Disparities in Mortgage Denials Based on Race and Debt-to-Income Ratio in Massachusetts and Worcester County

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Abstract

In the United States, homeownership provides economic stability, wealth accumulation, and intergenerational mobility. However, achieving equitable homeownership faces systemic discrepancies and discriminatory practices, including disparities in loan denials based on race. This study, utilizing 2021 Home Mortgage Disclosure Act data from Massachusetts and Worcester County, investigates disparities in mortgage approval using exploratory and regression analyses with key creditworthiness factors and debt-to-income ratios. The findings contribute to discussions on fair lending and inform policy initiatives on fostering equitable access to homeownership.

Extended Abstract

Homeownership stands as a fundamental pillar of economic stability, wealth accumulation, and intergenerational wealth transfer in the United States. However, achieving equitable homeownership faces significant hurdles due to deep-rooted systemic disparities, discriminatory practices, and exploitative lending. Historical policies such as redlining have ingrained racial inequities in housing access and financial resources, thereby perpetuating substantial wealth disparities between Black and White households. Despite legislative efforts like the Fair Housing Act of 1968, racial discrimination in the housing market persists, manifesting in disparities in mortgage approval rates based on race and socioeconomic factors.

This study contributes to the ongoing discourse by investigating mortgage denial rates in Massachusetts and Worcester County, focusing on socioeconomic determinants, particularly race and debt-to-income ratio (DTI). The analysis encompasses the top four mortgage lenders in these regions and employs logistic regression models to predict loan denial probabilities. By examining the interaction between borrower characteristics and lender policies, the study sheds light on how race and DTI influence mortgage approval outcomes.

Exploratory data analysis reveals disparities in mortgage approval rates, with Black and Native American homebuyers securing mortgages proportionate to their population shares, while Asian/Pacific Islander individuals obtain a larger share. Conversely, Hispanic/Latino borrowers in Worcester County secure a slightly higher proportion of mortgages compared to their population share, contrasting with White borrowers who secure the majority of mortgages in both regions. However, loan denial rates are consistently higher for racial minority groups compared to White applicants, with DTI emerging as a leading reason for denial.

Logistic regression results underscore significant disparities in mortgage approval probabilities, with Native Americans facing the highest likelihood of loan denial in Massachusetts. Black, Asian, and Hispanic/Latino applicants also encounter elevated odds of denial compared to White applicants. The analysis of DTI further reveals stark disparities, with applicants with high DTI (>50%) facing substantially higher odds of denial, particularly evident among Black applicants. Moreover, incorporating lender variables into the regression models indicates lower denial probabilities for all lenders in both regions. The interaction term for race and lender suggests a

reduction in denial probabilities for each racial group compared to the non-interaction term, emphasizing the influence of lender policies on approval outcomes. Similarly, the interaction term for DTI and lender demonstrates variability but lesser effects on denial probabilities, highlighting the complex interplay between borrower attributes and lender practices.

Overall, this study underscores the multifaceted nature of mortgage approval disparities, highlighting the role of race, DTI, and lender policies in shaping access to homeownership. Massachusetts currently has programs aimed at promoting fair lending practices, increasing financial literacy, and addressing systemic barriers to homeownership for marginalized communities in Massachusetts, such as the Community Investment Tax Credit program, Affordable Housing Trust Fund, and the Massachusetts Division of Banks conducting fair lending examinations to ensure compliance with regulations.

To further promote fair lending and equitable access to homeownership, policymakers may consider implementing various measures including expanding down payment assistance programs aimed at low-to-moderate-income households, increasing funding for homeownership counseling services tailored to marginalized communities, and enforcing fair lending laws more rigorously to prevent discriminatory practices. Additionally, initiatives targeting the racial wealth gap, such as providing grants or subsidies to first-time homebuyers from historically marginalized communities, could help reduce disparities in homeownership rates.

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1.0 Introduction

Homeownership serves as a cornerstone of economic stability and wealth accumulation in the United States. However, the journey towards equitable homeownership has been fraught with challenges, marked by systemic disparities, discriminatory practices, and predatory lending (Apgar & Calder, 2005; Harkness, 2016; Kuebler, 2013; NCRC, 2008; Office of Economic Policy, 2023; Rice & Swesnik, 2012; Urban Institute, n.d.; Young et al., 2022). During the 20th century, cities, financial institutions, and the federal government actively engaged in the segregation and deprivation of investment in Black communities and other communities of color (Ramakrishnan et al., 2021). This was accomplished through policies like redlining, which affected thousands of cities. The consequence of limited access to homeownership and other capital forms has contributed to substantial racial disparities in wealth that persist to this day (Fishback et al., 2021; Goodman & Mayer, 2018; Kuebler, 2013; Ky & Lim, 2022; Office of Economic Policy, 2023; Urban Institute, n.d.).

The typical Black household now holds less than a quarter (23.3%) of the wealth of a typical white household, a decline from over a third (34.6%) before the Great Recession. Housing disparities contribute significantly to the overall $3 trillion median Black-white wealth gap, constituting 38.4% (approximately $1.18 trillion) of this disparity (Manhertz, 2021). Both differences in homeownership and home values contribute equally to the housing portion of the overall Black-white wealth gap. Figure 1 demonstrates how eliminating these housing disparities could potentially reduce the wealth gap to $1.8 trillion. The gap would remain substantial, considering other wealth inequities beyond housing (Manhertz, 2021).

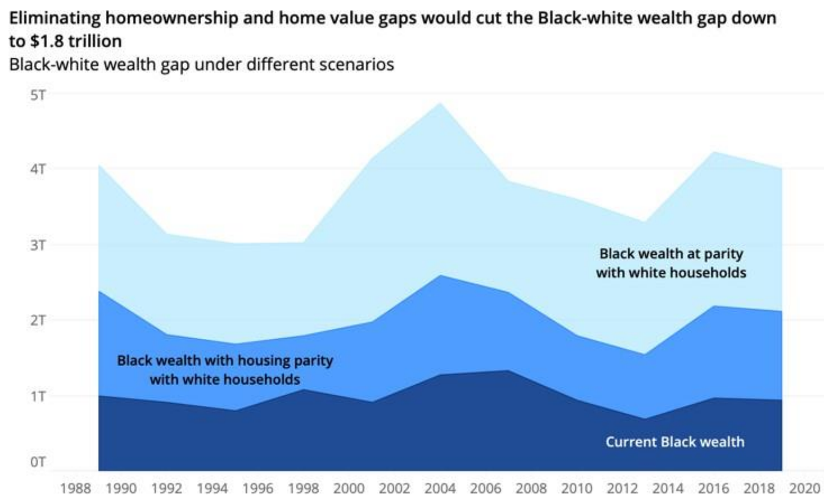


Figure 1. Homeownership and the Black-white wealth gap (Manhertz, 2021)

The Fair Housing Act was passed in 1968 and aimed to eradicate explicit discrimination and inequalities within the housing market, with the overarching goal of eradicating residential segregation (Zonta, 2019). Studies have shown that since then, overt racial housing discrimination has declined but discrimination persists; individuals of color are more likely to face mortgage denials or higher interest rates even when their income and creditworthiness are similar to white applicants. (Apgar & Calder, 2005; Bhutta et al., 2022; Bhutta & Hizmo, 2019; Campen et al., 2007; Cherian, 2014; Kuebler, 2013; Popick, 2022; Zonta, 2019). Martinez & Kirchner (2021) recently found in their study that White applicants were being approved disproportionately versus applicants of color with the same debt-to-income ratio (DTI), a significant measure in the mortgage application approval process (Bank of America, n.d.; CFPB, 2023b; JPMorgan Chase, n.d.), at all levels.

This study contributes to the discourse by examining mortgage denial rates in Massachusetts and Worcester County, focusing on socioeconomic and financial factors, particularly race and DTI. The terms "loan" and "mortgage" are used interchangeably throughout. It begins with an overview of homeownership disparities, discussing the legacy of redlining and racial homeownership gaps. Using 2021 Home Mortgage Disclosure Act data, the analysis explores the share of home loans by population and race, denial reasons by race, and top lenders. Four logistic regression models predict loan denial, incorporating sociodemographic variables, lenders, and interaction terms with race and DTI.

Results show disparities for minority groups compared to Whites, highlighting the influence of lenders and borrower characteristics on denial likelihood. Native Americans in Massachusetts face a statistically significant 2.1 times higher likelihood of loan denial, albeit from a small sample size, while all Native American applicants in Worcester County were approved, thus omitted from the analysis. Black applicants face a significant disadvantage, being 2.5 times more likely to face mortgage denial in Massachusetts and 1.8 times more likely in Worcester County compared to White applicants. Similarly, Asian and Hispanic or Latino applicants also encounter elevated odds of denial, indicating the presence of racial and ethnic disparities in mortgage approval processes across both regions.

Furthermore, the DTI analysis revealed increased odds of denial for those with a DTI >50% compared to those with a healthy DTI ≤ 35%, as they are 49.7 and 67.5 times as likely to be denied a loan. However, White applicants were approved 38% of the time, whereas Black applicants received approval only 18% of the time with a DTI >50%. Adding the lender variable to the logistic regression equation indicated lower chances of denial for the top four lenders in both Massachusetts and Worcester County compared to the other lenders in the data. This effect is the same for all lender-race and lender-DTI interaction terms when compared to the non-interaction terms. These results highlight how different factors, such as the lender involved and borrower attributes such as race and debt-to-income ratio, influence the likelihood of loan denial.

These results suggest that in Massachusetts, disparities in loan approval rates are glaring, with Native Americans, Black, Asian/Pacific Islanders, and Hispanic/Latino applicants facing elevated odds of denial compared to their White counterparts. Examination of debt-to-income ratios uncovers further inequities, particularly evident among Black applicants, where those with a high DTI (>50%) encounter significantly higher odds of denial.

Massachusetts currently has programs aimed at promoting fair lending practices, increasing financial literacy, and addressing systemic barriers to homeownership for marginalized communities in Massachusetts, such as the Community Investment Tax Credit program incentivizing support for affordable housing and financial education, the Affordable Housing Trust Fund supporting the development of affordable housing units, and the Massachusetts Division of Banks conducting fair lending examinations to ensure compliance with regulations.

To further promote fair lending and equitable access to homeownership, policymakers may consider implementing various measures including expanding down payment assistance programs aimed at low-to-moderate-income households, increasing funding for homeownership counseling services tailored to marginalized communities, and enforcing fair lending laws more rigorously to prevent discriminatory practices. Additionally, initiatives targeting the racial wealth gap, such as providing grants or subsidies to first-time homebuyers from historically marginalized communities, could help reduce disparities in homeownership rates (Apgar & Calder, 2005; Harkness, 2016; NCRC, 2008; Ross & Massachusetts Alliance Against Predatory Lending, 2011; Zinn & Reynolds, 2022).

2.0 Background

This chapter summarizes the multidimensional landscape of homeownership, focusing on its significance, racial gaps, and the lasting impact of historical redlining. The analysis extends to Boston and Worcester, detailing the specific legacies in these cities. It describes persisting discrimination through disparities in loan origination, exploring the role of HMDA data as a research tool.

2.1 The Significance of Homeownership

Homeownership is a fundamental component of the American dream, a marker of socioeconomic status, and helps Americans build wealth (Kuebler, 2013; Ramakrishnan et al., 2021; Yun & Evangelou, 2016). Homeownership is the best path for most people to build financial assets and attain wealth, particularly critical for those with lower incomes and limited opportunities for alternative investments (Campen et al., 2007; Cherian, 2014; Office of Economic Policy, 2023). Harkness & Newman's study in 2003 affirmed that low-income households derive substantial stability and wealth from homeownership. Notably, home equity constitutes a significant portion of their total assets among minority homeowners (Harkness & Newman, 2003; Kuebler, 2013).

Housing builds assets and wealth when homeowners can afford to buy a home, successfully pay subsequent mortgage payments, and benefit from their home's equity and price appreciation (Ramakrishnan et al., 2021). The Federal Reserve's 2020 Survey of Consumer Finances reports that homeowners have a net worth more than 40 times greater than renters, with a median net worth of $255,000 and $6,300 respectively (Acolin et al., 2021). Furthermore, home prices in the United States have steadily appreciated over the long term. From 1992 to 2023, home prices increased by an average of approximately 5.4% annually (CEIC, 2023). Households not in the top 10% of wealth derive a greater share of their wealth from the equity in their homes compared to their wealth from financial assets, businesses, or other elements of non-retirement wealth (Office of Economic Policy, 2023). Other economic benefits of owning a home include access to leverage, protection against rising rent costs, tax deductions for mortgage interest and property taxes, and low capital gains taxes relative to other investments (Office of Economic Policy, 2023).

Homeownership can provide pathways to upward economic mobility and enables the intergenerational transfer of wealth through asset inheritance, which helps future generations attain homeownership and build wealth, and so on (Cherian, 2014; Ramakrishnan et al., 2021; Young et al., 2022). Homeownership also provides many tangible social benefits including boosting the educational performance of children, higher participation in civic and volunteering activities, improved healthcare outcomes, lowered crime rates, and lessening welfare dependency (Cherian, 2014; Goodman & Mayer, 2018; Yun & Evangelou, 2016).

2.2 Legacy of Discrimination: Homeownership Gaps and Redling

Both historically and presently, the benefits of homeownership have not been shared equally (Apgar & Calder, 2005; Harkness, 2016; Kuebler, 2013; NCRC, 2008; Office of Economic Policy, 2023; Rice & Swesnik, 2012; Urban Institute, n.d.; Young et al., 2022). Figure 2 demonstrates the racial homeowner gaps over time using data from the U.S. Census Bureau. During the second quarter of 2022, the homeownership rate among white households was 75 percent, while it was 45 percent for Black households, 48 percent for Hispanic households, and 57 percent for non-Hispanic households of other races. Like the persistent disparities in overall racial wealth, these discrepancies in homeownership rates have seen minimal change over the past three decades, as illustrated in Figure 2. Notably, the gap between Black and white homeownership rates in 2020 mirrored that of 1970, indicating a lack of significant progress in narrowing this divide (Office of Economic Policy, 2023).

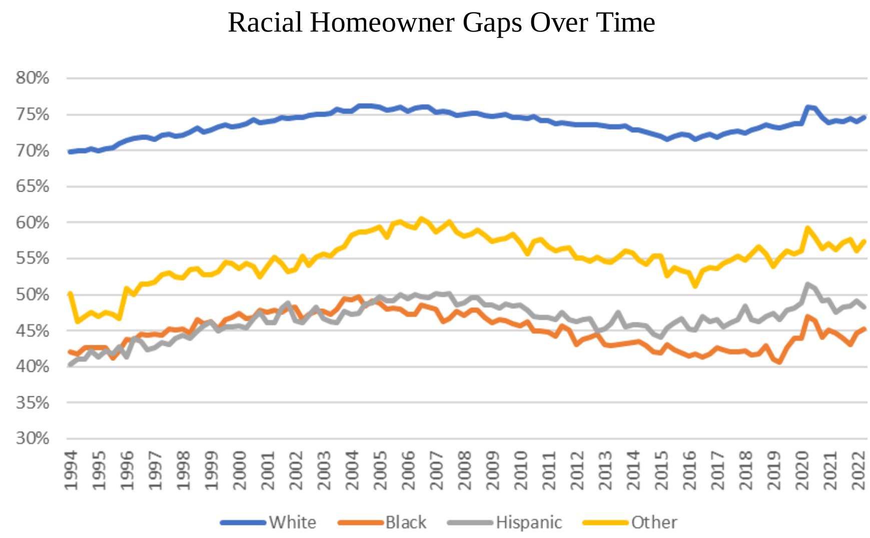


Figure 2. The proportion of all households that are homeowners. Hispanic includes anyone of Hispanic ethnicity regardless of race. Other include people who are Asian, Native Hawaiian or Pacific Islander, American Indian or Alaska Native, and those who report two or more races (U.S. Census Bureau, 2022).

This homeownership gap is attributable to many factors, including socioeconomic and household compositional differences. This includes differences in inheritances, family income, and education (Goodman & Mayer, 2018). On average White males, as opposed to minorities, have higher average salaries, greater wealth, higher levels of education, and a higher probability of being married. These factors collectively contribute to a greater likelihood of White males being homeowners (Campen et al., 2007; Choi et al., 2019; Commonwealth of Massachusett, n.d.; Goodman & Mayer, 2018; Kuebler, 2013; Urban Institute, n.d.).

2.2.1 Redling in Boston and Worcester

Past discriminatory policies and lending practices supported white homeownership, excluding many minority households from similar benefits (Fishback et al., 2021; Goodman & Mayer, 2018; Kuebler, 2013; Ky & Lim, 2022; Office of Economic Policy, 2023; Urban Institute, n.d.). This began as early as the 1930s. There is evidence that the Federal Housing Administration rarely insured loans in low-income, urban neighborhoods, where most Black Americans lived (Best & Mejía, 2022; Fishback et al., 2021; Franco & Mitchell, 2018; Office of Economic Policy, 2023; Ofulue, 2021). Furthermore, the Homeowners' Loan Corporation (HOLC), an agency of the federal government, created hundreds of redlining maps of metropolitan neighborhoods that marked neighborhoods in different colors, designating their suitability for loans. Redlined areas were typically considered high-risk and undesirable for lending. These maps became infamous for perpetuating housing discrimination (Best & Mejía, 2022; De los Santos et al., 2021; Fishback et al., 2021; Franco & Mitchell, 2018; Ofulue, 2021).

Redlining Map of Boston (1935-1940)

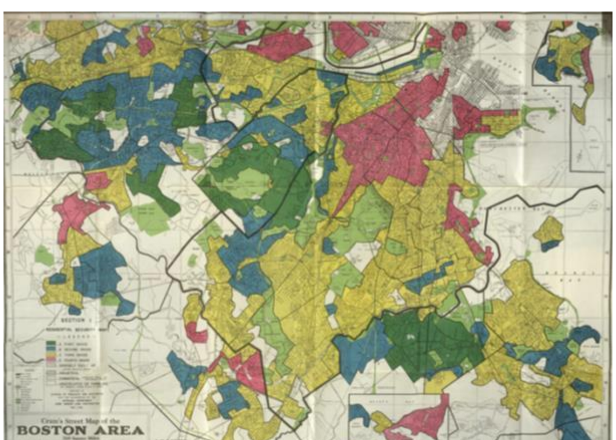


Figure 4. Redlining Map of Boston from 1935-1940 (Commonwealth of Massachusett, n.d.).

Redlining Map of Worcester (1936)

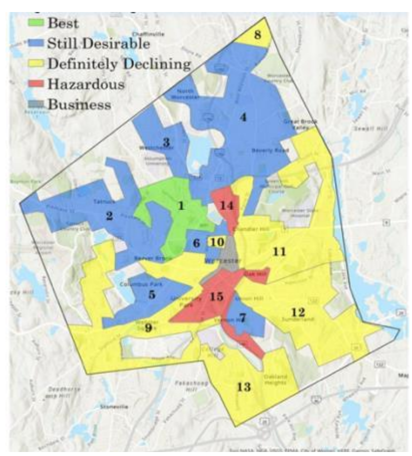


Figure 3. Redlining Map of Worcester (1936) (Worcester Regional Research Bureau, 2022).

In Massachusetts, redlining maps were implemented in major cities like Boston and Worcester, as illustrated in Figures 3 and 4. The color-coded maps signified the “risk” level of different areas, with red indicating hazardous, yellow for declining, blue for desirable, and green for best. Notably, areas labeled “best” received an A grade and were colored green, while those designated “hazardous” received a D grade and were colored red (Fishback et al., 2021; Franco & Mitchell, 2018; Ofulue, 2021; Worcester Regional Research Bureau, 2022).

HOLC ratings for Boston exposed systemic biases, automatically designating areas with Black families as hazardous, irrespective of income. For example, Roxbury, with excellent public transit and schools, was redlined due to the “infiltration of Negros” (Ofulue, 2021). Conversely, a neighborhood in Milton was deemed blue solely because of the presence of "one Negro family" (Ofulue, 2021), while a neighborhood in Jamaica Plains, without Black residents, received a green label. Presently, Boston ranks as the 20th most segregated city in the U.S. according to 2020 Census Data (Othering & Belonging Institute, n.d.). The Index of Dissimilarity in Boston has increased from 60% in 2010 to 68.8% in 2020, underscoring persistent challenges in achieving residential integration and the legacy of redlining (Ofulue, 2021).

In Worcester, the city was divided into 15 neighborhoods during the redlining era, as shown in Figure 3. The southern half, particularly the center, was concentrated in “definitely declining” and “hazardous” categories, including parts of present-day Oak Hill, Canal District, and Green Island neighborhoods. Descriptions of “hazardous” areas in Worcester revealed discriminatory assessments by HOLC assessors, characterizing these zones as “inhabited by the lower class” with residential buildings in “poor condition” (Worcester Regional Research Bureau, 2022). These assessments often included references to specific races and ethnicities, particularly noting immigrant settlements. For instance, HOLC's assessment in Main South, classified as “definitely declining,” mentioned a small Black resident population but noted they were “not spreading to adjacent streets” (Worcester Regional Research Bureau, 2022).

A report from the Worcester Regional Research Bureau (2022) compared the 1936 redlining map to present-day data from the American Community Survey. The study revealed that neighborhoods redlined by HOLC continue to experience higher poverty rates, poorer environmental conditions, lower median incomes, a higher percentage of renters compared to homeowners, and a higher percentage of people of color (Lavery, 2022; Worcester Regional

Research Bureau, 2022). These areas also scored higher on the Social Vulnerability Index, a CDC measurement indicating communities in need of support (Worcester Regional Research Bureau, 2022).

This discriminatory practice introduced a financial dimension to racial segregation. Areas deemed hazardous were denied access to capital investments that could enhance housing and economic opportunities for residents (Commonwealth of Massachusett, n.d.; Franco & Mitchell, 2018; Lavery, 2022; Ofulue, 2021; Worcester Regional Research Bureau, 2022). Despite being banned over 50 years ago the legacy of redlining persists, as reflected in both Boston and Worcester. with disparities between redlined and greenlined areas evident across various aspects of life (Columbia University Mailman School of Public Health, 2021; De los Santos et al., 2021; Franco & Mitchell, 2018; Hanks et al., 2018; Ofulue, 2021). Green areas that received capital investments could advocate for amenities like parks, while redlined areas were targeted for public housing and highways, resulting in hotter environments due to asphalt-heavy construction. The ramifications include food apartheid, educational disparities, and disproportionate policing (Franco & Mitchell, 2018; Ofulue, 2021). Redlining obstructed intergenerational accumulation, widening the socioeconomic gap between Black and white communities (Hanks et al., 2018; Ofulue, 2021).

2.3 Persisting Discrimination through Loan Origination Differences

Enacted in April 1968 as Title VIII of the Civil Rights Act, the Fair Housing Act aimed to eradicate explicit discrimination and inequalities within the housing market, with the overarching goal of eradicating residential segregation. This legislation specifically barred discrimination in the sale or rental of housing, housing financing, and the provision of brokerage services based on an individual's membership in a protected class, encompassing factors such as race, color, and national origin (Zonta, 2019). While overt racial housing discrimination has declined, evidence suggests that discrimination continues to persist (Apgar & Calder, 2005; Bhutta et al., 2022; Bhutta & Hizmo, 2019; Campen et al., 2007; Cherian, 2014; Kuebler, 2013; Popick, 2022; Zonta, 2019).

Research utilizing data from the Home Mortgage Disclosure Act (HMDA) indicates differences in mortgage origination, approval versus denial rates, and unequal access to credit among racial groups (Bhutta et al., 2022; Campen et al., 2007; Cherian, 2014; Federal Reserve Bank of Boston, 1992; Ky & Lim, 2022; NCRC, 2008; Rice & Swesnik, 2012; Zinn & Reynolds, 2022). These studies reveal that individuals of color are more likely to face mortgage denials or higher interest rates, even when their income and creditworthiness are similar to white applicants.

In their 2022 study, Bhutta et al. (2022) demonstrated that even after accounting for variables such as debt-to-income ratio, loan-to-value ratio, income, and the income level of the statistical area, Black and Latino applicants consistently faced higher denial rates compared to their white counterparts within the same neighborhoods. Black applicants were found to be 1.8 to 2.5 times more likely to experience denial than white applicants with similar observable borrower characteristics, while Latino borrowers were 1.5 times as likely to face denial compared to their white counterparts across various neighborhood types. Martinez & Kirchner (2021) had similar findings in their study; financial institutions were almost twice as likely to deny Black applicants conventional mortgages in 2019 compared to White applicants who had similar financial characteristics. Lenders were also more likely to deny Latino, Asian/Pacific Islander, and Native American applicants than their White counterparts when we held the key financial characteristics constant, ranging from 40% to 70% more likely to be denied.

2.3.1 Home Mortgage Disclosure Act (HMDA) Data

The studies mentioned in section 2.3, including works by Bhutta & Hizmo (2019), Cherian (2014), and Popick (2022), use Home Mortgage Disclosure Act (HMDA) data to analyze mortgage lending. HMDA is a legislative act established by Congress in 1975 and mandates that certain lending institutions provide detailed information about mortgage loan applications, including data about the applicants, the loans, the type and location of properties, and the outcomes of loan applications (Bhutta et al., 2022; Cherian, 2014; Popick, 2022). In the words of David Uejio, the acting Director of the Consumer Financial Protection Bureau in 2021, HMDA data “can help pinpoint potential discriminatory lending patterns, and address unjustified disparities in lending outcomes and credit pricing that drive racial and economic inequality” (Consumer Financial Protection Bureau, 2021). It is important to note that HMDA data alone cannot definitively determine the existence of racial disparities in lending or whether individual lenders have violated fair lending laws.

2.3.2 HMDA Data Limitations: Credit Scores

Since 2018, HMDA data fields have included expanded information like the combined loan-to-value ratio, debt-to-income ratio, borrower credit score, and credit factors relevant to loan decisions. Studies conducted before this expansion were limited to illustrating raw, unadjusted disparities between groups (e.g., race and ethnicity), lacking the ability to account for these crucial creditworthiness factors (Popick, 2022). For instance, a study by Glantz & Martinez (2018) relying on 2015-2016 HMDA data revealed higher denial rates for Black, Latino, Asian, and Native American applicants compared to Whites in various cities. However, these results presented raw, unadjusted disparities, potentially overstating the observed differences. (Ky & Lim, 2022; Popick, 2022).

The absence of key creditworthiness factors in pre-2018 studies posed challenges in assessing variations in credit risk resulting from these patterns. For example, credit scores, predicting consumer delinquency or default, serve as a pivotal gatekeeper to loan approval(Campisi, 2021; Consumer Financial Protection Bureau, 2015; NCRC, 2008). The modern credit score system considers various factors, including payment history, amounts owed, credit history length, new credit, and credit mix, and was initially introduced to eliminate bias (Campisi, 2021).

However, research indicates that credit scores do not consistently provide equal opportunity, particularly for people of color. On average, they tend to have lower credit scores, with more than 1 in 5 Black consumers and 1 in 9 Hispanic consumers having FICO scores below 620, compared to 1 out of every 19 white individuals in the sub-620 category (Campisi, 2021). This difference is not attributable to personal actions but is a result of limited time to build comparable credit histories and generational wealth disparities (Campisi, 2021; NCRC, 2008). Furthermore, approximately 45 million Americans are "credit invisible," lacking any credit history with nationwide credit reporting agencies, with higher rates among Black and Hispanic individuals and those residing in low-income neighborhoods. 15% of Black Americans are “credit invisible” compared to 9% of White Americans (Ney, 2021).

To address the limitation of credit factor differences, researchers often had to merge HMDA data with third-party information. Studies like Bhutta & Hizmo (2019) and Bartlett et al. (2022) did this using companies such as Optimal Blue and Black Knight Financial Services, which provide loan performance data, including credit factors of borrowers. Matching is typically based on property address, geographic area (e.g., census tract), loan amount, and other features. Due to differences in reporting, achieving 100 percent matching is not usually possible (Bhutta et al., 2022).

The expanded HMDA data, introduced in 2018, now includes credit-related information that is omitted from the public HMDA data, providing researchers with a more comprehensive tool to analyze how applicants and borrowers experience the mortgage market without the need for complex data matching procedures. A study conducted by Popick (2022) using 2020 expanded HMDA data concluded that interest rate differences between Black and White borrowers persist even at higher credit scores. Complementing this, Ky & Lim (2022) utilized the confidential expanded HMDA data from 2018 to 2020 to illustrate that people of color face higher mortgage application denial rates. Particularly, Black borrowers are 2.9 percentage points more likely to have their mortgage applications denied compared to similar White borrowers, while Asian applicants are 2.2 percentage points more likely to face denial, and Latinx applicants are 1.5 percentage points more likely.

Despite these improvements, limitations in the expanded HMDA data still exist. For instance, it does not provide information on mortgage applicants who shopped for loans, the mortgage products considered, product offerings made by potential lenders, or multiple applications from the same applicant(s) (Bhutta et al., 2022; Cherian, 2014; Ky & Lim, 2022). Additionally, HMDA data do not encompass all the factors used by lenders in pricing or underwriting. There are concerns that variables employed in loan decisions may be racially biased, leading to disparities even after controlling for factors like credit score, debt-to-income ratio, and loan-to-value ratio. These disparities may be attributed to either the importance lenders place on non-HMDA reportable data fields or biases, whether intentional or unintentional (Bhutta et al., 2022; Cherian, 2014; Ky & Lim, 2022).

2.3.3 Debt-to-Income Ratio (DTI) Approval Differences

While credit score is a significant factor in the mortgage application review process, lenders also scrutinize an applicant’s debt-to-income ratio (DTI). DTI is one of the most critical financial variables in loan approval decision-making. According to the Consumer Financial Protection Bureau (CFPB), it is “one way lenders measure your ability to manage the monthly payments to repay the money you plan to borrow” (CFPB, 2023b). Computed by dividing all of the applicant’s monthly debt payments by their gross monthly income, DTI serves as a fundamental indicator of financial health and repayment capacity (Bank of America, n.d.; CFPB, 2023b; JPMorgan Chase, n.d.).

Most lenders prefer a debt-to-income ratio of 36% or less, with optimal financing terms typically available for those achieving a premium level of sub-35% DTI. Falling between 35% and 50% can still make applicants eligible for some approvals. Securing the most stable mortgage features and consistent terms, such as interest rates, according to the Consumer Financial Protection Bureau (CFPB), is achievable with a ratio of monthly debt to income up to 43% (Bank of America, n.d.; CFPB, 2023b; JPMorgan Chase, n.d.; Martinez & Kirchner, 2021). JPMorgan Chase categorizes DTI into four categories: healthy (≤ 35%), manageable (36% - 42%), nearing unmanageable (43% - 49%), and struggling (>50%) (JPMorgan Chase, n.d.).

Using this definition of DTI categories by JPMorgan Chase, Martinez & Kirchner (2021) identified DTI as the most significant predictor in determining mortgage approvals or denials based on their analysis of public data. They discovered that lenders approved Black applicants with "healthy," "manageable," and "nearing unmanageable" DTIs about 80% of the time, while their approval rate for White applicants in those categories was approximately 90%. However, the most glaring contrast emerged in loan approval rates for Black applicants categorized as "struggling," compared to their White counterparts with similar debt burdens. Lenders approved White applicants with a debt-to-income ratio of 50% or more at more than twice the rate as Black applicants in the same category. Furthermore, lending rates were notably lower for Latino, Native American, and Asian/Pacific Islander applicants compared to White applicants in the "struggling" category. Interestingly, lenders tended to approve White applicants with lower income levels and similar DTIs at higher rates than their Black counterparts across the "healthy," "manageable," and "nearing unmanageable" categories. Only in the "struggling" category did lenders approve loans to higher-earning Black applicants at the same rate as less affluent White applicants (Martinez & Kirchner, 2021).

This study by Martinez & Kirchner (2021) introduced a dimension to the existing literature by exploring the significance of DTI in mortgage lending decisions. Similarly, this study aims to contribute to this growing body of research by examining the impact of debt-to-income ratios on mortgage lending decisions.

2.4 Predatory Lending Practices

Predatory lending practices further compound the systemic injustices faced by borrowers of color in the loan approval process. By exploiting vulnerabilities and perpetuating financial exploitation, these practices underscore the need for comprehensive reforms to address both the discriminatory underpinnings of loan approval decisions and the predatory lending tactics that disproportionately harm communities of color. Predatory lending encompasses any discriminatory, unethical, and exploitative lending practices in which financial institutions or lenders take advantage of borrowers (Agarwal et al., 2014; Campen et al., 2007). Often involving high-pressure sales tactics and deceptive strategies, these practices disproportionately affect minority borrowers, pushing them into higher-cost subprime mortgages, setting the stage for future financial challenges (Apgar & Calder, 2005; Campen et al., 2007; Ross & Massachusetts Alliance Against Predatory Lending, 2011).

Once the loan is extended, the lender has the option to sell it to government-sponsored entities (GSEs) like Fannie Mae and Freddie Mac, which utilize mortgages to create mortgage-backed securities for investors on the secondary market (Murray, 2010). The introduction of a secondary market for subprime loans, although potentially advantageous for borrowers, introduces incentives that may contribute to both predatory lending practices and appraisal inflation. The separation of loan ownership from its originator in the secondary market can undermine incentives for responsible lending. Some originators profit from high origination fees, and the ability to quickly resell loans may reduce motivation to ensure borrower repayment.

Additionally, lenders working with brokers who receive up-front fees but do not bear default risks can lead to unscrupulous practices. These circumstances collectively undermine efforts to combat predatory lending in the subprime lending sector (United States General Accounting Office, 2004). Borrowers saddled with unfavorable loan terms may face higher monthly payments, rendering them more vulnerable to short-term economic distress. This vulnerability is exacerbated among borrowers of color, who run a higher risk of foreclosure and accumulate home equity at a much slower pace compared to their White counterparts. (Apgar & Calder, 2005; Campen et al., 2007; Ross & Massachusetts Alliance Against Predatory Lending, 2011). The impact of foreclosures is far-reaching, devastating cities and neighborhoods by eroding local property values, attracting crime, and depleting a city's property tax base (Campen et al., 2007; Ross & Massachusetts Alliance Against Predatory Lending, 2011).

An example of this is the Massachusetts foreclosure crisis and its impacts from the housing value crash in 2006. The foreclosure process initially appeared to target predatory mortgages and communities of color, particularly in inner-city areas. However, the repercussions extended to the entire state. Subprime mortgages played a significant role in the early wave of foreclosures, as they were strategically marketed through specific broker networks in various regions. Internal documents from major mortgage lenders revealed a deliberate targeting of communities and ethnic networks for subprime mortgage marketing, leading to a racial bias in mortgage eligibility and loan modifications (Ross & Massachusetts Alliance Against Predatory Lending, 2011).

Foreclosure consequences are not limited to those who lose their homes; they extend to the entire community and the intergenerational transfer of wealth (Ross & Massachusetts Alliance Against Predatory Lending, 2011). Between 2007 and 2009, the economic losses experienced by Massachusetts residents amounted to a staggering $4.1 billion per month at its worst. Massachusetts as a whole suffered a roughly 20% loss in property value from the height of the housing bubble through 2011 (Ross & Massachusetts Alliance Against Predatory Lending, 2011). Mark Zandi, Moody's chief economist, characterized the foreclosure crisis as the "biggest threat to U.S. economic growth" (Ross & Massachusetts Alliance Against Predatory Lending, 2011). High foreclosure rates undermine not only the financial stability of families but also the overall economic well-being of the communities they are part of. These distressing consequences perpetuate a cycle of neighborhood instability, stigmatization, and financial hardship that lingers long after the initial predatory lending transgressions.

2.5 Denial Likelihood by Race and Debt to Income Ratio in Massachusetts and Worcester County Mortgage Lending

The research goal of this project is to investigate potential discriminatory practices within the mortgage markets of Massachusetts and Worcester County using 2021 Home Mortgage Disclosure Act data. The primary research questions include whether applicants of color were more likely to be denied a mortgage compared to White borrowers, even when possessing similar financial characteristics. Additionally, the study aims to examine whether people are being disproportionally approved at different debt-to-income ratios based on race.

The study will evaluate the likelihood of loan denials based on socioeconomic and financial factors, with a particular focus on race and debt-to-income ratio. Furthermore, the research will investigate denial rates related to debt-to-income ratio using the JPMorgan Chase (n.d.) categories as discussed in section 2.3.2.

By shedding light on these disparities, this research seeks to contribute to the ongoing discourse on fair lending practices and provide insights that may inform policy initiatives aimed at promoting greater equity and transparency within the mortgage lending industry.

3.0 Models and Data Description

The objective of this chapter is to present four logistic regression models. The first model is designed to predict the probability of loan denial based on various demographic and financial variables. The second model adds a lender variable, focusing on the top four lenders operating within Massachusetts and Worcester County. The third model incorporates an interaction term between each lender and each race. The fourth model incorporates an interaction term between each lender and debt-to-income category as defined by JPMorgan Chase (n.d.): healthy (≤ 35%), manageable (36% - 42%), nearing unmanageable (43% - 49%), and struggling (>50%).

3.1 Data Description

The dataset used in this analysis is derived from the 2021 Massachusetts Home Mortgage Disclosure Act (HMDA) data obtained from the Consumer Financial Protection Bureau (CFPB). The most recent download of this dataset was conducted on October 31, 2023. The dataset is limited to first-lien conventional mortgages for home purchase transactions involving one-to-four-unit properties. The focus is on cases where the borrower intends to occupy the property and cases with a clear loan outcome; only loans made, and loans denied. There are 61,245 loans for Massachusetts and 7,360 for Worcester County included. Lenders are identified by the reported LEI code, an identification number for legal entities wishing to participate in international financial transactions, and matched using the LEI search tool by the Global Legal Entity Identifier Foundation.

County names and median property values are extracted from the 2021 American Survey Data and integrated into the dataset. This integration aligns county names in the HMDA dataset and their corresponding median property values. The incorporation of median property values establishes a standardized measure, facilitating the evaluation of relative property values across different cities, towns, and counties.

3.2 Exploratory Data Analysis

Exploratory Data Analysis (EDA) is an initial step in data analysis that involves examining and summarizing data characteristics. This can include data visualization, correlation matrices, and statistical methods to identify patterns, trends, outliers, and relationships within the data. This stage ensures data suitability for analysis by understanding existing patterns and relationships before formal modeling or statistical testing is undertaken (Tiwari, 2023).

Similar to the EDA done by Martinez & Kirchner (2021) and Muñoz (2010) to understand loan characteristics, denial reasons by race, debt-to-income (DTI) approval rates by race, and the share of loans by race in Worcester County and Massachusetts were examined. The Massachusetts' result was compared to the national CFPB 2021 Mortgage Market Activity and Trends report. This approach aims to understand the relationship between race, DTI, and loan approval rates that may not be revealed by the regression models.

3.3 Logistic Loan Denial Model

The loan denial model takes the form of a binary logistic regression model to predict the likelihood of loan denial based on a set of independent variables. The binomial logit is a method for estimating equations with binary (dummy) dependent variables. It avoids the issue of unboundedness present in the linear probability model by using a variant of the cumulative logistic function (Studenmund, 2016). The estimated logistic regression equation is expressed by Equation 1. The dependent variable in the analysis is "Loan Denial," representing loan denials coded as 1 and approvals coded as 0. The coefficients (β) associated with each independent variable signify the change in the log odds of loan denial for a one-unit increase in the respective independent variable, with all other variables held constant. A detailed version of the logistic regression, variable descriptions, and the reference variables used is in Appendix A Tables A1 and A2. This model will be applied to Massachusetts and Worcester County.

(1) Logistic Loan Denial Model

$$\begin{gathered}\mathrm{L{:}\,P(Loan\ Denial)} = \beta_0 + \beta_1\mathrm{Race_i} + \beta_2\mathrm{Sex_i} + \beta_3\mathrm{Age_i} + \beta_4\mathrm{DTI_i} + \\ \beta_5\mathrm{Down\ Payment\ Flag_i} - \beta_6\mathrm{Income_i} + \beta_7\mathrm{Loan\ Amount_i} + \\ \beta_8\mathrm{Property\ Value\ Ratio_i} + \beta_9\mathrm{Co\ Applicant\ Status_i} + \beta_{10}\mathrm{Mortgage\ Term_i} + \\ \beta_{11}\mathrm{Credit\ Model_i} + \beta_{12}\mathrm{AUS_i} + \varepsilon\end{gathered}$$

3.3.1 Variables

For the variable "Race," dummy variables were created for Black, Asian, Native American, Hispanic or Latino, and White applicants. Applicants identifying their ethnicity as Hispanic or Latino, regardless of race, were grouped into the combined category "Hispanic or Latino." Asian and Pacific Islander (PI) applicants were grouped into an "Asian/PI" category. Debt-to-Income Ratio (DTI) categories were categorized into "healthy" (35% or less, reference variable), "manageable" (36% - 42%), "nearing unmanageable" (43% - 49%), and "struggling"

(50% or more) as per JPMorgan Chase (n.d.). The "Down Payment Flag" was introduced to differentiate between applicants based on their combined loan-to-value (LTV) ratio, specifically distinguishing those with an LTV ratio of 80% or lower from others.

Due to right skewness and income concentration at the lower end with outliers, the logarithm of income was used to address these issues. Only records with income greater than zero were included. Similarly, for loan amounts, logarithmic transformation was applied to address right skewness and a wide gap between the lowest and highest loans. Regarding credit scoring models, the FICO 98 version was combined with other FICO models, and the two Vantage models were grouped under the "other" credit model option. Equifax, representing 33.03% of applicants, was chosen as the reference variable due to its prevalence in the dataset.

Table 1 provides an overview of the summary statistics for various variables across different iterations of the loan denial regression, both for Massachusetts and Worcester County. The inclusion of statistics such as observations, minimum and maximum values, mean, standard deviation, and the hypothesized signs provides valuable information about the distribution and characteristics of the variables in the dataset.

Notably, there is a difference in hypothesized signs for DTI ratios between manageable and nearing unmanageable. A manageable DTI (between 36% and 41%) suggests that approval is possible for larger loans or loans with strict lenders, although they would like to see the debt reduced before approval. However, a nearing unmanageable DTI, between 42% and 49%, suggests to lenders that the borrower might not be able to meet payments for another line of credit therefore increasing the odds of denial compared to a manageable DTI (JPMorgan Chase, n.d.).

Table 1. Summary Statistics of Logistic Loan Denial Model for Massachusetts and Worcester County

* Binary variables	(I) Massachusetts						(II) Worcester County					
Variable Name	Obs	Min	Max	Mean	Std Dev	Hypothesized Sign	Obs	Min	Max	Mean	Std Dev	Hypothesized Sign
White*	44,802	0	1	0.73	0.44	-	5,342	0	1	0.8	.40	-
Black*	2,964	0	1	0.05	0.21	+	410	0	1	0.06	.24	+
Hispanic or Latino*	4,696	0	1	0.08	0.27	+	614	0	1	.08	.28	+
Native American*	143	0	1	0.00	0.05	+	15	0	1	0.003	.06	+
Asian/PI*	8,640	0	1	0.14	0.35	+	979	0	1	0.14	.34	+
Male*	36,832	0	1	0.60	0.49	-	4419	0	1	0.60	.49	-
Female*	24,176	0	1	0.40	0.49	+	2910	0	1	0.40	.49	+
Age	61,248	<25	>74	40	15.72	+	7,360	<25	>74	40	13.34	+
DTI	61294	<20%	50% - 60%	20%<30%		+	7361	<20%	50% - 60%	30%<36%		+
Healthy DTI (≤35%)*	30,912	0	1	0.50	0.50	-	3,512	0	1	0.48	0.50	-
Manageable DTI (36% - 42%)*	16,912	0	1	0.28	0.45	-	2,111	0	1	0.29	0.45	-
Nearing unmanageable DTI (43% - 49%)*	11,763	0	1	0.39	0.16	+	1,542	0	1	0.21	0.41	+
Struggling DTI (>50%)*	1,661	0	1	0.03	0.16	+	195	0	1	0.03	0.16	+
Loan to Value Ratio (LTV)	61,206	3.5	196.8	79.66	15.36	+	7,359	4.49	126.51	80.01	14.76	+
Income (in 000's)	61,248	0	13,780	170.9	232.21	-	7,360	0	9,310	150.12	191.93	-
Loan Amount (in 000's)	61,248	5	6935	499.47	328.72	+	7,360	5	2,805	447.17	262.035	+
Property Value Ratio	61,248	.07	10	1.32	.95	-	7,360	.17	9.8	1.59	1.02	-
Co-Applicant Status*	61,248	0	1	.55	.50	-	7,360	0	1	.58	.49	-
Mortgage (Loan) Term	61,248	1	480	352.52	35.14	-	7,360	60	480	353.16	34.54	-
Credit Model	61,248	1	9	2.66	2.14	-	7,360	1	9	2.70	2.16	-
AUS	61,248	1	7	2.08	1.74	-	7,360	1	7	1.88	1.49	-

3.4 Top Four Individual Lender Models with Race and Debt-to-Income Categories

The lender model, Equation 2, includes the same variables as Equation 1 with the addition of a lender variable. The top four lenders for Massachusetts and Worcester County, respectively, were used, and separate regression iterations for each lender provided a clearer understanding of how each lender's policies and practices affect loan denial without the potential confounding effects of including multiple lenders in the same regression model.

(2) Logistic Lender Model Equation

$$\mathrm{L{:}\,P(Loan\ Denial)} = \beta_0 + \beta_1\mathrm{Race_i} + \beta_2\mathrm{Sex_i} + \beta_3\mathrm{Age_i} + \beta_4\mathrm{DTI_i} + \beta_5\mathrm{Down\ Payment\ Flag_i} - \beta_6\mathrm{Income_i} + \beta_7\mathrm{Loan\ Amount_i} + \beta_8\mathrm{Property\ Value\ Ratio_i} + \beta_9\mathrm{Co\ Applicant\ Status_i} + \beta_{10}\mathrm{Mortgage\ Term_i} + \beta_{11}\mathrm{Credit\ Model_i} + \beta_{12}\mathrm{AUS_i} + \beta_{13}\mathrm{Lender_i} + \varepsilon$$

Equation 3 adds a lender and interaction variable for each race, while Equation 4 includes interaction variables for each lender and debt-to-income (DTI) ratio category.

(3) Logistic Lender-Race Interaction

$$\mathrm{L{:}\,P(Loan\ Denial)} = \beta_0 + \beta_1\mathrm{Race_i} + \beta_2\mathrm{Sex_i} + \beta_3\mathrm{Age_i} + \beta_4\mathrm{DTI_i} + \beta_5\mathrm{Down\ Payment\ Flag_i} - \beta_6\mathrm{Income_i} + \beta_7\mathrm{Loan\ Amount_i} + \beta_8\mathrm{Property\ Value\ Ratio_i} + \beta_9\mathrm{Co\ Applicant\ Status_i} + \beta_{10}\mathrm{Mortgage\ Term_i} + \beta_{11}\mathrm{Credit\ Model_i} + \beta_{12}\mathrm{AUS_i} + \beta_{13}\mathrm{(Lender * Race)_i} + \varepsilon$$

(4) Logistic Lender-DTI Ratio Interaction

$$\mathrm{L{:}\,P(Loan\ Denial)} = \beta_0 + \beta_1\mathrm{Race_i} + \beta_2\mathrm{Sex_i} + \beta_3\mathrm{Age_i} + \beta_4\mathrm{DTI_i} + \beta_5\mathrm{LTV_i} - \beta_6\mathrm{Income_i} + \beta_7\mathrm{Loan\ Amount_i} + \beta_8\mathrm{Property\ Value\ Ratio_i} + \beta_9\mathrm{Co\ Applicant\ Status_i} + \beta_{10}\mathrm{Mortgage\ Term_i} + \beta_{11}\mathrm{Credit\ Model_i} + \beta_{12}\mathrm{AUS_i} + \beta_{13}\mathrm{(Lender * DTI\ Category)_i} + \varepsilon$$

In Massachusetts, 436 lending institutions took part in lending, issuing a total of 61,143 loans. In Worcester County, 281 lending institutions different lending institutions participated in lending activities totaling 7,327 loans. Table 2 and Table 3 display the top four lenders for both geographical areas, including their respective number of loans, the share of total loans, and their ranking among the top 100 lenders in the United States according to the 2021 Scotsman Guide.

Table 2. Top Four Massachusetts Lenders

Lender Name	Number of Applications	Number of Loans	Share of Total Loans	2021 Top Overall Lenders Rank in the US
1. Guaranteed Rate, Inc.	4,541	4,401	7.41%	8
2. Leader Bank, National Association	3,930	3,886	6.42%	N/A
3. Fairway Independent Mortgage Corporation	3,107	2,988	5.07%	4
4. United Wholesale Mortgage, LLC	2,342	2,215	3.82%	1

Table 3. Top Four Worcester County Lenders

Lender Name	Number of Applications	Number of Loans	Share of Total Loans	2021 Top Overall Lenders Rank in the US
1. Fairway Independent Mortgage Corporation	584	566	7.93%	4
2. United Wholesale Mortgage, LLC	435	410	5.91%	1
3. Guaranteed Rate, Inc.	374	366	5.08%	8
4. Total Mortgage Services, LLC	345	340	4.69%	N/A

Table 4 includes summary statistics for the top four individual lenders in Massachusetts and key variables such as race, sex, DTI categories, and loan-to-value ratio (LTV). Table 5 includes summary statistics for the top four individual lenders in Worcester County with the same key variable summaries.

Table 4. Top Four Massachusetts Lenders Summary Statistics

Lender Name	**1. Guaranteed Rate, Inc.**					**2. Leader Bank, National Association**					**3. Fairway Independent Mortgage Corporation**					**4. United Wholesale Mortgage, LLC**					
*Binary variables	Obs	Mean	Std Dev	Min	Max	Obs	Mean	Std Dev	Min	Max	Obs	Mean	Std Dev	Min	Max	Obs	Mean	Std Dev	Min	Max	Hypothesized Signs
White*	3,283	0.72	0.45	0	1	2,798	0.71	0.45	0	1	2,451	0.79	0.41	0	1	1,381	0.59	0.49	0	1	-
Black*	178	0.04	0.19	0	1	53	0.01	0.12	0	1	165	0.05	0.22	0	1	106	0.05	0.21	0	1	+
Hispanic or Latino*	265	0.06	0.23	0	1	103	0.03	0.16	0	1	153	0.05	0.22	0	1	346	0.15	0.35	0	1	+
Native American*	14	0	0.06	0	1	1	0	0.02	0	1	5	0	0.04	0	1	2	0	0.03	0	1	+
Asian/PI*	801	0.18	0.38	0	1	975	0.25	0.43	0	1	333	0.11	0.31	0	1	507	0.22	0.41	0	1	+
Male*	2,702	0.6	0.49	0	1	2,457	0.63	0.48	0	1	1,729	0.56	0.5	0	1	1,413	0.6	0.49	0	1	-
Female*	1,810	0.4	0.49	0	1	1,458	0.37	0.48	0	1	1,371	0.44	0.5	0	1	911	0.39	0.49	0	1	+
Healthy DTI (≤ 35%)*	2,380	0.52	0.5	0	1	2,628	0.67	0.47	0	1	1,535	0.49	0.5	0	1	857	0.37	0.48	0	1	-
Manageable DTI (36% - 42%)*	1,236	0.27	0.45	0	1	894	0.23	0.42	0	1	891	0.29	0.45	0	1	689	0.29	0.46	0	1	-
Nearing unmanageable DTI (43% - 49%)*	825	0.18	0.39	0	1	392	0.1	0.3	0	1	630	0.2	0.4	0	1	722	0.31	0.46	0	1	+
Struggling DTI (>50%)*	100	0.02	0.15	0	1	16	0.71	0.45	0	1	51	0.79	0.41	0	1	74	0.59	0.49	0	1	+
LTV	4,541	79.95	14.158	7.75	113.56	3,930	77.86	14.31	11.14	105.08	3,107	81.71	14.407	12.97	110.38	2,342	82.84	13.66	12.56	113.04	+
Total Applications	4,541					3,930					3,107					2,342					
Loans Approved	4,401					3,886					2,988					2,215					
Loans Denied	140					44					199					127					

Table 5. Top Four Lenders Worcester County Summary Statistics

Lender Name	**1. Fairway Independent Mortgage Corporation**					**2. United Wholesale Mortgage, LLC**					**3. Guaranteed Rate, Inc.**					**4. Total Mortgage Services, LLC**					
*Binary variables	Obs	Mean	Std Dev	Min	Max	Obs	Mean	Std Dev	Min	Max	Obs	Mean	Std Dev	Min	Max	Obs	Mean	Std Dev	Min	Max	Hypothesized Signs
White*	476	0.82	0.39	0	1	244	0.56	0.5	0	1	264	0.71	0.46	0	1	261	0.76	0.43	0	1	-
Black*	25	0.04	0.2	0	1	17	0.04	0.19	0	1	14	0.04	0.19	0	1	36	0.1	0.31	0	1	+
Hispanic or Latino*	30	0.05	0.22	0	1	75	0.17	0.38	0	1	18	0.05	0.21	0	1	30	0.09	0.28	0	1	+
Native American*	1	0	0.04	0	1	0	0	0	0	0	3	0.01	0.09	0	1	0	0	0	0	0	+
Asian/PI*	52	0.09	0.29	0	1	99	0.23	0.42	0	1	75	0.2	0.4	0	1	18	0.05	0.22	0	1	+
Male*	329	0.56	0.5	0	1	275	0.63	0.48	0	1	237	0.63	0.48	0	1	186	0.54	0.5	0	1	-
Female*	254	0.43	0.5	0	1	157	0.36	0.48	0	1	133	0.36	0.48	0	1	159	0.46	0.5	0	1	+
Healthy DTI (≤ 35%)*	284	0.49	0.5	0	1	158	0.36	0.48	0	1	196	0.52	0.5	0	1	141	0.41	0.49	0	1	+
Manageable DTI (36% - 42%)*	174	0.3	0.46	0	1	136	0.31	0.46	0	1	104	0.28	0.45	0	1	113	0.33	0.47	0	1	+
Nearing unmanageable DTI (43% - 49%)*	117	0.2	0.4	0	1	127	0.29	0.46	0	1	64	0.17	0.38	0	1	89	0.26	0.44	0	1	-
Struggling DTI (>50%)*	9	0.02	0.12	0	1	14	0.03	0.18	0	1	10	0.03	0.16	0	1	2	0.01	0.08	0	1	+
LTV	584	81.03	13.78	27.03	107.09	435	82.99	14.70	35.37	113.04	374	80.48	13.41	21.195	100	345	86.47	13.52	17.79	101.25	+
Total Applications	584					435					374					345					
Loans Approved	566					410					366					340					
Loans Denied	18					25					8					5					

4.0 Findings

This section includes the results of the exploratory data analysis of the share of home loans by population and race, denial reason by race and top four lenders for each geographic area, and debt-to-income ratio categories as defined by JPMorgan Chase (n.d.). The results of the four logistic regression models presented in Chapter 3 are examined.

4.1 Exploratory Data Analysis

This segment presents the findings from the exploratory data analysis, encompassing the distribution of home loans across demographic groups based on population and race, the reasons for denial categorized by race, the prominence of the top four lenders in each geographical area, and the classification of debt-to-income ratio categories.

4.1.1 Share of Home Loans by Population and Race

Exploratory data analysis of the mortgage data in Massachusetts and Worcester County uncovers patterns related to population distribution and the proportion of home purchase loans compared to the 2022 population estimate data (U.S. Census Bureau, 2023). Figure 5 shows the share of mortgages by race compared to the 2022 Massachusetts population. Similarly, Figure 6 shows the share of mortgages by race compared to the Worcester County population.

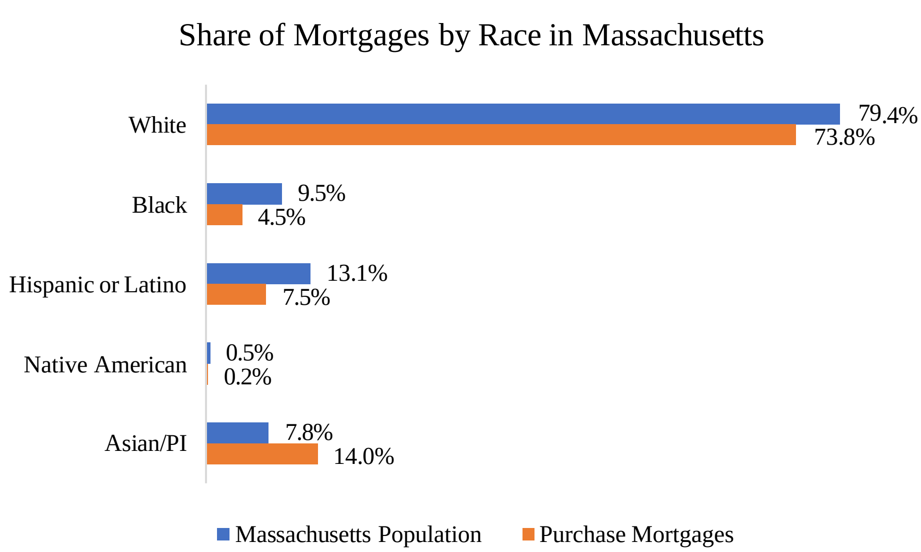


Figure 5. Share of Mortgages by Race in Massachusetts

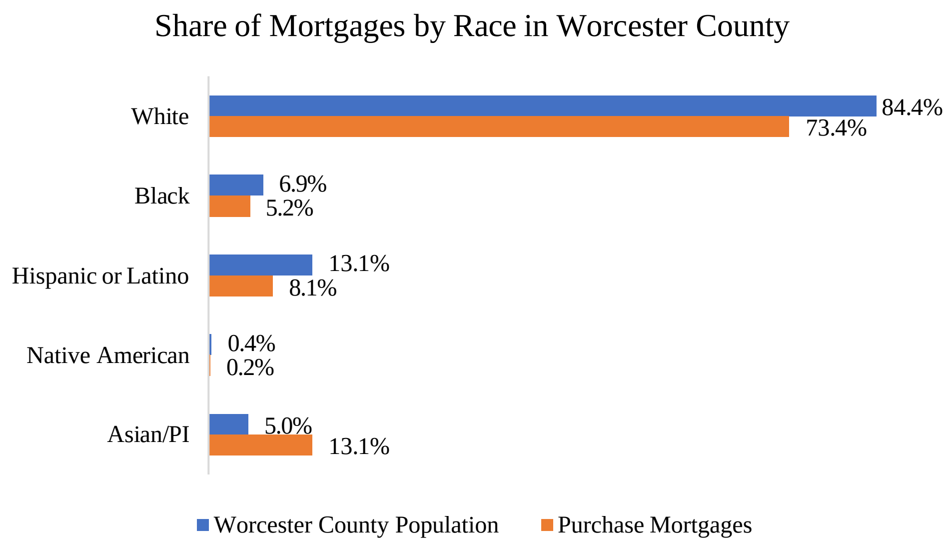


Figure 6. Share of Mortgages by Race in Worcester County

In Worcester County, Black, and Native American homebuyers secure a comparable percentage of mortgages to their respective population shares, as shown in Figure 6. Black homebuyers hold 5.2% of mortgages, similar to their population representation of 6.9%. Native Americans secure 0.2% of mortgages, aligning closely with their 0.4% population share Asian/PI individuals secure a larger proportion of mortgages in Massachusetts and Worcester County compared to their population share. In Massachusetts, Asian/PI individuals make up 7.8% of the population yet hold 14% of mortgages. This trend continues in Massachusetts, where the Asian/PI population is 5% and they hold 13.1% of all mortgages.

Conversely, Hispanic or Latinos residing in Worcester County represent 13.1% of the population, the same as the state average, yet obtain a slightly larger share of mortgages at 8.1% compared to the 7.5% in Massachusetts. White residents in both Worcester County and Massachusetts secure the most mortgages, aligning closely with their respective population shares of 84.4% and 79.4%. The results in Tables 5 and 6 corroborate a similar analysis that was conducted by the Woodstock Institute in collaboration with Mortgage Lending Matters using 2021 HMDA data for a Massachusetts-level analysis. (Woodstock Institute & Partnership for Financial Equity, 2023).

4.1.2 Denial Reasons by Race and Lender

Loan denial rates were higher for all racial groups compared to White applicants in both Massachusetts and Worcester County as highlighted in Table 5. This finding aligns with the national CFPB 2021 Mortgage Market Activity and Trends report, which found that nationally, Black and Hispanic borrowers had notably higher denial rates in 2021 than non-Hispanic White and Asian borrowers (CFPB, 2022). The denial percentages of loan applicants by race in Massachusetts and Worcester County are presented in Table 6. Denial rates range from 4% for White applicants to 11% for Native American applicants in Massachusetts. In Worcester County, denial rates ranged from 4% for White applicants to 11% for Black applicants.

Table 6. Loan Denial Percentage by Race in Massachusetts and Worcester County

	(I) Massachusetts		(II) Worcester County	
Race	**Denial %**	**Most Common Denial Reason**	**Denial %**	**Most Common Denial Reason**
White	4%	DTI (35%)	4%	DTI (38%)
Black	5%	DTI (42%)	11%	DTI (48%)
Hispanic or Latino	8%	DTI (36%)	8%	DTI (33%)
Native American	11%	DTI (31%)	0%	N/A
Asian/PI	6%	DTI (39%)	7%	Other (44%)

Total applications: N= 61,245 and N= 7,360

Additionally, the analysis highlights that irrespective of race, debt-to-income ratio (DTI) is the most common denial reason in both Massachusetts and Worcester County. In Massachusetts, DTI was cited as the leading cause of denial in various instances, ranging from 31% to 42%. Similarly, in Worcester County, DTI accounted for a significant proportion of denials, ranging from 33% to 48%.

The high approval rate for Native Americans may be attributed to the small sample size (143 and 15 respectively) and/or the Section 184 Indian Home Loan Guarantee Program which aims to make homeownership more accessible for Native American and Alaska Native families alike. Section 184 offers financing with low down payment and flexible underwriting, which facilitates homeownership and increases access to capital in Native American Communities. Furthermore, Section 184 guarantees home mortgage loans made to Native borrowers, assuring the lender that its investment will be repaid in full in the event of foreclosure. Massachusetts is a participating full approval state (U.S. Department of Housing and Urban Development, n.d.)

Table 7 provides insight into the denial percentages by race for the top four Massachusetts lenders. There are notable disparities in denial rates across racial groups.

Table 7. Denial Percentage by Race for the Top Four Massachusetts Lenders

	1. Guaranteed Rate, Inc.		2. Leader Bank, National Association		3. Fairway Independent Mortgage Corporation		4. United Wholesale Mortgage, LLC	
Race	Denial %	Most Common Denial Reason	Denial %	Most Common Denial Reason	Denial %	Most Common Denial Reason	Denial %	Most Common Denial Reason
White	2.65%	DTI (34%)	1.00%	DTI (50%)	2.86%	DTI (33%)	4.06%	DTI (45%)
Black	4.49%	DTI (75%)	0% (All 53 applications approved)	N/A (All 53 applications approved)	11.52%	DTI and Collateral (both 32%)	7.55%	DTI (75%)
Hispanic or Latino	5.66%	DTI (40%)	1.94%	Credit history (50%) and Collateral (50%)	4.58%	DTI and other (both 29%)	7.51%	DTI (54%)
Native American	7.14%	DTI (100%)	0%	N/A (The 1 applications approved)	0% (All 5 applications approved)	N/A (All 5 applications approved)	0% (All 2 applications approved)	N/A (All 2 applications approved)
Asian/PI	3.75%	DTI (50%)	1.54%	DTI (53%)	6.91%	DTI, collateral, and other (all 17%)	7.30%	DTI (59%)
Overall	3.11%		1.15%		3.83%		5.42%	

Total applications: N= 4,541, 3,930, 3,107, 2,342

White applicants generally face lower denial rates across all lenders, with denial percentages ranging from 1.00% to 4.06%, primarily due to high debt-to-income ratios (DTI). In contrast, Black applicants experienced higher denial rates than White applicants, ranging from 4.49% to 11.53%, except for Leader Bank, National Association where all 53 Black applicants were approved. Fairway Independent Mortgage Corporation exhibits the highest denial rates for Black applicants at 11.52%. DTI was the most common denial reason for Black applicants. Hispanic or Latinos also face higher denial rates overall compared to White applicants, from

1.94% from Leader Bank, National Association to 7.51% from United Wholesale Mortgage, LLC. Asian/Pacific Islander (PI) applicants generally encounter lower denial rates ranging from 1.54% to 7.30%, albeit with varying common denial reasons such as DTI and collateral. Native American applicants have a low denial rate with the highest at 7.14% and three of the four lenders approving all applicants. However, the small sample size should be noted, with only 1 to 5 applicants for the top two to four lenders who approved all applicants.

Table 8 highlights similar results for the top four Worcester County lenders. Comparing the denial rates for different racial groups between Massachusetts and Worcester County reveals notable differences.

Table 8. Denial Percentage by Race for the Top Four Worcester County Lenders

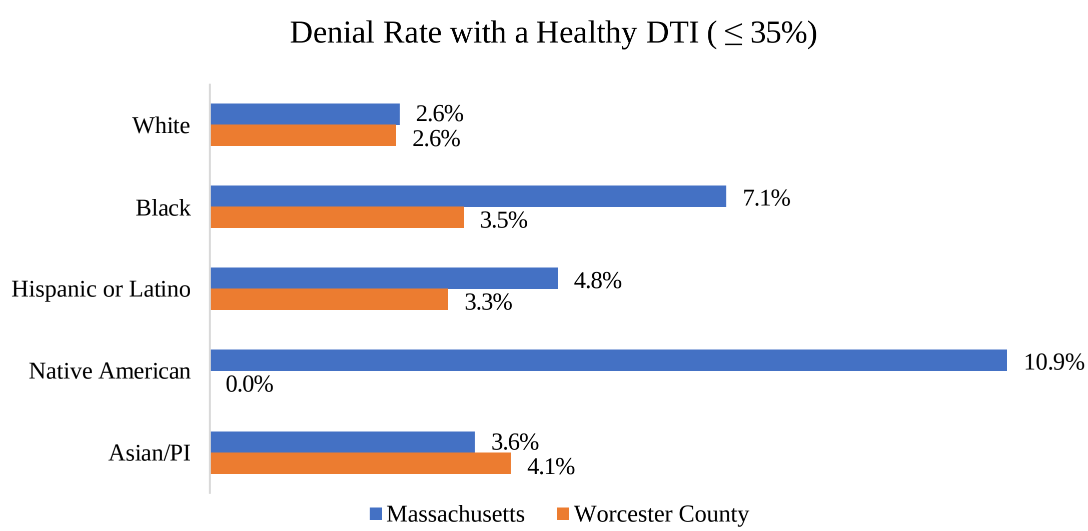
	1. Fairway Independent Mortgage Corporation		2. United Wholesale Mortgage, LLC		3. Guaranteed Rate, Inc.		4. Total Mortgage Services, LLC	
Race	**Denial %**	**Most Common Denial Reason**	**Denial %**	**Most Common Denial Reason**	**Denial %**	**Most Common Denial Reason**	**Denial %**	**Most Common Denial Reason**
White	2.31%	Collateral (27%)	4.51%	DTI and collateral (both 36%)	1.89%	DTI and collateral (both 40%)	0.77%	DTI (100%)
Black	12.00%	DTI, credit history, collateral (all 33%)	11.76%	DTI (50%)	0% (All 14 applications approved)	N/A (All 14 applications approved)	2.87%	Employment history (100%)
Hispanic or Latino	3.33%	Other (100%)	6.67%	DTI and credit history (both 40%)	5.56%	DTI (100%)	3.33%	Other (100%)
Native American	0% (All 1 application approved)	N/A (All 1 application approved)	0% (No applications)	N/A (No applications)	0% (All 1 applications approved	N/A (All 1 applications approved)	N/A (No applications)	N/A (No applications)
Asian/PI	5.77%	DTI, credit history, collateral (all 33%)	7.07%	DTI (71%)	2.67%	Employment history and other (both 50%)	5.56%	Collateral (100%)
Overall	**3.08%**		**5.75%**		**2.14%**		**1.45%**	

Total loans: N= 4,401, 3,866, 2,988, 2,215

In Worcester County, White applicants generally face slightly higher denial rates compared to Massachusetts, ranging from 0.77% to 4.51%, with collateral and debt-to-income (DTI) ratio being the most common denial reason. The denial rates for Black applicants in Worcester County are considerably higher, ranging from 0% to 12.00%, with DTI, credit history, and collateral being common denial reasons, mirroring the trend observed in Massachusetts. Hispanic or Latino applicants also experience higher denial rates in Worcester County, ranging from 3.33% to 6.67%, primarily due to DTI and credit history. Native American applicants have lower denial rates overall, although the sample size is small, and Asian/PI applicants encounter denial rates similar to those in Massachusetts, with DTI and collateral being common denial reasons.

4.1.3 Debt to Income Category Denial Percentages by Race and Lender

The CFPB 2021 Mortgage Market Activity and Trends report does not include debt-to-income (DTI) ratio categories. Further examination of approval rates revealed consistent denial patterns in three DTI categories (healthy, manageable, and nearing unmanageable) as demonstrated in Figure 7; White, Asian/PI, and Native American applicants were denied at a rate of approximately 2 - 4%, while Black applicants experienced denial rate at a slightly lower rate of about 7%.



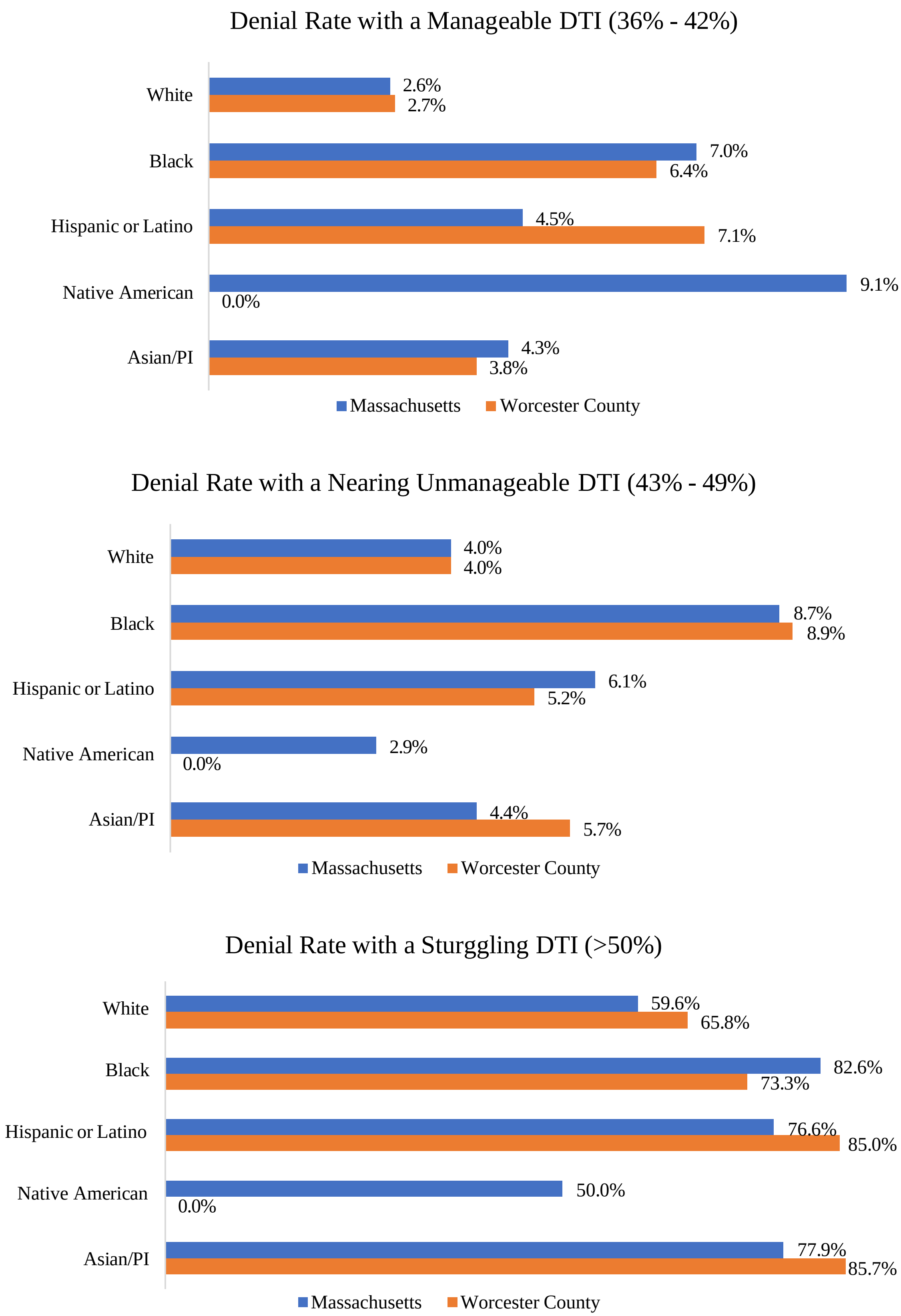


Figure 7. Approval Rates by DTI Category

However, a large disparity is in the struggling DTI category (DTI of 50% or more). Black unqualified applicants were at least twice as likely to be denied loans as their Black counterparts. With a struggling DTI, White applicants were denied about 60% of the time compared to approximately 83% for Black applicants, consistent with findings from Martinez & Kirchner (2021). This contrast suggests a potentially disproportionate approval rate for unqualified applicants based on race.

Denial rates by lender and race with a struggling DTI are illustrated in Figures 8 and 9. Missing values indicate no observations for the corresponding race and lender combination. A denial rate of 0% indicates that all applications were approved.

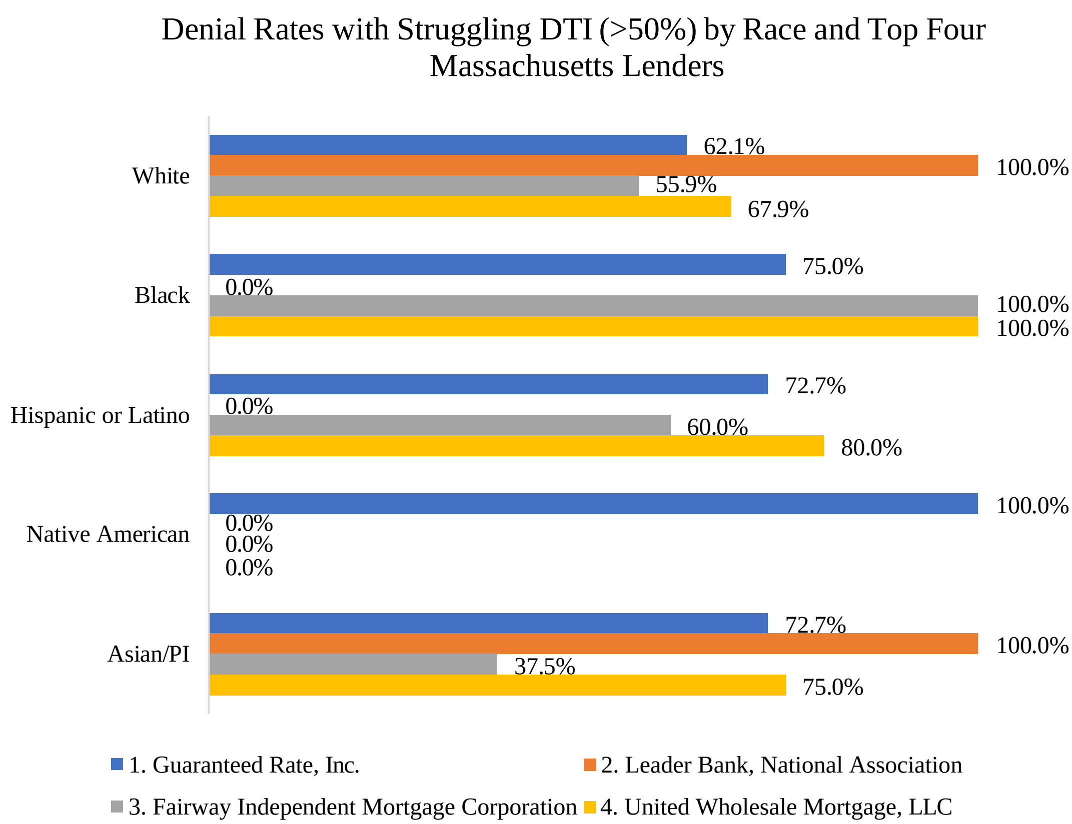


Figure 8. Denial Rates with Struggling DTI (>50%) by Race and Top Four Massachusetts Lenders

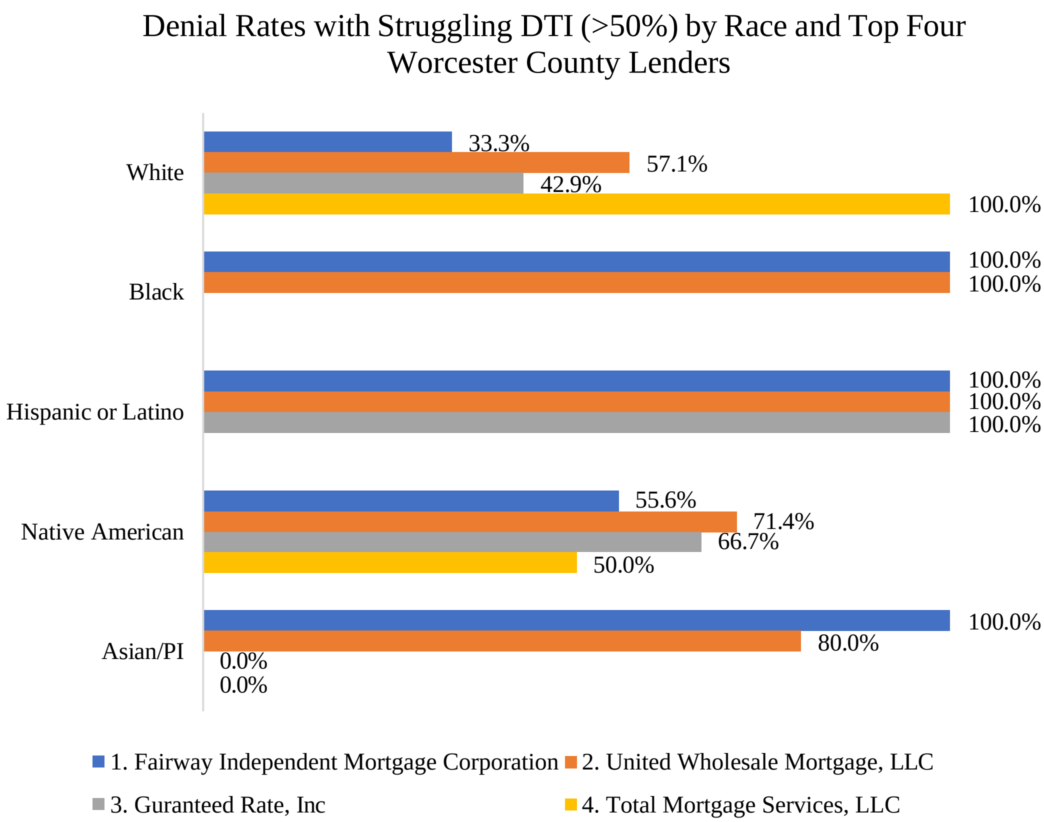


Figure 9. Denial Rates with Struggling DTI Ratio (>50%) by Race and Top Four Worcester County Lenders

Disparities are more pronounced with the addition of the top four lenders, as demonstrated in Figures 8 and 9. For instance, all Black applicants were denied loans by Fairway Independent Mortgage Corporation and United Wholesale Mortgage, LLC in both Massachusetts and Worcester County. Similar trends are observed for Hispanic or Latino applicants, who experienced a 100% denial rate across all lenders in Table 9. Conversely, Native American, and Asian/PI applicants faced varying denial rates across different lenders, from 37.5% to 100% in Massachusetts and 0% to 100% in Worcester County. White applicants were denied about 60% of the time in both Massachusetts and Worcester County as highlighted by Tables 8 and 9.

In this lender-specific analysis, it's important to note that there are fewer observations for certain racial groups compared to the statewide analysis that includes all lenders. This can influence the interpretation of denial rates, as small sample sizes may lead to greater variability in the results.

4.2 Regression Results for Logistic Loan Denial Models

This section presents results for all four logistic regression models: Logistic Loan Denial Model, Logistic Lender Model Equation, Logistic Lender-Race Interaction, and Logistic Lender-DTI Ratio Interaction.

4.2.1 Regression Results for Logistic Loan Denial Model

Table 9 shows the regression results of the logistic regression of the logistic loan denial model. Complete regression results are in Appendix A Tables A3 and A4.

Table 9. Logistic Regression Results of Loan Denial for Massachusetts and Worcester County

	(I) Massachusetts		(II) Worcester County	
Variable	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**
Black	0.91***	(0.08)	0.60*	(0.22)
Hispanic or Latino	0.49***	(0.07)	0.57 *	(0.20)
Native American	0.72*	(0.33)	Omitted	
Asian/PI	0.49***	(0.06)	0.60***	(0.17)
Female	-0.11**	(0.04)	-0.05	(0.13)
Age less than 25	-0.02	(0.13)	0.01	(0.35)
Age 25 to 34	-0.11*	(0.06)	-0.18	(0.17)
Age 45 to 54	0.21***	(0.06)	0.30	(0.18)
Age 55 to 64	0.34	(0.07)	0.54*	(0.20)
Age 65 or older	-0.17	(0.10)	0.27	(0.28)
Manageable DTI	-0.02	(0.06)	0.11	(0.17)
Nearing unmanageable DTI	3.91***	(0.08)	4.21***	(0.22)
Struggling DTI	0.27	(0.06)	0.35	(0.17)
Less than 20% down payment	0.09	(0.05)	-0.02	(0.14)
Income	-0.16*	(0.05)	-0.12	(0.15)
Loan Amount	-0.34	(0.06)	0.05	(0.20)
Property Value Ratio	0.04	(0.03)	-0.05	(0.11)
No Co-Applicant	0.27*	(0.05)	0.38*	(0.14)
Less than 30 yr. mortgage	-0.14	(0.10)	0.24	(0.28)
More than 30 yr. mortgage	0.82***	(0.20)	0.67*	(0.55)
Equifax credit model	-0.17	(0.05)	-0.14	(0.16)
FICO credit model	-0.07	(0.05)	0.01	(0.15)
More than 1 credit model	-0.29*	(0.12)	0.21	(0.31)
Other credit model	0.89***	(0.18)	1.17	(0.61)
LP AUS	-0.53	(0.05)	-0.48	(0.14)
Other AUS	0.59	(0.11)	0.05	(0.42)
Constant	1.48*	(0.68)	-3.83	(2.31)

* p<0.05, ** p<0.01, *** p<0.001
N=61,245 for Massachusetts and N = 7,360 for Worcester County

After fitting the logistic regression model to predict loan denial, goodness-of-fit tests were conducted to assess the model's appropriateness. Coefficients estimated by ML are tested using the likelihood ratio (LR) and Wald tests. The LR test yielded a significant chi-square statistic for both models, indicating the model's overall significance. The Wald test indicated that including the independent variables creates a statistically significant improvement in the fit of the model. The Hosmer-Lemeshow test (Long & Freese, 2014) designed to assess goodness of fit, resulted in a non-significant p-value of (0.5908) and (0.0614) respectfully, suggesting that both models fit the data well, supporting their goodness of fit. These combined results indicate that both logistic regression models are statistically significant and provide a reasonable fit to the observed data, assuring the reliability of the analysis.

Table 10. Logistic Regression Tests of Loan Denial for Massachusetts and Worcester County

	(I) Massachusetts		(II) Worcester County	
Test	**chi-square (26)**	**P-Value**	**chi-square (25)**	**P-Value**
LR	5563.27	$p < 0.0001$	725.69	$p < 0.0001$
Wald Test	4974.53	$p < 0.0001$	608.87	$p < 0.0001$
Hosmer-Lemeshow Test	6.51	0.5908	14.89	0.0614

The variance inflation factor (VIF) was used as a method to detect the severity of multicollinearity. A high VIF indicates that multicollinearity has increased the estimated variance of the estimated coefficient by a lot, yielding a decreased t-score (Studenmund, 2016). A common rule of thumb is that $VIF(\beta_i) > 4$ warrants further investigation, and $VIF(\beta_i) > 10$ indicates severe multicollinearity (Pennsylvania State University, 2018; Studenmund, 2016). There were no explanatory variables in either regression that the VIF exceeded 4. VIF results are in Table A5.

4.2.2 Interpreting the Signs of Coefficients

In both Massachusetts and Worcester County iterations, the observed signs of the coefficients generally align with the hypothesized signs as seen in Table 4 and Table 9. For demographic factors, such as race (Black, Hispanic or Latino, Native American, Asian/Pacific Islanders), the signs match the expected negative direction in Table 3, indicating that Blacks, Hispanics or Latinos, Native Americans, and Asians/PIs are more likely to be denied a loan compared to their White counterparts. Similarly, the observed signs for certain economic indicators, such as positive signs of income and down payment, correspond to a higher likelihood of approval.

There are notable differences where the observed sign differs from the hypothesized negative effect. The negative sign for female is unexpected but may find support in studies such as Loya (2023), which have shown that recently single-applicant women generally perform similarly or outperform single-applicant men in the mortgage market even across ethno-racial groups. The negative coefficient of the loan amount suggests that a higher loan amount is linked to a decrease in the odds of loan denial. This observation may be attributed to interactions with other variables in the model, such as the loan-to-value ratio. In essence, it implies that as the loan amount increases, the likelihood of loan denial decreases. The CFPB (2022) in their 2021 National Mortgage Market Activity and Trends report highlights a consistent rise in median loan amounts for home purchase loans across all categories. This trend is likely because of the general increase in median home prices. Therefore, the negative coefficient aligns with broader industry trends, reflecting the ongoing escalation of home prices and the corresponding adjustments in loan amounts.

Moreover, the impacts of age, debt-to-income ratio, loan amount, and credit model variables exhibit varying signs across different subcategories. Certain age groups, such as ages 45 to 54 and 55 to 64, demonstrate positive effects, whereas the age group 25 to 34 and those with less than a 30-year mortgage display negative effects. Similar patterns arise in DTI categories, indicating that higher DTI positively affects the likelihood of denial. Variables associated with credit models, such as Equifax and FICO credit models, as well as the number of credit models used, yield diverse effects. Negative coefficients for Equifax and FICO credit models suggest a decrease in the odds of loan denial, while positive coefficients for using multiple credit models and other credit models indicate an increase in the odds of loan denial.

While the observed signs largely correspond with the anticipated relationships in Table 4 the unexpected gender dynamics and counterintuitive associations with loan amounts emphasize the complex nature of mortgage approval processes. This analysis emphasizes the importance of considering multiple interactions and contextual factors to understand the variables influencing loan outcomes.

4.2.3 Effect of Race/Ethnicity and DTI Category on Loan Denial Likelihood

In a logistic model, the value of the coefficients differs from those in the linear probability model or ordinary least squares regression, as they signify the rate of change in the log odds concerning variations in the independent variable, instead of directly indicating the rate of change in the dependent variable. As noted by Long & Freese (2001), the log odds "has little substantive meaning for most" (p.133) when it comes to interpretation. An alternative approach is to exponentiate both sides of the equation. Each exponentiated coefficient yields the odds ratio, which represents the ratio of two odds. This ratio signifies how a one-unit change in the predictor variable affects the odds of the event occurring while keeping all other variables constant. The odds ratio can then be interpreted as follows: "For a unit change in x_k, the odds are expected to change by a factor of $\exp(\beta_k)$, holding all other variables constant" (Long & Freese, 2001).

Particularly relevant for categorical predictors, the odds ratio compares the odds of the event occurring for each category of the predictor relative to the reference category, assuming all other variables remain constant (Dickinson, 2022; Long & Freese, 2001). An odds ratio of less than 1 indicates a negative relationship, meaning that higher values of the predictor are associated with lower odds of the event. In this case, an odds ratio of less than 1 implies a decrease in the odds of loan denial, while a ratio greater than 1 suggests an increase. The odds ratio will be used to interpret the slope coefficients of the Massachusetts and Worcester models. A complete table of odds ratios is Appendix A. Odds ratios for race/ethnicity for a conventional mortgage compared to white applicants are in Table 11 for both Massachusetts and Worcester County.

Table 11. Odds of Denial by Race in Massachusetts and Worcester County

Race/Ethnicity	Likelihood of Denial for a Conventional Mortgage Compared to White Applicants	
	Massachusetts	**Worcester County**
Black	2.5 times as likely to be denied***	1.8 times as likely to be denied***
Hispanic Or Latino	1.6 times as likely to be denied***	1.8 times as likely to be denied***
Native American	2.1 times as likely to be denied*	Omitted
Asian/PI	1.6 times as likely to be denied***	1.8 times as likely to be denied***

*** p<0.001, ** p<0.01, * p<0.05

The analysis of loan denial likelihood by race and ethnicity in Massachusetts and Worcester County reveals significant disparities compared to White applicants, holding all other variables constant. Notably, the odds ratio indicates that Native Americans are 2.1 times more likely to face loan denial in Massachusetts, which is statistically significant. However, it's important to note the small sample size, with only 16 out of 143 Native American applicants being denied loans. This limited sample size may result in wider confidence intervals and less precise estimates of the true odds ratio in the population. All 15 Native American applicants in Worcester County were approved, therefore omitting them from the analysis.

Black applicants face a significant disadvantage, being 2.5 times as likely to experience mortgage denial in Massachusetts and 1.8 times as likely in Worcester County compared to White applicants. Similarly, Asian applicants encounter elevated odds of denial, being 1.6 times as likely in Massachusetts and 1.8 times as likely in Worcester County. Hispanic or Latino applicants also face increased odds, being 1.4 times as likely in Massachusetts and 1.6 times as likely in Worcester County. These findings suggest the existence of racial and ethnic disparities in mortgage approval processes in Massachusetts and Worcester County.

Another layer of analysis is the incorporation of the debt-to-income (DTI) ratio, which allows insight into the relationship between DTI and approval rates. Table 12 illustrates the likelihood of denial across various DTI categories, comparing them to a healthy DTI (≤ 35%) while holding all other variables constant.

Table 12. Odds of Denial by Debt-to-Income Ratio Categories and Race

DTI Category	Likelihood Of Denial for a Conventional Mortgage Compared to Healthy DTI (≤ 35%)	
	Massachusetts	**Worcester County**
Manageable (36% - 42%)	0.98 times as likely to be denied	1.1 times as likely to be denied**
Nearing unmanageable (43% - 49%)	1.3 times as likely to be denied***	1.4 times as likely to be denied***
Struggling (>50%)	49.7 times as likely to be denied***	67.5 times as likely to be denied

*** p<0.001, ** p<0.01, * p<0.05

The increased odds of denial for the Struggling DTI category, 49.7 and 67.5 times as likely to be denied, align with the low observed approval rates in Figure 8. When considering Figure 8 and Table 12, it is noteworthy that White applicants were approved 38% of the time, whereas Black applicants received approval only 18% of the time with a Struggling DTI. These differences can be attributed to the regression model holding all other variables constant, including factors like income and higher down payment, which exhibit a negative relationship with loan denial. This contrasts with a straightforward examination of raw denial percentages.

4.3 Lender-Specific Logistic Loan Denial Regression Results

The addition of the independent variable "lender" to the regression model, Equation 1, provides an understanding of how different financial institutions influence loan denial. Incorporating the lender variable can help assess whether specific lenders exhibit distinct approval patterns. This approach enables the identification of potential disparities in lending outcomes among various lenders, highlighting differences in underwriting criteria, risk assessment methods, and loan approval standards. Examining the demographic and financial variables can suggest any biases or discriminatory practices that may exist within the lenders.

Complete regression results for each iteration of Equation 2 for each of the top four lenders in Massachusetts and Worcester County are in Appendix B Tables B1 to B8. F-test results are in Tables B9 and B10. Table 13 displays an abbreviated list of results including race, debt-to-income ratio, and each lender variable for the top four lenders in order. Standard errors are denoted in parentheses. These results are from Massachusetts and Worcester County and each lender's respective logistic regression.

Table 13. Massachusetts and Worcester County Lender-Specific Logistic Loan Denial Regression Results

	Massachusetts				Worcester County			
	Guaranteed Rate, Inc	Leader Bank, National Association	Fairway Independent Mortgage Corp.	United Wholesale Mortgage, LLC	Fairway Independent Mortgage	United Wholesale Mortgage, LLC	Guaranteed Rate, Inc	Total Mortgage Services, LLC
Black	.904*** (.075)	.887*** (.075)	.905*** (.075)	.906*** (0.75)	.905*** (.075)	.906*** (.075)	.904*** (.075)	.915*** (.075)
Hispanic or Latino	.484*** (.071)	.472*** (0.71)	.484*** (.071)	.488*** (.071)	.484*** (.071)	.488*** (.071)	.484*** (.071)	.487*** (.071)
Native American	.726** (.33)	.698** (.329)	.715** (.33)	.717** (.33)	.715** (.33)	.717** (.33)	.726** (.33)	.72** (.33)
Asian/PI	.489*** (.06)	.515*** (.06)	.488*** (.06)	.489*** (.06)	.488*** (.06)	.489*** (.06)	.489*** (.06)	.484*** (.06)
Manageable DTI	-.02 (.058)	-.038 (.058)	-.019 (0.58)	-.019 (.058)	-.019 (.058)	-.019 (.058)	-.02 (.058)	-.016 (.058)
Nearing unmanageable DTI	.269*** (.061)	.242*** (.061)	.271*** (.061)	.271*** (.061)	.271*** (.061)	.271*** (.061)	.269*** (.061)	.273*** (.061)
Struggling DTI	3.912*** (.076)	3.874*** (.076)	3.905*** (.076)	3.907*** (.076)	3.905*** (.076)	3.907*** (.076)	3.912*** (.071)	3.904*** (.076)
Lender	-.309*** (.101)	-1.157*** (.168)	-.109 (.11)	-.038 (.112)	-.109 (.11)	-.038 (.112)	-.309*** (.101)	-.815*** (.248)

* p<0.05, ** p<0.01, *** p<0.001

In Massachusetts, the size and magnitude of the added lender variable varies on their impact on loan approvals. Notably, Guaranteed Rate, Inc. exhibits a statistically significant negative coefficient of -0.309 indicating that, on average, applicants applying through this lender are less likely to face loan denials compared to the other 423 lenders. Conversely, Leader Bank, National Association demonstrates a much larger negative coefficient of -1.157 suggesting a substantial reduction in the odds of loan denial for applicants associated with this lender. In contrast, Fairway Independent Mortgage Corp. showcases a non-significant coefficient of -0.109 implying that this lender's influence on loan denials is not statistically distinguishable from the baseline. Similarly, United Wholesale Mortgage, LLC presents a non-significant coefficient of -0.038 indicating no significant impact on loan denial rates compared to the other 423 lenders.

The coefficients show slight variations between Massachusetts and Worcester County, although not statistically significant. The regression results for Massachusetts lenders, including Guaranteed Rate, Inc. and Leader Bank, National Association, exhibit negative coefficients, indicating a decreased likelihood of loan denial compared to the other lenders. However, the standard errors associated with these coefficients differ slightly, with Guaranteed Rate, Inc. displaying a more statistically significant impact (-0.309 with a standard error of 0.101) compared to Leader Bank, National Association (-1.157 with a standard error of 0.168). In contrast, Fairway Independent Mortgage Corp. and United Wholesale Mortgage, LLC, present non-significant coefficients in both Massachusetts and Worcester County, suggesting minimal impact on loan denial rates.

Calculating the odds ratio from each coefficient reveals the likelihood of denial compared to the other 432 lending institutions in Massachusetts and the other 277 lending institutions in Worcester County. These other intuitions are the reference group and will be referred to as "other lenders" in analyses. An odds ratio of less than 1 implies a decrease in the odds of loan denial, while a ratio greater than 1 suggests an increase.

Table 14. Massachusetts and Worcester County Lender-Specific Loan Denial Odds Ratio Results

Likelihood of Denial Compared to Other Lenders							
Massachusetts				**Worcester County**			
Guaranteed Rate, Inc	Leader Bank, National Association	Fairway Independent Mortgage Corp.	United Wholesale Mortgage, LLC	Fairway Independent Mortgage	United Wholesale Mortgage, LLC	Guaranteed Rate, Inc	Total Mortgage Services, LLC
.734***	.315***	.897	.963	.897	.963	.734***	.443***

*** p<0.001, ** p<0.01, * p<0.05

All the lenders demonstrate an odds ratio of less than 1. Guaranteed Rate, Inc. shows a moderate impact on loan denial with an odds ratio of 0.734. Leader Bank, National Association exhibits a less substantial effect, with a lower odds ratio of 0.315, indicating lower chances of denial. In terms of statistical significance for the chosen variables, the majority of coefficients across all variables and lenders are statistically significant.

In Worcester County, United Wholesale Mortgage, LLC, presents the highest odds ratio of all lenders at 0.963. Fairway Independent Mortgage shows a relatively moderate impact on loan denial, with an odds ratio of 0.897. This indicates a slight decrease in the likelihood of denial for applicants associated with this lender. By contrast, Guaranteed Rate, Inc., exhibits a less significant effect on loan denial with an odds ratio of 0.734. Lastly, Total Mortgage Services, LLC, stands out with an odds ratio of 0.443, suggesting the lowest impact on loan denial and a significantly lower likelihood of approval compared to the other lenders in Worcester County.

4.4 Lender-Specific Race Interaction Logistic Loan Denial Regression Results

This section presents the results of Equation 3, which includes an interaction variable, Lender*Race, in the Logistic Loan Denial Equation (Equation 1). This addition allows us to explore how the relationship between loan denial and independent variables such as lender and race may vary depending on the levels of another variable, such as race. These interaction variables help assess whether the impact of a lender on loan denial differs across different racial groups, indicating potential disparities in loan approval based on the applicant's race.

For instance, a significant interaction between a lender and race suggests that the lender's influence on loan approval or denial varies depending on the racial background of the applicant. Complete regression results for the top four Massachusetts and Worcester County Lender*Race interactions are provided in Appendix C Tables C1 to C8. Table 15 displays the Massachusetts and Worcester County lender-specific race interactions alongside the non-interaction terms for race for comparison. While the coefficients and odds ratios for the non-interaction race variables indicate the direct impact of race on loan approval outcomes across all lenders combined, the interaction variables (Lender*Race) capture the differential impact of race on loan approval outcomes specific to each lender. Significant differences in the coefficients and odds ratios between the race variables and their corresponding interaction terms suggest that the relationship between race and loan approval is influenced by the lender. A coefficient of 0 indicates that all applications were either approved or denied in that regression iteration.

Table 15. Massachusetts and Worcester County Lender-Specific Race Interaction Logistic Loan Denial Regression Results

	Massachusetts				Worcester County			
	Guaranteed Rate, Inc	Leader Bank, National Association	Fairway Independent Mortgage Corp.	United Wholesale Mortgage, LLC	Fairway Independent Mortgage	United Wholesale Mortgage, LLC	Guaranteed Rate, Inc	Total Mortgage Services, LLC
Black	.946*** (.195)	.923*** (.075)	.889 (.077)	.919*** (.076)	.889*** (.077)	.919*** (.076)	.946*** (.076)	.925*** (.076)
Hispanic or Latino	.502*** (.119)	.497*** (.071)	.502*** (.071)	.483*** (.073)	.502*** (.071)	.483*** (.073)	.502*** (.072)	.493*** (.071)
Native American	.799** (.74)	.729** (.33)	.748*** (.332)	.728** (.331)	.748** (.332)	.728** (.331)	.799** (.333)	.636** (.34)
Asian/PI	.516*** (.102)	.552*** (.061)	.477** (.061)	.5*** (.061)	.477*** (.061)	.5*** (.061)	.516*** (.061)	.492*** (.06)
Lender*Black	-1.074*** (.139)	0	.295 (.273)	-.503 (.431)	.295 (.273)	.088 (.245)	-1.074 (.406)	-.818 (.498)
Lender*Hispanic or Latino	-.167 (.279)	-.634 .(719)	-.571 (.445)	.088 (.245)	-.571 (.445)	0	-.167 (.329)	-.377 (.619)
Lender*Native American	-1.323** (.324)	0	0	0	0	-.208 (.22)	-1.323 (1.218)	2.027 (1.224)
Lender*Asian/PI	-.447** (.14)	-1.15** (.281)	.245 (.246)	-.208 (.22)	.245 (.246)	-.019 (.058)	-.447** (.219)	-.55 (.694)

*** p<0.001, ** p<0.01, * p<0.05

For Black applicants the non-interaction coefficients are consistently high across lenders, ranging from 0.889 to 0.946, all statistically significant. The interaction terms (Lender*Black) show varying impacts across lenders in both Massachusetts and Worcester County. For instance, Guaranteed Rate, Inc. in Massachusetts shows a notable negative coefficient (-1.074), indicating an increased likelihood of loan denial for Black applicants associated with this lender. Conversely, Fairway Independent Mortgage Corp. in Massachusetts demonstrates a contrasting positive coefficient (0.295), suggesting a potentially higher likelihood of loan approval for Black applicants under this lender.

Non-interaction coefficients for Hispanic or Latino applicants are consistent across lenders, ranging from 0.483 to 0.502. All of which are statistically significant. However, the interaction terms show mixed effects. Some lenders exhibit negative coefficients, such as Leader Bank, and National Association (-0.634), and others positive coefficients, like United Wholesale Mortgage, LLC (0.088). This indicates variations in the impact of Hispanic or Latino status on loan approval depending on the lender.

The non-interaction coefficients for Asian/PI applicants are also consistent and statistically significant across lenders, ranging from .477 to .552. This is a similar pattern for Native American applicants, ranging from -.636 to .799 in Massachusetts and Worcester County. There is slightly more variability compared to Black and Hispanic or Latino applicants. The interaction terms for Native American applicants generally are 0 since all applications were either approved or denied depending on the lender.

The patterns for Worcester County lenders are comparable to those for Massachusetts lenders, with consistent coefficients for non-interaction terms across racial groups. Interaction terms in Worcester County also exhibit varying impacts across lenders, with some lenders showing negative coefficients for certain racial groups (e.g., Black) and positive coefficients for others (e.g., Hispanic or Latino). Notably, the impact of the lender on loan approval for Native American applicants seems more pronounced in Worcester County, with significant negative coefficients in the interaction terms for some lenders (-1.323 for Guaranteed Rate, Inc.).

Table 16 displays the odds ratio results for the likelihood of denial compared to a White applicant using other lenders. In this dataset, an odds ratio of 1 indicates that all applicants were either approved or denied. Therefore, the model concludes that there is no difference in the odds of being approved or denied between the group being analyzed and the reference group.

Table 16. Massachusetts and Worcester County Lender-Specific Race Interaction Loan Denial Odds Ratio Results

Likelihood of Denial Compared to a White Applicant Using Other Lenders								
	Massachusetts				Worcester County			
	Guaranteed Rate, Inc	Leader Bank, National Association	Fairway Independent Mortgage Corp.	United Wholesale Mortgage, LLC	Fairway Independent Mortgage	United Wholesale Mortgage, LLC	Guaranteed Rate, Inc	Total Mortgage Services, LLC
Black	2.5***	2.5***	2.5***	2.5***	1.8***	1.8***	1.8***	1.8***
Hispanic Or Latino	1.6***	1.6***	1.6***	1.6***	1.8***	1.8***	1.8***	1.8***
Native American	2.0*	2.0*	2.0*	2.0*	2.1**	2.1**	2.2**	1.89**
Asian/PI	1.6***	1.6***	1.6***	1.6***	1.8***	1.8***	1.8***	1.8***
Lender*Black	.342	1	1.343	.604	1.343	1.092	.342	.441
Lender*Hispanic or Latino	.846	.531	.565	1.092	.565	1	.846	.686
Lender*Native American	.266	1	1	1	1	.812	.266	7.594*
Lender*Asian/PI	.64***	.317**	1.278	.812	1.278	.981	.64**	.577

*** p<0.001, ** p<0.01, * p<0.05

In Massachusetts, the odds ratios for the interaction term Black applicants range from 0.342 to 1.343. Fairway Independent Mortgage Corp. shows the highest odds ratio of 1.343, suggesting a 34.3% higher likelihood of loan denial for Black applicants when using this lender compared to white applicants who use other lenders.

Similarly, in Worcester County, the odds ratios for the interaction term for Black applicants range from 0.342 to 1.092. Fairway Independent Mortgage and United Wholesale Mortgage, LLC both show odds ratios slightly above 1, indicating a higher likelihood of loan denial for Black applicants relative to white applicants when using these lenders. Notably, Total Mortgage Services, LLC, stands out with a particularly high odds ratio of 7.594, suggesting a significantly elevated likelihood of loan denial for Black applicants compared to white applicants when using this lender.

4.5 Massachusetts and Worcester County Lender-Specific Debt to Income Ratio Loan Denial Regression Results

This section features the results of Equation 4 for both Massachusetts and Worcester County. The addition of the interaction variable between lender and debt-to-income (DTI) ratio (Lender*DTI Category) demonstrates how the relationship between loan denial and the independent variables (e.g., lender and DTI Category) varies depending on the levels of another variable (e.g., DTI Category). These interaction variables help capture whether the effect of the lender on loan denial differs across different DTI ratio categories and can determine whether certain lenders are more or less likely to deny loans to applicants. Compete results for the Lender-Specific Debt to Income Ratio Loan Denial regressions are located in Appendix D Tables D1 to D8.

Table 17 displays the Massachusetts and Worcester County lender-specific DTI categories interactions alongside the non-interaction terms for DTI categories for comparison.

Table 17. Massachusetts and Worcester County Lender-Specific Debt to Income Ratio Loan Denial Regression Results

	Massachusetts				Worcester County			
	Guaranteed Rate, Inc	Leader Bank, National Association	Fairway Independent Mortgage Corp.	United Wholesale Mortgage, LLC	Fairway Independent Mortgage	United Wholesale Mortgage, LLC	Guaranteed Rate, Inc	Total Mortgage Services, LLC
Manageable DTI	.02 (.059)	.011 (.058)	-.004 (.058)	.02 (.059)	-.004 (.058)	-.004 (.058)	.02 (.058)	-.009 (.058)
Nearing unmanageable DTI	.298 (.083)	.291 (.061)	.251 (.062)	.298 (.083)	.251 (.062)	.282 (.062)	.298 (.062)	.285 (.061)
Struggling DTI	3.877 (3.72)	3.89 (.076)	3.908 (.076)	3.877 (3.72)	3.908 (.076)	3.878 (.077)	3.877 (.077)	3.906 (.076)
Lender* Manageable DTI	-1.017*** (.107)	-1.179*** (.383)	-.369 (.24)	-.493 (.285)	-.369 (.24)	-.493 (.285)	-1.017 (.295)	-.78 (.455)
Lender* Nearing unmanageable DTI	-.589** (.135)	-1.09** (.453)	.329 (.181)	-.231 (.203)	.329 (.181)	-.231 (.203)	-.589 (.244)	-1.375 (.585)
Lender*Struggling DTI	.466** (.37)	0	-.041 (.305)	.594 (.285)	-.041 (.305)	.594 (.285)	.466 (.232)	.179 (.822)

*** p<0.001, ** p<0.01, * p<0.05

Each lender exhibits varying impacts on loan denial rates across DTI categories, with different coefficients, odds ratios, and statistical significance for the interaction terms. In Massachusetts, the non-interaction terms for manageable DTI, nearing unmanageable DTI, and struggling DTI range from -0.004 to 0.02, indicating relatively minor effects on loan denial rates. Conversely, the interaction terms for manageable DTI across lenders exhibit larger coefficients, ranging from -1.017 to -1.179, implying a more substantial impact on loan denial rates associated with manageable DTI when considering the influence of specific lenders.

Similarly, in Worcester County, the non-interaction terms for manageable DTI, nearing unmanageable DTI, and struggling DTI range from -0.009 to 0.298, suggesting comparable minor effects on loan denial rates. However, the interaction terms for manageable DTI display varying coefficients across lenders, ranging from -0.369 to -1.017, indicating differing impacts on loan denial rates associated with manageable DTI depending on the lender involved.

While the coefficients of the non-interaction terms for manageable DTI are smaller in magnitude, the corresponding odds ratios are larger. This is because, in logistic regression, the coefficients represent the change in the log odds of the outcome variable (e.g., loan denial) associated with a one-unit change in the predictor variable (e.g., manageable DTI), holding other variables constant. Therefore, a smaller coefficient suggests a smaller change in the log odds of loan denial for a one-unit change in manageable DTI.

However, when exponentiated to calculate the odds ratio, this smaller change in log odds corresponds to a larger change in the odds of loan denial. Therefore, although the coefficient may be smaller, the corresponding odds ratio can be larger due to the mathematical transformation involved in interpreting logistic regression coefficients. This concept is highlighted by the results in Table 18, which presents the odds ratios for loan denial compared to applicants with a healthy debt-to-income (DTI) ratio (≤ 35%) using other lenders as a reference group.

Table 18. Massachusetts and Worcester County Lender-Specific Debt to Income Ratio Loan Denial Odds Ratio Results

Likelihood of Denial Compared to a Healthy DTI (≤ 35%) Using the Other Lenders								
	Massachusetts				Worcester County			
	Guaranteed Rate, Inc	Leader Bank, National Association	Fairway Independent Mortgage Corp.	United Wholesale Mortgage, LLC	Fairway Independent Mortgage	United Wholesale Mortgage, LLC	Guaranteed Rate, Inc	Total Mortgage Services, LLC
Manageable DTI	1.02	1.011	.996	1.02	.996	.996	1.02	.991
Nearing unmanageable DTI	1.347	1.337	1.285	1.347	1.285	1.326	1.347	1.33
Struggling DTI	48.288	48.909	49.776	48.288	49.776	48.308	48.288	49.686
Lender* Manageable DTI	.362***	.307***	.692***	.611***	.692	.611*	.362**	.458*
Lender* Nearing unmanageable DTI	.555**	.336	1.39	.794	1.39*	.794	.555	.253**
Lender*Struggling DTI	1.593**	1	.96	1.81	.96	1.81	1.593	1.196

*** p<0.001, ** p<0.01, * p<0.05

The odds ratios for interaction terms generally exhibit more variability but lesser effects in terms of denial likelihood compared to non-interaction terms. This indicates that the influence of DTI categories on loan denial rates is moderated by the lender involved. For instance, for a manageable DTI in Massachusetts, the odds ratios for non-interaction terms range from 0.996 to 1.02. The corresponding interaction terms (Lender*Manageable DTI) show more variability, with odds ratios ranging from 0.307 to 0.692. This suggests even less influence of a manageable DTI on loan denial rates, and it varies significantly depending on the lender involved.

Similarly, in Worcester County, the odds ratios for non-interaction terms for manageable DTI range from 0.991 to 1.02, while the interaction terms display greater variation, ranging from 0.362 to 0.611. Again, this indicates that the relationship between manageable DTI and loan denial rates is influenced by the specific lender.

For nearing unmanageable DTI, both in Massachusetts and Worcester County, the odds ratios for non-interaction terms are consistently higher compared to the interaction terms across most lenders. This suggests that the impact of nearing unmanageable DTI on loan denial rates is more uniform across lenders, with less variability attributable to lender-specific factors.

5.0 Discussion and Conclusion

This study contributes to the ongoing dialogue surrounding mortgage approval disparities by examining denial rates in Massachusetts and Worcester County, focusing on socioeconomic factors, particularly race and debt-to-income ratio (DTI). This analysis includes an investigation into the practices of the top four mortgage lenders in these regions, providing additional insight into the factors influencing loan denial outcomes.

Exploring homeownership disparities and the historical context of redlining contextualizes our findings within broader racial homeownership gaps. The examination of denial rates among different racial groups reveals disparities, with Black and Native American homebuyers experiencing higher denial rates compared to their White counterparts, even after controlling for other variables such as income and DTI.

The logistic regression models further explain the magnitude of these disparities, highlighting statistically significant differences in denial probabilities between racial groups. The analysis also uncovers disparities in loan approval rates based on DTI, with applicants with higher DTI facing significantly higher odds of denial, particularly among Black borrowers. Interestingly, despite similar DTI levels, White applicants are approved at higher rates than their Black counterparts, suggesting potential biases in the mortgage approval process.

Moreover, the inclusion of lender-specific variables in the regression models suggests significant effects on denial probabilities, with certain lenders demonstrating lower probabilities of denial across all racial groups. The interaction terms for race and lender further emphasize the differential influence of lender practices on loan approval outcomes across races, underscoring the need for greater transparency and accountability in lending institutions.

While the HMDA data used in this study lacks credit scores, prior research incorporating credit scores has consistently shown disparities in mortgage approval rates based on race and ethnicity (Bartlett et al., 2022; Bhutta et al., 2022; Bhutta & Hizmo, 2019; Campisi, 2021; Cherian, 2014; Ky & Lim, 2022; Popick, 2022). Researchers have attempted to address these limitations by merging HMDA data with third-party information, but challenges remain due to differences in reporting and data matching. Although the expanded HMDA data introduced in 2018 includes credit-related information, it still has limitations, such as not capturing all factors used by lenders in pricing or underwriting decisions. Consequently, racial disparities in mortgage approval rates persist, underscoring the need for continued efforts to address systemic biases in the lending process (Bartlett et al., 2022; Bhutta et al., 2022; Bhutta & Hizmo, 2019; Campisi, 2021; Cherian, 2014; Ky & Lim, 2022; Popick, 2022).

These findings align with broader critiques of the credit score system, which has been criticized for perpetuating inequalities. Despite efforts to eliminate bias, credit scores tend to disadvantage people of color, who often have lower scores due to systemic factors such as limited credit history and generational wealth disparities. Furthermore, a significant portion of the population, particularly Black and Hispanic individuals, lack any credit history, exacerbating disparities in mortgage approval (Campisi, 2021; Consumer Financial Protection Bureau, 2015; NCRC, 2008; Ney, 2021).

Overall, these findings underscore the complex interplay of socioeconomic factors, racial disparities, and lender practices in shaping access to homeownership. In Massachusetts, existing policy initiatives such as the Community Investment Tax Credit program incentivize support for affordable housing and financial education, while the Affordable Housing Trust Fund supports the development of affordable housing units. Additionally, the Massachusetts Division of Banks conducts fair lending examinations to ensure compliance with regulations (Commonwealth of Massachusetts, n.d.-b, n.d.-a, n.d.-c).

To further promote fair lending and equitable access to homeownership, policymakers may consider implementing measures such as expanding down payment assistance programs targeted at low-to-moderate-income households, increasing funding for homeownership counseling services tailored to marginalized communities, and implementing stricter enforcement of fair lending laws to prevent discriminatory lending practices. Initiatives to address the racial wealth gap, such as providing grants or subsidies to first-time homebuyers from historically marginalized communities, could help mitigate disparities in homeownership rates. (Apgar & Calder, 2005; Harkness, 2016; NCRC, 2008; Ross & Massachusetts Alliance Against Predatory Lending, 2011; Zinn & Reynolds, 2022). By shedding light on the mechanisms underlying mortgage denial rates, this study aims to inform efforts aimed at fostering equitable access to homeownership for all individuals, irrespective of race or socioeconomic status in Massachusetts and Worcester County.

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Appendix A. Logistic Loan Denial Model Regression and Diagnostics

(1) Logistic Loan Denial Model

$$L: P(\widehat{D_i = 1}) = \beta_0 + \beta_1 \text{Black} + \beta_2 \text{Asian} + \beta_3 \text{Native American} + \beta_4 \text{Hispanic or Latino} + \beta_5 \text{Age less than 25}$$
$$+ \beta_6 \text{Age 25 to 34} + \beta_7 \text{Age 45 to 54} + \beta_8 \text{Age 55 to 64} + \beta_9 \text{Age 65 or Older} + \beta_{10} \text{Female} + \beta_{11} \text{Manageable DTI}$$
$$+ \beta_{12} \text{Nearing unmanageable DTI} + \beta_{13} \text{Struggling DTI} + \beta_{14} \text{Down Payment Flag} - \beta_{15} \log(\text{income}) + \beta_{16} \log(\mathit{loan\ amount})$$
$$+ \beta_{17} \text{Property Value Ratio} + \beta_{18} \text{Co Applicant} + \beta_{19} \text{Less than 30 Year Mortgage} + \beta_{20} \text{More than 30 Year Mortgage}$$
$$+ \beta_{21} \mathit{Experian\ Credit\ Model} + \beta_{22} \mathit{FICO\ Credit\ Model} + \beta_{23} \mathit{More\ than\ One\ Credit\ Model} + \beta_{24} \mathit{LP\ AUS}$$
$$+ \beta_{25} \mathit{Other\ AUS}$$

Table A1. Variable Descriptions of Logistic Loan Denial Model

Name	Definition (CFPB, 2023)	Category
LOAN DENIAL	The action taken on the covered loan or application, is adapted from the action taken variable.	
RACE	Race of the applicant or borrower	Black Asian Native American Hispanic or Latino
SEX	Sex of the applicant or borrower.	Female
AGE	The age of the applicant.	Less than 25 Age 25-34 Age 45-54 Age 55-64 Age 65 or older
DEBT TO INCOME RATIO (DTI)	The ratio, as a percentage, of the applicant's or borrower's total monthly debt to the total monthly income relied on in making the credit decision.	Manageable DTI Nearing unmanageable DTI Struggling DTI
DOWN PAYMENT FLAG*	The ratio of the total amount of debt secured by the property to the value of the property relied on in making the credit decision (adapted from LTV ratio).	Less than 20% down payment
INCOME	The gross annual income, in thousands of dollars, relied on in making the credit decision, or if a credit decision was not made, the gross annual income relied on in processing the application.	Continuous variable
LOAN AMOUNT	The amount of the covered loan, or the amount applied for.	Continuous variable
PROPERTY VALUE RATIO*	The value of the property securing the covered loan or, in the case of an application, proposed to secure the covered loan, relied on in making the credit decision divided by the median property value by county.	Continuous variable
CO-APPLICANT STATUS*	Whether the applicant had a co-applicant or not	No co-applicant
MORTGAGE (LOAN) TERM	The number of months after which the legal obligation will mature or terminate, or would have matured or terminated.	More than 30-year mortgage Less than 30-year mortgage
CREDIT MODEL (APPLICANT CREDIT SCORE TYPE)	The name and version of the credit scoring model used to generate the credit score, or scores, relied on in making the credit decision	Experian FICO More than one credit model Other credit model
AUS	The automated underwriting system(s) (AUS) used by the financial institution to evaluate the application.	Loan Prospector (LP) Other

**indicates a generated variable*

Table A2: Omitted/Reference Variables

Category Name	Reference Variable
Race	White
Sex	Male
Age	Age 34-44
DTI	Healthy DTI
Down Payment Flag	20 percent or more down payment
Co-Applicant Status	Co-applicant (Yes)
Mortgage Term	30-year mortgage
Credit Model	Equifax credit model
AUS	Desktop Underwriter (DU)

Table A3: Logistic Loan Denial Model for Massachusetts

Loan Denial	Coef.	Odds Ratio	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Black	.906	2.474	.075	12.06	0	.759	1.053	***
Hispanic or Latino	.487	1.628	.071	6.89	0	.349	.626	***
Native American	.718	2.05	.33	2.17	.03	.071	1.365	**
Asian	.488	1.629	.06	8.16	0	.371	.605	***
Hispanic or Latino	.487	1.628	.071	6.89	0	.349	.626	***
Female	-.114	.892	.044	-2.59	.01	-.2	-.028	***
Age less than 25	-.023	.977	.126	-0.18	.855	-.271	.225	
Age 25-34	-.11	.896	.057	-1.95	.052	-.221	.001	*
Age 45-54	.206	1.228	.063	3.26	.001	.082	.329	***
Age 55-64	.343	1.41	.07	4.87	0	.205	.481	***
Age 65 or older	-.174	.84	.098	-1.78	.075	-.366	.018	*
Manageable DTI	-.019	.981	.058	-0.33	.745	-.132	.094	
Nearing unmanageable DTI	.27	1.31	.061	4.44	0	.151	.39	***
Struggling DTI	3.906	49.723	.076	51.56	0	3.758	4.055	***
Less than 20 percent down payment flag	.092	1.096	.046	1.99	.046	.001	.182	**
Income	-.157	.855	.05	-3.14	.002	-.255	-.059	***
Loan Amount	-.338	.713	.061	-5.58	0	-.457	-.219	***
Property Value Ratio	.044	1.045	.033	1.34	.181	-.02	.108	
No Co-Applicant	.274	1.316	.047	5.83	0	.182	.367	***
Less than 30 year mortgage	-.14	.87	.097	-1.45	.148	-.329	.05	
More than 30 year mortgage	.818	2.265	.198	4.13	0	.429	1.206	***
Equifax Credit Model	-.169	.844	.053	-3.17	.002	-.274	-.065	***
FICO Credit Model	-.073	.93	.053	-1.38	.168	-.176	.031	
More than 1 credit model	-.289	.749	.123	-2.34	.019	-.531	-.047	**
Other Credit Model	.887	2.428	.179	4.95	0	.536	1.238	***
LP AUS	-.533	.587	.051	-10.39	0	-.633	-.432	***
Other AUS	.594	1.812	.106	5.60	0	.386	.802	***
Constant	1.477	4.381	.679	2.18	.029	.147	2.807	**

Mean dependent var	0.050	SD dependent var	0.219
Pseudo r-squared	0.228	Number of obs	61140
Chi-square	5579.255	Prob > chi2	0.000
Akaike crit. (AIC)	18925.546	Bayesian crit. (BIC)	19169.111

*** *p<.01*, ** *p<.05*, * *p<.1*

Table A4: Logistic Loan Denial Model for Worcester County

Loan Denial	Coef.	Odds Ratio	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Black	.596	1.814	.22	2.70	.007	.164	1.027	***
Hispanic or Latino	.567	1.764	.197	2.88	.004	.181	.954	***
Native American	0	1	.	.	.	.	.	
Asian	.605	1.831	.173	3.50	0	.266	.943	***
Hispanic or Latino	.567	1.764	.197	2.88	.004	.181	.954	***
Female	-.047	.955	.127	-0.37	.713	-.295	.202	
Age less than 25	.005	1.005	.348	0.01	.988	-.677	.688	
Age 25-34	-.177	.838	.167	-1.06	.29	-.504	.151	
Age 45-54	.303	1.354	.184	1.65	.099	-.057	.664	*
Age 55-64	.541	1.718	.202	2.68	.007	.146	.936	***
Age 65 or older	.265	1.304	.277	0.96	.338	-.278	.809	
Manageable DTI	.109	1.115	.165	0.66	.509	-.215	.433	
Nearing unmanageable DTI	.353	1.423	.174	2.03	.042	.012	.693	**
Struggling DTI	4.212	67.488	.225	18.76	0	3.772	4.652	***
Less than 20 percent down payment flag	-.019	.982	.141	-0.13	.896	-.296	.259	
Income	-.12	.887	.149	-0.81	.42	-.412	.172	
Loan Amount	.054	1.055	.199	0.27	.787	-.337	.445	
Property Value Ratio	-.055	.947	.108	-0.51	.612	-.266	.157	
No Co-Applicant	.379	1.461	.139	2.72	.006	.106	.652	***
Less than 30 year mortgage	.243	1.275	.284	0.86	.392	-.314	.8	
More than 30 year mortgage	.665	1.945	.552	1.21	.228	-.416	1.747	
Equifax Credit Model	-.139	.87	.158	-0.88	.38	-.448	.171	
FICO Credit Model	.013	1.013	.153	0.08	.932	-.286	.312	
More than 1 credit model	.207	1.231	.31	0.67	.504	-.401	.816	
Other Credit Model	1.169	3.217	.61	1.92	.055	-.027	2.364	*
LP AUS	-.485	.616	.138	-3.52	0	-.755	-.214	***
Other AUS	.049	1.05	.422	0.12	.908	-.778	.876	
Constant	-3.832	.022	2.314	-1.66	.098	-8.368	.704	*

Mean dependent var	0.052	SD dependent var	0.222
Pseudo r-squared	0.242	Number of obs	7337
Chi-square	727.885	Prob > chi2	0.000
Akaike crit. (AIC)	2331.495	Bayesian crit. (BIC)	2510.912

*** *p<.01*, ** *p<.05*, * *p<.1*

Table A5: VIF Diagnostics for Logistic Loan Denial Model

	(I) Massachusetts		(II) Worcester County	
Variable	**VIF**	**1/VIF**	**VIF**	**1/VIF**
log_loan_a~t	3.22	0.310638	3.71	0.269842
log_income	2.99	0.334156	3.26	0.306540
property_v~o	2.25	0.443769	2.78	0.359372
age_25_34	1.46	0.684079	1.50	0.665254
equifax_cr~l	1.39	0.720689	1.40	0.712191
fico_credi~l	1.39	0.721229	1.40	0.715860
nearing_ma~T	1.36	0.734790	1.38	0.722255
age_45_54	1.32	0.758518	1.34	0.747643
age_55_64	1.28	0.779343	1.30	0.768442
managable_~I	1.26	0.792759	1.28	0.781044
age_65_or_~r	1.21	0.826330	1.22	0.822916
struggling~I	1.18	0.850679	1.17	0.856940
no_coappli~t	1.15	0.866683	1.16	0.861456
other_aus	1.14	0.877974	1.11	0.900139
lesss_than~e	1.13	0.886824	1.11	0.903876
more_than_~l	1.12	0.894548	1.10	0.905535
age_less_25	1.09	0.919142	1.10	0.906081
less_than_~g	1.07	0.932859	1.07	0.932045
asian_dummy	1.06	0.940802	1.06	0.945598
hispanic_l~y	1.05	0.951452	1.06	0.947388
LP_aus	1.05	0.954164	1.05	0.952520
black_dummy	1.04	0.964474	1.03	0.966227
female_dummy	1.03	0.968262	1.03	0.969826
other_cred~l	1.02	0.977076	1.02	0.982676
more_than_~e	1.01	0.989754	1.02	0.984708
native_ame~y	1.01	0.993427	1.01	0.991756
Mean VIF	1.36		1.41	

Appendix B. Logistic Lender Model Regression Results

Table B1. Massachusetts Lender 1 - Guaranteed Rate, Inc

	Coef.	Odds Ratio	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Black	.904	2.469	.075	12.04	0	.757	1.051	***
Hispanic or Latino	.484	1.623	.071	6.85	0	.346	.623	***
Native American	.726	2.068	.33	2.20	.028	.08	1.373	**
Asian	.489	1.631	.06	8.17	0	.372	.606	***
Female	-.113	.893	.044	-2.57	.01	-.199	-.027	**
Age less than 25	-.026	.974	.127	-0.21	.837	-.274	.222	
Age 25-34	-.109	.896	.057	-1.93	.054	-.22	.002	*
Age 45-54	.202	1.223	.063	3.19	.001	.078	.325	***
Age 55-64	.339	1.404	.07	4.81	0	.201	.477	***
Age 65 or older	-.179	.836	.098	-1.83	.067	-.371	.013	*
Manageable DTI	-.02	.98	.058	-0.35	.728	-.133	.093	
Nearing unmanageable DTI	.269	1.308	.061	4.41	0	.149	.388	***
Struggling DTI	3.912	50.009	.076	51.58	0	3.764	4.061	***
Less than 20 percent down payment flag	.067	1.07	.047	1.44	.15	-.024	.159	
Income	-.159	.853	.05	-3.19	.001	-.257	-.061	***
Loan Amount	-.323	.724	.061	-5.31	0	-.443	-.204	***
Property Value Ratio	.039	1.04	.033	1.18	.237	-.025	.103	
No Co-Applicant	.273	1.314	.047	5.81	0	.181	.366	***
Less than 30 year mortgage	-.133	.876	.096	-1.37	.169	-.322	.057	
More than 30 year mortgage	.799	2.223	.198	4.03	0	.41	1.187	***
Equifax Credit Model	-.166	.847	.053	-3.11	.002	-.271	-.062	***
FICO Credit Model	-.069	.934	.053	-1.30	.194	-.172	.035	
More than 1 credit model	-.304	.738	.123	-2.47	.014	-.546	-.063	**
Other Credit Model	.874	2.397	.179	4.88	0	.523	1.225	***
LP AUS	-.518	.596	.051	-10.06	0	-.618	-.417	***
Other AUS	.596	1.815	.106	5.62	0	.388	.804	***
Guaranteed Rate, Inc	-.309	.734	.101	-3.05	.002	-.507	-.11	***
Constant	1.323	3.756	.681	1.94	.052	-.012	2.659	*

Mean dependent var	0.050	SD dependent var	0.219
Pseudo r-squared	0.229	Number of obs	61140
Chi-square	5589.162	Prob > chi2	0.000
Akaike crit. (AIC)	18917.639	Bayesian crit. (BIC)	19170.225

*** *p<.01*, ** *p<.05*, * *p<.1*

Table B2. Massachusetts Lender 2 - Leader Bank, National Association

	Coef.	Odds Ratio	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Black	.887	2.428	.075	11.82	0	.74	1.034	***
Asian	.515	1.674	.06	8.60	0	.398	.633	***
Native American	.698	2.009	.329	2.12	.034	.052	1.344	**
Hispanic or Latino	.472	1.603	.071	6.67	0	.333	.61	***
Female	-.112	.894	.044	-2.56	.011	-.199	-.026	**
Age less than 25	-.035	.965	.126	-0.28	.78	-.283	.213	
Age 25-34	-.11	.896	.057	-1.94	.052	-.221	.001	*
Age 45-54	.193	1.212	.063	3.05	.002	.069	.316	***
Age 55-64	.334	1.397	.07	4.75	0	.196	.472	***
Age 65 or older	-.177	.838	.098	-1.81	.07	-.369	.014	*
Manageable DTI	-.038	.963	.058	-0.65	.514	-.151	.075	
Nearing unmanageable DTI	.242	1.273	.061	3.96	0	.122	.361	***
Struggling DTI	3.874	48.122	.076	51.14	0	3.725	4.022	***
Less than 20 percent down payment flag	.044	1.045	.046	0.96	.339	-.046	.135	
Income	-.155	.857	.05	-3.11	.002	-.252	-.057	***
Loan Amount	-.305	.737	.061	-5.01	0	-.424	-.186	***
Property Value Ratio	.029	1.029	.033	0.88	.378	-.035	.093	
No Co-Applicant	.274	1.315	.047	5.82	0	.182	.366	***
Less than 30 year mortgage	-.132	.876	.096	-1.37	.172	-.321	.057	
More than 30 year mortgage	.778	2.177	.198	3.94	0	.39	1.165	***
Equifax Credit Model	-.157	.855	.053	-2.94	.003	-.261	-.052	***
FICO Credit Model	-.065	.937	.053	-1.23	.22	-.168	.039	
More than 1 credit model	-.25	.779	.124	-2.02	.044	-.493	-.007	**
Other Credit Model	.858	2.359	.178	4.82	0	.509	1.207	***
LP AUS	-.532	.587	.051	-10.37	0	-.633	-.432	***
Other AUS	.576	1.779	.106	5.44	0	.368	.784	***
Leader Bank, National Association	-1.157	.315	.168	-6.89	0	-1.486	-.828	***
Constant	1.119	3.061	.681	1.64	.101	-.216	2.454	

Mean dependent var	0.050	SD dependent var	0.219
Pseudo r-squared	0.231	Number of obs	61140
Chi-square	5645.559	Prob > chi2	0.000
Akaike crit. (AIC)	18861.242	Bayesian crit. (BIC)	19113.828

**** p<.01, ** p<.05, * p<.1*

Table B3. Massachusetts Lender 3 - Fairwary Indep.

	Coef.	Odds Ratio	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Black	.905	2.473	.075	12.06	0	.758	1.053	***
Asian	.488	1.629	.06	8.15	0	.37	.605	***
Native American	.715	2.044	.33	2.16	.03	.068	1.363	**
Hispanic or Latino	.484	1.623	.071	6.84	0	.346	.623	***
Female	-.113	.893	.044	-2.58	.01	-.2	-.027	***
Age less than 25	-.021	.979	.126	-0.17	.867	-.269	.227	
Age 25-34	-.109	.897	.057	-1.93	.054	-.22	.002	*
Age 45-54	.205	1.228	.063	3.25	.001	.081	.329	***
Age 55-64	.343	1.409	.07	4.86	0	.205	.481	***
Age 65 or older	-.175	.839	.098	-1.79	.073	-.367	.016	*
Manageable DTI	-.019	.981	.058	-0.33	.743	-.132	.094	
Nearing unmanageable DTI	.271	1.311	.061	4.44	0	.151	.39	***
Struggling DTI	3.905	49.648	.076	51.53	0	3.756	4.053	***
Less than 20 percent down payment flag	.108	1.114	.049	2.21	.027	.012	.203	**
Income	-.157	.854	.05	-3.15	.002	-.255	-.06	***
Loan Amount	-.338	.713	.061	-5.57	0	-.456	-.219	***
Property Value Ratio	.043	1.044	.033	1.33	.184	-.021	.108	
No Co-Applicant	.274	1.315	.047	5.82	0	.181	.366	***
Less than 30 year mortgage	-.141	.868	.097	-1.46	.143	-.331	.048	
More than 30 year mortgage	.817	2.263	.198	4.12	0	.428	1.205	***
Equifax Credit Model	-.169	.845	.053	-3.16	.002	-.273	-.064	***
FICO Credit Model	-.072	.93	.053	-1.36	.172	-.176	.031	
More than 1 credit model	-.289	.749	.123	-2.34	.019	-.53	-.047	**
Other Credit Model	.883	2.417	.179	4.92	0	.531	1.234	***
LP AUS	-.528	.59	.052	-10.24	0	-.629	-.427	***
Other AUS	.583	1.791	.107	5.46	0	.373	.792	***
Fairwary Indep	-.109	.897	.11	-0.99	.322	-.325	.107	
Constant	1.473	4.363	.679	2.17	.03	.143	2.803	**

Mean dependent var	0.050	SD dependent var	0.219
Pseudo r-squared	0.228	Number of obs	61140
Chi-square	5580.257	Prob > chi2	0.000
Akaike crit. (AIC)	18926.544	Bayesian crit. (BIC)	19179.130

*** *p<.01, ** p<.05, * p<.1*

Table B4. Massachusetts Lender 4 - United Wholesale Mortgage

	Coef.	Odds Ratio	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Black	.906	2.473	.075	12.06	0	.758	1.053	***
Asian	.489	1.631	.06	8.16	0	.372	.607	***
Native American	.717	2.049	.33	2.17	.03	.07	1.365	**
Hispanic or Latino	.488	1.63	.071	6.90	0	.35	.627	***
Female	-.114	.892	.044	-2.59	.009	-.2	-.028	***
Age less than 25	-.023	.977	.126	-0.18	.857	-.271	.225	
Age 25-34	-.11	.896	.057	-1.95	.051	-.221	.001	*
Age 45-54	.206	1.229	.063	3.26	.001	.082	.33	***
Age 55-64	.343	1.409	.07	4.87	0	.205	.481	***
Age 65 or older	-.174	.84	.098	-1.78	.075	-.366	.018	*
Manageable DTI	-.019	.981	.058	-0.32	.746	-.132	.094	
Nearing unmanageable DTI	.271	1.311	.061	4.45	0	.152	.391	***
Struggling DTI	3.907	49.742	.076	51.56	0	3.758	4.055	***
Less than 20 percent down payment flag	.09	1.094	.047	1.93	.054	-.002	.181	*
Income	-.158	.854	.05	-3.16	.002	-.256	-.06	***
Loan Amount	-.338	.714	.061	-5.57	0	-.456	-.219	***
Property Value Ratio	.044	1.045	.033	1.34	.182	-.02	.108	
No Co-Applicant	.274	1.316	.047	5.83	0	.182	.366	***
Less than 30 year mortgage	-.14	.87	.097	-1.45	.148	-.329	.05	
More than 30 year mortgage	.816	2.262	.198	4.12	0	.428	1.205	***
Equifax Credit Model	-.17	.844	.053	-3.18	.001	-.274	-.065	***
FICO Credit Model	-.073	.929	.053	-1.39	.165	-.177	.03	
More than 1 credit model	-.291	.748	.123	-2.36	.018	-.533	-.049	**
Other Credit Model	.886	2.425	.179	4.94	0	.534	1.237	***
LP AUS	-.531	.588	.051	-10.32	0	-.632	-.43	***
Other AUS	.595	1.813	.106	5.60	0	.387	.803	***
United Wholesale Mortgage	-.038	.963	.112	-0.33	.739	-.258	.183	
Constant	1.476	4.375	.679	2.17	.03	.146	2.806	**

Mean dependent var	0.050	SD dependent var	0.219
Pseudo r-squared	0.228	Number of obs	61140
Chi-square	5579.367	Prob > chi2	0.000
Akaike crit. (AIC)	18927.434	Bayesian crit. (BIC)	19180.020

**** p<.01, ** p<.05, * p<.1*

Table B5. Worcester County Lender 1 - Fairway Indep.

	Coef.	Odds Ratio	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Black	.905	2.473	.075	12.06	0	.758	1.053	***
Asian	.488	1.629	.06	8.15	0	.37	.605	***
Native American	.715	2.044	.33	2.16	.03	.068	1.363	**
Hispanic or Latino	.484	1.623	.071	6.84	0	.346	.623	***
Female	-.113	.893	.044	-2.58	.01	-.2	-.027	***
Age less than 25	-.021	.979	.126	-0.17	.867	-.269	.227	
Age 25-34	-.109	.897	.057	-1.93	.054	-.22	.002	*
Age 45-54	.205	1.228	.063	3.25	.001	.081	.329	***
Age 55-64	.343	1.409	.07	4.86	0	.205	.481	***
Age 65 or older	-.175	.839	.098	-1.79	.073	-.367	.016	*
Manageable DTI	-.019	.981	.058	-0.33	.743	-.132	.094	
Nearing unmanageable DTI	.271	1.311	.061	4.44	0	.151	.39	***
Struggling DTI	3.905	49.648	.076	51.53	0	3.756	4.053	***
Less than 20 percent down payment flag	.108	1.114	.049	2.21	.027	.012	.203	**
Income	-.157	.854	.05	-3.15	.002	-.255	-.06	***
Loan Amount	-.338	.713	.061	-5.57	0	-.456	-.219	***
Property Value Ratio	.043	1.044	.033	1.33	.184	-.021	.108	
No Co-Applicant	.274	1.315	.047	5.82	0	.181	.366	***
Less than 30 year mortgage	-.141	.868	.097	-1.46	.143	-.331	.048	
More than 30 year mortgage	.817	2.263	.198	4.12	0	.428	1.205	***
Equifax Credit Model	-.169	.845	.053	-3.16	.002	-.273	-.064	***
FICO Credit Model	-.072	.93	.053	-1.36	.172	-.176	.031	
More than 1 credit model	-.289	.749	.123	-2.34	.019	-.53	-.047	**
Other Credit Model	.883	2.417	.179	4.92	0	.531	1.234	***
LP AUS	-.528	.59	.052	-10.24	0	-.629	-.427	***
Other AUS	.583	1.791	.107	5.46	0	.373	.792	***
Fairway Indep	-.109	.897	.11	-0.99	.322	-.325	.107	
Constant	1.473	4.363	.679	2.17	.03	.143	2.803	**

Mean dependent var	0.050	SD dependent var	0.219
Pseudo r-squared	0.228	Number of obs	61140
Chi-square	5580.257	Prob > chi2	0.000
Akaike crit. (AIC)	18926.544	Bayesian crit. (BIC)	19179.130

*** *p<.01, ** p<.05, * p<.1*

Table B6. Worcester County Lender 2 - United Wholesale Mortgage, LLC

	Coef.	Odds Ratio	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Black	.906	2.473	.075	12.06	0	.758	1.053	***
Asian	.489	1.631	.06	8.16	0	.372	.607	***
Native American	.717	2.049	.33	2.17	.03	.07	1.365	**
Hispanic or Latino	.488	1.63	.071	6.90	0	.35	.627	***
Female	-.114	.892	.044	-2.59	.009	-.2	-.028	***
Age less than 25	-.023	.977	.126	-0.18	.857	-.271	.225	
Age 25-34	-.11	.896	.057	-1.95	.051	-.221	.001	*
Age 45-54	.206	1.229	.063	3.26	.001	.082	.33	***
Age 55-64	.343	1.409	.07	4.87	0	.205	.481	***
Age 65 or older	-.174	.84	.098	-1.78	.075	-.366	.018	*
Manageable DTI	-.019	.981	.058	-0.32	.746	-.132	.094	
Nearing unmanageable DTI	.271	1.311	.061	4.45	0	.152	.391	***
Struggling DTI	3.907	49.742	.076	51.56	0	3.758	4.055	***
Less than 20 percent down payment flag	.09	1.094	.047	1.93	.054	-.002	.181	*
Income	-.158	.854	.05	-3.16	.002	-.256	-.06	***
Loan Amount	-.338	.714	.061	-5.57	0	-.456	-.219	***
Property Value Ratio	.044	1.045	.033	1.34	.182	-.02	.108	
No Co-Applicant	.274	1.316	.047	5.83	0	.182	.366	***
Less than 30 year mortgage	-.14	.87	.097	-1.45	.148	-.329	.05	
More than 30 year mortgage	.816	2.262	.198	4.12	0	.428	1.205	***
Equifax Credit Model	-.17	.844	.053	-3.18	.001	-.274	-.065	***
FICO Credit Model	-.073	.929	.053	-1.39	.165	-.177	.03	
More than 1 credit model	-.291	.748	.123	-2.36	.018	-.533	-.049	**
Other Credit Model	.886	2.425	.179	4.94	0	.534	1.237	***
LP AUS	-.531	.588	.051	-10.32	0	-.632	-.43	***
Other AUS	.595	1.813	.106	5.60	0	.387	.803	***
United Wholesale Mortgage, LLC	-.038	.963	.112	-0.33	.739	-.258	.183	
Constant	1.476	4.375	.679	2.17	.03	.146	2.806	**

Mean dependent var	0.050	SD dependent var	0.219
Pseudo r-squared	0.228	Number of obs	61140
Chi-square	5579.367	Prob > chi2	0.000
Akaike crit. (AIC)	18927.434	Bayesian crit. (BIC)	19180.020

*** *p<.01, ** p<.05, * p<.1*

Table B7. Worcester County 3 - Guaranteed Rate, Inc

	Coef.	Odds Ratio	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Black	.904	2.469	.075	12.04	0	.757	1.051	***
Asian	.489	1.631	.06	8.17	0	.372	.606	***
Native American	.726	2.068	.33	2.20	.028	.08	1.373	**
Hispanic or Latino	.484	1.623	.071	6.85	0	.346	.623	***
Female	-.113	.893	.044	-2.57	.01	-.199	-.027	**
Age less than 25	-.026	.974	.127	-0.21	.837	-.274	.222	
Age 25-34	-.109	.896	.057	-1.93	.054	-.22	.002	*
Age 45-54	.202	1.223	.063	3.19	.001	.078	.325	***
Age 55-64	.339	1.404	.07	4.81	0	.201	.477	***
Age 65 or older	-.179	.836	.098	-1.83	.067	-.371	.013	*
Manageable DTI	-.02	.98	.058	-0.35	.728	-.133	.093	
Nearing unmanageable DTI	.269	1.308	.061	4.41	0	.149	.388	***
Struggling DTI	3.912	50.009	.076	51.58	0	3.764	4.061	***
Less than 20 percent down payment flag	.067	1.07	.047	1.44	.15	-.024	.159	
Income	-.159	.853	.05	-3.19	.001	-.257	-.061	***
Loan Amount	-.323	.724	.061	-5.31	0	-.443	-.204	***
Property Value Ratio	.039	1.04	.033	1.18	.237	-.025	.103	
No Co-Applicant	.273	1.314	.047	5.81	0	.181	.366	***
Less than 30 year mortgage	-.133	.876	.096	-1.37	.169	-.322	.057	
More than 30 year mortgage	.799	2.223	.198	4.03	0	.41	1.187	***
Equifax Credit Model	-.166	.847	.053	-3.11	.002	-.271	-.062	***
FICO Credit Model	-.069	.934	.053	-1.30	.194	-.172	.035	
More than 1 credit model	-.304	.738	.123	-2.47	.014	-.546	-.063	**
Other Credit Model	.874	2.397	.179	4.88	0	.523	1.225	***
LP AUS	-.518	.596	.051	-10.06	0	-.618	-.417	***
Other AUS	.596	1.815	.106	5.62	0	.388	.804	***
Guaranteed Rate, Inc	-.309	.734	.101	-3.05	.002	-.507	-.11	***
Constant	1.323	3.756	.681	1.94	.052	-.012	2.659	*

Mean dependent var	0.050	SD dependent var	0.219
Pseudo r-squared	0.229	Number of obs	61140
Chi-square	5589.162	Prob > chi2	0.000
Akaike crit. (AIC)	18917.639	Bayesian crit. (BIC)	19170.225

*** *p<.01, ** p<.05, * p<.1*

Table B8. Worcester County Lender 4 - Total Mortgage Services, LLC

Logistic regression

denied_binary	Coef.	Odds Ratio	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Black	.915	2.498	.075	12.18	0	.768	1.063	***
Asian	.484	1.623	.06	8.10	0	.367	.602	***
Native American	.72	2.055	.331	2.18	.029	.072	1.368	**
Hispanic or Latino	.487	1.627	.071	6.88	0	.348	.625	***
Female	-.113	.893	.044	-2.57	.01	-.199	-.027	**
Age less than 25	-.016	.984	.126	-0.13	.899	-.264	.232	
Age 25-34	-.11	.896	.057	-1.94	.053	-.221	.001	*
Age 45-54	.209	1.232	.063	3.31	.001	.085	.332	***
Age 55-64	.342	1.408	.07	4.85	0	.204	.48	***
Age 65 or older	-.176	.839	.098	-1.80	.072	-.368	.016	*
Manageable DTI	-.016	.984	.058	-0.28	.777	-.129	.097	
Nearing unmanageable DTI	.273	1.313	.061	4.47	0	.153	.392	***
Struggling DTI	3.904	49.595	.076	51.52	0	3.755	4.052	***
Less than 20 percent down payment flag	.078	1.081	.046	1.69	.091	-.012	.169	*
Income	-.16	.852	.05	-3.21	.001	-.258	-.062	***
Loan Amount	-.341	.711	.061	-5.63	0	-.459	-.222	***
Property Value Ratio	.044	1.045	.033	1.35	.178	-.02	.108	
No Co-Applicant	.275	1.316	.047	5.84	0	.182	.367	***
Less than 30 year mortgage	-.141	.869	.096	-1.46	.144	-.33	.048	
More than 30 year mortgage	.808	2.244	.198	4.08	0	.42	1.196	***
Equifax Credit Model	-.174	.841	.053	-3.25	.001	-.278	-.069	***
FICO Credit Model	-.077	.926	.053	-1.45	.146	-.18	.027	
More than 1 credit model	-.299	.742	.123	-2.43	.015	-.54	-.058	**
Other Credit Model	.878	2.406	.179	4.90	0	.527	1.229	***
LP AUS	-.532	.587	.051	-10.38	0	-.633	-.432	***
Other AUS	.599	1.82	.106	5.64	0	.391	.807	***
Total Mortgage Services, LLC	-.815	.443	.248	-3.28	.001	-1.301	-.328	***
Constant	1.539	4.661	.678	2.27	.023	.21	2.868	**

Mean dependent var	0.050	SD dependent var	0.219
Pseudo r-squared	0.229	Number of obs	61140
Chi-square	5592.772	Prob > chi2	0.000
Akaike crit. (AIC)	18914.029	Bayesian crit. (BIC)	19166.615

**** p<.01, ** p<.05, * p<.1*

Table B9: F-test for Logistic Lender Model Equation for Massachusetts

(1) [denied_binary]interact_MA1_manageableDTI = 0
(2) [denied_binary]interact_MA1_nearmanageableDTI = 0
(3) [denied_binary]interact_MA1_strugDTI = 0
(4) [denied_binary]interact_MA1_black = 0
(5) [denied_binary]interact_MA1_asian = 0
(6) [denied_binary]interact_MA1_NA = 0
(7) [denied_binary]interact_MA1_HL = 0
(8) [denied_binary]interact_MA2_mangDTI = 0
(9) [denied_binary]o.interact_MA2_strugDTI = 0
(10) [denied_binary]interact_MA2_nearmangDTI = 0
(11) [denied_binary]o.interact_MA2_black = 0
(12) [denied_binary]interact_MA2_asian = 0
(13) [denied_binary]o.interact_MA2_NA = 0
(14) [denied_binary]interact_MA2_HL = 0
(15) [denied_binary]interact_MA3_black = 0
(16) [denied_binary]interact_MA3_asian = 0
(17) [denied_binary]o.interact_MA3_NA = 0
(18) [denied_binary]interact_MA3_HL = 0
(19) [denied_binary]interact_MA3_strugDTI = 0
(20) [denied_binary]interact_MA3_nearmangDTI = 0
(21) [denied_binary]interact_MA3_mangDTI = 0
(22) [denied_binary]interact_MA4_mangDTI = 0
(23) [denied_binary]interact_MA4_strugDTI = 0
(24) [denied_binary]interact_MA4_nearmangDTI = 0
(25) [denied_binary]interact_MA4_black = 0
(26) [denied_binary]interact_MA4_asian = 0
(27) [denied_binary]o.interact_MA4_NA = 0
(28) [denied_binary]interact_MA4_HL = 0
Constraint 9 dropped
Constraint 11 dropped
Constraint 13 dropped
Constraint 17 dropped
Constraint 27 dropped

chi2(23) = 80.40
Prob > chi2 = 0.0000

The F-test results indicate that the coefficients for the variables associated with lender interactions, race, and DTI categories are jointly significant in predicting loan denial. The chi-squared statistic of 80.40 with 23 degrees of freedom yields a p-value of 0.0000, indicating that the combined effect of these variables is statistically significant. Therefore, we can reject the null hypothesis that all these coefficients are equal to zero, suggesting that at least one of the coefficients is significantly different from zero in predicting loan denial.

Table B10: F-test for Logistic Lender Model Equation for Worcester County Lender

```
 (1)   [denied_binary]interact_1WC_mangDTI = 0
 (2)   [denied_binary]interact_1WC_nearmangDTI = 0
 (3)   [denied_binary]interact_1WC_strugDTI = 0
 (4)   [denied_binary]interact_1WC_black = 0
 (5)   [denied_binary]interact_1WC_asian = 0
 (6)   [denied_binary]o.interact_1WC_NA = 0
 (7)   [denied_binary]interact_1WC_HL = 0
 (8)   [denied_binary]interact_2WC_mangDTI = 0
 (9)   [denied_binary]interact_2WC_nearmangDTI = 0
 (10)  [denied_binary]interact_2WC_strugDTI = 0
 (11)  [denied_binary]interact_2WC_black = 0
 (12)  [denied_binary]interact_2WC_asian = 0
 (13)  [denied_binary]o.interact_2WC_NA = 0
 (14)  [denied_binary]interact_2WC_HL = 0
 (15)  [denied_binary]interact_3WC_mangDTI = 0
 (16)  [denied_binary]interact_3WC_nearmangDTI = 0
 (17)  [denied_binary]interact_3WC_strugDTI = 0
 (18)  [denied_binary]interact_3WC_black = 0
 (19)  [denied_binary]interact_3WC_asian = 0
 (20)  [denied_binary]interact_3WC_NA = 0
 (21)  [denied_binary]interact_3WC_HL = 0
 (22)  [denied_binary]interact_4WC_mangDTI = 0
 (23)  [denied_binary]interact_4WC_nearmangDTI = 0
 (24)  [denied_binary]interact_4WC_strugDTI = 0
 (25)  [denied_binary]interact_4WC_black = 0
 (26)  [denied_binary]interact_4WC_asian = 0
 (27)  [denied_binary]interact_4WC_NA = 0
 (28)  [denied_binary]interact_4WC_HL = 0
       Constraint 6 dropped
       Constraint 13 dropped

           chi2( 26) =   65.31
         Prob > chi2 =    0.0000
```

The F-test results indicate that at least one of the coefficients associated with the interaction variables is statistically different from zero. The chi-square statistic of 65.31 with 26 degrees of freedom yields a p-value of 0.0000, suggesting strong evidence against the null hypothesis that all coefficients are equal to zero. Therefore, we reject the null hypothesis and conclude that there is a statistically significant relationship between the interaction variables and the outcome variable (loan denial) in the model.

Appendix C. Logistic Lender-Race Interaction Regression Results

Table C1. Lender-Race Interaction Massachusetts Lender 1 - Guaranteed Rate, Inc

denied_binary	Coef.	Odds Ratio	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Black	.946	2.576	.195	12.47	0	2.22	2.989	***
Asian	.516	1.676	.102	8.45	0	1.487	1.889	***
Native American	.799	2.223	.74	2.40	.016	1.157	4.268	**
Hispanic or Latino	.502	1.652	.119	6.98	0	1.435	1.902	***
Female	-.115	.892	.039	-2.60	.009	.818	.972	***
Age less than 25	-.027	.974	.123	-0.21	.833	.76	1.248	
Age 25-34	-.112	.894	.051	-1.98	.047	.8	.999	**
Age 45-54	.2	1.222	.077	3.18	.001	1.08	1.383	***
Age 55-64	.34	1.405	.099	4.82	0	1.224	1.613	***
Age 65 or older	-.175	.839	.082	-1.79	.074	.693	1.017	*
Manageable DTI	-.019	.981	.057	-0.34	.736	.876	1.098	
Nearing unmanageable DTI	.269	1.309	.08	4.42	0	1.162	1.475	***
Struggling DTI	3.917	50.228	3.811	51.61	0	43.287	58.282	***
Less than 20 percent down payment flag	.076	1.079	.05	1.64	.101	.985	1.181	
Income	-.156	.855	.043	-3.14	.002	.775	.943	***
Loan Amount	-.332	.718	.044	-5.46	0	.637	.808	***
Property Value Ratio	.04	1.041	.034	1.22	.223	.976	1.11	
No Co-Applicant	.274	1.315	.062	5.81	0	1.199	1.442	***
Less than 30 year mortgage	-.133	.875	.084	-1.38	.167	.724	1.057	
More than 30 year mortgage	.813	2.254	.447	4.10	0	1.528	3.325	***
Equifax Credit Model	-.168	.845	.045	-3.16	.002	.761	.938	***
FICO Credit Model	-.071	.931	.049	-1.35	.179	.84	1.033	
More than 1 credit model	-.302	.739	.091	-2.45	.014	.581	.941	**
Other Credit Model	.88	2.412	.432	4.91	0	1.698	3.427	***
LP AUS	-.525	.592	.03	-10.23	0	.535	.654	***
Other AUS	.593	1.809	.192	5.59	0	1.47	2.228	***
Lender*Black	-1.074	.342	.139	-2.65	.008	.154	.757	***
Lender*Hispanic or Latino	-.167	.846	.279	-0.51	.611	.444	1.613	
Lender*Native American	-1.323	.266	.324	-1.09	.277	.024	2.897	
Lender * Asian	-.447	.64	.14	-2.04	.041	.417	.982	**
Constant	1.401	4.06	2.759	2.06	.039	1.072	15.379	**

Mean dependent var	0.050	SD dependent var	0.219
Pseudo r-squared	0.229	Number of obs	61140
Chi-square	5594.707	Prob > chi2	0.000
Akaike crit. (AIC)	18918.095	Bayesian crit. (BIC)	19197.743

*** *p<.01*, ** *p<.05*, * *p<.1*

Table C2. Lender-Race Interaction Massachusetts Lender 2 - Leader Bank, National Association

denied_binary	Coef.	Odds Ratio	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Black	.923	2.516	.075	12.27	0	.775	1.07	***
Asian	.552	1.737	.061	9.10	0	.433	.671	***
Native American	.729	2.072	.33	2.21	.027	.081	1.376	**
Hispanic or Latino	.497	1.644	.071	7.00	0	.358	.636	***
Female	-.116	.891	.044	-2.63	.009	-.202	-.029	***
Age less than 25	-.031	.97	.126	-0.24	.808	-.279	.217	
Age 25-34	-.111	.895	.057	-1.95	.051	-.222	0	*
Age 45-54	.2	1.221	.063	3.16	.002	.076	.323	***
Age 55-64	.34	1.405	.07	4.83	0	.202	.478	***
Age 65 or older	-.171	.843	.098	-1.74	.081	-.362	.021	*
Manageable DTI	-.028	.973	.058	-0.48	.631	-.141	.085	
Nearing unmanageable DTI	.257	1.293	.061	4.22	0	.138	.377	***
Struggling DTI	3.897	49.232	.076	51.42	0	3.748	4.045	***
Less than 20 percent down payment flag	.074	1.077	.046	1.60	.109	-.016	.164	
Income	-.155	.857	.05	-3.11	.002	-.252	-.057	***
Loan Amount	-.328	.72	.061	-5.42	0	-.447	-.21	***
Property Value Ratio	.038	1.039	.033	1.16	.248	-.026	.102	
No Co-Applicant	.276	1.318	.047	5.86	0	.183	.368	***
Less than 30 year mortgage	-.135	.873	.096	-1.40	.161	-.324	.054	
More than 30 year mortgage	.81	2.249	.198	4.09	0	.422	1.198	***
Equifax Credit Model	-.166	.847	.053	-3.10	.002	-.27	-.061	***
FICO Credit Model	-.071	.931	.053	-1.35	.177	-.175	.032	
More than 1 credit model	-.276	.759	.124	-2.24	.025	-.518	-.034	**
Other Credit Model	.876	2.402	.179	4.90	0	.526	1.227	***
LP AUS	-.534	.587	.051	-10.40	0	-.634	-.433	***
Other AUS	.584	1.793	.106	5.50	0	.376	.792	***
Lender*Black	0	1	.	.	.	.	.	
Lender*Hispanic or Latino	-.634	.531	.719	-0.88	.378	-2.043	.775	
Lender*Native American	0	1	.	.	.	.	.	
Lender*Asian	-1.15	.317	.281	-4.09	0	-1.701	-.599	***
Constant	1.363	3.908	.679	2.01	.045	.032	2.694	**

Mean dependent var	0.051	SD dependent var	0.219
Pseudo r-squared	0.229	Number of obs	61081
Chi-square	5604.041	Prob > chi2	0.000
Akaike crit. (AIC)	18898.644	Bayesian crit. (BIC)	19160.222

*** *p<.01*, ** *p<.05*, * *p<.1*

note: Lender*Black != 0 predicts failure perfectly; all applications approved; omitted and 56 obs not used.
note: Lender*Native American != 0 predicts failure perfectly; all applications approved; omitted and 3 obs not used.

Table C3. Lender-Race Interaction Massachusetts Lender 3 - Fairway Indep.

denied_binary	Coef.	Odds Ratio	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Black	.889	2.432	.077	11.52	0	.737	1.04	***
Asian	.477	1.612	.061	7.82	0	.358	.597	***
Native American	.748	2.113	.332	2.25	.024	.098	1.399	**
Hispanic or Latino	.502	1.652	.071	7.04	0	.362	.642	***
Female	-.114	.893	.044	-2.58	.01	-.2	-.027	***
Age less than 25	-.024	.976	.126	-0.19	.847	-.272	.224	
Age 25-34	-.109	.897	.057	-1.92	.055	-.22	.002	*
Age 45-54	.207	1.229	.063	3.27	.001	.083	.33	***
Age 55-64	.343	1.41	.07	4.87	0	.205	.481	***
Age 65 or older	-.173	.841	.098	-1.77	.077	-.365	.019	*
Manageable DTI	-.018	.982	.058	-0.32	.749	-.131	.095	
Nearing unmanageable DTI	.269	1.309	.061	4.42	0	.15	.389	***
Struggling DTI	3.908	49.816	.076	51.57	0	3.76	4.057	***
Less than 20 percent down payment flag	.086	1.089	.047	1.82	.068	-.006	.178	*
Income	-.156	.855	.05	-3.13	.002	-.254	-.058	***
Loan Amount	-.338	.713	.061	-5.58	0	-.457	-.219	***
Property Value Ratio	.044	1.045	.033	1.33	.183	-.021	.108	
No Co-Applicant	.274	1.316	.047	5.83	0	.182	.367	***
Less than 30 year mortgage	-.14	.869	.097	-1.45	.147	-.329	.049	
More than 30 year mortgage	.816	2.262	.198	4.12	0	.428	1.204	***
Equifax Credit Model	-.168	.845	.053	-3.16	.002	-.273	-.064	***
FICO Credit Model	-.072	.93	.053	-1.37	.17	-.176	.031	
More than 1 credit model	-.288	.75	.123	-2.33	.02	-.53	-.046	**
Other Credit Model	.889	2.432	.179	4.96	0	.537	1.24	***
LP AUS	-.535	.586	.051	-10.42	0	-.635	-.434	***
Other AUS	.599	1.821	.106	5.63	0	.391	.808	***
Lender*Black	.295	1.343	.273	1.08	.28	-.241	.831	
Lender*Hispanic or Latino	-.571	.565	.445	-1.28	.199	-1.443	.301	
Lender*Native American	0	1	.	.	.	.	.	
Lender*Asian	.245	1.278	.246	1.00	.319	-.237	.728	
Lender*Hispanic or Latino	-.571	.565	.445	-1.28	.199	-1.443	.301	
Constant	1.477	4.38	.679	2.18	.03	.146	2.808	**

Mean dependent var	0.050	SD dependent var	0.219
Pseudo r-squared	0.228	Number of obs	61132
Chi-square	5583.021	Prob > chi2	0.000
Akaike crit. (AIC)	18926.951	Bayesian crit. (BIC)	19197.575

*** *p<.01*, ** *p<.05*, * *p<.1*

Table C4. Lender-Race Interaction Massachusetts Lender 4 - United Wholesale Mortgage

Logistic regression

denied_binary	Coef.	Odds Ratio	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Black	.919	2.507	.076	12.14	0	.771	1.067	***
Asian	.5	1.649	.061	8.19	0	.381	.62	***
Native American	.728	2.071	.331	2.20	.028	.08	1.376	**
Hispanic or Latino	.483	1.622	.073	6.63	0	.341	.626	***
Female	-.114	.892	.044	-2.59	.01	-.2	-.028	***
Age less than 25	-.021	.979	.126	-0.17	.868	-.269	.227	
Age 25-34	-.11	.896	.057	-1.94	.052	-.221	.001	*
Age 45-54	.206	1.229	.063	3.27	.001	.082	.33	***
Age 55-64	.343	1.41	.07	4.87	0	.205	.481	***
Age 65 or older	-.173	.841	.098	-1.77	.076	-.365	.018	*
Manageable DTI	-.019	.981	.058	-0.33	.743	-.132	.094	
Nearing unmanageable DTI	.273	1.314	.061	4.48	0	.154	.393	***
Struggling DTI	3.907	49.772	.076	51.55	0	3.759	4.056	***
Less than 20 percent down payment flag	.088	1.092	.046	1.89	.059	-.003	.178	*
Income	-.16	.852	.05	-3.20	.001	-.258	-.062	***
Loan Amount	-.337	.714	.061	-5.56	0	-.456	-.218	***
Property Value Ratio	.044	1.045	.033	1.36	.175	-.02	.108	
No Co-Applicant	.274	1.315	.047	5.82	0	.182	.366	***
Less than 30 year mortgage	-.139	.87	.097	-1.44	.149	-.329	.05	
More than 30 year mortgage	.817	2.263	.198	4.12	0	.428	1.205	***
Equifax Credit Model	-.171	.843	.053	-3.21	.001	-.276	-.066	***
FICO Credit Model	-.075	.928	.053	-1.42	.157	-.178	.029	
More than 1 credit model	-.294	.745	.123	-2.39	.017	-.536	-.053	**
Other Credit Model	.884	2.422	.179	4.93	0	.533	1.236	***
LP AUS	-.53	.589	.051	-10.31	0	-.63	-.429	***
Other AUS	.595	1.813	.106	5.60	0	.387	.803	***
Lender*Black	-.503	.604	.431	-1.17	.243	-1.349	.342	
Lender*Hispanic or Latino	.088	1.092	.245	0.36	.719	-.393	.569	
Lender*Native American	0	1	.	.	.	.	.	
Lender*Asian	-.208	.812	.22	-0.94	.345	-.639	.224	
Constant	1.479	4.389	.679	2.18	.029	.149	2.81	**

Mean dependent var	0.050	SD dependent var	0.219
Pseudo r-squared	0.228	Number of obs	61129
Chi-square	5581.784	Prob > chi2	0.000
Akaike crit. (AIC)	18927.878	Bayesian crit. (BIC)	19198.500

*** *p<.01*, ** *p<.05*, * *p<.1*

Table C5. Lender-Race Interaction Worcester County Lender 1 - Fairway Indep.

Logistic regression

denied_binary	Coef.	Odds Ratio	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Black	.889	2.432	.077	11.52	0	.737	1.04	***
Asian	.477	1.612	.061	7.82	0	.358	.597	***
Native American	.748	2.113	.332	2.25	.024	.098	1.399	**
Hispanic or Latino	.502	1.652	.071	7.04	0	.362	.642	***
Female	-.114	.893	.044	-2.58	.01	-.2	-.027	***
Age less than 25	-.024	.976	.126	-0.19	.847	-.272	.224	
Age 25-34	-.109	.897	.057	-1.92	.055	-.22	.002	*
Age 45-54	.207	1.229	.063	3.27	.001	.083	.33	***
Age 55-64	.343	1.41	.07	4.87	0	.205	.481	***
Age 65 or older	-.173	.841	.098	-1.77	.077	-.365	.019	*
Manageable DTI	-.018	.982	.058	-0.32	.749	-.131	.095	
Nearing unmanageable DTI	.269	1.309	.061	4.42	0	.15	.389	***
Struggling DTI	3.908	49.816	.076	51.57	0	3.76	4.057	***
Less than 20 percent down payment flag	.086	1.089	.047	1.82	.068	-.006	.178	*
Income	-.156	.855	.05	-3.13	.002	-.254	-.058	***
Loan Amount	-.338	.713	.061	-5.58	0	-.457	-.219	***
Property Value Ratio	.044	1.045	.033	1.33	.183	-.021	.108	
No Co-Applicant	.274	1.316	.047	5.83	0	.182	.367	***
Less than 30 year mortgage	-.14	.869	.097	-1.45	.147	-.329	.049	
More than 30 year mortgage	.816	2.262	.198	4.12	0	.428	1.204	***
Equifax Credit Model	-.168	.845	.053	-3.16	.002	-.273	-.064	***
FICO Credit Model	-.072	.93	.053	-1.37	.17	-.176	.031	
More than 1 credit model	-.288	.75	.123	-2.33	.02	-.53	-.046	**
Other Credit Model	.889	2.432	.179	4.96	0	.537	1.24	***
LP AUS	-.535	.586	.051	-10.42	0	-.635	-.434	***
Other AUS	.599	1.821	.106	5.63	0	.391	.808	***
Lender*Black	.295	1.343	.273	1.08	.28	-.241	.831	
Lender*Hispanic or Latino	-.571	.565	.445	-1.28	.199	-1.443	.301	
Lender*Native American	0	1	.	.	.	.	.	
Lender*Asian	.245	1.278	.246	1.00	.319	-.237	.728	
Constant	1.477	4.38	.679	2.18	.03	.146	2.808	**

Mean dependent var	0.050	SD dependent var	0.219
Pseudo r-squared	0.228	Number of obs	61132
Chi-square	5583.021	Prob > chi2	0.000
Akaike crit. (AIC)	18926.951	Bayesian crit. (BIC)	19197.575

**** p<.01, ** p<.05, * p<.1*

Table C6. Lender-Race Interaction Worcester County Lender 2 - United Wholesale Mortgage, LLC

denied_binary	Coef.	Odds Ratio	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Black	.919	2.507	.076	12.14	0	.771	1.067	***
Asian	.5	1.649	.061	8.19	0	.381	.62	***
Native American	.728	2.071	.331	2.20	.028	.08	1.376	**
Hispanic or Latino	.483	1.622	.073	6.63	0	.341	.626	***
Female	-.114	.892	.044	-2.59	.01	-.2	-.028	***
Age less than 25	-.021	.979	.126	-0.17	.868	-.269	.227	
Age 25-34	-.11	.896	.057	-1.94	.052	-.221	.001	*
Age 45-54	.206	1.229	.063	3.27	.001	.082	.33	***
Age 55-64	.343	1.41	.07	4.87	0	.205	.481	***
Age 65 or older	-.173	.841	.098	-1.77	.076	-.365	.018	*
Manageable DTI	-.019	.981	.058	-0.33	.743	-.132	.094	
Nearing unmanageable DTI	.273	1.314	.061	4.48	0	.154	.393	***
Struggling DTI	3.907	49.772	.076	51.55	0	3.759	4.056	***
Less than 20 percent down payment flag	.088	1.092	.046	1.89	.059	-.003	.178	*
Income	-.16	.852	.05	-3.20	.001	-.258	-.062	***
Loan Amount	-.337	.714	.061	-5.56	0	-.456	-.218	***
Property Value Ratio	.044	1.045	.033	1.36	.175	-.02	.108	
No Co-Applicant	.274	1.315	.047	5.82	0	.182	.366	***
Less than 30 year mortgage	-.139	.87	.097	-1.44	.149	-.329	.05	
More than 30 year mortgage	.817	2.263	.198	4.12	0	.428	1.205	***
Equifax Credit Model	-.171	.843	.053	-3.21	.001	-.276	-.066	***
FICO Credit Model	-.075	.928	.053	-1.42	.157	-.178	.029	
More than 1 credit model	-.294	.745	.123	-2.39	.017	-.536	-.053	**
Other Credit Model	.884	2.422	.179	4.93	0	.533	1.236	***
LP AUS	-.53	.589	.051	-10.31	0	-.63	-.429	***
Other AUS	.595	1.813	.106	5.60	0	.387	.803	***
Lender*Black	-.503	.604	.431	-1.17	.243	-1.349	.342	
Lender*Hispanic or Latino	.088	1.092	.245	0.36	.719	-.393	.569	
Lender*Native American	0	1	.	.	.	.	.	
Lender*Asian	-.208	.812	.22	-0.94	.345	-.639	.224	
Constant	1.479	4.389	.679	2.18	.029	.149	2.81	**

Mean dependent var	0.050	SD dependent var	0.219
Pseudo r-squared	0.228	Number of obs	61129
Chi-square	5581.784	Prob > chi2	0.000
Akaike crit. (AIC)	18927.878	Bayesian crit. (BIC)	19198.500

**** p<.01, ** p<.05, * p<.1*

Note: Lender*Native American!= 0 predicts failure perfectly; interact_2WC_NA omitted and 11 obs not used.

Table C7. Lender-Race Interaction Worcester County Lender 3 - Guaranteed Rate, Inc

denied_binary	Coef.	Odds Ratio	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Black	.946	2.576	.076	12.47	0	.798	1.095	***
Asian	.516	1.676	.061	8.45	0	.397	.636	***
Native American	.799	2.223	.333	2.40	.016	.146	1.451	**
Hispanic or Latino	.502	1.652	.072	6.98	0	.361	.643	***
Female	-.115	.892	.044	-2.60	.009	-.201	-.028	***
Age less than 25	-.027	.974	.127	-0.21	.833	-.275	.221	
Age 25-34	-.112	.894	.057	-1.98	.047	-.223	-.001	**
Age 45-54	.2	1.222	.063	3.18	.001	.077	.324	***
Age 55-64	.34	1.405	.07	4.82	0	.202	.478	***
Age 65 or older	-.175	.839	.098	-1.79	.074	-.367	.017	*
Manageable DTI	-.019	.981	.058	-0.34	.736	-.132	.094	
Nearing unmanageable DTI	.269	1.309	.061	4.42	0	.15	.389	***
Struggling DTI	3.917	50.228	.076	51.61	0	3.768	4.065	***
Less than 20 percent down payment flag	.076	1.079	.046	1.64	.101	-.015	.167	
Income	-.156	.855	.05	-3.14	.002	-.254	-.059	***
Loan Amount	-.332	.718	.061	-5.46	0	-.45	-.213	***
Property Value Ratio	.04	1.041	.033	1.22	.223	-.024	.104	
No Co-Applicant	.274	1.315	.047	5.81	0	.181	.366	***
Less than 30 year mortgage	-.133	.875	.096	-1.38	.167	-.323	.056	
More than 30 year mortgage	.813	2.254	.198	4.10	0	.424	1.201	***
Equifax Credit Model	-.168	.845	.053	-3.16	.002	-.273	-.064	***
FICO Credit Model	-.071	.931	.053	-1.35	.179	-.175	.032	
More than 1 credit model	-.302	.739	.123	-2.45	.014	-.544	-.06	**
Other Credit Model	.88	2.412	.179	4.91	0	.529	1.232	***
LP AUS	-.525	.592	.051	-10.23	0	-.625	-.424	***
Other AUS	.593	1.809	.106	5.59	0	.385	.801	***
Lender*Black	-1.074	.342	.406	-2.65	.008	-1.869	-.279	***
Lender*Hispanic or Latino	-.167	.846	.329	-0.51	.611	-.813	.478	
Lender*Native American	-1.323	.266	1.218	-1.09	.277	-3.709	1.064	
Lender*Asian	-.447	.64	.219	-2.04	.041	-.875	-.018	**
Constant	1.401	4.06	.68	2.06	.039	.069	2.733	**

Mean dependent var	0.050	SD dependent var	0.219
Pseudo r-squared	0.229	Number of obs	61140
Chi-square	5594.707	Prob > chi2	0.000
Akaike crit. (AIC)	18918.095	Bayesian crit. (BIC)	19197.743

**** p<.01, ** p<.05, * p<.1*

Table C8. Lender-Race Interaction Worcester County Lender 4 - Total Mortgage Services, LLC

Logistic regression

denied_binary	Coef.	Odds Ratio	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Black	.925	2.521	.076	12.23	0	.777	1.073	***
Asian	.492	1.635	.06	8.20	0	.374	.609	***
Native American	.636	1.89	.34	1.87	.061	-.03	1.303	*
Hispanic or Latino	.493	1.638	.071	6.95	0	.354	.633	***
Female	-.113	.893	.044	-2.58	.01	-.2	-.027	***
Age less than 25	-.019	.982	.126	-0.15	.883	-.266	.229	
Age 25-34	-.11	.896	.057	-1.93	.053	-.221	.001	*
Age 45-54	.207	1.23	.063	3.29	.001	.084	.331	***
Age 55-64	.344	1.41	.071	4.88	0	.206	.482	***
Age 65 or older	-.174	.841	.098	-1.77	.076	-.365	.018	*
Manageable DTI	-.018	.982	.058	-0.32	.749	-.131	.095	
Nearing unmanageable DTI	.272	1.312	.061	4.46	0	.152	.391	***
Struggling DTI	3.908	49.801	.076	51.56	0	3.759	4.057	***
Less than 20 percent down payment flag	.087	1.091	.046	1.88	.06	-.003	.178	*
Income	-.157	.854	.05	-3.15	.002	-.255	-.06	***
Loan Amount	-.339	.713	.061	-5.59	0	-.458	-.22	***
Property Value Ratio	.044	1.045	.033	1.35	.177	-.02	.108	
No Co-Applicant	.274	1.315	.047	5.82	0	.182	.366	***
Less than 30 year mortgage	-.139	.87	.097	-1.45	.148	-.329	.05	
More than 30 year mortgage	.815	2.26	.198	4.12	0	.427	1.204	***
Equifax Credit Model	-.17	.844	.053	-3.18	.001	-.274	-.065	***
FICO Credit Model	-.075	.928	.053	-1.42	.157	-.178	.029	
More than 1 credit model	-.292	.747	.123	-2.37	.018	-.534	-.05	**
Other Credit Model	.885	2.422	.179	4.94	0	.533	1.236	***
LP AUS	-.535	.586	.051	-10.42	0	-.635	-.434	***
Other AUS	.594	1.811	.106	5.60	0	.386	.802	***
Lender*Black	-.818	.441	.498	-1.64	.101	-1.795	.159	
Lender*Hispanic or Latino	-.377	.686	.619	-0.61	.543	-1.59	.837	
Lender*Native American	2.027	7.594	1.224	1.66	.098	-.372	4.427	*
Lender*Asian	-.55	.577	.694	-0.79	.428	-1.91	.809	
Constant	1.491	4.442	.679	2.20	.028	.161	2.821	**

Mean dependent var	0.050	SD dependent var	0.219
Pseudo r-squared	0.228	Number of obs	61140
Chi-square	5585.974	Prob > chi2	0.000
Akaike crit. (AIC)	18926.828	Bayesian crit. (BIC)	19206.476

**** p<.01, ** p<.05, * p<.1*

Appendix D. Logistic Lender-DTI Interaction Regression Results

Table D1. Lender-DTI Interaction Massachusetts Lender 1 - Guaranteed Rate, Inc

denied_binary	Coef.	Odds Ratio	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Black	.903	2.468	.185	12.03	0	2.13	2.859	***
Asian	.49	1.632	.098	8.17	0	1.451	1.835	***
Native American	.718	2.049	.679	2.17	.03	1.071	3.922	**
Hispanic or Latino	.484	1.623	.115	6.85	0	1.413	1.864	***
Female	-.114	.893	.039	-2.58	.01	.819	.973	***
Age less than 25	-.012	.988	.125	-0.10	.923	.771	1.265	
Age 25-34	-.105	.9	.051	-1.85	.064	.806	1.006	*
Age 45-54	.207	1.23	.078	3.27	.001	1.087	1.392	***
Age 55-64	.346	1.413	.1	4.91	0	1.231	1.623	***
Age 65 or older	-.163	.85	.083	-1.67	.095	.702	1.029	*
Manageable DTI	.02	1.02	.059	0.35	.729	.911	1.143	
Nearing unmanageable DTI	.298	1.347	.083	4.84	0	1.194	1.52	***
Struggling DTI	3.877	48.288	3.72	50.32	0	41.521	56.16	***
Less than 20 percent down payment flag	.076	1.079	.05	1.65	.1	.986	1.182	*
Income	-.155	.857	.043	-3.10	.002	.777	.945	***
Loan Amount	-.329	.719	.044	-5.43	0	.639	.81	***
Property Value Ratio	.04	1.041	.034	1.23	.22	.976	1.11	
No Co-Applicant	.277	1.319	.062	5.88	0	1.203	1.446	***
Less than 30 year mortgage	-.131	.877	.084	-1.36	.174	.727	1.059	
More than 30 year mortgage	.808	2.243	.442	4.09	0	1.524	3.301	***
Equifax Credit Model	-.168	.845	.045	-3.16	.002	.761	.938	***
FICO Credit Model	-.074	.928	.049	-1.40	.16	.837	1.03	
More than 1 credit model	-.29	.748	.092	-2.36	.018	.589	.952	**
Other Credit Model	.879	2.408	.43	4.93	0	1.698	3.416	***
LP AUS	-.526	.591	.03	-10.21	0	.534	.654	***
Other AUS	.602	1.826	.193	5.70	0	1.485	2.246	***
Lender* Manageable DTI	-1.017	.362	.107	-3.45	.001	.203	.644	***
Lender* Nearing unmanageable DTI	-.589	.555	.135	-2.41	.016	.344	.895	**
Lender*Struggling DTI	.466	1.593	.37	2.00	.045	1.01	2.513	**
Constant	1.358	3.89	2.642	2.00	.046	1.028	14.728	**

Mean dependent var	0.050	SD dependent var	0.219
Pseudo r-squared	0.229	Number of obs	61140
Chi-square	5607.019	Prob > chi2	0.000
Akaike crit. (AIC)	18903.782	Bayesian crit. (BIC)	19174.410

**** p<.01, ** p<.05, * p<.1*

Table D2. Lender-DTI Interaction Massachusetts Lender 2 - Leader Bank, National Association

Logistic regression

denied_binary	Coef.	Odds Ratio	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Black	.898	2.454	.075	11.97	0	.751	1.045	***
Asian	.489	1.63	.06	8.14	0	.371	.606	***
Native American	.713	2.041	.329	2.17	.03	.068	1.359	**
Hispanic or Latino	.479	1.615	.071	6.79	0	.341	.618	***
Female	-.115	.891	.044	-2.62	.009	-.201	-.029	***
Age less than 25	-.022	.979	.126	-0.17	.864	-.269	.226	
Age 25-34	-.109	.897	.057	-1.92	.055	-.22	.002	*
Age 45-54	.202	1.223	.063	3.19	.001	.078	.325	***
Age 55-64	.336	1.399	.071	4.76	0	.197	.474	***
Age 65 or older	-.173	.841	.098	-1.77	.076	-.365	.018	*
Manageable DTI	.011	1.011	.058	0.19	.849	-.103	.125	
Nearing unmanageable DTI	.291	1.337	.061	4.75	0	.171	.41	***
Struggling DTI	3.89	48.909	.076	51.26	0	3.741	4.039	***
Less than 20 percent down payment flag	.08	1.083	.046	1.74	.082	-.01	.171	*
Income	-.155	.856	.05	-3.12	.002	-.253	-.058	***
Loan Amount	-.33	.719	.061	-5.44	0	-.449	-.211	***
Property Value Ratio	.042	1.043	.033	1.29	.197	-.022	.106	
No Co-Applicant	.275	1.317	.047	5.85	0	.183	.368	***
Less than 30 year mortgage	-.136	.873	.097	-1.41	.16	-.325	.053	
More than 30 year mortgage	.808	2.244	.198	4.09	0	.421	1.195	***
Equifax Credit Model	-.169	.844	.053	-3.17	.002	-.274	-.065	***
FICO Credit Model	-.074	.929	.053	-1.40	.161	-.178	.029	
More than 1 credit model	-.27	.764	.123	-2.19	.029	-.512	-.028	**
Other Credit Model	.88	2.412	.179	4.93	0	.53	1.23	***
LP AUS	-.528	.59	.051	-10.30	0	-.629	-.428	***
Other AUS	.593	1.809	.106	5.60	0	.385	.801	***
Lender* Manageable DTI	-1.179	.307	.383	-3.08	.002	-1.93	-.429	***
Lender* Nearing unmanageable DTI	-1.09	.336	.453	-2.40	.016	-1.979	-.201	**
Lender*Struggling DTI	0	1	.	.	.	.	.	
Constant	1.376	3.957	.679	2.02	.043	.044	2.707	**

Mean dependent var	0.050	SD dependent var	0.218
Pseudo r-squared	0.227	Number of obs	61124
Chi-square	5519.785	Prob > chi2	0.000
Akaike crit. (AIC)	18893.386	Bayesian crit. (BIC)	19154.985

*** *p*<.01, ** *p*<.05, * *p*<.1

Note: Lender*Struggling DTI != 0 predicts success perfectly; all denied; omitted and 16 obs not used.

Table D3. Lender-DTI Interaction Massachusetts Lender 3 - Fairway Indep

denied_binary	Coef.	Odds Ratio	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Black	.904	2.469	.075	12.04	0	.757	1.051	***
Asian	.487	1.628	.06	8.14	0	.37	.604	***
Native American	.716	2.046	.33	2.17	.03	.069	1.363	**
Hispanic or Latino	.488	1.63	.071	6.90	0	.35	.627	***
Female	-.115	.892	.044	-2.60	.009	-.201	-.028	***
Age less than 25	-.021	.979	.126	-0.16	.87	-.269	.227	
Age 25-34	-.109	.897	.057	-1.92	.055	-.22	.002	*
Age 45-54	.207	1.23	.063	3.28	.001	.083	.331	***
Age 55-64	.344	1.411	.07	4.88	0	.206	.482	***
Age 65 or older	-.172	.842	.098	-1.76	.079	-.364	.02	*
Manageable DTI	-.004	.996	.058	-0.06	.95	-.118	.11	
Nearing unmanageable DTI	.251	1.285	.062	4.03	0	.129	.372	***
Struggling DTI	3.908	49.776	.076	51.08	0	3.758	4.057	***
Less than 20 percent down payment flag	.09	1.094	.048	1.88	.06	-.004	.183	*
Income	-.157	.854	.05	-3.15	.002	-.255	-.059	***
Loan Amount	-.338	.713	.061	-5.58	0	-.457	-.219	***
Property Value Ratio	.043	1.044	.033	1.32	.186	-.021	.107	
No Co-Applicant	.274	1.316	.047	5.83	0	.182	.367	***
Less than 30 year mortgage	-.139	.87	.097	-1.44	.149	-.329	.05	
More than 30 year mortgage	.817	2.264	.198	4.12	0	.429	1.205	***
Equifax Credit Model	-.169	.845	.053	-3.16	.002	-.273	-.064	***
FICO Credit Model	-.072	.931	.053	-1.36	.174	-.175	.032	
More than 1 credit model	-.289	.749	.123	-2.34	.019	-.531	-.047	**
Other Credit Model	.885	2.423	.179	4.94	0	.534	1.236	***
LP AUS	-.533	.587	.051	-10.36	0	-.634	-.432	***
Other AUS	.595	1.812	.107	5.58	0	.386	.803	***
Lender* Manageable DTI	-.369	.692	.24	-1.54	.124	-.838	.101	
Lender* Nearing unmanageable DTI	.329	1.39	.181	1.82	.068	-.025	.683	*
Lender*Struggling DTI	-.041	.96	.305	-0.13	.894	-.638	.556	
Constant	1.479	4.387	.679	2.18	.029	.148	2.809	**

Mean dependent var	0.050	SD dependent var	0.219
Pseudo r-squared	0.228	Number of obs	61140
Chi-square	5585.159	Prob > chi2	0.000
Akaike crit. (AIC)	18925.642	Bayesian crit. (BIC)	19196.270

*** *p<.01, ** p<.05, * p<.1*

Table D4. Lender-DTI Interaction Massachusetts Lender 4 - United Wholesale Mortgage, LLC

denied_binary	Coef.	Odds Ratio	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Black	.906	2.475	.075	12.08	0	.759	1.053	***
Asian	.487	1.627	.06	8.11	0	.369	.605	***
Native American	.717	2.049	.329	2.18	.029	.072	1.363	**
Hispanic or Latino	.49	1.633	.071	6.91	0	.351	.629	***
Female	-.114	.892	.044	-2.59	.01	-.2	-.028	***
Age less than 25	-.018	.982	.126	-0.14	.887	-.265	.23	
Age 25-34	-.112	.894	.057	-1.97	.049	-.223	-.001	**
Age 45-54	.204	1.226	.063	3.23	.001	.08	.328	***
Age 55-64	.342	1.408	.07	4.85	0	.204	.48	***
Age 65 or older	-.171	.843	.098	-1.75	.08	-.362	.02	*
Manageable DTI	-.004	.996	.058	-0.08	.939	-.118	.109	
Nearing unmanageable DTI	.282	1.326	.062	4.58	0	.161	.403	***
Struggling DTI	3.878	48.308	.077	50.61	0	3.727	4.028	***
Less than 20 percent down payment flag	.088	1.092	.046	1.90	.058	-.003	.179	*
Income	-.159	.853	.05	-3.19	.001	-.257	-.061	***
Loan Amount	-.337	.714	.061	-5.56	0	-.455	-.218	***
Property Value Ratio	.046	1.047	.033	1.40	.163	-.018	.109	
No Co-Applicant	.274	1.315	.047	5.82	0	.181	.366	***
Less than 30 year mortgage	-.133	.875	.096	-1.38	.167	-.322	.056	
More than 30 year mortgage	.815	2.26	.197	4.13	0	.428	1.202	***
Equifax Credit Model	-.172	.842	.053	-3.22	.001	-.277	-.067	***
FICO Credit Model	-.076	.927	.053	-1.43	.152	-.179	.028	
More than 1 credit model	-.286	.751	.123	-2.33	.02	-.527	-.045	**
Other Credit Model	.883	2.419	.179	4.94	0	.533	1.234	***
LP AUS	-.532	.587	.052	-10.33	0	-.633	-.431	***
Other AUS	.598	1.818	.106	5.65	0	.39	.805	***
Lender* Manageable DTI	-.493	.611	.285	-1.73	.084	-1.052	.066	*
Lender* Nearing unmanageable DTI	-.231	.794	.203	-1.13	.257	-.63	.168	
Lender*Struggling DTI	.594	1.81	.285	2.08	.037	.034	1.153	**
Constant	1.473	4.361	.678	2.17	.03	.144	2.801	**

Mean dependent var	0.050	SD dependent var	0.219
Pseudo r-squared	0.229	Number of obs	61140
Chi-square	5588.861	Prob > chi2	0.000
Akaike crit. (AIC)	18921.940	Bayesian crit. (BIC)	19192.568

*** *p<.01, ** p<.05, * p<.1*

Table D5. Lender-DTI Interaction Worcester County Lender 1- Fairway Indep.

denied_binary	Coef.	Odds Ratio	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Black	.904	2.469	.075	12.04	0	.757	1.051	***
Asian	.487	1.628	.06	8.14	0	.37	.604	***
Native American	.716	2.046	.33	2.17	.03	.069	1.363	**
Hispanic or Latino	.488	1.63	.071	6.90	0	.35	.627	***
Female	-.115	.892	.044	-2.60	.009	-.201	-.028	***
Age less than 25	-.021	.979	.126	-0.16	.87	-.269	.227	
Age 25-34	-.109	.897	.057	-1.92	.055	-.22	.002	*
Age 45-54	.207	1.23	.063	3.28	.001	.083	.331	***
Age 55-64	.344	1.411	.07	4.88	0	.206	.482	***
Age 65 or older	-.172	.842	.098	-1.76	.079	-.364	.02	*
Manageable DTI	-.004	.996	.058	-0.06	.95	-.118	.11	
Nearing unmanageable DTI	.251	1.285	.062	4.03	0	.129	.372	***
Struggling DTI	3.908	49.776	.076	51.08	0	3.758	4.057	***
Less than 20 percent down payment flag	.09	1.094	.048	1.88	.06	-.004	.183	*
Income	-.157	.854	.05	-3.15	.002	-.255	-.059	***
Loan Amount	-.338	.713	.061	-5.58	0	-.457	-.219	***
Property Value Ratio	.043	1.044	.033	1.32	.186	-.021	.107	
No Co-Applicant	.274	1.316	.047	5.83	0	.182	.367	***
Less than 30 year mortgage	-.139	.87	.097	-1.44	.149	-.329	.05	
More than 30 year mortgage	.817	2.264	.198	4.12	0	.429	1.205	***
Equifax Credit Model	-.169	.845	.053	-3.16	.002	-.273	-.064	***
FICO Credit Model	-.072	.931	.053	-1.36	.174	-.175	.032	
More than 1 credit model	-.289	.749	.123	-2.34	.019	-.531	-.047	**
Other Credit Model	.885	2.423	.179	4.94	0	.534	1.236	***
LP AUS	-.533	.587	.051	-10.36	0	-.634	-.432	***
Other AUS	.595	1.812	.107	5.58	0	.386	.803	***
Lender* Manageable DTI	-.369	.692	.24	-1.54	.124	-.838	.101	
Lender* Nearing unmanageable DTI	.329	1.39	.181	1.82	.068	-.025	.683	*
Lender*Struggling DTI	-.041	.96	.305	-0.13	.894	-.638	.556	
Constant	1.479	4.387	.679	2.18	.029	.148	2.809	**

Mean dependent var	0.050	SD dependent var	0.219
Pseudo r-squared	0.228	Number of obs	61140
Chi-square	5585.159	Prob > chi2	0.000
Akaike crit. (AIC)	18925.642	Bayesian crit. (BIC)	19196.270

*** *p<.01, ** p<.05, * p<.1*

Table D6. Lender-DTI Interaction Worcester County Lender 2 - United Wholesale Mortgage, LLC

Logistic regression

denied_binary	Coef.	Odds Ratio	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Black	.906	2.475	.075	12.08	0	.759	1.053	***
Asian	.487	1.627	.06	8.11	0	.369	.605	***
Native American	.717	2.049	.329	2.18	.029	.072	1.363	**
Hispanic or Latino	.49	1.633	.071	6.91	0	.351	.629	***
Female	-.114	.892	.044	-2.59	.01	-.2	-.028	***
Age less than 25	-.018	.982	.126	-0.14	.887	-.265	.23	
Age 25-34	-.112	.894	.057	-1.97	.049	-.223	-.001	**
Age 45-54	.204	1.226	.063	3.23	.001	.08	.328	***
Age 55-64	.342	1.408	.07	4.85	0	.204	.48	***
Age 65 or older	-.171	.843	.098	-1.75	.08	-.362	.02	*
Manageable DTI	-.004	.996	.058	-0.08	.939	-.118	.109	
Nearing unmanageable DTI	.282	1.326	.062	4.58	0	.161	.403	***
Struggling DTI	3.878	48.308	.077	50.61	0	3.727	4.028	***
Less than 20 percent down payment flag	.088	1.092	.046	1.90	.058	-.003	.179	*
Income	-.159	.853	.05	-3.19	.001	-.257	-.061	***
Loan Amount	-.337	.714	.061	-5.56	0	-.455	-.218	***
Property Value Ratio	.046	1.047	.033	1.40	.163	-.018	.109	
No Co-Applicant	.274	1.315	.047	5.82	0	.181	.366	***
Less than 30 year mortgage	-.133	.875	.096	-1.38	.167	-.322	.056	
More than 30 year mortgage	.815	2.26	.197	4.13	0	.428	1.202	***
Equifax Credit Model	-.172	.842	.053	-3.22	.001	-.277	-.067	***
FICO Credit Model	-.076	.927	.053	-1.43	.152	-.179	.028	
More than 1 credit model	-.286	.751	.123	-2.33	.02	-.527	-.045	**
Other Credit Model	.883	2.419	.179	4.94	0	.533	1.234	***
LP AUS	-.532	.587	.052	-10.33	0	-.633	-.431	***
Other AUS	.598	1.818	.106	5.65	0	.39	.805	***
Lender* Manageable DTI	-.493	.611	.285	-1.73	.084	-1.052	.066	*
Lender* Nearing unmanageable DTI	-.231	.794	.203	-1.13	.257	-.63	.168	
Lender*Struggling DTI	.594	1.81	.285	2.08	.037	.034	1.153	**
Constant	1.473	4.361	.678	2.17	.03	.144	2.801	**

Mean dependent var	0.050	SD dependent var	0.219
Pseudo r-squared	0.229	Number of obs	61140
Chi-square	5588.861	Prob > chi2	0.000
Akaike crit. (AIC)	18921.940	Bayesian crit. (BIC)	19192.568

*** *p*<.01, ** *p*<.05, * *p*<.1

Table D7. Lender-DTI Interaction Worcester County Lender 3 - Guaranteed Rate, Inc

denied_binary	Coef.	Odds Ratio	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Black	.903	2.468	.075	12.03	0	.756	1.05	***
Asian	.49	1.632	.06	8.17	0	.372	.607	***
Native American	.718	2.049	.331	2.17	.03	.069	1.367	**
Hispanic or Latino	.484	1.623	.071	6.85	0	.346	.623	***
Female	-.114	.893	.044	-2.58	.01	-.2	-.027	***
Age less than 25	-.012	.988	.126	-0.10	.923	-.26	.235	
Age 25-34	-.105	.9	.057	-1.85	.064	-.216	.006	*
Age 45-54	.207	1.23	.063	3.27	.001	.083	.33	***
Age 55-64	.346	1.413	.07	4.91	0	.208	.484	***
Age 65 or older	-.163	.85	.098	-1.67	.095	-.354	.028	*
Manageable DTI	.02	1.02	.058	0.35	.729	-.094	.134	
Nearing unmanageable DTI	.298	1.347	.062	4.84	0	.177	.418	***
Struggling DTI	3.877	48.288	.077	50.32	0	3.726	4.028	***
Less than 20 percent down payment flag	.076	1.079	.046	1.65	.1	-.015	.167	*
Income	-.155	.857	.05	-3.10	.002	-.252	-.057	***
Loan Amount	-.329	.719	.061	-5.43	0	-.448	-.211	***
Property Value Ratio	.04	1.041	.033	1.23	.22	-.024	.104	
No Co-Applicant	.277	1.319	.047	5.88	0	.184	.369	***
Less than 30 year mortgage	-.131	.877	.096	-1.36	.174	-.319	.058	
More than 30 year mortgage	.808	2.243	.197	4.09	0	.421	1.194	***
Equifax Credit Model	-.168	.845	.053	-3.16	.002	-.273	-.064	***
FICO Credit Model	-.074	.928	.053	-1.40	.16	-.178	.029	
More than 1 credit model	-.29	.748	.123	-2.36	.018	-.53	-.05	**
Other Credit Model	.879	2.408	.178	4.93	0	.529	1.229	***
LP AUS	-.526	.591	.051	-10.21	0	-.626	-.425	***
Other AUS	.602	1.826	.106	5.70	0	.395	.809	***
Lender* Manageable DTI	-1.017	.362	.295	-3.45	.001	-1.595	-.44	***
Lender* Nearing unmanageable DTI	-.589	.555	.244	-2.41	.016	-1.068	-.111	**
Lender*Struggling DTI	.466	1.593	.232	2.00	.045	.01	.922	**
Constant	1.358	3.89	.679	2.00	.046	.027	2.69	**

Mean dependent var	0.050	SD dependent var	0.219
Pseudo r-squared	0.229	Number of obs	61140
Chi-square	5607.019	Prob > chi2	0.000
Akaike crit. (AIC)	18903.782	Bayesian crit. (BIC)	19174.410

**** p<.01, ** p<.05, * p<.1*

Table D8. Lender-DTI Interaction Worcester County Lender 4 - Total Mortgage Services, LLC

denied_binary	Coef.	Odds Ratio	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Black	.914	2.495	.075	12.16	0	.767	1.062	***
Asian	.485	1.624	.06	8.11	0	.368	.602	***
Native American	.723	2.061	.331	2.19	.029	.075	1.371	**
Hispanic or Latino	.487	1.627	.071	6.88	0	.348	.626	***
Female	-.113	.893	.044	-2.56	.01	-.199	-.027	**
Age less than 25	-.021	.98	.126	-0.16	.871	-.268	.227	
Age 25-34	-.11	.896	.057	-1.94	.052	-.221	.001	*
Age 45-54	.205	1.228	.063	3.25	.001	.081	.329	***
Age 55-64	.342	1.408	.07	4.86	0	.204	.48	***
Age 65 or older	-.175	.839	.098	-1.79	.073	-.367	.017	*
Manageable DTI	-.009	.991	.058	-0.16	.874	-.122	.104	
Nearing unmanageable DTI	.285	1.33	.061	4.67	0	.165	.405	***
Struggling DTI	3.906	49.686	.076	51.47	0	3.757	4.054	***
Less than 20 percent down payment flag	.082	1.086	.046	1.78	.075	-.008	.173	*
Income	-.158	.854	.05	-3.16	.002	-.256	-.06	***
Loan Amount	-.34	.712	.061	-5.61	0	-.459	-.221	***
Property Value Ratio	.044	1.045	.033	1.35	.178	-.02	.108	
No Co-Applicant	.275	1.316	.047	5.84	0	.183	.367	***
Less than 30 year mortgage	-.14	.87	.096	-1.45	.148	-.329	.049	
More than 30 year mortgage	.812	2.251	.198	4.10	0	.423	1.2	***
Equifax Credit Model	-.173	.841	.053	-3.24	.001	-.278	-.068	***
FICO Credit Model	-.076	.926	.053	-1.44	.148	-.18	.027	
More than 1 credit model	-.296	.744	.123	-2.40	.016	-.537	-.054	**
Other Credit Model	.882	2.415	.179	4.92	0	.53	1.233	***
LP AUS	-.532	.587	.051	-10.38	0	-.633	-.432	***
Other AUS	.599	1.82	.106	5.64	0	.391	.807	***
Lender* Manageable DTI	-.78	.458	.455	-1.71	.086	-1.672	.112	*
Lender* Nearing unmanageable DTI	-1.375	.253	.585	-2.35	.019	-2.52	-.229	**
Lender*Struggling DTI	.179	1.196	.822	0.22	.828	-1.432	1.79	
Constant	1.51	4.527	.678	2.23	.026	.181	2.839	**

Mean dependent var	0.050	SD dependent var	0.219
Pseudo r-squared	0.229	Number of obs	61140
Chi-square	5591.923	Prob > chi2	0.000
Akaike crit. (AIC)	18918.878	Bayesian crit. (BIC)	19189.506

*** *p<.01, ** p<.05, * p<.1*