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Abstract

This paper introduces a measure of credit score performance that abstracts from the influence of "situational factors." Using this measure, we study the role and effectiveness of credit scoring that underlied subprime securities during the mortgage boom of 2000-2006. Parametric and nonparametric measures of credit score performance reveal different trends, especially on originations with low credit scores. The paper demonstrates an increasing trend of reliance on credit scoring not only as a measure of credit risk but also as a means to offset other riskier attributes of the origination. This reliance led to deterioration in loan performance even though average credit quality—as measured in terms of credit scores—actually improved over the years.

JEL Codes: G21, D82, D86.

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1 Introduction

Over the last couple of decades, technological advances and private arrangements of information sharing have increased the use of credit scoring in almost all forms of loan origination (Altman and Saunders, 1998). However, the use of credit scoring is not without its limitations (Mester, 1997; Avery et al. 2000). For example, origination credit scores cannot account for "situational factors" such as local economic conditions or business cycle peaks and troughs (Avery et al. 2004). However, despite such limitations, most approval processes continue to use credit scores as a measure of borrower creditworthiness at the time of loan origination (Avery et al., 2003; Brown et al, 2010). Therefore, it is important for both academics and policymakers alike to evaluate the usage and performance of credit scoring as a measure of credit risk on the origination.

In this paper, we introduce a simple metric of credit score performance that abstracts from situational factors described in Avery et al. (2004). This metric helps us determine the impact of credit scoring and its usage in terms of observed loan performance data. To this end, we study the role and effectiveness of credit scoring that underlies subprime securities during the mortgage boom of 2000-2006. Studying the sample of subprime borrowers is important for two reasons.[1] First, the securitized subprime market has rapidly evolved since the turn of this century. Hence, a study of the loans from this time period allows us to understand the role of credit scoring for a full credit cycle—that is, from the early years of this market, through its "boom years," until its ultimate collapse.

Second, it helps us understand the role played by credit scoring in the structure and performance of the some of the riskiest securities to trade in global financial markets. While there are historical examples of lending to the riskiest segments of the population, the use of credit scoring to quantify credit risk in such segments is a fairly recent phenomenon and this study allows us to derive important policy lessons on the usage of credit scoring in subprime markets. Such policy questions are increasingly relevant given the recent re-emergence of subprime mortgages even after the collapse of this market in 2008.[2]

This paper presents evidence demonstrating an increased reliance on credit scoring over the cohorts from 2000 through 2006 in the securitized subprime universe. This reliance in turn led to an increase in credit scores on subprime originations over the years—not only in absolute terms, but also after adjusting for other attributes on the origination. The increase in credit scores was largely restricted to subprime originations and cannot be explained by changes in the credit scores for the overall (credit-eligible) U.S. population.[3] In addition, we find strong

[1] In an earlier study, Pennington-Cross (2003) examined the contrasting performance of credit scoring for the prime versus subprime mortgage market. For a survey of recent work on subprime mortgages and the recent housing crisis during this period, see Levitin and Wachter (2010) and Agarwal et al. (2010).

[2] Androitis (2011) provides anecdotal evidence of the re-emergence of subprime loans in the U.S.

[3] Anecdotal evidence has been provided showing that credit scoring itself is subject to manipulation (Foust

evidence to suggest that higher credit scores on originations were used not only as a measure of determining ex ante credit risk, but also as a means to adjust for other riskier attributes of the origination—such as lack of full documentation and higher loan-to-value (LTV) ratios.

In order to determine how this adjustment affects credit quality, we introduce a simple metric for credit score performance in terms of ex post loan performance. Our metric the difference between the survival probabilities for originations in a higher credit score group and that for originations in its immediately lower credit score group *within the same cohort*. This measure, calculated for both high and low levels of credit scores, is tracked over the cohorts from 2000 through 2006.[4] Significantly, our metric has two advantages. First, it helps abstract from situational factors that are known to vary with each cohort: for example, key macroeconomic indicators, local unemployment rate, and house price trends. Second, we can obtain both nonparametric and parametric estimates of this metric. The nonparametric estimates use the Kaplan and Meier (1958) product limit estimator, whereas the equivalent parametric estimates are extracted from the Cox (1972) relative risk hazard model.

As we demonstrate below, nonparametric and parametric measures reveal different trends in credit score performance depending on the level of credit scores. At low levels of credit scores, nonparametric estimates show deterioration in credit score performance over the cohorts. In contrast, this trend of deterioration is reversed when we control for other attributes on the origination: Our parametric estimates at low credit score levels reveal an improvement in credit score performance. On the other hand, credit score performance for high credit scores levels shows improvement over the same years—in terms of both our non-parametric and parametric measures.

These results can be explained in terms of the patterns of credit score usage described above. Significantly, the usage patterns also vary with the credit score level. For low credit-score levels, there is strong evidence of increase in credit scores over the cohorts with increased riskiness in other origination attributes. As a result, credit score performance at low levels of the credit score shows deterioration over the cohorts in terms of our non-parametric measure. For the same reason, this declining trend is reversed if we control other origination attributes: We record an improvement in credit score performance in terms of our parametric measure.

The pattern is somewhat different at high credit score levels—the pattern of adjustment of riskier attributes with higher credit scores is not significantly large to begin with and remains roughly unchanged over the years. Therefore, in terms of both parametric and nonparametric measures, credit score performance at high credit score levels shows improvement over the cohorts. In summary, although our results provide little evidence of deterioration in the perfor-

and Pressman, 2008). In such cases, increases in a borrower's credit score occur without any increase in their creditworthiness. We discuss this issue in greater detail in Section 6.

[4] Needless to say, the exact numerical estimates vary with the grouping of credit scores. However, as shown below, all results in the paper are robust to different groupings of credit scores (see Appendix).

mance of credit scores per se, they question the pattern of credit score usage over the cohorts.

The results in this paper find broader support in the literature on credit scoring and information sharing. Lenders evaluating an application for credit either collect information from the applicant first-hand or receive this information from agencies and credit bureaus. Such information primarily includes the prior credit history of the borrower. Credit scoring is described as a summary measure of this information set on the borrower in terms of a single metric or score that is viewed as a measure of future credit risk. Theoretical studies have demonstrated the importance of information sharing in mitigating the problems of adverse selection (Jappelli and Pagano, 1993), moral hazard (Vercammen, 1995; Padilla and Pagano, 2000) and overlending (Bennardo et al., 2009) that plague credit markets. Most of these studies predict that information sharing lowers default rates for the individual borrower. Several empirical papers and experimental studies have confirmed these predictions (see Brown et al., 2009, Brown and Zehnder, 2010 and references therein).

However, information sharing and can also affect credit market outcomes adversely. This can happen in several ways. First, information sharing potentially enhances the ability of lenders to accurately measure credit risk. In some scenarios, this may increase lending volumes, especially to borrowers of low credit quality. Therefore, while information sharing is likely to reduce default rates for a given credit grade, aggregate default rates may increase because of an increase in the proportion of lower-grade borrowers in the credit-eligible pool (Brown et al., 2009). Second, information sharing has been shown to increase default rates by reducing the incentives for screening. Keys et al. (2010) demonstrate how securitization distorts incentives with lax screening on higher credit grades in comparison with those with lower grades. Using a regression discontinuity design, they find paradoxically higher default rates on borrowers with marginally higher credit grades around an ad hoc screening cutoff.

This study points to a third way in which information sharing has led to adverse credit market outcomes. In the case of subprime mortgages, there was an attempt over the years to increase origination credit scores as a means of compensating for the increased risk in other originations attributes. As demonstrated below, this pattern of loan origination led to higher default rates on originations of later cohorts especially those with low credit scores. In conclusion, we observe that over-reliance on credit scoring to the extent of including other riskier attributes on the origination can become common practice and can have deleterious effects on market outcomes. Notably, the deterioration in loan performance occurs even though average credit quality (as measured in terms of credit scores) actually improved over the cohorts.

The data and trends on credit scores in the securitized subprime universe are described in Section 2. Section 3 discusses the patterns of credit scoring use over the various cohorts. The parametric and nonparametric measures are explained in Section 4 and their estimates of credit score performance are provided in Section 5. Section 6 concludes.

2 Data and Trends in Credit Scoring

We use loan-level data on over nine million first-lien mortgage originations from the CoreLogic Loan Performance data repository on B&C securities (subprime mortgages) during 2000-2006.[5] Among other elements of the mortgage contract, the data include a measure of ex ante credit risk—namely, the borrower's FICO score at origination.[6] Figure 1 shows the cumulative distribution function (cdf) of the FICO scores on subprime originations of earlier cohorts (2000-02, in red) along with those of later cohorts (2004-06, in black). The figures show that the probability that a subprime borrower has a lower credit score is significantly higher on originations during earlier cohorts than on originations of later cohorts. Clearly, origination FICO of subprime mortgages improved significantly over time. Using more formal methods below, we verify that the distribution of credit scores on later cohorts first-order stochastically dominates the distribution of credit scores on earlier cohorts (Rothschild and Stiglitz, 1970).

An important concern here is whether the observed improvement is due to a shift in the underlying distribution of FICO scores for the entire U.S. We confirm that changes in the borrower density for the credit-eligible population for the U.S. cannot explain the full improvement in the credit quality on subprime originations. In order to show this, we obtain the population credit scores for the U.S. from the FRBNY-Equifax Consumer Credit Panel, which comprises a 5 percent random sample of U.S. individuals (aged 19 and over) with credit reports from 1999 to 2009 (Lee and Van der Klaauw, 2010).[7] The results are plotted in dotted lines in Figure 1. At higher credit scores, the cdf of credit scores on subprime originations is above those for the population. This is expected, since borrowers with higher credit scores are less likely to opt for a subprime mortgage (Pennington-Cross, 2003). Next, for the lowest credit scores, the cdf on originations is below those for the population. Again, there is likely to be a greater proportion of borrowers with lower credit scores in the population than among those with subprime mortgages. Finally, the data reveal a marginal improvement in the credit score distribution from 2000-2002 to 2004-2006 for the population as well.

However, while we find that the improvement in credit scores on subprime originations is statistically significant across these cohorts, this is not the case for borrowers in the entire population. For example, Figure 2 compares the credit scores on subprime originations (cohorts)

[5] It is widely regarded as a comprehensive database for subprime originations and captures over 90 percent of the mortgages that have been securitized as subprime. Details on this database; including its evolution, coverage, and comparison with other mortgage databases, are available in GAO (2010).

[6] The FICO score is the best-known and most widely used credit score model in the United States. It is statistical summary measure of information from a consumer's credit files and ranges between 300 and 850. Fair Isaac (2007) claims, "A credit score is a number that summarizes your credit risk, based on a snapshot of your credit report at a particular point in time. A credit score helps lenders evaluate your credit report and estimate your credit risk."

[7] Strictly speaking, the credit scores obtained from this longitudinal panel are derived from the methodology used by Equifax to mimic the proprietary algorithm used by Fair Isaac Corporation. Therefore, while they are a close match, the credit scores for each individual may not be identical under the two algorithms.

of 2000 and 2006 with those in the population for the same years. As before, the cdf of credit scores on subprime originations of 2006 first-order stochastically dominates that on subprime originations of 2000. However, with the population credit scores for the same years, we fail to establish the case for first-order stochastic dominance.

2.1 Test for Stochastic Dominance: Subprime Originations and U.S. Population

The hypotheses stated above are best verified in terms of the statistical tests for stochastic dominance developed in Anderson (1996). Following Anderson (1996), the hypothesis of *first-order stochastic dominance* of distribution A over B is tested by comparing the two cdfs at various points in the distribution.

Let x_A and x_B be the empirical frequency vectors based on samples of size n_A and n_B, drawn respectively from the population distributions A and B. The Anderson test of stochastic dominance is based on a comparison of the cumulative distributions $F_A(\cdot)$ and $F_B(\cdot)$ at the deciles of the pooled sample. Anderson also shows that under the null of common population distribution (no dominance), and the assumption of independence of the two samples,

$$\alpha = \frac{x_A}{n_A} - \frac{x_B}{n_B}$$

is asymptotically normally distributed with mean zero. The hypothesis of first-order dominance of A over B requires that no element of α be significantly greater than zero while at least one element is significantly less.

Panel A of Table 1 presents the results of the test for credit scores during 2004-2006 over those during 2000-2002. The numbers in the second column show, for each decile of credit scores, the difference in the cumulative probabilities across the distributions (cohorts) for subprime originations. We also report the 95% confidence intervals for the differences in parentheses below. The third column reports t-statistics for the test of significance. The same results for the population are then presented in the fourth and fifth columns.

For both subprime originations and the general population, the distribution of credit scores on later cohorts is seen to stochastically dominate those on earlier cohorts. However, at all deciles (save the last, with highest credit scores) the difference in probabilities for the subprime originations are significantly greater than that for the population. For example, the probability of having a FICO score greater than 600 (the fourth decile) is 11.63 percent higher for later cohorts in subprime originations, but it is only 0.46 percent higher in the general population.

Panel B of Table 1 presents the results of the Anderson (1996) test for first-order stochastic dominance of the credit score distribution of 2006 over that of 2000. For the credit score distribution on subprime originations, the null of no dominance is rejected in favor of the alternative of first-order stochastic dominance. However, we fail to establish first-order stochastic dominance for the same years in the population credit distributions. In particular, one finds that for the fifth decile, the difference α is significantly *greater* than zero. In summary, our results indicate that the distribution of credit scores on later cohorts is seen to stochastically dominate those on earlier cohorts. For credit score distributions on subprime originations, this difference is both economically and statistically significant. However, the improvement in credit risk for the population is at best marginal and not always significantly different across the different cohorts.

3 Use of Credit Scoring on Originations

Why were credit scores higher for subprime originations in later years? This feature of the data is best understood when one considers that there was an increase in credit risk in terms of other characteristics on the origination. As has been well documented, there has been an increase in the proportion of originations with higher LTV and originations lacking full documentation over the years in our sample (see Mayer et al., 2009). Below, we present evidence to show that lenders' sought to temper overall risk on the origination by increasing FICO scores on originations with other riskier attributes such as higher LTV and the lack of full documentation on the mortgage.

Table 2 reports the percentage of loans that provide full documentation and those without full documentation under various FICO score groups (panel A). Panel B shows the percentage of loans under various FICO score groups for different intervals of LTV. In all FICO score groups shown in Table 2, there is a decline in the percentage of borrowers in the lowest FICO group (<620) with an increase in the percentage of borrowers in the next two categories, namely, 620-659 and 660-719. The percentage of borrowers in the highest category ($\geq$720) throughout the years remains roughly the same. This result suggests an overall increase in credit score on both high- and low-risk originations.

Panel A of Table 3 reports the coefficients of a least-squares regression of FICO scores on other origination attributes by cohort. While we do not intend to attribute any causal interpretation, the results demonstrate the equilibrium relationship between credit scores and other origination characteristics. Not surprisingly, most of the coefficients have the expected sign—for example, origination credit scores increase with the LTV and the lack of full documentation on the origination. Moreover, an increase in the magnitude (absolute values) of these coefficients over the cohorts appears to suggest that the strength of adjustment of increased FICO for riskier attributes increased over this period. The evidence suggests that the increase in credit scores over the cohorts can be explained in large measure as adjustment for the increased riskiness in other attributes on the originations. Panel B of Table 3 reports the estimates for the full sample (all cohorts) of the regression presented in Panel A. In addition to the regressors in Panel A, Columns (1) and (2) include dummy variables that take the value 1 for cohorts 2003-2006 and

2004-2006 respectively; and zero otherwise. The results show that even after adjusting for other attributes on the originations there is an overall increase in FICO scores from the earlier cohorts to the later cohorts. Accompanying the increase in credit risk exposure on certain origination attributes (such as lack of full documentation and high LTV) was a trend that attempted to offset this higher credit risk by increasing the average quality of borrowers (as measured by their credit scores) to whom such loans were made. Taken together the evidence suggests that not only did FICO scores increase over the cohorts for high-risk and low-risk originations, but also that these credit scores were increasingly used to adjust for other riskier attributes on the origination.

The evidence of an overall increase in credit scores prompted assertions that creditworthy prime borrowers may have been misled by originators into subprime products (Brooks and Simon, 2007). However, consistent with the evidence presented above, Foote et al., (2008) argue that originations to borrowers with such high credit scores were marked as subprime because of other attributes on the origination. In order for borrowers with such high credit scores to originate prime mortgages, the risk on other attributes of the origination would have to be lower as well. In summary, originations of later cohorts include a significantly large proportion of borrowers with higher credit scores. However, as noted previously, these high credit scores were used to offset other riskier attributes on the origination.

As mentioned earlier, we are not the first to observe this trend over the subprime cohorts towards higher FICO scores. Practitioners have often referred this phenomenon as a movement in the subprime segment towards the Alt-A market segment (Bhattacharya et al., 2006). Some observers have even described this as a creation of "the Alt-B" market segment (Zimmerman, 2006).[8] This leads to some obvious queries: Could high origination credit scores offset other riskier attributes on the origination? Did the performance of FICO scores withstand the situational factors, such as the reversal in home price increases around 2005-2006? We attempt to answer these questions in the next two sections, where we first devise a metric for FICO score performance and then examine how such scores performed over the cohorts of subprime mortgages.

4 A Performance Metric for Credit Scoring

In this section, we study the performance of ex ante credit scoring as measures of credit risk in terms of ex post default. Any accurate measure of credit score performance needs to distinguish between information available at the time of origination and events that occur subsequent to the origination of the loan. Otherwise, the metric of origination credit score performance is

[8] For example, Zimmerman (2006, p. 106) observes, "... FICOs in subprime at 624 in 2004 are at a record high level. In part, the increase in subprime FICOs reflects the rapid move by subprime issuers into the lower end of the Alt-A market, sometimes referred to as the Alt-B or the "gap" part of the non-agency market."

biased by situational factors that influence default. Keeping this in mind, we opt for a metric for credit score performance that is independent of the year of origination.

Our metric for credit score performance is the difference in survival probabilities for an origination with a higher FICO in comparison to one with a lower FICO in the same cohort. We derive nonparametric and parametric estimates of this difference in probabilities. For ease of exposition, we split our sample into originations belonging to different FICO score groups. Next, we calculate, as a first pass, the nonparametric estimates of the (unconditional) survival probabilities for originations within each FICO score group. As a result, our measure of origination credit score performance is the difference in the survival probabilities of a given origination FICO score group to that of its immediately lower FICO score group of the same cohort. Since, both credit score groups are of the same cohort they are each subject to the same underwriting trends and macro shocks (events), allowing us to net out the effects of these factors in our measure of credit score performance. We formalize our measure below.

4.1 Nonparametric Estimates

Formally, the *survival* probability of a 90-day delinquency event beyond loan age t is given by $S(t) \equiv P(T > t)$, where T denotes the duration in months from the month of origination. Let $t_1 < t_2 < ... < t_m$ denote the observed age in months at the time of event in a sample size of N originations, $N \geq m$. Also, let n_j be the number of surviving mortgages just prior to month t_j. A surviving mortgage is defined as one that has neither defaulted nor been paid-off prior to age t_j. If we define d_j as the number of mortgages that default at age t_j, then the Kaplan-Meier estimator of the survivor function is

$$\hat{S}_{NP}(t) \equiv \hat{P}(T > t) = \prod_{j|t_j \leq t} (1 - \frac{d_j}{n_j}) = \prod_{j|t_j \leq t} (1 - \hat{\lambda}_j) \tag{1}$$

where $\hat{\lambda}_j = \frac{d_j}{n_j}$ is the nonparametric hazard estimate.

For ease of exposition, we split our sample into originations belonging to mutually exclusive and exhaustive FICO score groups, $\mathcal{F}_1, ..., \mathcal{F}_n$. To do this we define n FICO group dummies, $f_1, ..., f_n$ such that $f_k = 1$ if FICO score the origination lies in the interval $\mathcal{F}_k$, $k = 1, ..., n$ and zero otherwise.

Our measure of origination credit score performance $\hat{Q}^c_{k,k-1}$ is the difference in the survival probabilities of a given origination FICO score group to that of its immediately lower FICO score group of the same cohort, c, where $c = 2001, 2002...., 2006$. For the nonparametric measure, we use the following

$$\hat{Q}^{c,NP}_{k,k-1}(t) = \hat{S}^c_{NP}(t, f_k = 1) - \hat{S}^c_{NP}(t, f_{k-1} = 1), \tag{2}$$

where $\hat{S}^c_{NP}(t, f_k = 1)$ is the nonparametric estimate of the survivor function, $\hat{S}_{NP}(t)$, for cohort

c and FICO score group $\mathcal{F}_k$.

4.2 Parametric Estimates

We turn to parametric measures of the metric wherein we derive the measure of credit score performance after controlling for other origination characteristics. For parametric estimates, the object of interest in a relative risk model is the hazard ratio (Cox, 1972), which has the interpretation of a multiplicative change in the instantaneous probability of delinquency for a marginal change in a particular risk characteristic:

$$h(t, \mathbf{x}, \beta) = h_0(t) \exp(\mathbf{x}\beta). \tag{3}$$

The estimated hazard ratio (HR) for marginal change in risk characteristic x_i is $\widehat{HR}(t, x_i = x_i + \Delta x_i) = \exp(\Delta x_i \widehat{\beta}_i)$, whereas the estimated hazard ratio for a given FICO score group, say $\mathcal{F}_k$, is given by

$$\widehat{HR}(t, f_k = 1) = \exp(\hat{\beta}_{f_k=1}), \tag{4}$$

where $\hat{\beta}_{f_k=1}$ is the coefficient of the regression for the FICO score group $\mathcal{F}_k$ (or the FICO score dummy, $f_k = 1$). Combining (3) and (4) for FICO score group k, the instantaneous probability of delinquency at age t is

$$\hat{h}(t, f_k = 1) = \hat{h}(t, f_1 = 1)^* \widehat{HR}(t, f_k = 1), \tag{5}$$

where $\hat{h}(t, f_k = 1)$ is a parametric estimate of the hazard rate at age t for the FICO group $\mathcal{F}_k$. We replace $\hat{h}(t, f_1 = 1)$ with its nonparametric equivalent, $\hat{\lambda}_j(t, f_1 = 1)$, given as

$$\hat{\lambda}_j(t, f_1 = 1) = \frac{d(t, f_1 = 1)}{n(t, f_1 = 1)},$$

where $d(t, f_1 = 1)$ is the number of delinquencies at age t with FICO scores in the interval $\mathcal{F}_1$ and $n(t, f_1 = 1)$ is the number of number of surviving mortgages (not in default or prepaid) at age t with FICO scores in the interval $\mathcal{F}_1$. Finally, we obtain an estimate of $\hat{h}(t, f_k = 1)$. Accordingly, the parametric estimates of the survivor function is calculated as

$$\hat{S}^c_P(t, f_k = 1) = \prod_{j|t_j \leq t} (1 - \hat{h}_j(t, f_k = 1)). \tag{6}$$

Using (2), we obtain the parametric estimates of the performance metric as $\hat{Q}^{c,P}_{k,k-1}(t)$.

5 Results

Table 4 reports the difference (increase) in probability of surviving a 90-day delinquency event two calendar years after origination.[9] For the purposes of this analysis, we split the sample into various FICO score groups. The results for two such groupings starting at a FICO of 540 are recorded here: the first at intervals of 40 points (Panel A) and the second at intervals of 20 points (Panel B). The rows in Table 4 show the percentage-point increases in survival probabilities for originations in a higher FICO score group relative to those in its immediately lower FICO score group.[10]

Three features of the nonparametric estimates of differences in survival probabilities as shown in Table 4 are noteworthy. First, there is a deterioration of credit score performance over the cohorts at low levels of FICO score (top rows in both panels). Second, the panels show an improvement in credit score performance at high FICO score levels (bottom rows in both panels). Third, these trends are robust if one considers bigger FICO score groups, and therefore, bigger transitions as shown in Panel A. In contrast, the trends are significantly noisier for smaller FICO groups and therefore smaller jumps in FICO scores as shown in Panel B. These results appear to suggest a degree of "lumpiness" to FICO scores. Having derived the nonparametric (unconditional) measures of credit score performance on loan default, we turn to parametric measures wherein we derive the measure of credit score performance after controlling for other origination characteristics. In a web appendix to this paper, we demonstrate that the results are robust if one uses different origination FICO score groups.

5.1 Parametric Measure of Credit Score Performance

We estimate the default regression (3) by using dummy variables for individual FICO score groups. The groups selected for this regression are the same as those given in Panel A of Table 4. The estimated hazard ratios are provided in Table 5 with the dummy for the lowest FICO score group (less than 540) chosen as the omitted dummy variable.

Table 6 reports the increases in probability of surviving a 90-day delinquency for originations in a higher FICO score group relative to those in its immediate lower FICO score group, after controlling for other attributes on the origination. For example, panel A of Table 6 shows parametric estimates for the difference in survival probabilities of adjacent FICO score groups

[9] The use of two calendar years as the size of the interval is motivated by the fact that most originations were designed in theory to ensure a refinance in two years (Gorton, 2008). Also, we follow the standard convention in using a serious delinquency (90-day delinquency) event as an indicator of default on the loan. Alternative definitions of default yield qualitatively similar results.

[10] Clearly a valid comparison of two FICO groups that are in the 40- or 20-point interval requires that the two groups have the same relative distribution of the sample. An alternative way of implementing this measure would involve measuring the increase in survival probabilities for a given increase in credit score and then averaging across all credit scores in the FICO score group. This second method yields materially similar results and the results are available on request.

such as those given in panel A of Table 4.[11] Clearly, after controlling for other attributes on the origination (as given by the regressions in Table 5), the increases in survival probabilities show a significant improvement over the cohorts. Notably, this result holds true for both high and low FICO score levels. At low levels of FICO scores, the deterioration in performance as seen in the nonparametric estimates (top rows in Table 4) above is now reversed (top rows in Table 6). Controlling for other attributes on the origination shows an improvement in FICO performance over the cohorts. Again this result holds at high levels of FICO, which means that evidence from the nonparametric estimates continues to hold in the parametric case (top rows of both panels in Table 6). In addition, once we control for other attributes on the origination, the noise in the trends of nonparametric estimates in Table 4 is significantly reduced in the trends obtained from the parametric estimates in Table 6.

5.2 Low FICO scores versus High FICO scores

Comparing the survival probabilities in Table 4 with those in Table 6 reveals an interesting trend. In the nonparametric case, we documented deterioration in FICO performance over the cohorts for originations at low FICO levels (top rows in both panels of Table 4). However, after controlling for other attributes, parametric estimates in Table 6 show that this trend is reversed. In contrast, the nonparametric case recorded an improvement in FICO performance at high FICO levels (bottom rows in both panels of Table 4). Notably, this trend continues to hold even after controlling for other attributes on the origination.

To explain these trends, we study the pattern of other riskier attributes on the origination. For the sake of exposition, we focus our attention on one such attribute, namely, LTV. Using the adjacent FICO score groups listed in Panel A of Table 4, we plot the (kernel) density functions for LTV for each adjacent group-pair in Figure 3. The plots in the left column show the distribution of LTV for the 2000-2002 cohorts, whereas plots in the right column show the distribution of LTV for the 2004-2006 cohorts, respectively. The top, middle, and bottom rows show the LTV distribution for adjacent FICO score group-pairs of less than 540 and 540-579, 580-619 and 620-659, and 660-699 and 700-739, respectively. Almost always, the LTV kernel density plot for the higher FICO score group (in red) lies to the right of the kernel density plot of its immediately lower FICO score group (in black). At high FICO score groups this difference is marginal but increases progressively as one moves to lower FICO score groups. Moreover, for the lower FICO score groups this difference appears to have increased significantly over the cohorts from 2000-2002 (top row, left column) to 2004-2006 (top row, right column). In contrast, the difference is marginal at high FICO score levels to begin with. In addition, there is hardly any change in these differences from the 2000-2002 cohorts (bottom row, left column)

[11] Panel B of Table 6 shows the same for the groups in Panel B of Table 4. In the interest of brevity, we do not provide the corresponding regression estimates for the groups in Panel B of Table 5. The results are available on request.

to the 2004-2006 cohorts (bottom row, right column) at high FICO levels.

Formally, we conduct Anderson's (1996) test for stochastic dominance described above for each of the six plots in Figure 6. The results are not stated here but are available on request. We are able to establish that in three of the six plots, the LTV distribution of the higher FICO score group stochastically dominates that in its immediately lower FICO group. In particular, the LTV distribution for the FICO group "540-579" stochastically dominates that for the "less than 540 FICO" score group for both 2000-2002 and 2004-2006 cohorts. Significantly, the value of α (see Section 2.1) recorded at every decile for the 2004-2006 cohorts is greater than the corresponding α recorded for the 2000-2002 cohorts. In addition, the LTV distribution for the FICO group "620-659" stochastically dominates that for the "580-619" score group for 2004-2006 cohorts but not for the 2000-2002 cohorts. Lastly, we fail to establish stochastic dominance of the LTV distribution for the FICO group "700-739" over that for the "660-699" FICO score group for both 2000-2002 and 2004-2006 cohorts. In summary, these results formalize what was described above—the difference between LTV on higher FICO score and lower FICO score originations increased from earlier cohorts to later cohorts. Significantly, these differences are more discernable at low levels of FICO scores than at high FICO score levels.

The contrast in the LTV distribution between high and low FICO score originations can help explain the anomalous trends in our performance metric over the cohorts. At low FICO score levels, the higher of the two adjacent FICO score groups is more likely to have riskier attributes on later cohorts than its immediately lower group. First, this lowers the unconditional performance of FICO improvement over the cohorts as shown by our nonparametric estimates in Table 4. Once we control for these riskier attributes, the trend is reversed—we witness an improvement in FICO performance over the cohorts. In contrast, there is a marginal difference in LTV between adjacent FICO score groups at high FICO score levels. Moreover, this difference does not show any discernible change over the cohorts in our sample. Our performance metric shows improvement over the years for the nonparametric case; and, even after controlling for other origination attributes, FICO performance at high score levels continues to show improvement over the cohorts.

While our results do not show deterioration in performance of credit scores, the methods by which these scores have been implemented remain questionable. As demonstrated above, higher credit score groups were more likely to include other riskier attributes on the origination than their immediately lower one. This trade-off grew stronger for later cohorts especially among low levels of FICO. Naturally, we witness deterioration over cohorts in terms of the unconditional metric of FICO performance for originations at low levels of FICO. However, controlling for such riskier attributes implies that FICO performance actually improved over the years even for originations with low FICO scores. In contrast, the trade-off between riskier attributes and higher credit scores was less pronounced at high FICO score levels. Consequently, we record an improvement in FICO performance in terms of our nonparametric as well as parametric measures.

6 Conclusion

Anecdotal evidence on credit scoring has pointed to possible manipulation that may increase the credit scores of borrowers without any real improvements in their creditworthiness (see Foust and Pressman, 2008 for details). In theory, score manipulation has minimum impact in terms of our metric if its occurrence were to be uniformly distributed. However, this is unlikely: A more probable scenario is one in which manipulation is more likely to occur at low levels of credit scores. Moreover, most anecdotal accounts argue that such manipulation increased over the years in our sample period. Therefore, if credit score manipulation affects default rates, it is most likely to be reflected in our results at low levels of FICO and for later cohorts.

More important, evidence of manipulation of credit scores should be reflected in anomalous behavior in terms of our parametric measure—a measure that controls for other characteristics on the origination. However, the evidence shows the opposite: parametric measures of FICO performance show improvement at all levels of FICO. This result is fairly robust and holds true for multiple variations of credit score groupings (see Appendix). In light of this, we conclude that evidence from our data does not reflect any anomalous behavior that would suggest that such manipulation was widespread. That is not to say that such instances of manipulation did not occur, but simply that given our large sample size, score manipulation would have to be fairly widespread to affect our results.

This paper has introduced a simple yet effective measure for evaluating the performance of credit scoring. As mentioned earlier, the advantage of using such a measure is twofold. First, it lends itself to both non-parametric and parametric estimation. Second, it minimizes the impact of situational factors on this measure of credit score performance. Using this measure, we find that credit score performance is robust to both high and low default environments. However, evidence suggests that some of the increase in credit scores over the cohorts can be explained as adjustment for the increased riskiness in other attributes on the originations. This was particularly true for low levels of credit scores—resulting in a sharp deterioration of credit score performance in terms of our nonparametric measure. Significantly, once we control for other (riskier) attributes in the origination, our parametric credit score performance shows improvement over the cohorts. This would suggest an over-reliance on credit scoring—not only as a measure of credit risk but also as a means to offset risk on other origination attributes. In part, this reliance led to deterioration in loan performance even though average credit quality—as measured in terms of credit scores—actually improved over the years.

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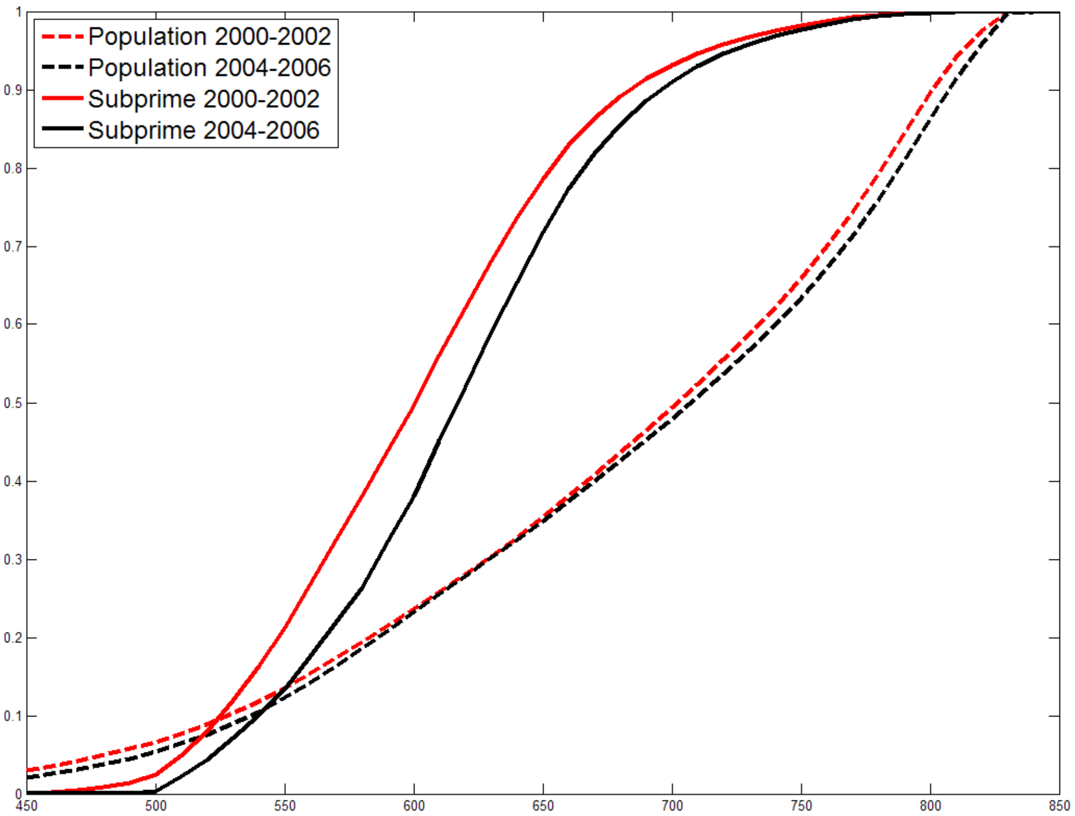

Figure 1: Plots showing the cumulative distribution function of credit scores during 2000-2002 and then during 2004-2006. The bold lines show the distribution of FICO scores on subprime originations. The dotted lines show the distribution of credit scores for U.S. individuals with credit reports.

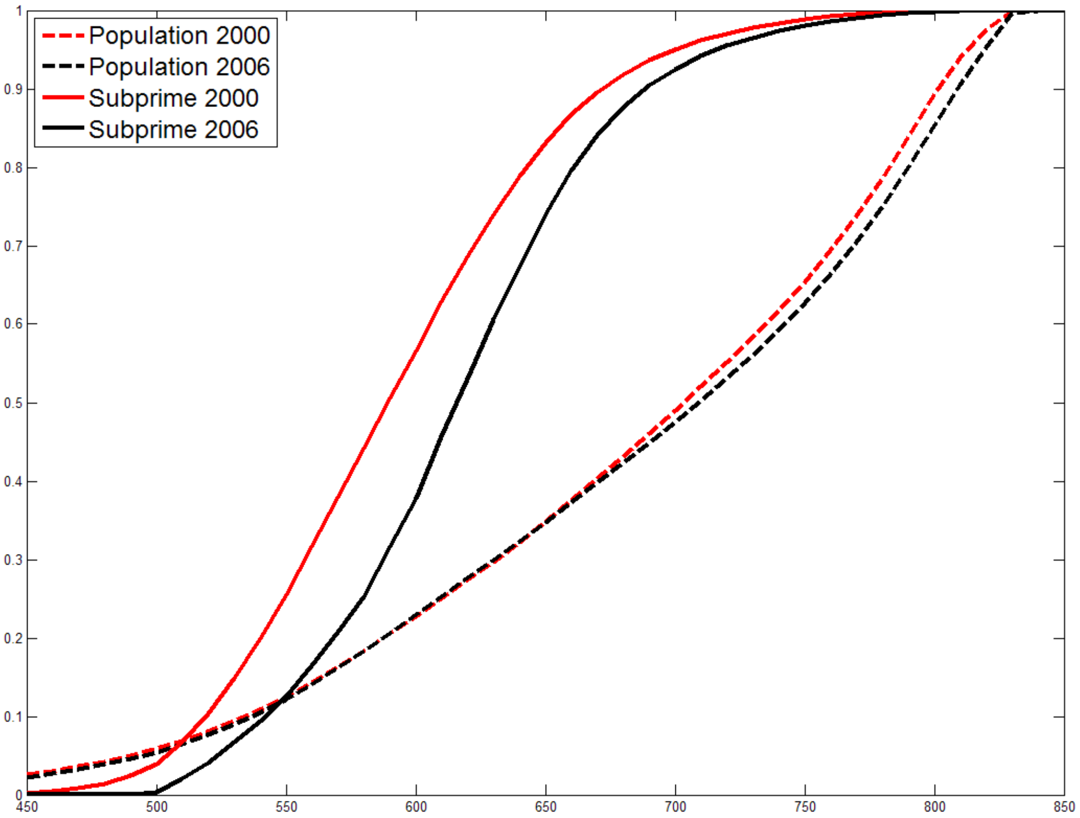

Figure 2: Plots showing the cumulative distribution function of credit scores for 2000 and then for 2006. The bold lines show the distribution of FICO scores on subprime originations. The dotted lines show the distribution of credit scores for U.S. individuals with credit reports.

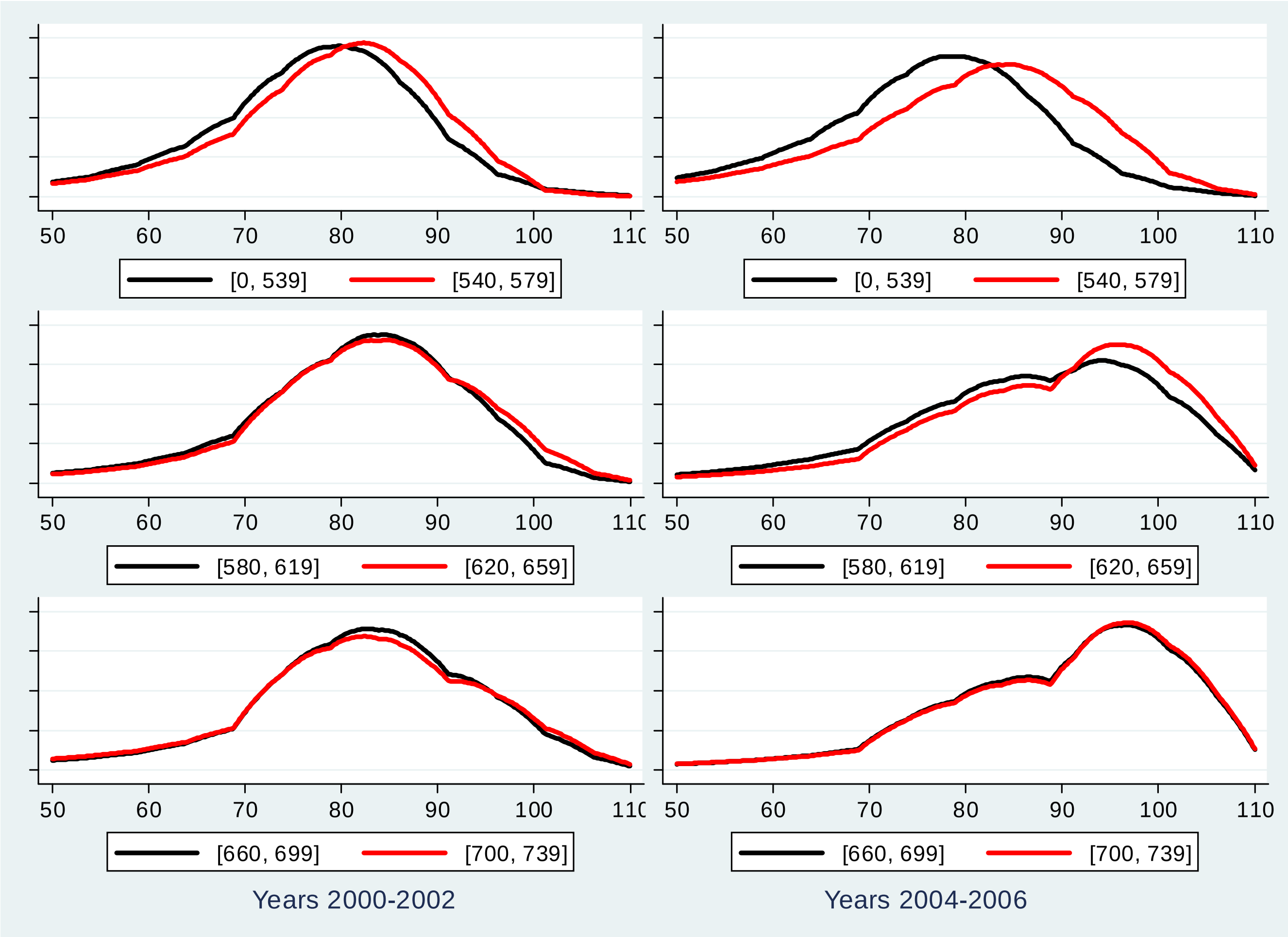

Figure 3: Kernel density plots of the LTV distribution for originations in adjacent FICO score groups. For each plot, the LTV distribution for the higher FICO score group (in red) is shown alongside the LTV distribution for the lower FICO score group (in black). In each case, the distribution of LTV is truncated to lie in the interval [50,110] for ease of exposition.

Table 1. Anderson (1996) Test for First Order Stochastic Dominance

Under the null of common population distribution (no dominance), and the assumption of independence of the two samples, $\alpha = x_A/n_A - x_B/n_B$ is asymptotically normally distributed with mean zero. The hypothesis of first-order dominance of A over B requires that no element of α be significantly greater than zero while at least one element is significantly less. The numbers in parentheses below report the 95% confidence interval.

Panel A: Dominance of 2004-2006 over 2000-2002

FICO	Subprime (α)	Subprime (t-stat)	Population (α)	Population (t-stat)
1st Decile	-0.0485	-185.5142	-0.0137	-26.2394
	(-0.049; -0.048)		(-0.0148; -0.0126)	
2nd Decile	-0.0855	-236.4047	-0.0123	-20.1941
	(-0.0862; -0.0848)		(-0.0134; -0.0112)	
3rd Decile	-0.1167	-269.4439	-0.0078	-11.1864
	(-0.1175; -0.1159)		(-0.0092; -0.0064)	
4th Decile	-0.1163	-251.3688	-0.0046	-6.304
	(-0.1171; -0.1155)		(-0.006; -0.0032)	
5th Decile	-0.1055	-220.7806	-0.0022	-2.8359
	(-0.1065; -0.1045)		(-0.0037; -0.0007)	
6th Decile	-0.091	-195.1928	-0.0022	-2.748
	(-0.0919; -0.0901)		(-0.0038; -0.0006)	
7th Decile	-0.0677	-160.1472	-0.0048	-5.655
	(-0.0685; -0.0669)		(-0.0065; -0.0031)	
8th Decile	-0.0401	-116.3653	-0.0088	-10.1431
	(-0.0408; -0.0394)		(-0.0105; -0.0071)	
9th Decile	-0.0114	-57.2645	-0.0186	-21.2404
	(-0.0118; -0.011)		(-0.0203; -0.0169)	

Panel B: Stochastic Dominance of 2006 over 2000

FICO	Subprime (α)	Subprime (t-stat)	Population (α)	Population (t-stat)
1st Decile	-0.0818	-150.3504	-0.0038	-4.2225
	(-0.0829; -0.0807)		(-0.0055; -0.0021)	
2nd Decile	-0.1402	-187.5339	-0.0023	-2.193
	(-0.1416; -0.1388)		(-0.0044; -0.0002)	
3rd Decile	-0.189	-210.3891	-0.0003	-0.2237
	(-0.1908; -0.1872)		(-0.0027; 0.0021)	
4th Decile	-0.1891	-196.2621	0.0018	1.4277
	(-0.191; -0.1872)		(-0.0007; 0.0043)	
5th Decile	-0.1725	-174.0648	0.0031	2.2935
	(-0.1744; -0.1706)		(0.0005; 0.0057)	
6th Decile	-0.1333	-139.3142	0.0026	1.8627
	(-0.1352; -0.1314)		(-0.0002; 0.0054)	
7th Decile	-0.0906	-106.6017	-0.001	-0.6988
	(-0.0923; -0.0889)		(-0.0039; 0.0019)	
8th Decile	-0.0477	-71.2206	-0.0074	-4.9046
	(-0.049; -0.0464)		(-0.0104; -0.0044)	
9th Decile	-0.0126	-35.869	-0.0224	-14.7166
	(-0.0133; -0.0119)		(-0.0254; -0.0194)	

Table 2: FICO distributions

Borrower credit score at the time of loan origination is denoted by *FICO* (an industry standard developed by the Fair Isaac Corporation) with a number in the range 300-850. Loans coded by the source as with a non-blank documentation code are classified as *Full-doc* whereas all other originations are classified as *Low doc*. CLTV denotes the combined loan-to-value ratio on the origination.

Panel A: FICO distribution conditional on Documentation level on loan by cohort

	Full doc loans				Low-doc			
Cohort	< 620	620-659	660-719	≥ 720	< 620	620-659	660-719	≥ 720
1998	65.6	18.9	11.5	4.0	56.7	21.7	16.2	5.4
1999	67.4	18.4	10.9	3.3	53.3	22.1	18.2	6.4
2000	72.1	16.9	8.6	3.3	59.1	21.3	15.0	4.6
2001	67.8	18.8	10.0	3.3	50.2	25.2	18.7	5.8
2002	64.4	20.2	11.4	4.0	42.1	27.2	23.2	7.5
2003	58.4	22.2	13.9	5.4	37.3	27.4	26.2	9.1
2004	58.8	22.5	13.7	5.0	38.0	27.8	26.1	8.1
2005	58.8	23.2	13.6	4.5	34.5	30.1	26.9	8.6
2006	61.3	23.7	11.5	3.4	35.7	32.3	24.9	7.1

Panel B: Distribution of FICO scores conditional on CLTV by cohort

	CLTV ≤ 80				80 < CLTV ≤ 90				90 < CLTV ≤ 100			
Cohort	< 620	620-659	660-719	≥ 720	< 620	620-659	660-719	≥720	< 620	620-659	660-719	≥720
1998	63.2	18.4	12.5	5.9	61.9	21.1	12.5	4.4	52.2	22.2	17.2	8.4
1999	65.1	18.0	12.1	4.8	63.9	20.6	11.8	3.7	44.2	23.5	23.1	9.2
2000	70.4	16.5	9.9	3.2	71.1	18.1	8.6	2.2	48.1	29.3	17.1	5.5
2001	66.0	18.1	11.7	4.2	65.8	21.0	10.6	2.6	44.0	30.8	18.9	6.3
2002	62.0	19.3	13.6	5.2	61.8	21.9	12.9	3.4	30.2	36.1	25.2	8.5
2003	59.2	19.4	15.1	6.3	55.8	23.7	15.7	4.7	30.2	33.6	26.5	9.7
2004	61.9	19.2	13.7	5.2	57.5	23.2	15.0	4.3	31.0	32.9	27.0	9.0
2005	60.7	20.6	13.8	5.0	55.9	23.6	15.8	4.7	32.7	33.2	25.9	8.2
2006	65.1	19.7	11.4	3.9	60.4	23.3	12.9	3.4	34.8	35.4	23.3	6.4

Table 3: Credit Score (FICO) Regression

OLS estimates with borrower FICO score as the left-hand side variable and other borrower characteristics as regressors. In addition to the variables shown here, we control for property type (dummies for single-family residence, condo, townhouse, co-operative, etc), property location (dummies for the state in which the property is located) and loan source (dummies for broker, realtor, wholesale, retail etc.) and number of units in the property. Home Value nth Quartile is a dummy that equals one if the value of the property lies in the n-th quartile of all property values in the data and zero otherwise.

Panel A: By Cohort

	Cohort						
	2000	2001	2002	2003	2004	2005	2006
Intercept	648.44***	635.03***	608.49***	622.87***	645.62***	648.62***	609.94***
CLTV	0.21***	0.27***	0.47***	0.57***	0.82***	0.93***	1.09***
Full-Doc	-10.78***	-18.55***	-18.07***	-19.93***	-24.4***	-21.22***	-19.58***
Owner Occupied	-26.21***	-27.62***	-27.68***	-27.22***	-31.61***	-36.13***	-36.7***
Second Home	-12.5***	-9.93***	-3.01***	-3.97***	-10.09***	-12.83***	-11.84***
Refinance (Cash Out)	-5.9***	-10.02***	-14.56***	-13.17***	-23.61***	-26.35***	-25.31***
Refinance (No Cash Out)	-6.31***	-14.88***	-18.86***	-16.27***	-19.69***	-18.53***	-15.13***
Home Value First Quartile	-7.97***	-5.93***	-6.56***	-12.48***	-12.51***	-15.69***	-16.22***
Home Value Second Quartile	-5.17***	-4.63***	-5.23***	-8.94***	-9.15***	-10.98***	-10.9***
Home Value Third Quartile	-3.44***	-2.86***	-3.6***	-5.47***	-7.35***	-8.76***	-8.26***
Adjusted R-Squared	0.0393	0.0642	0.0870	0.0959	0.1646	0.1932	0.2268

Panel B: For all Cohorts (full sample)

	(1)	(2)
Intercept	616.09***	617.07***
Dummy for 2003-2006 cohorts	9.39***	
Dummy for 2004-2006 cohorts		3.79***
CLTV	0.82***	0.85***
Full-Doc	-19.92***	-20.33***
Owner Occupied	-34.45***	-34.44***
Second Home	-8.88***	-9***
Refinance (Cash Out)	-20.86***	-20.55***
Refinance (No Cash Out)	-13.07***	-13.19***
Home Value First Quartile	-14.17***	-13.47***
Home Value Second Quartile	-9.39***	-8.91***
Home Value Third Quartile	-7.3***	-7.09***
Adjusted R-Squared	0.1829	0.1779

Table 4: Increase in Survival Probabilities for Improvements in FICO score (groups)
The numbers show a percentage point increase in the Kaplan-Meier survival probabilities (for the first two years after origination) of originations in the higher FICO score group relative to those in the lower FICO score group.

Panel A.
The FICO score groups used below are “less than 540", “540-579", “580-619" … “700-739" and “greater than or equal to 740".

	Cohort						
Improvement in FICO score	2000	2001	2002	2003	2004	2005	2006
[< 540] to [540 – 579]	8.17	7.46	5.75	4.17	4.73	4.95	5.52
[540 – 579] to [580 – 619]	4.45	4.24	3.57	3.38	3.88	3.04	1.68
[580 – 619] to [620 – 659]	3.35	2.87	2.91	3.24	4.48	4.33	2.10
[620 – 659] to [660 – 699]	1.95	2.37	2.54	2.43	2.79	4.59	4.64
[660 – 699] to [700 – 739]	1.41	1.44	1.96	1.52	1.50	2.56	4.14
[700 – 739] to [≥740]	0.91	1.10	0.81	0.84	1.30	2.57	7.84
Average All	3.37	3.25	2.92	2.60	3.11	3.68	4.32

Panel B.
The FICO score groups used below are "less than 541", "541-560", "561-580" … "721-740" and "greater than or equal to 741".

	Cohort						
Improvement in FICO score	2000	2001	2002	2003	2004	2005	2006
[< 541] to [541 – 560]	6.68	6.16	4.53	3.10	3.47	3.70	3.90
[541 – 560] to [561 – 580]	2.82	2.50	2.36	1.97	2.30	2.02	2.76
[561 – 580] to [581 – 600]	2.16	2.31	1.80	1.55	1.55	0.80	-0.27
[581 – 600] to [611 – 620]	1.78	1.22	1.10	1.56	2.29	2.73	1.40
[611 – 620] to [621 – 640]	1.94	1.67	1.69	1.73	2.62	1.83	0.84
[621 – 640] to [641 – 660]	1.16	1.52	1.62	1.83	1.78	2.78	1.53
[641 – 640] to [661 – 680]	1.07	1.16	1.30	1.10	1.38	2.23	3.01
[661 – 640] to [681 – 700]	0.58	0.78	0.90	0.84	1.05	1.94	1.99
[681 – 640] to [711 – 720]	0.94	0.89	1.19	0.67	0.62	0.94	2.17
[711 – 640] to [721 – 740]	0.00	0.25	0.41	0.71	0.60	1.19	1.91
[721 – 740] to [≥741]	1.06	0.90	0.56	0.47	0.93	1.79	6.71
Average All	1.83	1.76	1.59	1.41	1.69	2.00	2.36

Table 5: Estimated Cox proportional hazard rate regression:

This table reports the estimated hazard ratios for the Cox proportional hazard regressions conducted for all loans originated in a given calendar year. FICO scores below 540 are treated as the base group. We control for property type (dummies for single-family residence, condo, townhouse, co-operative, etc), property location (dummies for the state in which the property is located) and loan source (dummies for broker, realtor, wholesale, retail etc.). *Home Value n*th *Quartile* is a dummy that equals one if the value of the property lies in the *n*-th quartile of all property values in the data and zero otherwise.

	Cohort						
	2000	2001	2002	2003	2004	2005	2006
FICO: 540-579	0.665***	0.684***	0.666***	0.676***	0.677***	0.702***	0.721***
FICO: 580-619	0.498***	0.503***	0.475***	0.457***	0.459***	0.492***	0.515***
FICO: 620-659	0.358***	0.36***	0.335***	0.292***	0.294***	0.338***	0.366***
FICO: 660-699	0.254***	0.237***	0.215***	0.173***	0.19***	0.239***	0.274***
FICO: 700-739	0.18***	0.159***	0.136***	0.106***	0.129***	0.185***	0.224***
FICO: >=740	0.145***	0.101***	0.095***	0.069***	0.082***	0.134***	0.169***
CLTV	1.009***	1.014***	1.015***	1.021***	1.026***	1.03***	1.032***
Full-Documentation	0.835***	0.809***	0.778***	0.693***	0.708***	0.655***	0.617***
Owner Occupied	0.785***	0.753***	0.759***	0.695***	0.657***	0.66***	0.639***
Second Home	0.636***	0.558***	0.572***	0.609***	0.607***	0.691***	0.668***
Refinance (Cash Out)	0.817***	0.74***	0.713***	0.664***	0.674***	0.708***	0.833***
Refinance (No Cash Out)	0.972**	0.866***	0.804***	0.679***	0.656***	0.694***	0.798***
Home Value First Quartile	0.912***	0.914***	0.914***	0.932***	0.789***	0.644***	0.583***
Home Value Second Quartile	0.933***	0.879***	0.879***	0.891***	0.773***	0.654***	0.631***
Home Value Third Quartile	0.933***	0.889***	0.864***	0.881***	0.817***	0.817***	0.805***
LR test	26943	33172	52179	96372	150783	218724	227077
(p-value)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Table 6: Parametric Estimates of Increase in Survival Probabilities for transitions between different FICO score groups

The numbers show parametric estimates of percentage point increases in estimated survival probabilities (for the first two years after origination) of originations in the higher FICO score group relative to those in the lower FICO score group. The estimated probabilities are calculated using the Cox proportional hazard model such as the one shown in Table 3.

Panel A.

The FICO score groups used below are “less than 540", “540-579", “580-619" … “700-739" and “greater than or equal to 740".

	Cohort						
Improvement in FICO score	2000	2001	2002	2003	2004	2005	2006
[< 540] to [540 – 579]	7.00	6.28	6.22	5.33	6.46	7.53	10.19
[540 – 579] to [580 – 619]	3.71	3.80	3.76	3.77	4.62	5.77	8.68
[580 – 619] to [620 – 659]	3.21	3.13	2.87	2.96	3.66	4.45	6.92
[620 – 659] to [660 – 699]	2.48	2.77	2.51	2.19	2.38	2.97	4.62
[660 – 699] to [700 – 739]	1.80	1.81	1.70	1.25	1.42	1.68	2.58
[700 – 739] to [≥740]	0.84	1.34	0.89	0.69	1.12	1.60	2.95
Average All	3.17	3.19	2.99	2.70	3.28	4.00	5.99

Panel B.

The FICO score groups used below are "less than 541", "541-560", "561-580" … "721-740" and "greater than or equal to 741".

	Cohort						
Improvement in FICO score	2000	2001	2002	2003	2004	2005	2006
[< 541] to [541 – 560]	5.75	5.12	4.85	4.08	5.04	5.72	7.52
[541 – 560] to [561 – 580]	2.52	2.30	2.62	2.37	2.72	3.24	5.10
[561 – 580] to [581 – 600]	1.84	1.85	1.69	1.71	2.15	2.85	4.15
[581 – 600] to [611 – 620]	1.26	1.60	1.63	1.78	2.28	2.86	4.17
[611 – 620] to [621 – 640]	2.12	1.77	1.41	1.52	1.92	2.20	3.72
[621 – 640] to [641 – 660]	1.13	1.48	1.62	1.41	1.49	2.04	2.94
[641 – 640] to [661 – 680]	1.59	1.50	1.26	1.08	1.18	1.42	2.40
[661 – 640] to [681 – 700]	0.55	1.00	0.88	0.81	0.98	1.12	1.58
[681 – 640] to [711 – 720]	1.21	0.92	0.92	0.55	0.62	0.74	1.25
[711 – 640] to [721 – 740]	0.59	0.74	0.56	0.50	0.51	0.68	0.95
[721 – 740] to [≥741]	0.57	0.83	0.55	0.39	0.80	1.19	2.31
Average All	1.74	1.74	1.63	1.47	1.79	2.19	3.28

APPENDIX

This appendix shows that results in Table 4 and Table 6 are robust to different groupings of credit scores.

Table A.4: Increase in Survival Probabilities for Improvements in FICO score (groups)
The numbers show a percentage point increase in the Kaplan-Meier survival probabilities (for the first two years after origination) of originations in the higher FICO score group relative to those in the lower FICO score group.

Panel A: The FICO score groups used below are “less than 520”, “520-559", “560-599" … “680-719" and “greater than or equal to 720".

	Cohort						
Improvement in FICO score	2000	2001	2002	2003	2004	2005	2006
[< 520] to [520 – 559]	8.54	7.88	6.60	3.96	4.40	4.46	4.67
[520 – 559] to [560 – 599]	5.36	5.11	4.17	3.56	4.12	3.58	3.80
[560 – 599] to [600 – 639]	3.80	3.30	2.86	3.26	4.36	3.89	1.59
[600 – 639] to [640 – 679]	2.67	2.78	3.02	3.12	3.66	4.67	3.11
[640 – 679] to [680 – 719]	1.62	1.83	2.15	1.79	2.14	3.63	4.72
[680 – 719] to [≥720]	1.16	1.42	1.51	1.37	1.51	2.84	7.16
Average All	3.86	3.72	3.38	2.84	3.36	3.85	4.17

Panel B: The FICO score groups used below are "less than 521", "521-560", "561-600" … "681-720" and "greater than or equal to 721".

	Cohort						
Improvement in FICO score	2000	2001	2002	2003	2004	2005	2006
[< 521] to [521 – 560]	8.45	7.90	6.54	3.83	4.38	4.49	4.62
[521 – 560] to [561 – 600]	5.34	5.10	4.16	3.62	4.11	3.49	3.67
[561 – 600] to [601 – 640]	3.71	3.13	2.77	3.15	4.28	3.88	1.63
[601 – 640] to [641 – 680]	2.66	2.88	3.06	3.19	3.71	4.74	3.24
[641 – 680] to [681 – 720]	1.59	1.82	2.14	1.75	2.08	3.60	4.63
[681 – 720] to [≥721]	1.17	1.32	1.45	1.38	1.53	2.82	7.21
Average All	3.82	3.69	3.35	2.82	3.35	3.83	4.17

Panel C: The FICO score groups used below are "less than 540", "540-579", "580-619" … "700-739" and "greater than or equal to 740".

	Cohort						
Improvement in FICO score	2000	2001	2002	2003	2004	2005	2006
[< 540] to [540 – 579]	8.17	7.46	5.75	4.17	4.73	4.95	5.52
[540 – 579] to [580 – 619]	4.45	4.24	3.57	3.38	3.88	3.04	1.68
[580 – 619] to [620 – 659]	3.35	2.87	2.91	3.24	4.48	4.33	2.10
[620 – 659] to [660 – 699]	1.95	2.37	2.54	2.43	2.79	4.59	4.64
[660 – 699] to [700 – 739]	1.41	1.44	1.96	1.52	1.50	2.56	4.14
[700 – 739] to [≥740]	0.91	1.10	0.81	0.84	1.30	2.57	7.84
Average All	3.37	3.25	2.92	2.60	3.11	3.68	4.32

Panel D: The FICO score groups used below are "less than 541", "541-580", "581-620" … "711-740" and "greater than or equal to 741".

	Cohort						
Improvement in FICO score	2000	2001	2002	2003	2004	2005	2006
[< 541] to [541 – 580]	8.13	7.47	5.77	4.15	4.71	4.82	5.45
[541 – 580] to [581 – 620]	4.42	4.19	3.54	3.40	3.97	3.18	1.70
[581 – 620] to [621 – 660]	3.33	2.87	2.89	3.21	4.41	4.38	2.20
[621 – 660] to [661 – 700]	1.94	2.31	2.55	2.42	2.75	4.51	4.60
[661 – 700] to [711 – 740]	1.29	1.47	1.89	1.45	1.48	2.56	4.14
[711 – 740] to [≥741]	1.06	1.05	0.81	0.88	1.29	2.50	7.89
Average All	3.36	3.22	2.91	2.59	3.10	3.66	4.33

Panel E: The FICO score groups used below are "less than 540", "540-559", "560-579" … "720-739" and "greater than or equal to 740".

	Cohort						
Improvement in FICO score	2000	2001	2002	2003	2004	2005	2006
[< 540] to [540 – 559]	6.77	6.17	4.50	3.16	3.46	3.71	3.88
[540 – 559] to [560 – 579]	2.72	2.47	2.37	1.87	2.38	2.24	2.94
[560 – 579] to [580 – 599]	2.26	2.34	1.83	1.59	1.42	0.51	-0.35
[580 – 599] to [600 – 619]	1.78	1.40	1.16	1.66	2.45	2.83	1.33
[600 – 619] to [620 – 639]	1.90	1.56	1.60	1.64	2.52	1.67	0.82
[620 – 639] to [640 – 659]	1.26	1.46	1.71	1.84	1.80	2.91	1.46
[640 – 639] to [660 – 679]	1.01	1.25	1.22	1.09	1.40	2.22	3.06
[660 – 639] to [680 – 699]	1.01	1.08	1.43	1.17	1.33	2.36	2.89
[680 – 639] to [700 – 719]	0.63	0.47	0.72	0.43	0.40	0.57	1.30
[700 – 639] to [720 – 739]	0.00	0.45	0.48	0.66	0.53	1.17	1.94
[720 – 739] to [≥740]	0.91	0.83	0.52	0.46	0.99	1.87	6.66
Average All	1.84	1.77	1.60	1.42	1.70	2.00	2.36

Panel F: The FICO score groups used below are "less than 541", "541-560", "561-580" … "721-740" and "greater than or equal to 741".

	Cohort						
Improvement in FICO score	2000	2001	2002	2003	2004	2005	2006
[< 541] to [541 – 560]	6.68	6.16	4.53	3.10	3.47	3.70	3.90
[541 – 560] to [561 – 580]	2.82	2.50	2.36	1.97	2.30	2.02	2.76
[561 – 580] to [581 – 600]	2.16	2.31	1.80	1.55	1.55	0.80	-0.27
[581 – 600] to [611 – 620]	1.78	1.22	1.10	1.56	2.29	2.73	1.40
[611 – 620] to [621 – 640]	1.94	1.67	1.69	1.73	2.62	1.83	0.84
[621 – 640] to [641 – 660]	1.16	1.52	1.62	1.83	1.78	2.78	1.53
[641 – 640] to [661 – 680]	1.07	1.16	1.30	1.10	1.38	2.23	3.01
[661 – 640] to [681 – 700]	0.58	0.78	0.90	0.84	1.05	1.94	1.99
[681 – 640] to [711 – 720]	0.94	0.89	1.19	0.67	0.62	0.94	2.17
[711 – 640] to [721 – 740]	0.00	0.25	0.41	0.71	0.60	1.19	1.91
[721 – 740] to [≥741]	1.06	0.90	0.56	0.47	0.93	1.79	6.71
Average All	1.83	1.76	1.59	1.41	1.69	2.00	2.36

Table A.6: Increase in Survival Probabilities for Improvements in FICO score (groups)
The numbers show parametric estimates of percentage point in the Kaplan-Meier survival probabilities (for the first two years after origination) of originations in the higher FICO score group relative to those in the lower FICO score group. The estimated probabilities are calculated after controlling for other attributes on the origination.

Panel A: The FICO score groups used below are “less than 520”, “520-559", “560-599" … “680-719" and “greater than or equal to 720".

	Cohort						
Improvement in FICO score	2000	2001	2002	2003	2004	2005	2006
[< 520] to [520 – 559]	6.47	5.36	5.50	4.27	5.61	6.17	8.05
[520 – 559] to [560 – 599]	4.22	4.26	4.18	4.03	4.77	6.03	9.19
[560 – 599] to [600 – 639]	2.82	2.98	2.78	3.05	3.71	4.65	7.13
[600 – 639] to [640 – 679]	2.64	2.74	2.51	2.36	2.63	3.40	5.35
[640 – 679] to [680 – 719]	1.69	2.05	1.77	1.52	1.70	2.03	3.27
[680 – 719] to [≥720]	1.49	1.66	1.29	0.94	1.20	1.67	2.86
Average All	3.22	3.18	3.01	2.70	3.27	3.99	5.98

Panel B: The FICO score groups used below are "less than 521", "521-560", "561-600" … "681-720" and "greater than or equal to 721".

	Cohort						
Improvement in FICO score	2000	2001	2002	2003	2004	2005	2006
[< 521] to [521 – 560]	6.45	5.52	5.57	4.30	5.63	6.25	8.16
[521 – 560] to [561 – 600]	4.26	4.16	4.14	4.03	4.76	6.03	9.18
[561 – 600] to [601 – 640]	2.83	3.02	2.78	3.03	3.71	4.63	7.09
[601 – 640] to [641 – 680]	2.56	2.71	2.51	2.37	2.61	3.36	5.29
[641 – 680] to [681 – 720]	1.77	2.03	1.76	1.49	1.68	2.01	3.23
[681 – 720] to [≥721]	1.45	1.61	1.26	0.95	1.20	1.66	2.85
Average All	3.22	3.18	3.00	2.70	3.27	3.99	5.97

Panel C: The FICO score groups used below are "less than 540", "540-579", "580-619" … "700-739" and "greater than or equal to 740".

	Cohort						
Improvement in FICO score	2000	2001	2002	2003	2004	2005	2006
[< 540] to [540 – 579]	7.00	6.28	6.22	5.33	6.46	7.53	10.19
[540 – 579] to [580 – 619]	3.71	3.80	3.76	3.77	4.62	5.77	8.68
[580 – 619] to [620 – 659]	3.21	3.13	2.87	2.96	3.66	4.45	6.92
[620 – 659] to [660 – 699]	2.48	2.77	2.51	2.19	2.38	2.97	4.62
[660 – 699] to [700 – 739]	1.80	1.81	1.70	1.25	1.42	1.68	2.58
[700 – 739] to [≥740]	0.84	1.34	0.89	0.69	1.12	1.60	2.95
Average All	3.17	3.19	2.99	2.70	3.28	4.00	5.99

Panel D: The FICO score groups used below are "less than 541", "541-580", "581-620" … "711-740" and "greater than or equal to 741".

	Cohort						
Improvement in FICO score	2000	2001	2002	2003	2004	2005	2006
[< 541] to [541 – 580]	7.05	6.33	6.24	5.37	6.51	7.56	10.38
[541 – 580] to [581 – 620]	3.66	3.76	3.76	3.76	4.63	5.79	8.62
[581 – 620] to [621 – 660]	3.25	3.17	2.88	2.95	3.63	4.42	6.86
[621 – 660] to [661 – 700]	2.45	2.72	2.51	2.18	2.38	2.95	4.53
[661 – 700] to [711 – 740]	1.78	1.84	1.67	1.23	1.40	1.66	2.59
[711 – 740] to [≥741]	0.94	1.27	0.89	0.69	1.11	1.62	2.95
Average All	3.19	3.18	2.99	2.70	3.28	4.00	5.99

Panel E: The FICO score groups used below are "less than 540", "540-559", "560-579" … "720-739" and "greater than or equal to 740".

	Cohort						
Improvement in FICO score	2000	2001	2002	2003	2004	2005	2006
[< 540] to [540 – 559]	5.76	5.06	4.82	4.02	4.96	5.70	7.29
[540 – 559] to [560 – 579]	2.39	2.32	2.63	2.40	2.77	3.22	5.16
[560 – 579] to [580 – 599]	1.97	1.93	1.71	1.71	2.11	2.80	4.13
[580 – 599] to [600 – 619]	1.21	1.50	1.59	1.79	2.29	2.90	4.22
[600 – 619] to [620 – 639]	2.06	1.78	1.43	1.53	1.95	2.21	3.74
[620 – 639] to [640 – 659]	1.25	1.47	1.60	1.40	1.51	2.08	2.99
[640 – 639] to [660 – 679]	1.60	1.55	1.27	1.07	1.16	1.42	2.45
[660 – 639] to [680 – 699]	0.45	1.00	0.88	0.84	1.01	1.14	1.63
[680 – 639] to [700 – 719]	1.25	0.88	0.93	0.55	0.62	0.74	1.18
[700 – 639] to [720 – 739]	0.72	0.78	0.59	0.49	0.51	0.69	1.04
[720 – 739] to [≥740]	0.40	0.88	0.53	0.40	0.80	1.17	2.27
Average All	1.73	1.74	1.64	1.47	1.79	2.19	3.28

Panel F: The FICO score groups used below are "less than 541", "541-560", "561-580" … "721-740" and "greater than or equal to 741".

	Cohort						
Improvement in FICO score	2000	2001	2002	2003	2004	2005	2006
[< 541] to [541 – 560]	5.75	5.12	4.85	4.08	5.04	5.72	7.52
[541 – 560] to [561 – 580]	2.52	2.30	2.62	2.37	2.72	3.24	5.10
[561 – 580] to [581 – 600]	1.84	1.85	1.69	1.71	2.15	2.85	4.15
[581 – 600] to [611 – 620]	1.26	1.60	1.63	1.78	2.28	2.86	4.17
[611 – 620] to [621 – 640]	2.12	1.77	1.41	1.52	1.92	2.20	3.72
[621 – 640] to [641 – 660]	1.13	1.48	1.62	1.41	1.49	2.04	2.94
[641 – 640] to [661 – 680]	1.59	1.50	1.26	1.08	1.18	1.42	2.40
[661 – 640] to [681 – 700]	0.55	1.00	0.88	0.81	0.98	1.12	1.58
[681 – 640] to [711 – 720]	1.21	0.92	0.92	0.55	0.62	0.74	1.25
[711 – 640] to [721 – 740]	0.59	0.74	0.56	0.50	0.51	0.68	0.95
[721 – 740] to [≥741]	0.57	0.83	0.55	0.39	0.80	1.19	2.31
Average All	1.74	1.74	1.63	1.47	1.79	2.19	3.28