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Abstract

Mortgage lenders have long used credit scores as a basis for estimating borrower risk. This risk differentiation is reflected in the coupon rate of the loan. In this study we examine the relationship between FICO scores and mortgage coupons to measure how effectively risk-based pricing has been used and to determine the dollar value of a favorable FICO score.

Our analysis shows that there is a significant relationship between FICO scores and coupon differentials although this relationship is not linear. That is, the penalty for being a weaker-than-average credit is greater than the benefit of being a stronger-than-average credit. We find that risk-based pricing has become more rational since 1998. The data show a trend towards greater differentiation in mortgage coupons over time. This reflects the improved efficiencies in differentiating along the credit spectrum.

Introduction

Access to mortgage credit at a fair and reasonable cost is a fundamental requirement of participation in the American dream of home ownership. The availability of mortgage credit in the U.S. grew dramatically since the end of World War II coinciding with the growth in the secondary mortgage operations of the primary government sponsored enterprises tasked with supporting the development of mortgage finance. As access to home ownership grew so did the standardization of the credit characteristics required of borrowers wishing to tap into the burgeoning mortgage market and subsequently to enjoy more favorable mortgage interest rates.

Establishing Mortgage Credit Standards

Mortgage credit differentiation was initiated by the government-sponsored enterprises Fannie Mae and later Freddie Mac, which set standards for what were called "prime" residential mortgage loans or "A" quality loans which were, by definition, the least likely to default. The agencies are further constrained in purchasing or securitizing only those loans that conformed to the size limits established each year by the Federal Housing Finance Board. Any loan that didn't meet agency definitions for quality or size was considered non-conforming. In fact if a loan was non-conforming for credit reasons, it was considered a sub-prime loan and assigned any one of a number of quality designations from "A-" through "B", "C" and "D" with expected performance declining as one moved down the alphabet. Loans that were non-conforming due to size but otherwise met agency quality guidelines were called prime jumbo loan or "A" quality jumbo loans[1]. The mortgage banks, commercial banks, bond insurers, mortgage insurers and rating agencies that operated in this non-agency non-conforming market embraced the agency credit guidelines that graded loans according to A, A-, B, C, and D scale (Figure 1). Thus, the early pioneers in the secondary mortgage market initiated the concept of mortgage loan quality or loan credit grades. From their beginning the agencies differentiated between those borrowers who would be considered prime borrowers, by virtue of meeting the agency credit guidelines and who all received the same mortgage loan rate for comparable products, from those borrowers who did not meet the guidelines. The problem that was created by this "something other than prime" was

[1] Another category, Alternative "A" (Alt-A), appeared in the mid 1990's and has grown to be a significant part of the non-conforming volume. Standard & Poor's defines an Alt-A loan as a first-lien mortgage loan that generally conforms to traditional prime credit guidelines, although the LTV, loan documentation, occupancy status or property type, etc. may cause the loan not to qualify under standard underwriting programs (LEVELS™ 5.6 Glossary).

that one lender's "A-" looked a lot like another lender's "B". It became impossible to clearly differentiate between loan and underwriting quality when relying on these broad alphabetic categories.

The Emergence of the Non-Prime[2] Home Equity Market

Prior to 1995, borrowers that were deemed to be non-prime or something less than "A" quality who needed to borrow short term would find that they were required to post collateral at a time when prime borrowers were allowed to borrow short term on an unsecured basis. Thus the initial "home equity" loan market (true closed end second mortgages) developed as a non-prime credit market. This explains why today many lenders, investors, analysts and Wall Street investment bankers refer to home equity loans as non-prime by virtue of the credit status of the original borrower in this market. Even today with the second mortgage market growing significantly across all quality categories the industry still lives in the non-prime shadow. Figure 2 shows the growth of prime, non-prime and other mortgage products from 1998 to 2003, in billions of dollars. The original entrants in this market were the finance companies that originated non-prime loans for their own portfolios. This began to change after the collapse of the savings & loan industry in the late 1980's.

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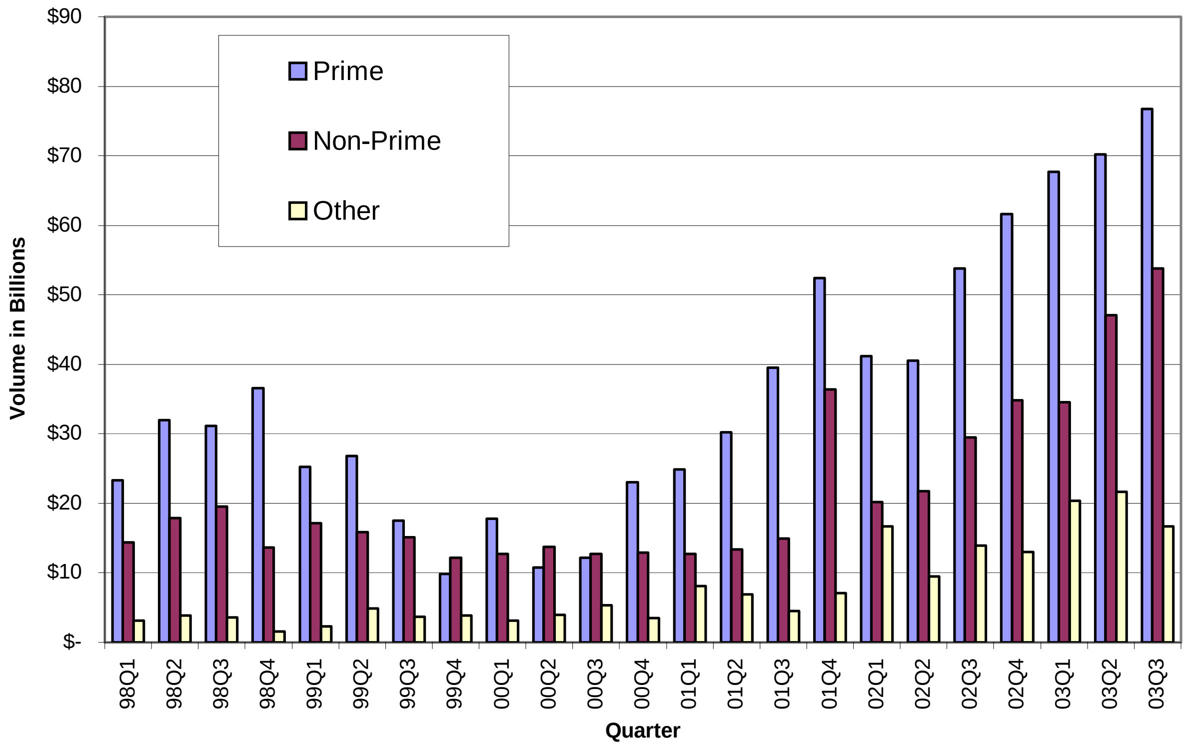
[2] Non-prime is a more descriptive term than sub-prime as it encompasses borrowers that exhibit "prime" performance behavior but nonetheless do not meet the agency definition for prime.

Figure 1: Standard & Poor's Loan Quality Guidelines

	A-	B	C	D
FICO (A > 660)	**633-659**	**612-632**	**590-611**	**520-589**
Mortgage Credit (past 12 months)	max. 2 × 30	max. 3 × 30	Max. 4 × 30 and max. 1 × 60	max. 5 × 30 and max. 2 × 60 and max. 1 × 90
Other Credit (past 12 months)	max. 2 × 30 and max. 1 × 60	max. 3 × 30 and max. 2 × 60	Max. 4 × 30 and max. 3 × 60	max. 4 × 30 and max. 3 × 60 and max. 2 × 90
Maximum Debt Ratio	45%	50%	55%	60%
Bankruptcies/ Notice of Default	None in the past 5 years	None in the past 3 years	None in the past 2 years	None in the past 1 year
Judgments not paid	<= $250	<= $500	<= $1,000	<= $1,500

In mid-1996 a review of pools rated by Standard & Poor's in late 1995 and early 1996 reveled the presence of a small but surprising proportion of loans in prime jumbo pools that were that clearly did not meet the "prime" loan performance profile. Standard & Poor's unique loan level analysis resulted in higher enhancement requirements in these securitizations unless the lower quality loans were removed. The development of risk sorting models like Standard & Poor's LEVELS™ allowed analysts to risk rank each loan included in pools submitted for ratings and contributed to the creation of execution alternatives for non-prime credits including Alt-A and non-prime loans. This coincided with the emergence of specialty lenders, which were focusing on procedures and programs to originate and securitize both first and second lien non-prime products.

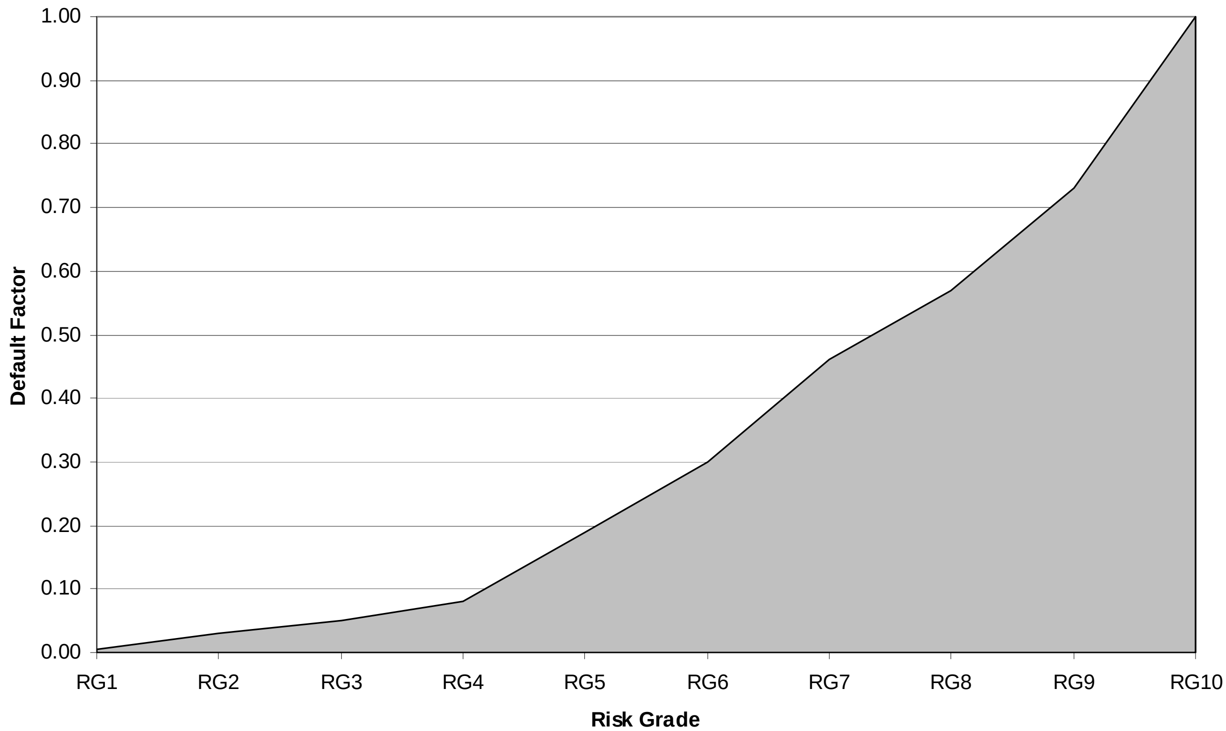
Figure 2: Growth In Markets 1998 to 2003



Alternative Measures of Risk

Until the mid 1990's all loans included in securitized pools in the non-conforming market were assumed to meet agency prime loan credit standards, i.e., all were assumed to be "A" quality loans and enjoyed the same relative mortgage interest rates (exclusive of buy-down and origination points). With the development of mortgage scoring models which evaluated a broad array of borrower loan and property characteristics it became possible for the first time to rank order mortgages from the least likely to default to the most likely. Standard & Poor's LEVELS™ was one of several models introduced in the mortgage market in the mid 1990's. It provided a loan ranking based on Standard & Poor's Risk Grades which bucketed loans into ten categories from Risk Grade 1 (RG1) representing the highest quality and the lowest relative probability of default to Risk Grade 10 (RG10) loans representing the highest risk and the highest probability of default. Today, loans ranked ordered in RG1 through RG5 reflect default probabilities consistent with those exhibited by pools of "A" quality loans originated from 1998 through 2003. Figure 3 plots the relative default factors, the probability of default for each RG relative to RG10. Thus the probability of default for a RG5 loan is about one-fifth that of a RG10 loan.

Figure 3: Standard & Poor's Risk Grade Default Factors (Relative to RG10)



The significance of creating a consistent means of stratifying risk in the non-conforming market allowed participants to quantify borrower and loan risk in a way that allowed for more granular pricing. Where the agencies would provide one mortgage rate for all borrowers qualifying for a particular product, originators in the non-conforming market could provide a range of coupons dependent on their ability to stratify risk. Where the agencies lumped all "A" quality borrowers into one bucket, non-conforming lenders now had five differentiated categories of risk (using the Standard & Poor's Risk Grades, or any number of gradations using their own models or matrices) and could now provide meaningful risk-based pricing.

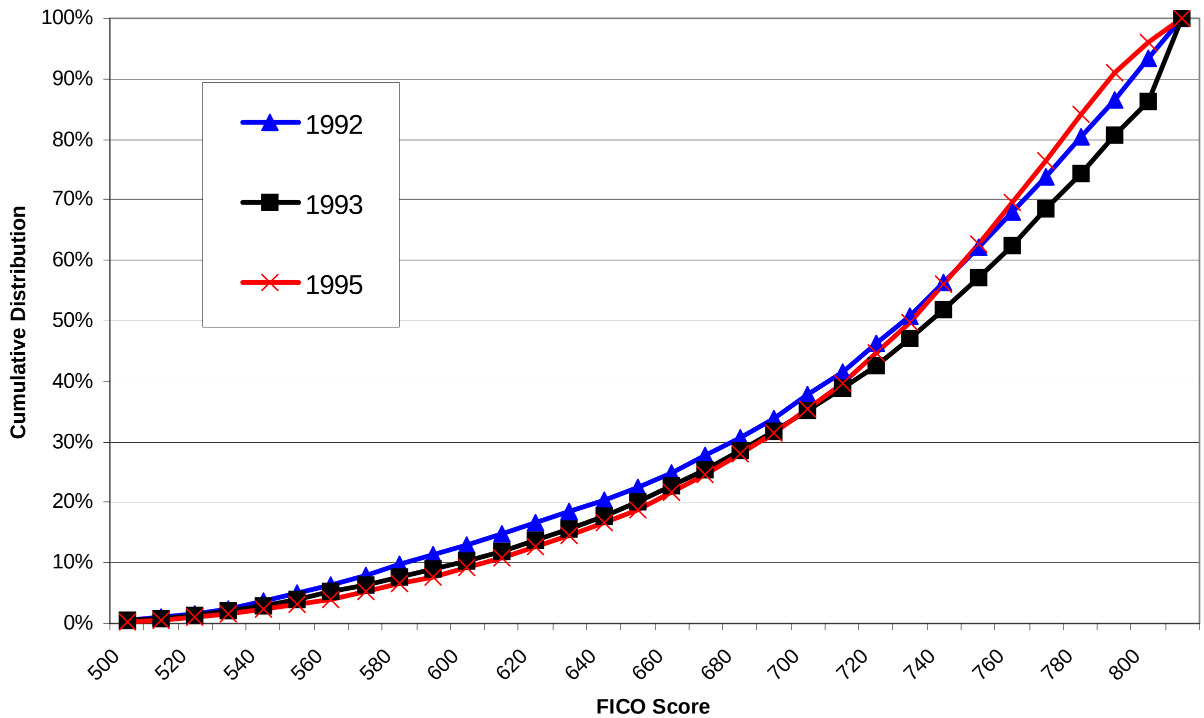
Mortgage Models and Critical Variables

In the course of building the first models, developers identified two key factors, loan-to-value (LTV) and consumer credit scores as the most significant variables contributing to the predictiveness of the models. Of these variables the consumer credit score created the most controversy.

The value of the consumer credit scores, developed by Fair Isaac's and Company (FICO), and readily available from the primary credit repositories (Experian, Trans Union, and Equifax), has been recognized for more than a decade by consumer credit providers. Standard & Poor's has reviewed consumer credit scores designed by Fair Issacs and provided as a FICO score by Experian, a BEACON Score by EquiFax and an IMPERICA score by Trans Union. These scores are used to measure the credit quality of individual borrowers. They incorporate the factors making up a borrower's credit history across a broad spectrum of trade lines including credit cards, auto finance, mortgage payments and other consumer obligations. FICO scores, in other words, are an indication of borrower's abilities to manage his or her finances.

The scores have several advantages when used in the models that have been developed and implemented over the past several years. The most significant advantages are their availability and their consistency of calculation by the three major repositories. Unlike scorecards that are developed by individual lenders FICO scores can be acquired at the time of an application for both mortgage credit or any other consumer credit by all lenders who subscribe to the service. In addition, because the FICO score is a calculation encompassing all the trade lines associated with a particular borrower's file the score has the advantage of being a leading indicator of mortgage performance. This is based on the rather intuitive behavior of individuals who are more inclined to begin to juggle their payments on their credit cards, their automobile payments, and other consumer payables before they begin to miss payments on their mortgages when they run into financial difficulties. This is particularly significant when one is reviewing portfolio performance on mortgages because trends in a borrower's FICO score can be a harbinger of difficulties that might occur in the immediate future in their mortgage payment ability. This information is useful not only in determining the future performance of a seasoned portfolio but it may also provide information in improving the servicing response on a particular loan and the initiation of appropriate steps to work with borrowers to try and mitigate any developments that may be forthcoming. Finally, the scores have been shown to stratify risk consistently over time (Figure 4).

Figure 4: Consumer Distribution By FICO Scores



While their advantages have driven their acceptance in the mortgage community, there are some notable disadvantages to the scores. These include the geographic disparity that often exists between an individual score record at any of the three repositories. This may create situations where the differences in score could have an impact on the credit availability and cost to individual borrowers. Standard & Poor's requirement for providing FICO scores was imbedded in its ratings criteria in 1998. It requires that lenders survey all the three repositories for borrower's scores and select the middle of the three scores if they are available on a particular borrower; it is this score that is used in the ratings process. The other significant disadvantage, the potential that scores were calculated with incorrect, missing or erroneous information, is more difficult to measure and ultimately correct (although the survey of all repositories is intended to mitigate the impact of missing information from a borrower's file).

The evolution in modeling residential mortgage risks that began in the U.S. in late 1995 has today penetrated every facet of the residential mortgage origination market. The use of credit scores is so pervasive for all mortgage products that the major originators have also incorporated mortgage scoring technologies in their underwriting process (Raiter, Gillis, Parisi, and Barnes, 1996; Raiter, 1997b). In 1998, when Standard & Poor's introduced its first version of the LEVELS™ model only 50% of the Prime mortgages submitted for rating included a credit score on the tape and less than 30% of the Non-prime mortgages incorporated a credit score in their underwriting data file. By the end of 2003, virtually 100% of the newly originated mortgages submitted for ratings incorporated credit scores and in some cases mortgage scores (Raiter and Warrack, 2002). These covered the complete gamut of residential mortgage products including Prime Jumbo First Lien mortgages, Non-prime First Lien mortgages, Alt-A credit first lien mortgages the same credit spectrum for second mortgages and High LTV mortgages.

Matrix Pricing: The First Step in Risk-Based Pricing

At the same time Standard & Poor's was incorporating FICO scores in it's rating methodology, it reviewed many of the concerns and significant issues raised by lenders, borrowers and regulators regarding the use of various consumer scores in the underwriting process. In particular the position of regulators with regard to the use of scores was studied closely. The Federal Reserve, in its bulletin titled 'Credit Risk, Credit Scoring, and the Performance of Home Mortgages', published in July, 1996 indicated that its study showed "Credit scores are useful engaging the relative levels of risk posed by both perspective mortgage borrowers and those with existing mortgages." The significance of the position taken by the regulators with regard to consumer credit cannot be overlooked as a contributing part of the evolution in risk-based pricing. Risk-based pricing is predicated on the ability to analyze application information in a manner that allowed for comprehensive risk ranking of relative quality among the borrowing applicants. It is no mystery that lenders immediately grasped the significance of the relationship between FICO scores and borrower LTV ratios in underwriting and pricing mortgage loans. In fact this risk reward relationship allowed lenders to get comfortable with the novel concept of moving out of the purely "prime" arena and into the emerging "non-prime" unknown.

Early proponents of risk-based pricing used these developments to build pricing matrices based on borrower FICO scores and loan LTV. Figure 5 represents a typical pricing sheet exhibiting the relationship between mortgage rate, FICO score and LTV as applied to the Alt-A and non-prime markets. The best "rate" for a 30 year, fixed, single-family mortgage is 8.875% (exclusive of points, if any) for a borrower with a FICO score of 660 or higher and an LTV of 65% or less. The "worst" rate is 12.125% for a borrower with a FICO score of 540 or less and an LTV of 65% or less. One should note that the lower the FICO score the lower the required LTV, in other words the lower a borrower's credit expectation, the greater the reliance on the collateral value by the lender. The matrix also highlights those borrowers who cannot get credit at any cost, i.e. those with low FICO scores and high LTV.

Figure 5: Sample Matrix Pricing Sheet

Credit Scores	**LTV Ranges**				
	90-85	**85-80**	**80-75**	**75-65**	**< 65**
> 660	9.750	9.250	9.125	9.000	8.875
651-660	9.875	9.375	9.250	9.125	9.000
641-650	10.000	9.500	9.375	9.250	9.125
631-640	10.250	9.875	9.750	9.625	9.500
621-630	10.375	10.000	9.875	9.750	9.625
611-620	10.500	10.125	10.000	9.875	9.750
601-610	-	10.375	10.250	10.125	10.000
591-600	-	10.500	10.375	10.250	10.125
581-590	-	10.625	10.500	10.375	13.250
571-580	-	-	-	11.000	10.875
561-570	-	-	-	11.125	11.000
551-560	-	-	-	11.250	11.125
541-550	-	-	-	-	12.000
<=540	-	-	-	-	12.125

Research conducted by Standard & Poor's suggests that not only has matrix pricing been rational but also that risk-based pricing has become more refined and expansive since it's implementation in 1998.

Data and Methodology

In this paper we consider the efficiency of risk-based pricing in the non-conforming mortgage market by studying the relative pricing of default risk. Default risk is measured by the borrower's FICO score and LTV at the time the loan was originated and pricing efficiency is measured by the mortgage rate of the loan relative to the average rate at that time. Standard & Poor's proprietary database includes loan-level data on more than 9.3 million residential mortgages that have been analyzed since 1998 and used as collateral for rated mortgage-backed securities. For this study we include loans that meet the following criteria:

- Fixed interest rate;
- 30-year original term;
- First liens;
- Secured by single family detached owner occupied properties; and
- First payment date of March, June, September, or December 1998-2003.

The data are divided into subsets for Prime, Non-prime and Alt-A loans and we model each subset separately. These constraints minimize any potential variation in mortgage interest rates caused by factors other than those of particular interest for this study. The numbers of loans that make up the underlying data are 71,269 for Prime, 53,941 for Alt-A, and 86,487 for Non-prime. We segregate the data into FICO score groupings and LTV groupings and calculate the average mortgage coupon for each group and origination period. We also extract the average mortgage loan size; loan balance data allow us to study the value of varying FICO scores.

The FICO groups are defined as: 741-760, 721-740, 701-720, 681-700, 661-680, 641-660, 621-640, 601-620, and 581-600, and the LTV groups are defined as: 69-71, 74-76, 79-81, 84-86, 89-90, and 94-96. Thus each period's data creates a 9 x 6 two-way table where the value in each cell of the table represents the average mortgage coupon for the loans in that group.

We fit a two-factor analysis of variance (ANOVA) model to the data. The two-factor ANOVA model has the form

$$Y_{ijk} = \mu_{..} + \alpha_i + \beta_j + \varepsilon_{ijk} \,,$$

where Y_{ijk} is the *k*-th observation for factor *A* at level *i*, and factor *B* at level *j*, $\mu_{..}$, is the grand mean, α_i and β_j are the effect of *A* and *B* at levels *i* and *j*, respectively, and the ε_{ijk} are error terms.

Since some of the cells for some periods have no observations the number of observations in each cell for the aggregate data is not equal resulting in an unbalanced design; these counts are summarized in Figures 6, 7, and 8 for Prime, Alt-A and Non-prime, respectively. Unequal sample sizes increase the complexity of two-factor ANOVA models and the usual ANOVA equations are inappropriate. Furthermore, the factor sums of squares are no longer orthogonal. To overcome this we use a regression approach to obtain the proper sums of squares for testing factor effects under unequal sample sizes. The regression model with nine FICO levels and six LTV levels is

$$Y_{ijk} = \mu_{..} + \alpha_1 X_{ijk1} + \alpha_2 X_{ijk2} + \cdots + \alpha_8 X_{ijk8} + \beta_1 X_{ijk9} + \cdots + \beta_5 X_{ijk13} + \varepsilon_{ijk} \,,$$

where

$$X_{ijkt} = \begin{cases} 1, \text{ if level } t \text{ of FICO} \\ -1, \text{ if level 9 of FICO}, \quad \text{for } t = 1, \ldots, 8, \\ 0, \text{ otherwise} \end{cases}$$

and

$$X_{ijkt} = \begin{cases} 1, \text{ if level } s \text{ of LTV} \\ -1, \text{ if level 6 of LTV}, \quad \text{for } s = 1, \ldots, 5, \text{ and } t = s + 8. \\ 0, \text{ otherwise} \end{cases}$$

The α_i, for $i = 1, \ldots, 8$, are the coefficients for each of the eight indicators associated with FICO, and the β_j, for $j = 1, \ldots, 5$, are the coefficients for each of the five indicators associated with LTV.

ANOVA models are especially useful in studying the impact that explanatory categorical variables have on a dependent variable of interest. Furthermore, ANOVA models do not require making any assumptions about the nature of the statistical relationship between the dependent and in dependent variables (Neter, Wasserman, and Kutner, 1990). And while FICO scores and LTVs are measured on a continuous scale our choice of grouping the data makes them nominal, or categorical. We use a cell means model in the analysis of the aggregate data with each cell having up to 24 observations (one for each quarter-end from 1998 through 2003). In the annual comparisons we have up to four observations in each cell. The cell means model is useful in applications involving unbalanced designs (Hocking, 1996).

Figure 6: Cell Counts for the Aggregate Model – Prime Loans

FICO Score	Loan-to-Value (LTV)					
	69-70	**74-76**	**79-81**	**84-86**	**89-91**	**94-96**
741-760	24	24	24	24	24	24
721-740	24	24	24	24	24	24
701-720	24	24	24	24	24	24
681-700	24	24	24	24	24	24
661-680	24	24	24	24	24	24
641-660	24	24	24	24	24	24
621-640	23	24	24	23	24	24
601-620	21	22	24	16	22	22
581-600	16	19	22	15	20	13

Figure 7: Cell Counts for the Aggregate Model – Alt-A Loans

FICO Score	Loan-to-Value (LTV)					
	69-70	**74-76**	**79-81**	**84-86**	**89-91**	**94-96**
741-760	24	24	24	22	24	24
721-740	24	24	24	23	24	24
701-720	24	24	24	24	24	24
681-700	24	24	24	24	24	24
661-680	24	24	24	24	24	24
641-660	24	24	24	24	24	24
621-640	24	24	24	23	24	24
601-620	22	24	24	22	23	22
581-600	11	19	23	17	21	17

The results from the fitted models allow us to study the main effects of FICO scores on the average coupon rate of the loans. Similarly we study the LTV impact and the effect of the interaction of FICO and LTV. An advantage of ANOVA models is the ability to collapse the model across a single variable to measure the impact that variable has on the dependent variable.

By calculating an amortization schedule based on the average loan size and the interest rate differentials resulting from the FICO score analysis we can estimate the cost in dollars that correspond to a 20 point change in FICO score. The interest payments on loans to borrowers with different FICO scores can vary by thousands of dollars over the life of the loan. These cost differences are quantified as the dollar value of 20 FICO points (DVOF).

Figure 8: Cell Counts for the Aggregate Model – Non-prime Loans

FICO Score	Loan-to-Value (LTV)					
	69-70	**74-76**	**79-81**	**84-86**	**89-91**	**94-96**
741-760	23	24	24	24	24	23
721-740	24	24	24	24	24	22
701-720	24	24	24	24	24	24
681-700	24	24	24	24	24	24
661-680	24	24	24	24	24	24
641-660	24	24	24	24	24	24
621-640	24	24	24	24	24	24
601-620	24	24	24	24	24	24
581-600	24	24	24	24	24	24

Analysis and Results

Risk-Based Pricing

Our modeling results show that FICO score and LTV are both significant variables in pricing mortgage risk at the time of loan origination. The results are consistent with those from the various mortgage-scoring models developed since the mid-1990s. These results hold for all three of the product types studied – Prime, Alt-A and Non-prime loans. We are most interested in the main effect of FICO score; these parameter estimates appear in Figure 9.

This table is interpreted as follows: the first column is the variable name, the second column is a description of the FICO range for that variable, the third column is the coefficient from the fitted model (in basis points) for Prime loans. These estimates give the main effect of FICO score on the average mortgage coupon rate. The next column is the corresponding *p*-value, where $p \le 0.05$ indicates the variable is statistically significant at a 0.05 level of significance. Columns 3 and 4 are repeated for Alt-A and Non-prime. The results in Figure 9 indicate that, all else being equal, the mortgage coupon charged on a Prime loan to a borrower with a FICO score in the range 741-760 would be about 18bps lower than the average coupon. On the other hand, a borrower with a FICO score in the range of 581-600 would pay about 32bps higher than the average coupon for the same loan. The changes in coupon corresponding to a 20-point change in FICO are not symmetric, and that the increase in rate for a lower FICO score is greater than the decrease in rate for a higher FICO score.

Figure 9: Estimated Model Parameters – Aggregate Data (FICO Score only)

		Prime		Alt-A		Non-prime	
Parameter	**FICO Score**	**Est. (bps)**	**p-value**	**Est. (bps)**	**p-value**	**Est. (bps)**	**p-value**
FICO1	741-760	-17.8	0.000	-36.2	0.000	-66.4	0.000
FICO2	721-740	-11.6	0.000	-28.7	0.000	-49.0	0.000
FICO3	701-720	-10.1	0.000	-22.0	0.000	-37.5	0.000
FICO4	681-700	-7.1	0.006	-14.6	0.000	-23.2	0.000
FICO5	661-680	-0.2	0.944	-8.6	0.000	-6.4	0.025
FICO6	641-660	0.7	0.793	-0.5	0.852	10.7	0.000
FICO7	621-640	0.9	0.718	10.8	0.000	32.1	0.000
FICO8	601-620	13.3	0.000	40.3	0.000	53.4	0.000
FICO9[3]	581-600	31.8	---	58.5	---	86.4	---

[3] There are nine factor levels that are represented by eight indicator variables that take on values {-1, 0, 1} to determine the nine levels. Thus the parameter for FICO9 is estimated from the coefficients for the eight FICO indicator variables. For example two indicator variables V_1 and V_2 are used to represent the three factor levels L_1, L_2, and L_3 as follows: $\begin{array}{c|cc} & V_1 & V_2 \\ \hline L_1 & 1 & 0 \\ L_2 & 0 & 1 \\ L_3 & -1 & -1 \end{array}$. In this case the coefficient for L_3 is $-V_1 - V_2$.

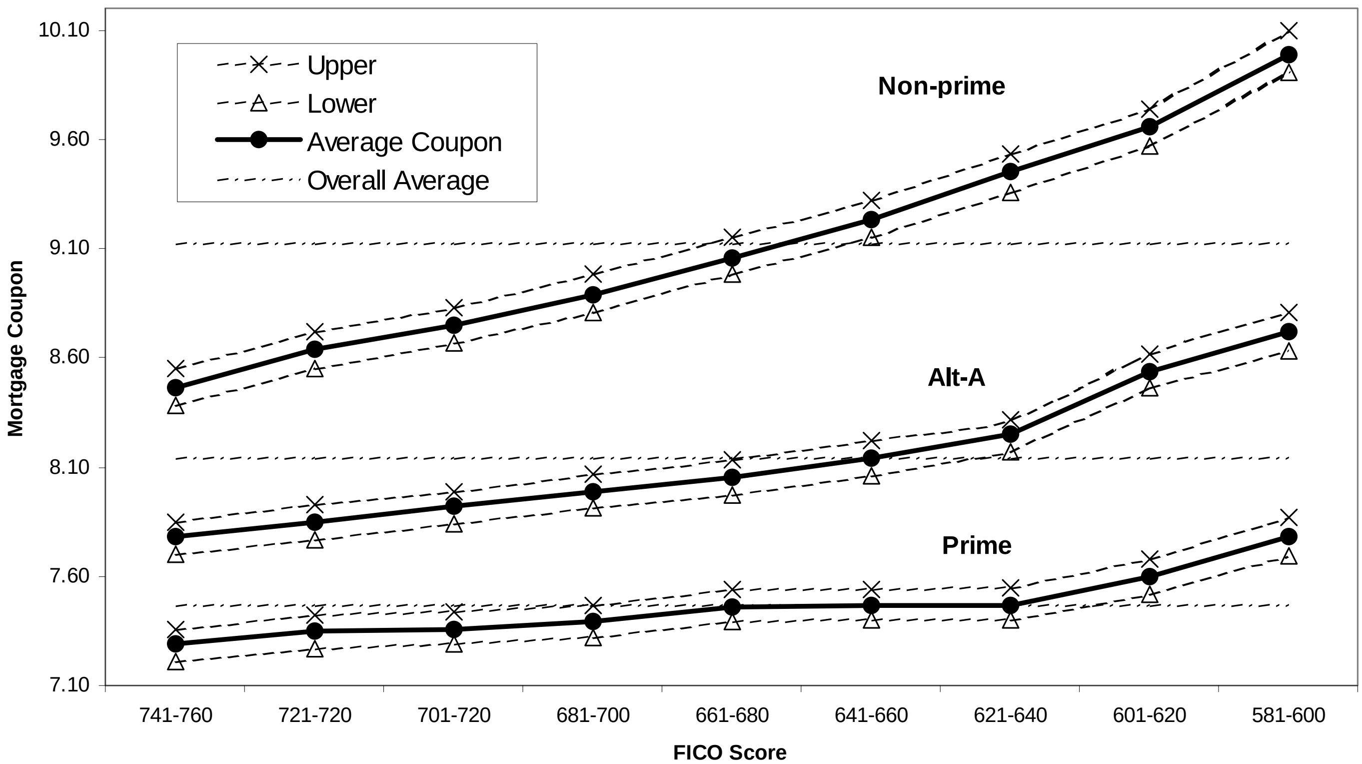
Note from Figure 9 that the estimated coefficients for FICO5, FICO6, and FICO7, are not statistically significant (with *p*-values well in excess of 0.05) indicating that there is no significant difference in mortgage rates for these three FICO groups for Prime loans. Also note that FICO6 is not significant for Alt-A loans but all of the estimates are significant for the Non-prime data.

These results are consistent with the results in Figure 10, which gives the average mortgage coupon and simultaneous 95% confidence intervals by FICO score. The average mortgage coupons and the confidence intervals are essentially identical for FICO scores between 621 and 680, for prime loans. We plot these results in Figure 11; note the relative risk-based pricing across the three product lines as well as across the FICO score levels.

Figure 10: Average Coupon with 95% Confidence Intervals by FICO Score (1998 – 2003)

FICO Score	Average	Lower Bound	Upper Bound
		Prime	
741-760	7.29	7.21	7.36
721-740	7.35	7.27	7.42
701-720	7.36	7.29	7.44
681-700	7.39	7.32	7.47
661-680	7.46	7.39	7.54
641-660	7.47	7.40	7.54
621-640	7.47	7.40	7.55
601-620	7.60	7.52	7.68
581-600	7.78	7.69	7.87
		Alt-A	
741-760	7.78	7.70	7.85
721-740	7.85	7.77	7.93
701-720	7.92	7.84	7.99
681-700	7.99	7.91	8.07
661-680	8.05	7.97	8.13
641-660	8.14	8.06	8.22
621-640	8.25	8.17	8.32
601-620	8.54	8.46	8.62
581-600	8.72	8.63	8.81
		Non-prime	
741-760	8.46	8.38	8.55
721-740	8.64	8.55	8.72
701-720	8.75	8.67	8.83
681-700	8.89	8.81	8.98
661-680	9.06	8.98	9.15
641-660	9.23	9.15	9.32
621-640	9.45	9.36	9.53
601-620	9.66	9.57	9.74
581-600	9.99	9.91	10.10

Figure 11: Graph of the Average Coupon and 95% Confidence Intervals by FICO Score



An implication of this is that risk-based pricing is more efficiently applied in the non-prime arena where lenders are more concerned about accurately pricing default risk in a market segment that is perceived to be of higher risk than in the prime or Alt-A loan arenas. This is visually evident from the graphs in Figure 11.

Comparing 1998 and 2003

We repeat the analysis for the 1998 data and the 2003 data separately to study how the impact of FICO has changed over time. These results provide us with insight as to how risk-based pricing has become more effectively used. Figure 12 summarizes these results for each product type and year. Several important observations can be made from the results in Figure 12. First we note that in 1998 there was no apparent rational pricing behavior in Prime and Alt-A lending (only 15bps spread between best and worst Prime credit, and 4bps for Alt-A). This is especially true for Alt-A for the change in mortgage coupon as FICO score changes is inconsistent and appears random. In contrast, rational risk-based pricing was used in the Non-prime lending practices in 1998 (128bps spread between best and worst Non-prime credit). Comparing the 1998 results with the 2003 results we note that risk-based pricing has become more rational across all of the three product types. It is also interesting to note that the differential between the best and worst credit scores is tightest for Prime (79bps), and widest for Non-prime (151bps).

Figure 12: Impact of FICO Score on Coupon 1998 vs. 2003

FICO	Prime		Alt-A		Non-prime	
	1998	**2003**	**1998**	**2003**	**1998**	**2003**
741-760	-0.111	-0.203	-0.061	-0.503	-0.536	-0.608
721-740	-0.080	-0.261	-0.035	-0.371	-0.560	-0.511
701-720	-0.043	-0.153	-0.022	-0.310	-0.260	-0.355
681-700	-0.034	-0.095	-0.041	-0.138	-0.213	-0.283
661-680	0.025	0.056	0.009	-0.009	0.013	-0.083
641-660	0.062	0.015	-0.020	0.131	0.065	0.086
621-640	0.065	0.014	0.066	0.177	0.315	0.305
601-620	0.076	0.039	0.127	0.492	0.432	0.543
581-600	0.040	0.588	-0.023	0.531	0.744	0.906

These differentials are greater when we consider the joint effects of FICO score and LTV. Recall the results above are for the effects of FICO scores across all LTV ranges. We find that a refinement into FICO groups and LTV groups exaggerate the separation between "best" and "worst" credit. For example, in Figure 13 we show the interest rate differentials by FICO score and LTV buckets for the 2003 Non-prime data.

Figure 13: Coupon Differentials (bps) by FICO and LTV (Non-prime loans 2003 data)

FICO	LTV					
	69-71	**74-76**	**79-81**	**84-86**	**89-91**	**94-96**
741-760	-87.8	-80.5	-76.0	-62.0	-42.7	-15.8
721-740	-78.1	-70.8	-66.3	-52.3	-33.0	-6.1
701-720	-62.5	-55.2	-50.7	-36.7	-17.4	9.5
681-700	-55.3	-48.0	-43.5	-29.5	-10.2	16.7
661-680	-35.3	-28.0	-23.5	-9.5	9.8	36.7
641-660	-18.4	-11.1	-6.6	7.4	26.7	53.6
621-640	3.5	10.8	15.3	29.3	48.6	75.5
601-620	27.3	34.6	39.1	53.1	72.4	99.3
581-600	63.6	70.9	75.4	89.4	108.7	135.6

Reading down any column (holding LTV constant) in Figure 13 we note that the numbers are monotonically increasing as risk increases. Similarly reading across any row (holding FICO score constant) the numbers are monotonically increasing as risk increases. As we move through the matrix towards better (upper left) and worse (lower right) credit the spreads relative to the average coupon adjust appropriately. There is about a 223bps difference between the best and worst risk profiles in the matrix.

For comparison, the average spread between the two credit extremes for non-prime loans in 1998 was about 153bps, or 70bps narrower. Comparing the spreads for prime loans we have 21bps in 1998 increasing to 165bps in 2003. Finally, the Alt-A spread was 28bps in 1998 and 171 bps in 2003. The monotonic relationships observed in Figure 13 for the 2003 non-prime data also exist in the prime and Alt-A data. The comparative spreads between the 1998 data and the 2003 data provide evidence of the increased effective use of risk-based pricing.

The Value of Better Mortgage Credit

We have seen how the coupon rate charged on a mortgage loan at origination is influenced by the borrower's perceived default risk measured by FICO score. This relationship translates into true dollar costs over the life of the loan. An improvement in the FICO score can indeed save the borrower thousands of dollars over time.

In this section we consider examples of mortgage costs for different borrower credit scores. We use the results from our analysis of the aggregate data for each product type since these are the most robust. For each product type we use the average loan balance for the aggregate data and the average coupon, adjusted for the FICO score effects. In addition we include in the cost of credit the average points collected at closing which are 1 point for Prime, 2 points for Alt-A and 4 points for Non-prime. Our loan characteristics are summarized in Figure 14.

Figure 14: Loan Characteristics for Value of Credit Example

	Prime	**Alt-A**	**Non-prime**
Original Balance	$380,083	$242,448	$113,081
Avg. Coupon	7.46%	8.14%	9.13%
Points	1	2	4

In each case we calculate the value of credit by creating a 30-year amortization schedule based on the loan characteristics in the table. Then sum the mortgage interest costs and points paid to arrive at the total. This is repeated for each FICO group's relative coupon rate. The results show that the difference in value is not uniform as we compare neighboring FICO groups as shown in Figure 10. Interpretation of the graph merits elaboration.

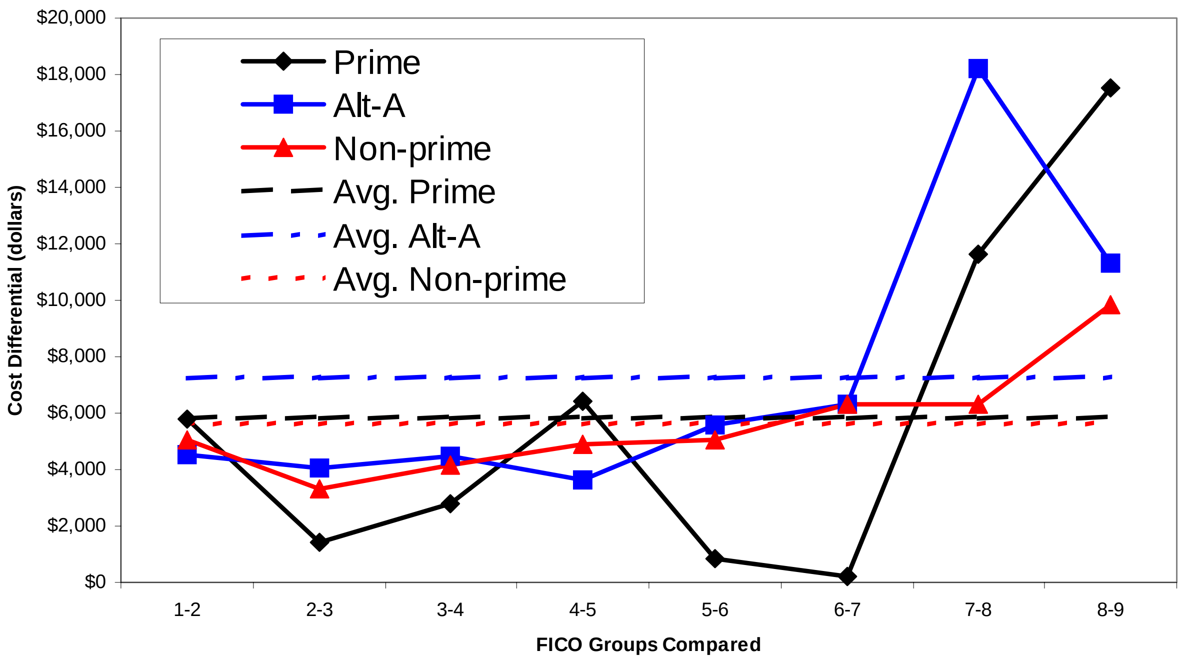
The vertical axis is the value differential measured in dollars between two neighboring FICO groups. So "1-2" on the horizontal axis means we are comparing the first two FICO groups, "741-760" to "721-740" and we see that the interest rate differential between these two groups results in a $4,534 difference for Alt-A, a $5,028 difference for Non-prime and a $5,828 difference for Prime. In other words, at the high end of the FICO scale (better credit) the dollar value of 20 FICO points (DVOF) is between $4,500 and $5,800. For Alt-A and Prime the DVOF reaches about $18,000 at low end of the FICO scale. The maximum DVOF for Non-prime is about $9,800.

The average DVOF is $5,828 for Prime, $7,262 for Alt-A, and $5,625 for Non-prime, but looking at the graph the average is not very stable. The most consistent results are for the Non-prime data. The incremental cost of moving 20 points in FICO scores varies quite a bit.

To go a step further we consider the joint effect of FICO score and LTV on loan pricing and the resulting difference in value. For compatibility with the prior case we again use the aggregate data. Note that because of the wider spreads observed in the 2003 data the impact on the relative cost of credit would be greater if we use the more current data.

In the case of prime loans the best credit – FICO score in the 741-760 range, and LTV in the 69-71 range – has a coupon of 7.15%, and the worst credit a coupon of 8.01%. This results in an interest rate cost differential of $80,805, or 21.3% of the original loan balance. For the Alt-A case the rates are 7.47% and 9.09%, with a cost differential of $99.453, or 41.0% of the original loan balance. In the non-prime case, the rates are 8.20% and 10.44% yielding a differential of $66,153 or 58.5% of the original loan balance. The DVOF is $10,101 for prime, $12,432 for Alt-A, and $8,269 for non-prime. That is, a 20-point difference in FICO score results in an average cost difference of $10,101 for an average prime loan over its life.

Figure 15: Comparative Cost of Credit for Change in FICO



Conclusion

The most significant conclusion from this research, a rather blinding flash of the obvious, is that good credit is worth more to borrowers than poor credit. This value proposition extends across the 3 products reviewed. In the prime arena the average savings on a 30- year fixed rate single-family mortgage for a high credit borrower relative to the lowest credit borrower was $46,622 (12.3% of the average loan balance), in the Alt-A arena the difference was $58,095 (24% of the average loan balance), and in the non-prime market the difference was $44,999 (a not insignificant 44.2% of the average loan balance). Each of these figures was converted into an average cost of a credit score differential of 20 FICO points. These were $5,828 for prime, $7,262 for Alt-A and $5,625 for sub prime, over the life of the respective loans. These are also not insignificant savings. When considering the joint impact of FICO and LTV we get an even greater savings of $80,805 (21.3% of the average loan balance) for prime, $99,453 (41.0%), for Alt-A, and $66,153 (58.5%) for non-prime.

In addition to the valuation of credit differentials and the value of managing your better credit better, the study highlighted the improvement in the use of risk-based pricing over the study period. From 1998 to 2003 there is a pronounced improvement in the granularity of the coupon bucketing as well as the concentration of populations in the relative buckets by risk and product type. This reflects the expanded use of not only matrix pricing systems but the implied use of the scoring models that were distributed across the non-conforming industry (particularly originators of the loans reviewed in the study) during this period. The data supports the position that risk-based pricing is a fact in the non conforming market and we would expect that as models continue to evolve and cover more and more products that the separation of credits and the pricing of those separate buckets will become more granular and refined. Clearly lenders have become more astute at accurately pricing mortgage loan risk-based on the borrower’s credit measured by FICO score, and the degree of collateral security measured by LTV over the last five years. There is no reason to expect the price of better credit to decline as a result of improved pricing vehicles.

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