Predatory lending characteristics and mortgage default

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ABSTRACT

In the wake of the housing bubble and subsequent crisis in mortgage foreclosures, exotic mortgages made to subprime borrowers, often labeled as "predatory" in nature, have taken a significant amount of blame for the large number of foreclosures. Mortgage loan characteristics which are often considered predatory include pre-payment penalties, negative amortization, balloon payments, interest-only mortgages, piggy-back loans, and no/low documentation loans. Subprime and Alt-A borrowers are most likely to have mortgages containing these characteristics since these borrowers represent a higher degree of default risk.

Using discriminant analysis, this study will measure the association between predatory loan characteristics and subsequent default. The data comes from CoreLogic Information Solutions, Inc. (CoreLogic), who accumulate mortgage loan data for forecasting and analytical purposes. The study will also include an independent variable measuring housing price change. The results indicate that predatory loan characteristics and the risk of default were related to each other in a statistically significant manner, but the relative magnitude of the relationship was weak. In contrast, the research findings indicate that the impact of housing price changes in explaining mortgage defaults was substantially larger. The study will also develop a multivariate logistic regression model which confirms these results.

Keywords: Predatory Lending, Subprime Mortgages, Defaults, Pre-payment Penalties, Foreclosues

INTRODUCTION

In the wake of the subprime mortgage crisis, significant attention has been given to predatory and abusive lending practices and their role in subsequent defaults and foreclosures. Generally, loans are considered predatory in nature when they contain terms that are abusive to borrowers and provide no tangible net benefit (Li and Ernst, 2006). Delgado, Erickson, and Piercy (2008) indicate that predatory lending occurs when lenders offer loan terms that the borrower cannot afford to repay. Predatory lending research has focused on abusive loan features such as prepayment penalties and balloon payments which are often associated with subprime loans (Li and Ernst, 2006; Elliehausen, Staten, Steinbuks, 2006; Pennington-Cross and Ho, 2008; and Goodman and Smith, 2009). In addition, a considerable amount of predatory lending research has centered on the effect of various state and federal anti-predatory lending laws and their impact on the flow and cost of subprime credit (Ferris and Stein, 2002; Elliehausen and Staten, 2004; Li and Ernst, 2006; Pennington-Cross and Ho, 2008).

As the aftermath of the housing bubble and resulting crash continued to unfold, President Barack Obama signed the Dodd-Frank Wall Street Reform and Consumer Protection Act on July 21, 2010. The bill targets lenders that make mortgages containing exotic loan features such as prepayment penalties, negative amortization, loan terms in excess of 30 years, and balloon payments. Lenders originating loans with these features may face legal counterclaims against foreclosures as well as large fines. In addition, the law requires the mortgage originator to retain 5% of the loan if the borrower does not meet minimum borrower standards, such as loan-to-value limitations and debt-to income standards. Opponents to this legislation argue that the new restrictions will unfairly limit home ownership and disproportionally restrict the ability of poor people and minorities to obtain mortgage loans, while consumer advocates claim that borrowers will now have credit protection from predatory lenders (Ulam, 2011).

The study will investigate the relative strength of loan characteristics, borrower characteristics, and economic characteristics (such as the decline in property values) in explaining mortgage defaults. Discriminant analysis (DA) is used to develop a model that identifies characteristics most strongly associated with mortgage default. The DA results are compared to results obtained using logistic regression, a technique widely used in similar studies.

Previous studies analyzed the impact of specific loan characteristics on default, and included loans in multiple jurisdictions. However, these studies ignore the impact of local and state regulation on mortgage lending, which can be significant. (Goodman and Smith, 2010). This study examines loans originating only in the Seattle-Tacoma metropolitan statistical area, an area where the federal Home Ownership and Protection Act (HOEPA) is the only law restricting mortgage lending practices.

This paper has three sections. Section One is a review of related research. Section Two discusses the methodologies used and the results of the tests. Section Three concludes with a summary of the results and proposed areas for future research.

I. RELATED RESEARCH

The review of related literature is divided into three sections. Section A describes predatory lending practices, Section B the effectiveness of anti-predatory legislation on curbing predatory practices, and Section C describes the relationship between foreclosures and abusive lending practices.

A. Predatory Lending Practices

Predatory lending is generally associated with loans that contain terms that are abusive to borrowers and provide no tangible net benefit. Bond, Musto, and Yilmaz (2009, p.7) define a predatory loan as, "one that the borrower would decline if he or she possessed the lender's information". They contend that information asymmetry between the borrower and lender is foundational to predatory lending. Predatory lending generally occurs in two situations; the first is when predatory lenders extract cash from a distressed borrower trying to avoid foreclosure by encouraging the borrower to refinance into a new loan knowing that they will most likely end up in foreclosure. The second situation is when predatory lenders encourage a borrower who is successfully paying down his mortgage to cash-out part of the existing equity by re-financing into a loan that ultimately ends up in foreclosure. (Bond, Musto, and Yilmaz, 2009).

Practices such as loan flipping, steering, and equity stripping are often classified as predatory. Loan flipping occurs when lenders refinance mortgages for the purpose of generating additional fees and interest. Steering occurs when a lender encourages a borrower to accept a loan with terms and costs that are significantly worse than other loans for which they could qualify. Equity stripping occurs when borrowers are encouraged to finance loan fees and mortgage insurance into the principal of their new loan. (Li and Ernst, 2006).

To discourage predatory lending practices, legislation targeted specific loan features considered abusive in nature, or contained provisions relating to borrower access to the courts. In response, lenders began to offer loans with new features, such as interest only loans and low documentation loans, which circumvented these laws and increased the purchasing power of borrowers. (Pennington-Cross, Chomsisengphet, Bostic, and Engel, McCoy, and Wachter, 2008).

Prepayment penalties have been a frequent target of loan regulation. These are fees that borrowers must pay if they prepay their mortgage within a specified time following origination. The fees are normally charged if the mortgage is repaid within the first two to three years. Consumer advocacy groups argue that prepayment penalties are inherently abusive, since they entrap borrowers with high cost loans, and since the borrower often does not receive a lower interest rate in return for accepting the prepayment penalty. Goldstein and Stohauerson (2003) summarized findings indicating that prepayment penalties are primarily used by subprime mortgage brokers to discourage borrowers from refinancing loans with yield-spread-premiums. Yield spread premiums are lender payments to the broker in exchange for brokers originating loans at above-market interest rates. The net impact is that the borrower becomes trapped in the higher rate loan for the duration of the prepayment penalty period. Ernst (2005) found that prepayment penalties are not accompanied by lower interest rates.

In contrast, some research indicates prepayment penalties are relatively benign. Elliehausen , Staten, and Steinbucks (2008) find that mortgage risk premiums are inversely related to use of a prepayment penalties. LaCour-Little and Holmes (2008) found that prepayment penalties result in lower cost loans.

Adjustable rate mortgages (ARMs) have also been a target of lending regulation. ARMs often feature low introductory "teaser" rates. Ambrose, LaCour-Little, and Huszar (2005) studied 3/27 ARM mortgages which provide borrowers with a fixed rate mortgage for three years and then converts to a ARM indexed to the one-year treasury note for the remainder of the loan. Depending on the performance of interest rates, borrowers with these mortgages may face significant increases in their monthly payments. Their findings indicate that default risk rises substantially when the introductory teaser rates ends.

Other potential predatory features include interest-only mortgages, pay-option mortgages, piggyback loans with no down payments, and low or no documentation loans. Interest-only loans contain a period of time where only interest is required to be paid. Payments increase significantly when the interest-only period ends. Pay-option mortgages allow the borrower to choose the payment amount in the early periods of the loan. Some pay-option loans have a payment that is lower than the amount of interest on the loan, resulting in negative amortization. Piggyback loans allow the borrower to finance both the primary mortgage and down payment in order to avoid the cost of mortgage insurance. Loans requiring little or no documentation of borrower income offer the potential for home borrowers to qualify for loans that they cannot afford, placing them at high risk for default and foreclosure (Fishbein and Woodall, 2006).

B. Effectiveness of Legislation in Curbing Predatory Practices

Recently, the Wall Street Reform and Consumer Protection Act (often referred to as the Dodd-Frank Act) was passed in an attempt to prevent lending institutions from marketing and originating subprime loans containing loan features believed to have contributed to the recent financial crisis. The law created the Consumer Financial Protection Bureau and established restrictions on specific loan features. (Ulam, 2011).

Prior to Dodd-Frank, the Home Ownership and Equity Protection Act (HOEPA) regulated prepayment penalties, balloon payments, prohibitions of joint financing of various insurance products, and required borrowers to participate in loan counseling. HOEPA provisions were triggered when loans met threshold APRs and financing fees. In the late 1990s, many states expanded HOEPA by enacting their own laws, often described as "mini-HOEPA" laws. Research indicates that the impact of state legislation is mixed in terms of reducing predatory practices while not impacting the flow or cost of subprime credit. (Ho and Pennington Cross, 2006).

North Carolina was one of the first states to pass mini-HOPEA legislation. A number of studies, conducted shortly after passage of this act in 1999, determined that this legislation was successful in curbing use of predatory loan characteristics but that it also caused a decline in the volume of loan originations, especially to low and moderate income borrowers. (Elliehausen and Staten, 2004; Burnett, Finkel, and Kaul, 2004; Harvey and Nigro, 2004; Quercia, Stegman, and Davis, 2004.)

Within a few years, more and more states began to adopt mini-HOPEA legislation. Evidence relating to the impact of these laws is also mixed. Li and Ernst (2006) found that anti-predatory lending laws have little impact on access to subprime credit or the related interest rates associated with the loans. A subsequent study by the same authors concluded that state mini-HOPEA legislation was effective at reducing the number of loans with abusive terms, and they also tended to lower interest rates (Li and Ernst, 2007). Ho and Pennington-Cross (2006) found that local predatory lending laws tend to reduce mortgage rejections without significantly reducing the overall volume of subprime credit. Pennington-Cross and Ho (2008) found that predatory lending laws have only a modest impact on the cost of credit, an indication that they do not impose a regulatory burden. Furthermore, they found that strong laws actually seem to be associated with reductions in APRs.

In contrast, Elliehausen, Staten, and Steinbucks (2006) find that originations in states with restrictive predatory lending laws declined, indicating that the laws appear to reduce the availability of high-cost mortgages. Bostic, *et.al.* (2008) found that states with more restrictive anti-predatory laws experienced reductions in subprime originations and increased subprime rejections. Goodman and Smith (2009) concluded that states with predatory lending laws and judicial foreclosure restrictions impose higher costs on financial institutions, who in turn adopt more restrictive lending standards, resulting in higher quality loans.

C. Default and Abusive Lending Practices

Not surprisingly, research shows that mortgages made to subprime borrowers have a higher probability of default than other mortgages. Bunce, Gruenstein, Herbert, and Scheessele (2000) found that subprime lending occurred disproportionally among low-income and African-American neighborhoods and that these loans experienced higher levels of foreclosures than prime loans. Likewise, Immergluck and Smith (2004) found that subprime lending has a substantial impact on neighborhood foreclosure levels, and that non-owner occupied subprime loans have an even higher propensity to result in foreclosure.

Research on specific predatory loan characteristics finds these characteristics are associated with higher mortgage default rates. Pennington-Cross and Ho (2006) found a higher incidence of default with variable-rate mortgages than fixed-rate mortgages, and also found the presence of prepayment penalties increased the default rate even further. Quecia, Stegman, and Davis (2007) found that loans with prepayment penalties and balloon payments are more likely to end up in foreclosure than loans without these characteristics. Ding, Quercia, Ratcliffe, and Li (2008) compared the default rate on mortgages originated by mortgage brokers vs. those originated through the Community Reinvestment Act, and found that the broker-originated loans had a higher default rate. Both sets of mortgages contained features usually labeled as abusive, such as variable interest rates and prepayment penalties. Rose (2008) extended the findings of previous studies by examining the default rates of mortgages with various combinations of predatory features. His results indicate that the relationship between foreclosures and predatory loan features is much more complex. Predatory loan characteristics found in sub-prime loans do not necessarily result in foreclosures in a uniform and consistent way across all loans. For example, the impact of long prepayment penalty periods, balloon payments, and no or low documentation on default rates can vary between fixed and variable loans. Amromin and Paulson (2009) found that cash-out mortgages were at greater risk of default, and that loans made to purchase a home are more likely to default than refinanced loans. LaCour-Little, Calhoun, and Yu (2011) studied "piggy-backs" which are mortgages containing junior liens simultaneously originated with the first mortgage. These mortgages are used by both prime and subprime borrowers to finance more than 80% of the value of a home, thereby avoiding private mortgage insurance. Their results suggest that high-cost piggy-back mortgages associated with subprime second lien loans were at a significantly greater risk of default and foreclosure.

Housing price declines have played a significant role in mortgage defaults. Several studies which analyzed housing price declines in addition to predatory lending variables concluded that price declines played a significant role in explaining mortgage defaults. For example, Immergluck (2008) studied the role of education and lack of buyer sophistication in mortgage default, and finds that housing price declines play a major role in default rates. Gerardi, Shapiro, and Willen (2007) found that subprime borrowers have a much higher default rate than prime borrowers, but that housing price depreciation also plays a major role.

Foote, Gerardi, Goette, and Willen (2008), found that the combination of increased subprime lending coupled with falling housing prices were the major factors resulting in the subprime lending crisis. Their results indicated that interest rate resets on ARMs did not significantly impact foreclosure rates, and they also found that the default rate on brokered loans was not significantly higher.

Mayer, Pence, and Sherund (2009) found that defaults and foreclosures were most closely related to the combination of loose underwriting standards and falling home prices. They found that abusive loan features did not play a major role in default. They conclude "…default rates were highest on these products because they were originated to the borrowers with the lowest credit scores and highest loan-to-value ratios (Mayer et al., 2009, p. 48)."

Gerardi, Lehnert, Sherlund, and Willen (2008) examined the impact of both underwriting standards and home prices on foreclosure. They sought to determine whether security analysts could have predicted the mortgage meltdown. In the first part of the study, a loan-level probit model was used to estimate the probability of default based on loan characteristics and risk factors which included FICO scores, LTV ratios, ARMs, low-documentation loans, and loans with nontraditional amortization. In order to evaluate this relationship, they split their sample of loans into two groups. The first group was composed of loans originated between 1999 and 2004, when minimal price fluctuation occurred. The second was composed of loans originated between 2005 and 2006, at the height of the housing bubble. If housing price declines had no impact on subsequent default, the model developed from the earlier group should have predicted default in the latter group. The authors concluded "These results are consistent with the view that a factor [home prices depreciation] other than underwriting changes was primarily responsible for the increase in mortgage defaults (p. 90)"

In the second part of the study, a housing price appreciation variable, derived from the Case-Shiller index and actual Massachusetts public records, was used in addition to the mortgage data to develop an options model that predicted foreclosure rates much more effectively.

Mayer, Pence, and Sherlund (2009) evaluated the default rates of various pools of mortgages with characteristics such as fixed and variable rate loans, FICO scores, LTVs, prepayment penalties, and negative amortization. In addition, they introduce macroeconomic factors such as the level of interest rates, unemployment, and housing price appreciation. They conclude that, "the final culprit [of foreclosures] the study will consider is changes in underlying macroeconomic conditions such as interest rates, unemployment and housing prices (p. 29)"

Landerman (2012) examines reasons why subprime borrowers with interest rates 50 basis points or more than the current market rates did not re-finance into a lower rate mortgage. She finds that they were unable to pay off their existing mortgages, many of which were underwater. She concludes, "the decline in house prices appears to have dampened the opportunity for all mortgage borrowers to pay off the principal balance of their loans as an alternative to delinquency (p. 5)."

In summary, the evidence regarding recent mortgage defaults is mixed. Many studies indicate there is a significant association between the presence of predatory loan characteristics and subsequent mortgage defaults. However, when examining the relationship between specific characteristics and default, the evidence becomes less clear, with various studies indicating contradictory effects for the same loan characteristics. Compounding this confusion is the data used in many of the past studies, which contain loans from multiple jurisdictions with varying legal and regulatory environments. Many state and local laws (mini-HOEPA laws) limit or even ban the use of specific loan features. This has an effect on the observable impact of remaining independent variables (Goodman and Smith, 2010). The study attempts to clarify these results by (1) including a comprehensive set of variables that potentially relate to loan defaults, including loan characteristics, borrower characteristics, and economic characteristics (housing price declines), and (2) including data from only the Seattle-Tacoma metropolitan statistical area, an area which has no mini-HOEPA legislation which confounds the relationship between loan characteristics and subsequent loan default.

II. Methodology and Findings

A. Data

Data containing variables for 237,141 mortgage loans originated in the Seattle-Tacoma area between January 1, 2001 and December 31, 2008, was obtained from CoreLogic. These represent all of the mortgages captured by CoreLogic in the Seattle-Tacoma SMA classified as subprime or ALT-A loans and originated on owner-occupied dwellings. The repayment status of these loans was reported through July, 2011. ALT-A loans are often identified as “near-prime” loans since they are made to borrowers with minor credit quality issues or who are unable to provide all necessary documentation required by the underwriter. Since ALT-A loans do not meet specific underwriting requirements, they cannot be sold to government sponsored enterprises such as Freddie Mac or Fannie Mae. Instead, these loans are securitized in the private market and sold as subprime loans. Most of the previous research on predatory loans includes only subprime and ALT-A loans, since they represent the bulk of the loans containing predatory features.

The CoreLogic data includes all dependent and independent variables used in the study except for the percentage change in housing price. Table 1 (Appendix), Variable Definitions, contains a list of all variables examined. The housing price variable was calculated using the origination and termination dates found in each loan record and calculating a percentage change in home price value over the life of each loan, or until July, 2011, whichever came first. The index value from the S&P/Case-Shiller Home Price Index for the Seattle-Tacoma MSA was used in this calculation. Loans with missing fields were excluded from further analysis which resulted in a total N of 143,781 loans.

The study defined defaulted loans as loans in which the borrower was 30 or more days late with their payment. Previous studies defined default as anywhere between 30 and 120 days past due. The study took the more conservative definition of a 30-day delinquency, consistent with the definition of default used by most lenders as “a breach of any of the terms of the mortgage contract, but most often associated with missed payments.” (Crews Cutts, and Merrill, 2008, p. 6.)

As an initial step, the default rates associated with each of the 12 independent variables, were calculated and tested for significant differences in default rates. Complete results of these tests of association are given in Table 2 (Appendix), Default Rates by Independent Variable. Significance tests for the 8 dichotomous variables employed a chi-square test, while a simple t-test could be used for the 4 continuous variables. The results indicated that the predatory variables were associated with higher default rates, which was expected and consistent with previous studies. This is important, as this indicates the variables used in the study are legitimate candidates to explain mortgage default. Furthermore, for each variable except one, the sign of the variable’s relationship to default was consistent with expectations. The one exception to this is the interest rate variable, which indicated that loans in default had a lower interest rate than those in current status (7.32% vs. 7.63%). This difference was statistically significant.

The expected frequency for each dichotomous variable in the chi-square test was calculated by taking the actual default/foreclosed and current/paid-off rates for the entire population of loans and applying them to each total count of each independent variable.

B. Discriminant Analysis

The research employed discriminant analysis (DA) to develop the relationship between default status and each of the 12 predictor variables. Loan status, a binary variable, was coded 0 if the loan was current, and 1 if the loan was in default. The model tested was:

$$P[Default] = f(\alpha + b_1[Fix/Variable] + b_2[Balloon\_Payment] + b_3[Prepayment\_Penalty]$$

$$+ b_4[Document] + b_5[Interest\_Only] + b_6[Interest\ Rate] + b_7[Negative\ Amortization] +$$

$$b_8[Purchase/Refinance] + b_9[Jumbo] + b_{10}[LTV] + b_{11}[FICO] + b_{12}[Price\_Inc\_Dec]) \quad (1)$$

B.1. Rationale for Using DA

There are several reasons why DA was chosen. First, the dependent variable, default status, represents a binary variable, which is best analyzed using statistical tools which address nonmetric, binary dependent variables such as discriminant analysis and logistical regression (Norusis, 2005).

Second, DA appeared to both provide greater fit and more detailed results for the model than logistic regression. A majority of the research studying risk factors affecting mortgage default and foreclosure use logistical regression, since this technique does not require the assumptions of normality and homogeneity of variance. Transformations of independent variables were made in an attempt to resolve issues of non-normality. The level of improvement noted was not significant. These results are available from the authors. (Ding, Quercia, Ratcliffe, and Li, 2008; Rose, 2008). However, Norusis (2005) points out that, “if the assumptions required for linear discriminant analysis are met, logistic regression is somewhat inferior to discriminant analysis from a statistical perspective.” (p. 293).

Third, DA generates findings that are not available with other tools. Most significantly, the structure matrix of the DA model provides information about the classification and strength of each independent variable to the overall results. In contrast, the coefficients of independent variables in logistic regression are much more difficult to interpret, with their impact varying with the level of the independent variable itself.

B.2. DA Results - Goodness of Fit

Wilks’ lambda indicates goodness-to-fit by testing whether the discriminate scores for default and current loans are equal. If they are, the discriminant function would have no power to distinguish between groups (Norusis, 2005). The results in Table 3 (Appendix) suggest that the model is very significant ($p<.000$) and that the null hypothesis that there is no significant difference between the discriminant scores of default and current loans can be rejected.

Eigenvalues represent another test of overall model significance. They represent the ratio of the between-groups sum of squares to the within-groups sums of squares, with larger eigenvalues representing greater explanatory power for the model. The eigenvalue of .214 in Table 4 (Appendix) was greater than 0, indicating explanatory power. Canonical correlation is similar to the R^2 in linear regression, as it indicates the amount of variance between the two groups that is explained by the model. Canonical correlation is calculated by taking the ratio of between-groups sum of squares to the total sum of squares. The variation explained by the model was 17.6% (the square root of the canonical correlation of 0.419).

B.3. Impact of Individual Variables

The structure matrix provides a way of obtaining the relative importance of each of the predictor variables by identifying structure correlation coefficients. The structure correlation coefficients represent the Pearson correlations between the values of the discriminant function and the values of the independent variables. The variables are sorted based on the absolute values of the correlation coefficients. Generally, a cut-off of 0.30 is used to distinguish between important and less important variables (Burns, R., and Burns, R., 2008).

As indicated by the structure matrix listed in Table 5 (Appendix), housing price changes are by far the most most important variable. The remaining independent variables are all below the 0.30 threshold of significance. This was extremely important, and suggests that changes in housing values swamp all other factors in explaining mortgage loan default. .

To further test this conclusion, the DA model was run without the housing price change variable. The resulting eigenvalue of 0.038 Table 6 (Appendix) is significantly less than 0.214 obtained from the original model using all independent variables. In addition, the proportion of the variation in default explained by the model, which is the square root of the canonical correlation, drops from 17.6% to 3.6%. This 14% decline in explanatory power is further evidence of the importance of the price appreciation variable.

The canonical discriminant function coefficients used to calculate discriminant scores for each loan are given in Table 7(Appendix). The resulting equation is:

$$D = .826 + 0.078\, X_1 - 0.264\, X_2 + 0.484\, X_3 + 0.111\, X_4 + 0.074\, X_5 - 0.073\, X_6 + 0.007\, X_7 + 0.050\, X_8 + 0.032\, X_9 + 0.013\, X_{10} - 0.002\, X_{11} + 4.797\, X_{12}$$

Group centroids represent the means of the discriminant scores for the two groups. When a discriminant score for a loan is calculated, the proximity to the centroid can be used to indicate group membership. Group centroids are given in Table 8 (Appendix). The histograms reflecting the distributions of each centroid can be found on the appendix on schedule Table 20 (Appendix) Group Centroid distributions.

B.4. Model Classification Ability

The classification matrix provides evidence of the ability of the model to effectively predict group membership. The classification matrix results are found in Table 12 (Appendix). The model correctly classified the loans that are current/paid off 99.5% of the time. However, the model was able to classify the default/foreclosed loans only 3.9% of the time.

B.5. Tests of Model Assumptions

DA makes several assumptions, including normality of variables, homogeneity of variance, and a sensitivity to outliers. DA assumes each explanatory variable is normally distributed. Normality tests of the independent variables of interest rate, LTV, FICO, and price increase/decrease do not fully support the assumption as seen schedule A-2 - Normality Test Statistics. While Klecka (1980) suggests that there may be some reduction in efficiency and accuracy, Lachenbruch (1975) has shown that discriminant analysis is quite robust even when violations of the normality assumptions occur. Kleinbaum, Kupper, and Muller (1988) echo this assertion, stating that "Such as assumption will almost certainly never hold exactly in actual practice, but moderate departures from homogeneity do not seem to affect the behavior of the discriminant function seriously." (page 565-566). Norusis validates this claim by stating that, "discriminant analysis is robust to violations of the assumption of multivariate normality; dichotomous predictors work reasonably well" (Norusis, 2005, p.293). The inability to fully support the assumption of normality, therefore, is not considered to be an issue in this research.

Homogeneity of variance is another assumption that is assumed using DA. Box's M was employed to test this. The results were statistically significant ($p<.05$), indicating that the null hypothesis of homogeneity must be rejected. However, this test is sensitive to violations of normality which are inherent in the binary and categorical independent variables used in this model. Klecka (1980) notes that both violations of normality and homogeneity of variance are less significant with large number of observations, indicating that "with large samples, however, we can ignore the tests of significance [Box's M] or interpret them conservatively when the data violate the assumptions" (p. 62).

The results produced by DA are also sensitive to outliers. A total of 1,232 outliers, defined as predicted values in excess of +/- 3 standard deviations from actual values, were identified and eliminated, and the DA results were run again without these cases. Eliminating the outliers generated a slight increase in the eigenvalues, but the overall results did not vary significantly. (These results are available from the authors.)

C. Logistic Regression

To further analyze mortgage default behavior, a logistic regression model was fitted to the data. Logistic regression is a technique that has been used in many past studies in this area.

A logistic model with a binary dependent variable can be fitted by using either binary logistic regression (BLR) or multinomial logistic regression (MLR). When BLR was originally used to fit the model, the Hosmer and Lemeshow test, which tests the null hypothesis that there is no difference between observed and model-predicted values, indicated a lack of fit. The results indicated that the model prediction does not significantly differ from the observed ($p=.000$).

When MLR was used, the Pearson and deviance chi-square tests indicated goodness of fit. Similar to the Hosmer and Lemeshow test, the Pearson and Deviance chi-square tests evaluate the null hypothesis that there is no difference between observed and model-predicted values. The results indicated that the model prediction does significantly differ from the observed ($p>.005$).

Unlike the BLR method, MLR performs a transformation procedure which internally aggregates cases to form subpopulations with identical covariate patterns. This transformation provides a valid goodness-to-fit test and more informative residuals when any independent variables are categorical or take on only a limited number value. The histogram for LTV Table 21 (Appendix) shows bi-model or categorical behavior, where the majority of cases fall into the LTV ratio categories of 80, 85, 90, 95, and 100. In addition, the output for both BLR and MLR are identical for the Pseudo R^2, coefficients, Wald statistics, and classification matrix. With these factors in mind, MLR was chosen for the analysis.

C.1. Goodness of Fit

The overall goodness of fit of the mortgage data to the MLS model was appropriate, as indicated by the significance found in the likelihood ratio, Pearson, and Deviance tests.

The change in the log-likelihood tests the null hypothesis that all population coefficients except the constant are zero (Norusis, 2005). The results indicate a statistically significant degree of fit in the MLR model.

Pearson and Deviance tests are two additional tests of goodness-of-fit. The Pearson and Deviance statistics have chi-square distributions with the displayed degrees of freedom. Results of this test, which are reported in Table 10 (Appendix), indicate a highly significant relationship between default rates and the set of independent variables.

The Cox and Snell statistic, or pseudo R^2, is similar to the R^2 in a linear regression model (Norusis, 2005). The pseudo R^2 measured by Cox and Snell indicated 19 percent of the variation in the default rate was explained by the set of independent variables.

C.2. Magnitude and Impact of Independent Variables

The strength of each independent variable to the overall model is identified using the -2 Log Likelihood ratio (-2LL). This ratio provides similar information to the results produced in the structure matrix used in DA. Logistic regression uses the maximum-likelihood method to estimate the parameters of the logistic model. The model selects the coefficients which make the observed results most likely. The best model generates the smallest -2LL value, indicating a high likelihood of the observed results. An iterative algorithm is used to estimate the parameters since the logistic regression model is non-linear.

The change in the likelihood value is used to determine how the fit of a model changes as variables are added or deleted from a model. Smaller -2LL scores are an indication of greater fit. The full model produces a -2LL of 63,172, as indicated in the top row of Table 15 (Appendix). This value can be used as a benchmark. Values for the -2LL score if specific independent variables were removed from the model are given in the body of Table 15 (Appendix). For example, if the Price Change (x12) variable were removed from the model, the -2LL score would increase from 63,172 to 89,804. This result indicated that the price change variable provides a greater contribution to the overall model than the other variables. By contrast, when the Interest Only (x5), Purchase/Refinance (x8), or Jumbo (x9) variables are removed from the model, the -2LL remains at 63,172, an indication that these variable provide little or no explanatory power to the overall model.

As a further indication of the power of the Price Change (x12) variable to explain default rates, this variable was removed from the logit model. The resulting Cox and Snell Pseudo R^2 drops form 19.9 percent down to 3.5 percent in Table 14 (Appendix).

The coefficients used in the logistic equation do not have a straightforward interpretation, unlike those of ordinary least squares. The reason for this is that the effect of increasing the level of an independent variable varies depending upon its location on the x scale. The “odds ratio” can be defined as ỳ / (1-ỳ), where ỳ = the predicted value of the dependent variable (mortgage default), given a set of independent variables. Using this definition, one interpretation of Bi coefficients is that the odds ratio is multiplied by e^{Bi} for any unit increase in xi. Model coefficients are identified in Table 17 (Appendix).

The coefficients (Bi) are used to develop the logit equation. The calculated logit indicates the probability that a loan is in default. The variables Interest Only (x5), Purchase/Refinance (x8), and Jumbo (x9), would normally be excluded in this calculation, since the -2LL ratio is virtually zero as indicated in table 15 (Appendix).

The process of calculating the probability of default/foreclosure is calculated in a two-step process. First, the logit value (L) is calculated for the individual record. Next, the probability of default (p) is calculated by $p = 1/(1+e^{-L})$. .

L = -1.108+(.013*LTV)-(.004*FICO)+(0.107*Price Change)-(0.138*Interest Rate)-(0.327*Fix/Var)+.668[Balloon]-.734[Prepayment Penalty]-.191[No/Low Doc]+.007[Interest Only]+.456[Negative Amortization]+.009[Purchase Refi]+.003[Jumbo]

The probability that this loan is in default is computed as follows:

$P(\text{default}) = 1/(1+e^{-L})$

e = base of natural logarithms (approximately 2.718)
For example, a loan from the sample representing a re-finance, jumbo, mortgage was originated with an LTV of 89.3%, the borrower had a FICO score of 584, and the loan contained a prepayment feature, an interest only feature, and an interest rate of 8.40%. In addition, the house experienced a decline in value of 28.7%. The probability of default was calculated as follows:

L = L = -1.108+(.013*89.3)-(.004*584)+(0.107*28.7)-(0.138*8.4)-(0.327)+(.668)-(.191)+(.456)
L = 0.208211

The coefficients for the dichotomous data are only included in the calculation when the category indicates a zero or that the loan characteristic is not present.
$P(\text{default}) = 1/(1+e^{-\text{Logit}}) = 1/(1+0.208211^{-1.013})$
P(default) = .5519 or 55.19% probability of default
This loan, with many of the features identified in previous research as predatory or abusive, was predicted to default by the model since probability of default is greater than 50%.

C.3. Model Classification Ability

As with DA, the classification matrix for logistic regression indicates how well the model predicts group membership. First, the logit scores and probability are calculated for each case. In the above example, the loan indicated a 55.19% chance of default. Second, cases with predicted probabilities of default greater than 50% are categorized as default foreclosed, while cases with predicted probabilities lower than a 50% categorized as current/paid-off. Again, the loan described above was both predicted and classified as default/foreclosed. The predicted groups are compared to the actual loan status and a percentage of correct classification is calculated. The results indicated that the model correctly classified 98.5% of the loans in current status correctly, but was only able to classify 15% of the defaulted loans correctly.

C.4. Tests of Model Assumptions

While logistic regression does not rely on the assumptions of normality and homogeneity of variance, it is sensitive to outliers, multicollinearity, and linearity. As was discussed earlier, tests for outliers and multicollinearity have been conducted and satisfied. However, testing for linearity in logistic regression requires analysis of the relationships between the dependent variable and the continuous independent variables. Testing can be done by categorizing continuous independent variables into categories with intervals of equal width so that the expected relationship between the categorical variables and the independent variables are linear. Next, the logistic regression is computed with the continuous variables in categorical form. The resulting regression should take linear form. This procedure was performed using the continuous variables of interest rate, LTV, FICO scores, and price increase/decrease. The FICO and interest rate variables yielded an almost perfect linear relationship. The price increase/decrease variable was stepwise linear but monotonically decreasing, which indicated linearity. However, LTV clearly did not demonstrate a linear relationship. Since the LTV had such a small impact on the model as indicated by the -2 log-likelihood of 147.1, the logistic model was re-run without the LTV variable. As anticipated, results were similar to the original model, as the Cox and Snell or Pseudo R^2 decreased by only 0.1%.to 19.8% as indicated in table 19 (Appendix).

D. Comparison of Discriminant Analysis and Logistic Regression Results

The DA and logit regression models produced similar results. The explanatory power provided by both models was almost identical, with the logit regression yielding a pseudo R^2 of 19%, while DA generated an 18% result for the same measure.

By far, the independent variable which provided the greatest explanatory power in both the DA and logit regression models was the price change variable (x12); and this was clearly evident in two ways. First, the structure matrix produced in the DA model showed that the price change variable provided a high discriminant loading of 0.926. None of the other variables produced a discriminant loading above 0.30. Similarly, the logit regression model produced a -2LL matrix indicating exclusion of the price/increase decrease variable would result in a far greater reduction of explanatory power than any other independent variable.

The magnitude of the price change variable was also clearly evident in the change in R^2 for both models when the variable was removed. When the price change variable was removed from the logit regression model, the pseudo R^2 dropped form 19.9% to 3.5%. When the price change variable was removed from the DA model, the variance explained by the model dropped from 17.6% to 3.6%.

While the signs of the coefficients produced by DA and logit regression were different for some of the variables, the sign for the price change variable, which provides the most explanatory power, was the same. There were differences, however, in the signs of the coefficients for Interest Only X5, negative amortization X7, purchase/refinance X8, and jumbo X9, independent variables. Contrary to expectations, the presence of an interest only feature, a negative amortization feature, a refinance classification, and a jumbo classification indicated a decrease in the probability of default in the logit model.

Finally, the classification matrices produced by both DA and MLR indicated that both models did a good job of predicting loans in current status, but were extremely weak at properly classifying loans in default . The MLR model correctly classified 98.5% percent of the loans that were current or paid off, but was only able to correctly classify 15% of the loans in default. The results parallel the classification power of DA which also correctly classified 98.5% of the current/paid off loans, but only 3.9% of the loans in default.

III. SUMMARY AND CONCLUSIONS

Based on the DA coefficients presented in Table 7 (Appendix), the presence of adjustable rate mortgages, prepayment penalties, no/low documentation loans, interest only loans, and negative amortization all increase the probability of foreclosure. The negative coefficient associated with the balloon payment variable seems to suggest a decrease in the probability of foreclosure, contrary to expectations.

The most important variable was clearly the price change variable. This result is indicated by both the structure matrix in Table 5 (Appendix) and the results obtained when running the DA model without the price change variable. When the DA model was run without the price change variable, the explained variation in the default rate fell to 3.6%, from 17.6% with the full model.

The recent housing bubble and mortgage foreclosure crisis that began in 2007 has wreaked havoc on the U.S. economy and resulted in many people losing their homes. A better understanding of the underlying causes of the recent spike in mortgage defaults is necessary to mitigate similar events from occurring in the future. A significant portion of the predatory lending research suggests that predatory lenders used abusive loan characteristics to take advantage of consumers in an environment of information asymmetry. However, research examining the relationship between the effectiveness of anti-predatory lending laws at preventing predatory lending and their impact on the availability of credit to borrowers has yielded mixed results (Bostic, Engel, McCoy, Pennington-Cross, and Wachter, 2008).

Previous studies of mortgage default have primarily included loans across multiple jurisdictions. Many local and state jurisdictions have enacted mini-HOEPA laws that restrict or prohibit the use of the loan characteristics evaluated in this study. The data contains loans originated only in the Seattle-Tacoma area where the confounding effects of mini-HOEPA laws are absent.

While the research finds a significant link between predatory lending characteristics and mortgage default, the explanatory power of these loan characteristics is limited. The results appear to run counter to the expectations that predatory loan characteristics explain a substantial portion of default rates. The model gains the majority of its explanatory power only after including a variable for housing price depreciation.

There are several limitations of this study. First, the location of the population studied was limited to the Seattle/Tacoma MSA in order to mitigate the confounding effects associated with mini-HOEPA laws. However, several other locations and cities, in addition to

Seattle/Tacoma, that did not have these laws around the country could have been selected, and may have yielded different results for reasons unknown at present.

Second, the findings were limited by the lack of information on the loan originators. Several studies have noted a higher default rate on broker-originated mortgages, and the research was unable to control for this variable in the data.

Third, the normality assumption required for DA was not fully supported, which could result in some reduction in efficiency and accuracy of the DA results. However, the literature as discussed by Lachenbruck (1975) and Norusis (2005) state that DA is robust to violations of this assumption. In addition, while the test of homogeneity of variance, required by DA, was not fully supported, Klecka (1980) indicates that these violations are less significant with large number of observations.

Fourth, the proxy for price appreciation associated with the underlying collateral for each loan was limited in its level of detail. The S&P/Case-Shiller Home Price Index captures depreciation at the MSA level. While this methodology has been used by several researchers, price depreciation by individual zip code or loan may have improved the model significance. Gerardi, Lehnert, Sherlund, and Willen (2008) examined the relationship between foreclosure and subprime loans by using a proprietary data set which contained the actual price paid at the time of sale, purchase, and foreclosure auction. This data yields an actual price decline by individual home rather than an MSA level.

Finally, explanatory power may have been increased by including economic variables in the study such as unemployment, inflation, and aggregate income levels. These variables may provide additional insight into other causes associated with mortgage default, but the study concludes the impact of housing price declines would still be highly significant.

In conclusion, the results of this study support the hypothesis that abusive loan characteristics are positively related to loan defaults. However, these characteristics have minimal power to predict mortgage default. This finding is contrary to portions of the predatory lending literature that predatory loan characteristics significantly increase the likelihood of borrower default. Furthermore, the large increase in explanatory power resulting from the inclusion of housing price changes in the model suggests that home price declines played a greater role in the borrower decision to default.

Appendices

Appendix
Table 1 - Variable Definitions

Variable	Definition
Dependent Variable:	
(y) Loan Status	Equals 1 if payment is late 30 or more days; 0 if payment was made within the last 30 days
Loan Characteristics	
(x_1) Variable/Fixed	Equals 1 if ARM; 0 if Fixed
(x_2) Balloon Code	Equals 1 if balloon payment; 0 if null
(x_3) Prepayment Penalty	Equals 1 if prepayment penalty; 0 if no prepayment penalty
(x_4) Document Type	Equals 1 if less than full doc., 0 if full doc.
(x_5) Interest Only	Equals 1 if payment includes interest only, 0 if both principal and interest included in payment
(x_6) Annual Interest rate	Interest Rate at loan closing
(x_7) Negative Amortize	Equals 1 if loan negatively amortizes in the beginning; 0 if loan does not amortize negatively
(x_8) Refinance/Purchase	Equals 1 if the purpose was to re-finance; Equals 0 if the purpose was to purchase
(x_9) Jumbo	Equals 1 for jumbo; Equals 0 for non-jumbo
Borrower Factors	
(x_{10}) Loan-to-Value (LTV)	LTV at closing
(x_{11}) FICO Score	FICO at closing
Economic Factors:	
(x_{12}) Price Increase/Decrease	Percentage increase/decrease in price since origination

Table 2: Default Rates by Independent Variable

Panel A: Dichotomous Variables

Characteristics of the Loan	*Category*	*% Current*	*% Default*	*N*	*Chi-Squared*	*Sig Level*
X1 – Fixed / Variable	Variable	90.8	9.2	172,655		
	Fixed	93.2	6.8	64,486	325.0	0.0000
X2 – Balloon Payment	No	91.7	8.3	194,933		
	Yes	90.4	9.6	42,208	79.0	0.0000
X3 – Prepayment Penalty	No	94.5	5.5	92,491		
	Yes	88.9	11.1	134,300	2,126.2	0.0000
X4 – No/Low Documentation	No	92.6	7.4	137,288		
	Yes	89.9	10.1	98,694	551.2	0.0000
X5 – Interest Only	No	92.5	7.5	170,977		
	Yes	88.8	11.2	66,164	831.7	0.0000
X7 – Negative Amortization	No	90.9	9.1	129,362		
	Yes	82.1	17.9	16,986	1,265.3	0.0000
X8 – Purchase / Refinance	Refi	90.6	9.4	121,150		
	Purchase	92.4	7.6	115,662	240.4	0.0000
X9 – Jumbo	No	91.8	8.2	208,929		
	Yes	88.9	11.1	28,212	279.2	0.0000

Panel B: Continuous Variables

Characteristics of the Loan	*Status*	*N*	*Mean*	*Std Dev*	*t*	*sig t*
X6 – Closing Interest Rate	Default	20,218	7.32	1.73		
	Current	216,923	7.63	2.14	-23.62	0.0000
Borrower Characteristics						
X10 – FICO Score	Default	20,218	649.88	74.47		
	Current	216,923	657.68	89.53	-13.97	0.0000
X11- LTV	Default	20,218	81.19	9.37		
	Current	216,923	83.44	12.85	-31.43	0.0000
Economic Characteristics						
X12 – Home Price Change	Default	20,218	-0.19	0.11		
	Current	216,923	0.11	0.21	-354.55	0.0000

Table 3: DA Model Significance

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.824	27824.976	12	.000

Table 4: Goodness of Fit – Full Model

Eigenvalues

Function	Eigenvalue	percent of Variance	Cumulative percent	Canonical Correlation
1	.214[a]	100.0	100.0	.419

a. First 1 canonical discriminant functions were used in the analysis.

Table 5: DA Structure Matrix

Structure Matrix

variable name	Function 1
Price Increase / Decrease	.926
Prepayment Penalty	.252
Negative Amortization	.208
Document	.130
LTV	-.107
Interest Only	.104
Fixed / Variable	.081
Jumbo	.080
FICO	-.079
Purchase / Refinance	.079
Interest Rate	-.063
Balloon Payment	.006

Table 6: Goodness of Fit Without Price Change Variable

Function	Eigenvalue	percent of Variance	Cumulative percent	Canonical Correlation
1	.038[a]	100.0	100.0	.191

a. First 1 canonical discriminant functions were used in the analysis.

Table 7: Discriminant Function Coefficients

	Function 1
Fixed / Variable	.078
Balloon Payment	-.264
Prepayment Penalty	.484
Document	.111
Interest Only	.074
Interest Rate	-.073
Negative Amortization	.007
Purchase / Refinance	.050
Jumbo	.032
LTV	.013
FICO	-.002
Price **-**Increase / **+**Decrease	4.797
(Constant)	.826

Unstandardized coefficients

Table 8: Group Centroids

Functions at Group Centroids

Status Code	Function 1
Current/Paid Off	-.156
Default/Foreclosed	1.367

Unstandardized canonical discriminant functions evaluated at group means

Table 9: Hosmer and Lemeshow Test

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	197.362	8	.000

Table 10: Pearson and Deviance Chi-square Tests

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	102071.664	143654	1.000
Deviance	63124.223	143654	1.000

Table 11: Model Fitness Test

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	94996.512			
Final	63171.593	31824.919	12	.000

Table 12: Classification Matrix

		From Group	Predicted Group Membership: Current/Paid Off	Predicted Group Membership: Default/Foreclosed	Total
Original	Count	Current/Paid Off	128383	662	129045
		Default/Foreclosed	14157	579	14736
	percent	Current/Paid Off	**99.5**	.5	100.0
		Default/Foreclosed	96.1	**3.9**	100.0

Table 13: Goodness-Of-Fit, Pearson and Deviance Statistics

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	102071.664	143654	1.000
Deviance	63124.223	143654	1.000

Table 14: Tests of Explanatory Power

Pseudo R-Square

Cox and Snell	.199
Nagelkerke	.411
McFadden	.335

Table 15: -2LL Ratio or Likelihood Ratio Tests

	Model Fitting Criteria	Likelihood Ratio Tests		
Effect	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	63,172	-	0	.
x1: Fixed/Variable Rate	63,291	119	1	.000
x2: Balloon Payment	63,565	393	1	.000
x3: Prepayment Penalty	64,109	938	1	.000
x4: No/Low Document	63,247	75	1	.000
x5: Interest Only	63,172	0	1	.782
x6: Interest Rate	63,642	471	1	.000
x7:Negative Amortization	63,353	181	1	.000
x8: Purchase/Refinance	63,172	0	1	.681
x9: Jumbo Loan	63,172	0	1	.910
x10: Loan to Value	63,172	147	1	.000
x11: FICO Score	63, 319	1,036	1	.000
x12 Price Change	89,804	26,632	1	.000

Table 16: Pseudo R-Square excluding the price increase/decrease variable

Cox and Snell	.035
Nagelkerke	.073
McFadden	.055

Table 17: Model Coefficients

Variable	B	Wald	Sig.	Exp(B)
Intercept	-1.108	69.073	.000	
Fixed/Variable Rate (x1) = 0	-.327	117.719	.000	1.387
Fixed/Variable Rate (x1) = 1	0			
Balloon Payment (x2) = 0	.668	387.263	.000	.513
Balloon Payment (x2) = 1	0			
Prepayment Penalty (x3) = 0	-.734	900.808	.000	2.082
Prepayment Penalty (x3) = 1	0			
No/Low Doc (x4) = 0	-.191	75.028	.000	1.210
No/Low Doc (x4) = 1	0			
Interest Only (x5) = 0	.007	.076	.782	.993
Interest Only (x5) = 1	0			
Interest Rate (x6)	-.138	467.936	.000	1.148
Negative Amortization (x7) = 0	.456	178.416	.000	.634
Negative Amortization (x7) = 1	0			
Purchase/Refinance (x8) = 0	.009	.169	.681	.991
Purchase/Refinance (x8) = 1	0			
Jumbo (x9) = 0	.003	.013	.910	.997
Jumbo (x9) = 1	0			
Loan to Value (x10)	.013	141.587	.000	.987
FICO Score (x11)	-.004	1204.589	.000	1.004
Price Change (x12)	.107	12560.268	.000	.899

*The coefficients for the dichotomous variables with a category of 1 are set to zero since there values are already included in the Intercept.
**The signs of the coefficients for the dichotomous variables should be reversed when evaluating the impact on default /foreclosure as a result of inclusion in the intercept.

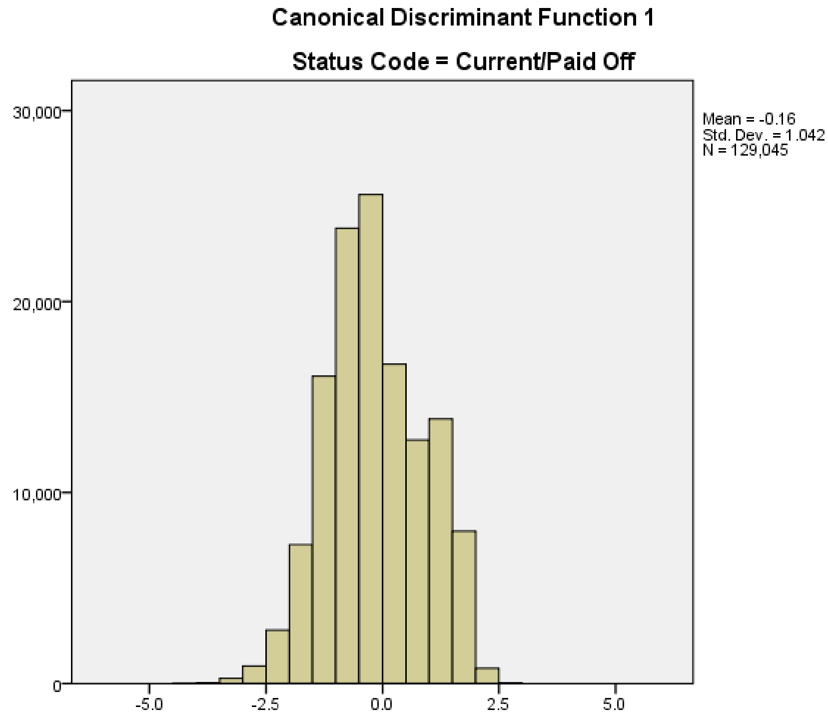
Table 18: Classification Matrix

Observed	Predicted		
	Current/Paid Off	Default/Foreclosed	Percent Correct
Current/Paid Off	126887	2158	98.3 %
Default/Foreclosed	12530	2206	15.0 %
Overall Percentage	97.0 %	3.0 %	89.8 %

Table 19: Goodness of Fit After Removing LTV from Model

Cox and Snell	.198
Nagelkerke	.409
McFadden	.333

Table 20: Group Centroid Distributions



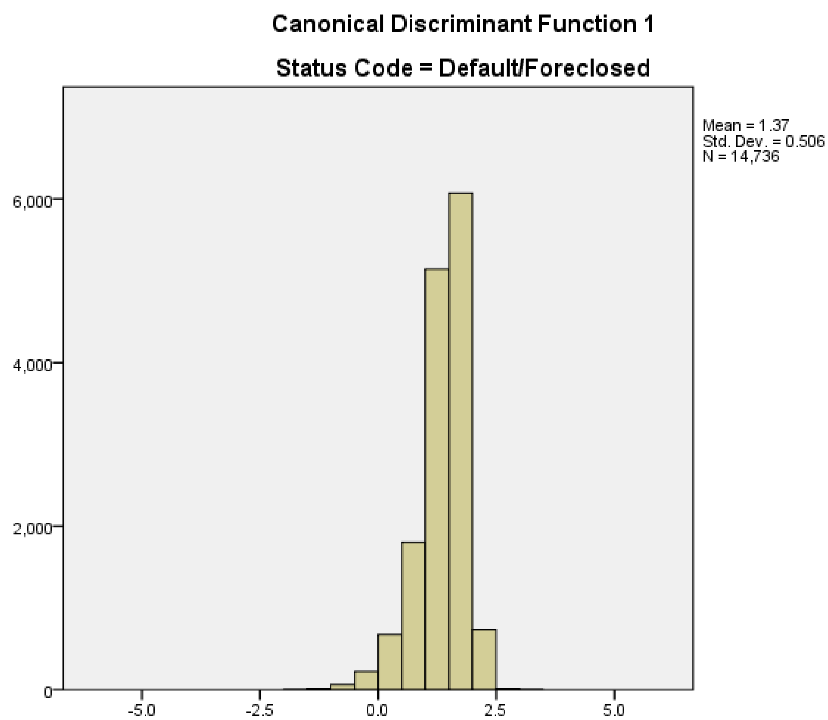
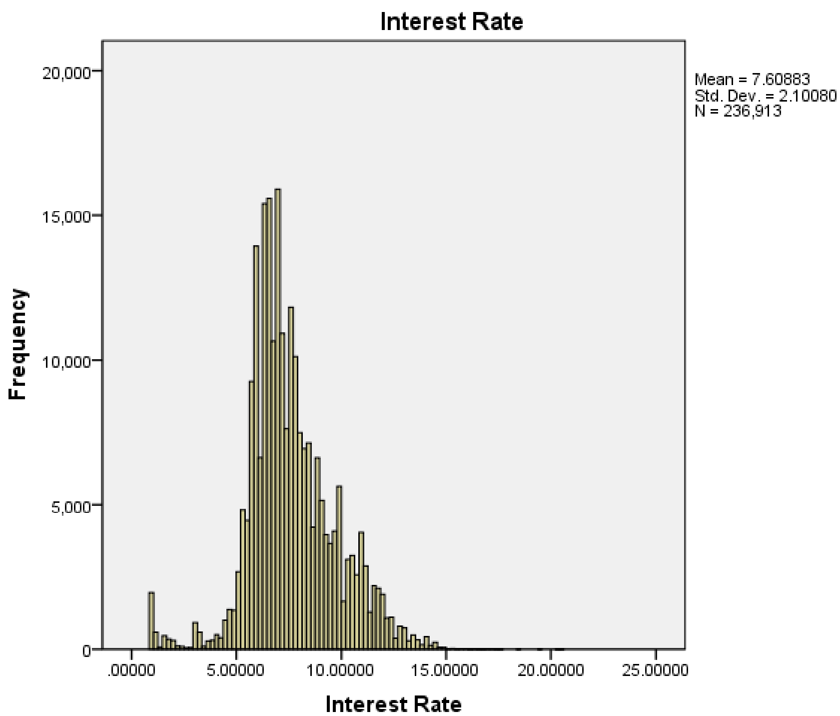
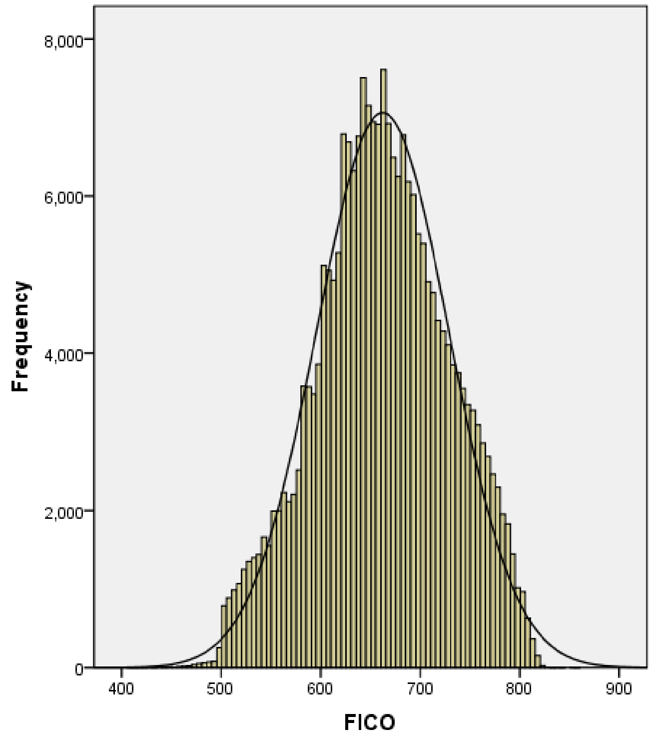


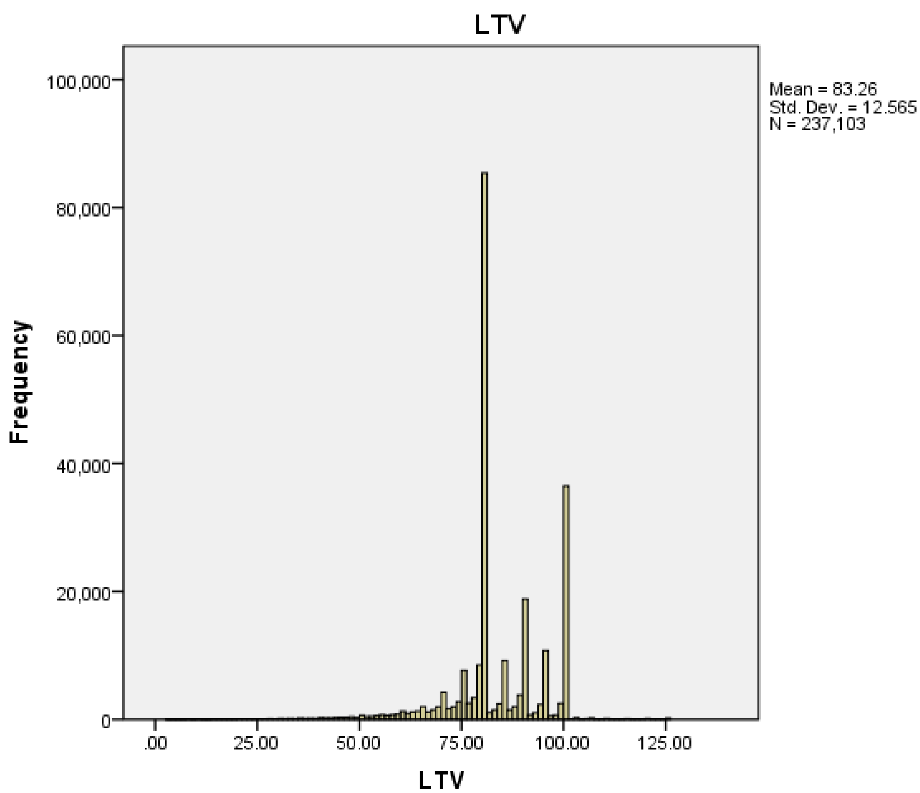
Table 21: Normality Test Statistics

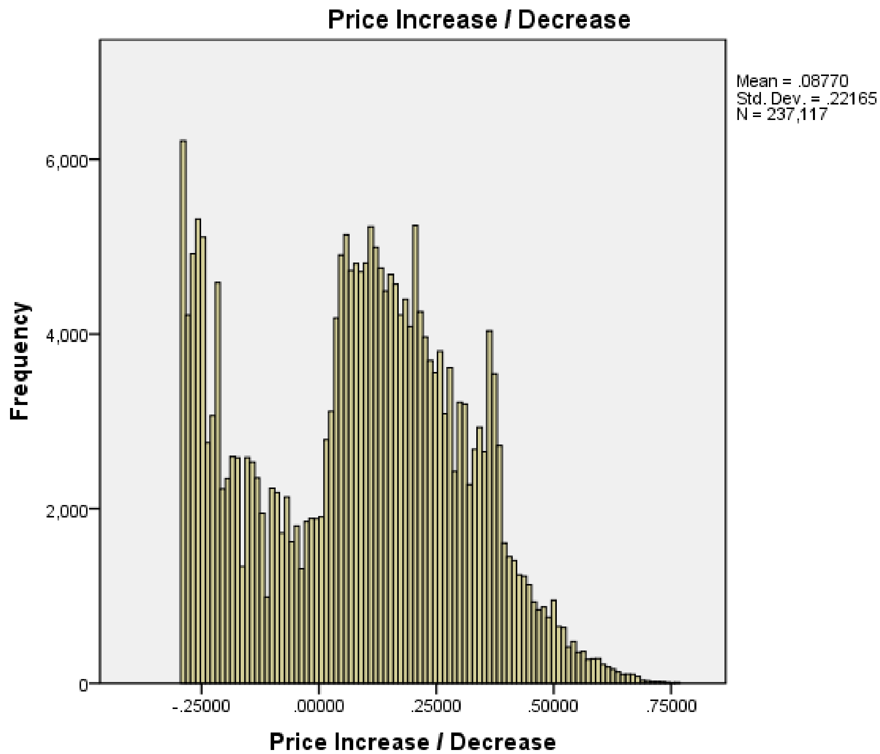
Statistics

		Interest Rate	FICO	LTV	Price Increase / Decrease
N	Valid	236913	235271	237103	237117
	Missing	228	1870	38	24
Mean		7.6088291	662.23	83.2595	.0877026
Median		7.2500000	662.00	80.0000	.1078700
Mode		6.50000	661	80.00	-.25870
Std. Deviation		2.10079813	66.440	12.56473	.22165499
Variance		4.413	4414.257	157.872	.049
Skewness		.306	-.084	-.931	-.049
Std. Error of Skewness		.005	.005	.005	.005
Kurtosis		1.113	-.396	3.267	-.806
Std. Error of Kurtosis		.010	.010	.010	.010
Sum		1802630.51800	155804593	19741086.82	20795.78209




8,000
6,000
4,000
2,000
0
Frequency
400
500
600
700
800
900
FICO


LTV
Mean = 83.26
Std. Dev. = 12.565
N = 237,103
100,000
80,000
60,000
40,000
20,000
0
Frequency
.00
25.00
50.00
75.00
100.00
125.00
LTV


Price Increase / Decrease
Mean = .08770
Std. Dev. = .22165
N = 237,117
Frequency
6,000
4,000
2,000
0
-.25000
.00000
.25000
.50000
.75000
Price Increase / Decrease

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