MORTGAGE LENDING IN THE DALLAS FT. WORTH METROPLEX:

SCREENING FOR RACIAL BIAS

USING HMDA DATA

by

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This thesis is dedicated with love to my babies, Samara and Samaya

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ABSTRACT

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This study will look at loan data to screen for potential lending discrimination in the Dallas-Ft. Worth Metroplex. The data used for screening purposes is the 2003 Home Mortgage Disclosure Act (HMDA) Loan Application Register (LAR). HMDA data does not provide a complete picture of an applicant's creditworthiness. It lacks important information such as an applicant's employment and credit histories. As a result, this study cannot make a conclusive finding of racial bias in mortgage lending in the Dallas-Ft. Worth Area. However, this study can determine if there are any indicators of racial bias that would warrant deeper investigation.

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CHAPTER 1

INTRODUCTION

The Home Mortgage Disclosure Act of 1975 (HMDA) was enacted by Congress to gauge whether individuals or particular areas were being unfairly denied for mortgage loans. HMDA requires lenders to report information on the location, loan amount, income, and the race/ethnicity and sex of the applicant(s) for each application taken by the lender. Lenders also report whether the application resulted in an origination, denial, or some other action. The data generated by HMDA reporting are available publicly and provide a detailed picture of how geographic lending patterns vary depending on the income status or the racial/ethnic make-up of neighborhoods.

Controversy has continually surrounded the mortgage lending industry because there continues to be a debate on whether there is equal access to mortgage lending regardless of race or ethnicity. The Home Mortgage Disclosure Act (HMDA) requires banks and other lending institutions to disclose certain information about the geographic distribution of both their home purchase and home improvement loans. The data collected has put into question whether lenders provide mortgage lending fairly across racial groups. Some people interpret the differences in lending patterns across racial groups as discrimination. Others associate the differences with variations in demand for housing and home loans across racial groups, as well as, lenders applying their credit standards legitimately.

There have been studies done providing support for both sides of the debate. The study from the Reserve Bank of Boston, Munnell et al. (1992, 1996) was the catalyst for much of the debate on racial bias in the mortgage lending industry. The article was entitled "Mortgage Lending in Boston – Interpreting HMDA Data". The results of the study found that minorities, namely Black and Hispanics, were much more likely to be rejected for mortgage loans than their white counterparts. Specifically, the HMDA data showed that minorities were denied mortgage loans twice as much as whites. However, HMDA data is limited on conclusively determining discrimination in mortgage lending because variables signifying an applicant's creditworthiness are omitted from the data. As a result, the Federal Reserve Bank of Boston collected additional variables that affected the mortgage lending decision. Still, race was found to play a significant role in the mortgage lending decision.

This paper will examine whether there is a suggestion of racial bias in the mortgage lending decisions made in the Dallas–Ft. Worth (DFW) Metroplex, and if so, to what extent. HMDA data from 2003 will be analyzed for any potential discriminatory lending patterns. Since HMDA data does not provide a complete picture of an applicant's creditworthiness, a conclusive finding of racial bias cannot be determined in this paper. However, this paper will identify if any indicators of racial bias exists in the mortgage lending market that would warrant further investigation.

The paper is structured as follows: Chapter 2 reviews the literature on discrimination in the mortgage lending industry; Chapter 3 presents the model used to examine the mortgage lending data and analyzes the data; Chapter 4 presents the results; and Chapter 5 is the conclusion.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

There has been an extensive amount of research on racial discrimination in mortgage lending. Most of the research focuses on whether discrimination exists in mortgage lending. Other research, however, focuses on various other aspects of discrimination in mortgage lending, such as the use of certain models, underwriting errors, and pricing decisions as an explanation or racial bias in mortgage lending.

2.2 Testing for Racial Bias

The following articles test to determine whether racial bias exists in mortgage lending. The most well known research was prepared by Munnel, Browne, McEneaney, and Tootle (1996) and known as the Federal Reserve Bank of Boston study. Mortgage lending data was collected to determine if race played a role in lending decisions. Courchane and Nickerson (1997) look at mortgage loan pricing at three banks as an indication of discrimination. Galster (1993) argues that differences in default rates across racial groups are not a reliable indicator of whether mortgage-lending discrimination exists or not. Black and Schweitzer (1985) tests whether discrimination really exists in mortgage lending and looks at the necessity of such rigid consumer protection laws. Avery, Beeson, and Calem (1997) examine the Federal Reserve System's program, which uses HMDA data to screen for fair lending compliance. The authors discuss the value and the shortcomings of the program. All these articles will be reviewed.

2.2.1 Munnel, Browne, McEneaney, and Tootle Review (1996)

Munnel, Browne, McEneaney, and Tootle wrote an article entitled "Mortgage Lending in Boston: Interpreting HMDA Data" in 1996 which discussed the study conducted by The Federal Reserve Bank of Boston investigating discrimination in mortgage lending. The paper explains that HMDA was passed to monitor whether minorities and low-income individuals have ample access to the mortgage market. The HMDA data collected from lending institutions in the Boston MSA showed considerably higher denial rates for Black and Hispanic applicants than for White applicants. The minority applicants were denied mortgage loans two to three times more often. Further, the HMDA data showed that even high-income minorities were more likely to be turned down for mortgages than low-income whites. The HMDA data collected included the applicant's race, gender, income, and whether the application was accepted or denied. This pattern of minority discrimination in mortgage lending was consistent from 1991 to 1993 based on the HMDA data.

A debate on the validity of these results ensued. Many argued that the HMDA data do not include pertinent information such as credit histories, debt burden, or loan-to-value ratios that significantly affect the lending decision. As a result, the Federal Reserve Bank of Boston asked the financial institutions to provide any additional financial, employment and property information that determines the outcome of the mortgage lending decision. This additional information provides a better picture of the mortgage applicants.

A survey was provided to the Boston area banks to collect additional variables affecting the mortgage lending decision. The additional variables for the study were grouped into various categories. The categories include variables that affect the probability of default, variables that affect the costs of default (if it was to occur), the loan characteristics, and personal characteristics. To gauge the probability of default, data such as net wealth, liquid assets, obligation ratios, loan-to-value, credit history, and income was collected. The cost of default was measured by collecting data on whether private mortgage insurance was purchased and on the neighborhood characteristics. Data collected on the loan characteristics included the loan's duration, whether the interest rate was fixed or adjustable, and the type of property. Some personal characteristics collected were the age, marital status, and number of dependents. In total 38 additional variables were collected that contribute to the outcome of a mortgage application.

The results determined that black and Hispanic mortgage applicants in the Boston area were turned down for mortgages more often than white applicants with similar characteristics. Although there was no evidence that race signaled the performance of a loan, it appeared that race was being used in the decision process.

2.2.2 Courchane and Nickerson Review (1997)

Courchane and Nickerson's article entitled "Discrimination Resulting From Overage Practices" discuss theoretical and empirical issues dealing with mortgage loan pricing or more specifically overages. The Office of the Comptroller of the Currency (OCC) identified three banks that had potential problems with mortgage pricing. The OCC examined the three banks to determine whether minority groups were being charged overages on mortgage loans more often than non-minority groups.

The authors determined there were three plausible explanations for overages in mortgage loans: asymmetric information, market power, and legal restrictions. The asymmetric information explanation says lenders will raise mortgage prices on groups of individuals they feel are a higher credit risk. These overages can represent a loan officer's personal preferences or affinities, if they are not carefully monitored. The market power explanation says that the borrower's high cost of finding possible lenders compromises his bargaining power on mortgage pricing, and thus, allows a lender to increase the mortgage price. The legal restrictions explanation says that the lender charges a higher mortgage price to account for inflexibility in the terms of mortgage contracts, especially when it comes to housing collateral.

In conclusion, the authors determined that by looking at the aggregate data for the three banks, it appeared the banks were charging overages that suggested a pattern of discrimination and would warrant a referral to the Department of Justice (DOJ). Upon further investigation, however, only one of the banks truly warranted a referral to the DOJ. With statistical analysis, it was determined that other factors, such as changes in lock dates or close dates caused the mortgage loans to be priced higher. Therefore, although asymmetric information is always considered as a possible explanation for discrimination in mortgage pricing, oftentimes the market power and legal restrictions explanations are more plausible after further investigation.

The author concludes from the empirical results that the effect of race in a model is quite sensitive to the model specifications. Specifically, the author found several problems with the model used in the Boston Fed study. The credit risk variable used in the Boston Fed model, according to the author, is not a good proxy for an applicant's credit risk and may include potential racial bias. Also, the variable liquid assets used to measure and applicant's ability to satisfy closing costs is not a good measure, as applicant's can satisfy closing costs from sources other than liquid assets. The modifications to the model do represent an improvement in both the credit risk variable and the measure of an applicant's ability to pay closing costs. However, race effects can not be considered precise because of the limitation of the data. Therefore, the author suggests that extreme caution is warranted when judging the magnitude, statistical significance, and even the sign of the race effect, since this information is used to monitor and target lenders practicing racial bias.

2.2.3 Galster Review (1993)

Galster's article entitled "The Facts of Lending Discrimination Cannot be Argued Away by Examining Default Rates" argues that differences in default rates across racial groups are not a reliable indicator or mortgage lending discrimination. The author theorizes that the risk of default for minority mortgagors is probably higher than that of white mortgagors overall. Therefore, even if the discrimination eliminated some of the default risk associated with minority applicants, the default rate of minority borrowers may not necessarily be lower than that of white borrowers.

Peter Brimelow and Leslie Spencer wrote an article in Forbes magazine (Janurary 4, 1993) denounced the claim of discrimination by the Federal Reserve Bank of Boston. They felt equal default rates for minority neighborhoods and white neighborhoods is evidence that discrimination does not exist in mortgage lending. The author contends that Brimelow and Spencer are wrong for two reasons. First, discrimination can exist despite the fact that there may be comparable pools of minority and white mortgage holders. Borrowers that were rejected initially may go on to find a mortgage somewhere else. Second, because of inequality among races, borrowers' financial situations are different. Minority borrowers are more likely to lose their income, have fewer assets to fall back on, and lose value in their homes. Therefore, minority borrowers, on average, will tend to have higher default rates than whites. As a result, the author concludes that default rates are not a reliable measure of whether discrimination exists in the mortgage market.

2.2.4 Black and Schweitzer Review (1985)

The article "Discrimination in Mortgage Lending" by Black et al. discusses a nationwide survey conducted by the FDIC. The survey addresses two specific issues: what are the economic criteria used in a bank's lending decisions; and does demographic information such as race and sex play a role in the lending decision.

Each bank included in the sample was mailed a form. The forms were used with every mortgage and home improvement loan of more than $4000. There were two parts to the form. The lenders were required to fill out Part I, when a loan decision was made. It requested information on the loan characteristics, as well as the financial state of the applicant. Part II of the form, filled out by the applicant, requested information on the personal characteristics of the applicant and co-applicant.

The author theorized three models to explain a bank's lending decision. The first model includes only the loan terms. The second model, in addition to the loan terms, includes the economic variables. The third model included loan terms and economic variables plus personal characteristics. Model three was used to test for discrimination. The results of the model showed that race played a significant role in the loan decision at a 90 percent confidence level. Specifically, the model showed that Blacks are less likely to be given loans vs. non blacks.

2.2.5 Avery, Beeson, and Calem Review (1997)

The Avery et al. article entitled "Using HMDA Data as a Regulatory Screen for Fair Lending Compliance" evaluates the Federal Reserve System program that uses HMDA data as a screen for fair lending. The program is designed to identify financial institutions that show a pattern of discrimination with minority applicants. The authors conclude that the HMDA program is very effective for screening lenders for potential lending bias.

2.3 Alternative Explanation for Racial Bias

The following articles suggest an alternative explanation to why there seems to be racial bias in the mortgage lending industry. Rosenblatt (1991) argues that borrower knowledge of a bank's underwriting rules significantly reduces the number of mortgage denials. In addition, he suggests that credit problems are the overwhelming reason for racial/ethnic differences in mortgage denials. Ferguson and Peters (1997) suggest that underwriting errors due to a bank's inexperience in underwriting different groups of people may explain the difference in mortgage denial rates. Another article by Stengel and Glennon (1999) develop bank specific models to test for lending discrimination. The authors theorize that models incorporating a bank's specific underwriting guidelines will better explain a bank's lending decisions. Horne (1997) examines the role race plays in mortgage lending based on model specification. Ferguson and Peters (1995) analyze a simple mortgage-lending model to determine what can be concluded from denial and default rates about lending discrimination. All these articles will be reviewed.

2.3.1 Rosenblatt Review (1997)

Rosenblatt's article entitled "A Reconsideration of Discrimination in Mortgage Underwriting with Data from a National Mortgage Bank" argues that mortgage denials only occur in a small number of cases because the borrower has not learned a lender's underwriting rules in advance. The author argues that foreknowledge of a lender's underwriting criteria presupposes borrowers to choose whether to apply for a conventional loan vs. other programs. The article goes on to state that mortgage loan denials are for the most part because of credit problems and generally account for racial differences in mortgage lending.

2.3.2 Ferguson and Peters Review (1997)

The Ferguson et al. article entitled "Cultural Affinity and Lending Discrimination: The Impact of Underwriting Errors and Credit Risk Distribution on Applicant Denial Rates" examines the effect of underwriting errors made by banks, when these errors are different across racial groups. The authors suggest that a particular bank develops a skill or affinity for assessing an applicant's creditworthiness. This affinity is usually targeted toward a particular market segment. Thus, the bank becomes very skillful in determining creditworthiness for that particular market. However, the banks will not necessarily have the skill/affinity to correctly assess other groups, thus causing substantially different denial rates across racial groups.

The authors determine that any conclusions drawn from denial rate analysis should be carefully examined. Although banks make underwriting errors that cause a difference in denial rates across different racial groups due to their affinities, the differences are not systematic according to the authors. In other words, the lending discrimination may be overstated or understated. Therefore, there should be some control for underwriting errors that may be closely correlated with racial bias.

2.3.3 Stengel and Glennon Review (1999)

The Stengel et al. article entitled "Evaluating Statistical Models of Mortgage Lending Discrimination: A Bank Specific Analysis" discusses the authors' efforts to develop a model specific to a bank to test for lending discrimination. By incorporating a bank's specific underwriting guidelines, a model can be developed that better explains a bank's mortgage lending decision process. In this study, the authors attempt to develop bank specific models for three national banks.

The authors' intent was to develop a statistical model that was specific to three different bank's underwriting policies. The model gauges the extent that a underwriter's discretion or judgment was used in determining lending decisions across different racial groups. The authors hypothesized that applicants having similar characteristics should have the same chance of being approved for a loan.

To test for post application discrimination, the authors used both a market-level (generic) model and a bank-specific model. The market-level model showed that of the three banks tested, two banks showed that minorities were more likely to be rejected for mortgage loans. The third bank showed no difference in mortgage lending decisions across racial groups. In general, the authors found that the market-level model performs poorly as a predictor of mortgage lending decisions. A large number of the explanatory variables were insignificant in the model. This suggests that the race variable may be providing inaccurate results due to correlation. The bank specific model that incorporates the bank's underwriting guidelines performs better at predicting a bank's mortgage lending decisions than the market-level model. Bank A showed no lending discrimination with the bank specific model. Bank B showed that race was a factor in the mortgage lending decision. Bank C was inconclusive, but upon further investigation, it was determined that race was not significant in the decision.

2.3.4 Horne Review (1997)

The Horne article entitled "Mortgage Lending, Race, and Model Specification" examines how race plays a role in mortgage lending with different model specifications. The author scrutinizes the results of the study conducted by the Federal Reserve Bank of Boston Munnell et al. (1992, 1996). This study found that Black and Hispanic applicants were more likely to be rejected for mortgage loans than Whites. The article compares the results from the Boston Fed model to various other model variations.

The author discovered a number of issues that affected the outcome of a model's specifications. First, the complicated interactions between variables, as well as the weights associated with the variables are not accurately depicted in the functional model. Second, the variables included in the model are not the best representatives of the factors that lenders are interested in. Third, some variables are missing from the model. Finally, the application outcome variable does not accurately represent a lender's desire to provide mortgage lending.

2.3.5 Ferguson and Peters Review (1995)

"What Constitutes Evidence of Discrimination in Lending?" by Ferguson et al. analyzes a simple model of bank lending to determine what can be deduced from the denial and default rates of an institution. The authors examine the Boston Fed study, which concluded that minorities were discriminated in the mortgage lending market in Boston. Many critics have argued that there are flaws with the study.

The authors examine the claims made by critics about default and denial rates. The first claim is that minority applicants are more likely to be denied mortgage loans due to lower average credit quality. The second claim is that if minorities and whites have equal default rates then they are being held to the same credit standard. Therefore, according to critics, there is no basis for the claims of lending discrimination.

The authors concluded unequal denial rates do not imply discrimination. Given a uniform credit standard, the authors state that minority applicants will have a higher denial rate because they have a lower average creditworthiness. In addition, the authors dispel the claim that equal default rates prove no discrimination exists. The default rate of minority borrowers will be higher than for the white borrowers due to the lower average creditworthiness. For default rates to be equal, minority applicants have to be held to a higher credit standard than white applicants. However, equal denial or default rates do not imply non-discrimination. In fact, equal denial rates indicate discrimination against the white applicants because they will be held to a higher credit standard. Equal default rates also indicate discrimination but n0t against minority applicants.

2.4 Conclusion

The previous research on racial bias in the mortgage lending industry has given varying opinions on both whether racial bias exists, and if so the reasoning behind the racial bias. Most of the articles reviewed found some indication of racial bias in the mortgage lending industry, although there were varying explanations for this phenomenon. Based on this research the hypothesis for this study is that minority applicants, Black and Hispanics, are more likely to be denied for mortgage loans than other racial groups.

CHAPTER 3

DATA ANALYSIS AND METHODOLOGY

3.1 Methodology

The loan data used for this study is the HMDA data from 2003. The data came directly from the Federal Financial Institutions Examination Council (FFIEC) via CD. Loan data from the Dallas and Ft. Worth-Arlington Metropolitan Statistical Areas (MSA) was targeted, along with the four most popular lending institutions in the area. Records from these four lending institutions were selected for inclusion in the dataset. Then, the data from these four lending institutions was further limited by only including loans for the purpose of purchasing a home. Once the dataset was defined, the data from each lending institution was downloaded to individual spreadsheets in Excel. Finally, all the data from the lending institutions were combined into one spreadsheet. There were 19,684 observations in the initial dataset.

Because the study focuses on the effect of race on mortgage lending, 6887 observations were deleted because race was not specified on the record. In addition, 1359 observations were deleted because the applicant's income was not provided. After running the standardized residuals for the LoanAmount and AppIncome, observations with residuals greater than 2.58, which are considered outliers at the .01 significance level, were identified. Due to outliers in the standardized residuals for AppIncome, 97 observations were deleted from the dataset. In addition, 212 observations were deleted due to outliers in the standardized residuals for LoanAmount. As a result, the dataset was reduced to a sample size of 11,129 observations. The research conducted was to determine if the HMDA data collected from the four major lending institutions in the DFW Metroplex suggested a tendency of lending bias against minority applicants trying to purchase a home. Minority applicants were defined as African Americans and Hispanics.

In order to determine what variables to include in the study an analysis of the HMDA loan application record (LAR) was conducted. The LAR includes the following fields as specified in Table 1.

Table 1. LAR Record

Fields	**Description**
AsofYear	Report year
Respondent ID	Identifier # of responding institution
Agency Code	Agency responsible for regulating institution
Loan Type	Type of loan
Loan Purpose	Purpose of the loan
Occupancy	Indicates whether property is occupied by owner
Loan Amount	Amount of the loan
Action Type	Action taken on the loan (i.e. approved, denied, etc.)
MA	Metropolitan area
State Code	Two-digit state identifier
County Code	Three-digit county identifier
Census Tract Number	Number identifying census tract
Applicant Race	Code to identify applicant's race
Co-Applicant Race	Code to identify co-applicant's race
Applicant Sex	Code to identify applicant's sex
Co-Applicant Sex	Code to identify co-applicant's sex
Applicant Income	Income of applicant

Table 1 *Continued.*

Denial Reason1	Primary reason loan was denied
Denial Reason2	Secondary reason loan was denied
Denial Reason3	Third reason loan was denied
Edit Status	System field
Sequence Number	System generated unique number
Population	Population of the census tract
Minority Population	Minority population of the census tract
Minority Population %	Minority population percent of the census tract
Median Income	Median income of the census tract
Tract to MA Income %	Comparison of income from tract to MA
Number of Owner-occupied units	Number of units that are owner occupied in tract
Number of 1-to-4-Family units	Number of 1-to-4 units in census tract.

After some preliminary analysis, it was determined that the fields listed in Table 2 would be included in the dataset for further analysis. All the variables were recoded into dummy variables, so the data could be analyzed more effectively. AppDeny indicating whether the loan was approved or denied was coded using the Action Type field. The Loan Type was broken down into conventional loan, FHA loan, and VA Loan. The LoanAmount variable was broken down into three dummy variables, LoanAmtGrp1, LoanAmtGrp2, and LoanAmtGrp3. Applicant and Co-applicant race were broken down into Black/Hispanic applicant, White Applicant, and Other applicant. Applicant and Co-applicant sex were broken down into male or female. Whether the property is owner-occupied was also coded. The ApplicantIncome variable was broken into three dummy variables, AppIncGrp1, AppIncGrp2, and AppGrp3. In addition, three sets of denial reasons were categorized into Financial and Other denial reasons. The denial reasons were coded for informational purposes only. This variable was not considered as an independent variable for the model, since all the applications denied were automatically given a denial reason. All these qualitative variables were coded with a value of one if the attribute was present and zero otherwise. AppDeny was the dependent variable or the variable of interest. All other variables were potential independent variables considered for the model. Table 2 describes how each variable was coded in the analysis.

Table 2. Variable Coding

Field Name	**Coding Rule**
AppDeny	Dummy Variable: 1 if Action Type = 3 (App Denied), 0 otherwise
ConvLoan	Dummy Variable: 1 if Loan Type =1, 0 otherwise
FHALoan	Dummy Variable: 1 if Loan Type=2, 0 otherwise
VALoan	Dummy Variable: 1 if Loan Type =3, 0 otherwise
OwnerOcc	Dummy Variable: 1 if Owner Occupied = 1, 0 otherwise
LoanAmtGrp1	Dummy Variable: 1 if LoanAmount < 100K, 0 otherwise
LoanAmtGrp2	Dummy Variable: 1 if LoanAmount btw 100K – 199K, 0 otherwise
LoanAmtGrp3	Dummy Variable: 1 if LoanAmount > 200K, 0 otherwise
BlkHispApp	Dummy Variable: 1 if App Race = 3 or 4, 0 otherwise
WhiteApp	Dummy Variable: 1 if App Race = 5, 0 otherwise
OtherApp	Dummy Variable: 1 if App Race = < 3 or > 5, 0 otherwise
BlkHispCoApp	Dummy Variable: 1 if CoApp Race = 3 or 4, 0 otherwise
WhiteCoApp	Dummy Variable: 1 if CoApp Race = 5, 0 otherwise
OtherCoApp	Dummy Variable: 1 if CoApp Race = < 3 or > 5, 0 otherwise
MaleApp	Dummy Variable: 1 if App Sex = 1, 0 otherwise
FemaleApp	Dummy Variable: 1 if App Sex = 2, 0 otherwise
MaleCoApp	Dummy Variable: 1 if CoApp Sex = 1, 0 otherwise
FemaleCoApp	Dummy Variable: 1 if CoApp Sex = 2, 0 otherwise
AppIncGrp1	Dummy Variable: 1 if AnnualIncome btw 1K – 50K, 0 otherwise
AppIncGrp2	Dummy Variable: 1 if AnnualIncome btw 51K – 100K, 0 otherwise
AppIncGrp3	Dummy Variable: 1 if AnnualIncome > 100K, 0 otherwise
DR1Finance	Dummy Variable 1 if Denial Reason >1 and <5, 0 otherwise
DR1Other	Dummy Variable: 1 if Denial Reason >5, 0 otherwise
DR2Finance	Dummy Variable 1 if Denial Reason >1 and <5, 0 otherwise
DR2Other	Dummy Variable: 1 if Denial Reason >5, 0 otherwise
DR3Finance	Dummy Variable 1 if Denial Reason >1 and <5, 0 otherwise
DR3Other	Dummy Variable: 1 if Denial Reason >5, 0 otherwise

3.2 Descriptive Statistics

Once the data was recoded, descriptive statistics and frequency information were run on the data to get an idea of the composition of the data. By running the frequency analysis, the author determined that 19.8% of the loans in the dataset were denied (Figure 1). Conventional loans made up 86.6% of the loans in the dataset. Of the 11129 observations, only 1280 (11.5%) were FHA loans and 190 (1.7%) were VA loans (Figure 2). Some 91.3% of the properties were owner-occupied. In addition, 66% of the applicants were White. The minority applicants of interest in this study, Blacks and Hispanics, made up 24.3% of the applicants (Figure 3). It was also determined that 72% of the primary applicants were male.

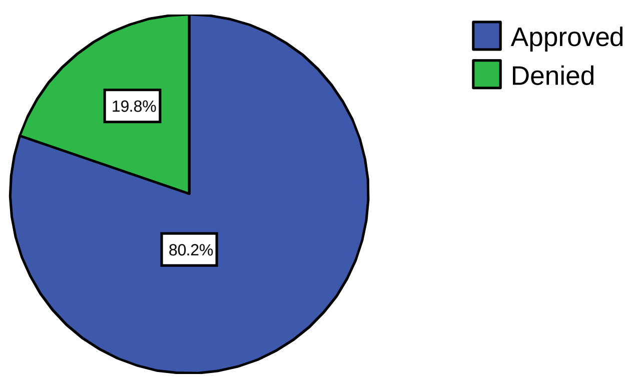

Figure 1. Percentage of Total Applications Denied/Approved

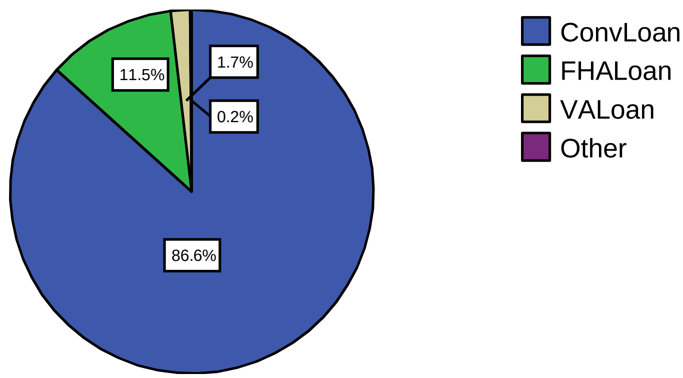

Figure 2. Breakdown of Loan Types

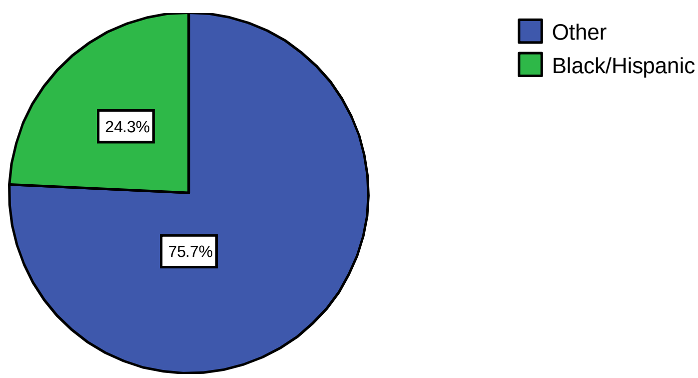

Figure 3. Percentage of Black and Hispanic Applicants in Dataset

3.3 Variable Relationships

Further analysis was done on the variables to get an idea of the relationship between select variables in the dataset. Cross tab analysis was used to see how variables such as applicant race, co-applicant race, applicant sex, co-applicant sex, loan amount, applicant income and loan type relate to the AppDeny variable. The cross tab results showed that there was a significant relationship between AppDeny and all the aforementioned variables. Specifically, the cross tab analysis for AppDeny and BlkHispApp showed that out of the 24.3% (2701) Black and Hispanic applicants in the dataset, 26.7% of them were denied mortgage loans compared to 17.3% for white applicants and 19.1% for other races. In addition, of all the applications denied, 32.8% of the applicants were Black or Hispanic. Table 3 shows the results from the cross tab analysis between AppDeny and AppRace. There were 5259 observations that indicated the race of the co-applicant. Cross tab results from the AppDeny and CoAppRace analysis showed that of the loans with a listed co-applicant, 73% were White co-applicants. Nearly 85% (3256) of all the White co-applicants were approved for loans. Additionally, of all the loans approved, White co-applicants made up 75%. In contrast, 17.5% (922) of these loans had Black/Hispanic co-applicants. 73.8% of the Black and Hispanic co-applicants were approved, and 26.2 % of these co-applicants were denied. These results were in line with the results from the AppDeny and BlkHispApp crosstab results. Some other key findings from the cross tab analysis are summarized below:

- Of loans with a co-applicant listed, only 15% of loans approved had a male co-applicant.
- 63.8% of the loans denied had a loan amount <100K
- 29.3% of the loans denied had a loan amount between 100K – 199K
- 50.5% of the loan denials came from applicants with an income <50K
- 32.1% of the loans denied came from applicants with an income between 51K – 100K

All the cross tab results are included in the appendix.

Table 3. Crosstab Results: AppDeny/AppRace

			AppRace			Total
			BlkHispApp	OtherApp	WhiteApp	
AppDeny	0	Count	1979	875	6077	8931
		% within AppDeny	22.2%	9.8%	68.0%	
		% within $AppRace	73.3%	80.9%	82.7%	
		% of Total	17.8%	7.9%	54.6%	80.2%
	1	Count	722	207	1269	2198
		% within AppDeny	32.8%	9.4%	57.7%	
		% within $AppRace	26.7%	19.1%	17.3%	
		% of Total	6.5%	1.9%	11.4%	19.8%
Total		Count	2701	1082	7346	11129
		% of Total	24.3%	9.7%	66.0%	100.0%

Percentages and totals are based on respondents.

Based on the cross tab analysis, a prediction was made on the expectation of the coefficient sign of each of the independent variables, if they are found significant enough to be included in the final model. There was an expectation that the following variables will have a positive coefficient sign: ConvLoan, BlkHispApp, BlkHispCoApp, FemaleApp, MaleCoApp, LoanAmtGrp1, and AppIncGrp1. The variables with an expected negative coefficient sign were FHALoan, OwnerOcc, AppIncGrp2, AppIncGrp3, WhiteApp, WhiteCoApp, MaleApp, FemaleCoApp, LoanAmtGrp2, and LoanAmtGrp3.

3.4 Model Prediction and Hypothesis

Because the dependent variable, AppDeny is qualitative, logistic regression analysis was employed for model prediction. Logistic regression makes a logistic transformation of *p*, also called taking the logit of *p*. Logit(*p*) is the log (to base *e*) of the odds or likelihood ratio that the dependent variable is 1. The logistic regression was run multiple times to determine the best predictors of the dependent variable. Initially, all the independent variables that exhibited any correlation to the AppDeny variable were included in the regression analysis.

The independent variables were examined in blocks or subsets; essentially each block of variables was an estimated model. Four models/blocks were estimated to determine the probability of the approve/deny loan decision using forward stepwise regression. In the first block, the BlkHispApp, WhiteApp, BlkHispCoApp, and WhiteCoApp variables were included. The second block included the LoanAmtGrp1, LoanAmtGrp2, LoanAmtGrp3, AppIncGrp1, AppIncGrp2, and AppIncGrp3 variables. The third block included the MaleApp, FemaleApp, MaleCoApp and FemaleCoApp variables. Finally, the fourth model, analyzed the ConvLoan, and OwnerOcc, variables.

After the first block of variables was run, the analysis determined that BlkHispApp and WhiteCoApp were significant to the model. From the second block of variables LoanAmtGrp1, LoanAmtGrp2, AppIncGrp1, and AppIncGrp3 were determined to be significant. The analysis from the third block of variables determined that MaleCoApp was significant. And finally, after adding the variables from the fourth block, the analysis found that ConvLoan and OwnerOcc were also significant to the model.

Based on the logistic regression, it was determined that the best model to predict AppDeny in this study included the following independent variables: BlkHispApp, WhiteCoApp, LoanAmtGrp1, LoanAmtGrp2, AppIncGrp1, AppIncGrp3, MaleCoApp, OwnerOcc, and ConvLoan. The following model is hypothesized:

$$\text{Logit}(p) = a + b_1x_1 + b_2x_2 + b_3x_3 + b_4x_4 + b_5x_5 + b_6x_6 + b_7x_7 + b_8x_8 + b_9x_9$$

where:

p = probability loan application will be denied
a = constant for AppDeny
x_1 = BlkHispApp
x_2 = WhiteCoApp
x_3 = LoanAmtGrp1
x_4 = LoanAmtGrp2
x_5 = AppIncGrp1
x_6 = AppIncGrp3
x_7 = MaleCoApp
x_8 = OwnerOcc
x_9 = ConvLoan

The regression equation is:

$$\text{Logit}(p) = -1.330 + .250x_1 + -.125x_2 + .184x_3 + -.296x_4 + .470x_5 + -.400x_6 + .404x_7 + -.577x_8 + .318x_9$$

The hypotheses for the model are as follows:

The null hypothesis is that Black and Hispanic mortgage applicants are not more likely to be denied: H_0: $B_{(\text{BlkHispApp})} = 0$

The alternative hypothesis is that Black and Hispanic mortgage applicants are more likely to be denied: H_1: $B_{(\text{BlkHispApp})} < 0$

CHAPTER 4

RESULTS AND ANALYSIS

Logistic regression is used to determine which independent variables are relevant in predicting the probability (p) is 1 rather than 0. Based on the regression analysis results, the estimated model is a good fit for the sample data. The coefficients in the model measure the predictor's independent contribution to variations in the dependent variable. If a coefficient is positive, its transformed log value will be greater than one, meaning that the modeled event is more likely to occur. If a coefficient is negative, its transformed log value will be less than one, and the odds of the event occurring decrease. The coefficients in the model are highly significant with the variables providing expected signs. Exp(B) is the predicted change in odds for a unit increase in the predictor. When Exp(B) is less than 1, increasing values of the variable correspond to decreasing odds (p) is 1. On the other hand, when Exp(B) is greater than 1, increasing values of the variable correspond to increasing odds of the event's occurrence.

The most common assessment of overall model fit in logistic regression is the Likelihood Ratio Test. The likelihood ratio test is based on –2 log likelihood (-2LL). This ratio tests the significance of the difference between the likelihood ratio (-2LL) for the predicted model minus the likelihood ratio for the reduced model (constant only model). The model chi square test is the measure of this difference. The model chi-square was 471.125 with a significance of .000 indicating that there is a significant relationship between the dependent variable and the independent variables included in the model and therefore rejecting the null hypothesis. In general, the model does an adequate job of predicting whether an applicant will be denied for a mortgage, based on the information in the dataset. In addition, the model supports the hypothesis that Black and Hispanic applicants (BlkHispApp) are more likely to be denied for mortgage loans compared to other racial groups.

The independent variables chosen for the final model are strong predictors of the probability of whether a loan application will be approved or denied. The Wald statistic (ratio of B to S.E. squared) for each of the independent variables is significant as indicated in Table 5. The change in –2LL when a term is removed from the model measures how much a variable contributes to the model: the larger the change in –2LL the more the variable contributes to the model. The AppIncGrp1 variable contributed to the model the most. Next were OwnerOcc and AppIncGrp3 respectively. The BlkHispApp, MaleCoApp, and ConvLoan variables fell in the middle. Finally, the WhiteCoApp, LoanAmtGrp1, and LoanAmtGrp2 variables contributed the least to the model. Table 5 displays these results.

The variables BlkHispApp, LoanAmtGrp1, AppIncGrp1, MaleCoApp, and ConvLoan have positive coefficients. In addition, Exp(B) for all five variables is greater than 1. Both of these statistics indicate that these predictors increase the likelihood of an application being denied. The other independent variables in the model, WhiteCoApp, LoanAmtGrp2, AppIncGrp3, and OwnerOcc, all have a negative coefficient and an Exp(B) of less than 1. These results indicate that these predictors increase the likelihood of an application not being denied.

Table 4. Final Regression Model

		B	S.E.	Wald	df	Sig.	Exp(B)	95.0% C.I.for EXP(B)	
								Lower	Upper
Step 2(b)	BlkHispApp	.250	.059	18.209	1	.000	1.284	1.145	1.440
	WhiteCoApp	-.125	.062	4.031	1	.045	.882	.781	.997
	LoanAmtGrp1	.184	.102	3.251	1	.071	1.203	.984	1.469
	LoanAmtGrp2	-.296	.106	7.843	1	.005	.744	.605	.915
	AppIncGrp1	.470	.060	61.743	1	.000	1.600	1.423	1.799
	AppIncGrp3	-.400	.075	28.495	1	.000	.670	.579	.776
	MaleCoApp	.404	.089	20.683	1	.000	1.497	1.258	1.782
	OwnerOcc	-.577	.083	48.833	1	.000	.562	.478	.660
	ConvLoan	.318	.081	15.435	1	.000	1.375	1.173	1.611
	Constant	-1.330	.158	70.493	1	.000	.264		

Table 5. Model if Term Removed

Variable		Model Log Likelihood	Change in -2 Log Likelihood	df	Sig. of the Change
	ConvLoan	-5302.722	16.125	1	.000
	OwnerOcc	-5317.906	46.493	1	.000
	BlkHispApp	-5303.685	18.051	1	.000
	MaleCoApp	-5304.508	19.698	1	.000
	AppIncGrp1	-5325.892	62.466	1	.000
	AppIncGrp3	-5309.218	29.116	1	.000
	WhiteCoApp	-5296.684	4.049	1	.044
	LoanAmtGrp1	-5296.318	3.318	1	.069
	LoanAmtGrp2	-5298.463	7.606	1	.006

CHAPTER 5

CONCLUSIONS

This study suggests that there is a bias towards Black and Hispanic when applying for a mortgage loans in the Dallas-Fort Worth Metroplex. The results of the model seem to support this conclusion. The coefficients of all the independent variables in the model appear to be reasonable and have the expected signs. In addition, the individual independent variables used in the final model contribute significantly to the explanatory power of the model or aptness of the model.

The model concludes that a Black or Hispanic applicant odds of being denied for a mortgage loan can be predicted by the Exp(B) statistic. Since the Exp(B) for BlkHispApp is 1.284 (greater than 1) as the value of the BlkHispApp increases, there is an increased probability that the application will be denied. The 95% confidence interval around the Exp(B) statistic is $P(1.145 <= \mu <= 1.440)$. That is, there is a 95% probability that the Exp(B) statistic will lie somewhere between 1.145 and 1.440.

Further analysis of the HMDA data found the most prevalent denial reason indicated for Black and Hispanic applicants was credit history, with debt-to-income ratio coming in second. However, without important information such as an applicant's employment and credit histories, the researcher can not know if bias did in fact influence the lending decisions. As a result, this study cannot make a conclusive finding of racial bias in mortgage lending in the Dallas-Ft. Worth Area. However, this study can determine if there are any indicators of racial bias that would warrant deeper investigation. Based on the results, there seems to be indicators of racial basis toward Hispanic and Black mortgage loan applicants. Additional investigation into this conclusion would definitely be warranted.

APPENDIX A

DESCRIPTIVES

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
AppDeny	11129	.00	1.00	.1975	.39813
ConvLoan	11129	.00	1.00	.8664	.34025
FHALoan	11129	.00	1.00	.1150	.31905
VALoan	11129	.00	1.00	.0171	.12955
OwnerOcc	11129	.00	1.00	.9126	.28248
BlkHispApp	11129	.00	1.00	.2427	.42873
OtherApp	11129	.00	1.00	.0972	.29628
WhiteApp	11129	.00	1.00	.6601	.47370
BlkHispCoApp	11129	.00	1.00	.0828	.27566
WhiteCoApp	11129	.00	1.00	.3448	.47532
OtherCoApp	11129	.00	1.00	.0449	.20715
MaleApp	11129	.00	1.00	.7198	.44910
FemaleApp	11129	.00	1.00	.2797	.44888
MaleCoApp	11129	.00	1.00	.0785	.26902
FemaleCoApp	11129	.00	1.00	.3943	.48872
LoanAmtGrp1	11129	.00	1.00	.5053	.49999
LoanAmtGrp2	11129	.00	1.00	.3933	.48850
LoanAmtGrp3	11129	.00	1.00	.1014	.30193
AppIncGrp1	11129	.00	1.00	.3681	.48232
AppIncGrp2	11129	.00	1.00	.3772	.48471
AppIncGrp3	11129	.00	1.00	.2547	.43568
Valid N (listwise)	11129				

APPENDIX B

FREQUENCIES

AppDeny

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	8931	80.2	80.2	80.2
	1.00	2198	19.8	19.8	100.0
	Total	11129	100.0	100.0	

OwnerOcc

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	973	8.7	8.7	8.7
	1.00	10156	91.3	91.3	100.0
	Total	11129	100.0	100.0	

LoanType

		Responses		Percent of Cases
		N	Percent	
LoanType(a)	ConvLoan	9642	86.8%	86.8%
	FHALoan	1280	11.5%	11.5%
	VALoan	190	1.7%	1.7%
Total		11112	100.0%	100.0%

AppRace

		Responses		Percent of Cases
		N	Percent	
AppRace(a)	BlkHispApp	2701	24.3%	24.3%
	OtherApp	1082	9.7%	9.7%
	WhiteApp	7346	66.0%	66.0%
Total		11129	100.0%	100.0%

CoAppRace

		Responses N	Responses Percent	Percent of Cases
CoAppRace(a)	BlkHispCoApp	922	17.5%	17.5%
	WhiteCoApp	3837	73.0%	73.0%
	OtherCoApp	500	9.5%	9.5%
Total		5259	100.0%	100.0%

AppSex

		Responses N	Responses Percent	Percent of Cases
AppSex(a)	MaleApp	8011	72.0%	72.0%
	FemaleApp	3113	28.0%	28.0%
Total		11124	100.0%	100.0%

CoAppSex

		Responses N	Responses Percent	Percent of Cases
CoAppSex(a)	MaleCoApp	874	16.6%	16.6%
	FemaleCoApp	4388	83.4%	83.4%
Total		5262	100.0%	100.0%

LoanAmtGrp

		Responses N	Responses Percent	Percent of Cases
LoanAmtGrp(a)	LoanAmtGrp1 <100K	5623	50.5%	50.5%
	LoanAmtGrp2 100K – 199K	4377	39.3%	39.3%
	LoanAmtGrp3 >200K	1129	10.1%	10.1%
Total		11129	100.0%	100.0%

AppIncGrp

		Responses		Percent of Cases
		N	Percent	
	AppIncGrp1 <51K	4097	36.8%	36.8%
	AppIncGrp2 51K – 100K	4198	37.7%	37.7%
	AppIncGrp3 >100K	2834	25.5%	25.5%
Total		11129	100.0%	100.0%

APPENDIX C

CROSSTABS

AppDeny*LoanType

			LoanType			Total
			ConvLoan	FHALoan	VALoan	
AppDeny	0	Count	7667	1088	160	8915
		% within AppDeny	86.0%	12.2%	1.8%	
		% within $LoanType	79.5%	85.0%	84.2%	
		% of Total	69.0%	9.8%	1.4%	80.2%
	1	Count	1975	192	30	2197
		% within AppDeny	89.9%	8.7%	1.4%	
		% within $LoanType	20.5%	15.0%	15.8%	
		% of Total	17.8%	1.7%	.3%	19.8%
Total		Count	9642	1280	190	11112
		% of Total	86.8%	11.5%	1.7%	100.0%

AppDeny*$AppRace

			AppRace			Total
			BlkHispApp	OtherApp	WhiteApp	
AppDeny	0	Count	1979	875	6077	8931
		% within AppDeny	22.2%	9.8%	68.0%	
		% within $AppRace	73.3%	80.9%	82.7%	
		% of Total	17.8%	7.9%	54.6%	80.2%
	1	Count	722	207	1269	2198
		% within AppDeny	32.8%	9.4%	57.7%	
		% within $AppRace	26.7%	19.1%	17.3%	
		% of Total	6.5%	1.9%	11.4%	19.8%
Total		Count	2701	1082	7346	11129
		% of Total	24.3%	9.7%	66.0%	100.0%

AppDeny*CoAppRace

			CoAppRace			Total
			BlkHispCoApp	WhiteCoApp	OtherCoApp	
AppDeny	0	Count	680	3256	408	4344
		% within AppDeny	15.7%	75.0%	9.4%	
		% within $CoAppRace	73.8%	84.9%	81.6%	
		% of Total	12.9%	61.9%	7.8%	82.6%
	1	Count	242	581	92	915
		% within AppDeny	26.4%	63.5%	10.1%	
		% within $CoAppRace	26.2%	15.1%	18.4%	
		% of Total	4.6%	11.0%	1.7%	17.4%
Total		Count	922	3837	500	5259
		% of Total	17.5%	73.0%	9.5%	100.0%

AppDeny*AppSex

			AppSex		Total
			MaleApp	FemaleApp	
AppDeny	0	Count	6498	2430	8928
		% within AppDeny	72.8%	27.2%	
		% within $AppSex	81.1%	78.1%	
		% of Total	58.4%	21.8%	80.3%
	1	Count	1513	683	2196
		% within AppDeny	68.9%	31.1%	
		% within $AppSex	18.9%	21.9%	
		% of Total	13.6%	6.1%	19.7%
Total		Count	8011	3113	11124
		% of Total	72.0%	28.0%	100.0%

AppDeny*CoAppSex

			CoAppSex		
			MaleCoApp	FemaleCoApp	Total
AppDeny	0	Count	672	3676	4348
		% within AppDeny	15.5%	84.5%	
		% within $CoAppSex	76.9%	83.8%	
		% of Total	12.8%	69.9%	82.6%
	1	Count	202	712	914
		% within AppDeny	22.1%	77.9%	
		% within $CoAppSex	23.1%	16.2%	
		% of Total	3.8%	13.5%	17.4%
Total		Count	874	4388	5262
		% of Total	16.6%	83.4%	100.0%

LoanAmtGrp*AppDeny

			AppDeny		
			0	1	Total
LoanAmtGrp	LoanAmtGrp1	Count	4221	1402	5623
		% within $LoanAmtGrp	75.1%	24.9%	
		% within AppDeny	47.3%	63.8%	
		% of Total	37.9%	12.6%	50.5%
	LoanAmtGrp2	Count	3734	643	4377
		% within $LoanAmtGrp	85.3%	14.7%	
		% within AppDeny	41.8%	29.3%	
		% of Total	33.6%	5.8%	39.3%
	LoanAmtGrp3	Count	976	153	1129
		% within $LoanAmtGrp	86.4%	13.6%	
		% within AppDeny	10.9%	7.0%	
		% of Total	8.8%	1.4%	10.1%
Total		Count	8931	2198	11129
		% of Total	80.2%	19.8%	100.0%

AppIncGrp*AppDeny

			AppDeny		Total
			0	1	
AppIncGrp	AppIncGrp1	Count	2988	1109	4097
		% within $AppIncGrp	72.9%	27.1%	
		% within AppDeny	33.5%	50.5%	
		% of Total	26.8%	10.0%	36.8%
	AppIncGrp2	Count	3493	705	4198
		% within $AppIncGrp	83.2%	16.8%	
		% within AppDeny	39.1%	32.1%	
		% of Total	31.4%	6.3%	37.7%
	AppIncGrp3	Count	2450	384	2834
		% within $AppIncGrp	86.5%	13.5%	
		% within AppDeny	27.4%	17.5%	
		% of Total	22.0%	3.5%	25.5%
Total		Count	8931	2198	11129
		% of Total	80.2%	19.8%	100.0%

$LoanAmtGrp*AppRace

			AppRace			Total
			BlkHispApp	OtherApp	WhiteApp	
LoanAmtGrp	LoanAmtGrp1	Count	1610	496	3517	5623
		% within $LoanAmtGrp	28.6%	8.8%	62.5%	
		% within $AppRace	59.6%	45.8%	47.9%	
		% of Total	14.5%	4.5%	31.6%	50.5%
	LoanAmtGrp2	Count	995	448	2934	4377
		% within $LoanAmtGrp	22.7%	10.2%	67.0%	
		% within $AppRace	36.8%	41.4%	39.9%	
		% of Total	8.9%	4.0%	26.4%	39.3%
	LoanAmtGrp3	Count	96	138	895	1129
		% within $LoanAmtGrp	8.5%	12.2%	79.3%	
		% within $AppRace	3.6%	12.8%	12.2%	
		% of Total	.9%	1.2%	8.0%	10.1%
Total		Count	2701	1082	7346	11129
		% of Total	24.3%	9.7%	66.0%	100.0%

$LoanAmtGrp*BlkHispApp*AppDeny Crosstabulation

AppDeny				BlkHispApp 0	BlkHispApp 1	Total
0	LoanAmtGrp	LoanAmtGrp1	Count	3100	1121	4221
			% within $LoanAmtGrp	73.4%	26.6%	
			% within BlkHispApp	44.6%	56.6%	
			% of Total	34.7%	12.6%	47.3%
		LoanAmtGrp2	Count	2951	783	3734
			% within $LoanAmtGrp	79.0%	21.0%	
			% within BlkHispApp	42.4%	39.6%	
			% of Total	33.0%	8.8%	41.8%
		LoanAmtGrp3	Count	901	75	976
			% within $LoanAmtGrp	92.3%	7.7%	
			% within BlkHispApp	13.0%	3.8%	
			% of Total	10.1%	.8%	10.9%
	Total		Count	6952	1979	8931
			% of Total	77.8%	22.2%	100.0%
1	LoanAmtGrp	LoanAmtGrp1	Count	913	489	1402
			% within $LoanAmtGrp	65.1%	34.9%	
			% within BlkHispApp	61.9%	67.7%	
			% of Total	41.5%	22.2%	63.8%
		LoanAmtGrp2	Count	431	212	643
			% within $LoanAmtGrp	67.0%	33.0%	
			% within BlkHispApp	29.2%	29.4%	
			% of Total	19.6%	9.6%	29.3%
		LoanAmtGrp3	Count	132	21	153
			% within $LoanAmtGrp	86.3%	13.7%	
			% within BlkHispApp	8.9%	2.9%	
			% of Total	6.0%	1.0%	7.0%
	Total		Count	1476	722	2198
			% of Total	67.2%	32.8%	100.0%

Percentages and totals are based on respondents.

a. Dichotomy group tabulated at value 1.

$AppIncGrp*BlkHispApp*AppDeny Crosstabulation

AppDeny				BlkHispApp 0	BlkHispApp 1	Total
0	AppIncGrp	AppIncGrp1	Count	1774	1214	2988
			% within $AppIncGrp	59.4%	40.6%	
			% within BlkHispApp	25.5%	61.3%	
			% of Total	19.9%	13.6%	33.5%
		AppIncGrp2	Count	2932	561	3493
			% within $AppIncGrp	83.9%	16.1%	
			% within BlkHispApp	42.2%	28.3%	
			% of Total	32.8%	6.3%	39.1%
		AppIncGrp3	Count	2246	204	2450
			% within $AppIncGrp	91.7%	8.3%	
			% within BlkHispApp	32.3%	10.3%	
			% of Total	25.1%	2.3%	27.4%
	Total		Count	6952	1979	8931
			% of Total	77.8%	22.2%	100.0%
1	AppIncGrp	AppIncGrp1	Count	614	495	1109
			% within $AppIncGrp	55.4%	44.6%	
			% within BlkHispApp	41.6%	68.6%	
			% of Total	27.9%	22.5%	50.5%
		AppIncGrp2	Count	525	180	705
			% within $AppIncGrp	74.5%	25.5%	
			% within BlkHispApp	35.6%	24.9%	
			% of Total	23.9%	8.2%	32.1%
		AppIncGrp3	Count	337	47	384
			% within $AppIncGrp	87.8%	12.2%	
			% within BlkHispApp	22.8%	6.5%	
			% of Total	15.3%	2.1%	17.5%
	Total		Count	1476	722	2198
			% of Total	67.2%	32.8%	100.0%

Percentages and totals are based on respondents.

a. Dichotomy group tabulated at value 1.

$AppIncGrp*$AppRace*AppDeny Crosstabulation

AppDeny				AppRace BlkHispApp	OtherApp	WhiteApp	Total
0	AppIncGrp	AppIncGrp1	Count	1214	212	1562	2988
			% within $AppIncGrp	40.6%	7.1%	52.3%	
			% within $AppRace	61.3%	24.2%	25.7%	
			% of Total	13.6%	2.4%	17.5%	33.5%
		AppIncGrp2	Count	561	418	2514	3493
			% within $AppIncGrp	16.1%	12.0%	72.0%	
			% within $AppRace	28.3%	47.8%	41.4%	
			% of Total	6.3%	4.7%	28.1%	39.1%
		AppIncGrp3	Count	204	245	2001	2450
			% within $AppIncGrp	8.3%	10.0%	81.7%	
			% within $AppRace	10.3%	28.0%	32.9%	
			% of Total	2.3%	2.7%	22.4%	27.4%
	Total		Count	1979	875	6077	8931
			% of Total	22.2%	9.8%	68.0%	100.0%
1	AppIncGrp	AppIncGrp1	Count	495	91	523	1109
			% within $AppIncGrp	44.6%	8.2%	47.2%	
			% within $AppRace	68.6%	44.0%	41.2%	
			% of Total	22.5%	4.1%	23.8%	50.5%
		AppIncGrp2	Count	180	64	461	705
			% within $AppIncGrp	25.5%	9.1%	65.4%	
			% within $AppRace	24.9%	30.9%	36.3%	
			% of Total	8.2%	2.9%	21.0%	32.1%
		AppIncGrp3	Count	47	52	285	384
			% within $AppIncGrp	12.2%	13.5%	74.2%	
			% within $AppRace	6.5%	25.1%	22.5%	
			% of Total	2.1%	2.4%	13.0%	17.5%
	Total		Count	722	207	1269	2198
			% of Total	32.8%	9.4%	57.7%	100.0%

Percentages and totals are based on respondents.

a. Dichotomy group tabulated at value 1.

$LoanAmtGrp*$AppRace*AppDeny Crosstabulation

AppDeny				AppRace			Total
				BlkHispApp	OtherApp	WhiteApp	
0	LoanAmtGrp	LoanAmtGrp1	Count	1121	402	2698	4221
			% within $LoanAmtGrp	26.6%	9.5%	63.9%	
			% within $AppRace	56.6%	45.9%	44.4%	
			% of Total	12.6%	4.5%	30.2%	47.3%
		LoanAmtGrp2	Count	783	363	2588	3734
			% within $LoanAmtGrp	21.0%	9.7%	69.3%	
			% within $AppRace	39.6%	41.5%	42.6%	
			% of Total	8.8%	4.1%	29.0%	41.8%
		LoanAmtGrp3	Count	75	110	791	976
			% within $LoanAmtGrp	7.7%	11.3%	81.0%	
			% within $AppRace	3.8%	12.6%	13.0%	
			% of Total	.8%	1.2%	8.9%	10.9%
	Total		Count	1979	875	6077	8931
			% of Total	22.2%	9.8%	68.0%	100.0%
1	LoanAmtGrp	LoanAmtGrp1	Count	489	94	819	1402
			% within $LoanAmtGrp	34.9%	6.7%	58.4%	
			% within $AppRace	67.7%	45.4%	64.5%	
			% of Total	22.2%	4.3%	37.3%	63.8%
		LoanAmtGrp2	Count	212	85	346	643
			% within $LoanAmtGrp	33.0%	13.2%	53.8%	
			% within $AppRace	29.4%	41.1%	27.3%	
			% of Total	9.6%	3.9%	15.7%	29.3%
		LoanAmtGrp3	Count	21	28	104	153
			% within $LoanAmtGrp	13.7%	18.3%	68.0%	
			% within $AppRace	2.9%	13.5%	8.2%	
			% of Total	1.0%	1.3%	4.7%	7.0%
	Total		Count	722	207	1269	2198
			% of Total	32.8%	9.4%	57.7%	100.0%

Percentages and totals are based on respondents.

a. Dichotomy group tabulated at value 1.

$AppIncGrp*$LoanAmtGrp*BlkHispCoApp Crosstabulation

BlkHispCoApp				LoanAmtGrp1	LoanAmtGrp2	LoanAmtGrp3	Total
0	AppIncGrp	AppIncGrp1	Count	2481	1236	7	3724
			% within $AppIncGrp	66.6%	33.2%	.2%	
			% within $LoanAmtGrp	48.2%	30.9%	.7%	
			% of Total	24.3%	12.1%	.1%	36.5%
		AppIncGrp2	Count	1513	2049	257	3819
			% within $AppIncGrp	39.6%	53.7%	6.7%	
			% within $LoanAmtGrp	29.4%	51.3%	24.2%	
			% of Total	14.8%	20.1%	2.5%	37.4%
		AppIncGrp3	Count	1155	709	800	2664
			% within $AppIncGrp	43.4%	26.6%	30.0%	
			% within $LoanAmtGrp	22.4%	17.8%	75.2%	
			% of Total	11.3%	6.9%	7.8%	26.1%
	Total		Count	5149	3994	1064	10207
			% of Total	50.4%	39.1%	10.4%	100.0%
1	AppIncGrp	AppIncGrp1	Count	250	123	0	373
			% within $AppIncGrp	67.0%	33.0%	.0%	
			% within $LoanAmtGrp	52.7%	32.1%	.0%	
			% of Total	27.1%	13.3%	.0%	40.5%
		AppIncGrp2	Count	145	214	20	379
			% within $AppIncGrp	38.3%	56.5%	5.3%	
			% within $LoanAmtGrp	30.6%	55.9%	30.8%	
			% of Total	15.7%	23.2%	2.2%	41.1%
		AppIncGrp3	Count	79	46	45	170
			% within $AppIncGrp	46.5%	27.1%	26.5%	
			% within $LoanAmtGrp	16.7%	12.0%	69.2%	
			% of Total	8.6%	5.0%	4.9%	18.4%
	Total		Count	474	383	65	922
			% of Total	51.4%	41.5%	7.0%	100.0%

Percentages and totals are based on respondents.

a. Dichotomy group tabulated at value 1.

$AppIncGrp*$AppRace*$LoanAmtGrp Crosstabulation

LoanAmtGrp[a]				AppRace: BlkHispApp	AppRace: OtherApp	AppRace: WhiteApp	Total
LoanAmtGrp1	AppIncGrp	AppIncGrp1	Count	1205	170	1356	2731
			% within $AppIncGrp	44.1%	6.2%	49.7%	
			% within $AppRace	74.8%	34.3%	38.6%	
			% of Total	21.4%	3.0%	24.1%	48.6%
		AppIncGrp2	Count	284	206	1168	1658
			% within $AppIncGrp	17.1%	12.4%	70.4%	
			% within $AppRace	17.6%	41.5%	33.2%	
			% of Total	5.1%	3.7%	20.8%	29.5%
		AppIncGrp3	Count	121	120	993	1234
			% within $AppIncGrp	9.8%	9.7%	80.5%	
			% within $AppRace	7.5%	24.2%	28.2%	
			% of Total	2.2%	2.1%	17.7%	21.9%
	Total		Count	1610	496	3517	5623
			% of Total	28.6%	8.8%	62.5%	100.0%
LoanAmtGrp2	AppIncGrp	AppIncGrp1	Count	504	131	724	1359
			% within $AppIncGrp	37.1%	9.6%	53.3%	
			% within $AppRace	50.7%	29.2%	24.7%	
			% of Total	11.5%	3.0%	16.5%	31.0%
		AppIncGrp2	Count	420	239	1604	2263
			% within $AppIncGrp	18.6%	10.6%	70.9%	
			% within $AppRace	42.2%	53.3%	54.7%	
			% of Total	9.6%	5.5%	36.6%	51.7%
		AppIncGrp3	Count	71	78	606	755
			% within $AppIncGrp	9.4%	10.3%	80.3%	
			% within $AppRace	7.1%	17.4%	20.7%	
			% of Total	1.6%	1.8%	13.8%	17.2%
	Total		Count	995	448	2934	4377
			% of Total	22.7%	10.2%	67.0%	100.0%
LoanAmtGrp3	AppIncGrp	AppIncGrp1	Count	0	2	5	7
			% within $AppIncGrp	.0%	28.6%	71.4%	
			% within $AppRace	.0%	1.4%	.6%	
			% of Total	.0%	.2%	.4%	.6%
		AppIncGrp2	Count	37	37	203	277
			% within $AppIncGrp	13.4%	13.4%	73.3%	
			% within $AppRace	38.5%	26.8%	22.7%	
			% of Total	3.3%	3.3%	18.0%	24.5%
		AppIncGrp3	Count	59	99	687	845
			% within $AppIncGrp	7.0%	11.7%	81.3%	
			% within $AppRace	61.5%	71.7%	76.8%	
			% of Total	5.2%	8.8%	60.9%	74.8%
	Total		Count	96	138	895	1129
			% of Total	8.5%	12.2%	79.3%	100.0%

Percentages and totals are based on respondents.

a. Dichotomy group tabulated at value 1.

BlkHispApp * Denial Reason1 Crosstabulation

			Denial Reason1									Total
			Debt to Income	Employ History	Credit History	Collateral	Insufficient Cash	Unverifiable Info	Incomplete Application	Other	
BlkHispApp	.00	Count	381	46	523	121	40	119	107	139	1476
		% within BlkHispApp	25.8%	3.1%	35.4%	8.2%	2.7%	8.1%	7.2%	9.4%	100.0%
		% within Denial Reason1	67.2%	68.7%	61.6%	65.8%	71.4%	79.3%	79.3%	73.2%	67.2%
		% of Total	17.3%	2.1%	23.8%	5.5%	1.8%	5.4%	4.9%	6.3%	67.2%
	1.00	Count	186	21	326	63	16	31	28	51	722
		% within BlkHispApp	25.8%	2.9%	45.2%	8.7%	2.2%	4.3%	3.9%	7.1%	100.0%
		% within Denial Reason1	32.8%	31.3%	38.4%	34.2%	28.6%	20.7%	20.7%	26.8%	32.8%
		% of Total	8.5%	1.0%	14.8%	2.9%	.7%	1.4%	1.3%	2.3%	32.8%
Total		Count	567	67	849	184	56	150	135	190	2198
		% within BlkHispApp	25.8%	3.0%	38.6%	8.4%	2.5%	6.8%	6.1%	8.6%	100.0%
		% within Denial Reason1	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
		% of Total	25.8%	3.0%	38.6%	8.4%	2.5%	6.8%	6.1%	8.6%	100.0%

WhiteApp * Denial Reason1 Crosstabulation

			Denial Reason1								Total
			Debt to Income	Employ History	Credit History	Collateral	Insufficient Cash	Unverifiable Info	Incomplete Application	Other	
WhiteApp	.00	Count	244	31	392	81	21	54	39	67	929
		% within WhiteApp	26.3%	3.3%	42.2%	8.7%	2.3%	5.8%	4.2%	7.2%	100.0%
		% within Denial Reason1	43.0%	46.3%	46.2%	44.0%	37.5%	36.0%	28.9%	35.3%	42.3%
		% of Total	11.1%	1.4%	17.8%	3.7%	1.0%	2.5%	1.8%	3.0%	42.3%
	1.00	Count	323	36	457	103	35	96	96	123	1269
		% within WhiteApp	25.5%	2.8%	36.0%	8.1%	2.8%	7.6%	7.6%	9.7%	100.0%
		% within Denial Reason1	57.0%	53.7%	53.8%	56.0%	62.5%	64.0%	71.1%	64.7%	57.7%
		% of Total	14.7%	1.6%	20.8%	4.7%	1.6%	4.4%	4.4%	5.6%	57.7%
Total		Count	567	67	849	184	56	150	135	190	2198
		% within WhiteApp	25.8%	3.0%	38.6%	8.4%	2.5%	6.8%	6.1%	8.6%	100.0%
		% within Denial Reason1	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
		% of Total	25.8%	3.0%	38.6%	8.4%	2.5%	6.8%	6.1%	8.6%	100.0%

APPENDIX D

REGRESSION ANALYSIS

Logistic Regression

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	11129	100.0
	Missing Cases	0	.0
	Total	11129	100.0
Unselected Cases		0	.0
Total		11129	100.0

a. If weight is in effect, see classification table for the total number of cases.

Dependent Variable Encoding

Original Value	Internal Value
.00	0
1.00	1

Block 0: Beginning Block

Classification Table[a,b]

			Predicted		
			AppDeny		Percentage Correct
	Observed		.00	1.00	
Step 0	AppDeny	.00	8931	0	100.0
		1.00	2198	0	.0
	Overall Percentage				80.2

a. Constant is included in the model.

b. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-1.402	.024	3467.014	1	.000	.246

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	BlkHispApp	109.656	1	.000
		WhiteApp	83.556	1	.000
		BlkHispCoApp	26.774	1	.000
		WhiteCoApp	78.459	1	.000
	Overall Statistics		139.565	4	.000

Block 1: Method = Forward Stepwise (Likelihood Ratio)

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	104.258	1	.000
	Block	104.258	1	.000
	Model	104.258	1	.000
Step 2	Step	32.570	1	.000
	Block	136.828	2	.000
	Model	136.828	2	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	10956.186[a]	.009	.015
2	10923.616[a]	.012	.019

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp (B)	95.0% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	BlkHispApp	.541	.052	108.081	1	.000	1.718	1.552	1.903
	Constant	-1.550	.029	2923.905	1	.000	.212		
Step 2[b]	BlkHispApp	.420	.056	56.572	1	.000	1.522	1.364	1.699
	WhiteCoApp	-.323	.057	31.985	1	.000	.724	.648	.810
	Constant	-1.416	.036	1519.203	1	.000	.243		

a. Variable(s) entered on step 1: BlkHispApp.

b. Variable(s) entered on step 2: WhiteCoApp.

Model if Term Removed

Variable		Model Log Likelihood	Change in -2 Log Likelihood	df	Sig. of the Change
Step 1	BlkHispApp	-5530.222	104.258	1	.000
Step 2	BlkHispApp	-5489.656	55.696	1	.000
	WhiteCoApp	-5478.093	32.570	1	.000

Variables not in the Equation

			Score	df	Sig.
Step 1	Variables	WhiteApp	2.250	1	.134
		BlkHispCoApp	.254	1	.614
		WhiteCoApp	32.147	1	.000
	Overall Statistics		32.198	3	.000
Step 2	Variables	WhiteApp	.038	1	.845
		BlkHispCoApp	.015	1	.902
	Overall Statistics		.052	2	.974

Block 2: Method = Forward Stepwise (Likelihood Ratio)

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	158.363	1	.000
	Block	158.363	1	.000
	Model	295.190	3	.000
Step 2	Step	70.961	1	.000
	Block	229.324	2	.000
	Model	366.152	4	.000
Step 3	Step	11.163	1	.001
	Block	240.487	3	.000
	Model	377.315	5	.000
Step 4	Step	6.530	1	.011
	Block	247.018	4	.000
	Model	383.845	6	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	10765.253[a]	.026	.042
2	10694.292[a]	.032	.051
3	10683.129[a]	.033	.053
4	10676.598[a]	.034	.054

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp (B)	95.0% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	BlkHispApp	.377	.056	44.731	1	.000	1.458	1.306	1.629
	WhiteCoApp	-.266	.058	21.349	1	.000	.766	.685	.858
	LoanAmtGrp1	.617	.050	154.26	1	.000	1.854	1.682	2.044
	Constant	-1.765	.048	1374.3	1	.000	.171		
Step 2[b]	BlkHispApp	.275	.058	22.489	1	.000	1.316	1.175	1.474
	WhiteCoApp	-.143	.060	5.757	1	.016	.866	.771	.974
	LoanAmtGrp1	.530	.051	108.31	1	.000	1.699	1.537	1.877
	AppIncGrp1	.456	.054	71.187	1	.000	1.577	1.419	1.753
	Constant	-1.917	.052	1372.6	1	.000	.147		
Step 3[c]	BlkHispApp	.267	.058	21.306	1	.000	1.306	1.166	1.464
	WhiteCoApp	-.115	.060	3.667	1	.056	.891	.792	1.003
	LoanAmtGrp1	.537	.051	110.79	1	.000	1.711	1.548	1.890
	AppIncGrp1	.377	.059	41.400	1	.000	1.457	1.299	1.634
	AppIncGrp3	-.232	.070	11.010	1	.001	.793	.691	.909
	Constant	-1.843	.056	1087.9	1	.000	.158		
Step 4[d]	BlkHispApp	.269	.058	21.566	1	.000	1.309	1.168	1.467
	WhiteCoApp	-.117	.060	3.739	1	.053	.890	.791	1.002
	LoanAmtGrp1	.310	.100	9.558	1	.002	1.364	1.120	1.660
	LoanAmtGrp2	-.271	.105	6.727	1	.009	.763	.621	.936
	AppIncGrp1	.381	.059	42.225	1	.000	1.464	1.305	1.642
	AppIncGrp3	-.289	.074	15.390	1	.000	.749	.649	.866
	Constant	-1.610	.105	234.85	1	.000	.200		

a. Variable(s) entered on step 1: LoanAmtGrp1.

b. Variable(s) entered on step 2: AppIncGrp1.

c. Variable(s) entered on step 3: AppIncGrp3.

d. Variable(s) entered on step 4: LoanAmtGrp2.

Block 3: Method = Forward Stepwise (Likelihood Ratio)

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	20.786	1	.000
	Block	20.786	1	.000
	Model	404.631	7	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	10655.812[a]	.036	.057

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp (B)	95.0% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	BlkHispApp	.246	.058	17.920	1	.000	1.280	1.142	1.434
	WhiteCoApp	-.173	.062	7.798	1	.005	.842	.746	.950
	LoanAmtGrp1	.309	.100	9.477	1	.002	1.362	1.119	1.659
	LoanAmtGrp2	-.274	.105	6.874	1	.009	.760	.619	.933
	AppIncGrp1	.390	.059	44.153	1	.000	1.477	1.316	1.657
	AppIncGrp3	-.295	.074	16.089	1	.000	.744	.644	.860
	MaleCoApp	.413	.088	21.868	1	.000	1.512	1.271	1.798
	Constant	-1.621	.105	237.7	1	.000	.198		

a. Variable(s) entered on step 1: MaleCoApp.

Model if Term Removed

Variable		Model Log Likelihood	Change in -2 Log Likelihood	df	Sig. of the Change
Step 1	MaleCoApp	-5338.299	20.786	1	.000

Variables not in the Equation

			Score	df	Sig.
Step 1	Variables	MaleApp	.573	1	.449
		FemaleApp	.666	1	.414
		FemaleCoApp	1.597	1	.206
	Overall Statistics		3.098	3	.377

Model if Term Removed

Variable		Model Log Likelihood	Change in -2 Log Likelihood	df	Sig. of the Change
Step 1	LoanAmtGrp1	-5461.808	158.363	1	.000
Step 2	LoanAmtGrp1	-5402.277	110.262	1	.000
	AppIncGrp1	-5382.627	70.961	1	.000
Step 3	LoanAmtGrp1	-5397.986	112.843	1	.000
	AppIncGrp1	-5362.432	41.735	1	.000
	AppIncGrp3	-5347.146	11.163	1	.001
Step 4	LoanAmtGrp1	-5343.262	9.925	1	.002
	LoanAmtGrp2	-5341.564	6.530	1	.011
	AppIncGrp1	-5359.586	42.574	1	.000
	AppIncGrp3	-5346.122	15.645	1	.000

Variables not in the Equation[a]

			Score	df	Sig.
Step 1	Variables	LoanAmtGrp2	.033	1	.856
		LoanAmtGrp3	.033	1	.856
		AppIncGrp1	71.677	1	.000
		AppIncGrp2	7.228	1	.007
		AppIncGrp3	38.975	1	.000
Step 2	Variables	LoanAmtGrp2	2.091	1	.148
		LoanAmtGrp3	2.091	1	.148
		AppIncGrp2	11.040	1	.001
		AppIncGrp3	11.040	1	.001
Step 3	Variables	LoanAmtGrp2	6.753	1	.009
		LoanAmtGrp3	6.753	1	.009

a. Residual Chi-Squares are not computed because of redundancies.

Block 4: Method = Forward Stepwise (Likelihood Ratio)

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	50.368	1	.000
	Block	50.368	1	.000
	Model	455.000	8	.000
Step 2	Step	16.125	1	.000
	Block	66.494	2	.000
	Model	471.125	9	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	10605.444[a]	.040	.064
2	10589.319[a]	.041	.066

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95.0% C.I.for EXP(B) Lower	Upper
Step 1[a]	BlkHispApp	.243	.058	17.311	1	.000	1.275	1.137	1.430
	WhiteCoApp	-.144	.062	5.381	1	.020	.866	.767	.978
	LoanAmtGrp1	.180	.102	3.079	1	.079	1.197	.979	1.463
	LoanAmtGrp2	-.344	.105	10.730	1	.001	.709	.577	.871
	AppIncGrp1	.459	.060	59.230	1	.000	1.583	1.408	1.779
	AppIncGrp3	-.373	.075	24.851	1	.000	.689	.595	.798
	MaleCoApp	.411	.089	21.496	1	.000	1.509	1.268	1.795
	OwnerOcc	-.600	.082	53.057	1	.000	.549	.467	.645
	Constant	-1.004	.135	55.193	1	.000	.366		
Step 2[b]	BlkHispApp	.250	.059	18.209	1	.000	1.284	1.145	1.440
	WhiteCoApp	-.125	.062	4.031	1	.045	.882	.781	.997
	LoanAmtGrp1	.184	.102	3.251	1	.071	1.203	.984	1.469
	LoanAmtGrp2	-.296	.106	7.843	1	.005	.744	.605	.915
	AppIncGrp1	.470	.060	61.743	1	.000	1.600	1.423	1.799
	AppIncGrp3	-.400	.075	28.495	1	.000	.670	.579	.776
	MaleCoApp	.404	.089	20.683	1	.000	1.497	1.258	1.782
	OwnerOcc	-.577	.083	48.833	1	.000	.562	.478	.660
	ConvLoan	.318	.081	15.435	1	.000	1.375	1.173	1.611
	Constant	-1.330	.158	70.493	1	.000	.264		

a. Variable(s) entered on step 1: OwnerOcc.

b. Variable(s) entered on step 2: ConvLoan.

Model if Term Removed

Variable		Model Log Likelihood	Change in -2 Log Likelihood	df	Sig. of the Change
Step 1	OwnerOcc	-5327.906	50.368	1	.000
Step 2	OwnerOcc	-5317.906	46.493	1	.000
	ConvLoan	-5302.722	16.125	1	.000

Variables not in the Equation

			Score	df	Sig.
Step 1	Variables	ConvLoan	15.530	1	.000
	Overall Statistics		15.530	1	.000

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BIOGRAPHICAL INFORMATION

Seanna Wesson is an alumnus of The University of Texas at Austin, where, as an undergraduate, she earned a BBA in Management Information Systems. She worked for five years in the field of Information Technology before returning to school to pursue an advanced degree. She graduated from The University of Texas at Arlington, earning her MBA in Finance in December of 1999. Seanna Wesson currently resides in the Houston area and works as a Financial Analyst for the City of Houston. In the near future, she plans to pursue various ventures in the area of Real Estate.