not affect the core qualitative pattern. Appendix Table A5 and A6 present regression results using loans that were originated and sold before 2020. The qualitative conclusion does not change when I use census tracts instead of counties as the unit for geographical area fixed effects.

As shown by Bhutta and Hizmo (2021), the number of points purchased by the borrower is an important determinant of the final coupon rate that the borrower receives. Following Bartlett et al.

(2022), I account for points purchased by adjusting the coupon rate where, for each point (1% of the loan amount) purchased, I add back 0.125% to the coupon rate. Appendix Tables A10 and A11 present the results. For both samples, the increasing relationship between borrower age and coupon rate is more pronounced, which means that, on average, older borrowers buy more points, which means that the baseline pattern cannot be explained by differences in point purchasing behavior across age groups.[32] Overall, the results presented in this section show that older individuals receive higher coupon rates on home purchase and refinance mortgages for reasons that are not related to LLPA credit risk.

I now compare the coefficients on the age variables with those on the race and ethnicity variables. In the main sample of loans, the coefficients on the Hispanic indicator variable are positive and statistically different from zero for home purchase loans, but not for refinance loans. On the other hand, the coefficients on the Black indicator variable is rarely positive and statistically different from zero.[33] Bartlett et al. (2022) find that Hispanic and Black borrowers face 9 bps and 3 bps higher coupon rates for home purchase and refinance mortgages, respectively. Compared to these estimates, age seems to be an equally important determinant of mortgage coupon rate.[34]

Lastly, interestingly enough, the coefficient on Female is consistently positive and statistically different from zero. The result indicates that female borrowers, receive higher coupon rates than male borrowers for reasons beyond the LLPA grid. Further exploration of this robust empirical pattern may be a fruitful avenue of future research, but is beyond the scope of this paper.

5.5 Age, Sex, and Coupon Rate

In the same spirit as Section 5.2, I exploit the large size of the data set to examine the conditional correlation between borrower age and coupon rate at each age value. Figure 2 presents a plot of coefficient estimates on individual age indicator variables from a regression specification where coupon rate is regressed onto age indicator variables, demographic indicator variables, and month by Fannie Mae's LLPA grid fixed effects. For this regression, I include mortgages sold to both Fannie Mae and Freddie Mac to

[32] See Appendix Table A9 for summary statistics on net points purchased by age group.

[33] The race and ethnicity results shown here are not necessarily comparable to those presented by Bartlett et al. (2022) because the two studies use very different samples of loans and different sets of demographic control variables.

[34] Omitting the age variables from the regression does not material change the estimates of the coefficient on the race and ethnicity variables and vice versa.

maximize the sample size. As discussed above, the core results do not change whether I use mortgages that were sold to Fannie Mae or those that were sold to Freddie Mac. Furthermore, pooling the sample and using Fannie Mae's LLPA grid fixed effects should not have material a impact on the results because, as shown in Figures A1 and A2, the two entities use very similar fee grids.

The top panel of Figure 2 exhibits several notable patterns. First, similarly to the by-age rejection probability figure, there seems to be a relatively smooth increase in coupon rate throughout the age spectrum. Second, the incremental increase in coupon rate seems to accelerate in old age. The bottom panel of Figure 2 presents a plot of coefficient estimates on individual age indicator variables and their interaction terms with the female indicator variable. The sample size for this regression is restricted to mortgages that I can identify the borrower as being male or female. The picture tells a similar story as the by-age rejection probability figure; that is, like male borrowers, female borrowers also face increasing coupon rate as they age. However, graphically, the increase seems slightly slower in old age. I formally test the observations discussed above by running the following regressions:

$$Coupon\,Rate_i = \alpha + \beta_1 \times Age_i + \beta_2 \times (Age_i \times 70{+}_i) + \gamma'\mathbf{x_i} + Month \times Grid\,FE + \epsilon_i \tag{6}$$

$$\begin{aligned} Coupon\,Rate_i = \alpha &+ \theta_1 \times Age_i + \theta_2 \times (Age_i \times 70{+}_i) \\ &+ \theta_3 \times (Age_i \times Female_i) + \theta_4 \times (Age_i \times 70 +_i \times Female_i) \\ &+ \gamma'\mathbf{x_i} + Month \times Grid\,FE + \epsilon_i. \end{aligned} \tag{7}$$

Columns 1 and 2 of Table 9 present the regression results. In column 1, the coefficient on the term $Age_i \times 70{+}_i$ is positive and statistically different from zero. Younger borrowers, on average, face a 0.16 bps increase in coupon rate for each year of aging, while older applicants face a 0.28 bps increase. Column 2 presents the regression results for the interaction between age and sex. The coefficient on the term $Age_i \times 70 +_i \times Female_i$ is negative but not statistically different from zero. Qualitatively, the result suggests that older female borrowers face slower increases in coupon rate than older male borrowers, but the result is not statistically significant.

Figure 3 presents the analogous plots for refinance mortgages, which exhibit similar visual patterns. Likewise, columns 3 and 4 of Table 9 present the respective results. Similar to home purchase mortgages, regression results presented in column 3 older show that older borrowers face larger marginal increases in coupon rates than younger borrowers. However, this result does not hold when I run regression equation 7, shown in column 4 of the same table. Furthermore, unlike the home purchase regression results, the triple interaction term, $Age_i \times 70+_i \times Female_i$ is positive but not statistically different from zero, which suggests that older female borrowers do not face smaller marginal coupon rate increases than older male borrowers. The regression results are similar when I include lender, lender by month, and lender by county fixed effects. Overall, this set of analysis suggests that coupon rates increase with borrower age and the increases accelerate in old age. However, there is no robust empirical pattern when age interacts with sex, which may stem from the fact that variation in coupon rates is small among conforming mortgages (Hurst et al., 2016).

6 Discussion of Potential Explanations

In this section, I provide a non-exhaustive list of possible explanations that could produce the empirical patterns presented above, but not to suggest that any one of the explanations discussed below is more plausible, causal, or quantitatively more important than the others. Since I use different regression specifications to study rejection probability and coupon rate, I discuss potential mechanisms for each set of results separately. For each set of results, the reader should interpret them as being driven by any combination of the listed explanations and those that are not listed in this section.

The potential explanations discussed below fall into two categories. First, age is *causally* affecting mortgage application outcomes. An example of this class of explanations is taste-based age discrimination. Second, age is a proxy for certain credit risks or is correlated with certain consumer behaviors. Examples of this class of explanations include omitted variable bias, age-based mortality risk, and differences in shopping behavior across age groups.

6.1 Application Rejection Results

6.1.1 Selection and Omitted Variable Bias

As mentioned in the methodology section, the regression results on rejection probability are conditional correlations, which means that they do not address the issues of selection and omitted variable bias. As such, it is possible that the sample of applicants used in the analyses presented thus far disproportionately includes older applicants who are in financial distress, which renders them less credit-worthy. By omitting measures of financial distress from the regressions, age becomes a proxy of financial distress and, hence, appears to be systematically correlated with mortgage application outcomes.

Anecdotally, would-be retirees prefer to avoid carrying debt into retirement. Therefore, it is possible that older individuals who carry a mortgage and, hence, apply for a rate-and-term refinance are in financial distress or weaker financial conditions than older individuals who do not carry any mortgage debt. The pertinent point is that unobservable financial conditions among older applicants in the sample must, generally, get worse with age to produce a spurious correlation between age and mortgage application rejection probability. This correlation structure is plausible, given that, as people age, their incomes are lower and their savings are depleted by retirement consumption.

Selection bias may also play an important role among the youngest applicants in the sample. In 2022, the median age among first-time home buyers is 33 years old and the median age of homeowners is 47 years old, which implies that it is very uncommon for individuals who are younger than 30 years old to buy new homes and, even more so, to refinance their existing mortgages.[35] Therefore, it is likely that individuals who are between 18 and 29 years old who appear in the CHMDA data set are highly irregular in that they are likely to have higher-than-average credit quality compared to other individuals in their age group. In addition, younger applicants may have older mortgage guarantors associated with the application. I cannot observe guarantor information in the data. Since I cannot fully control for such unobservable credit quality, it is likely that the conditional rejection probability for applications associated with younger individuals in the sample is too low and the conditional rejection probability for

[35] The statistics are gathered from the ascent and the National Association of Realtors.
https://www.fool.com/the-ascent/mortgages/articles/this-is-the-average-age-of-first-time-home-buyers/.
https://www.nar.realtor/sites/default/files/documents/2021-home-buyers-and-sellers-generational-trends-03-16-2021.pdf.

applications associated with older individuals in the sample is too high. Together, these two effects are likely causing the age gap in rejection probabilities to be too large.

Furthermore, it is important to note that the sample of mortgage applications that I study is composed of only single-borrower applications. Since the probability of entering into a partnership or a co-habitation arrangement is likely to be correlated with age and partnership status (e.g., marital status) is likely to be correlated with financial well-being, it is possible that older individuals who appear in the sample of analysis were negatively selected into the sample, which would explain the systematic correlation between age and worse mortgage application outcomes.

Lastly, the selection bias explanation can also explain the insufficient collateral rejection result. It is intuitive that financial distress leads to significant deterioration of the property because the owner cannot afford work that maintains the property's structural integrity and, hence, the owner's refinance application is more likely to be rejected for insufficient collateral.

6.1.2 Age-Related Mortality Risk

A potentially creditworthiness-relevant variable that is highly correlated with age is life expectancy or age-related mortality risk. In the event that a borrower dies, it is typically the case that an executor or administrator will be appointed to manage the estate, which includes the mortgage and the associated property. The executor will identify the heir who may choose to sell the property and pay back the loan or work with the lender to take over the mortgage. In the rare even that an heir cannot be identified, the executor will use the estate's assets to pay off the loan. If the estate's assets are insufficient, then the executor could try to sell the property to pay off the loan, offer the lender a deed-in-lieu of foreclosure, or arrange a short sale. Ultimately, in the event that there are insufficient funds to pay off the loan, the lender may choose to foreclose on the property.

From an economic perspective, the borrower's death is an event that causes *uncertainty* in loan performance for the lender because the likelihood of the loan being paid off early (prepayment risk) or entering foreclosure (default and recovery risk) is higher. All else being equal, this uncertainty or set of risks is higher for older borrowers than for younger borrowers because the former group has significantly higher age-related mortality risk. Therefore, a rational and risk-averse lender should consider age-related mortality risk when making lending decisions.[36]

The age-related mortality risk explanation could drive the correlations presented above because the regression results appear consistent with well-known facts about mortality risk presented in Figure A3. First, Figure 1 shows that, much like mortality risk, the probability of rejection generally increases with age. Second, the same figure shows that the increase in rejection probability accelerates in old age, which is consistent with the fact increases in mortality risk are much larger in old age. Third, the difference in rejection probability between men and women becomes larger in old age, which agrees with the fact that the difference in mortality risk between men women diverges in old age. Lastly, the positive correlation between applicant age and the probability that the application gets rejected for insufficient collateral is in line with the idea that, all else equal, lenders may require the borrower to put up more collateral or take out a smaller loan as age-related mortality risk increases with age.

6.1.3 Other Explanations

Due to systematic correlation structures between demographic variables (e.g., race, ethnicity, sex, and age) and economically-relevant variables (e.g., income and credit score), facially demographic-blind statistical models can produce different outcomes across demographic groups. For example, Fuster et al. (2022) shows that implementing facially race-blind machine learning models in the context of mortgage lending decisions will likely cause Black and Hispanic borrowers to be worse off. Similarly, Amornsiripanitch (2020) shows that conventional property tax assessment methods produce regressive residential property tax rates, which adversely impacts any demographic group that tends to own less expensive homes. For the current paper, it is plausible that lenders do not use borrower age to make lending decisions, but the correlations presented above still manifest in the data because age is systematically correlated with "permissible" variables such that a facially age-blind statistical underwriting model still yields different outcomes across age groups.

In principle, it is plausible that taste-based age discrimination is a factor that is driving the rejection probability results. However, in this paper, I do not explore whether taste-based age discrimination contributes to the correlations documented above and so I cannot rule in or rule out the explanation.

[36] As discussed in Section 2, lenders that use either an empirically driven or judgemental credit scoring system can consider a borrower's age to determine a pertinent element of creditworthiness. Examples listed in the section includes the interaction between loan term, life expectancy, and net collateral value.

6.2 Coupon Rate Results

As discussed in Section 4, I use the LLPA grid regression specification to estimate the conditional correlation between borrower age and coupon rate. Following the argument made by Bartlett et al. (2020), this approach yields excess differences in coupon rate across age groups that have nothing to do with the LLPA grid that the GSEs use to price individual mortgages. If the LLPA grid is the only credit-risk-relevant factor that lenders use to price mortgages, then any remaining statistically significant loadings on the age group variables can be interpreted as stemming from factors unrelated to credit risk, both observable and unobservable. Following this logic, the discussion below will not address omitted variable bias that stems from unobservable credit quality, age-related mortality risk, and unintended consequences of statistical models as potential explanations.

Differences in shopping behavior across age groups could explain the positive correlation between borrower age and coupon rate. Since search can be costly (Hortaçsu and Syverson, 2004), it is plausible that, due to higher likelihood of physical or mental fatigue and technology aversion, older borrowers perform a less comprehensive search of potential lenders than younger borrowers. Therefore, older borrowers end up receiving less favorable coupon rates because they cannot provide competing rates for lenders to match.

Along similar veins, market segmentation or differences in the degree of competition can also give rise to the coupon rate result. Suppose that lenders specialize in different segments of the mortgage market (e.g., by geography, loan amount range, credit score range, etc.) that happen to be correlated with age, then if the degree of competition across these market segments varies such that the competition is less intense for mortgages associated with older individuals, then the age gap in mortgage coupon rate result could arise.

Lastly, in principle, taste-based age discrimination can cause a positive relationship between borrower age and coupon rate. However, as mentioned in the previous section, I do not explore whether taste-based age discrimination contributes to the correlation between age and coupon rate and so I cannot rule in or rule out the explanation.

7 Caveats

The goals of this paper are to (1) document the conditional correlations between applicant age and mortgage application outcomes and (2) discuss potential mechanisms that *may* drive the correlations. At its core, this paper seeks to draw attention to the potentially important issue of age and mortgage access, much like the way in which the seminal work by Munnell et al. (1996) drew attention to the importance of race and ethnicity in mortgage lending decisions. This paper does not seek to make any welfare or normative statement about whether older individuals should have easier access to credit.

Since the results touch upon the issue of fair lending, additional caveats need to be discussed. First, as stated in the methodology section and throughout the paper, the regression results show correlations and not causal relationships. Therefore, the results do not necessarily show that lenders are making lending decisions based on age because the correlations presented above are not necessarily informative about the underwriting models that lenders use. To be able to make such definitive statements, I would need to perform a fair lending analysis of an individual lender's activities, which is not an accurate description of the analyses presented above and is beyond the scope of this paper.

Second, since the correlations presented above are not necessarily informative about the variables that are considered in lenders' underwriting models, it follows that the results do not provide definitive evidence of whether or not the lenders that appear in the sample of analysis are legally or illegally using borrower age to make lending decisions. Therefore, I cannot take a stand on whether the lenders that I study are violating fair lending laws. This point is especially important given that the results shown in Section 5.2 may suggest that, in some instances, age and sex have an effect on lending decisions. The latter, sex, being a variable that ECOA does not allow lenders to consider.

8 Conclusion

This paper is the first to use a large data set of mortgage applications to document stylized facts about the relationship between applicant age and mortgage application outcomes. Since the mortgage market is one of the largest retail credit markets, the analyses presented here, to the best of my knowledge, serve as the most systematic study of the relationship between age and credit access. I find that, conditional on a rich set of applicant, loan, and property characteristics, older applicants for a mortgage refinance generally face higher rejection probabilities. This empirical pattern is robust within lenders and across loan types. The same pattern also appears among cash-out refinance mortgage applications. By exploring loan officers' reasons for rejection, I find that insufficient collateral appears to be a significant contributor. Using the LLPA grid identification strategy from Bartlett et al. (2022), I find that older borrowers face higher coupon rates on home purchase and refinance mortgages that were sold to Fannie Mae and Freddie Mac. Together, the empirical results suggest that, for a large part of the market for simple refinance and home purchase mortgages, older individuals who apply for such credit alone systematically face higher access barriers.

The results presented above should be interpreted as a set of carefully estimated conditional correlations, which implies that mortgage access barriers are not necessarily raised by age itself because age may be a proxy for certain risks or omitted variables that are highly correlated with age. As such, potential explanations for the documented empirical patterns include, but are not limited to, selection bias, age-related mortality risk, differential impacts from statistical underwriting models, differences in shopping behavior across age groups, taste-based age discrimination, and market segmentation.

In relation to the larger literature on the disparity in mortgage application outcomes across different subgroups of the population, the results presented in this paper suggest that, relative to his or her race and ethnicity, an applicant's age may be an equally important correlate of mortgage access. As a practical matter to researchers, regression specifications that study the relationship between mortgage application outcomes and any variable of interest should condition on applicant/borrower age. More importantly, given its economic importance and many unexplored potential explanations, the relationship between age and credit access should be an active area of economic research, especially when aging becomes a more pressing policy concern.

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Figure 1: Marginal Difference in Rejection Probability by Age

This figure plots the estimated differences in rejection probability of mortgage refinance applications associated with applicants with ages older than 24 years old. The top figure plots the point estimates from a regression that includes all rate-and-term mortgage refinance applications. The reference group is composed of applications associated with applicants with ages between 18 and 24. The bottom figure plots the point estimates for rate-and-term mortgage refinance applications associated with applicants who are either male or female. The blue dots are regression coefficients for male applicants with the respective ages. The red dots are regression coefficients from the interaction term between Age and the Female indicator variable. Both regression specifications include the full set of control variables and month by tract fixed effects. Heteroskedasticity-robust standard errors are clustered at the lender level. Data source: CHMDA.

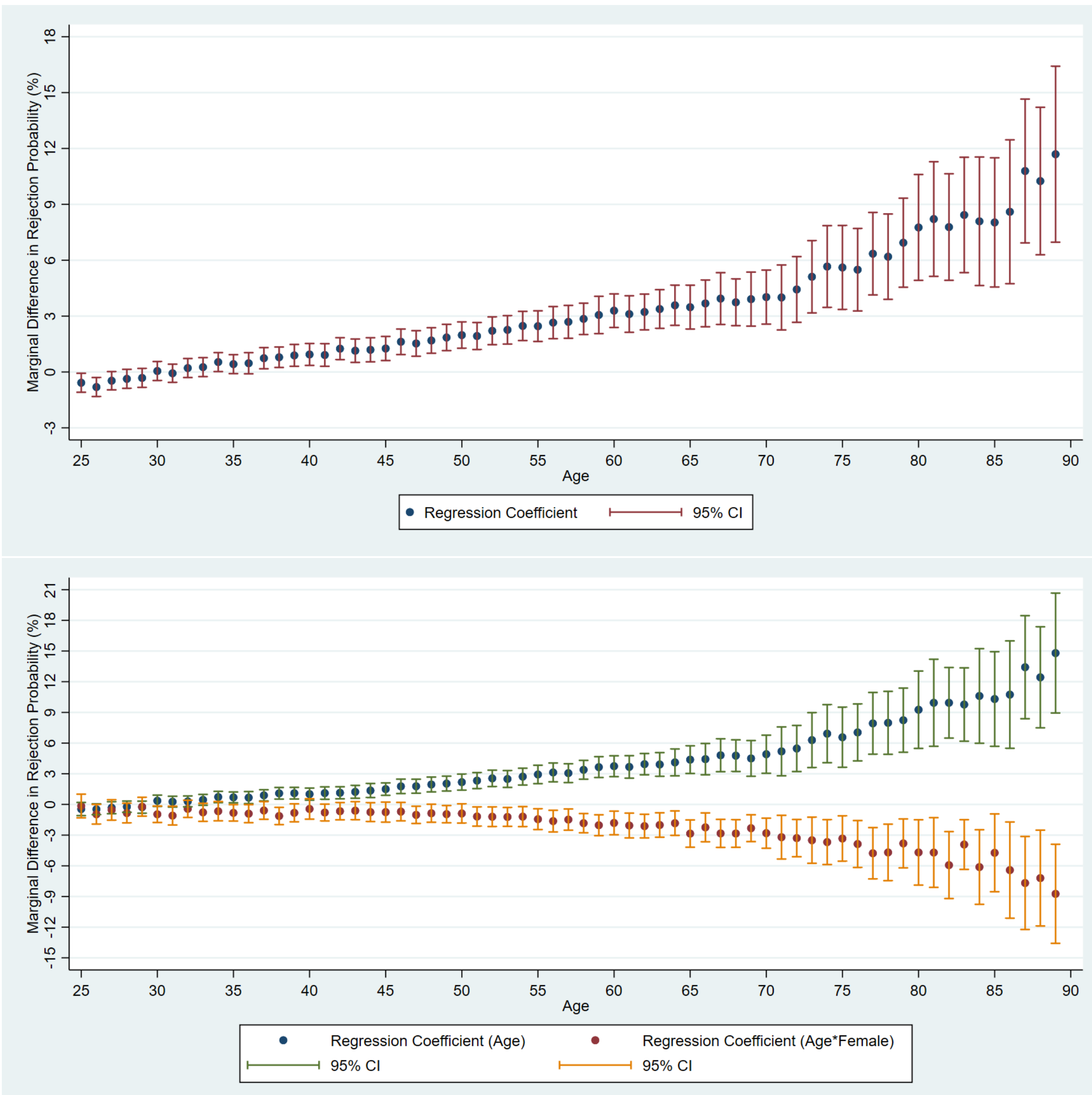


Figure 2: Marginal Difference in Coupon Rate by Age – Home Purchase

This figure plots the estimated differences in coupon rate of originated and sold home purchase mortgages associated with applicants with ages older than 24 years old. The top figure plots the point estimates from a regression that includes eligible home purchase mortgages that were sold to either Fannie Mae or Freddie Mac. The reference group is composed of mortgages associated with applicants with ages between 18 and 24. The bottom figure plots the point estimates for home purchase mortgages associated with applicants who are either male or female. The blue dots are regression coefficients for male applicants with the respective ages. The red dots are regression coefficients from the interaction term between Age and the Female indicator variable. Both regression specifications include demographic controls and month by Fannie Mae LLPA grid fixed effects. Heteroskedasticity-robust standard errors are clustered at the lender level. Data source: CHMDA.

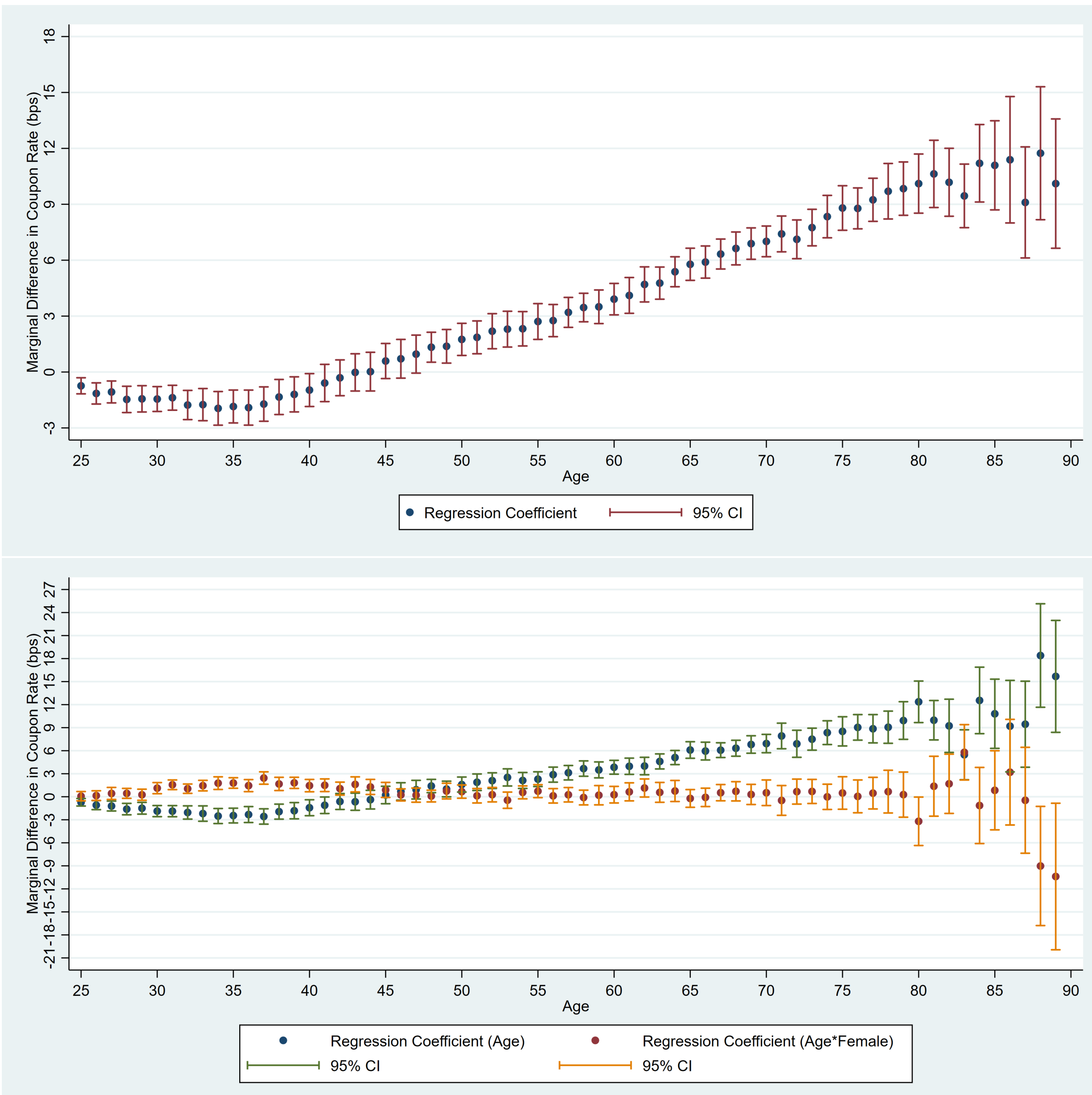


Figure 3: Marginal Difference in Coupon Rate by Age – Refinance

This figure plots the estimated differences in coupon rate of originated and sold refinance mortgages associated with applicants with ages older than 24 years old. The top figure plots the point estimates from a regression that includes eligible refinance mortgages that were sold to either Fannie Mae or Freddie Mac. The reference group is composed of mortgages associated with applicants with ages between 18 and 24. The bottom figure plots the point estimates for refinance mortgages associated with applicants who are either male or female. The blue dots are regression coefficients for male applicants with the respective ages. The red dots are regression coefficients from the interaction term between Age and the Female indicator variable. Both regression specifications include demographic controls and month by Fannie Mae LLPA grid fixed effects. Heteroskedasticity-robust standard errors are clustered at the lender level. Data source: CHMDA.

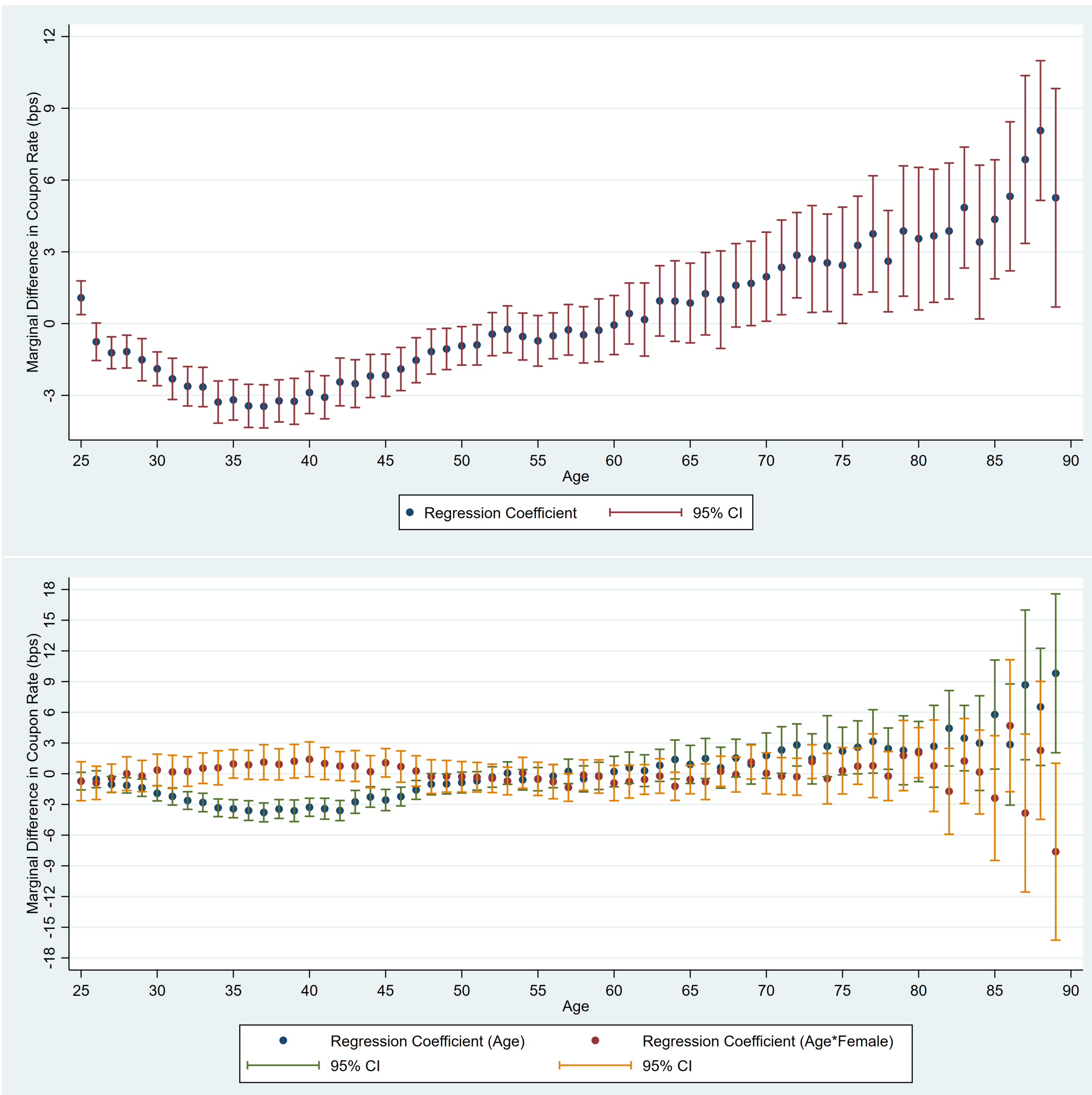


Table 1: Applicant and Application Characteristics by Age Group – Refinance

This table presents summary statistics on applicant and application characteristics by age group. The sample is composed of rate-and-term mortgage refinance applications that have one applicant and are associated with properties that have no more than four housing units. The top panel presents average applicant characteristics by age group. Annual income, loan amount, and property value are reported in thousands of dollars and adjusted for inflation using 2016 as the base year. The bottom panel presents application characteristics by age group. The column "Row Total" presents the total number of applications that have each characteristic. The remaining columns present the percentage of applications in each age group that have each characteristic. Data source: CHMDA.

Applicant Characteristics	18-24	25-29	30-39	40-49	50-59	60-69	70+
Credit Score	713.71	736.91	747.76	742.86	739.19	742.70	746.41
Income	52.14	69.58	97.96	115.60	108.52	88.50	67.86
CLTV	82.47	80.17	75.00	70.58	67.14	63.64	61.90
DTI	37.21	35.74	35.00	35.33	36.27	38.26	40.98
Loan Amount	181.65	219.39	261.01	271.57	245.65	214.17	201.73
Property Value	231.27	288.00	372.04	422.48	407.33	378.86	372.76
AUS Approved	0.57	0.67	0.69	0.67	0.62	0.59	0.41

Application Characteristics	Row Total	18-24	25-29	30-39	40-49	50-59	60-69	70+
Total	5,915,231	0.8%	5.5%	24.9%	26.5%	21.4%	12.7%	8.1%
Term < 15	216,676	0.3%	1.6%	10.2%	19.3%	26.3%	18.7%	23.6%
Term = 15	911,026	0.4%	3.5%	21.8%	29.7%	25.8%	13.1%	5.8%
30 > Term > 15	722,760	0.7%	5.3%	25.6%	28.7%	22.0%	11.6%	6.1%
Term ≥ 30	4,064,769	0.9%	6.3%	26.3%	25.8%	20.1%	12.5%	8.1%
First Home	5,441,707	0.9%	5.8%	25.6%	26.8%	21.4%	12.7%	6.8%
Second Home	99,236	0.2%	1.5%	12.1%	23.5%	30.2%	21.4%	11.2%
Investment Home	374,288	0.4%	2.7%	17.9%	24.0%	19.1%	10.9%	24.9%
Total Units = 1	5,769,883	0.8%	5.5%	25.0%	26.7%	21.5%	12.8%	7.7%
Total Units = 2	98,245	1.0%	6.3%	23.0%	21.4%	19.2%	11.6%	17.5%
Total Units = 3	26,411	1.0%	5.4%	19.9%	19.8%	17.8%	10.4%	25.8%
Total Units = 4	20,692	0.5%	3.8%	16.8%	18.7%	16.5%	10.1%	33.5%
Subordinated Lien	71581	0.4%	1.9%	14.6%	26.3%	28.3%	16.3%	12.2%
ARM	227,143	0.5%	3.2%	18.9%	26.0%	22.5%	13.5%	15.5%
Jumbo	187,011	0.1%	1.1%	19.4%	34.2%	24.6%	11.4%	9.3%
Non-conforming	290,557	0.3%	2.4%	20.8%	31.4%	24.0%	12.7%	8.4%
Balloon Payment	50,946	0.4%	1.5%	7.6%	11.8%	12.8%	9.2%	56.7%
Business Purpose	169,308	0.4%	2.5%	16.1%	21.3%	16.9%	10.0%	32.8%
HOEPA	2,473	0.6%	2.9%	19.0%	27.1%	26.0%	15.5%	8.8%
Interest Only	44,144	0.3%	1.3%	12.3%	24.0%	23.1%	14.7%	24.3%
Negative Amortization	444	1.1%	2.3%	9.7%	17.1%	27.0%	15.8%	27.0%
FHA	568,625	1.6%	7.6%	26.9%	28.4%	21.0%	10.4%	4.2%
VA	710,151	1.0%	5.9%	22.6%	21.0%	20.9%	14.9%	13.7%
FSA	11,515	5.4%	19.1%	33.6%	20.7%	13.2%	5.9%	2.0%

Table 2: Age and Refinance Application Rejection

This table reports OLS regression results where mortgage application rejection indicator variable is regressed on age group indicator variables and selected demographic indicator variables. The dependent variable is an indicator variable that equals 100 if the mortgage application is rejected and zero otherwise. The reference group is composed of applications associated with borrowers with ages between 18 and 24 years old. Refer to the Appendix for a detailed discussion of control variables and variable definitions. Average Outcome reports the unconditional average of the dependent variable for the sample of qualified observations without accounting for singleton observations that were dropped. Heteroskedasticity-robust standard errors are clustered at the lender level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data source: CHMDA.

	(1)	(2)	(3)	(4)
25 – 29	-0.48**	-0.81***		-0.82***
	[0.23]	[0.20]		[0.20]
30 – 39	0.45*	-0.19		-0.15
	[0.25]	[0.25]		[0.25]
40 – 49	1.33***	0.38		0.39
	[0.31]	[0.29]		[0.29]
50 – 59	2.44***	1.07***		0.96***
	[0.38]	[0.30]		[0.30]
60 – 69	3.49***	1.54***		1.35***
	[0.53]	[0.33]		[0.33]
70+	5.54***	2.70***		2.44***
	[1.04]	[0.49]		[0.49]
Female	-1.53***	-1.10***	-0.96***	
	[0.15]	[0.12]	[0.11]	
Hispanic	1.56***	1.70***	1.53***	
	[0.38]	[0.32]	[0.30]	
Black	2.62***	2.21***	2.30***	
	[0.41]	[0.39]	[0.33]	
Average Outcome		17.5%		
Controls	Y	Y	Y	Y
Tract × Month FE	Y	Y	Y	Y
Lender × Year-Quarter FE	-	Y	Y	Y
Observations	5,319,506	5,308,638	5,308,638	5,308,638
R-squared	0.45	0.52	0.52	0.52

Table 3: Age and Refinance Application Rejection by Loan Type

This table reports OLS regression results where mortgage application rejection indicator variable is regressed on age group indicator variables. The dependent variable is an indicator variable that equals 100 if the mortgage application is rejected and zero otherwise. The reference group is composed of loan applications associated with borrowers with ages between 18 and 24 years old. Guaranteed loan applications are applications associated with VA, FHA, or FSA loans. The non-conforming loan sample is composed of jumbo loan applications or loan applications that the automated underwriting system classified as being ineligible for the GSEs to purchase. Refer to the Appendix for a detailed discussion of control variables and variable definitions. Average Outcome reports the unconditional average of the dependent variable for the sample of qualified observations without accounting for singleton observations that were dropped. Heteroskedasticity-robust standard errors are clustered at the lender level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data source: CHMDA.

	(1)	(2)	(3)	(4)	(5)	(6)
25 − 29	-0.1	-0.34	-0.73	-1.18***	1.02	-3.02
	[0.28]	[0.23]	[0.47]	[0.39]	[4.92]	[4.35]
30 − 39	0.82***	0.29	-0.35	-1.19*	3.45	-0.84
	[0.30]	[0.24]	[0.65]	[0.64]	[5.00]	[4.49]
40 − 49	1.51***	0.71***	0.04	-1.27	4.98	0.52
	[0.34]	[0.24]	[0.83]	[0.90]	[4.96]	[4.45]
50 − 59	2.34***	1.17***	0.64	-1.12	6.56	1.74
	[0.42]	[0.30]	[0.87]	[0.77]	[5.11]	[4.60]
60 − 69	2.91***	1.18***	2.28*	-0.15	7.43	2.04
	[0.52]	[0.38]	[1.27]	[0.60]	[5.18]	[4.58]
70+	3.98***	1.49**	5.04**	1.73***	8.94*	2.21
	[0.82]	[0.65]	[2.26]	[0.49]	[5.11]	[4.50]
Sample	Conforming		Guaranteed		Non-Conforming	
Average Outcome	15.8%		19.3%		36.1%	
Controls	Y	Y	Y	Y	Y	Y
Tract × Month FE	Y	Y	Y	Y	Y	Y
Lender × Year-Quarter FE	-	Y	-	Y	-	Y
Observations	3,720,505	3,708,454	892,724	888,734	125,479	118,929
R-squared	0.52	0.59	0.42	0.52	0.63	0.71

Table 4: Age, Sex, and Refinance Application Rejection

This table reports OLS regression results where mortgage application rejection indicator variable is regressed on applicant's age. The dependent variable is an indicator variable that equals 100 if the mortgage application is rejected and zero otherwise. Age is the applicant's age in years at the time of application. 70+ is an indicator variable that equals 1 if the applicant is older than 69 years old. Female is an indicator variable that equals one if the application is associated with a female borrower. The sample used in columns 3 and 4 excludes applications associated with applicants whose sexes are unknown. Refer to the Appendix for a detailed discussion of control variables and variable definitions. Heteroskedasticity-robust standard errors are clustered at the lender level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data source: CHMDA.

	(1)	(2)	(3)	(4)
Age	0.103***	0.062***	0.116***	0.074***
	[0.015]	[0.008]	[0.017]	[0.008]
Age × 70+	0.234***	0.181***	0.288***	0.227***
	[0.052]	[0.033]	[0.068]	[0.042]
Age × Female			-0.044***	-0.042***
			[0.010]	[0.006]
Age × Female × 70+			-0.139**	-0.107**
			[0.057]	[0.042]
Controls	Y	Y	Y	Y
Tract × Month FE	Y	Y	Y	Y
Lender × Year-Quarter FE	-	Y	-	Y
Observations	5,238,964	5,227,308	4,701,071	4,689,168
R-squared	0.447	0.522	0.457	0.531

Table 5: Age and Refinance Application Rejection Reasons

This table reports OLS regression results where rejection reason indicator variables are regressed on age group indicator variables. All dependent variables are multiplied by 100. The dependent variable for each column is as follows. Column 1: the application was rejected because of high debt-to-income ratio. Column 2: the application was rejected because of insufficient work history. Column 3: the application was rejected because of insufficient credit history. Column 4: the application was rejected because of insufficient collateral. Column 5: the application was rejected because of insufficient cash for down payment and fees. Column 6: the application was rejected because of unverifiable information. Column 7: the application was rejected because the application was incomplete. Column 8: the application was rejected because the borrower's application for mortgage insurance was rejected. Column 9: the application was rejected because of reasons not listed above. This set of regressions uses the same control variables as the baseline rejection regressions. The reference group is composed of loan applications associated with borrowers with ages between 18 and 24 years old. Refer to the Appendix for a detailed discussion of control variables. Average Outcome reports the unconditional average of the dependent variable for the sample of qualified observations without accounting for singleton observations that were dropped. Heteroskedasticity-robust standard errors are clustered at the lender level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data source: CHMDA.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	DTI	Job Hist	Cred Hist	Collateral	Cash	Info	Incomplete	Insurance	Other
25 – 29	0.07	-0.16***	-0.08	-0.01	-0.06	-0.05	-0.16	-0.01	-0.38***
	[0.13]	[0.04]	[0.10]	[0.09]	[0.05]	[0.05]	[0.16]	[0.01]	[0.11]
30 – 39	0.16	-0.15***	0.30**	0.30**	-0.05	-0.07	-0.38*	-0.01	-0.29**
	[0.12]	[0.04]	[0.13]	[0.12]	[0.05]	[0.05]	[0.19]	[0.01]	[0.13]
40 – 49	0.33***	-0.15***	0.61***	0.53***	-0.04	-0.08	-0.51**	-0.01	-0.24*
	[0.12]	[0.04]	[0.16]	[0.14]	[0.05]	[0.05]	[0.22]	[0.01]	[0.14]
50 – 59	0.47***	-0.12***	0.64***	0.74***	-0.02	-0.02	-0.29	-0.01	-0.24*
	[0.12]	[0.04]	[0.15]	[0.18]	[0.06]	[0.06]	[0.21]	[0.01]	[0.14]
60 – 69	0.34***	-0.24***	0.52***	0.94***	-0.04	0.01	0.13	-0.01	-0.12
	[0.12]	[0.05]	[0.14]	[0.21]	[0.06]	[0.06]	[0.22]	[0.01]	[0.13]
70+	-0.01	-0.43***	0.63***	1.33***	0.00	-0.09	1.06***	-0.01	0.17
	[0.11]	[0.06]	[0.15]	[0.26]	[0.06]	[0.07]	[0.37]	[0.01]	[0.15]
Average Outcome	4.8%	0.3%	3.9%	2.2%	0.7%	0.9%	4.1%	0.01%	2.7%
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Tract × Month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Lender × Year-Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	5,308,638	5,308,638	5,308,638	5,308,638	5,308,638	5,308,638	5,308,638	5,308,638	5,308,638
R-squared	0.60	0.22	0.46	0.34	0.27	0.25	0.36	0.27	0.30

Table 6: Age and Refinance Application Rejection Reasons – Counterfactual Estimates

This table reports OLS regression results where modified mortgage application rejection indicator variable is regressed on age group indicator variables. The dependent variable for columns 1 and 2 is an indicator variable that equals 100 if the mortgage application is rejected for reasons other than "insufficient collateral" and zero otherwise. The dependent variable for columns 3 and 4 is an indicator variable that equals 100 if the mortgage application is rejected for reasons other than "other" and zero otherwise. The reference group is composed of loan applications associated with borrowers with ages between 18 and 24 years old. Refer to the Appendix for a detailed discussion of control variables and variable definitions. Heteroskedasticity-robust standard errors are clustered at the lender level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data source: CHMDA.

	(1)	(2)	(3)	(4)
Dependent Variable:	Rejected Not For Collateral		Rejected Not For "Other"	
25 – 29	-0.51**	-0.80***	-0.14	-0.43**
	[0.24]	[0.21]	[0.18]	[0.18]
30 – 39	0.07	-0.49*	0.65***	0.09
	[0.27]	[0.27]	[0.21]	[0.23]
40 – 49	0.67**	-0.15	1.44***	0.62**
	[0.33]	[0.32]	[0.25]	[0.26]
50 – 59	1.46***	0.33	2.51***	1.31***
	[0.36]	[0.29]	[0.34]	[0.27]
60 – 69	2.19***	0.60**	3.41***	1.66***
	[0.48]	[0.30]	[0.48]	[0.32]
70+	3.71***	1.37***	5.02***	2.53***
	[0.92]	[0.46]	[0.81]	[0.49]
Controls	Y	Y	Y	Y
Tract × Month FE	Y	Y	Y	Y
Lender × Year-Quarter FE	-	Y	-	Y
Observations	5,319,506	5,308,638	5,319,506	5,308,638
R-squared	0.44	0.51	0.43	0.50

Table 7: Age and Coupon Rate on Home Purchase Mortgages

This table reports OLS regression results where coupon rate is regressed on age group indicator variables. The sample includes home purchase mortgages that were originated and sold to Fannie Mae. The dependent variable is the coupon rate on the mortgage reported in basis points. The reference group is composed of loans associated with borrowers with ages between 18 and 24 years old. Each specification includes month by Fannie Mae's LLPA grid fixed effects. Refer to the Appendix for a detailed discussion of control variables. Average Outcome reports the unconditional average of the dependent variable for the sample of qualified observations without accounting for singleton observations that were dropped. Heteroskedasticity-robust standard errors are clustered at the lender level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data sources: CHMDA and Fannie Mae.

	(1)	(2)	(3)	(4)	(5)
25 – 29	-1.125***	-1.053***	-1.405***	-1.342***	-0.924***
	[0.381]	[0.266]	[0.273]	[0.278]	[0.251]
30 – 39	-1.484**	-1.460***	-1.939***	-1.867***	-1.261***
	[0.576]	[0.390]	[0.403]	[0.399]	[0.362]
40 – 49	0.248	0.062	-0.419	-0.355	0.076
	[0.638]	[0.437]	[0.410]	[0.408]	[0.355]
50 – 59	2.535***	1.936***	1.797***	1.820***	1.923***
	[0.559]	[0.367]	[0.316]	[0.312]	[0.269]
60 – 69	5.371***	4.194***	4.731***	4.670***	4.380***
	[0.506]	[0.362]	[0.246]	[0.242]	[0.237]
70+	8.502***	6.986***	7.870***	7.779***	7.175***
	[0.456]	[0.348]	[0.429]	[0.438]	[0.420]
Female	0.943***	1.053***	0.844***	0.803***	0.803***
	[0.176]	[0.167]	[0.124]	[0.126]	[0.126]
Hispanic	2.704***	1.431***	1.839***	1.771***	1.168***
	[0.608]	[0.358]	[0.362]	[0.350]	[0.326]
Black	-0.039	0.174	0.578	0.603	0.992***
	[0.628]	[0.472]	[0.401]	[0.386]	[0.317]
Average Outcome			391.22 bps		
Demographic Controls	Y	Y	Y	Y	Y
Month × Grid FE	Y	Y	Y	Y	Y
County FE	-	Y	-	-	-
Lender FE	-	-	Y	-	-
Month × Lender FE	-	-	-	Y	-
Lender × County FE	-	-	-	-	Y
Observations	977,423	977,316	977,365	972,940	939,903
R-squared	0.86	0.86	0.88	0.89	0.89

Table 8: Age and Coupon Rate on Refinance Mortgages

This table reports OLS regression results where coupon rate is regressed on age group indicator variables. The sample includes rate-and-term refinance mortgages that were originated and sold to Fannie Mae. The dependent variable is the coupon rate on the mortgage, reported in basis points. The reference group is composed of loans associated with borrowers with ages between 18 and 24 years old. Each specification includes month by Fannie Mae's LLPA grid fixed effects. Refer to the Appendix for a detailed discussion of control variables. Average Outcome reports the unconditional average of the dependent variable for the sample of qualified observations without accounting for singleton observations that were dropped. Heteroskedasticity-robust standard errors are clustered at the lender level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data sources: CHMDA and Fannie Mae.

	(1)	(2)	(3)	(4)	(5)
25 – 29	-1.162***	-0.969***	-1.519***	-1.387***	-1.005**
	[0.435]	[0.371]	[0.429]	[0.402]	[0.447]
30 – 39	-2.673***	-2.277***	-3.153***	-2.895***	-2.371***
	[0.469]	[0.363]	[0.453]	[0.433]	[0.456]
40 – 49	-1.715***	-1.243***	-2.453***	-2.211***	-1.736***
	[0.452]	[0.367]	[0.405]	[0.366]	[0.405]
50 – 59	-0.037	0.371	-1.057***	-0.866**	-0.474
	[0.493]	[0.433]	[0.396]	[0.353]	[0.388]
60 – 69	1.239	1.371*	-0.154	-0.054	0.14
	[0.778]	[0.706]	[0.602]	[0.605]	[0.533]
70+	3.532***	3.433***	1.502*	1.553*	1.492**
	[0.958]	[0.861]	[0.812]	[0.844]	[0.698]
Female	2.211***	2.229***	1.819***	1.693***	1.733***
	[0.182]	[0.173]	[0.152]	[0.155]	[0.167]
Hispanic	-0.883	-0.05	-0.868**	-0.940**	-0.293
	[0.724]	[0.382]	[0.351]	[0.370]	[0.215]
Black	0.343	0.654	-0.248	-0.323	0.238
	[0.496]	[0.439]	[0.336]	[0.345]	[0.303]
Average Outcome			339.9 bps		
Demographic Controls	Y	Y	Y	Y	Y
Month × Grid FE	Y	Y	Y	Y	Y
County FE	-	Y	-	-	-
Lender FE	-	-	Y	-	-
Month × Lender FE	-	-	-	Y	-
Lender × County FE	-	-	-	-	Y
Observations	657,963	657,731	657,867	653,116	627,069
R-squared	0.82	0.83	0.84	0.85	0.86

Table 9: Age, Sex, and Coupon Rate

This table reports OLS regression results where coupon rate is regressed on applicant's age. The sample includes mortgages that were originated and sold to Fannie Mae or Freddie Mac. The dependent variable is the coupon rate on the mortgage, reported in basis points. Age is the applicant's age in years at the time of application. 70+ is an indicator variable that equals 1 if the applicant is older than 69 years old. Female is an indicator variable that equals one if the application is associated with a female borrower. Columns 1 and 2 present regression results for home purchase mortgages. Columns 3 and 4 present regression results for rate-and-term refinance mortgages. The sample used in columns 2 and 4 excludes applications associated with applicants whose sexes are unknown. All specifications include the full set of demographic controls and month by Fannie Mae's LLPA grid fixed effects. Refer to the Appendix for a detailed discussion of control variables and variable definitions. Heteroskedasticity-robust standard errors are clustered at the lender level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data source: CHMDA.

	(1)	(2)	(3)	(4)
Age	0.16***	0.15***	0.09***	0.09***
	[0.01]	[0.01]	[0.02]	[0.02]
Age × 70+	0.12***	0.13**	0.08**	0.06
	[0.04]	[0.06]	[0.04]	[0.06]
Age × Female		0.01		-0.02***
		[0.01]		[0.01]
Age × Female × 70+		-0.03		0.04
		[0.07]		[0.06]
Loan Purpose	Home Purchase		Refinance	
Demographic Controls	Y	Y	Y	Y
Month × Grid FE	Y	Y	Y	Y
Observations	1,723,309	1,617,229	1,148,933	1,037,100
R-squared	0.86	0.86	0.82	0.82

A Appendix

A.1 CHMDA Definition of Simple and Cash-Out Refinance Mortgages

The following definitions are gathered from "A Guide to HMDA Reporting: Getting It Right!" The document is available at `https://www.ffiec.gov/hmda/pdf/2021Guide.pdf`. All analyses presented in this paper exclude line of credit.

Refinancing – A Refinancing is a Closed-End Mortgage Loan or Open-End Line of Credit in which a new Dwelling-secured debt obligation satisfies and replaces an existing Dwelling-secured debt obligation by the same borrower. 12CFR 1003.2(p). Generally, whether the new debt obligation satisfies and replaces an existing obligation is determined by reference to the parties' contract and applicable law. In order for a Covered Loan to be a Refinancing, both the new and existing transactions must be secured by a Dwelling. Only one borrower need be the same on the new and existing transactions. Comments 2(p)-1, -3, and -4.

Cash-out Refinancing – A Financial Institution reports a Covered Loan or an Application as a cash-out Refinancing if it is a Refinancing and the Financial Institution considered it to be a cash-out Refinancing when processing the Application or setting the terms under its or an investor's guidelines. For example, if a Financial Institution considers a loan product to be a cash-out Refinancing under an investor's guidelines because of the amount of cash received by the borrower at closing or account opening, it reports the transaction as a cash-out Refinancing. If a Financial Institution does not distinguish between a cash-out Refinancing and a Refinancing under its own guidelines, sets the terms of all Refinancings without regard to the amount of cash received by the borrower at loan closing or account opening, and does not offer loan products under investor guidelines, it reports all Refinancings as Refinancings, not cash-out Refinancings. Comment 4(a)(3)-2.

A.2 Additional Details on Borrower Age Under Regulation B

This section discusses additional details on the way in which, with respect to Regulation B, borrower age could be considered under an empirically driven credit scoring system.

The Official Staff Comment for 1002.6(b)(2)-2 states that "age may be taken directly into account in a credit scoring system that is "demonstrably and statistically sound," as defined in § 1002.2(p), with one limitation: Applicants age 62 years or older must be treated at least as favorably as applicants who are under age 62. If age is scored by assigning points to an applicant's age category, elderly applicants must receive the same or a greater number of points as the most favored class of non-elderly applicants."

Per the Official Staff Comment for 1002.6(b)(2)-2.i, a credit scoring system is considered to use age as predictive factor if it "segment[s] the population and use[s] different scorecards based on the age of an applicant." An exception to the requirement that the credit scoring system does not make elderly applicants worse off is when the system "uses a [credit scoring] card covering a wide age range that encompasses elderly applicants" because, in this case, "the credit scoring system is not deemed to score age." In either case, section § 1002.11(b)(1)(iv) of Regulation B, as referenced in the main text, implies that age, nonetheless, could be considered "in an empirically derived, demonstrably and statistically sound, credit scoring system to determine a pertinent element of creditworthiness."

A.3 Regression Variable Definition

This section lists all explanatory variables that I include in the regressions presented in this paper. The non-demographic control variables (e.g., non-age, non-sex, non-race, non-ethnicity related variables) are excluded from all LLPA grid regressions.

Age Group Indicator Variables – A set of indicator variables that captures the age group in which the applicant associated with each loan application belongs to. The age groups are 18 to 24, 25 to 29, 30 to 39, 40 to 49, 50 to 59, 60 to 69, 70 or older, and missing age. The regression uses loans associated with applicants in the first age group as the reference group. The missing age group indicator variable is included in the estimation but omitted from the regression outputs.

Age – The applicant's age in years.

70+ – An indicator variable that equals 1 if the applicant is older than 69 years old and zero otherwise.

Credit Score Indicator Variables – Applications are sorted into groups according to the applicant's credit score value. The reference group is made up of applications with credit score values that are less than 580. The remaining groups are formed by twenty-point increments of credit score values up to 759. The final group is made up of applicants who have credit scores greater than 759. Applications associated with applicants who have missing credit score values form a separate group.

CLTV Indicator Variables – Applications are sorted into groups according to the loan's CLTV value. The reference group is made up of applications with CLTV values between 0 and 60. The remaining groups are formed by five-point increments of CLTV values up to 104. The final group is made up of loans with CLTV values greater than 104. Loans that have negative or missing CLTV values form a separate group.

Loan Term Indicator Variables – Applications are sorted into group according to the requested loan's term. The reference group is made up of applications with loan term values that are shorter than 180 months. The remaining groups are: $180 \leq \text{term} < 240$, $240 \leq \text{term} < 360$, $\text{term} = 360$, and $\text{term} > 360$.

DTI Indicator Variables – Applications are sorted into groups according to the loan's DTI value. The reference group is made up of applications with DTI values between 0 and 35. The remaining groups are formed by two-point increments of DTI values up to 49. The final group is made up of loans with DTI values greater than 49. Loans that have missing DTI values form a separate group.

Income Indicator Variables – Applications are sorted into groups according to the applicant's annual income. The reference group is made up of applications with income values between 0 and \$25,000. The remaining groups are formed by \$25,000 increments of income values up to \$249,999. The final group is made up of loans with income values greater than \$249,999. Loans that have missing income values form a separate group.

Loan Amount Indicator Variables – Applications are sorted into groups according to the loan amount. The reference group is made up of applications with loan amounts between 0 and \$50,000. The remaining groups are formed by \$50,000 increments of loan amounts up to \$749,999. The final group is made up of loans with loan amounts greater than \$749,999.

Other Loans – An indicator variable that equals one if, besides the loan under consideration, the property has other loans associated with it and zero otherwise. This information can be inferred from comparing the loan's LTV ratio with the given CLTV ratio. When the CLTV ratio is larger than the LTV ratio, the situation implies that there is other debt associated with the same property, which is the case where Other Loans would equal to one.

Smaller Debt – An indicator variable that equals one if there is other debt associated with the property and the loan under consideration has a smaller amount than the other outstanding debt and zero otherwise. Using the same comparison as to the construction of Other Loans, the amount of the "other debt" can be calculated and when the amount of debt under consideration is smaller than the amount of the "other debt," then Smaller Debt would equal one.

LTV > CLTV – An indicator variable that equals one if the LTV on the loan under consideration is larger than the CLTV and zero otherwise. LTV is different from the CLTV because CLTV includes other loans that are associated with the property. The situation where LTV is larger than CLTV can arise due to data error or when the property is under-appraised and the lender required that the appraised value be used to calculate CLTV instead of the sale price.

Subordinated Lien – An indicator variable that equals one if the loan is secured by a subordinated lien and zero otherwise.

Prepayment Penalty – An indicator variable that equals one if the loan has a prepayment penalty clause and zero otherwise.

Second Home – An indicator variable that equals one if the loan is associated with a second home and zero otherwise.

Investment Home – An indicator variable that equals one if the loan is associated with an investment property and zero otherwise.

Multiple Units – An indicator variable that equals one if the loan is associated with a property that has more than one housing unit and zero otherwise.

HOEPA – An indicator variable that equals one if the loan is considered to be a high-cost loan under the Home Ownership and Equity Protection Act (HOEPA) and zero otherwise.

Business Purpose – An indicator variable that equals one if the applicant states that the loan is meant for business or commercial purpose and zero otherwise.

Balloon Payment – An indicator variable that equals one if the loan has a balloon payment feature and zero otherwise.

Interest-Only Payment – An indicator variable that equals one if the loan is an interest-only payment loan and zero otherwise.

Negative Amortization – An indicator variable that equals one if the loan has a negative amortization feature and zero otherwise. The reference group is composed of loans that are exempted from reporting this feature.

No Negative Amortization – An indicator variable that equals one if the loan has no negative amortization feature and zero otherwise. The reference group for this variable and *Negative Amortization* contains loans that are exempted from reporting this feature.

Non-Fully Amortizing Feature – An indicator variable that equals one if the loan has non-fully amortizing features and zero otherwise. The reference group is composed of loans that are exempted from reporting this feature.

No Non-Fully Amortizing Feature – An indicator variable that equals one if the loan has no non-fully amortizing features and zero otherwise. The reference group is composed of loans that are exempted from reporting this feature.

Female – An indicator variable that equals one if there is at least one female applicant associated with the loan application and zero otherwise.

Asian – An indicator variable that equals one if there is at least one Asian applicant associated with the loan application and zero otherwise.

Black – An indicator variable that equals one if there is at least one Black applicant associated with the loan application and zero otherwise.

Hispanic – An indicator variable that equals one if there is at least one Hispanic applicant associated with the loan application and zero otherwise.

Other Minority – An indicator variable that equals one if there is at least one minority applicant who is not Asian or Black associated with the loan application and zero otherwise.

Unknown sex – An indicator variable that equals one if there is at least one applicant whose sex is unknown and zero otherwise.

Unknown Race – An indicator variable that equals one if there is at least one applicant whose race is unknown and zero otherwise.

Unknown Ethnicity – An indicator variable that equals one if there is at least one applicant whose ethnicity is unknown and zero otherwise.

Manufactured Home – An indicator variable that equals one if the property associated with the loan is a manufactured home and zero otherwise.

FSA Loan – An indicator variable that equals one if the loan is a USDA Farm Service Agency guaranteed loan and zero otherwise.

FHA Loan – An indicator variable that equals one if the loan is a Federal Housing Agency guaranteed loan and zero otherwise.

VA Loan – An indicator variable that equals one if the loan is a U.S. Department of Veterans Affairs guaranteed loan and zero otherwise.

Ineligible – An indicator variable that equals one if the loan amount exceeds the conforming loan limit for the associated property's county and year or is determined by at least one AUS that the loan is not eligible to be purchased by the GSEs and zero otherwise.

AUS Approved – An indicator variable that equals one if the loan application was approved by at least one AUS and zero otherwise.

ARM – An indicator variable that equals one if the loan is an adjustable rate loan and zero otherwise. The variable is constructed from the variable INTRO RATE PERIOD, which indicates the number of months until the first date the coupon rate may change after account opening.

Unknown ARM Status – An indicator variable that equals one if there is insufficient information to indicate whether the loan is fixed rate or adjustable rate and zero otherwise. The variable is constructed from the variable INTRO RATE PERIOD, which indicates the number of months until the first date the coupon rate may change after account opening. Unknown ARM equals one if INTRO RATE PERIOD is negative or missing.

A.4 Appendix Figures

Figure A1: Fannie Mae LLPA Grid

This figure presents Fannie Mae's loan-level price adjustment grid, also called Exhibit 19, for eligible mortgages backed by single-family homes. This information was published on April 6, 2022. The information in this grid has not changed since 2018. This information is used to construct the LLPA grid fixed effects that are included in the rejection and coupon rate regressions presented in the main text. Data source: Fannie Mae.

Table 1: All Eligible Loans – LLPA by Credit Score/LTV Ratio

Representative Credit Score	LTV Range									
	Applicable for all loans with terms greater than 15 years									
	≤ 60.00%	60.01 – 70.00%	70.01 – 75.00%	75.01 – 80.00%	80.01 – 85.00%	85.01 – 90.00%	90.01 – 95.00%	95.01 – 97.00%	>97.00%	SFC
≥ 740	0.000%	0.250%	0.250%	0.500%	0.250%	0.250%	0.250%	0.750%	0.750%	N/A
720 – 739	0.000%	0.250%	0.500%	0.750%	0.500%	0.500%	0.500%	1.000%	1.000%	N/A
700 – 719	0.000%	0.500%	1.000%	1.250%	1.000%	1.000%	1.000%	1.500%	1.500%	N/A
680 – 699	0.000%	0.500%	1.250%	1.750%	1.500%	1.250%	1.250%	1.500%	1.500%	N/A
660 – 679	0.000%	1.000%	2.250%	2.750%	2.750%	2.250%	2.250%	2.250%	2.250%	N/A
640 – 659	0.500%	1.250%	2.750%	3.000%	3.250%	2.750%	2.750%	2.750%	2.750%	N/A
620 – 639	0.500%	1.500%	3.000%	3.000%	3.250%	3.250%	3.250%	3.500%	3.500%	N/A
< 620[1]	0.500%	1.500%	3.000%	3.000%	3.250%	3.250%	3.250%	3.750%	3.750%	N/A

Figure A2: Freddie Mac Credit Fee Grid

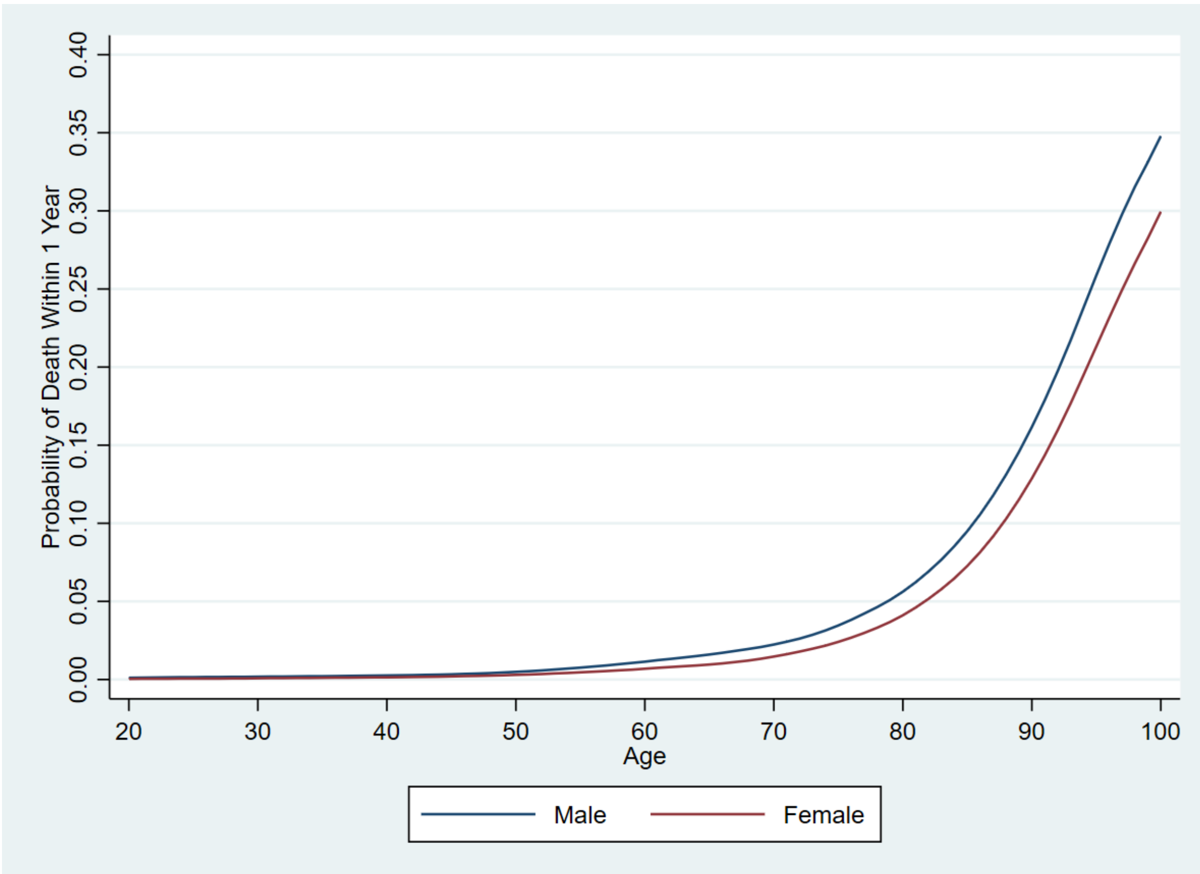
This figure presents Freddie Mac's loan-level credit fee grid for eligible mortgages backed by single-family homes published. This information was published on May 4, 2022. The information in this grid has not changed since 2018. This information is used to construct the loan-level pricing grid fixed effects that are included in the rejection and coupon rate regressions presented in the Appendix. Data source: Freddie Mac.

INDICATOR SCORE / LOAN-TO-VALUE [1, 2, 3]

Product	Credit Score [1, 2]	LTV Ratios							
		All Eligible							
		≤ 60%	> 60% & ≤ 70%	> 70% & ≤ 75%	> 75% & ≤ 80%	> 80% & ≤ 85%	> 85% & ≤ 90%	> 90% & ≤ 95%	> 95%
All Eligible Product	≥ 740	0.00%	0.25%	0.25%	0.50%	0.25%	0.25%	0.25%	0.75%
	≥ 720 & < 740	0.00%	0.25%	0.50%	0.75%	0.50%	0.50%	0.50%	1.00%
	≥ 700 & < 720	0.00%	0.50%	1.00%	1.25%	1.00%	1.00%	1.00%	1.50%
	≥ 680 & < 700	0.00%	0.50%	1.25%	1.75%	1.50%	1.25%	1.25%	1.50%
	≥ 660 & < 680	0.00%	1.00%	2.25%	2.75%	2.75%	2.25%	2.25%	2.25%
	≥ 640 & < 660	0.50%	1.25%	2.75%	3.00%	3.25%	2.75%	2.75%	2.75%
	≥ 620 & < 640	0.50%	1.50%	3.00%	3.00%	3.25%	3.25%	3.25%	3.50%
	< 620	0.50%	1.50%	3.00%	3.00%	3.25%	3.25%	3.25%	3.75%

Figure A3: Probability of Death Within One Year by Age and Sex

This figure plots the probability of death within one year by age for men and women living in the United States. The blue line plots the probability of death for men and the red line plots the probability of death for women. Data source: Social Security Agency's 2019 Actuarial Life Table.



A.5 Appendix Tables

Table A1: Loan Purpose Distribution Across Age Groups

This table reports the distribution of mortgage application purposes across age groups. Panel A reports the within-column percentages of applications that fall in each loan purpose group. Panel B reports the within-row percentages of applications that fall in each age group. Data source: CHMDA.

Panel A	Percentage of Column Total							
	Total	18-24	25-29	30-39	40-49	50-59	60-69	70+
Column Total	22,040,333	644,146	1,801,227	5,258,593	5,168,253	4,473,641	2,758,945	1,935,528
Home Purchase	40.3%	87.7%	72.5%	50.8%	36.2%	29.5%	24.4%	25.3%
Home Improvement	2.0%	0.6%	0.8%	1.5%	2.1%	2.5%	2.6%	3.2%
Rate-and-Term Refinance	27.1%	7.5%	18.2%	28.0%	30.4%	28.3%	27.4%	26.8%
Cash-out Refinance	15.0%	1.5%	3.8%	9.8%	16.1%	20.2%	21.8%	20.1%
Other	2.2%	0.8%	1.0%	1.7%	2.3%	2.8%	3.0%	2.5%
Not Applicable	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%
Line of Credit (LOC)	13.2%	1.9%	3.7%	8.3%	12.9%	16.7%	20.6%	21.4%
Reverse Mortgage (non LOC)	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.2%	0.5%

Panel B	Percentage of Row Total							
	Row Total	18-24	25-29	30-39	40-49	50-59	60-69	70+
Home Purchase	8,888,876	6.4%	14.7%	30.0%	21.0%	14.8%	7.6%	5.5%
Home Improvement	451,187	0.8%	3.2%	17.3%	24.1%	24.8%	16.1%	13.7%
Rate-and-Term Refinance	5,962,149	0.8%	5.5%	24.7%	26.4%	21.3%	12.7%	8.7%
Cash-out Refinance	3,316,049	0.3%	2.1%	15.5%	25.1%	27.2%	18.1%	11.7%
Other	488,635	1.0%	3.8%	18.1%	24.2%	25.8%	17.0%	10.1%
Not Applicable	8,467	1.5%	4.3%	18.1%	20.6%	15.8%	8.2%	31.6%
Line of Credit (LOC)	2,910,713	0.4%	2.3%	14.9%	22.9%	25.7%	19.5%	14.3%
Reverse Mortgage (non LOC)	14,257	0.0%	0.0%	0.1%	0.1%	0.1%	30.9%	68.7%
Total	22,040,333	2.9%	8.2%	23.9%	23.4%	20.3%	12.5%	8.8%

Table A2: Age and Refinance Application Rejection (2018 – 2019)

This table reports OLS regression results where mortgage application rejection indicator variable is regressed on age group indicator variables. The dependent variable is an indicator variable that equals 100 if the mortgage application is rejected and zero otherwise. The reference group is composed of applications associated with borrowers with ages between 18 and 24 years old. Refer to the Appendix for a detailed discussion of control variables and variable definitions. The sample includes rate-and-term refinance mortgage applications from 2018 and 2019. Heteroskedasticity-robust standard errors are clustered at the lender level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data source: CHMDA.

	(1)	(2)
25 – 29	-0.48	-0.98***
	[0.37]	[0.33]
30 – 39	0.57	-0.49
	[0.43]	[0.40]
40 – 49	1.84***	0.3
	[0.49]	[0.44]
50 – 59	3.40***	1.29***
	[0.59]	[0.45]
60 – 69	4.52***	1.77***
	[0.80]	[0.54]
70+	7.01***	3.29***
	[1.19]	[0.75]
Controls	Y	Y
Tract × Month FE	Y	Y
Lender × Year-Quarter FE	-	Y
Observations	1,546,393	1,536,652
R-squared	0.52	0.59

Table A3: Age and Cash-Out Refinance Application Rejection

This table reports OLS regression results where mortgage application rejection indicator variable is regressed on age group indicator variables. The dependent variable is an indicator variable that equals 100 if the mortgage application is rejected and zero otherwise. The reference group is composed of loan applications associated with borrowers with ages between 18 and 24 years old. Refer to the Appendix for a detailed discussion of control variables and variable definitions. In columns 1 and 2, the sample includes all cash-out refinance applications from 2018 to 2020 and that are associated with properties that have up to 4 housing units. In columns 3 and 4, the sample includes all cash-out refinance applications from 2018 and 2019 and that are associated with properties that have up to 4 housing units. Average Outcome reports the unconditional average of the dependent variable for the sample of qualified observations without accounting for singleton observations that were dropped. Heteroskedasticity-robust standard errors are clustered at the lender level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data source: CHMDA.

	(1)	(2)	(3)	(4)
25 − 29	-1.25**	-1.38**	-0.70	-1.05
	[0.63]	[0.58]	[0.89]	[0.80]
30 − 39	-0.90	-1.61***	-0.87	-1.65**
	[0.73]	[0.61]	[0.88]	[0.76]
40 − 49	-0.10	-1.28**	-0.05	-1.25
	[0.78]	[0.64]	[0.93]	[0.79]
50 − 59	1.13	-0.65	1.13	-0.73
	[0.82]	[0.66]	[0.94]	[0.80]
60 − 69	2.57***	-0.14	2.77***	-0.21
	[0.91]	[0.69]	[1.04]	[0.79]
70+	4.29***	0.81	4.73***	0.96
	[1.13]	[0.81]	[1.23]	[0.84]
Female	-2.15***	-1.69***	-2.16***	-1.71***
	[0.20]	[0.15]	[0.25]	[0.18]
Hispanic	1.77***	1.95***	1.83***	2.16***
	[0.25]	[0.14]	[0.29]	[0.17]
Black	3.73***	2.41***	4.10***	2.81***
	[0.29]	[0.16]	[0.28]	[0.20]
Sample	All	All	2018-9	2018-9
Average Outcome	25.9%		30.2%	
Controls	Y	Y	Y	Y
Tract × Month FE	Y	Y	Y	Y
Lender × Year-Quarter FE	-	Y	-	Y
Observations	2,607,380	2,598,295	1,505,669	1,498,289
R-squared	0.57	0.63	0.58	0.64

Table A4: Borrower Characteristics by Age Group – GSE Purchased Mortgages

This table presents summary statistics on borrower characteristics by age group. The sample is composed of originated mortgages that were sold to Fannie Mae or Freddie Mac. The top panel presents average borrower characteristics by age group for home purchase mortgages. The bottom panel presents average borrower characteristics by age group for refinance mortgages. Annual income, loan amount, and property value are reported in thousands of dollars and adjusted for inflation using 2016 as the base year. Data source: CHMDA.

Home Purchase	18-24	25-29	30-39	40-49	50-59	60-69	70+
Credit Score	733.80	750.49	755.50	750.20	751.50	761.64	774.89
Income	48.88	63.84	82.68	92.99	88.92	73.58	60.40
LTV	90.19	88.82	86.88	84.53	81.72	77.15	73.95
DTI	36.24	36.42	36.57	36.70	36.28	37.15	38.99
Loan Amount	166.36	213.51	259.21	265.63	234.70	200.31	185.15
Property Value	188.17	245.32	305.29	323.13	296.21	268.46	259.77

Refinance	18-24	25-29	30-39	40-49	50-59	60-69	70+
Credit Score	734.42	753.14	762.12	757.02	755.36	762.94	773.37
Income	56.42	72.09	94.46	106.28	100.00	82.02	64.29
LTV	80.18	78.81	74.76	70.93	67.73	64.04	60.71
DTI	35.55	34.53	33.76	33.70	33.99	34.87	37.28
Loan Amount	200.39	240.86	287.92	301.80	278.29	239.53	214.94
Property Value	256.63	313.11	394.94	438.29	425.74	390.08	372.01

Table A5: Age and Coupon Rate on Home Purchase Mortgages (2018 – 2019)

This table reports OLS regression results where coupon rate is regressed on age group indicator variables. The sample includes home purchase mortgages that were originated in 2018 and 2019 and sold to Fannie Mae. The dependent variable is the coupon rate on the loan, reported in basis points. The reference group is composed of loans associated with borrowers with ages between 18 and 24 years old. Each specification includes demographic controls and month by Fannie Mae's LLPA grid fixed effects. Refer to the Appendix for a detailed discussion of control variables. Heteroskedasticity-robust standard errors are clustered at the lender level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data sources: CHMDA and Fannie Mae.

	(1)	(2)	(3)	(4)	(5)
25 – 29	-1.09**	-1.07***	-1.42***	-1.44***	-0.85***
	[0.47]	[0.33]	[0.30]	[0.31]	[0.28]
30 – 39	-1.18	-1.30**	-1.74***	-1.79***	-1.04**
	[0.77]	[0.51]	[0.47]	[0.47]	[0.41]
40 – 49	0.65	0.24	-0.14	-0.16	0.37
	[0.90]	[0.61]	[0.50]	[0.52]	[0.43]
50 – 59	3.06***	2.17***	2.18***	2.22***	2.32***
	[0.80]	[0.52]	[0.41]	[0.42]	[0.35]
60 – 69	6.20***	4.57***	5.25***	5.25***	4.81***
	[0.67]	[0.49]	[0.36]	[0.38]	[0.36]
70+	9.59***	7.43***	8.65***	8.78***	7.92***
	[0.61]	[0.48]	[0.47]	[0.48]	[0.49]
Demographic Controls	Y	Y	Y	Y	Y
Month × Grid FE	Y	Y	Y	Y	Y
County FE	-	Y	-	-	-
Lender FE	-	-	Y	-	-
Month × Lender FE	-	-	-	Y	-
Lender × County FE	-	-	-	-	Y
Observations	531,627	531,454	531,573	528,327	505,371
R-squared	0.62	0.64	0.68	0.70	0.72

Table A6: Age and Coupon Rate on Refinance Mortgages (2018 – 2019)

This table reports OLS regression results where coupon rate is regressed on age group indicator variables. The sample includes rate-and-term refinance mortgages that were originated in 2018 and 2019 and sold to Fannie Mae. The dependent variable is the coupon rate on the loan, reported in basis points. The reference group is composed of loans associated with borrowers with ages between 18 and 24 years old. Each specification includes demographic controls and month by Fannie Mae's LLPA grid fixed effects. Refer to the Appendix for a detailed discussion of control variables. Heteroskedasticity-robust standard errors are clustered at the lender level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data sources: CHMDA and Fannie Mae.

	(1)	(2)	(3)	(4)	(5)
25 – 29	-3.21***	-3.05***	-3.42***	-3.28***	-3.15***
	[0.86]	[0.74]	[0.70]	[0.71]	[0.67]
30 – 39	-3.67***	-3.37***	-4.14***	-3.99***	-3.52***
	[0.91]	[0.74]	[0.69]	[0.71]	[0.67]
40 – 49	-1.88**	-1.52**	-2.55***	-2.41***	-2.00***
	[0.82]	[0.67]	[0.59]	[0.61]	[0.61]
50 – 59	-0.23	0.06	-1.05*	-0.86	-0.74
	[0.84]	[0.72]	[0.64]	[0.68]	[0.67]
60 – 69	1.11	0.95	0.13	0.25	0.18
	[0.93]	[0.82]	[0.77]	[0.87]	[0.79]
70+	4.00***	3.48***	2.64***	2.56**	2.06**
	[1.08]	[1.02]	[0.96]	[1.13]	[1.02]
Demographic Controls	Y	Y	Y	Y	Y
Month × Grid FE	Y	Y	Y	Y	Y
County FE	-	Y	-	-	-
Lender FE	-	-	Y	-	-
Month × Lender FE	-	-	-	Y	-
Lender × County FE	-	-	-	-	Y
Observations	151,320	150,933	151,215	147,714	135,400
R-squared	0.70	0.71	0.73	0.74	0.77

Table A7: Age and Coupon Rate on Home Purchase Mortgages – Freddie Mac Sample

This table reports OLS regression results where coupon rate is regressed on age group indicator variables. The sample includes originated home purchase mortgages that were sold to Freddie Mac. The dependent variable is the coupon rate on the loan, reported in basis points. The reference group is composed of applications associated with borrowers with ages between 18 and 24 years old. Each specification includes demographic controls and month by Freddie Mac's credit fee grid fixed effects. Refer to the Appendix for a detailed discussion of control variables. Average Outcome reports the unconditional average of the dependent variable for the sample of qualified observations without accounting for singleton observations that were dropped. Heteroskedasticity-robust standard errors are clustered at the lender level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data sources: CHMDA and Freddie Mac.

	(1)	(2)	(3)	(4)	(5)
25 – 29	-1.295***	-0.928***	-1.495***	-1.460***	-0.795***
	[0.318]	[0.231]	[0.252]	[0.237]	[0.240]
30 – 39	-1.851***	-1.418***	-2.276***	-2.204***	-1.354***
	[0.385]	[0.310]	[0.294]	[0.260]	[0.283]
40 – 49	0.177	0.447	-0.528	-0.457	0.231
	[0.419]	[0.398]	[0.363]	[0.323]	[0.375]
50 – 59	2.506***	2.334***	1.879***	1.894***	2.168***
	[0.421]	[0.436]	[0.337]	[0.293]	[0.374]
60 – 69	4.954***	4.170***	4.454***	4.413***	4.196***
	[0.381]	[0.352]	[0.280]	[0.262]	[0.305]
70+	7.996***	6.843***	7.788***	7.783***	7.109***
	[0.427]	[0.343]	[0.318]	[0.353]	[0.289]
Average Outcome			397.66 bps		
Demographic Controls	Y	Y	Y	Y	Y
Month × Grid FE	Y	Y	Y	Y	Y
County FE	-	Y	-	-	-
Lender FE	-	-	Y	-	-
Month × Lender FE	-	-	-	Y	-
Lender × County FE	-	-	-	-	Y
Observations	746,312	746,152	746,272	743,173	718,459
R-squared	0.87	0.87	0.88	0.89	0.89

Table A8: Age and Coupon Rate on Refinance Mortgages – Freddie Mac Sample

This table reports OLS regression results where coupon rate is regressed on age group indicator variables. The sample includes originated rate-and-term refinance mortgages that were sold to Freddie Mac. The dependent variable is the coupon rate on the loan, reported in basis points. The reference group is composed of loans associated with borrowers with ages between 18 and 24 years old. Each specification includes demographic controls and month by Freddie Mac's credit fee grid fixed effects. Refer to the Appendix for a detailed discussion of control variables. Average Outcome reports the unconditional average of the dependent variable for the sample of qualified observations without accounting for singleton observations that were dropped. Heteroskedasticity-robust standard errors are clustered at the lender level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data sources: CHMDA and Freddie Mac.

	(1)	(2)	(3)	(4)	(5)
25 – 29	-1.318***	-0.848*	-1.492***	-1.098**	-1.077**
	[0.476]	[0.443]	[0.441]	[0.466]	[0.439]
30 – 39	-3.460***	-2.636***	-3.481***	-2.985***	-2.722***
	[0.583]	[0.514]	[0.489]	[0.507]	[0.487]
40 – 49	-2.806***	-1.874***	-2.968***	-2.518***	-2.199***
	[0.641]	[0.585]	[0.491]	[0.508]	[0.484]
50 – 59	-1.334**	-0.457	-1.765***	-1.350***	-1.093***
	[0.648]	[0.621]	[0.452]	[0.481]	[0.421]
60 – 69	0.032	0.641	-0.785	-0.473	-0.365
	[0.890]	[0.835]	[0.563]	[0.605]	[0.478]
70+	1.792	2.048*	0.624	1.019	0.797
	[1.214]	[1.134]	[0.784]	[0.815]	[0.665]
Average Outcome			338.03 bps		
Demographic Controls	Y	Y	Y	Y	Y
Month × Grid FE	Y	Y	Y	Y	Y
County FE	-	Y	-	-	-
Lender FE	-	-	Y	-	-
Month × Lender FE	-	-	-	Y	-
Lender × County FE	-	-	-	-	Y
Observations	491,274	490,976	491,223	488,179	467,906
R-squared	0.83	0.84	0.85	0.86	0.86

Table A9: Net Points Purchased Summary Statistics by Age Group

This table reports the average and the standard deviation of the net number of points purchased by each age group. One point would be reported as the integer 1. Net points purchased is calculated as the dollar amount of points that the borrower purchased subtracted by the dollar amount of lender credit that the borrower received. Net dollar amounts are converted to number of points as one percent of loan amount equals to one point. The top panel presents the summary statistics for home purchase mortgages and the bottom panel presents the summary statistics for refinance mortgages. The sample of mortgages used to produce the calculations are the same sample of mortgages that are used to estimate the regressions presented in Tables ?? and ??. Data source: CHMDA.

Home Purchase	n	Mean	S.D.
18 – 24	99,538	0.01	0.76
25 – 29	287,137	0.03	0.72
30 – 39	562,087	0.06	0.71
40 – 49	345,383	0.09	0.72
50 – 59	240,393	0.11	0.75
60 – 69	135,944	0.12	0.77
70+	53,471	0.09	0.76

Refinance	n	Mean	S.D.
18 – 24	9,615	0.11	0.82
25 – 29	82,689	0.08	0.81
30 – 39	352,178	0.08	0.81
40 – 49	308,981	0.13	0.84
50 – 59	211,014	0.22	0.88
60 – 69	128,307	0.36	0.95
70+	56,781	0.45	1.00

Table A10: Age and Coupon Rate on Home Purchase Mortgages (Points-Adjusted)

This table reports OLS regression results where coupon rate is regressed on age group indicator variables. The sample includes originated home purchase mortgages that were sold to Fannie Mae. The dependent variable is the coupon rate on the loan, reported in basis points, adjusted for the number of points that the borrower purchased. One percent of the loan amount is equal to one point. Following Bartlett et al. (2022), each point adds 12.5 basis points to the coupon rate. The reference group is composed of loan applications associated with borrowers with ages between 18 and 24 years old. Each specification includes demographic controls and month by Fannie Mae's LLPA grid fixed effects. Refer to the Appendix for a detailed discussion of control variables. Average Outcome reports the sample's unconditional average of the dependent variables. Heteroskedasticity-robust standard errors are clustered at the lender level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data sources: CHMDA and Fannie Mae.

	(1)	(2)	(3)	(4)	(5)
25 – 29	-0.962**	-0.864***	-1.371***	-1.308***	-0.802***
	[0.413]	[0.286]	[0.316]	[0.317]	[0.283]
30 – 39	-1.131*	-1.126***	-1.912***	-1.849***	-1.138***
	[0.609]	[0.415]	[0.487]	[0.476]	[0.421]
40 – 49	0.771	0.529	-0.328	-0.278	0.24
	[0.669]	[0.485]	[0.461]	[0.454]	[0.398]
50 – 59	3.250***	2.559***	2.064***	2.069***	2.221***
	[0.628]	[0.500]	[0.302]	[0.304]	[0.274]
60 – 69	6.242***	4.884***	5.154***	5.071***	4.797***
	[0.737]	[0.659]	[0.341]	[0.358]	[0.354]
70+	9.131***	7.390***	8.132***	8.028***	7.428***
	[0.682]	[0.636]	[0.482]	[0.505]	[0.510]
Demographic Controls	Y	Y	Y	Y	Y
Month × Grid FE	Y	Y	Y	Y	Y
County FE	-	Y	-	-	-
Lender FE	-	-	Y	-	-
Month × Lender FE	-	-	-	Y	-
Lender × County FE	-	-	-	-	Y
Observations	977,423	977,316	977,365	972,940	939,903
R-squared	0.86	0.86	0.88	0.89	0.89

Table A11: Age and Coupon Rate on Refinance Mortgages (Points-Adjusted)

This table reports OLS regression results where point-adjusted coupon rate is regressed on age group indicator variables. The sample includes originated rate-and-term refinance mortgages that were sold to Fannie Mae. The dependent variable is the coupon rate on the loan, reported in basis points, adjusted for the number of points that the borrower purchased. One percent of the loan amount is equal to one point. Following Bartlett et al. (2022), each point adds 12.5 basis points to the coupon rate. The reference group is composed of loan applications associated with borrowers with ages between 18 and 24 years old. Each specification includes demographic controls and month by Fannie Mae's LLPA grid fixed effects. Refer to the Appendix for a detailed discussion of control variables. Average Outcome reports the sample's unconditional average of the dependent variables. Heteroskedasticity-robust standard errors are clustered at the lender level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data sources: CHMDA and Fannie Mae.

	(1)	(2)	(3)	(4)	(5)
25 – 29	-0.888*	-0.416	-1.532***	-1.454***	-0.936*
	[0.460]	[0.391]	[0.488]	[0.472]	[0.495]
30 – 39	-2.343***	-1.567***	-3.354***	-3.150***	-2.395***
	[0.508]	[0.403]	[0.550]	[0.539]	[0.543]
40 – 49	-1.015	-0.147	-2.559***	-2.381***	-1.670***
	[0.617]	[0.579]	[0.482]	[0.455]	[0.480]
50 – 59	1.619*	2.366**	-0.611	-0.497	0.021
	[0.950]	[0.951]	[0.469]	[0.441]	[0.447]
60 – 69	4.845***	5.039***	1.642*	1.635*	1.615**
	[1.763]	[1.640]	[0.936]	[0.958]	[0.741]
70+	8.768***	8.551***	4.374***	4.302***	3.794***
	[2.209]	[1.994]	[1.308]	[1.370]	[0.995]
Demographic Controls	Y	Y	Y	Y	Y
Month × Grid FE	Y	Y	Y	Y	Y
County FE	-	Y	-	-	-
Lender FE	-	-	Y	-	-
Month × Lender FE	-	-	-	Y	-
Lender × County FE	-	-	-	-	Y
Observations	657,963	657,731	657,867	653,116	627,069
R-squared	0.82	0.82	0.85	0.86	0.87