Searching for Age and Gender Discrimination in Mortgage Lending

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Abstract:

This paper tests for the presence of age and gender discrimination in the loan underwriting process. We modify the tools used during the past exams to test for racial discrimination and apply them here to test for the presence of disparate treatment on the basis of age and gender. Using HMDA data along with data from 18 fair lending exams recently conducted by the OCC, between1996 – 2001, we find no evidence of systematic discrimination on the basis of age or gender. Further, the tools used and tested for in this analysis are now readily available for use in future fair lending exams.

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Introduction

Bank regulators monitoring fair lending and compliance issues in mortgage markets focus almost exclusively on racial disparities. This emphasis on racial disparities is not surprising given the attention racial discrimination has received, both politically and socially, since the civil rights legislation of the 1960s. However, it should not be forgotten that in addition to race, the Equal Credit Opportunity Act (ECOA), implemented in 1974, promotes the availability of credit to all creditworthy applicants without regard to color, religion, national origin, gender, marital status, or age.

This paper evaluates the impact of age and gender in mortgage markets by looking at the role they play in the mortgage granting decision. Specifically, how do age and gender affect the probability of being denied a mortgage? We focus on age and gender for two reasons. First, the passage of FIRREA in 1989 required banks to collect data at the individual loan level making bank data more readily available. Of the prohibited factors noted in ECOA, FIRREA required that data be collected for only race and gender. Although FIRREA does not specifically require banks to collect age information, it is included in the mortgage application. Second, the parallels to the extensive body of work on age and gender discrimination in the labor market literature make such an analysis more intuitive and appealing. Using data from 18 fair lending exams recently conducted by the Office of the Comptroller of the Currency (OCC), we examine whether age or gender plays a role in banks' underwriting decisions of mortgage applications.[1]

The remainder of the paper is structured as follows. Section I presents a brief theoretical discussion of taste-based discrimination, drawing parallels to the models of labor market discrimination. Section II presents empirical results testing the effects of both age and gender in previous fair lending exams. Section III concludes the discussion.

Theoretical Discussion

Discrimination occurs when people are treated on the bases of factors other than their individual merits, such as race, gender, age, nationality, and religion. In the case of mortgage markets, discrimination takes place when people are, for example, denied a mortgage because of factors not related

[1] The data used in this study were collected as part of official OCC fair lending exams. They are therefore strictly confidential and cannot be released to the public or shared with other researchers.

to their ability to repay the loan, but rather on some personal characteristics, such as age and gender. Regulation B, the regulation implementing ECOA in 1974, clearly states that people may not be denied a loan on the basis of their age or gender.[2]

The ability of a bank to discriminate is a direct function of the market environment in which it operates (Becker, 1957). That is, the more competitive the market environment, the less opportunity banks have to discriminate. Market competition, therefore, plays an important role in determining banks' ability to decide on a loan on bases other than loan worthiness, or ability to pay.

When a bank decides on a loan on factors other than qualifications, it practices taste-based discrimination. Taste-based discrimination occurs merely because the bank *wants to* exclude a certain person, or a group, from obtaining a loan. There is no economics consideration, but rather the bank relies on the personal characteristics of the people to determine whether or not a loan should be granted.

A discriminatory bank can either offer higher rates to those they consider undesirable applicants or turn them down. If, for the sake of simplicity, we assume a perfectly competitive market, an individual bank will take interest rates as given and thus is a price taker. To further simplify the analysis we assume that all people, regardless of race, gender or age, are equally creditworthy. In this environment the rates offered to females and males are equal, or:

$$r_f = r_m$$

where r_f and r_m represent the mortgage rates offered to female and male applicants, respectively. These rate comparisons could as easily be made for other groups, such as black vs. whites or young vs. old applicants. Since the market sets rates, an individual bank cannot offer different groups different rates. A discriminatory loan officer will, however, receive a negative utility from granting a loan to a female applicant. Since the loan officer cannot offer higher rates to females to compensate for the loss in utility, the only possible outcome is to deny the loan. Effectively, rates to female applicants as seen by the discriminating loan officer are:

$$r_f\,(1\text{-}d) \leq r_m$$

[2] According to Regulation B, a bank is allowed to use age as a predictive factor in scorecards as long as some specific criteria, such as the elderly being treated at least as favorable as other age groups, and there is a statistical basis for considering age in the decision-making process. Age may also be used in a case-by-case basis to determine creditworthiness.

where d is the discrimination coefficient (ranging between 0 and 1, where 0 implies no discrimination). The larger d is, the lower the perceived rate leading to lower perceived profits. Since the loan officer cannot change the rate, she cannot raise the rates to females to account for the loss of utility associated with granting a loan to a female applicant. Effectively, a positive d indicates that the perceived rates to females were lower than that to males, making the loan less profitable. Therefore, the higher the discriminatory coefficient the greater the disutility associated with granting the loan, making it more likely that female applicants be denied.

In this environment, it could be argued that over time a bank that employs loan officers who receive positive utility from discriminating will ultimately be competed out of the market. In the "real world," however, banks are likely to have market power making such an outcome unlikely. The fact that the mortgage market is not perfectly competitive provides the necessary lending environment for taste-based discrimination. Factors, such as information asymmetries and market concentration, would provide such an environment. Although the lending environment has changed considerably over the past few years because of advancements in Internet lending for example, there are still lingering information asymmetries that provide banks with varying degrees of market power. While such advancements will potentially continue to change the lending environment for years to come, and possibly reduce the still lingering information asymmetries, the vast majority of loans made today are still made through the "traditional" channels.

The empirical analysis that follows tests the hypothesis that a discriminatory loan officer will accept or deny a loan on the basis of the applicant's age or gender, ceteris paribus.

Empirical Analysis

This paper uses data from statistically modeled fair lending exams recently conducted by the OCC to test for evidence of gender and age discrimination. Specifically, we test whether each variable affects the underwriting decision. Data from 18 statistically modeled fair lending exams are available for the gender analysis while data from only 10 such exams are available for the age analysis. The primary reason for this difference is that HMDA requires lenders to report information on gender, but not on age. Although age is always requested on a mortgage application, and therefore should be available for all fair lending exams, age data were available in electronic form for only 10 of the 18 exams. The fact that age data is not always available in electronic form is important as it suggests that focusing on age disparities during a fair lending exam may be significantly more costly than both gender and race analyses. The analysis that follows consists of two parts. The first is a bivariate analysis to identify highest areas of risk. The second is a multivariate analysis mirroring what is conducted during an actual exam.

It should be stated before continuing that although the analysis may suggest that discrimination is present at some banks, model findings in fair lending exams are never conclusive. In the event that a disparity is found the OCC always conducts further analysis, such as comparative file review, prior to making any discrimination claims.

A Test for Gender Discrimination

Each calendar year, the OCC uses a risk-based fair lending approach, which attempts to identify lenders and products posing the highest fair lending risk. The goal of this process is to best allocate limited exam resources. Analysis of HMDA data is one aspect of this risk-based process, so this is where we begin the gender analysis. Specifically, using HMDA data from the 18 exams in this study, we analyze bivariate relationships between denial rates and gender. The purpose is to determine whether denial rate disparities by gender posed sufficient fair lending risk to merit allocation of the OCC's resources.

Table 1 presents denial rate disparities for females relative to males for each of the 18 exams analyzed in this study.[3] Following the OCC's screening process, denial rate disparities were calculated by type and purpose of the loan. The table only presents results for the loan type and purpose with the highest denial rate disparity for each exam. Only products with at least 50 applications were considered. For comparison purposes, Table 1 also presents denial rate disparity results for the product and race that showed the largest denial rate disparity as well. The racial disparities are all relative to Whites. All calculations are based on HMDA data for the year prior to when the exam was conducted. In addition, a number of filters were applied to the data to create more homogenous populations for the analysis. First,

[3] These results are based only on the gender of the primary applicant. We also analyzed a second definition of gender that incorporated information about the co-applicant as well. Specifically, the "Female" group was defined as applications involving a female as either the primary or co-applicant. The results using this definition of gender differed little from the definition using only the primary applicant.

purchased loans, and applications for non-owner-occupied or multifamily property were excluded. Second, withdrawn and incomplete applications were excluded. Third, for the gender disparities, applications where the HMDA gender variable equals 3 (Information not provided) or 4 (Not applicable) were excluded. Finally, for the racial disparities, applications where the HMDA race variable equals 6 (Other), 7 (Information not provided), or 8 (Not applicable) were excluded.

The results from Table 1 clearly suggest that fair lending risk was higher for race than gender for each exam. Only one exam had a denial rate disparity for gender greater than two. Although HMDA data is only one piece of evidence used during the OCC's screening process, the results in Table 1 provide a strong argument for focusing on racial disparities instead of gender disparities. This is especially true given the OCC's limited resources.

The second component of the gender analysis is to estimate multivariate models of the underwriting decision and test the extent to which gender plays a role. This portion of the analysis is based on the multivariate models that were estimated as part of the actual exams. For each exam, the OCC estimated the following general model specification:

$$P(D=1) = X\beta + F\delta + \varepsilon$$

The matrix D indicates whether a mortgage application was denied. The matrix X consists of a set of control variables capturing the legitimate economic factors a lender considers during its underwriting process. Different lenders consider different factors, and the OCC estimates bank-specific models, so the composition of X differs across exams. In general, though, X contains measures of product characteristics, creditworthiness or history, employment/income stability, assets, and compensating factors. The matrix F contains prohibited factors and ε is an IID random error term, which we assume is drawn from a logistic probability density.

Each of the exams included in this study focused on racial disparities, so F consists of indicator variables for race. Focusing on gender disparities is merely a matter of replacing those racial indicator variables with an indicator variable for gender. If sufficient controls for the economic factors determining the underwriting decision were included in the models, the estimates of the gender coefficients provide reliable evidence of the existence of gender discrimination.

One problem with using past fair lending data is that the sample designs were created based on racial disparities being the focal point of the exam. For each exam, the OCC used non-proportional, stratified random sampling where strata were based on race and the action taken on the application. Strata with small numbers of applications in the population were typically over-sampled to ensure reliable estimates.

These sampling designs create two problems for the current gender analysis. First, there is limited variation in the gender variable for some exams. Table 2 presents the numbers of approved and denied applications by gender for each of the exams included in this study. As the table shows, there are a number of instances when the strata size is less than 50, which is the OCC's policy cutoff determining when statistical modeling is appropriate. As expected, strata sizes are consistently highest for approved males and lowest for denied females. These small strata sizes affect the reliability of the statistical results. Unfortunately, little can be done about this problem. The second problem introduced by the sampling designs is that the samples are not representative of each lender's applicant pool. As a result, we present weighted estimates where the weight for each application is constructed as the inverse of the probability that the application was included in the sample. Weighting ensures that the racial composition of the sample reflects the racial composition of the applicant pool.

Table 3 shows the estimated gender effects for each of the 18 exams included in this study. For each exam, the final model specification used during the exam is estimated with an indicator variable for gender replacing the indicator variables for racial groups. The dependent variable equals 1 if the applicant is denied and 0 otherwise, and a weighted logit estimator is used to estimate each model. The gender variable equals 1 if the applicant is male and 0 otherwise, so a negative coefficient estimate suggests that females are more likely to be denied than males. The table presents information on sample size, goodness of fit, and sign and significance of the gender coefficient. As indicated by grey shading in the table, for three exams, we can reject at the 95 percent confidence level the null hypothesis that the gender parameter equals zero. Interestingly, two of these coefficients are positive suggesting males are more likely to be denied credit than females.

The results in table 3 contain two main points. First, there is limited evidence that gender is related to the underwriting decision. While this raises some concern, these results should not be viewed as conclusive because race, not gender, was the focal point of each exam. Had gender been the focal point, additional analyses would have been conducted, and this may have affected the statistical findings. Second, surprisingly, the evidence generally suggests that males are more likely to be denied. The coefficient estimate is positive for 10 of the 18 exams, and two of the three significant results. Self-selection bias based on applicant's decisions to enter the applicant pool, omitted variable bias, and discrimination are three potential explanations for these findings. Unfortunately, it is difficult to investigate these explanations, because the detailed information necessary from these exams is no longer available.

A Test for Age Discrimination

Date of birth is always requested on the mortgage application, so age of the applicant is always available during a fair lending exam. However, because HMDA does not require lenders to report age information, age data may not always be maintained in electronic form. The costs associated with an age analysis are therefore higher than that of both gender and race. For the 18 exams included in this study, age data were available in electronic form for only 10. Using data for these 10 exams, we examine two relationships between age and the underwriting decision. Specifically, we test whether or not the elderly are more likely to be denied mortgages than younger applicants. As previously noted, age is a prohibited factor but can be used in the credit decisions as long as the elderly are treated at par with younger applicants.[4] Second, it is common industry practice to split applicants into groups on the basis of age. This paper evaluates whether the age split risk relationship commonly observed in credit scoring models apply to the process of underwriting mortgages. That is, are the youngest and the elderly applicants treated less favorably than other applicants?

Similar to the gender analysis, we begin by conducting a bivariate analysis to form an initial characterization of the relationships between age and the underwriting decision. Specifically, we test whether applicants 24 years of age and younger, and applicants 62 years and older are more likely to be denied. Unlike the gender analysis, age data are not available for the entire population, so this analysis is

[4] More specifically, Regulation B requires that a credit scoring system that uses age must be empirically derived demonstrably and statistically sound (EDDSS) unless age is evaluated on a case-by-case basis in a judgmental system. Even if the model is EDDSS, it does not meet the Regulation B requirements if the elderly do not receive at least as many points as the most favored group.

based on the samples that were used for the actual exams. As previously noted, for each exam, non-proportional, stratified random sampling was used with strata defined by race and the underwriting decision. Therefore, to create statistics that are representative of the population, we again apply weights equal to the inverse of the probability that an application was included in the sample.

Table 4 presents the weighted denial rate disparity results for the 10 exams where age data were available. Gray shading indicates the null hypothesis that there is no association between the denial rates, and the prohibited factor was rejected at the 95 percent confidence level based on a chi-square test statistic.[5] As the table shows, for young applicants, the null hypothesis of no association is rejected at the 95 percent confidence level for six of the 10 exams. For elderly applicants, the null hypothesis is rejected for three of the 10 exams. Compared with the bivariate gender results from Table 1, age appears to present more fair lending risk.

Similar to the gender analysis, the sampling designs used during the fair lending exams caused limited variation for the age variables. Table 5 presents the numbers of approved and denied applications for both the Young (24 and under) and Elderly (62 and older) age groups. In every instance, the strata sizes are less than the OCC's standard of 50 applications. This suggests that there are insufficient numbers of applicants 24 years of age and under, and applicants 62 years of age and older, to conduct a multivariate analysis similar to that done with gender. As an alternative, we partition each continuous age variable into four age groups roughly corresponding to the shape of estimated age-earnings profiles – age 30 and under, 31 to 40, 41 to 54, and 55 and up.

The final model from the fair lending exam again is the specification we estimate, with the race indicator variables replaced by age indicator variables. Similar to the gender analysis, the dependent variable equals 1 if the applicant is denied and 0 otherwise, and we use a weighted logit estimator to estimate each model. The age group 41 to 54 is always the excluded category, so all age estimates are relative to that age group. Individuals aged 41-54 are typically in the highest earnings period of the life cycle, settled down, have jobs and income stability, and assets and wealth. As a result, if lenders discriminate on the basis of age by using age as a proxy for creditworthiness, we would expect the coefficients on each of the other three age groups to be positive.

[5] A Fisher's Exact test is used when there are small numbers of denials or approvals in an age category.

Table 6 shows the results for the 10 exams. Applicants age 55 and older appear more likely, in general, than applicants 41 to 54 to be denied, as seven of the 10 exams show a positive coefficient estimate. However, none of these results were statistically significant at the 95 percent confidence level. The youngest age group, age 30 and under, showed both negative and positive effects with only one statistically significant estimate, a negative effect for exam 14. Overall, these results suggest that lenders are not considering age during the underwriting process. By controlling for the legitimate economic factors that lenders consider during the underwriting process, many of the statistically significant effects from the bivariate analysis presented in Table 5 disappear. This matches our expectations that age is highly correlated with these economic factors.

Conclusion

According to ECOA, credit should be made available to creditworthy applicants without regard to color, religion, national origin, sex, marital status, or age. Regulators have typically focused their resources on the role played by race in the underwriting process. This paper analyzes whether other prohibited factors mentioned in ECOA pose sufficient fair lending risk to merit regulators' time and resources as well. Specifically, using publicly available HMDA data along with data from 18 fair lending exams recently conducted by the OCC, we examine whether there is potential evidence of age and gender discrimination. Initial bivariate analyses, similar to that conducted by the OCC during its screening process, suggested that age, but not gender, may have posed sufficient fair lending risk to expend additional resources on a full exam. The multivariate model results, which controlled for the legitimate economic factors lenders consider during their underwriting decisions, suggest very limited evidence of disparate treatment by age or gender. Only three of 18 tests for gender discrimination were statistically significant, and two of the three suggested that males were the disadvantaged group. Similarly, only three of the 30 tests for age discrimination were statistically significant. All three suggested that applicants younger than 41 to 54 were less likely to be denied. Although the results presented in this paper indicate that age and gender did not play a significant role in the underwriting decisions in past exams, we now have the necessary tools developed and tested for use during future fair lending exams.

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Table 1: Denial Rate Disparities by Gender and Race for 18 Lenders Recently Examined by the OCC*

Product Codes: CHP Conventional Home Purchase; CHI Conventional Home Improvement; CR Conventional Refinance; GHP Government Home Purchase; GHI Government Home Improvement; GR Government Refinance

	Gender		Race		
Exam	Product	Denial Rate Disparity	Product	Race	Denial Rate Disparity
1	CHP	1.2	CHP	Black	2.0
2	CHP	1.2	CHP	Black	2.0
3	CHP	1.3	CHP	Black	3.2
4	CR	2.7	CR	Black	5.3
5	CHP	1.2	CHP	Indian	2.7
6	CHP	1.3	CHI	Hispanic	2.1
7	CR	1.3	CR	Black	2.2
8	CR	1.6	GHP	Black	3.5
9	GHI	1.7	CR	Hispanic	2.5
10	CR	1.1	CR	Hispanic	1.5
11	CHP	1.6	CHI	Black	1.7
12	CHP	1.5	CHP	Black	1.9
13	CR	1.5	CR	Black	2.2
14	CHI	1.4	CR	Black	2.3
15	CHP	1.4	CHI	Black	3.3
16	CHP	1.4	CHP	Hispanic	3.5
17	CHP	1.2	CHP	Black	3.4
18	GHP	1.5	CHP	Black	4.0

* All denial rate disparities are calculated using HMDA data from the year prior to when the actual exam was conducted. Only the products and racial groups with the largest disparity are presented. Gender disparities are relative to Males, and racial disparities are relative to Whites.

Table 2: Sample Sizes by Gender and Action Using Data from 18 Exams Recently Conducted by the OCC					
		Male		Female	
Exam	Sample Size	Denied	Approved	Denied	Approved
1	301	101	119	37	44
2	362	98	152	47	65
3	287	65	132	18	72
4	716	69	372	75	200
5	239	49	124	22	44
6	395	77	223	22	73
7	425	73	175	65	112
8	338	81	169	27	61
9	479	125	244	46	64
10	439	127	181	59	72
11	458	104	197	68	89
12	333	78	153	41	61
13	316	64	125	59	68
14	340	56	188	24	72
15	1614	333	893	103	285
16	394	159	131	50	54
17	203	49	78	34	42
18	1255	393	472	245	145

Table 3: Multivariate Tests of Gender Differences for 18 Exams Recently Conducted by the OCC

Model specification is identical to the final model specification used during the exam.
A weighted logit estimator is used to estimate each model.
The dependent variable equals 1 if applicant is denied and 0 otherwise.
The gender indicator variable equals 1 for males and 0 for females.

Exam	Sample Size*	Psuedo-Rsquare	Sign	Significant at 95% level
1	259	0.38	Negative	No
2	360	0.38	Positive	No
3	284	0.34	Positive	Yes
4	716	0.51	Positive	No
5	232	0.41	Positive	No
6	343	0.45	Positive	No
7	425	0.44	Positive	No
8	326	0.37	Negative	No
9	479	0.57	Negative	No
10	391	0.45	Positive	No
11	458	0.60	Positive	No
12	307	0.42	Negative	No
13	233	0.31	Negative	Yes
14	340	0.47	Negative	No
15	1613	0.51	Negative	No
16	375	0.56	Positive	Yes
17	196	0.62	Positive	No
18	1212	0.64	Negative	No

* Sample sizes are slightly lower than in Table 2, because some independent variables contained missing values for some applications.
Gray shading indicates the null hypothesis that the gender parameter equals zero can be rejected at the 95 percent confidence level.

Table 4: Test of Differences in Denial Percentages by Age for 10 Lenders Recently Examined by the OCC

Statistics are weighted to account for non-proportional sampling.

	Young (24 and under) vs. all other ages		Elderly (62 and older) vs. all other ages	
Exam	Denial Rate Disparity	Chi-sq	Denial Rate Disparity	Chi-sq
4	1.16	0.42	1.55	0.04
7	1.39	0.23	0.63	0.13
8	1.96	0.00	1.94	0.00
9	1.61	0.00	0.42	0.00
10	1.89	0.01*	0.90	0.16
11	4.48	0.00*	1.18	0.32
12	1.69	0.00	1.00	0.94
14	1.94	0.00	0.90	0.18
16	1.16	0.39	0.91	0.78
17	0.46	0.26*	0.88	0.75

* Based on Fisher's Exact test, because of small strata sizes.
Gray shading indicates the null hypothesis that there is no association between the denial rates, and the prohibited factor can be rejected at the 95 percent confidence level.

Table 5: Sample Sizes by Age and Action Using Data from 10 Exams Recently Conducted by the OCC								
	Young (24 and under) vs. all other ages				Elderly (62 and older) vs. all other ages			
	Young		Other		Elderly		Other	
Exam	Denied	Approved	Denied	Approved	Denied	Approved	Denied	Approved
4	6	15	74	189	4	7	76	197
7	7	15	92	183	5	29	94	269
8	24	20	114	267	8	10	130	277
9	10	11	96	216	4	19	102	208
10	3	0	174	317	23	52	154	265
11	2	0	133	191	20	22	115	169
12	6	4	166	281	27	41	145	244
14	8	8	111	205	7	9	112	204
16	17	25	102	168	4	6	115	187
17	2	16	78	244	5	19	75	241

Table 6: Multivariate Tests of Age Differences for 10 Exams Recently Conducted by the OCC

Model specification is identical to the final model specification used during the exam.
A weighted logit estimator is used to estimate each model.
The dependent variable equals 1 if applicant is denied and 0 otherwise.
The age group 41 – 54 is the excluded category.
95 percent confidence levels are used for hypothesis tests.

			Age 30 and under		Age 31 to 40		Age 55 and older	
Exam	N	Psuedo-Rsquare	Sign	Significant	Sign	Significant	Sign	Significant
4	281	0.33	Negative	No	Negative	Yes	Negative	No
6	345	0.46	Negative	No	Negative	No	Negative	No
7	425	0.45	Negative	No	Negative	No	Positive	No
8	322	0.39	Negative	No	Negative	No	Positive	No
9	494	0.57	Negative	No	Negative	No	Positive	No
10	293	0.51	Positive	No	Positive	No	Positive	No
11	457	0.62	Positive	No	Negative	Yes	Positive	No
12	306	0.42	Positive	No	Positive	No	Positive	No
13	232	0.28	Negative	No	Negative	No	Positive	No
14	340	0.48	Negative	Yes	Negative	No	Negative	No