Racial Stratification in the Mortgage Market: The Role of Co-applicants

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Abstract
Unequal access to homeownership has long been central to racial stratification. Ample research demonstrates the large racial disparities that exist in access and outcomes within the mortgage process at both the individual and neighborhood levels. However, the underlying assumption in most of these studies is that the couples applying for a mortgage are racially homogenous. As the volume of interracial couples increases in the mortgage market, it is important to incorporate the ethno-racial variation in mortgage outcomes. This paper draws on annual data from the Home Mortgage Disclosure Act (HMDA) from 2010 to 2016 to assess racial disparities in loan outcomes associated with different racial couplings. I show that, racial disparities in loan outcomes vary tremendously when factoring the ethno-racial identity of the co-applicant. In particular, interracial couples that involve a black or Latino partner do worse than mono-racial couples. On the other hand, white and Asian partners tend to better across mortgage loan outcomes.

Introduction

Homeownership is the cornerstone of financial security for most Americans, especially for blacks and Latinos. The racial disparities in access to homeownership is a major part of inequality (Oliver and Shapiro 2006), as black and Latino households are less likely to take advantage of federal, state, and municipal housing subsidies, tax-favored form of investment, contributing to ethno-racial disparities in tax liabilities and inheritance that perpetuate inequality today and across generations. In addition to household benefits, homeownership is also associated with neighborhood amenities such as better public schools, lower crime, and increased social networks (Charles 2003; Massey 2005; Yinger 1995). Equal access to homeownership remains fleeting, despite decades of anti-discrimination laws and regulation. Since 2016, the homeownership rate for Non-Hispanic whites (hereafter “whites”) has hovered around 73 percent, 57 percent for Asians, 46 percent and 42 for Hispanics (hereafter “Latinos”) and Non-Hispanic blacks (hereafter “blacks”) (Callis and Kresin 2016; Joint Center for Housing Studies of Harvard University 2016). In addition, the 2007 recession and its aftermath had impeded the progress of homeownership convergence amongst racial groups. For African Americans, homeownership rates were lower in 2016 than in 1994 and the disparities with whites higher (Joint Center for Housing Studies of Harvard University 2016).

Disparate access to homeownership across racial groups is strongly linked to racial stratification even after accounting for economic and preferential differences. The mortgage industry has a long history of racial discrimination. Audit studies continue to demonstrate poor treatment of black and Latino loan applicants, whom are more likely to be steered into poorer neighborhoods, smaller and more expensive loans than similar white couples (Massey 2005; Squires 2007; Stuart 2003; Williams, Nesiba, and McConnell 2005). While the levels of discrimination have fallen across multiple decades due to laws and regulations such as the Hair Housing Act of 1968 and Community Reinvestment Act of 1977, unequal treatment remains (Ross and Turner 2005; Turner et al. 2002; Yinger 1995). More specifically, the shift from outright denials to receiving high cost loans, continued to cost minority borrowers in the housing market prior to the 2007 housing crisis (Weller 2010).

Research on racial disparities in homeownership has primarily focused on racial homogenous applicants ignoring the increase in inter-racial couples across ethnic and racial groups. This growing segment of the U.S. population adds an additional dimension in studying racial inequality. In addition, the increase of inter-racial couples is not equal across racial groups thus shifting how to examine racial inequality. For instance, more than 25 percent of Asian and Latino marriages are inter-racial, mostly marrying whites (Lee and Bean 2007). On the other hand, less than 10 percent of white and black marriages are with a partner of another race (Lee and Bean 2007). The growth of interracial couples and marriages has been on the rise since the late 1960s. In 2016, inter-racial marriages accounted for one in twelve marriages (Lee and Bean 2016). As the number of interracial couples continues to increase, it is important to understand how these couples are being racialized and performing in the mortgage market. Measures of racial disparities in housing must account for the racial variation that is growing and becoming a significant part of the mortgage applicant pool.

Accordingly, in this paper I draw on the Home Mortgage Disclosure Act (HMDA) to compare ethno-racial variation of both the primary and secondary mortgage applicants in loan application outcomes. My main objective is to examine how racial stratification in the mortgage market shifts when including the ethno-racial identity of the co-applicant in the mortgage market. Because most studies that study race in housing assume that the couples are of the same race and ethnicity, I also detail demographic, economic, loan, and locational characteristics of the various ethno-racial combinations across mortgage applicants. And finally, I also examine the inter-related impact of the primary applicant's race and the secondary applicant's race on application outcomes. The results highlight that racialized outcomes, particularly related to high cost lending, vary considerably with important interactions between the race of both primary and secondary applicants.

Theoretical background

The two broad theoretical perspectives in understanding racial disparities in homeownership includes one that focuses on demographic and human capital differences across groups and one that focuses on discrimination and racial stratification. Neoclassical economic theories expect homeownership to reflect differential tastes and preferences based on life-cycle characteristics such as age, marriage, and childbearing, subject to financial and employment constraints. As a result, homeownership is shaped by human capital and financial characteristics, and is often more available to those with more resources such as those with higher levels of income, education, with a professional career, and among those who are married and have children (Dwyer 2007). Finally, socio-demographic characteristics account for a large share of the homeownership rate differences among racial and ethnic minority groups (Flippen 2001b).

Large differences in homeownership remain even after accounting for economic and demographic characteristics thus emphasizing the importance of racial stratification and discrimination in housing inequality (Flippen 2010; Haurin, Herbert, and Rosenthal 2007; Rugh and Massey 2010). Discriminatory actions in the homeownership process, as demonstrated by audit studies shows that minority buyers are regularly steered into predominantly minority communities and will receive lower quality service throughout their home buying experience (Turner et al. 2002; Yinger 1998). The discriminatory experiences of minorities often leads to application withdrawals, poor service, and steering into lower income and less desirable neighborhoods (Yinger 1998). Also, minority borrowers are more likely to receive high cost loans and face loans with less favorable terms. In addition to studies on individual discrimination, homeownership also impacts the spatial organization of groups and levels of residential segregation. Minorities are concentrated in older neighborhoods with lower levels of housing stock to purchase due to increased levels of multi-family rentals (Dwyer and Phillips Lassus 2015; Flippen 2001a; Kain and Quigley 1975).

Interracial Couples

The concentration of Asian and Latino households is forcing a shift in racial boundaries in certain areas of the country, while other areas continue to prove that the traditional black-white boundary remains strong and clear. The patterns of interracial couples vary across regions and gender. In locations with higher levels of Asians and Latinos, such as California, the level of interracial couples is also higher. In areas with small minority populations, such as West Virginia and Maine, they exhibit small levels of interracial couples (Lee and Bean 2016). In addition, southern states that have large black populations also exhibit low levels of interracial couples (Lee and Bean 2016). As it pertains to the gender dynamics and spatial location of interracial couples, relationships with white men are associated with living in whiter neighborhoods, while relationships with a white woman are associated with residing in neighborhoods that have a higher concentration of non-whites (Wright, Holloway, and Ellis 2013).

The impact of interracial couples on racial stratification in the mortgage market is unclear. On the one hand, positive loan outcomes among these interracial groups might suggest that disadvantages because of racial status might be fading for nonwhite groups. However, poor loan outcomes across interracial couples may suggest that the racialized hierarchy continues to be reified and reproduced itself in the housing market. If the loan outcomes are mixed across interracial borrowers, the structure of the racialized hierarchy may support a white-black relationship or white-non-white relationship depending on the racial group(Bonilla-Silva 2013; Charles 2000; Lee and Bean 2016; Massey 2005).

Data and Methods

To address the issue of how the race and ethnicity of the co-borrower shape disparities in institutional mortgage outcomes after the Great Recession (2010-2016), I draw on publicly available data from the Home Mortgage Disclosure Act (HMDA) for the years 2010 through 2016. As part of the Community Reinvestment Act (CRA) mandate to monitor the services, lending, and investments in low-income and minority neighborhoods, all financial institutions with a national charter are required to submit HMDA information annually to the Federal Financial Institutions Examination Council (FFIEC). Financial institutions are examined by various tests depending on their size and strategic plan for fulfilling the needs of low-income communities. CRA-regulated financial institutions face major sanctions, such as the inability to merge with other banks or limitations in the growth of their lending business, if they receive a poor rating from their CRA examination. These potential penalties are expected to dampen discrimination against minority borrowers and boost lending in low-income areas.

The HMDA dataset is comprised of a record for every loan application received, including primary borrower, co-borrower, institutional, loan, and property characteristics. Borrower characteristics include demographic and income information, while institutional characteristics include the name of the lender, loan status, and type of loan originated. The loan characteristics include loan amount, type, purpose of the loan, outcome of the application, reason for denial, and high cost loan indicators. Property characteristics include the property type, and census tract identifier.

One important limitation of the public HMDA dataset is that it lacks information on the borrower's credit score, the down payment amount, sale price of the home, and the exact interest rate of the loan. In spite of these limitations, the HMDA dataset is a broadly representative sample of home lending in the United States, covering 80 percent of all originated mortgages (Avery et al. 2007). In addition, HMDA is the only public national mortgage dataset that includes borrowers' race and application neighborhood (Bradford 2002). As such, it is by far the most commonly used source of information on racial disparities in access to mortgage credit.

I restrict the HMDA sample to non-institutional two-person applicants requesting financing for owner-occupied single-family homes (1-4 units) in the United States, through a conventional or jumbo mortgage (i.e., Veteran's Association and re-finance applications are not included). In addition, only borrowers that completed their application and were vetted by their primary lender are considered. That is, mortgages that were bought by other financial institutions and recorded in the HMDA dataset are excluded, because they were already documented as a mortgage transaction by the initial financial institution. In addition, I employed list-wise deletion for observations containing missing data. Previous evaluations of the issue of missing data in HMDA have shown that data quality improved dramatically after 2003, when reporting rules and guidelines were made more stringent. While missing values hinder analyses of re-financing loans applications, they are generally not a concern for mortgage origination observations (Faber 2013). Our analysis ends with 2016 because this is the last year for which the completed data file is available. Finally, I restrict the sample to primary and secondary applicants that are white, black, Latino, and Asians, excluding American

Indians, and Native Hawaiians due to small sample sizes in certain regions within the United States.

In addition to using HMDA data from 2010 to 2016, this study also uses locational data from the Bureau of Labor Statistics, Federal Housing Finance Agency, and private data from Experian Credit Company. Annual county-level unemployment rate data from 2010 to 2016 was used from the bureau of labor statistics. List-wise deletion was used for counties without an unemployment rate for any given year. The Federal Housing Finance Agency measures housing prices across the country through the quarterly housing price index. The housing price index captures the volume and sales price of homes within a Metropolitan Statistical Areas (MSA). The index begins at 100 and rises accordingly. For this study, the quarterly results of the housing price index were aggregated annually from 2010 to 2016 and list-wise deletion was used for any missing observations. Finally, I used the 2010 average Experian credit score for the top 100 MSA's in the country. The top 100 MSA's were determined by the population size of the MSA as determined by the 2010 Census. The Experian average credit scores include all borrowers and their different credit accounts within a given MSA.

The dataset after adjusting, merging, and using list-wise deletion in this study contains roughly 3.95 million completed mortgage applications from 2004 to 2015. Due to the massive size of the dataset, I took a stratified sample of 147 thousand observations based on ethno-racial groups of both the primary and secondary borrowers to conduct the descriptive and multivariate analysis. Ultimately, 30 percent of dataset was randomly selected for most pairs but for ethno-racial pairs that were significantly over-represented only 1.5 percent was selected. The pairs that significantly over-represent include ethno-racially homogenous pairings such as white primary borrowers with a white co-applicant, a black primary borrower with a black co-applicant, a Latino primary borrower with a Latino co-applicant, and an Asian primary applicant with an Asian co-applicant. Several different stratified samples were used to verify consistent results from the multivariate analyses.

Model specification

The dependent variable for this analysis is the outcome of the completed loan application, based on information provided from the Federal Financial Institutions Examination Council and the Consumer Financial Protection Bureau (http://www.ffiec.gov/hmda) (http://www.consumerfinance.gov/hmda). There are four possible outcomes to all applications: they can be granted a conventional loan, approved for a high cost loan, denied a mortgage due to bad credit, or denied a mortgage due to other reasons.

First, I define a high cost loan. High cost loans are defined as any loan originated with an above-market annual percentage interest rate (APR). After 2009, a mortgage loan is flagged as a high cost loan in HMDA when the APR is 1.5 points higher than the survey-based (Freddie Mac Mortgage Market Survey) APR estimate currently offered on comparable prime mortgage loans. HMDA only provides information on accepted or offered high cost loans, thus there is no data on high cost loan rejections.

Once I designate a high cost loan, I define conventional loans as all originated or offered loans that are not high cost. For denied mortgage loans, the HMDA dataset contains information on reasons for denial. I distinguish between denials in two ways. First, mortgage denials that reflect bad credit or "credit-worthiness," include reasons such as high debt to income ratio, employment history, credit history, insufficient collateral, and insufficient cash. The second type of a mortgage denial includes the listed reason for denial was "other." The end result is a dependent variable distinguishing between conventional loan approvals; high cost loan approvals, bad credit denials, and other denials. This specification allows us to test for ethno-racial disparities for different loan types and the economic and non-economic reasons for a loan denial.

The primary independent variables of interest relate to the race and ethnicity of the primary borrower and co-borrower. These variables are defined by the race and ethnicity of the primary borrower of the loan application and the race and ethnicity of the co-borrower. In the multivariate setting, I interact the race/ethnicity of the primary borrower and the racial composition the co-applicant, distinguishing between white primary borrowers with a white co-applicant, white primary applicants with a black co-borrower, and so on. Moreover, to ensure that our measure of racial disparities across and among ethno-racial groups is not reflecting the economic variation across applicants and neighborhoods, I also control for the mean household income for the census tract in which the property is located (distinguishing between those with a median income of less than $50,000; $50,000 to $60,000; $60,000 to $80,000; and a median income above $80,000).

Finally, I control for the economic characteristics of the borrowers, including gender of both the primary and secondary borrowers, and the total income of applicants (distinguishing between nine categories rising in $25,000 increments, with incomes below $25,000 being the lowest and $200,000 and above being the highest). Property characteristics include the loan amount (divided into nine categories with less than $100,000 being the lowest and $800,000 and above being the highest) and U.S. region in which the property is located, as defined according to Census guidelines (http://www2.census.gov/geo/docs/maps-data/maps/reg_div.txt). In addition, I control for the percent of Non-Hispanic whites in the census tract (distinguishing between those neighborhoods with less than 25 percent whites; 25 percent to 50 percent white; 50 percent to 75 percent white; and above 75 percent white). The additional controls for location characteristics include annual average county unemployment rate, annual average MSA housing price index, and the 2010 average MSA credit score.

Analytic strategy and methods

The first step in our analysis is to provide descriptive statistics of completed mortgage applications. Second, I show the bivariate relationship between mortgage outcomes by race and ethnicity of primary and secondary applicants. Finally, I assess a multivariate analysis using a multi-level hierarchal linear model with a multinomial outcome (HLM) on the loan outcome (acceptance into a conventional loan (reference), acceptance into a subprime loan, a mortgage denial due to poor credit, and a mortgage denial due to other reasons). The model examines ethno-racial differences between primary and secondary borrowers controlling for observed individual and locational characteristics.

Homeownership research is challenging because the process of obtaining a mortgage depends on assessing risk at both the individual and neighborhood levels. The two-level hierarchal linear model for multinomial outcomes, also known as a multi-level random effects model, takes advantage of the hierarchical nature of the HMDA data structure. In this study, applicants are nested within the neighborhoods the property they are applying to is located in. The nested nature of HMDA provides HLM a tremendous advantage over the use of a conventional logistic OLS regression.

The benefits of using a hierarchal linear model includes improving estimation of effects within individual units, the testing of hypotheses in regards to cross-level effects, and the portioning of variance and covariance components among levels (Raudenbush and Bryk 2002; Skrondal and Rabe-Hesketh 2004). HLM is able to efficiently use all the covariates in the dataset and provide separate prediction equations for white, black, Latino, and Asian primary borrowers across the race and ethnicity of the co-borrowers. The coefficients produced using HLM are subject-specific rather than population averages coefficients, which is helpful because this study is concerned with racial disparities at the individual level. In addition, HLM is able to identify differentiating effects from one level to the next, thus allowing for the variability in the second level to effect the estimated parameters in level one (Raudenbush and Bryk 2002). Finally, HLM draws on the estimation of variance and covariance components with unbalanced, nested data (Long and Freese 2014).

The notation of the two-level hierarchal linear model used in this study is:

$$Level\ 1:$$

$$\log\left[\frac{\rho_{ij}}{1-\rho_{ij}}\right] = \beta_{0j} + \beta_{1j}X_{1ij} + \beta_{2j}X_{2ij} + \ldots + \beta_{Qj}X_{Qij} + r_{ij}$$

$$= \beta_{0j} + \sum_{q=1}^{Q} \beta_{qj}X_{qij} + r_{ij} \text{ where } r_{ij} \sim N(0,\sigma^2),$$

I denote the outcome for person *i* in neighborhood (census tract) *j as* $\log\left[\frac{\rho_{ij}}{1-\rho_{ij}}\right]$. This outcome is represented as a function of individual characteristics, X_{qij}, and a model error r_{ij}. The regression coefficients $\beta_{qj}, q = 0, \ldots, Q$, indicate in neighborhood j as a function of the measured person characteristics (Long and Freese 2014; Raudenbush and Bryk 2002).

$$Level\ 2:$$

$$\beta_{qj} = \gamma_{q0} + \gamma_{q1}W_{1j} + \gamma_{q2}W_{2j} + \ldots + \gamma_{qS_q}W_{S_qj} + u_{qj}$$

$$= \gamma_{q0} + \textstyle\sum_{s=1}^{S_q} \gamma_{qs}W_{sj} + u_{qj} \text{ for each } q = 0, \ldots, Q ,$$

Where, a unique set of predictors $W_s\ (\mathrm{s} = 1, \ldots, S_q)$ may be specified for each β_q.

The effects for each neighborhood, captured in the set of β_{qj}s vary across units. Each β_{qj} is an outcomes variable that depends on a set of neighborhood-level variables, W_{sj}, and a unique neighborhood effect, u_{qj}. The γ_{qs} coefficients capture the influence of neighborhood variables, W_{sj}, on the within-neighborhood relationships represented by β_{qj}.

The HLM also contains some limitations that can inaccurately produce results. First, if the level-two model is inappropriately specified, the parameters at the second level will be biased and lead to distortion in each group's estimated equation (Raudenbush and Bryk 2002). If an omitted level-two predictor is associated with a level-one predictor the coefficient for that level-one predictor will be estimated with bias (Raudenbush and Bryk 2002). Secondly, if variances depend systematically as a function of level-one or level-two predictors, the model consequences may be serious (Raudenbush and Bryk 2002; Skrondal and Rabe-Hesketh 2004). Finally, the HLM is computationally intensive and is not suited to successfully execute datasets above 150 thousand observations.

Descriptive Results

Figure 1 presents my dependent variable, the outcome of completed loan applications, by race, ethnicity of the primary borrower and co-applicant. The figure clearly shows large racial disparities in application outcomes across and within racial groups. Across primary ethno-racial groups, black and Latino primary loan applicants were less likely to be approved for a conventional loan, more likely to be approved for a high cost loan, and more likely to have their application denied both due to bad credit and other reasons. On the other hand, Asian applicants seem to perform like whites on all these loan outcomes.

The figure also highlights dramatic racial differences among primary ethno-racial groups. Regardless of the racial identity of the primary applicant, black and Latino co-borrowers have the lowest levels of receiving a conventional loan and are more likely to obtain a high cost loan. For instance, among white primary borrowers, over 90 percent of applicants with a white co-borrower obtained a conventional loan while, only 85 percent of applicants with a black or Latino co-borrower are offered a conventional loan. The five-point difference between white, and black and Latino co-borrowers seems to be due to the increased proportion of high cost loans black and Latino co-borrowers receive. Primary applicants with an Asian co-borrower appear to perform slightly better than white co-borrowers.

Denials due to bad credit and other reasons show a marked variation by race and ethnicity. Across ethno-racial groups, whites and Asians appear that they are less likely to be denied for bad credit than black and Latino primary borrowers. Among ethno-racial groups, black and Latino co-borrowers have higher levels of being rejected for bad credit. Asian co-applicants perform slightly worse than white-co-applicants. When assessing mortgage denials due to other reasons across ethno-racial groups, white primary borrowers perform better than black, Latino, and Asian primary borrowers. Among ethno-racial groups, there does not appear to be dramatic differences across the various ethno-racial co-borrowers.

Table 1 presents average demographic, loan, and locational characteristics overall and by race of the primary applicant and co-applicant. For ease of interpretation, I present summary averages for each ethno-racial combination of applicants. The stratified sample of approximately 145 thousand observations provides enough ethno-racial group variation in the results. About 60 percent of the sample has a white primary borrower, followed by 20 percent black, 12 percent Latino, and 7 percent Asian.

The overall proportion of applications had male primary borrowers with a female co-borrower. Across ethno-racial groups, white, blacks, Asians remain relatively consistent, whereas Latino primary applicants have the lowest levels of having a male primary applicant and a female secondary applicant. The shift for Latino primary applicants occurs from an increased volume of applications with a female primary applicant and a male co-applicant. Among ethno-racial groups, Asian co-borrowers have the highest levels of having a male primary applicant and a female secondary applicant, while black co-borrowers have the lowest levels.

The income distribution for all applicants tends to center between 50 thousand dollars to 150 thousand dollars. However, there is a sharp spike in applicants with an income of 200 thousand dollars or more. The income distribution remains relatively consistent across primary ethno-racial groups. Among primary ethno-racial groups, the income distribution is slightly skewed towards lower income for black and Latino co-borrowers. On the other hand, the income distribution is skewed towards higher incomes for Asian co-borrowers.

As it pertains to the loan amount requested, the overall distribution is centered between a 100 thousand dollars and 300 thousand dollars. Across primary ethno-racial groups, black primary applicants are applying for slightly smaller mortgage loans. Latino primary borrowers seek slightly more expensive mortgage loans, while the loan amount distribution for primary Asian borrowers resembles the distribution for primary white borrowers. Among primary ethno-racial groups, applicants with an Asian co-borrower are applying for slightly higher mortgage loan amounts. On the other hand, applicants with a black-borrower are applying for lower mortgage loan amounts. The loan amount distribution for Latino co-borrowers resembles that of white co-borrowers.

The overwhelming majority of applicants are applying in predominately white neighborhoods and more expensive communities. Over 80 percent of borrowers applied in neighborhoods with 50 percent whites or more. Across primary ethno-racial groups, blacks, Latinos, and Asians, applied in more diverse neighborhoods compared to white applicants. Among primary ethno-racial groups, borrowers with a white co-borrower were applying in predominantly white neighborhoods. On the other hand, applicants with a black, Latino, or Asian co-applicant sought more diverse neighborhoods and applied more heavily in predominantly minority communities. Over 85 percent of applications were in communities with an average household income of 60 thousand dollars or more. Across primary ethno-racial groups, black primary borrowers sought homes in lower income neighborhoods. Also, Asian primary borrowers to a lesser extent sought homes in lower income neighborhoods. The distribution of the average household income in the neighborhood for Latino primary borrowers resembles that of white primary borrowers. Among primary ethno-racial groups, applicants with black and Latino co-borrowers applied in lower income neighborhoods. The majority of Asian and white co-borrowers, sought homes in higher income neighborhoods.

The location and economic conditions of the area also vary by race and ethnicity. Most homes were located in the Southern and Western regions of the United States. The distribution of the location of homes remained stable across ethno-racial groups. Among primary ethno-racial borrowers, black and Latino co-borrowers applied outside of the Midwest and Northeast. Asian co-borrowers were more concentrated in the West compared to the other ethno-racial co-borrowers. The overall county average unemployment rate hovered around 7 percent. Black and Latino primary applicants sought homes in slightly more unemployed areas than white and Asian primary applicants. Among, ethno-racial primary groups, black, Latino, and Asian co-borrowers applied in higher unemployed areas. The overall 2010 average MSA credit score was 690 and remained stable and relatively consistent across and within ethno-racial groups. The average MSA housing price index of the sample was 216. Latino primary borrowers applied in areas with slightly more expensive housing prices compared to whites and blacks, while Asian primary borrowers applied in the most expensive areas. The housing price index remained consistent among ethno-racial co-borrowers.

Multivariate Results

Figure 2, displays stark difference when examining the odds ratios for obtaining a high cost mortgage loan versus a conventional mortgage among co-applicants. In general, a rigid social hierarchy emerges across ethno-racial groups. Across ethno-racial groups, white and Asian primary applicants generally outperform their black and Latino counterparts given a specific co-borrower. For example, the odds ratios for a white (Asian) primary borrower with a Latino co-applicant, is 1.43 (1.20) times compared to 2.88 (2.13) times for a black (Latino) primary applicant. Given the ethno-racial composition of the primary borrower, black co-borrowers have the highest odds of accepting a high cost loan followed by Latinos, whites, and Asians. The only exception to his pattern occurs with an Asian primary borrower and black co-borrower as the odds ratios of obtaining a high cost loan resembles those of their black and Latino primary borrower counterparts.

A similar pattern of racial stratification exists when examining the high costs (versus conventional) odds ratios among racial and ethnically homogenous mortgage applicants. Homogenous whites and Asian mortgage applicants drastically outperform their black and Latino counterparts. For example, the odd ratios for a high cost loan (versus a conventional loan) is 1 (.75) times for racially homogenous white (Asian) applicants compared to 2.89 (2.13) times for racially homogenous black (Latino) counterparts.

Regardless of the racial and ethnic classification of the primary borrower, mortgage applicants with a white and Asian co-borrower outperform their black and Latino co-applicants counterparts. Among each racial group of the primary borrower, the odds ratios for obtaining a high cost loan (versus conventional loan) are highest when a mortgage application has a black co-borrower; followed by Latino, white, and Asian co-borrower. The L-shaped pattern holds firm across the primary borrower's ethno-racial groups. For example, among mortgage applicants with a white primary borrower, the odd ratios of obtaining a high cost loan (versus a conventional loan), when their co-applicant is black (Latino) is 1.67 (1.43) times, compared to 1 (.67) times when their co-applicant is white (Asian). Similarly, among mortgage applicants with a Latino primary borrower, the odd ratios when their co-applicant is black (Latino) is 2.41 (2.13) times compared to 1.48 (1.25) times when their co-applicant is white (Asian).

As shown in figure 3, the ethno-racial disparities and patterns slightly change when examining the odds ratios for mortgage rejections due to other reasons versus a conventional mortgage among co-applicants. Across ethno-racial groups, white primary applicants generally outperform their black, Latino, and Asian counterparts given a specific co-borrower. For example, the odds ratios for a mortgage denial due to other reasons (versus a conventional loan) for a white primary borrower with a Latino co-applicant, is 1.19 times compared to 2.37 times for a black primary borrower, 2.05 times for a Latino primary borrower, and 1.71 times for an Asian primary borrower. Also, the range in which white primary borrowers are likely to be denied due to other reasons is much smaller than that of the other ethno-racial groups. For instance, the odds ratios for primary white applicants and a given co-borrower ranges from 1 to 1.55 times while the odd ratios for their black counterpart ranges from 1.80 to 2.72 times more likely to be denied due to other reasons (versus conventional).

A similar racial hierarchy exists when comparing denials due to other reasons (versus a conventional origination) in racially homogenous mortgage applications. Homogenous white pairs (reference group) are least likely to rejected for other reasons; followed by Asians, Latinos, and blacks. For instance, black applicants are 2.72 times more likely to denied a mortgage due to other reasons, Latinos 2.05 times, and Asians 1.59 times compared to their white counterparts.

The ethno-racial classification of the co-borrower among mortgage applicants reinforces the pattern of racial hierarchy that was found among primary applicants. The pattern formed among each primary applicant ethno-racial group resembles a declining line as black co-applicants fare the worse, followed by Latinos and Asians. Again, white co-applicants are the least likely to be rejected due to other reasons among each ethno-racial group. For instance, among black primary borrowers, black co-borrowers are 2.72 times, Latino co-borrowers are 2.37 times, Asian co-borrowers are 1.99 times, and white co-borrowers are 1.80 times more likely to be denied a mortgage due to other reasons. Mortgage applications with a black co-borrower among each ethno-racial primary group have the highest odds of being rejected due to other reasons except in the case of Latino primary applicants. For example, white primary applicants with a black co-applicant are 1.55 times more likely to be denied a mortgage due to other reasons compared to white homogenous applicants.

Figure 4, displays the ethno-racial differences of odd ratios for mortgage denials due to bad credit (versus a conventional loan). In general, white primary applicants outperform the other ethno-racial groups. For instance, the odds ratios for a mortgage denial due to bad credit for a white primary borrower with a Latino co-applicant, is 1.13 times compared to 1.86 times for a black primary borrower, 1.70 times for a Latino primary borrower, and 1.41 times for an Asian primary borrower. In addition, there is less variation in mortgage denials due to bad credit for white primary applicants with different ethno-racial co-applicants compared to other primary applicant groups. For example, the odds ratios for a bad credit denial for white primary applicants range from .98 times to 1.18 times compared to Latino primary borrowers whose range is between 1.21 times to 1.76 times.

Among ethno-racially homogenous applications, black pairs are most likely to be denied a mortgage due to bad credit (versus conventional) compared to the other ethno-racial homogenous pairs. White homogenous pairs (reference group) are the least likely to de denied for bad credit. For instance, black pairs are 2.25 times more likely to denied for bad credit compared to 1.69 times for Latino pairs, 1.49 times for Asian pairs compared to a white homogenous couple.

Similar patterns of racial hierarchy are found when assessing ethno-racial disparities of co-applicants among primary applicants. In general, there is a declining pattern formed among each primary applicant ethno-racial group as black co-applicants fare worse in terms of being denied a mortgage due to bad credit followed Latino and Asian co-applicants. Once again, white co-applicants are the least likely to be rejected due to bad credit within each primary applicant ethno-racial group. For example, among Latino primary borrowers, black co-borrowers are 1.76 times, Latino co-borrowers are 1.70 times, Asian co-borrowers are 1.35 times, and white co-borrowers are 1.21 times more likely to be denied a mortgage due to bad credit. In the case of Latino and Asian co-borrowers, the order of racial hierarchy is less clear. For example, among white and Latino primary applicant groups, the pattern of racial hierarchy remains consistent. However, among black and Asian primary applicant groups, the odds of being rejected due to bad credit for Asian co-borrowers increases above the level of Latinos within the Asian primary applicant group and increases above both black and Latino levels within the black primary applicant group. This shift in racial hierarchy suggests that the racial hierarchy for Asians is more fluid compared to the rigid structure for black and Latino applicants.

Conclusions and directions for additional research

The mortgage industry is a key component in the perpetuation of racial inequality in homeownership. The highly racialized outcomes in the mortgage industry requires a continuous study of the evolution in the lending industry and warrants additional attention to how access to homeownership is shaped by inter-racial couples. Drawing on HMDA data, I document variation in racial disparities in access to mortgage outcomes.

The continued strength of race in structuring mortgage access is overwhelming. Black primary applicants are substantially more likely to be steered into high cost loans or rejected, either due to bad credit or unspecified reasons when accounting for the race, ethnicity of the co-borrower. On the other hand, white primary borrowers face the least obstacles and observe the most favorable mortgage outcomes across racial groups. For the most part, Latino and Asian primary applicants experience outcomes somewhere in the middle between white and black primary applicants. Furthermore, the differences across primary racial groups were not only statistically significant, they were also substantively large. The implications for racial stratification are profound even if there is missing information on applicant characteristics. When examining racial disparities in mortgage outcomes between racially homogenous couples, a distinct pattern emerges. Black and Latino homogenous couples on one end and their white and Asian counterparts on the other. More specifically, black and Latino couples experience much poorer mortgage outcomes than their white and Asian counterparts.

I also demonstrate the impact of the co-borrowers in racialized mortgage outcomes. More specifically, tremendous variation in mortgage outcomes exists between primary racial groups when considering the race and ethnicity of the co-borrower. Overall, black and Latino co-borrowers among primary applicant racial groups face the largest disadvantage relative to white co-borrowers in mortgage outcomes. The performance of Asian co-borrowers varies depending on the mortgage outcome of interest. For high cost loans, Asian co-borrowers outperform their white counterparts. However, for mortgage denial due to poor credit or unspecified reasons, Asian co-applicants perform slightly worse than their white counterparts. These findings are consistent with the widening body of literature that displays the rigid racial stratification structure in homeownership. In spite of having a white co-borrower, black and Latino primary borrowers significantly underperform their white counterparts. Finally, the racial stratification patterns exhibited by including the ethno-racial groups of the co-borrowers demonstrates the large mortgage outcome differences that exist across inter-racial couples.

The implications of these patterns for ethno-racial stratification are overwhelming. These findings add to previous literature demonstrating the shifts of racial disparities in lending. Racial disparities in the mortgage market expands and contracts when considering the race and ethnicity of the co-borrower. Couples with a black or Latino applicant are less likely to obtain a conventional mortgage and more likely to experience an adverse mortgage outcome. Thus, the racially stratified mortgage market, constrains homeownership opportunities for black and Latino applicants and limits the efforts of using homeownership to close the racial wealth gap.

These findings also show the need for better data on racial disparities in mortgage lending. The lack of information on applicant credit information and economic circumstances of the co-borrower limits the ability to hold lenders accountable for discrimination. The CRA should add information on credit scores of all applicants, down payments, loan-to-income ratios, sales price of the home, and other economic factors that potentially affect mortgage loan outcomes among minority applicants.

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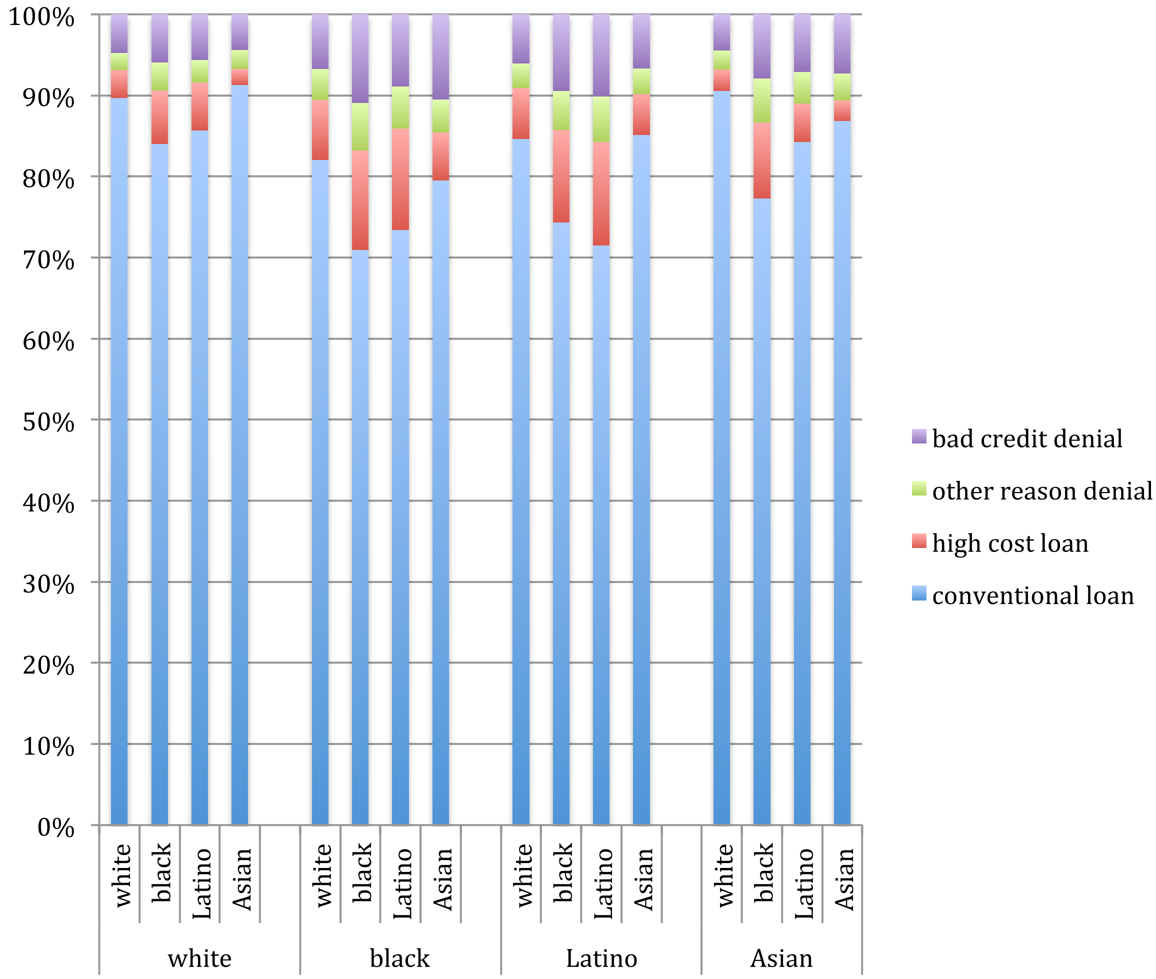
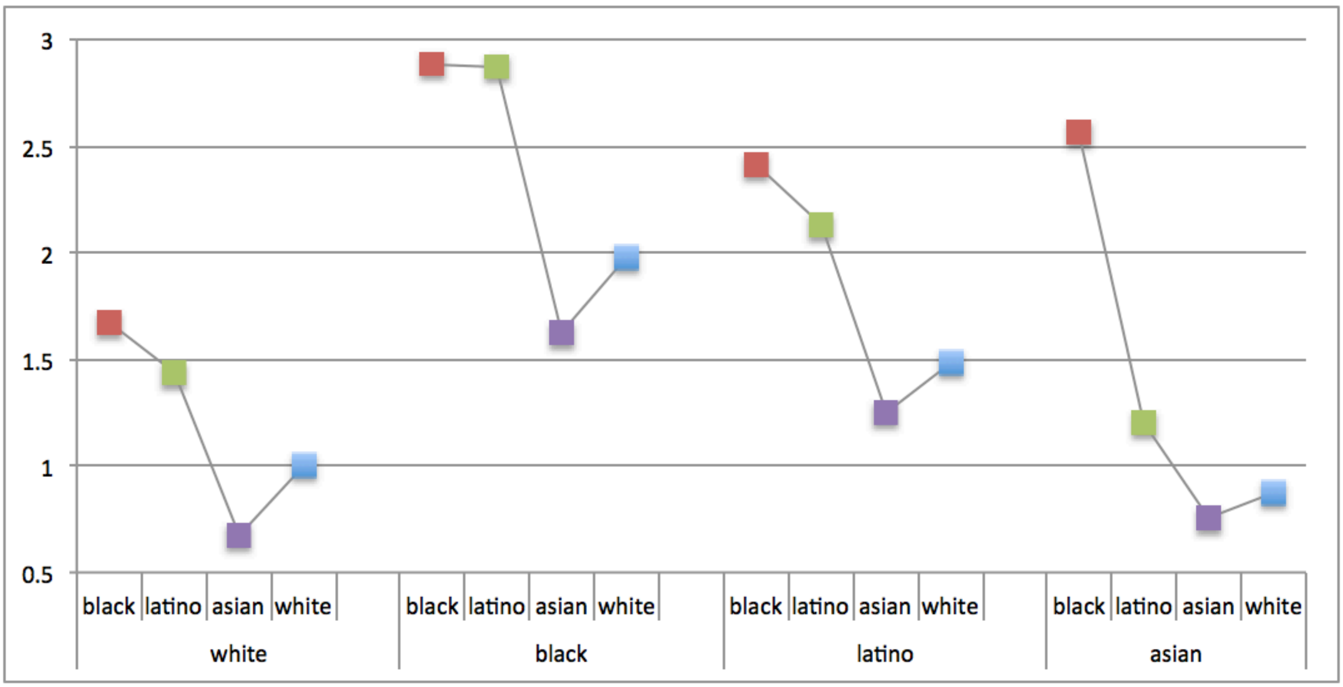
Figure 1: Loan Application Outcomes, by Race and Ethnicity of Primary and Co-borrower



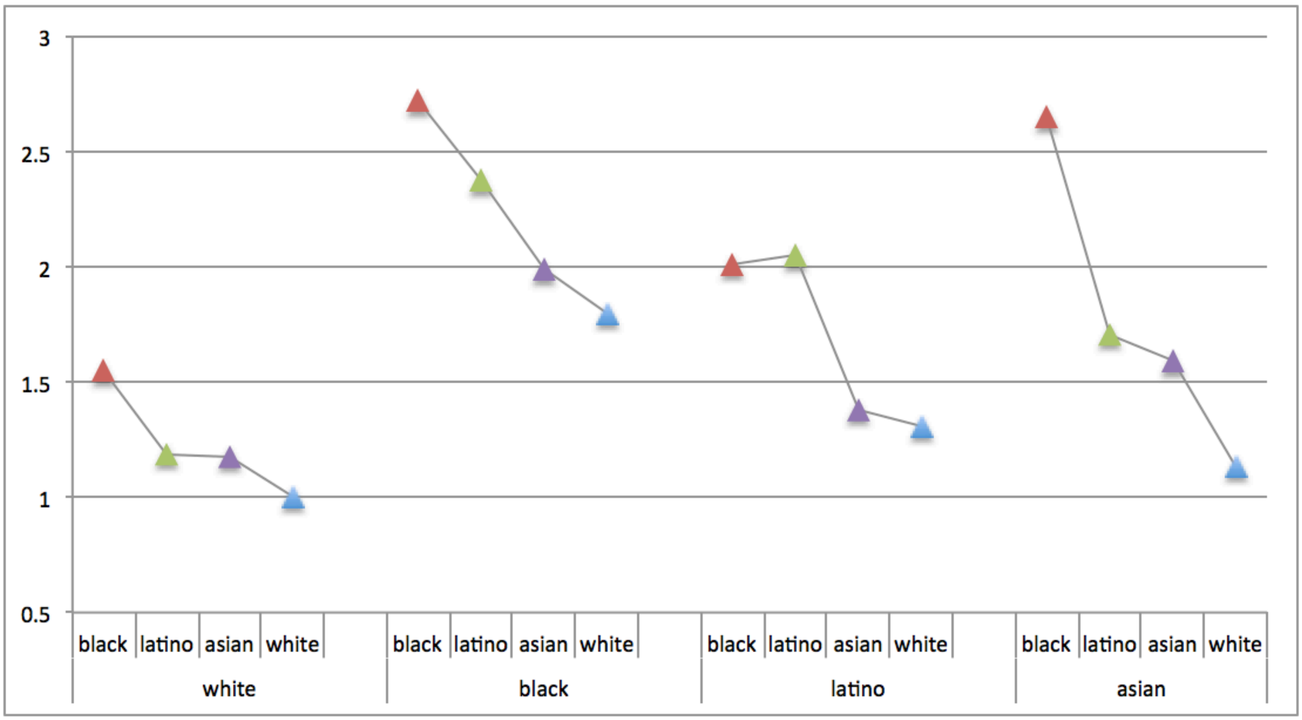
Source: HMDA

Figure 2: Odds Ratios From Multinomial Hierarchial Linear Models Predicting Loan Application Outcomes: **High Cost Loan Origination** (Ref= Conventional Origination, and White applicants with a White co-applicant)



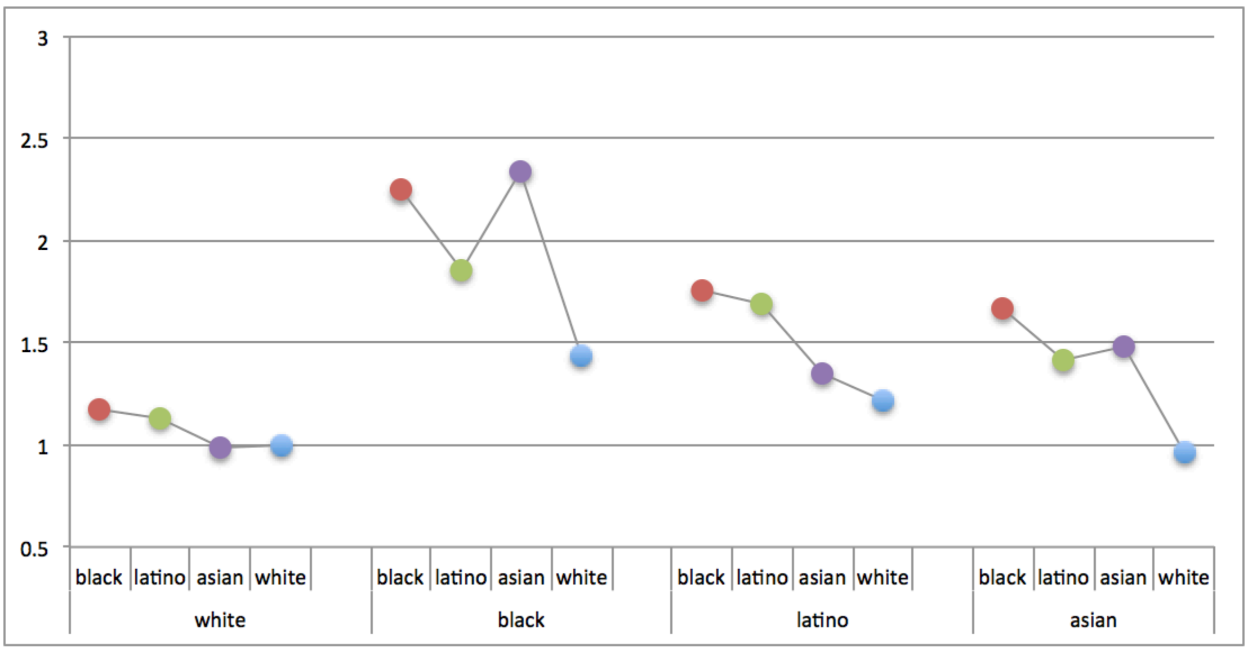
* Source: Odds Ratios from Appendix A

Figure 3: Odds Ratios From Multinomial Hierarchial Linear Models Predicting Loan Application Outcomes: **Other Reason Mortgage Denial** (Ref= Conventional Origination, and White applicants with a White co-applicant)



* Source: Odds Ratios from Appendix A

Figure 4: Odds Ratios From Multinomial Hierarchial Linear Models Predicting Loan Application Outcomes: **Bad Credit Mortgage Denial** (Ref= Conventional Origination, and White applicants with a White co-applicant)



* Source: Odds Ratios from Appendix A

Table 1: Borrower Characteristics, by race and ethnicity of primary and co-borrower: 2010-2016

Primary Applicant	All	white				black				Latino				Asian			
Co-applicant		white	black	Latino	Asian	white	black	Latino	Asian	white	black	Latino	Asian	white	black	Latino	Asian
Race, Ethnicity of Primary Applicant																	
Non-Hispanic W	61.77																
Black	19.96																
Hispanic	11.74																
Asian	6.53																
Sex of Applicants (% Primary - Co-applicant)																	
Male - Female	74.67	77.97	52.03	72.83	87.57	74.53	49.58	69.85	82.16	58.12	47.38	64.52	75.44	79.79	66.24	78.99	86.88
Female - Male	19.64	16.78	42.04	21.62	9.05	19.71	42.99	17.47	12.68	36.07	44.32	29.10	16.63	14.13	23.55	15.02	8.75
Male - Male	3.30	2.89	2.98	3.41	2.27	3.38	3.03	7.45	3.35	3.72	2.84	4.25	4.97	3.17	3.82	2.96	1.56
Female - Female	2.39	2.36	2.96	2.14	1.12	2.38	4.39	5.23	1.81	2.08	5.46	2.12	2.96	2.91	6.40	3.03	2.81
Household Income (%)																	
< 25k	0.63	0.54	0.56	0.48	0.47	0.62	1.57	2.27	0.47	0.29	1.75	0.64	1.24	0.77	1.02	1.28	0.62
25k - 50k	8.12	7.34	8.59	7.73	5.20	9.09	11.92	22.03	8.52	4.52	11.35	7.34	11.48	8.92	14.19	10.71	9.22
50k - 75k	17.16	16.56	18.76	18.26	11.83	19.34	22.80	30.19	16.63	11.55	17.03	16.03	14.12	19.28	25.00	25.39	17.66
75k - 100k	19.18	19.7	21.46	20.88	15.08	20.82	25.00	19.84	17.57	15.29	16.81	18.67	12.70	22.10	21.08	20.40	19.38
100k - 125k	15.82	16.41	16.55	16.71	14.68	16.52	16.42	11.66	15.29	14.88	12.45	15.45	11.70	16.44	14.89	15.56	17.5
125k - 150k	11.39	11.95	11.01	11.87	12.41	10.80	8.16	5.18	13.35	12.10	11.57	12.04	9.96	10.85	8.28	10.17	10.31
150k - 175k	7.73	7.73	7.10	7.27	9.57	7.140	5.02	3.33	8.18	10.04	6.99	9.08	8.34	7.22	5.00	6.73	8.28
175k - 200k	5.43	5.28	4.89	5.09	7.69	4.69	2.82	1.79	4.69	7.51	7.86	5.22	6.85	4.64	3.17	3.84	5.00
> 200k	14.55	14.51	11.08	11.7	23.07	10.99	6.28	3.71	15.29	23.82	14.19	15.52	23.61	9.79	7.37	5.93	12.03
Loan Amount (%)																	
< 100k	5.61	6.75	6.68	5.05	3.30	5.51	7.95	10.39	3.22	3.13	6.33	2.64	3.66	7.37	10.00	5.66	4.38
100k - 200k	28.19	30.03	31.84	29.78	18.27	31.75	38.18	39.43	23.27	18.06	24.89	22.67	19.00	32.03	37.47	35.76	28.91
200k - 300k	27.48	27.75	28.93	29.47	23.15	29.24	28.35	28.71	27.57	25.10	26.20	26.46	20.72	29.39	27.63	30.91	26.09
300k - 400k	17.30	16.55	15.95	17.95	18.68	16.95	15.17	13.12	17.51	19.94	19.21	20.8	18.91	16.24	14.19	16.30	18.59
400k - 500k	9.65	9.06	8.10	8.97	13.34	8.32	5.65	4.77	13.15	13.35	9.61	12.30	13.60	7.79	6.29	6.94	10.47
500k - 600k	4.28	3.49	3.49	3.57	7.55	3.40	2.82	1.83	6.98	6.77	5.46	5.28	7.28	3.23	2.42	2.09	5.62
600k - 700k	2.77	2.25	2.30	1.92	5.55	2.11	0.73	0.85	3.09	4.92	4.15	3.99	5.90	1.50	0.91	1.01	1.72
700k - 800k	1.45	1.25	0.91	1.04	2.98	0.87	0.73	0.37	1.74	2.46	1.09	1.61	3.71	0.82	0.38	0.34	1.88
> 800k	3.28	2.87	1.79	2.24	7.18	1.85	0.42	0.52	3.49	6.27	3.06	4.25	7.23	1.63	0.70	1.01	2.34

Source: HMDA

Table 1: Borrower Characteristics, by race and ethnicity of primary and co-borrower: 2010-2016

Primary Applicant	All	white				black				Latino				Asian			
Co-applicant		white	black	Latino	Asian	white	black	Latino	Asian	white	black	Latino	Asian	white	black	Latino	Asian
Percent Whites In Census Tract (%)																	
< 25%	6.66	1.57	7.12	6.66	4.88	7.21	19.56	33.42	14.89	5.02	16.16	14.55	14.17	6.25	22.96	18.52	15.62
25% - 50%	13.24	6.28	14.11	15.20	13.93	15.41	22.49	25.50	25.29	13.09	22.27	21.76	22.75	14.22	23.06	24.51	26.41
50% - 75%	30.97	23.94	32.50	34.95	34.26	35.12	33.05	26.59	36.02	33.48	37.55	38.18	34.91	32.38	29.62	35.15	30.63
> 75%	49.14	68.22	46.28	43.18	46.93	42.25	24.90	14.49	23.81	48.41	24.02	25.50	28.17	47.15	24.35	21.82	27.34
Household Income In Census Tract (%)																	
< 50k	7.00	4.74	8.33	7.44	4.81	8.16	14.02	21.92	8.72	5.34	11.35	8.95	5.47	8.80	13.60	11.85	10.31
50k - 60k	7.56	6.71	8.87	8.17	5.11	8.48	12.03	15.93	6.91	5.53	8.52	7.15	5.92	8.70	12.47	11.38	8.91
60k - 80k	23.26	23.33	25.09	24.78	17.89	25.51	31.69	28.84	26.16	18.17	21.83	22.47	16.67	26.13	26.61	31.65	23.91
> 80k	62.18	65.22	57.70	59.62	72.19	57.85	42.26	33.31	58.22	70.96	58.30	61.43	71.94	56.37	47.31	45.12	56.88
Region of Home (%)																	
Northeast	11.30	14.92	13.27	8.91	10.65	8.60	12.03	5.54	6.24	11.39	8.52	7.73	10.91	12.33	10.70	11.52	11.41
Midwest	16.50	23.67	19.79	12.60	13.37	13.17	10.77	7.37	7.58	15.36	14.85	7.98	11.77	20.30	13.28	11.04	11.09
South	37.71	37.21	42.04	42.15	28.29	40.70	50.21	41.70	30.38	29.88	37.55	33.16	29.64	42.35	63.06	46.06	40.00
West	34.48	24.21	24.91	36.34	47.69	37.52	26.99	45.39	55.80	43.36	39.08	51.13	47.67	25.01	12.96	31.38	37.5
Average Unemployment Rate (Cou	6.93	6.72	6.83	7.00	6.91	7.07	7.20	7.75	7.53	6.88	7.01	7.34	6.97	6.84	6.98	7.30	7.08
2010 Average Credit Score (MSA)	690	692	691	687	694	687	687	683	688	693	692	689	693	691	687	686	691
Average Housing Price Index (MSA	215.53	210.77	212.71	217.73	223.17	216.07	211.60	213.15	216.64	221.61	219.99	217.67	221.25	210.33	208.14	209.80	212.39
Observations	144523	43660	4296	24992	16317	21598	956	4803	1491	10531	458	1553	4426	5457	1860	1485	640

Source: HMDA

(p.2 of 2)

Appendix A: Odds Ratios from Multinomial Hierarchial Linear Model of Loan Outcomes (Ref= Convetional Originatior
High Cost Loan Origination

		Odds Ratios		Std. Error	95% Confidence Interval	
Race, Ethnicity of Primary Applicant and Secondary Applicant (ref=white * white)						
White *	Black	1.67	***	0.12	1.46	1.91
	Latino	1.43	***	0.06	1.33	1.55
	Asian	0.67	***	0.04	0.59	0.76
Black *	White	1.98	***	0.12	1.76	2.22
	Black	2.89	***	0.23	2.46	3.38
	Latino	2.87	***	0.25	2.42	3.41
	Asian	1.62	**	0.28	1.15	2.28
Hispanic *	White	1.48	***	0.06	1.37	1.60
	Black	2.41	***	0.27	1.94	3.00
	Latino	2.13	***	0.12	1.90	2.38
	Asian	1.25		0.16	0.98	1.60
Asian *	White	0.87	*	0.06	0.76	0.99
	Black	2.57	***	0.44	1.84	3.58
	Latino	1.20		0.15	0.94	1.54
	Asian	0.75	**	0.08	0.62	0.92
Sex of Applicants (ref= Male - Female)						
	Female - Male	1.17	***	0.04	1.10	1.24
	Male - Male	1.34	***	0.09	1.18	1.52
	Female - Female	1.16	*	0.08	1.01	1.34
Household Income ($25,000)		0.83	***	0.01	0.81	0.84
Loan Amount ($100,000)		0.92	***	0.01	0.90	0.95
Percent Whites In Census Tract (%) (ref= >75% white)						
	>25%	1.62	***	0.09	1.46	1.80
	25% - 50%	1.46	***	0.06	1.34	1.59
	50% - 75%	1.33	***	0.05	1.25	1.43
Household Income In Census Tract (1000's) (ref= >80k)						
	< 50k	1.86	***	0.09	1.69	2.04
	50k - 60k	1.83	***	0.08	1.68	1.99
	60k - 80k	1.53	***	0.05	1.44	1.63
Region of Home (ref= South)						
	Northeast	0.98		0.08	0.83	1.16
	Midwest	0.85	*	0.06	0.74	0.98
	West	0.99		0.05	0.90	1.09
Average County Unemployment Rate (Year)						
	2010	1.08		0.05	0.99	1.19
	2011	0.99		0.08	0.85	1.16
	2012	0.93		0.07	0.80	1.08
	2013	1.38	***	0.10	1.20	1.58
	2014	0.76	**	0.07	0.63	0.92
	2015	0.74	**	0.08	0.60	0.91
	2016	1.32	***	0.08	1.18	1.48
Average MSA Housing Price Index (Year)						
	2010	1.00		0.00	0.99	1.00
	2011	0.98	**	0.01	0.97	0.99
	2012	1.02	**	0.01	1.01	1.04
	2013	1.01		0.01	0.99	1.03
	2014	0.99		0.01	0.98	1.00
	2015	0.99		0.01	0.97	1.00
	2016	1.01	*	0.00	1.00	1.02
2010 Average MSA Credit Score		0.99	***	0.00	0.98	0.99
Constant		363.70	***	454.37	31.43	4208.61

*** p<.001, ** p<.01, * p<.05

Appendix A: Odds Ratios from Multinomial Hierarchial Linear Model of Loan Outcomes (Ref= Convetional Origination): Other Reason Denial

		Odds Ratios		Std. Error	95% Confidence Interval	
Race, Ethnicity of Primary Applicant and Secondary Applicant (ref=white * white)						
White *	Black	1.55	***	0.14	1.29	1.85
	Latino	1.19	***	0.06	1.07	1.32
	Asian	1.18	**	0.07	1.04	1.33
Black *	White	1.80	***	0.14	1.54	2.11
	Black	2.72	***	0.29	2.20	3.36
	Latino	2.37	***	0.30	1.86	3.03
	Asian	1.99	***	0.41	1.33	2.98
Hispanic *	White	1.31	***	0.07	1.18	1.45
	Black	2.01	***	0.32	1.47	2.74
	Latino	2.05	***	0.16	1.76	2.38
	Asian	1.38	*	0.21	1.02	1.87
Asian *	White	1.13		0.08	0.98	1.31
	Black	2.65	***	0.56	1.75	4.02
	Latino	1.71	***	0.24	1.30	2.24
	Asian	1.59	***	0.15	1.32	1.91
Sex of Applicants (ref= Male - Female)						
	Female - Male	1.15	***	0.05	1.06	1.24
	Male - Male	1.54	***	0.12	1.32	1.79
	Female - Female	1.60	***	0.14	1.36	1.89
Household Income ($25,000)		0.86	***	0.01	0.84	0.88
Loan Amount ($100,000)		1.07	***	0.02	1.04	1.10
Percent Whites In Census Tract (%) (ref= >75% white)						
	>25%	1.07		0.08	0.93	1.23
	25% - 50%	1.09		0.06	0.97	1.21
	50% - 75%	1.03		0.04	0.94	1.12
Household Income In Census Tract (1000's) (ref= >80k)						
	< 50k	1.75	***	0.11	1.54	1.98
	50k - 60k	1.45	***	0.09	1.28	1.63
	60k - 80k	1.34	***	0.06	1.24	1.45
Region of Home (ref= South)						
	Northeast	1.34	**	0.13	1.11	1.63
	Midwest	0.98		0.09	0.82	1.17
	West	0.90		0.06	0.80	1.02
Average County Unemployment Rate (Year)						
	2010	1.15	*	0.07	1.02	1.29
	2011	0.98		0.10	0.81	1.18
	2012	0.88		0.08	0.74	1.06
	2013	1.01		0.09	0.85	1.20
	2014	1.14		0.14	0.91	1.45
	2015	0.95		0.13	0.73	1.23
	2016	0.94		0.07	0.82	1.09
Average MSA Housing Price Index (Year)						
	2010	1.01		0.00	1.00	1.01
	2011	1.00		0.01	0.98	1.01
	2012	1.00		0.01	0.98	1.02
	2013	1.01		0.01	0.99	1.03
	2014	0.99		0.01	0.97	1.00
	2015	1.01		0.01	1.00	1.03
	2016	1.00		0.00	0.99	1.01
2010 Average MSA Credit Score		0.99	***	0.00	0.98	0.99
Constant		369.76	***	561.44	18.86	7250.77

*** p<.001, ** p<.01, * p<.05 (p.2 of 3)

Appendix A: Odds Ratios from Multinomial Hierarchial Linear Model of Loan Outcomes (Ref= Convetional Origination): Bad Credit Denial

		Odds Ratios		Std. Error	95% Confidence Interval	
Race, Ethnicity of Primary Applicant and Secondary Applicant (ref=white * white)						
White *	Black	1.18	*	0.08	1.03	1.35
	Latino	1.13	***	0.04	1.05	1.22
	Asian	0.98		0.05	0.90	1.08
Black *	White	1.44	***	0.09	1.28	1.62
	Black	2.25	***	0.18	1.91	2.64
	Latino	1.86	***	0.18	1.54	2.25
	Asian	2.34	***	0.32	1.80	3.06
Hispanic *	White	1.21	***	0.05	1.13	1.31
	Black	1.76	***	0.21	1.40	2.21
	Latino	1.69	***	0.10	1.51	1.90
	Asian	1.35	**	0.15	1.09	1.67
Asian *	White	0.96		0.05	0.86	1.07
	Black	1.67	**	0.30	1.17	2.37
	Latino	1.41	***	0.15	1.15	1.73
	Asian	1.49	***	0.10	1.31	1.69
Sex of Applicants (ref= Male - Female)						
	Female - Male	1.25	***	0.04	1.18	1.32
	Male - Male	1.83	***	0.10	1.64	2.03
	Female - Female	1.45	***	0.10	1.28	1.65
Household Income ($25,000)		0.77	***	0.01	0.76	0.79
Loan Amount ($100,000)		1.21	***	0.01	1.19	1.24
Percent Whites In Census Tract (%) (ref= >75% white)						
	>25%	1.01		0.05	0.91	1.13
	25% - 50%	1.05		0.04	0.97	1.14
	50% - 75%	0.98		0.03	0.92	1.04
Household Income In Census Tract (1000's) (ref= >80k)						
	< 50k	1.53	***	0.07	1.40	1.68
	50k - 60k	1.34	***	0.06	1.23	1.46
	60k - 80k	1.16	***	0.04	1.10	1.24
Region of Home (ref= South)						
	Northeast	1.26	***	0.09	1.10	1.45
	Midwest	1.04		0.07	0.92	1.19
	West	0.65	***	0.03	0.59	0.71
Average County Unemployment Rate (Year)						
	2010	1.16	***	0.05	1.07	1.26
	2011	0.91		0.07	0.79	1.05
	2012	1.16	*	0.08	1.02	1.32
	2013	0.96		0.06	0.85	1.09
	2014	0.90		0.08	0.76	1.07
	2015	1.02		0.10	0.84	1.24
	2016	0.95		0.05	0.85	1.05
Average MSA Housing Price Index (Year)						
	2010	1.02	***	0.00	1.01	1.02
	2011	0.98	***	0.01	0.97	0.99
	2012	1.01		0.01	0.99	1.02
	2013	1.00		0.01	0.98	1.01
	2014	1.00		0.01	0.99	1.01
	2015	1.02	***	0.01	1.01	1.03
	2016	0.99	***	0.00	0.98	0.99
2010 Average MSA Credit Score		0.99	***	0.00	0.99	1.00
Constant		8.30		9.23	0.94	73.34

*** p<.001, ** p<.01, * p<.05 (p.3 of 3)