A WRITTEN STATEMENT OF FAIR ISAAC CORPORATION

ON THE FAIR CREDIT REPORTING ACT

HOW IT FUNCTIONS FOR CONSUMERS AND THE ECONOMY

BEFORE THE U.S. HOUSE OF REPRESENTATIVES

COMMITTEE ON FINANCIAL SERVICES

SUBCOMMITTEE ON FINANCIAL INSTITUTIONS AND CONSUMER CREDIT

WASHINGTON, D.C.

JUNE 4, 2003

Introduction. Mr. Chairman and members of the subcommittee, my name is Cheri St. John. I am the Vice President of Global Scoring Solutions for Fair Isaac Corporation. Thank you for the opportunity to testify before you today regarding the critical role played by uniform national credit reporting standards and credit scores in creating a robust national credit market that helps consumers get the credit they deserve, and get it faster.

Fair Isaac Corporation. Fair Isaac Corporation is the preeminent provider of creative analytics that unlock value for people, businesses and industries. Founded in 1956, Fair Isaac helps thousands of companies in over sixty countries acquire customers more efficiently, increase customer value, reduce fraud and credit losses, lower operating expenses, and make more credit available to more people. Fair Isaac pioneered the development of statistically-based credit risk evaluation systems, commonly called "credit scoring systems," and is the world's leading developer of those systems. Thousands of credit grantors use scores commonly known as "FICO® scores" generated by Fair Isaac-developed scoring systems implemented at the national credit reporting agencies. Fair Isaac has also developed custom scoring systems for hundreds of the nation's leading banks, credit card issuers, finance companies, retailers, insurance companies, and telecommunication providers.

Over the last forty years credit scoring has become an important part of most credit decisions. Fair Isaac believes that some form of credit scoring is now used in the majority of consumer credit decisions, and the most widely used credit scores in the U.S. today are FICO scores. A FICO Score is a 3-digit number that tells lenders how likely a borrower is to repay as agreed. FICO Scores use information from consumer credit reports to provide a snapshot of credit risk at a particular point in time. Scores can change over time, as that credit risk prediction reflects changes in underlying behaviors.

Fair Isaac has also given consumers a place in the credit reporting process by pioneering consumer credit empowerment with its myFICO.com score explanation website. Millions of consumers have already taken steps to control their credit lives by using myFICO to obtain informative, actionable credit-information services including the FICO scores that lenders use, and to help improve and protect their overall financial health.

Fair Isaac is a leading developer of insurance scores. Over 350 insurance companies use Fair Isaac insurance scores that they obtain through national credit reporting agencies. Although insurance scores utilize credit data, they differ from credit scores in that insurance scores are developed based on insurance premium and loss history and predict future insurance loss ratio relativity. Like credit scores, insurance scores do <u>not</u> consider a person's income, marital status, gender, ethnic group, religion, nationality or neighborhood, and the scores are applied consistently from one consumer to the next. A strong statistical correlation has been repeatedly demonstrated between credit data and insurance loss ratio[1], and insurance scores have become a valuable component in determining insurability and the rate assigned. Insurers use insurance scores to accelerate their processing for applicants and renewal shareholders, to concentrate additional underwriting attention on higher-risk individuals, and to better manage operational strategies. Consumers benefit from lower rates. Insurers have stated that 60-75% of their policy holders pay lower premiums because of insurance scoring. Fair Isaac has been supportive of the efforts of insurance score users to educate consumers and agents about insurance scoring.[2]

With credit scoring, more people get credit, they get it faster, and it's more affordable. FICO scores mean more people have access to credit. Credit scores allow lenders to better assess the risk and tailor credit for each consumer's needs. FICO scores are used in almost

[1] See, *Predictiveness of Credit History for Insurance Loss Ratio Relativities*, October 1999; Attachment 1: *Insurance Bureau Scores vs. Loss Ration Relativities*, Tillinghast-Towers Perrin, December 1996, Attachment 2; *A Statistical Analysis of the Relationship Between Credit History and Insurance Losses,* Bureau of Business Research (McCombs School of Business) at the University of Texas, March, 2003 available at http://www.utexas.edu/depts/bbr/bbr_creditstudy.pdf.

[2] See e.g., *Answers to Your Questions About Insurance Bureau Scores*, Attachment 3.

every sector of the nation's economy: for mortgages, credit cards, auto loans, personal loans, even cell phone service. More people can get credit regardless of their credit history because credit scores allow lenders to safely assess and account for the risk of consumers who have no existing relationship with the lender, who have never entered the lender's branches, and who may have been turned away in the past by other lenders. Lenders use scores not only to evaluate applications, but also to manage the credit needs of existing customers by extending additional credit or helping consumers avoid overextending themselves. FICO scores are also used by lenders and securities firms as to aid securitization of credit portfolios which provides lenders the capital they need to make credit available to more consumers. FICO scores are accepted, reliable, and trusted to the point that even regulators including federal bank examiners, and security rating agencies, use them to help ensure the safety and soundness of the financial system.[3]

FICO scores mean people get credit faster. "Instant credit" at a retailer, an auto dealer, over the phone, or on the Internet would not be possible without credit scores. Even mortgage loans that used to take weeks can now be done in minutes. Removing information from credit reports, or even varying reported information from state to state, would make the process of obtaining credit more difficult for consumers. Among the tremendous lending advances in the U.S. over the last decade has been the streamlining of the lending process, so that credit approvals – not just on credit cards but on installment loans, mortgages, home equity lines of credit and even commercial loans to small businesses – can be made faster with less manual review and with less paperwork and requests for data. All of this has occurred while lenders have not only preserved but strengthened their visibility and control over their risk exposure. These gains stand to be lost if weaker or inconsistent data reduces the predictiveness of credit scores. If the reliability of credit scores diminishes, for the reasons discussed, lenders will need to use other techniques to bolster their risk assessment. Consumers will likely have to complete more paperwork, supply additional types of information not required today, and wait longer for decisions. This would be a setback

[3] See Attachment 4 for examples of Federal agencies that use FICO scores.

for the national economy, and it would inconvenience and potentially harm consumers searching for credit.

FICO scores mean people pay less for their credit. Scores make credit more affordable by reducing the cost of evaluating applications, reducing loan losses, reducing the cost of managing credit portfolios, reducing marketing costs with prescreening, and cutting the cost of capital with securitization. This efficient flow of credit and capital has a large part to play in the continued robustness of the American economy. By enabling lenders to extend credit quickly while managing their risk, credit reports and credit scores have made credit more accessible, at lower rates, to more people.

More data means smarter scores. Smarter scores help everyone get the credit they deserve.

Fair Isaac supports renewal of the national uniformity provisions of the FCRA. The current uniform credit reporting system helps both consumers and lenders. Complete and consistent credit information increases the predictive power of the scoring system.[4] If national uniformity in credit information is lost, scores will be less predictive and consumers will be hurt. Lenders will be less able to precisely distinguish risk. The likely result is that consumers in states that allow less information, for example a state that might restrict information on mild delinquency, will have access to fewer credit products and pay higher prices for credit because lenders will have to increase prices overall to cover the increased risk. Moreover, the consumers with better payment records will lose the benefit of always paying on time every time and end up paying higher prices. With less information to work with, scores would be less able to distinguish between those consumers who pay their bills every time and consumers who occasionally miss payments. Lenders will have to charge the same price for both groups, thereby making the consumers with better credit records pay the increased costs currently paid by the less reliable

[4] See, *A Clarification of the Consumer Federation of America's Observations about Credit Score Accuracy*, Attachment 5, for Fair Isaac observations about the December 17, 2002 report, "Credit Score Accuracy and Implications for Consumers," issued by the Consumer Federation of America.

credit risks. A consumer should not be charged more because of someone else's debts. If states pass legislation affecting the content of credit reports, many consumers could get a lower score than their actual risk level warrants. Complete and consistent data makes scores smarter, which helps everyone get the credit they deserve.

State regulation of credit reporting works against a national economy because smaller states would likely experience a greater negative impact from inconsistent and varied state regulation of credit reporting. As credit data becomes fragmented, credit scores would need to adapt to utilize available data. Smaller, less populous states may bear a heavier burden for at least two reasons. First, the market will likely prioritize the redevelopment of scores to serve the larger markets, i.e. the more populous states. Second, smaller states would have a smaller pool of available data on which to conduct research to refine and develop smarter scores for those markets. Either of these developments would mean residents of smaller states would be at a disadvantage in credit markets because with less sophisticated scoring, lenders would have to raise prices and reduce credit availability to respond to the diminished ability to assess risk in smaller markets. The cost and availability of credit should be determined by the credit risk of each consumer rather than the state of residence and therefore Fair Isaac supports the renewal of the national uniformity provisions of the FCRA.

Lenders must make a credit decision, and they must predict the future in doing so. Lenders can use a variety of decision making techniques to predict the future, ranging from a simple subjective evaluation of application and credit history information by a loan officer, to predictive technologies, including credit scoring. When a creditor switches from judgmental decisions to scoring, it is common to see a 20-30% increase in the number of applicants accepted with no increase in the loss rate. Lenders should use all the information that is legally, economically and efficiently available to make the best and fairest possible decision for each individual with whom they do business. FICO scores, when used properly, make a tremendous contribution in doing just that. FICO scores use only legal data as inputs, and only those factors proven to be predictive of credit risk.[5] Scores are also more consistent from consumer to consumer because they apply the same factors the same way, each time.

Studies have concluded that the same Fair Isaac credit score indicates the same level of risk regardless of the income level of the consumer or whether the consumer resides in an area with a high percentage of minority residents, with differences consistently favoring the low to moderate income ("LMI") and high minority area ("HMA") applicants.[6] Those same studies indicate that credit scoring is a far more predictive screen for both the LMI and HMA applicants than is judgmental decision making. Finally, the multiple scorecard systems developed by Fair Isaac and resident at the three main U.S. credit bureaus were proven to be more predictive than a single scorecard developed for the HMA population for the study.

Fair Isaac credit scores transform the economics and efficiency of the credit decision to allow all relevant information to be brought to bear so that no information that is favorable to an individual is omitted from the decision process. Credit scoring scientifically, and therefore fairly, balances and weighs *positive* information along with any negative information in credit reports. In essence, full positive credit reporting and scoring have "democratized" credit granting – information about all consumers is available to all lenders for a fair evaluation. Scoring has transformed credit granting so that it is no longer simply based on who you know. State regulation that limits the nature and quality of the credit data available will only diminish the value of this powerful and beneficial tool.

People who know their scores--and improve their credit health--have more credit power.

National uniformity in credit data empowers consumers by promoting consumer awareness and understanding of their credit standing, helps prevent identify theft, and facilitates an efficient

[5] See Attachment 6, available free at http://www.myfico.com/Offers/RequestOffer.asp for the major factors used to calculate the FICO score and other educational information about credit scoring.
[6] See, *The Effectiveness of Scoring on Low-to-Moderate Income and High Minority Area Populations*, a Fair Isaac Paper dated August, 1997, Attachment 7.

national labor pool. Consumers can get expert explanations of their current FICO scores and copies of their current credit reports from www.myFICO.com, and learn how to improve their credit scores with more responsible credit behavior.[7] Consumers will find it harder to understand and take charge of their credit if the rules for credit reporting vary by state because credit scores and reports may change without a change in the consumer's credit behavior if new state laws or a move by the consumer to another state changes the availability of data. The problem would be compounded for consumers that bank, do business in or own property in multiple states with varied regulatory approaches. Even if the consumer perseveres through that confusion, differing state rules will likely diminish the quality of consumer credit products. State restrictions on credit reporting will tend to cause consumer products to adopt the lowest common denominator to create a single, affordable national standard. The FCRA has created a uniform system that empowers consumers to manage their credit standing and permits the creation of sophisticated products to help them. Well-meaning state regulation should not be allowed to diminish a consumer's role in managing his credit standing.

Consistent, Quality Data helps Prevent Identity Theft

Renewal of the FCRA uniformity provisions helps both consumers and the financial industry prevent identity theft. Congress recognized the need for reliable and consistent data to prevent fraud when it created an exception to the data sharing restrictions in section 502 (e) (3) (B) of the Gramm- Leach-Bliley Act so that data can be shared to prevent fraud. Well-meaning restrictions on data reporting and sharing will hurt those they intend to protect by reducing the ability of both consumers and the financial industry to prevent identity theft and other types of financial fraud. The industry tries to prevent fraud like identity theft by using analytics to detect potential fraud. Robust, consistent and reliable data improves the performance of analytic fraud detectors. Consumers also prevent identity theft by utilizing services available at myFICO.com and other sources to monitor their credit reports for suspicious activity. The Federal Trade Commission

[7] See Attachment 6 available free at
http://www.myfico.com/Offers/RequestOffer.asp for the major factors used to calculate the FICO score and other educational information about credit scoring.

states that one of the best ways for a consumer to catch identity theft early is for the consumer to monitor his credit report.[8] Reliable, credit data of a consistent nature makes it easier for consumers to protect themselves against identify theft because they can learn one data format and rely on certain types of data to be there such that they can easily detect suspicious activity. If credit data varied and was inconsistent from state to state, consumers would not be able to tell whether changes to their credit reports are from state regulation or from suspicious activity. Even if a consumer continues to monitor despite shifting data content, he/she might stop using their credit report to monitor for identity theft as they learn time and again that changes in the report are due to changes in state laws rather than suspicious activity.

Uniform Credit Reporting Promotes a National Labor Pool

If uniform national credit reporting is eliminated, consumers will find it more difficult to move from state to state in search of employment, or do business or own property in more than one state. A consumer that moves to a state with different credit reporting laws will at best be confused by the changes to his/her score and credit report that are generated solely by a change in available data. Worse, that consumer may find that he/she is unable to obtain credit or must pay more for it. Credit cost and availability should be based on each consumer's behavior, not on the state of residence.

Credit scoring and the national credit reporting system created by the FCRA has many benefits for both individual consumers and our nation's economy. I thank you for the opportunity to share with you Fair Isaac's expertise and experience in this important area.

[8] See, Attachment 8, available at http://www.consumer.gov/idtheft/risk.htm

FairIsaac®

Predictiveness of Credit History for Insurance Loss Ratio Relativities

A Fair, Isaac Paper

October 1999

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Table of Contents

1. Introduction

In this discussion, Fair, Isaac summarizes its efforts in addressing regulators' concerns and issues on the use of credit history and insurance bureau scores in underwriting decisions.

Background of Fair, Isaac's insurance bureau scores

Since 1956, Fair, Isaac has been developing scoring models that use data to improve business decisions. Leading financial institutions throughout the world have used Fair, Isaac scoring models to make faster, more consistent and more predictive decisions on the creditworthiness of individual applicants and customers.

Concurrently, Fair, Isaac researched ways to use data to help insurers better predict loss ratio relativity. In the late 1980s, Fair, Isaac introduced scoring models (also called "scorecards") to the insurance industry. Fair, Isaac's custom scoring models are developed from an individual insurer's data; the model may analyze application information, motor vehicle records, loss history, credit data and other sources of data to statistically forecast loss ratio.

In the early 1990s, Fair, Isaac introduced insurance bureau scores. These scores are developed by analyzing very large samples of the major types of auto and home insurance policies to determine the correlation between information on consumer credit bureau reports and subsequent insurance loss ratio. Insurance bureau scores forecast the likely loss ratio relativities of individuals on a scale: the higher the score, the lower the risk. These scores are available from major credit bureaus for each of the major types of auto and home policies. They enable insurers of all sizes to obtain the benefits of scoring.

Insurance bureau scores are now used by many leading personal lines insurers in the U.S. and Canada as an aid to improving the speed, consistency and objectivity of the underwriting process. Typically, insurers use these scores not to deny coverage to high-risk applicants, but rather to approve low-risk applicants more quickly, allowing underwriters to focus attention on potentially higher risk portions of their book of business and to better determine the quality of a book of business in advance. Among the benefits are saved resources, faster approvals and more controlled management.

Distinction between insurance bureau scores and credit bureau scores

It should be pointed out that it is inappropriate and may be illegal to use credit bureau scores to evaluate insurance risk. Each kind of score predicts a specific outcome. Credit scores were developed to predict the likelihood of future credit behavior. Insurance bureau scores, on the other hand, were developed specifically to predict the likely loss ratio performance of homeowner or automobile applicants or policyholders. Also, a wide variety of federal and state laws and regulations restrict an insurer's use of certain types of information for insurance underwriting purposes.

NAIC white paper on use of credit in underwriting decisions

In 1994, the National Association of Insurance Commissioners (NAIC) assigned its Credit Reports Subgroup to write a white paper on the subject of the use of consumer credit data in underwriting. The white paper, *Credit Reports and Insurance Underwriting*, presented differing views of various aspects of the use of credit reports in underwriting. It also presented recommendations on the use of consumer credit information in underwriting, including recommendations for consumer protection.

Fair, Isaac participated in the ongoing discussions with NAIC and commissioned an independent study to document the correlation between insurance bureau scores and loss ratio relativities. The study, performed by actuarial consultants Tillinghast-Towers Perrin, was included in the white paper's Appendix. The findings supported the relationship of credit data and loss ratio: In the examination of nine books of business, eight books showed a 99% confidence level in a relationship, the ninth book showed a 92% confidence level.

The white paper was formally approved and adopted by the NAIC in December 1996. Regulatory agencies in individual states can adopt none, any or all of the white paper's recommendations. Many states have accepted the use of credit information in aiding underwriting decisions; others continue to oppose or question it.

Ongoing concerns by regulators

Since the adoption of the white paper, regulators in each state have been determining the allowability of credit data and insurance bureau scores in underwriting decisions.

Questions that often occur include the following:

- Where does the data that goes into a scoring model come from?
- How does credit relate to loss ratio in home and automobile insurance?
- What credit elements are used in the Fair, Isaac scoring models (scorecards)?
- How accurate is a credit report?
- Is the use of credit history and scores discriminatory?

Fair, Isaac educational efforts

Fair, Isaac actively addresses regulatory concerns and issues by presenting fundamental concepts on credit data, general predictive technology and scoring results. The discussion in this paper was developed with the goal of sharing these concepts with a wider audience and providing a better foundation for further discussions. No in-depth analysis is included in this discussion. Fair, Isaac continues to do analytical studies in these areas, and will release results when available.

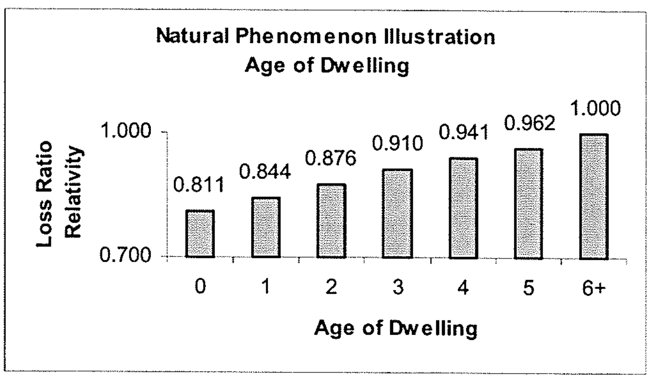
Terminology

Several terms should be defined for better understanding of this paper. "Losses" are total limit incurred losses and allocated loss adjustment expense, developed for 12 to 24 months, excluded for catastrophes and large losses. "Premiums" are total limit premiums including all rating factors. A "loss ratio" is the ratio of losses to premiums. A "loss ratio relativity" for an attribute (class) is the ratio of the attribute loss ratio to the average loss ratio across all attributes for a characteristic.

Methodology used by Fair, Isaac matches current underwriting practices

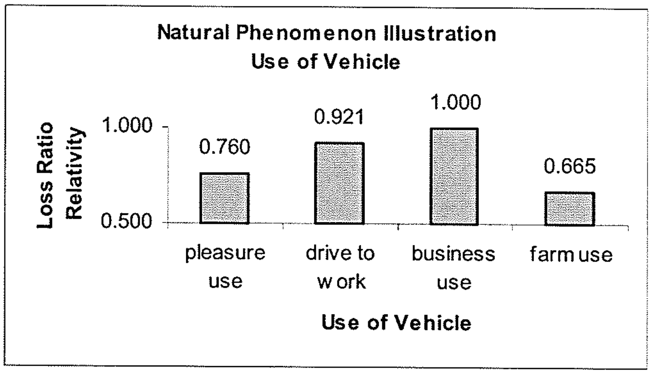
In current regulatory review practice, regulators review individual insurance underwriting programs by examining the correlation between the underwriting characteristics of policies and the loss ratios for those same policies. The examples below in Figures 1-3 are illustrative of that natural correlation.

FIGURE 1. AGE OF DWELLING VS. LOSS RATIO RELATIVITIES



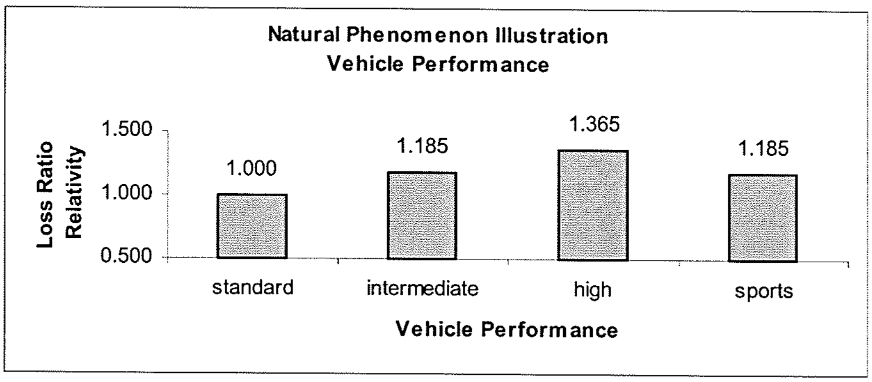
Loss ratio relativity was lowest for policies with new homes and increased as the homes got older.

FIGURE 2. USE OF VEHICLE VS. LOSS RATIO RELATIVITIES



Business use had higher loss ratio relativity than drive to work, pleasure use and farm use, in that order.

FIGURE 3. VEHICLE PERFORMANCE VS. LOSS RATIO RELATIVITIES



Loss ratio relativities were highest for high-performance vehicles, followed by intermediate, sports and standard vehicles.

As can be seen from these figures, there is a relationship between the above underwriting characteristics and loss ratio relativities. This relationship is typically reflected in various class plans.

In its insurance bureau scores, Fair, Isaac uses the same standard of evaluation; that is, the scores are developed to determine the correlation between a set of characteristics and loss ratio relativities.

2. Credit data

Introduction

Insurance bureau scores are based on the information in an individual applicant's credit report, which is based on information resident at the major credit bureaus. This section discusses the makeup and accuracy of that data.

The makeup of credit data

An example of a credit report can be found in the *Trans Union Training Guide* included in the supplementary information. This guide shows a credit report with various types of information, including:

- Inquiry information
- Demographic information
- Special messages (which highlight specific credit file conditions that may include suspected fraud or presence of a consumer statement)
- Credit summary (which provides a "snapshot" of all activity on the consumer's credit report, including total numbers of public records, collection accounts, trades, revolving and/or credit accounts, installment accounts, inquiries and other summarized information)
- Public record (which contains information obtained from county, state and federal courts, including information on civil judgments or tax liens, bankruptcies and public record information)
- Collections (which identifies accounts transferred to a professional debt-collecting firm)
- Trades (which provides an ongoing historical and current record of buying and payment activities, a payment pattern displaying either 12 or 24 months)
- Inquiries (which displays those companies that have viewed the credit file in the last two years)

For the past four decades, Fair, Isaac has researched these data elements and, for the financial services industry, built scoring models based on characteristics that have been found to be predictive of credit performance.

Over 10 years ago, Fair, Isaac began researching the relationship between consumer credit characteristics and insurance loss ratio relativities. A subset of these characteristics were found to be predictive of loss ratio relativities and are used to build insurance bureau scoring models, as discussed in later sections of this paper.

Accuracy of credit data

Because insurance bureau scores are based on credit bureau data, the accuracy of that data is of paramount importance to lenders and consumers.

It should be pointed out that widely inaccurate bureau data would produce inaccurate scores. The ability of insurance bureau scores to consistently forecast insurance performance is a testament to the overall quality of credit bureau data.

In addition, a number of studies show the error rate in credit reports to be relatively low.

Study by Associated Credit Bureaus

In 1992, Associated Credit Bureaus (ACB), a Washington D.C.-based trade group, commissioned Arthur Andersen to do a study of the accuracy of credit reports. In brief summary, of the 15,202 credit application declines used in the study, 2% (304) disputed the information on their credit reports. Errors in the credit report affected the outcomes of only 0.2%(36) of the sample: that is, even when errors were found and corrected, they were significant enough to affect the final outcome in only 0.2% (36) of the sample.

Study by Trans Union

Briefly, the Trans Union study used 400,000 consumers who's insurance was impacted by the use of credit history. There were 30,000 adverse actions taken and 50 (0.2% = 50/30,000) consumers disputed their credit history as reported. Twenty (0.07% = 20/30,000) corrections were made to credit reports.

For individuals who feel that the data in their consumer credit reports is inaccurate, all three major credit bureaus have procedures in place for checking and correcting disputed information.

It should also be pointed out that correcting information might not substantially alter a score. Because the score is the result of balancing all the predictive data in a credit file, both positive and negative, the correction of one or even two errors may not have a significant impact on the score. Improved credit responsibility, over time, will positively influence the score.

Motor Vehicle Records Study

Insurance Research Council released a study on the "Adequacy of Motor Vehicle Records in Evaluation of Driver Performance" in 1991. In the Executive Summary, some results were reported as follows:

- "Accident reporting is getting worse as states weaken their reporting requirements and place additional limitations on public access to motor vehicle records. A 1990 survey of 39 states and the District of Columbia found that publicly available records contained information on only 40% of a sample of 27,629 known accidents serious enough to meet each state's accident reporting requirements. A similar study conducted in 1983 found information on 48% of the reportable accidents."
- "Traffic citations and convictions also are severely under-reported on official state driver records. On average, only 19% of the drivers in the study had a conviction recorded in connection with accident surveyed, even though well over 60% of the drivers were considered legally at fault."

The above and other points in the Executive Summary give the impression that motor vehicle records (MVRs) have a relatively high error rate; yet these reports are generally accepted and used routinely in the determination of rating factors for calculation of policy premiums.

In contrast, the credit report error rate is lower. In view of the error rate of MVRs, the credit report error rate should not be an issue.

Fair Credit Reporting Act (FCRA)

The Fair Credit Reporting Act (FCRA) is a federal statute introduced in 1970, with major amendments effective on September 30, 1997. (The following discussion does not represent Fair, Isaac's legal opinion nor should it be relied upon to make any decision by anyone.)

Basically, the statue requires "consumer reporting agencies" to adopt procedures governing accuracy, access to and utilization of "consumer reports." It imposes accuracy-oriented obligations on furnishers of information. It requires users of consumer reports to use them only for certified permissible purposes. These purposes include use in connection with credit transactions involving the consumer, credit extensions/review of accounts/collections, underwriting insurance or other legitimate business need for the information in connection with a business transaction initiated by the consumer.

The FCRA allows consumers access to their files and provides for a complaint procedure, and requires users to give notice to applicants or policyholders when adverse actions (such as denial of credit or insurance) are taken.

The FCRA also covers the use of credit information in prescreening, including use for a "firm offer of credit or insurance" in a "transaction not initiated by consumer." It also permits making such an offer conditional, subject to verification of the information in the credit report or application at the time of acceptance, in order to ensure the consumer still meets the prescreen criteria. The user may also condition an offer based on information in the application that meets pre-established criteria, or on the furnishing of required collateral as disclosed in the offer.

Consumer opinion survey

In 1994, the Equifax credit bureau commissioned a consumer privacy survey. In the Executive Summary, on page vii, it states:

> "When asked about the information that should be considered when auto insurance companies decide to issue auto insurance policies, the American public distinguishes clearly between information that is relevant and that which is not. Among a list of 14 items that auto insurance companies might consider in their decision to issue auto insurance policies . . . 63% feel it is fair to consider listing of paying bills."

Analyzing a credit report: the relationship of credit behavior and credit risk

The relationship of credit behavior and credit risk needs to be understood before making the connection between credit behavior and insurance loss ratio relativities.

(Important note: This exercise is for educational purposes only. It should be pointed out that it is inappropriate and may be illegal to use credit bureau scores to evaluate insurance risk. Each kind of score predicts a specific outcome. Credit scores were developed to predict the likelihood of future credit behavior. Insurance bureau scores, on the other hand, were developed specifically to predict the likely loss ratio performance of homeowner or automobile applicants or policyholders. Also, a wide variety of federal and state laws and regulations restrict an insurer's use of certain types of information for insurance underwriting purposes.)

For the financial services industry, Fair, Isaac developed a booklet, *Analyzing a Credit Report: Facts and Fallacies About Credit Risk* (see supplementary information) that discusses credit behavior trends. Going through the booklet, one can learn of the following:

- **Fallacy.** An adverse public record or major delinquency always indicates unacceptable risk.
  Fact. A negative item may not denote high risk. Recency and severity must be considered. The older the occurrence, the less the risk.
- **Fallacy.** A good credit risk carries a lot of credit cards, all with balances.
  Fact. Balances owed on a large number of credit cards generally indicate greater risk. Moderate credit card usage is "safer" from a risk perspective.
- **Fallacy.** Someone with very little credit history would be too great a risk.
  Fact. Even files with short credit histories may represent acceptable risk, depending on other factors, such as very low outstanding balances.
- **Fallacy**. A large number of inquiries are a sure sign of high risk.
  Fact. Several inquiries may not indicate high risk. Factor in the length of file history and number of trade lines.
- **Fallacy.** A good deal of bankcard credit indicates low risk.
  Fact. Too many bankcards, even with zero or low balances, mean the holder could take on too much credit. Having a few bankcards, but not too many, is best.

An exercise in this booklet allows interested parties to test their credit report analysis skills. Doing the exercise provides insight into the relationship between credit behavior and financial risk that, in turn, enables a better understanding of the correlation between credit behavior and insurance loss ratio relativities discussed in this paper.

3. Relationship of credit behavior and loss ratio for personal lines insurance

Overview

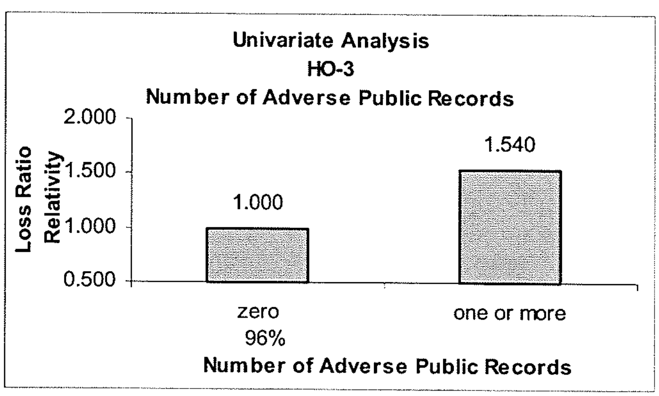
With the background of the discussion in the earlier sections on current underwriting review practices, the nature of credit report information, and the relationship between credit behavior and credit risk, it is clearer how some credit characteristics can correlate with insurance loss ratios, as illustrated below.

(Please note that the following illustrations are not examples of scoring, which is based on predictive technology and forecasts future losses as discussed in subsequent sections of this paper. Rather, these illustrations are based on correlating single credit characteristics with losses that have already been experienced.)

Personal property insurance

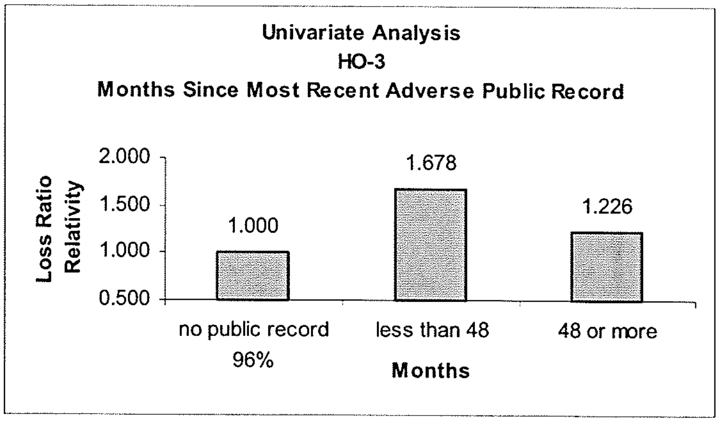
For personal property insurance—using a dataset of approximately 230,000 policies with claims, 1 million policies without claims and corresponding credit information on those policy holders taken from 11 archives of credit history from consumer credit bureaus—the relationship of five credit characteristics and loss ratio relativities are summarized as follows:

FIGURE 4. NUMBER OF ADVERSE PUBLIC RECORDS VS. LOSS RATIO RELATIVITIES



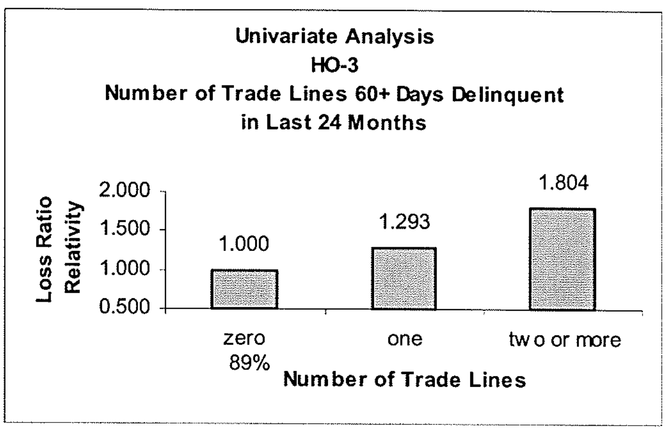
Of this population, 96% did not have any adverse public records. Of the remaining 4% having one or more adverse public records, loss ratio was 54% higher than those without any adverse public records.

FIGURE 5. MONTHS SINCE MOST RECENT ADVERSE PUBLIC RECORD VS. LOSS RATIO RELATIVITIES



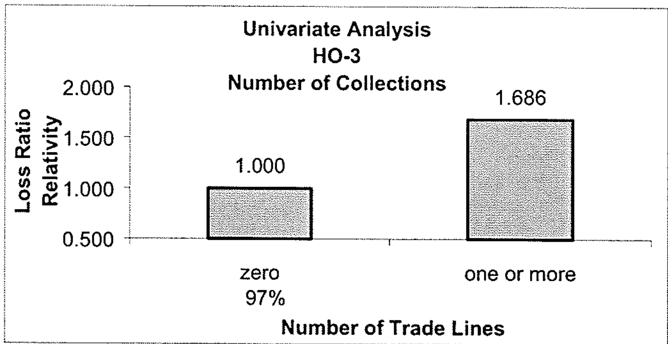
The same 96% of the population did not have any adverse public records. Of the remaining 4%, those having the most recent adverse public records (less than 48 months) were found to have 68% higher loss ratio than those without any adverse public records. Those having less recent adverse public records (more than 48 months) were found to have a 23% higher loss ratio than those without any adverse public records.

FIGURE 6. NUMBER OF TRADE LINES 60+ DAYS DELINQUENT IN LAST 24 MONTHS VS. LOSS RATIO RELATIVITIES



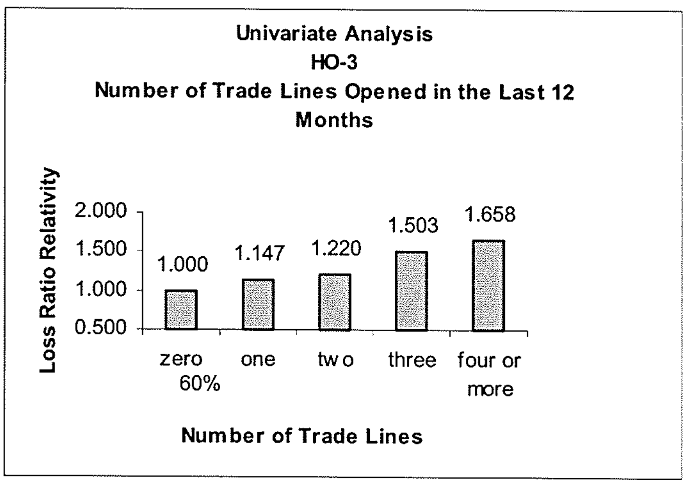
Of this population, 89% did not have any trade lines in delinquency for more than 60 days in the last two years. For people with one such delinquency, loss ratio was 29% higher than those without such delinquency. For those with two or more such delinquencies, loss ratio was 80% higher than those without.

FIGURE 7. NUMBER OF COLLECTIONS VS. LOSS RATIO RELATIVITIES



Of this population, 97% did not have collection accounts established. Among the remaining 3% who did have such accounts, loss ratio was 69% higher.

FIGURE 8. NUMBER OF TRADE LINES OPENED IN THE LAST 12 MONTHS VS. LOSS RATIO RELATIVITIES

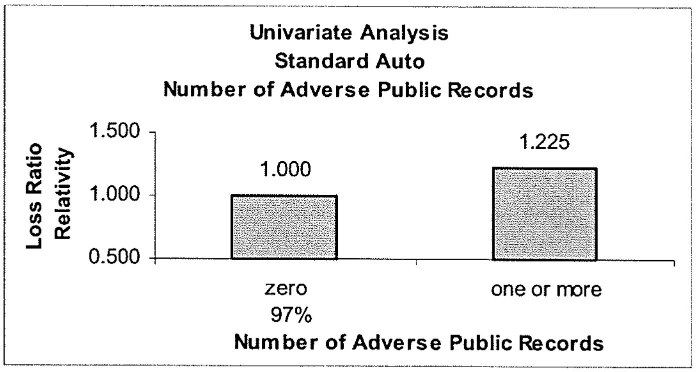


Of this population, 60% did not open any trade lines in the last year. People who opened one trade line in the last year had a loss ratio 15% higher on average than people who did not; two trade lines in the last two years, 22% higher; three trade lines, 50% higher; four or more trade lines, 66% higher.

Personal auto insurance

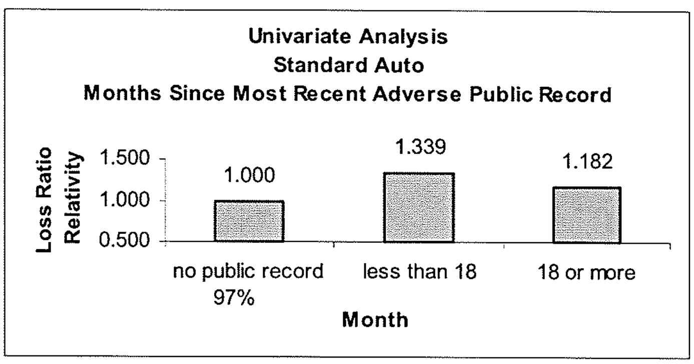
For personal auto—using a dataset of 350,000 policies with claims, 1 million policies without claims and corresponding credit information on those policy holders taken from six archives of credit history from consumer credit bureaus—the relationship of five credit characteristics to loss ratio relativities are summarized as follows:

FIGURE 9. NUMBER OF ADVERSE PUBLIC RECORDS VS. LOSS RATIO RELATIVITIES



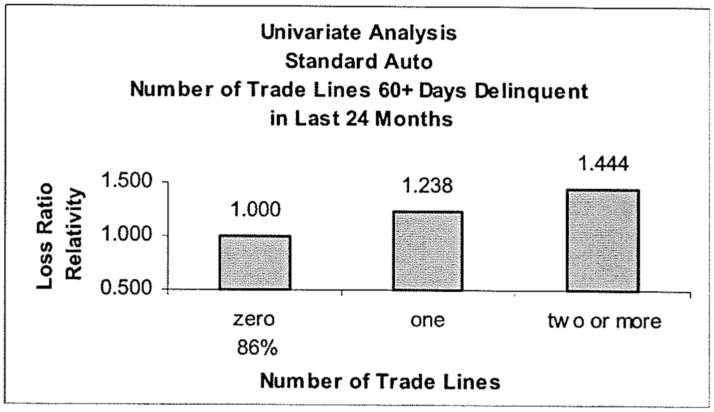
Of this population, 97% did not have any adverse public records. Of the remaining 3% that had one or more adverse public records, loss ratio was found to be 23% higher than those without any adverse public records.

FIGURE 10. MONTHS SINCE MOST RECENT ADVERSE PUBLIC RECORD VS. LOSS RATIO RELATIVITIES



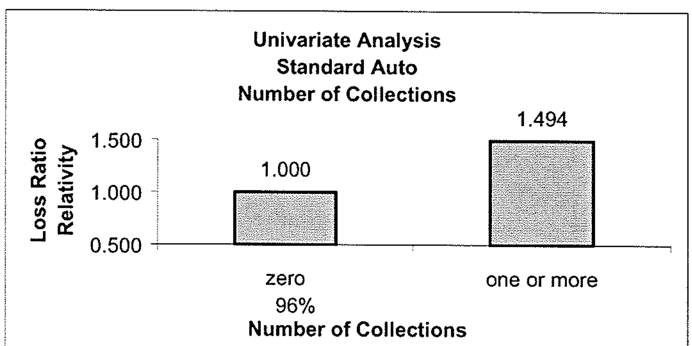
Again, 97% of the population did not have any adverse public records. Of the remaining 3%, those having the most recent adverse public records (less than 18 months) were found to have 34% higher loss ratio than those without any adverse public records. Those having less recent adverse public records (more than 18 months) were found to have 18% higher loss ratio than those without any adverse public records.

FIGURE 11. NUMBER OF TRADE LINES 60+ DAYS DELINQUENT IN LAST 24 MONTHS VS. LOSS RATIO RELATIVITIES



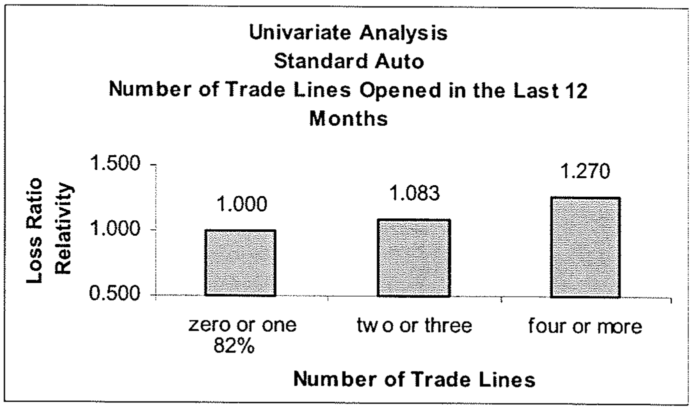
Of this population, 86% did not have any trade lines in delinquency for more than 60 days in the last two years. For people with one such delinquency, loss ratio was 24% higher than those without such delinquency. For those with two or more such delinquencies, loss ratio was 44% higher than those without.

FIGURE 12. NUMBER OF COLLECTIONS VS. LOSS RATIO RELATIVITIES



Of this population, 96% did not have collection accounts established. Of the remaining 4% that had collections accounts set up, loss ratio was 49% higher.

FIGURE 13. NUMBER OF TRADE LINES OPENED IN THE LAST 12 MONTHS VS. LOSS RATIO RELATIVITIES



Of this population, 82% opened just one or zero trade lines in the last year. People who opened two or three trade lines in the last year had a loss ratio 8% higher than people in the first group; four or more trade lines opened in the last year, 27% higher.

Summary

Given that loss ratio relativity includes the original premium surcharges and discounts, the above 10 charts show that credit information can further separate insurance policies in terms of loss ratio relativity.

4. General scoring technology

Brief summary

Statistical linear regression techniques can be applied to each of the five credit characteristics described in Figure 4 through Figure 13 in the previous section. In this manner, 10 separate scoring models (five models for auto and five models for homeowners) could be built. However, these simple scoring models, each with only a single credit characteristic, would not provide a powerful prediction of loss ratio relativities.

To develop a scoring model with powerful predictive capabilities, statistical multiple regression techniques and other technologies are used. These techniques draw on the predictive power of multiple characteristics to rank-order individuals or accounts by a given outcome, such as loss ratio relativity.

The fundamental functions of these techniques are to identify the predictive characteristics and describe the relationship with the dependent variable outcome. These techniques are taught at universities and documented in textbooks and papers. Some of the statistical techniques used in developing models are described in a Fair, Isaac paper titled "A Discussion of Data Analysis and Modeling Techniques" (See supplementary information).

While the general statistical methodologies are in the public domain, Fair, Isaac's scoring technology, and our scoring models, are proprietary. Fair, Isaac protects its investment in these unique scoring models, which have substantial commercial value and qualify as trade secrets under many public information access laws.

Causal vs. statistical relationship

It is important to note that statistical techniques in general do not determine a causal relationship between predictive characteristics and outcomes. Instead, these techniques numerically describe the statistical relationship between such variables. Other fields than insurance or financial services have used these same statistical techniques to discover relationships, without identifying causal relationships. In the medical field, for example, the identification of a statistical relationship between particular genes and symptoms of diseases such as Alzheimer's, Parkinson's and Huntington's was hailed as a medical breakthrough, even though the causal relationship remained unknown.

The point is that while the exact causal relationship between credit characteristics and loss ratio relativities is not known, there is a demonstrated statistical relationship between the two.

Scoring definitions

Score

The numerical total of points associated with each attribute in the scoring model. A score is calculated for each individual application or policy.

Scoring model (scorecard)

An algorithm or table comprised of a list of characteristics, each of which has two or more attributes and a numeric score weight attached to each attribute. The total weights constitute the score. Scoring models rank-order individuals or policies in a specific population according to a given outcome, e.g., loss ratio relativity.

Characteristic

A variable (such as "number of trade lines" or "number of collections") taken from a source of information such as a credit report. A number of characteristics, which have been determined to be predictive of a certain outcome, are found in a scoring model.

Attribute

One of the possible values of a characteristic. For example, for the characteristic "number of trade lines," the attributes might be "zero," "one," "two to four," "more than four," and so on.

Score weight

A numerical or point value attached to an attribute.

Reason codes

Reasons returned by a model, along with a score, that explain the up to four most important factors influencing the individual's score. (See supplemental information)

Scoring model example for homeowner insurance

The property insurance scoring model example in Figure 14, based on the credit characteristics shown in Figures 4 to 8, shows how a score might be calculated. (This example is a very simplified example of a scoring model for purposes of illustration.)

Each of the five characteristics has a set of attributes. Each attribute was assigned a weight. In general, the more predictive a characteristic is of loss ratio relativities, the higher the weights for its attributes. Each applicant will acquire one attribute from each characteristic. The sum of the weights is the score. Lower scores correlate with higher loss ratio relativities and higher scores correlate with lower loss ratio relativities.

FIGURE 14. PROPERTY INSURANCE SCORING MODEL EXAMPLE

Number of Adverse Public Records	**zero**	**one or more**			
	30	**0**			
Months Since Most Recent Adverse Public Record	**no public record**	**less than 48**	**48 or more**		
	30	**0**	**10**		
Number of Trade Lines 60+ Days Delinquent in Last 24 Months	**zero**	**one**	**two or more**		
	25	**10**	**0**		
Number of Collections	**zero**	**one or more**			
	20	**0**			
Number of Trade Lines Opened in the Last 12 Months	**zero**	**one**	**two**	**three**	**four or more**
	20	**10**	**5**	**3**	**0**

The minimum score from this example is 0 and the maximum is 125.

5. Results: Relationship of insurance bureau scores to loss ratio relativities

Score vs. loss ratio relativities

After years of research and experience in building predictive models, Fair, Isaac began developing scoring models for personal lines insurance. These models, resident at national consumer credit agencies, deliver scores (called "insurance bureau scores") that are based on credit information in an individual's credit report. These scoring models evaluate many predictive characteristics, which yields a much more powerful prediction than analysis of a single characteristic. The relationship of insurance bureau scores to loss ratio relativities is show in the examples below.

FIGURE 15. PROPERTY INSURANCE BUREAU SCORES VS. LOSS RATIO RELATIVITIES FOR HOMEOWNER POLICIES

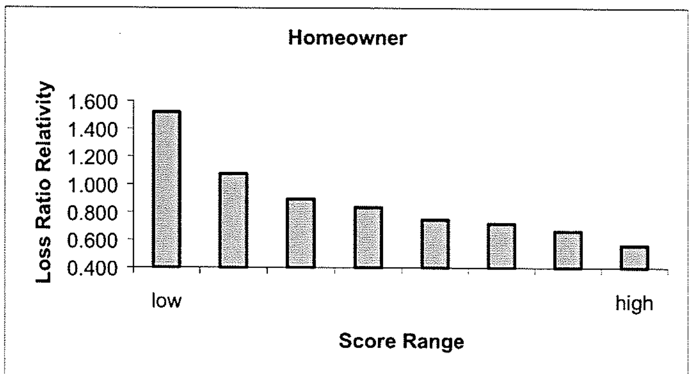
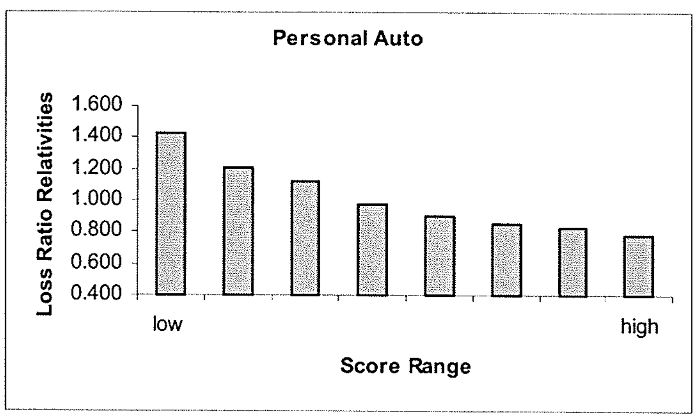


FIGURE 16. AUTO INSURANCE BUREAU SCORES VS. LOSS RATIO RELATIVITIES FOR PERSONAL AUTO POLICIES



The distributions from these scoring models show a downward sloping relationship between loss ratio relativities and insurance bureau scores: the lower the score, the higher the loss ratio relativities, and the higher the score, the lower the loss ratio relativities. Were there no relationship, there would be no downward or upward sloping observed.

Validations

These scoring models are validated by individual samples of books of business, as illustrated in Figures 17 and 18.

FIGURE 17. VALIDATION OF INSURANCE BUREAU SCORES VS. LOSS RATIO FOR PROPERTY INSURANCE

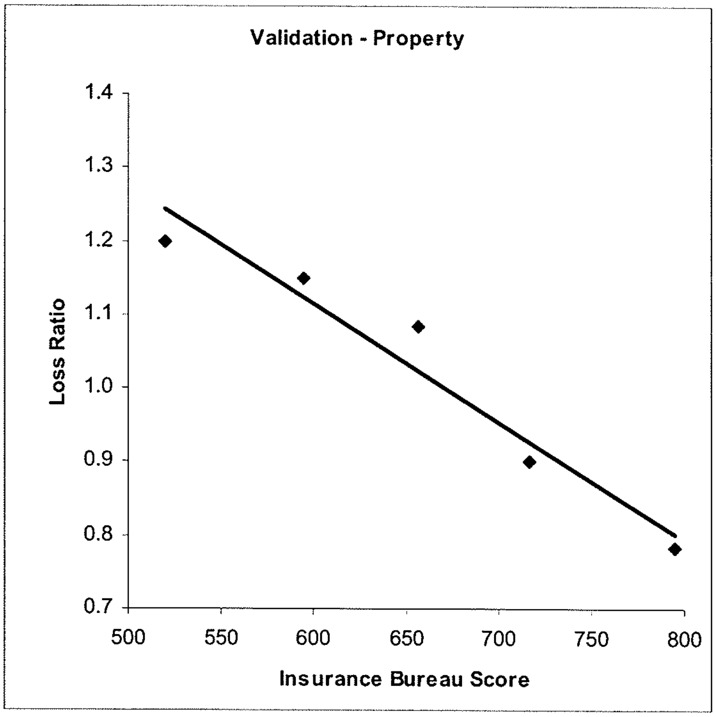
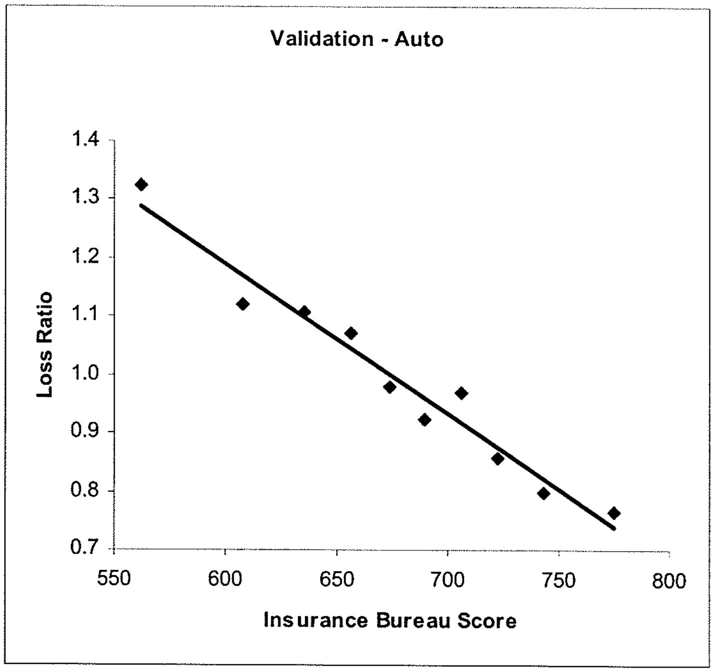


FIGURE 18. VALIDATION OF INSURANCE BUREAU SCORES VS. LOSS RATIO FOR PERSONAL AUTO INSURANCE



The average scores (in quintiles) of groups of property and personal auto policies were plotted against their actual loss ratios, as shown in Figures 17 and 18. By fitting linear trend lines to the data, downward sloping relationships can be observed, validating the relationship between insurance bureau scores and loss ratio relativities. (More validations can be found in the supplementary information.)

Independent validation by Tillinghast

In response to the discussions from the early drafts of the NAIC white paper, in 1996 Fair, Isaac commissioned Tillinghast-Towers Perrin to independently validate the relationship between insurance bureau scores and loss ratio relativities. (The study can be found in the supplementary information.)

In the Conclusions section of this report, it states:

"The data for all companies included in this study except Company 2 indicates at least a 99% probability that a relationship exists. The data for Company 2 indicates a 92% probability that there is a relationship. A layman's interpretation of this result could be that it is very likely there is a correlation between insurance bureau scores and loss ratio relativities."

"Common sense" relationship of scores and insurance behavior

While only the statistical relationship between credit characteristics and insurance performance has been discussed and no causal relationship explanation has been offered, the relationship between how people maintain their credit and property is simply "common sense." One can imagine that when a person utilizes one's resource well to maintain a home or a car in safe operating conditions, he or she is probably maintaining his or her finance and credit as well. For instance, when the car battery, headlights, motor oil level, etc., are checked; driveway, trees and bushes, etc., are cleared; and stove and house heater are maintained regularly, there is less chance for an accident. Good credit managers are usually good risk managers.

Discrimination studies

While Fair, Isaac has not performed any discrimination studies using insurance bureau scores, other parties have completed such studies. Results from such an analysis were reported by the American Insurance Association (AIA) in their testimony at the December 1998 NAIC public hearing in Orlando. A press release regarding the results and the testimony was titled "Income Does Not Have a Clear Impact on Credit Score" (March 31, 1999).

As stated in the press release, "Using credit scoring as a tool to underwrite and price premium for new applicants for insurance or to evaluate insurance renewals does not discriminate against lower income populations, according to an analysis by (a member company of) the American Insurance Association."

Further, the release says:

> According to Michael Lovendusky, AIA assistant general counsel, "AIA presented then and now important evidence that credit scores do not unfairly discriminate against or even negatively impact lower income groups."

The scoring model developed by Fair, Isaac, the release goes on to say:

> "...uses characteristics from the credit history, such as public notices, credit account trade line, and additional credit inquiries. It makes no use or reference to personal characteristics, such as income, net worth, ethnicity and location. The model was developed with data from over a dozen insurers using over 1.4 million policies representing over $1.5 billion in earned premium and nearly $900 million in incurred losses."

The analysis concluded the score is not significantly correlated with income for policyholders and that there is no evidence that scores unfairly discriminate against lower income groups. (Please note that while references quoted above refer to "credit scores," it is clear from the last paragraph on model development that the reference is to "insurance bureau scores."

Fair, Isaac hopes that other studies will be available to illuminate the impact of the underwriting use of credit history or insurance bureau scores on protected classes.

Equal Credit Opportunity Act (ECOA) and Fair Housing Act (FHA)

While the 1974 federal statute Equal Credit Opportunity Act (ECOA) has no application to the insurance industry, Fair, Isaac insurance scoring models follow ECOA guidelines. In its scoring model development, Fair, Isaac does not include any discriminatory characteristics as defined by the ECOA; these include data elements of age, gender, income, location, marital status, nationality, net worth, race and religion.

The Fair Housing Act applies to residential real estate-related transactions, including homeowner's insurance. Fair, Isaac's insurance scoring models comply with the guidelines of this federal statute and do not take into account a person's race, color, religion, sex, handicap, familial status or national origin.

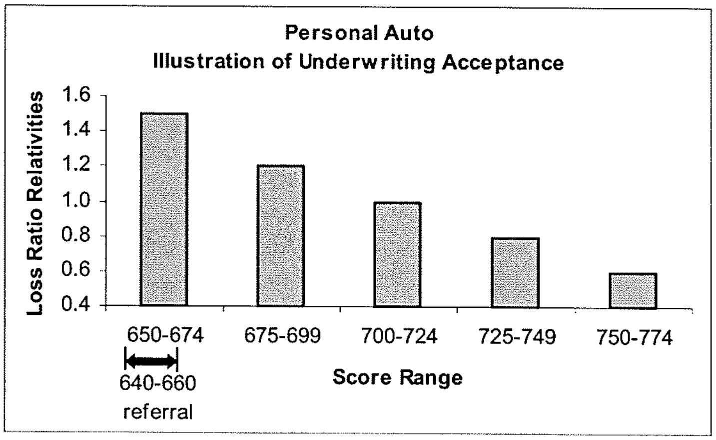
6. Use of insurance bureau scores

Insurance bureau scores are used by many leading personal lines insurers in the United States and Canada to support the underwriting process. Because they are easily available from large credit bureaus, they provide insurers of any size with an efficient way to make faster, better, more consistent decisions in underwriting.

Underwriting evaluation

Insurance bureau scores can improve underwriting efficiency. Using scores, current underwriting programs can be "profiled" by identifying the score ranges that fall within or outside the programs.

FIGURE 19. ILLUSTRATION OF UNDERWRITING ACCEPTANCE



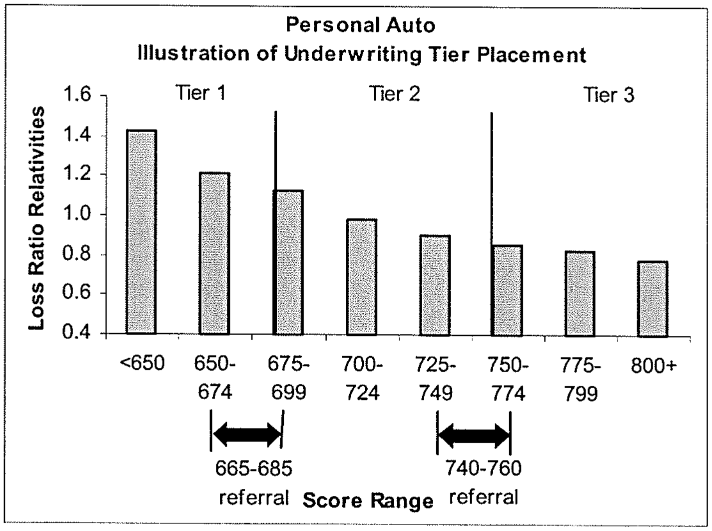
As an example, scores are appended to each policy of a personal auto program with losses developed for two to three years. Losses and premiums are totaled by predetermined score range. A possible result of insurance bureau scores vs. loss ratio relativities distribution is shown in Figure 19. The score range of 650 to 774 would identify risks qualifying for the program in the past. Underwriters would review policies at various high and low score ranges to verify that the scores are predicting losses properly.

Management can then decide to maintain the policy volume of the program by accepting risks with scores in the range of 650 to 774 or grow the policy volume by actively marketing to risks in the same range. Management may even decide to implement a referral range of 640 to 660; thus those risks close to the low end of the score range would receive more underwriting attention before a final decision is made.

Tier placement

Similar to the process for using scores in underwriting acceptance, scores can be appended to policies from several underwriting programs, with losses developed for two to three years. Again, losses and premiums are totaled by score range. Also, the score range for each program is backed out. A possible resulting insurance bureau scores vs. loss ratio relativities distribution is shown in Figure 20, with three programs or tiers assumed. Tier 1 includes policies with scores less than 675; Tier 2 from 675 to 749; Tier 3 from 750 and above.

FIGURE 20. ILLUSTRATION OF UNDERWRITING TIER PLACEMENT



Once again, referral ranges can be set up to identify policies in the range from 665 to 685 in order to confirm the decisions for risks going into Tier 1 versus Tier 2; and from 740 to 760 to confirm the placement of risks in Tier 2 vs. Tier 3. Perhaps, other underwriting investigations may be appropriate for these referred policies.

Following the discussion above, existing programs can be modified by changing the score ranges and referral ranges. New programs can be created and tested in a similar fashion.

Agent/sales management

Average insurance bureau scores and score ranges can be determined by source of business—agent or sales representative. Trends in score averages and score ranges can be monitored and analyzed over time. Goals and objectives can be established in terms of score average and range.

Management information

Trends and development in score averages, deviation and ranges can be reported to management regularly, together with other management information. They can also be used in planning, scenario testing, and formulating strategic initiatives and corrective actions.

7. Summary

Insurance bureau scores based on credit data enable insurers of all sizes to improve the speed, objectivity and consistency of their underwriting.

The correlation between credit information and insurance loss potential can be empirically demonstrated on a characteristic by characteristic basis. Insurance bureau scores are based on multiple characteristics. Their power in forecasting loss ratio has been validated by independent agencies such as Tillinghast-Towers-Perrin, as well as Fair, Isaac.

Several studies have shown that the accuracy of credit reports is very high, especially when compared to the accuracy of motor vehicle reports, which are nevertheless accepted in underwriting.

The use of insurance bureau scores can help underwriters streamline risk evaluation. Borderline risks can be quickly identified. This efficiency helps underwriters to approve good risks more rapidly, place risks more accurately and focus underwriting attention on risks that need it.

No discriminatory characteristics, as defined by the ECOA or FHA, are used in insurance bureau scores. In fact, insurance bureau scores provide objective evaluations that can offset underwriters' personal biases. As a result, they help to facilitate consistent underwriting, as well as to remedy and control discrimination.

Supplemental Information

Analyzing a Credit Report Facts and Fallacies,
Fair, Isaac, 1999

A Discussion of Data Analysis and Modeling Techniques,
Fair, Isaac White Paper, June, 1995

Insurance Bureau Scores vs. Loss Ratio Relativities,
Tillinghast-Towers Perrin

Insurance Monitor, Fair, Isaac, 1999

"Principles Needed to Guide Use of Credit Information,"
National Underwriter, Lamont D. Boyd, May 16, 1996

The TransUnion Credit Report Training Guide, TransUnion

TransUnion Reason Codes

About Fair, Isaac

Fair, Isaac and Company, Inc. (NYSE:FIC) is the preeminent provider of creative analytics that unlock value for people, businesses and industries. The company's predictive modeling, decision analysis, intelligence management, decision management systems and consulting services power more than 25 billion mission-critical customer decisions a year. Founded in 1956, Fair, Isaac helps thousands of companies in over 60 countries acquire customers more efficiently, increase customer value, reduce fraud and credit losses, lower operating expenses and enter new markets more profitably. Most leading banks and credit card issuers rely on Fair, Isaac solutions, as do insurers, retailers, telecommunications providers, healthcare organizations and government agencies. Through the *www.myfico.com* Web site, consumers use the company's FICO® scores, the standard measure of credit risk, to manage their financial health. As of August 2002, HNC Software Inc., a leading provider of high-end analytic and decision management software, is part of Fair, Isaac. For more information, visit *www.fairisaac.com.*

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Fair Isaac®

Insurance Bureau Scores
vs
Loss Ratio Relativities

Prepared by:
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TILLINGHAST–TOWERS PERRIN
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December 10, 1996

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Tillinghast-Towers Perrin

December 10, 1996

Mr. Lamont D. Boyd, CPCU, AIM
Senior Marketing Representative
Fair, Isaac
120 North Redwood Drive
San Rafael, California 94903-1996

Dear Mr. Boyd:

Attached is our analysis of the data provided to calculate the P-Value of the slope parameter from the regression analysis of Insurance Bureau Scores and loss ratio relativities. We hope this study is useful in your discussions with the insurance industry regulators.

Thank you for the opportunity to work with you and your staff on this project. We will be happy to answer any questions that may arise.

Sincerely,

TILLINGHAST — TOWERS PERRIN

By: Wayne D. Holdredge
Wayne D. Holdredge, ACAS, MAAA

WDH:jfb

Attachment

Table of Contents

Purpose

Tillinghast –Towers Perrin (Tillinghast) was retained by Fair, Isaac and Co., Inc. (Fair, Isaac) to analyze certain data to be provided to Tillinghast by numerous property/casualty insurance companies. Specifically, based on each set of data provided, we were asked to calculate and report on the P-Value of the slope parameter from the regression analysis of Insurance Bureau Scores based on consumer credit information, and loss ratio relativities.

The purpose of calculating P-Values is to measure the confidence or statistical significance of the relationship between the Insurance Bureau Scores and loss ratio relativities. P-Values are defined on pages 8 to 9.

Distribution and Use

The results of our analysis are being provided to Fair, Isaac for its use in discussions with the National Association of Insurance Commissioners (NAIC) about the use of Insurance Bureau Scores in underwriting personal insurance. A copy of this report in its entirety may be provided to the NAIC during the course of these discussions. Further, Fair, Isaac may release copies of this report to state insurance regulators and legislators, Fair, Isaac insurance company prospects and clients and to the press provided that:

1. The entire report is provided;

2. Fair, Isaac maintains a list of the names of the parties to whom copies of the report are given and provides that list to Tillinghast; and

3. Fair, Isaac advises each party to whom a copy of such report is given that such party may contact Tillinghast to discuss the report. Tillinghast will notify Fair, Isaac when it is contacted by a recipient of the report.

Any other use or further distribution of the report is not authorized without Tillinghast prior written consent.

Reliances and Limitations

Data, as identified later in this report, was provided by individual insurance companies to Fair, Isaac who in turn sent the data to Tillinghast. We confirmed with the person responsible for providing the data at each insurance company that the data we relied on is correct and is from that company's book of business.

We understand that different groupings of the same data could produce different P-Values. However, the way the data was subtotaled when it was provided to us appears reasonable to us.

We were requested to determine and give a report on a particular statistic from the regression of certain Insurance Bureau Scores and loss ratio relativity information provided by insurance companies. No analysis of or opinion on any other aspects of the use of Insurance Bureau Scores in underwriting personal insurance is offered by Tillinghast or implied from the conclusions of this report.

Throughout this report, the word "relationship" is used interchangeably with the word "correlation."

Conclusions

Fair, Isaac requested data from a number of insurance companies, several of which, as shown below, have already responded to the request for data. The following P-Values of the slope parameters were calculated from all of the data provided to us up to this point.

Company	Line of Business	P-Value	Probability (1 - P-Value)
1	Auto	.0009	.9991
2	Homeowners	.0833	.9167
3*	Homeowners	.0002	.9998
4	Auto	.0038	.9962
5	Personal Property	.0001	.9999
6	Homeowners	.0068	.9932
7	Homeowners	.0061	.9939
8*	Auto	.0000	1.0000
9	Homeowners	.0038	.9962

* Companies 3 and 8 are the same company. Its homeowners and auto submissions are designated as separate companies.

From the data and P-Values, we conclude that the indication of a relationship between Insurance Bureau Scores and loss ratio relativities is highly statistically significant. In a more technical sense, the conclusion is that it is very unlikely that Insurance Bureau Scores and loss ratio relativities are not correlated b- on this data.

The data for all companies included in this study except Company 2 indicates at least a 99% probability that a relationship exists. The data for Company 2 indicate a 92% probability that there is a relationship. A layman's interpretation of this result could be that it is very likely there is a correlation between Insurance Bureau Scores and loss ratio relativities.

Data

The data we received for each company is included as we received it in Exhibit I. In each case there are four columns of numbers:

- Score Interval
- Midpoint
- Earned Premium
- Loss Ratio Relativity

We are assured by Fair, Isaac and the individual companies that this data is representative of each company's entire block of business. The time frames from which the data is taken are not the same for all companies, although our understanding is that it represents relatively recent experience. Also note that the Insurance Bureau Scores were determined prior to the experience underlying the loss ratios.

The score intervals in the first column were selected to produce 10 groups with approximately equal volume. In three instances, Company 6, Company 7 and Company 9, the score intervals were established to create fewer groups with similar volume. The data could have been grouped numerous other ways, and perhaps different groupings would have produced different results. The groupings of the data as presented to us seemed reasonable and appropriate for this analysis.

In the second column is the midpoint of each of the intervals shown in the first column. For the first and last intervals, the midpoint is the mean of the scores in that interval.

The third column shows the percentage of the total premium from the risks with the corresponding Insurance Bureau Scores in the first column. As stated above, the intervals were selected so that approximately 10% of the total premium (except for Company 6, 7 and 9) was included in each interval.

The loss ratio relativities in the last column are not loss ratios. They are the relativities of the loss ratios for each interval to the total loss ratio. For example, a loss ratio relativity of 1.20 for a given interval means that the loss ratio for the group of insureds with Insurance Bureau Scores in that interval was 20% greater than the loss ratio for all the company's insureds in this study. From this information we are not able to conclude anything about the absolute level of the loss ratios, only the loss ratio relativities.

P-Value

Detailed explanations of the P-Value as we have calculated it are contained in most statistical text books. For a rigorous definition of this statistic, the reader is encouraged to reference one of those texts. In the following paragraphs we explain the P-Value in general terms only.

For purposes of this analysis, we tested the hypothesis that there was no correlation between Insurance Bureau Scores and loss ratio relativities. If this hypothesis is true, the loss ratio relativities as shown in Exhibit II will be randomly distributed about the line representing the loss ratio relativity of 1.00. If the hypothesis is false, the loss ratio relativities will be randomly distributed about some other reasonably identifiable line.

The P-Value is a test statistic to test this hypothesis. If the hypothesis is true and the loss ratio relativities are randomly distributed above and below the loss ratio relativity = 1.00 line on the graphs in Exhibit II, the P-Value will be high. If the hypothesis is false and the loss ratio relativities do not appear to be randomly above and below the loss ratio relativity line = 1.00, the P-Value will be low. A low P-Value means it is unlikely that the differences between the actual results and the initial hypothesis are due to random variation. This means it is unlikely the initial hypothesis is correct.

While no statistical test will allow us to reject the initial hypothesis absolutely, this test indicates that it is very unlikely the initial hypothesis is valid. That is, there is very strong evidence of correlation between Insurance Bureau Scores and loss ratio relativities, (i.e., we should reject the hypothesis that there is no correlation between Insurance Bureau Scores and loss ratio relativities).

This test does not identify what that correlation is or how strong the correlation is but only whether the conclusion of the existence of a correlation is significant or not. From simply viewing the graphs in Exhibit II, it seems clear that higher loss ratio relativities are associated with lower Insurance Bureau Scores.

COMPANY 1

Score & Loss Ratio Relativity Summary

Score Interval	Midpoint	Earned Premium	Loss Ratio Relativity
813 or More	850.0	10.2%	0.657
768-812	790.0	9.9%	0.584
732-767	749.5	11.0%	0.692
701-731	716.0	10.9%	0.683
675-700	687.5	10.4%	1.184
651-674	662.5	9.8%	0.793
626-650	638.0	9.9%	1.332
601-625	613.0	10.0%	1.280
560-600	580.0	9.4%	1.214
559 or Less	525.0	8.6%	1.752
Total		100.0%	1.000

COMPANY 2

Score & Loss Ratio Relativity Summary

Score Interval	Midpoint	Earned Premium	Loss Ratio Relativity
840 or More	854.0	10.0%	0.607
823-839	831.0	10.0%	0.813
806-822	814.0	10.0%	0.626
789-805	797.0	10.0%	1.342
771-788	779.5	10.0%	1.059
748-770	759.0	10.0%	1.019
721-747	734.0	10.0%	1.322
686-720	703.0	10.0%	0.810
635-685	660.0	10.0%	0.986
635 or Less	592.0	9.9%	1.417
Total		100.0%	1.000

COMPANY 3

Score & Loss Ratio Relativity Summary

Score Interval	Midpoint	Earned Premium	Loss Ratio Relativity
826 or More	845.0	10.0%	0.723
803-826	814.5	10.0%	0.903
782-803	792.5	10.0%	0.895
759-782	770.5	10.0%	0.795
737-759	748.0	10.0%	1.073
710-737	723.5	10.0%	0.941
680-710	695.0	10.0%	0.912
640-680	660.0	10.0%	1.115
583-640	611.5	10.0%	1.221
583 or Less	535.0	10.0%	1.421
Total		100.0%	1.000

COMPANY 4

Score & Loss Ratio Relativity Summary

Score Interval	Midpoint	Earned Premium	Loss Ratio Relativity
832 or More	859.0	10.0%	0.672
803-832	817.5	10.0%	1.027
767-803	785.0	10.0%	0.823
739-767	753.0	10.0%	1.036
720-739	729.5	10.0%	0.775
691-720	705.5	10.0%	1.000
668-691	679.5	10.0%	1.041
637-668	652.5	10.0%	1.023
602-637	619.5	10.0%	1.251
602 or Less	571.0	10.0%	1.351
Total		100.0%	1.000

COMPANY 5

Score & Loss Ratio Relativity Summary

Score Interval	Midpoint	Earned Premium	Loss Ratio Relativity
845 or More	857.0	10.0%	0.800
830-845	837.5	10.0%	0.919
814-830	822.0	10.0%	0.740
798-814	806.0	10.0%	0.733
779-798	788.5	10.0%	0.855
757-779	768.0	10.0%	0.889
730-757	743.5	10.0%	0.993
695-730	712.5	10.0%	1.143
643-695	669.0	10.0%	1.300
643 or Less	600.0	10.0%	1.628
Total		100.0%	1.000

COMPANY 6

Score & Loss Ratio Relativity Summary

Score Interval	Midpoint	Earned Premium	Loss Ratio Relativity
810 and up	837.5	19.7%	0.656
765-809	777.0	20.1%	0.795
715-764	739.5	20.8%	0.911
645-714	679.5	20.2%	1.066
Below 645	600.0	19.2%	1.593
Total		100.0%	1.000

COMPANY 7

Score & Loss Ratio Relativity Summary

Score Interval	Midpoint	Earned Premium	Loss Ratio Relativity
750 and up	795.0	21.3%	0.783
685-749	717.0	25.8%	0.900
630-684	657.0	19.6%	1.083
560-629	594.5	19.3%	1.150
Below 560	520.0	13.9%	1.200
Total		100.0%	1.000

COMPANY 8

Score & Loss Ratio Relativity Summary

Score Interval	Midpoint	Earned Premium	Loss Ratio Relativity
755 or More	775.0	8.9%	0.767
732-754	743.0	9.3%	0.798
714-731	722.5	9.6%	0.859
698-713	705.5	9.9%	0.969
682-697	689.5	10.3%	0.922
666-681	673.5	9.7%	0.978
647-665	656.0	10.5%	1.070
625-646	635.5	10.2%	1.107
592-624	608.0	10.7%	1.122
591 or Less	562.0	10.8%	1.324
Total		100.0%	1.000

COMPANY 9

Score & Loss Ratio Relativity Summary

Score Interval	Midpoint	Earned Premium	Loss Ratio Relativity
780 and up	815.0	16.8%	0.637
745-779	762.0	13.7%	0.715
710-744	727.0	13.9%	0.734
670-709	689.5	15.0%	0.807
635-669	652.0	12.1%	0.909
590-634	612.0	11.2%	1.241
530-589	559.5	9.8%	1.357
Below 530	495.0	7.5%	2.533
Total		100.0%	1.000

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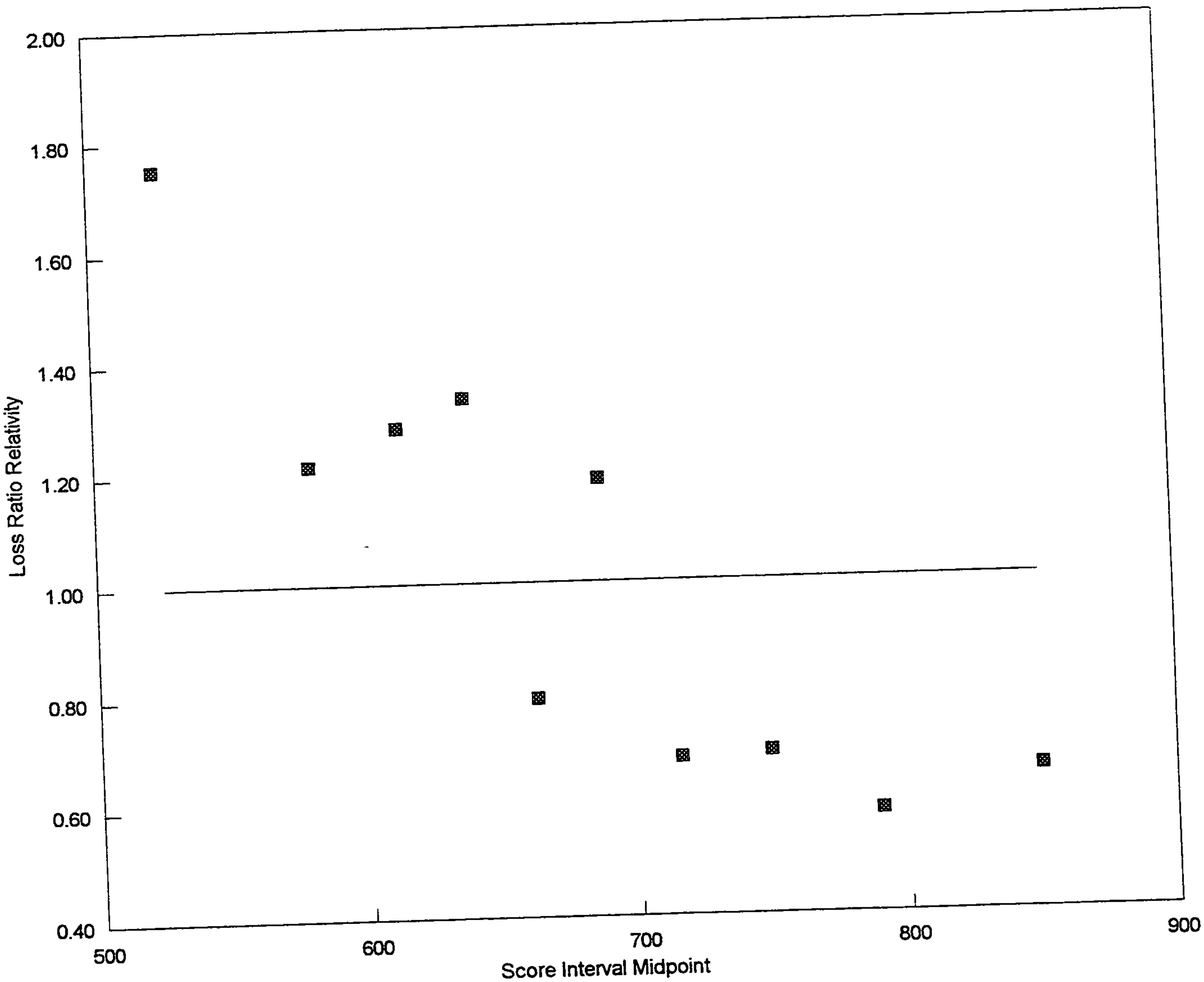
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800
900
Score Interval Midpoint

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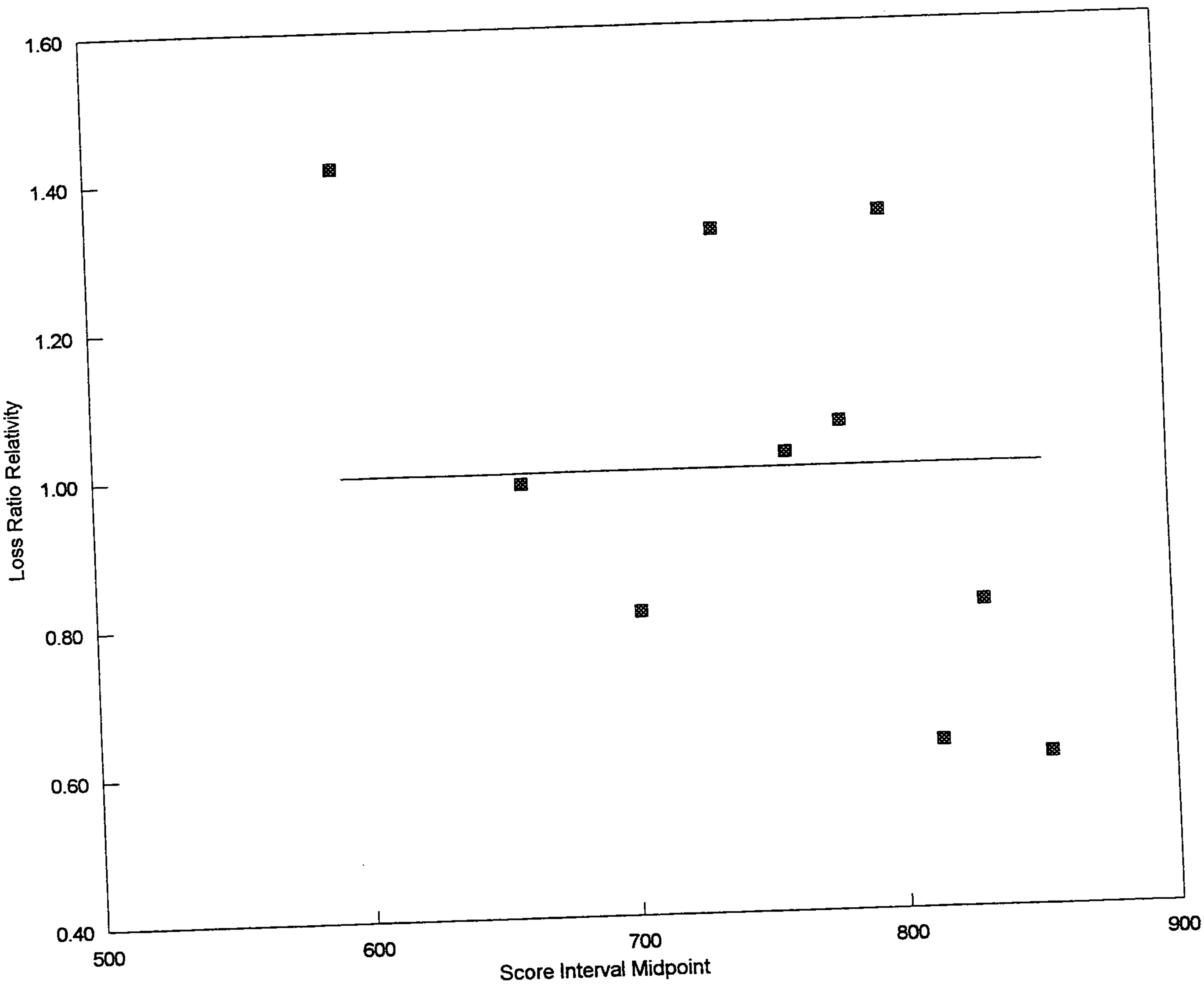
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Score Interval Midpoint

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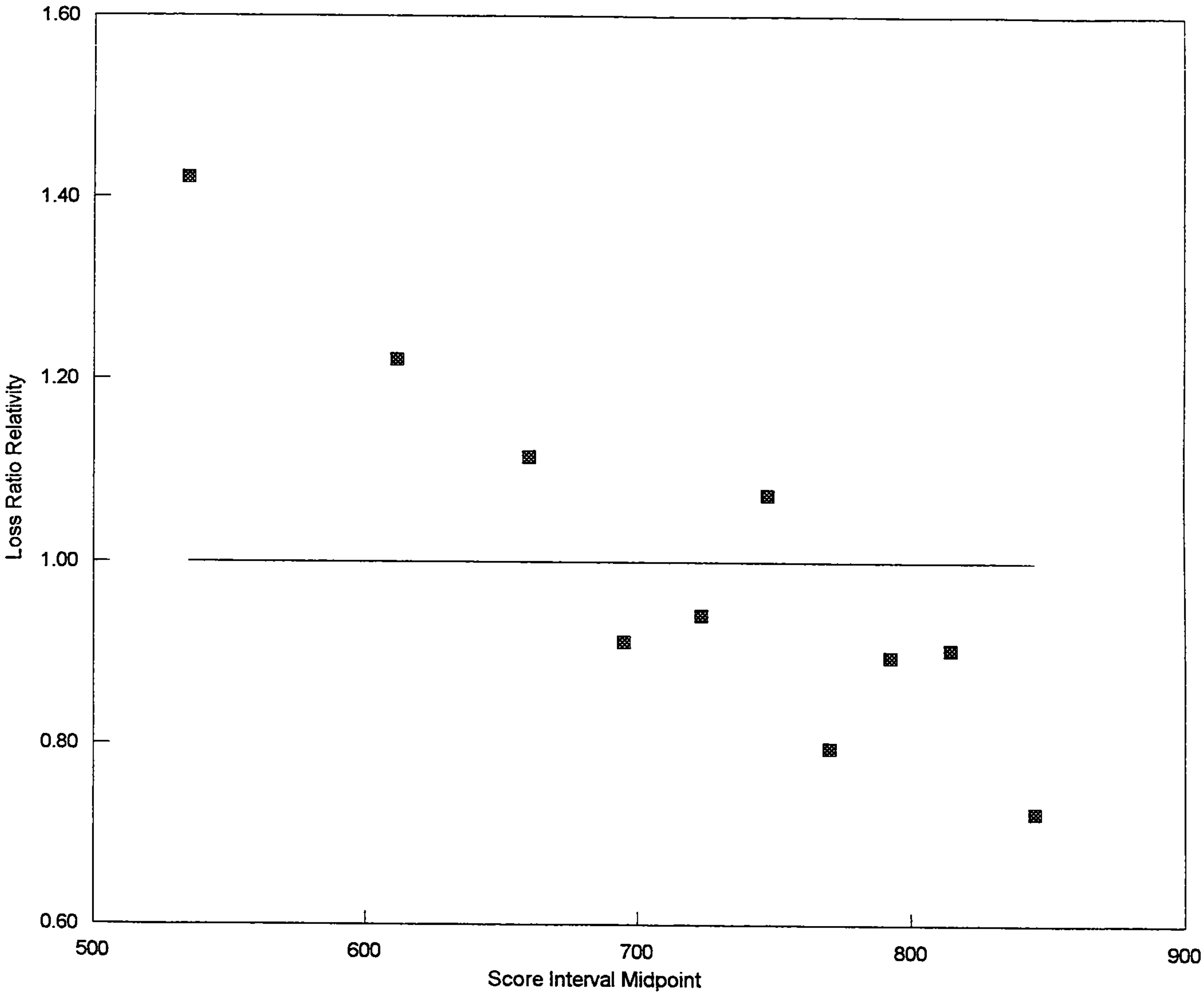
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Score Interval Midpoint

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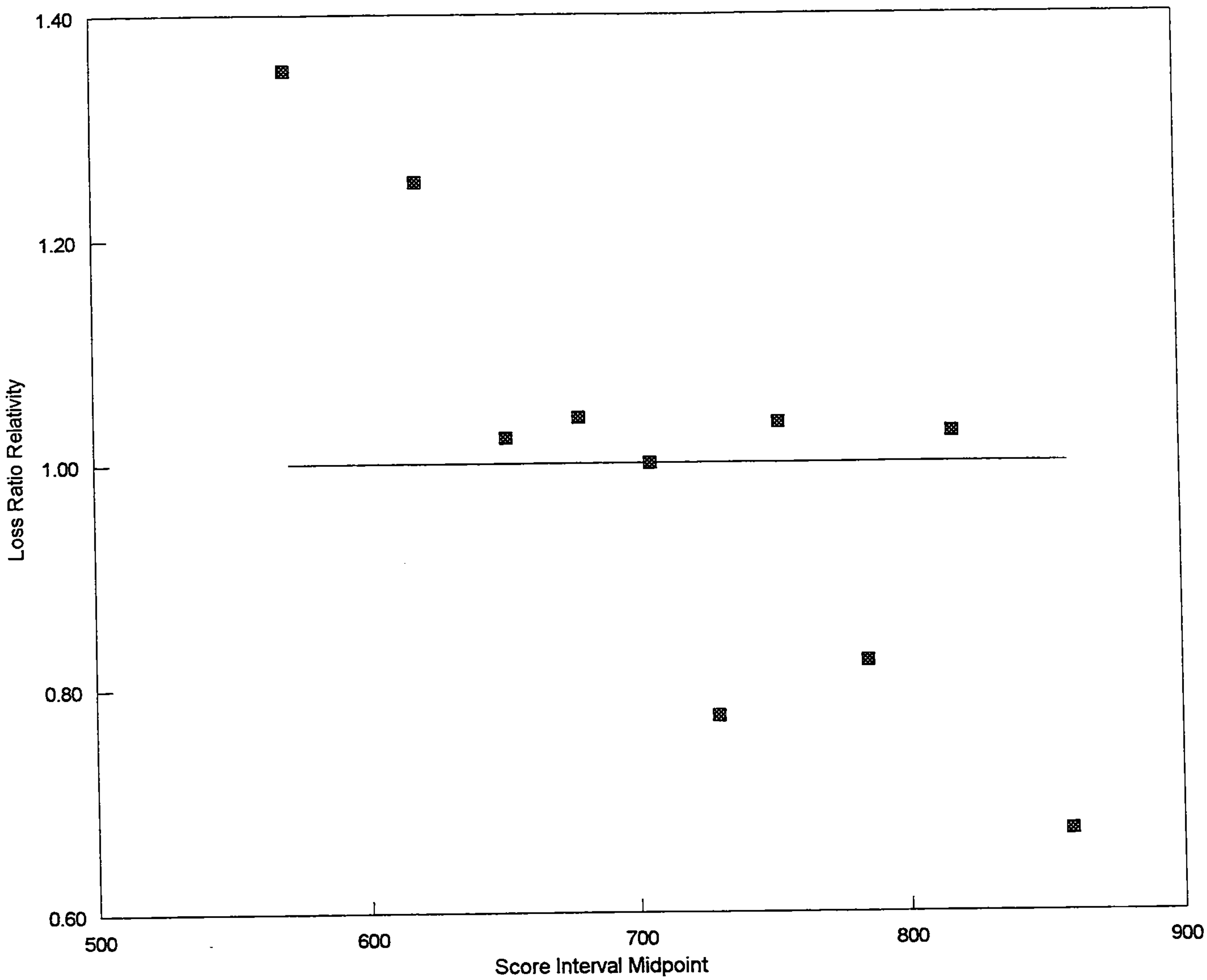
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Loss Ratio Relativity
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Score Interval Midpoint

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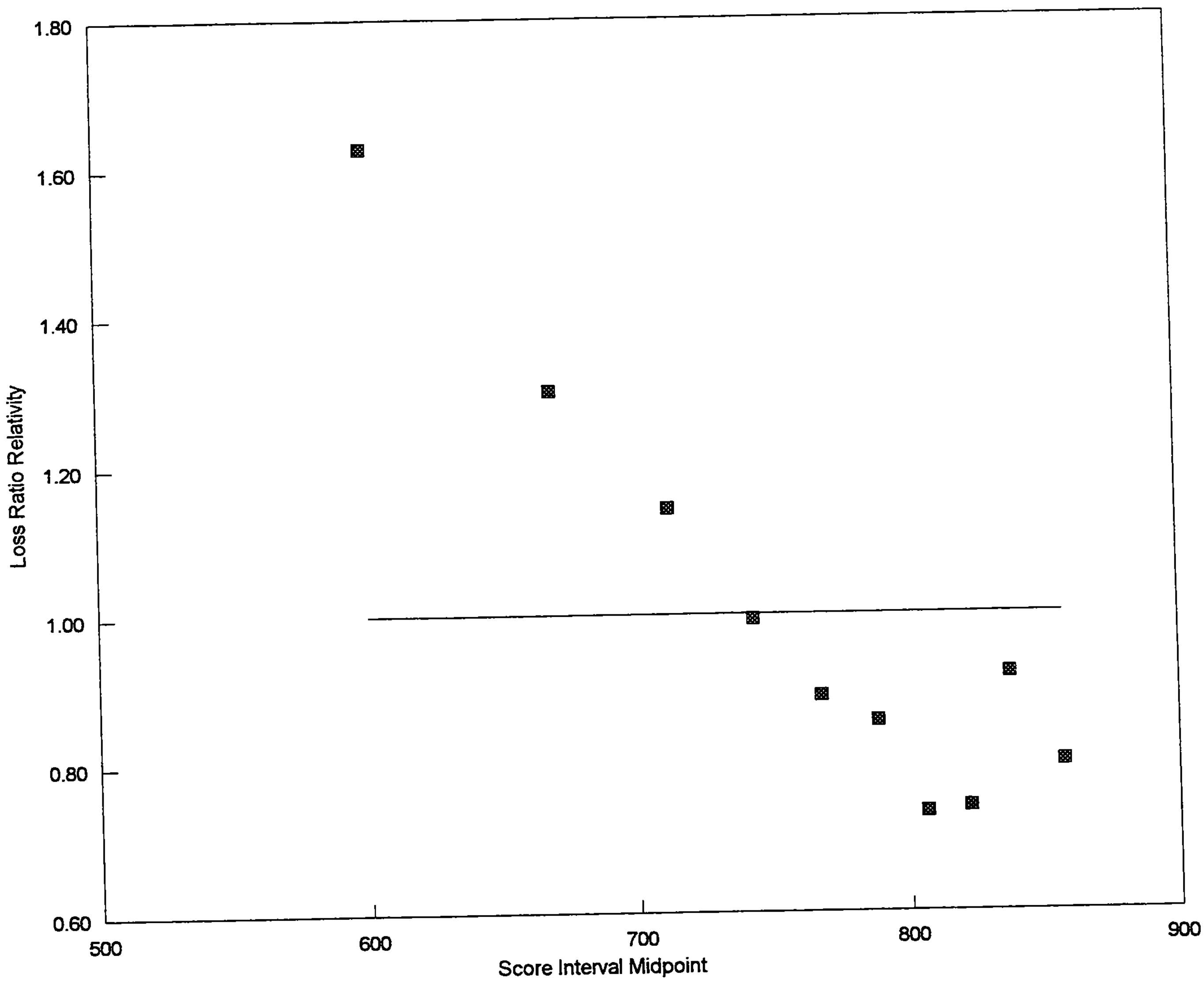
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Loss Ratio Relativity
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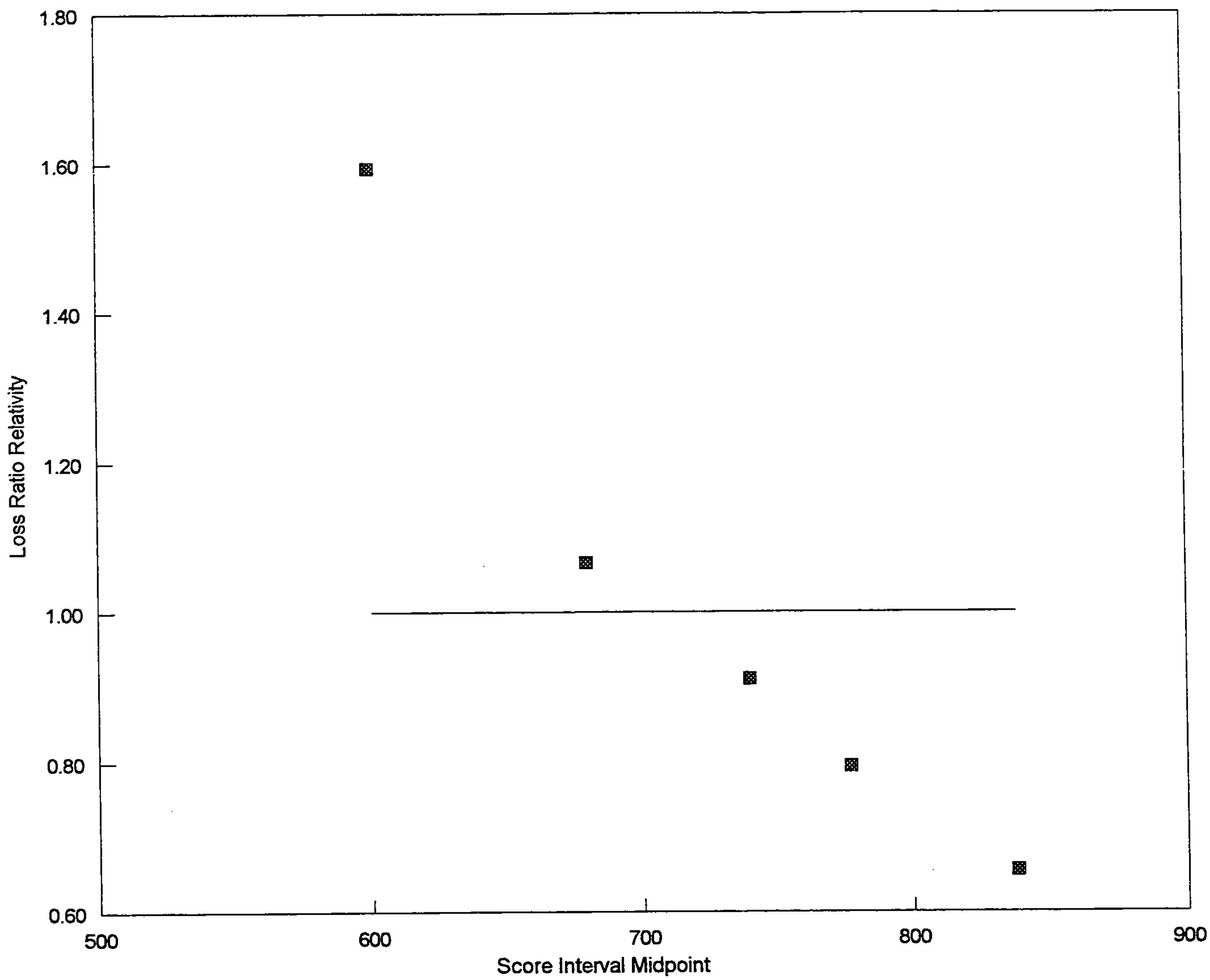
700
800
900
Score Interval Midpoint

Company 6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Loss Ratio Relativity
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Score Interval Midpoint

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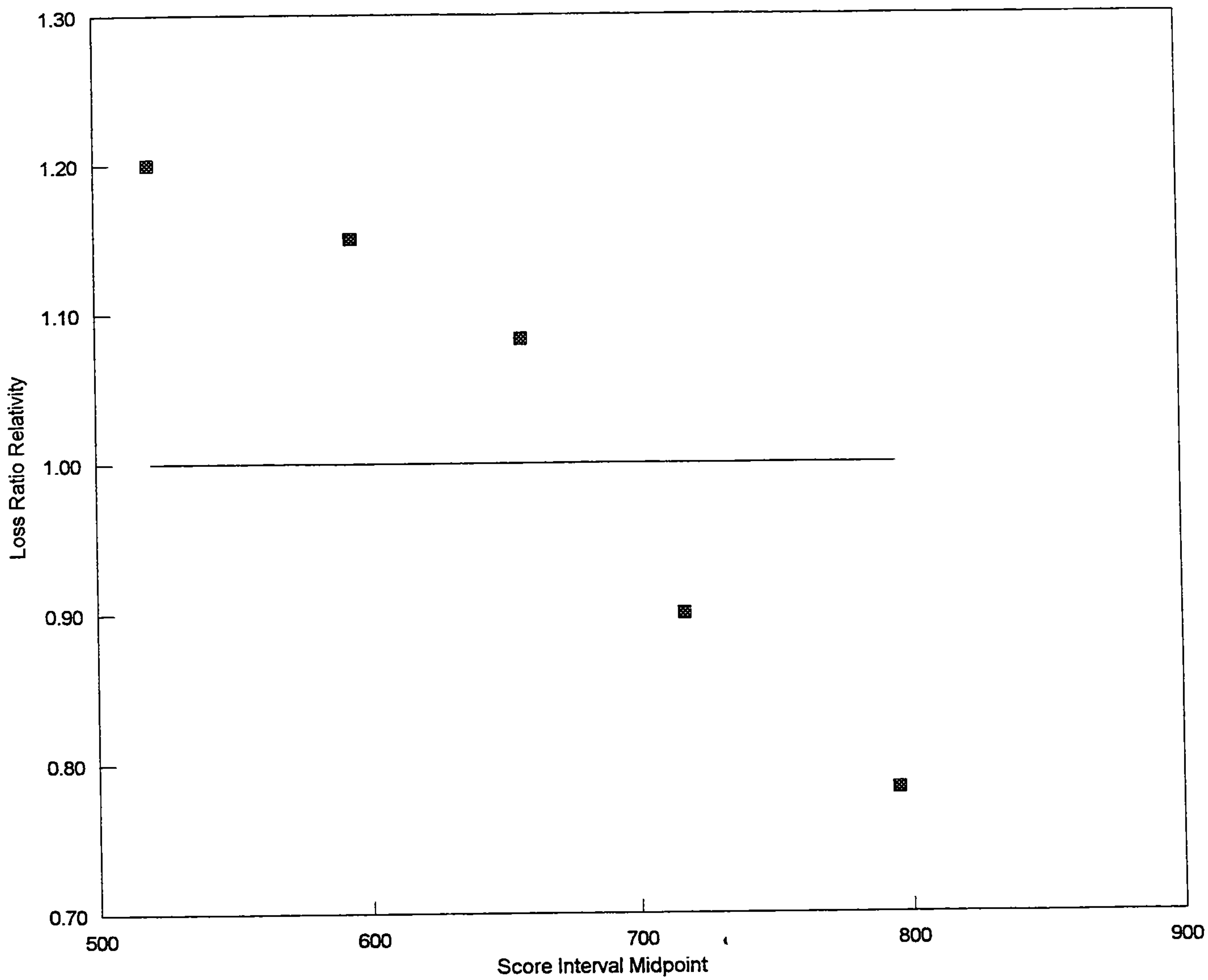
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Score Interval Midpoint

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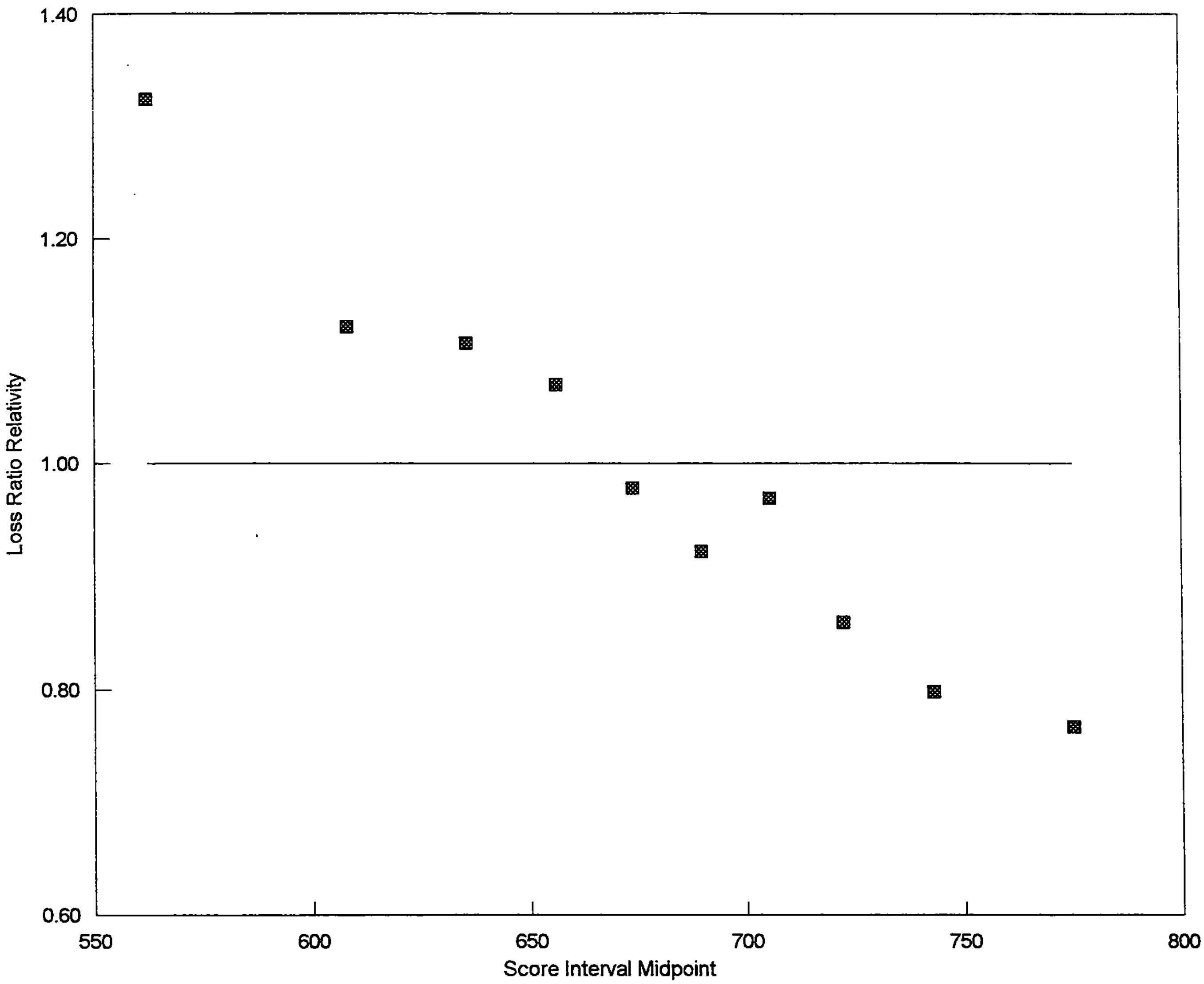
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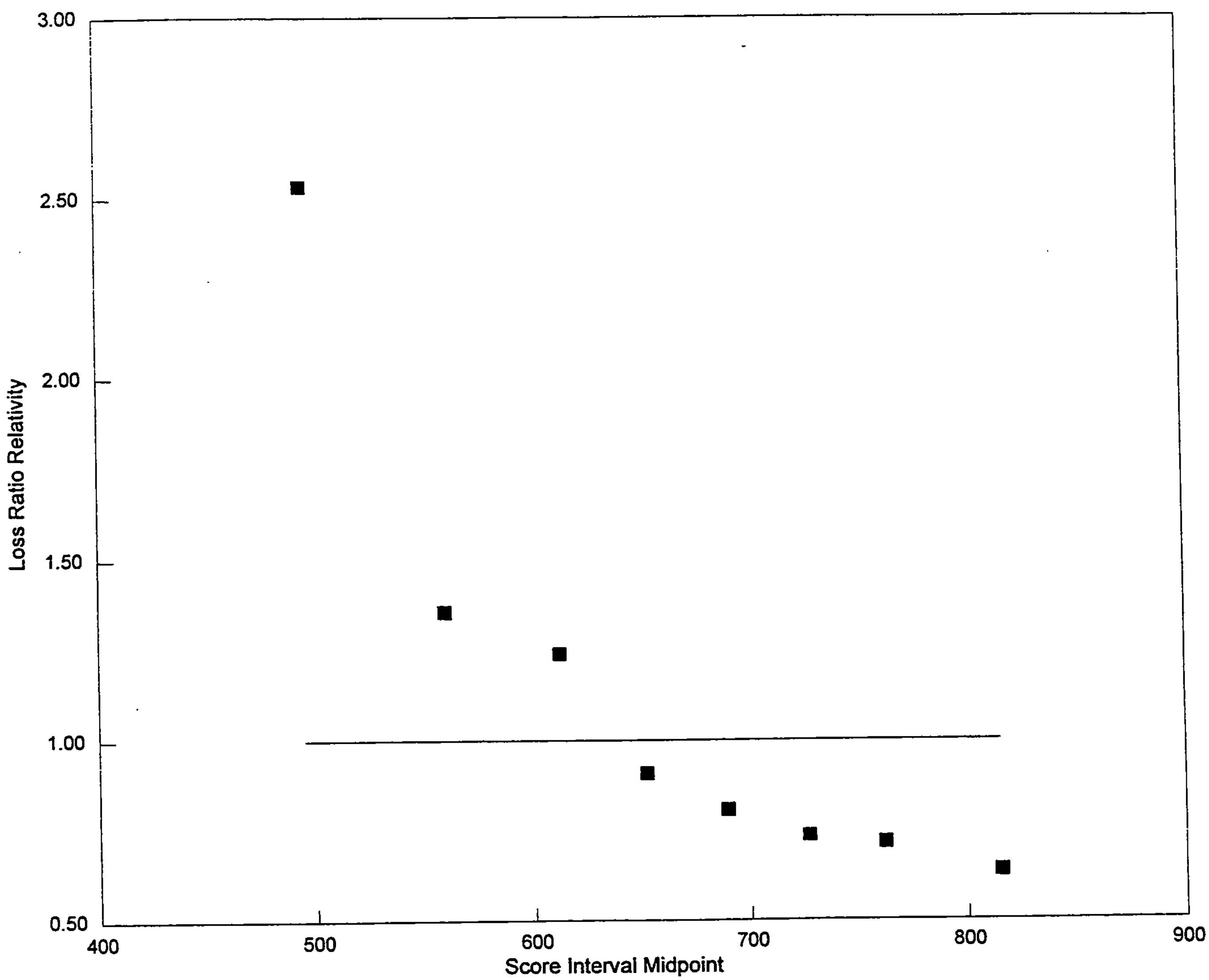
Score Interval Midpoint

Company 9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Loss Ratio Relativity
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800
900
Score Interval Midpoint

FairIsaac®

ANSWERS

to Your Questions About Insurance Bureau Scores

[1] WHAT IS AN INSURANCE BUREAU SCORE?

An Insurance Bureau Score is a snapshot of a consumer's insurance risk picture at a particular point in time based on credit report information. Insurers use Insurance Bureau Scores along with motor vehicle records, loss reports or application information to evaluate new and renewal auto and homeowner insurance policies. It helps them decide, "If we accept this applicant or renew this policy, will we likely be exposed to more losses than our collected premiums will allow us to handle?"

Insurance Bureau Scores are based solely on information in consumer credit reports. The scores are dynamic, changing as new information is added to a consumer's credit report. Insurers will typically ask for a current score when they receive a new application for insurance so they have the most recent information available.

[2] WHERE DO INSURANCE BUREAU SCORES COME FROM?

Insurance Bureau Scores are based on information from consumer credit reports that insurers get from the three major credit reporting agencies: Equifax, Experian (formerly known as TRW) and TransUnion. Information used in scoring includes:

- Outstanding debt
- Length of credit history
- Late payments, collections, bankruptcies
- New applications for credit
- Types of credit in use

[3] WHAT'S NOT INCLUDED IN AN INSURANCE BUREAU SCORE?

Insurance Bureau Scores do not use the following information:

- Ethnic group
- Religion
- Gender
- Familial Status
- Handicap
- Nationality
- Age
- Marital Status
- Income
- Address

[4] WHY DO INSURANCE COMPANIES USE INSURANCE BUREAU SCORES?

Insurance companies use scores to help them issue new and renewal insurance policies. Insurance Bureau Scores provide an objective, accurate and consistent tool that insurers use with other applicant information to better anticipate claims, while streamlining the decision process so they can issue policies more efficiently. By better anticipating claims, insurers can better control risk, enabling them to offer insurance coverage to more consumers at a fairer cost.

[5] HOW DO YOU KNOW IT WORKS?

Independent tests by insurance companies and a major consulting firm compared Insurance Bureau Scores against the claims history of policyholders. The tests demonstrated that the scores do predict the likelihood of claims.

[6] HOW CAN I FIND OUT MY SCORE?

While you can get copies of your credit reports from credit reporting agencies, only insurance companies can get Insurance Bureau Scores. However, your insurance company or its agent can tell you the main reasons behind your score.

Keep in mind that your score is one of many pieces of information an underwriter uses to review a policy. Factors like motor vehicle reports and application information also impact an insurer's decision. Also, remember that the score changes as new information is added to your credit report.

Your score will improve over time through a pattern of responsible credit use.

An Insurance Bureau Score is a snapshot of your insurance risk picture at a particular point in time based on credit report information.

Review your credit reports once a year and report any errors to the credit reporting agencies.

Insurance Bureau Scores provide underwriters an objective, accurate and consistent tool that, used with other underwriting information, helps them issue new and renewal insurance policies.

ANSWERS to Your Questions About Insurance Bureau Scores

FairIsaac

[7] HOW CAN I IMPROVE MY SCORE?

An Insurance Bureau Score is a snapshot of your insurance risk picture based on information in your credit report that reflects your credit payment patterns over time, with more emphasis on recent information. To improve a score, you should:

- Pay bills on time. Delinquent payments and collections can have a major negative impact on a score.
- Keep balances low on unsecured revolving debt like credit cards. High outstanding debt can affect a score.
- Apply for and open new credit accounts only as needed.

You can increase your score over time by using credit responsibly. It's also a good idea to periodically obtain a copy of your credit reports from the three major credit reporting agencies to check for any inaccuracies.

[8] WHAT IF I AM TURNED DOWN FOR INSURANCE?

If consumer credit information played a role in an insurer's decision to decline your insurance policy, the federal Fair Credit Reporting Act (FCRA) requires that the insurer tell you, and give you the name of the credit reporting agency that provided the information. In these situations, you are entitled by law to receive a free copy of your credit report to review, in order to help you understand how to better manage your credit or to challenge any errors that might appear on your report.

[9] WHAT IF THE INFORMATION IN MY CREDIT REPORT IS WRONG?

If you find errors in your credit report, you should report the errors to the credit reporting agency. By law, the credit reporting agency must investigate and respond to your request within 30 days. If you are in the process of applying for an insurance policy, you should immediately notify your insurance company about any incorrect information in your report. Small errors may have little or no effect on the score. If there are significant errors, the insurance company may choose to disregard the score and rely more on other underwriting information to make a decision on your application.

Make sure the information in your credit report is correct by reviewing your credit report from each credit reporting agency at least once a year. Call these numbers to order a copy *(a fee may be required)*:

Equifax: *800 685 1111*   TransUnion: *800 888 4213*   Experian (formerly TRW): *888 397 3742*

Fair, Isaac and Company (NYSE: FIC) is the preeminent provider of creative analytics that unlock value for people, businesses and industries. The company's predictive modeling, decision analysis, intelligence management and decision engine systems power more than 14 billion decisions a year.

For more information, visit *www.fairisaac.com*, email *info@fairisaac.com* or call *1-800-999-2955.*

SCORING FACTS AND FALLACIES

FALLACY: *With scoring, computers are making the underwriting decisions.*

FACT: Computers don't make underwriting decisions, people do. While a computer does calculate an Insurance Bureau Score, the score is only one of several pieces of information that underwriters use to help make a decision on new and renewal policies. Some insurance companies use scores to help them decide when to ask for more information from the applicant.

FALLACY: *A poor score will haunt me forever.*

FACT: Just the opposite is true. An Insurance Bureau Score is a snapshot of your insurance risk picture at a particular point in time. Your score changes as new information is added to your credit reporting agency file. Over time, your score changes gradually as you change the way you handle your credit responsibilities. Because recent credit information is more predictive than older information, past credit problems will impact your score less as time passes. Insurance companies typically request a current score when you submit a new application so they have the most recent information available.

FALLACY: *Insurance Bureau Scores are unfair to minorities.*

FACT: Insurance Bureau Scores do not consider ethnic group, religion, gender, marital status, nationality, age, income or address. Only credit-related information is included.

Insurance Bureau Scores have proven to be an accurate and consistent measure of insurance risk for all people who have some credit history. In other words, at a given score both non-minority and minority applicants present an equal level of insurance risk, or the likelihood of future insurance claims.

FALLACY: *Scoring is an invasion of my privacy.*

FACT: Insurance companies have used consumer credit information to assist in their underwriting decisions since the FCRA was enacted in 1970. An Insurance Bureau Score is simply a number that provides an objective and consistent summary of that credit information. In fact, by using scores, some insurance companies don't need to ask for as much information on their application forms.

FALLACY: *My Insurance Bureau Score will be hurt if I contact several insurance companies who each access my credit report.*

FACT: Insurance company requests or "inquiries" are not considered by Insurance Bureau Scores and will not affect your score.

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Attachment 4

The following United States Government agencies utilize Fair Isaac credit scores.

Army and Air Force Exchange Services
Office of Comptroller of the Currency
Fannie Mae
Farm Credit Services
Freddie Mac
Internal Revenue Service
SLM Financial Corporation
Small Business Administration
Small Business Loan Center
Student Loan Corporation
Student Loan Marketing Association
Office of Superintendent of Financial Institutions
Office of Thrift Supervision
US Agencies Management Service
US Department of Housing and Urban Development (HUD)

Attachment 5

A Clarification of the Consumer Federation of America's Observations about Credit Score Accuracy

The December 17, 2002 report, "Credit Score Accuracy and Implications for Consumers," issued by the Consumer Federation of America ("CFA Report") challenges the accuracy of credit scores by pointing out the differences between consumers' scores at the three US credit reporting agencies. The more sensational findings, reported in the national media, assert that 40 million consumers are at risk of being misclassified into the subprime market, and that 1 in 3 consumers had credit scores that were 50 points apart. Although the CFA Report contains some valuable observations about the importance of accurate data, it also contains are a number of errors with respect to credit scoring, perhaps because Fair Isaac's scoring expertise was not sought in the preparation of the CFA Report. This paper will therefore provide reliable information about credit scoring to correct some of the misstatements in the report.

Certainly score gaps of 50, and in some cases 100 points between a consumer's different FICO® scores obtained from different consumer reporting agencies are a legitimate concern. The CFA Report itself acknowledges the cause of the difference in scores is the differences in data available from different sources. Therefore, it is clear that varied and inconsistent state regulation of the credit reporting industry will only make the problem worse. Moreover, the financial industry understands that scores generated with different data will produce different results and takes steps to account for the differences. In addition, the competitors in the credit reporting industry continue to improve their systems in an effort to offer data that is more valuable for predicting risk of nonpayment.

The real causes of score differences

The CFA Report acknowledges the most important factor in score differences: differences in the data held at the three national credit reporting agencies. Some regional lenders report to one or two but not all three agencies. Additionally, the timing of when information from credit grantors is loaded to the credit file at the three reporting agencies can create short-term differences—not, as the CFA report labels them, inaccuracies.

The consumer credit industry has been addressing this issue for years. FICO® scoring systems are built to derive the maximum reliable predictive information from the data at each agency. Each credit reporting agency has unique data strengths. Fair Isaac capitalizes on those strengths to build the most effective model for each agency.

The CFA Report states that one in five files has contradictory data on the date of last activity. We know this, and this is why Fair Isaac models evaluate the date of last activity only in rare cases. Similarly, the CFA report notes that a high percentage of files have conflicting information on the number of times a consumer has been delinquent on a particular credit obligation. Fair Isaac analysts have also observed this, and as a result this information is generally not included in our models. Moreover, Fair Isaac accounts for data issues such as fragmented or duplicate files, which the CFA report references, in the model development process.

In building Fair Isaac scoring systems, the first priority is to produce the most predictive score possible. The second priority is to make the scores consistent across the credit reporting agencies. The models are built to derive the most value from a given agency's data, and therefore the Fair Isaac scoring systems are not exactly alike at each credit reporting agency. In general, this <u>increases</u> the accuracy of the credit scores from each agency.

Identical scoring systems at all three reporting agencies, built by ignoring known differences in data fields and integrity, would make FICO scores less reliable and would not necessarily decrease score differences. Consumers, lenders and the national economy all benefit from having the most predictive scores possible from each credit reporting agency.

Report's own "accuracy" flawed

The CFA Report contains a number of misstatements, both of fact and interpretation. Some of the report's errors have little impact, but others may mislead readers or even misdirect consumers to take actions that are not in their best interest.

Here are the major points that need correction:

- **Scoring formulas are "untested."** This is false on several counts. Credit scoring is under regulatory oversight, and the Office of the Comptroller of the Currency has reviewed our scores and adverse action codes several times. On other levels, Fannie Mae and Freddie Mac extensively tested FICO scores in the mid-1990s before recommending that the scores be used by mortgage brokers. And of course, Fair Isaac and FICO score users continually review the scores' effectiveness. Fair Isaac performs exhaustive tests of the scores during every redevelopment.

- **Scores "function as a shorthand version of an applicant's credit history."** Scores translate an individual's credit history into an assessment of risk—that is, the likelihood of being paid back. Scores are not a "grade" of past credit behavior but a forecast of future credit behavior. This is not a matter of semantics,. it's a crucial point in understanding how scores work.

- **Credit scores are a "lottery" where some consumers win and some lose.** While perfect risk assessment is not possible at the individual level, FICO scores are the most accurate method for determining credit risk based on credit reports. Certainly they result in fairer, more objective and more accurate assessments than human judgment alone. The CFA report says "Scores should be determined fairly and based on complete, current and accurate information." FICO scores are determined fairly and are based solely on the information in credit reports that has proven to be predictive of credit risk. Although Fair Isaac welcomes any efforts to improve the data available to its scoring systems, varied state regulation will erode rather than improve data quality.

- **Credit scores exacerbate discrepancies in credit report data.** This is an untrue statement. FICO scoring systems minimize the impact of data discrepancies because they do not focus on a single piece of information, but rather evaluate dozens of types of predictive information in combination. This is a major advantage scoring systems have over manual review. The tremendous experience of Fair Isaac developers in analyzing credit data enables Fair Isaac to avoid placing weight on unreliable data.

Is there a major problem with the accuracy of FICO scores? We do not believe so, and we don't find evidence of such a problem in the CFA Report. The fact is that FICO scores perform very well. That's why lenders feel confident using FICO scores to market, book and manage accounts for the full range of credit products. That's why investors use FICO scores to assess credit portfolios for securitization. That's why regulators rely on FICO scores to ensure the safety and soundness of the nation's financial institutions.

Handling score differences

More and more lenders are using scores from two if not three credit reporting agencies, in making individual credit decisions. Because scores from the three agencies can differ, lenders have looked at ways to determine which score to use. Some lenders use "tri-odds" to determine the risk of a prospect with differing scores. Fair, Isaac has also researched various methods for choosing scores or combining them. Fair Isaac also recommends that lenders do a more thorough manual review if during the application process there is a large difference in scores.

The CFA Report calls for federal oversight of the validity and fairness of all credit scoring systems. "All" is a sweeping word here, and would appear to encompass any company's internally developed systems, as well as systems built by Fair Isaac and others. Credit scoring is already highly regulated by a number of measures, including the Fair Credit Reporting Act and the Equal Credit Opportunity Act. The FCRA and ECOA have proven to do a good job of protecting the interests of consumers and additional regulation is unnecessary.

The CFA Report is not without value.

Other messages of the CFA report have value:

- Consumers should care what is in their credit reports, should check their reports and their scores periodically, and take steps to correct any discrepancies.
- The credit industry should continue to improve the integrity of its data.
- Credit grantors should take reporting data very seriously.

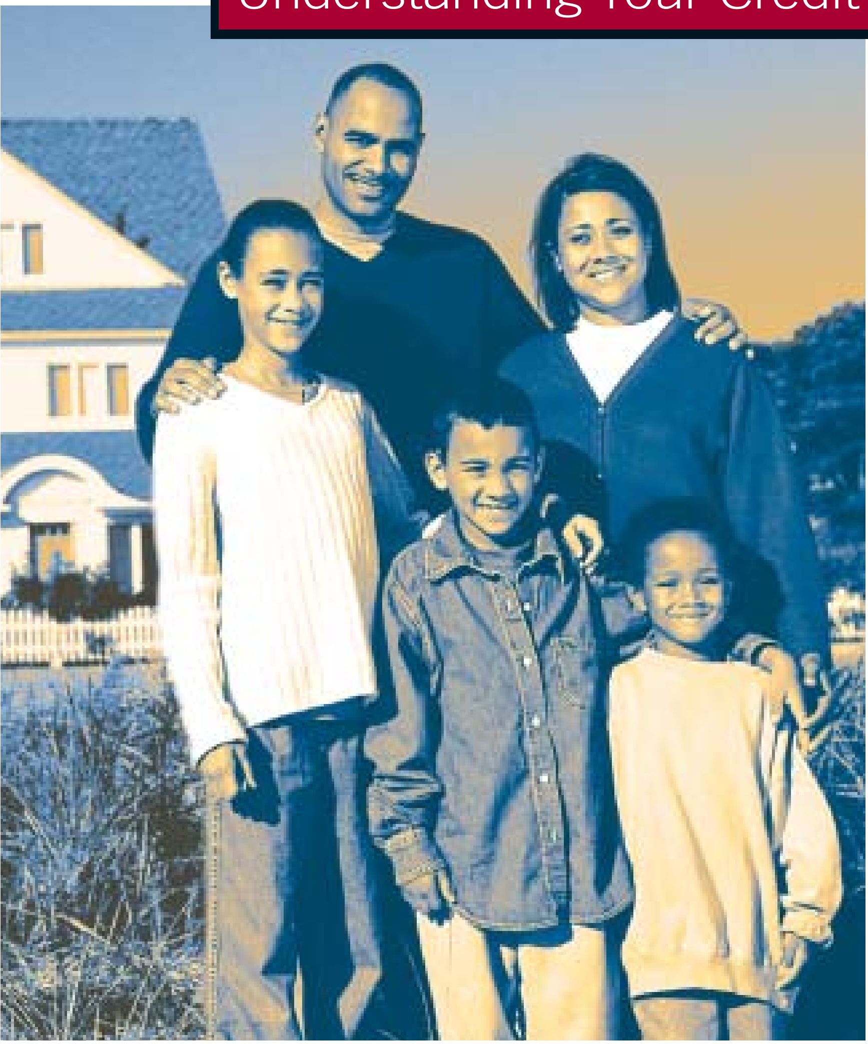
Improving Data Accuracy

Although the CFA Report does not mention it, consumers now have more opportunity than ever to correct information in their credit reports, and to understand how the information in their reports impacts their credit score. Millions of consumers have already used the tools available through Fair Isaac's myFICO℠ service (www.myfico.com) to take better control of their credit. In January 2003, Fair Isaac launched the first three-bureau credit report product for consumers that included the FICO score, making it easy for consumers to review and correct their information at all three agencies. Fair Isaac innovation made it possible for consumers to play a larger role in understanding and managing their credit health, and more and more consumers are recognizing the value of learning how lenders see them. Fair Isaac and other participants in consumer credit services will continue to develop new products and services to empower consumers to take charge of their credit health, including providing better tools for consumers to help the consumer reporting agencies maintain complete and accurate credit information about them. The burden of correct information is borne not just by consumers, of course, but by the credit reporting agencies and their subscribers. Fair Isaac endorses the credit reporting agencies' continual efforts to advance their data aggregation processes and improve the integrity of the data they house and share.

Fair Isaac also encourages lenders to report complete information on a monthly basis to all three credit reporting agencies and to spend some time verifying the accuracy of their reporting process. Fair Isaac's ScoreNet® Service consultants have worked closely with clients, helping them ensure they accurately report and receive data from the credit reporting agencies.

In contrast to the CFA, Fair Isaac believes consumers will benefit from extending the FCRA provisions that prohibit states from enacting varied and inconsistent regulation of credit reporting. The CFA itself states that scores should be based on "complete, current and accurate information." History has shown that a multitude of conflicting state laws will reduce, rather than expand, the information available in credit reports, and make that information more inconsistent. Incomplete, inconsistent data would aggravate the very problems the CFA Report criticizes.

Understanding Your Credit Score



Fair Isaac®

Contents

Your Credit Score—A Vital Part of Your Credit Health

When you're applying for credit—whether it's a credit card, a car loan, a personal loan or a mortgage—lenders will want to know your credit risk level. To understand your credit risk, most lenders will look at your credit score.

Your credit score influences the credit that's available to you, and the terms (interest rate, etc.) that lenders offer you. It's a vital part of your credit health.

Understanding credit scoring can help you manage your credit health. By knowing how your credit risk is evaluated, you can take actions that will lower your credit risk—and thus raise your score—over time. A better score means better financial options for you.

WHAT IS A CREDIT SCORE?

A credit score is a number lenders use to help them decide: "If I give this person a loan or credit card, how likely is it that I will get paid back on time?" A score is a snapshot of your credit risk at a particular point in time.

The most widely used credit scores are FICO® scores. Lenders use FICO scores to make billions of credit decisions every year. Fair, Isaac develops FICO scores based solely on information in consumer credit reports maintained at the credit reporting agencies.

This booklet can help you improve your credit health by helping you understand how credit scoring works.

More information on credit scoring can be found online at *www.myfico.com*.

What is your credit score?

Once you know how scoring works, you may want to take the next step by finding out what your FICO score is today, and what steps you could take to improve it.

You can get your FICO score through Fair, Isaac's myFICO℠ service. When you order your score through the myFICO service, you also get the credit report it's based on, and tips on how to improve your score specifically.

You can check your FICO score online at *www.myfico.com*. For information on services available through the myFICO service, see page 16.

Does my score alone determine whether I get credit?

No. Most lenders use a number of facts to make credit decisions, including your FICO score. Lenders look at information such as the amount of debt you can reasonably handle given your income, your employment history, and your credit history.

Based on their perception of this information, as well as their specific underwriting policies, lenders may extend credit to you although your score is low, or decline your request for credit although your score is high.

How Credit Scoring Helps You

Credit scores give lenders a fast, objective measurement of your credit risk. Before the use of scoring, the credit granting process could be slow, inconsistent and unfairly biased.

Credit scores—especially FICO scores, the most widely used credit bureau scores—have made big improvements in the credit process. Because of credit scores:

- **People can get loans faster.** Scores can be delivered almost instantaneously, helping lenders speed up loan approvals. Today many credit decisions can be made within minutes—or online, within seconds. Even a mortgage application can be approved in hours instead of weeks for borrowers who score above a lender's "score cutoff." Scoring also allows retail stores, Internet sites and other lenders to make "instant credit" decisions.

- **Credit decisions are fairer.** Using credit scoring, lenders can focus only on the facts related to credit risk, rather than their personal feelings. Factors like your gender, race, religion, nationality and marital status are not considered by credit scoring.

- **Older credit problems count for less.** If you have had poor credit performance in the past, credit scoring doesn't let that haunt you forever. Past credit problems fade as time passes and as recent good payment patterns show up on your credit report. And credit scores weigh any credit problems against the positive information that says you're managing your credit well.

■ **More credit is available.** Lenders who use credit scoring can approve more loans, because credit scoring gives them more precise information on which to base credit decisions. It allows lenders to identify individuals who are likely to perform well in the future, even though their credit report shows past problems. Even people whose scores are lower than a lender's cutoff for "automatic approval" benefit from scoring. Many lenders offer a choice of credit products geared to different risk levels. Most have their own separate guidelines, so if you are turned down by one lender, another may approve your loan. The use of credit scores gives lenders the confidence to offer credit to more people, since they have a better understanding of the risk they are taking on.

■ **Credit rates are lower overall.** With more credit available, the cost of credit for borrowers decreases. Automated credit processes, including credit scoring, make the credit granting process more efficient and less costly for lenders, who in turn have passed savings on to their customers. And by controlling credit losses using scoring, lenders can make rates lower overall. Mortgage rates are lower in the United States than in Europe, for example, in part because of the information —including credit scores—available to lenders here.

How fast does my score change?

Your score can change whenever your credit report changes. But your score probably won't change a lot from one month to the next. In a given three-month time period, only about one in four people has a 20-point change in their credit score.

While a bankruptcy or late payments can lower your score fast, improving your score takes time. That's why it's a good idea to check your score 6–12 months before applying for a big loan, so you have time to take action if needed. If you are actively working to improve your score, you'd want to check it quarterly or even monthly to review changes.

How can mistakes get on my credit report?

If your credit report contains errors, it is often because the report is incomplete, or contains information about someone else. This typically happens because:

- **You applied for credit under different names** (Robert Jones, Bob Jones, etc.).
- **Someone made a clerical error in reading or entering name or address information from a hand-written application.**
- **You gave an inaccurate Social Security number, or the number was misread by the lender.**
- **Loan or credit card payments were inadvertently applied to the wrong account.**

Your Credit Report—The Basis of Your Score

Credit reporting agencies maintain files on millions of borrowers. Lenders making credit decisions buy credit reports on their prospects, applicants and customers from the credit reporting agencies.

Your report details your credit history as it has been reported to the credit reporting agency by lenders who have extended credit to you. Your credit report lists what types of credit you use, the length of time your accounts have been open, and whether you've paid your bills on time. It tells lenders how much credit you've used and whether you're seeking new sources of credit. It gives lenders a broader view of your credit history than do other data sources, such as a bank's own customer data.

Your credit report reveals many aspects of your borrowing activities. All pieces of information should be considered in relationship to other pieces of information. The ability to quickly, fairly and consistently consider all this information is what makes credit scoring so useful.

CHECK YOUR CREDIT REPORT

You should review your credit report from each credit reporting agency at least once a year and especially before making a large purchase, like a house or car. To request a copy, contact the credit reporting agencies directly:

- *Equifax: (800) 685-1111, www.equifax.com*
- *Experian (formerly TRW): (888) 397-3742, www.experian.com*
- *TransUnion: (800) 888-4213, www.transunion.com*

If you find an error, the credit reporting agency must investigate and respond to you within 30 days. If you are in the process of applying for a loan, immediately notify your lender of any incorrect information in your report.

WHAT'S IN YOUR CREDIT REPORT?

Although each credit reporting agency formats and reports this information differently, all credit reports contain basically the same categories of information.

CREDIT BUREAU REPORT

IDENTIFYING INFORMATION

I. Wishfor Credit	12 Lost Lane	Sam's Gas & Oil
805 Main St.	Somewhere, USA 66666	Attendant
Anytown, America 77777	Date of Birth: 1-25-50	1980
	SS# 888-88-8888	

TRADE LINE INFORMATION

INDUSTRY	DATE REPORTED	DATE OPENED	HIGH CREDIT	BALANCE	CURRENT RATING	HISTORICAL DELINQUENCY
Bankcard	7–02	3–88	$ 5,000	$ 0	Current	120+, 6 yrs ago
Auto loan	7–02	7–95	8,000	1,500	Current	
Retail	5–02	6–91	1,000	0	30 days	
Retail	6–02	11–98	750	300	Current	
Pers finance	5–02	6–96	2,000	1,400	Current	

INQUIRIES THAT YOU INITIATE

DATE	INDUSTRY	DATE	INDUSTRY	DATE	INDUSTRY
7-01-02	Bank	6-01-02	Auto finance	10-25-01	Bank
6-15-01	Retail	11-01-01	Retail		

OTHER INQUIRIES

DATE	INDUSTRY	DATE	INDUSTRY	DATE	INDUSTRY
6-15-02	Oil company	2-07-02	Bank	3-23-01	Bank

PUBLIC RECORD / COLLECTION ITEMS

7-01 COLLECTION $500 9-00 COLLECTION $750

9-99 JUDGMENT $1000 Satisfied 3-00

IDENTIFYING INFORMATION. Your name, address, Social Security number, date of birth and employment information are used to identify you. These factors are not used in credit bureau scoring. Updates to this information come from information you supply to lenders.

TRADE LINES. These are your credit accounts. Lenders report on each account you have established with them. They report the type of account (bankcard, auto loan, mortgage, etc), the date you opened the account, your credit limit or loan amount, the account balance and your payment history.

INQUIRIES. When you apply for a loan, you authorize your lender to ask for a copy of your credit report. This is how inquiries appear on your credit report. The inquiries section contains a list of everyone who accessed your credit report within the last two years. The report you see lists both "voluntary" inquiries, spurred by your own requests for credit, and "involuntary" inquires, such as when lenders order your report so as to make you a pre-approved credit offer in the mail. See page 14 for more information.

PUBLIC RECORD AND COLLECTION ITEMS. Credit reporting agencies also collect public record information from state and county courts, and information on overdue debt from collection agencies. Public record information includes bankruptcies, foreclosures, suits, wage attachments, liens and judgments.

Is credit scoring unfair to minorities?

No. Scoring does not consider your gender, race, nationality or marital status. In fact, the Equal Credit Opportunity Act prohibits lenders from considering this type of information when issuing credit.

Independent research has shown that credit scoring is not unfair to minorities or people with little credit history. Scoring has proven to be an accurate and consistent measure of repayment for all people who have some credit history. In other words, at a given score, non-minority and minority applicants are equally likely to pay as agreed.

How Scoring Works

Along with the credit report, lenders can also buy a credit score based on the information in the report. That score is calculated by a mathematical equation that evaluates many types of information from your credit report at that agency. By comparing this information to the patterns in hundreds of thousands of past credit reports, the score identifies your level of future credit risk.

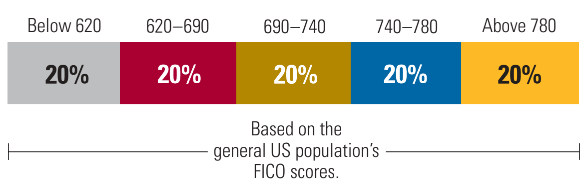
In order for a FICO score to be calculated on your credit report, the report must contain at least one account which has been open for six months or greater. In addition, the report must contain at least one account that has been updated in the past six months. This ensures that there is enough information—and enough recent information—in your report on which to base a score.

ABOUT FICO SCORES

Credit bureau scores are often called “FICO scores” because most credit bureau scores used in the US and Canada are produced from software developed by Fair, Isaac and Company (FICO). FICO scores are provided to lenders by the three major credit reporting agencies: Equifax, Experian and TransUnion.

FICO scores provide the best guide to future risk based solely on credit report data. The higher the score, the lower the risk. But no score says whether a specific individual will be a “good” or “bad” customer. And while many lenders use FICO scores to help them make lending decisions, each lender has its own strategy, including the level of risk it finds acceptable for a given credit product. There is no single “cutoff score” used by all lenders.

How Do People Score?



MORE THAN ONE FICO SCORE

In general, when people talk about "your score," they're talking about your current FICO score. But in fact there are three different FICO scores developed by Fair, Isaac—one at each of the three main US credit reporting agencies. And these scores have different names.

Credit Reporting Agency	FICO Score Name
Equifax & Equifax Canada	BEACON®
Experian	Experian/Fair, Isaac Risk Model
TransUnion & TransUnion Canada	EMPIRICA®

The FICO scores from all three credit reporting agencies are widely used by lenders. The FICO score from each credit reporting agency considers only the data in your credit report at that agency.

Fair, Isaac develops all three FICO scores using the same methods and rigorous testing. These FICO scores provide the most accurate picture of credit risk possible using credit report data.

WILL YOUR SCORES BE DIFFERENT?

FICO scores range from about 300 to 850. Fair, Isaac makes the scores as consistent as possible between the three credit reporting agencies. If your information were exactly identical at all three credit reporting agencies, your scores from all three would be within a few points of each other.

But here's why your FICO scores may in fact be different at the three credit reporting agencies. The way lenders and other businesses report information to the credit reporting agencies sometimes results in different information being in your credit report at the three agencies. The agencies may also report the same information in different ways. Even small differences in the information at the three credit reporting agencies can affect your scores.

Since lenders may review your score and credit report from any of the three credit reporting agencies, it's a good idea to check your credit report from all three and make sure they're all right.

Are FICO scores the only credit risk scores?

No. While FICO scores are the most commonly used credit risk scores in the US, lenders may use other scores to evaluate your credit risk. These include:

- **Application risk scores.** Many lenders use scoring systems that include the FICO score but also consider information from your credit application.
- **Customer risk scores.** A lender may use these scores to make credit decisions on its current customers. Also called "behavior scores," these scores generally consider the FICO score along with information on how you have paid that lender in the past.
- **Other credit bureau scores.** These scores may evaluate your credit report differently than FICO scores, and in some cases a higher score may mean more risk, not less risk as with FICO scores.

When purchasing a credit score for yourself, make sure to get the FICO score, as this is the score most lenders will look at in making credit decisions on you.

Getting a better score

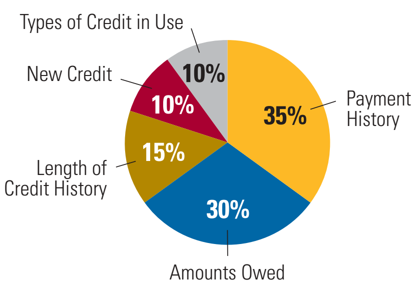
The next few pages give some tips for getting a better FICO score. It's important to note that raising your score is a bit like getting in shape: It takes time and there is no quick fix. In fact, quick-fix efforts can backfire. The best advice is to manage credit responsibly over time.

For information on how to monitor your FICO score's progress, see page 16.

What a FICO Score Considers

Listed on the next few pages are the five main categories of information that FICO scores evaluate, along with their general level of importance. Within these categories is a complete list of the information that goes into a FICO score. Please note that:

- **A score takes into consideration all these categories of information, not just one or two.** No one piece of information or factor alone will determine your score.
- **The importance of any factor depends on the overall information in your credit report.** For some people, a given factor may be more important than for someone else with a different credit history. In addition, as the information in your credit report changes, so does the importance of any factor in determining your score. Thus, it's impossible to say exactly how important any single factor is in determining your score—even the levels of importance shown here are for the general population, and will be different for different credit profiles.
- **Your FICO score only looks at information in your credit report.** Lenders often look at other things when making a credit decision, however, including your income, how long you have worked at your present job and the kind of credit you are requesting.
- **Your score considers both positive and negative information in your credit report.** Late payments will lower your score, but establishing or re-establishing a good track record of making payments on time will raise your score.



How a Score Breaks Down

These percentages are based on the importance of the five categories for the general population. For particular groups—for example, people who have not been using credit long—the importance of these categories may be different.

1. Payment History

What is your track record?

Approximately 35% of your score is based on this category.

The first thing any lender would want to know is whether you have paid past credit accounts on time. This is also one of the most important factors in a credit score.

Late payments are not an automatic "score-killer." An overall good credit picture can outweigh one or two instances of, say, late credit card payments. But having *no* late payments in your credit report doesn't mean you will get a "perfect score." Some 60%–65% of credit reports show no late payments at all. Your payment history is just one piece of information used in calculating your score.

Your score takes into account:

- **Payment information on many types of accounts.** These will include credit cards (such as Visa, MasterCard, American Express and Discover), retail accounts (credit from stores where you do business, such as department store credit cards), installment loans (loans where you make regular payments, such as car loans), finance company accounts and mortgage loans.

- **Public record and collection items—reports of events such as bankruptcies, foreclosures, suits, wage attachments, liens and judgments.** These are considered quite serious, although older items and items with small amounts will count less than more recent items or those with larger amounts. Bankruptcies will stay on your credit report for 7–10 years, depending on the type.

- **Details on late or missed payments ("delinquencies") and public record and collection items.** The score considers how late they were, how much was owed, how recently they occurred and how many there are. A 60-day late payment is not as risky as a 90-day late payment, in and of itself. But recency and frequency count too. A 60-day late payment made just a month ago will affect a score more than a 90-day late payment from five years ago.

- **How many accounts show no late payments.** A good track record on most of your credit accounts will increase your credit score.

✓ TIPS for Raising Your Score

- **Pay your bills on time.** Delinquent payments and collections can have a major negative impact on your score.

- **If you have missed payments, get current and stay current.** The longer you pay your bills on time, the better your score.

- **Be aware that paying off a collection account, or closing an account on which you previously missed a payment, will not remove it from your credit report.** The score will still consider this information, because it reflects your past credit pattern.

- **If you are having trouble making ends meet, contact your creditors or see a legitimate credit counselor.** This won't improve your score immediately, but if you can begin to manage your credit and pay on time, your score will get better over time. And you won't lose points for seeing a credit counselor.

✓ TIPS for Raising Your Score

- **Keep balances low on credit cards and other "revolving credit."** High outstanding debt can affect a score.
- **Pay off debt rather than moving it around.** The most effective way to improve your score in this area is by paying down your revolving credit. In fact, owing the same amount but having fewer open accounts may lower your score.
- **Don't close unused credit cards as a short-term strategy to raise your score.**
- **Don't open a number of new credit cards that you don't need, just to increase your available credit.** This approach could backfire and actually lower your score.

2. Amounts Owed

How much is too much?

Approximately 30% of your score is based on this category.

Having credit accounts and owing money on them does not mean you are a high-risk borrower with a low score. However, owing a great deal of money on many accounts can indicate that a person is overextended, and is more likely to make some payments late or not at all. Part of the science of scoring is determining how much is *too* much for a given credit profile.

Your score takes into account:

- **The amount owed on all accounts.** Note that even if you pay off your credit cards in full every month, your credit report may show a balance on those cards. The total balance on your last statement is generally the amount that will show in your credit report.
- **The amount owed on all accounts, and on different types of accounts.** In addition to the overall amount you owe, the score considers the amount you owe on specific types of accounts, such as credit cards and installment loans.
- **Whether you are showing a balance on certain types of accounts.** In some cases, having a very small balance without missing a payment shows that you have managed credit responsibly, and may be slightly better than carrying no balance at all. On the other hand, closing unused credit accounts that show zero balances and that are in good standing will not raise your score.
- **How many accounts have balances.** A large number can indicate higher risk of over-extension.
- **How much of the total credit line is being used on credit cards and other "revolving credit" accounts.** Someone closer to "maxing out" on many credit cards may have trouble making payments in the future.
- **How much of installment loan accounts is still owed, compared with the original loan amounts.** For example, if you borrowed $10,000 to buy a car and you have paid back $2,000, you owe (with interest) more than 80% of the original loan. Paying down installment loans is a good sign that you are able and willing to manage and repay debt.

3. Length of Credit History

How established is yours?

Approximately 15% of your score is based on this category.

In general, a longer credit history will increase your score. However, even people who have not been using credit long may get high scores, depending on how the rest of the credit report looks.

Your score takes into account:

- **How long your credit accounts have been established, in general.** The score considers both the age of your oldest account and an average age of all your accounts.
- **How long specific credit accounts have been established.**
- **How long it has been since you used certain accounts.**

✓ TIPS for Raising Your Score

- **If you have been managing credit for a short time, don't open a lot of new accounts too rapidly.** New accounts will lower your average account age, which will have a larger effect on your score if you don't have a lot of other credit information. Also, rapid account buildup can look risky if you are a new credit user.

What FICO scores ignore

FICO scores consider a wide range of information on your credit report, as shown on pages 8–13. However, they do *not* consider:

- **Your race, color, religion, national origin, sex and marital status.** US law prohibits credit scoring from considering these facts, as well as any receipt of public assistance, or the exercise of any consumer right under the Consumer Credit Protection Act.
- **Your age.** Other types of scores may consider your age, but FICO scores don't.
- **Your salary, occupation, title, employer, date employed or employment history.** Lenders may consider this information, however.
- **Where you live.**
- **Any interest rate being charged on a particular credit card or other account.**
- **Any items reported as child/family support obligations or rental agreements.**
- **Certain types of inquiries (requests for your credit report or score).** The score does *not* count any requests you make, any requests from employers, and any requests lenders make without your knowledge. For details, see page 14.
- **Any information not found in your credit report.**
- **Any information that is not *proven* to be predictive of future credit performance.**

✓TIPS for Raising Your Score

- **Do your rate shopping for a given auto or mortgage loan within a focused period of time.** FICO scores distinguish between a search for a single loan and a search for many new credit lines, in part by the length of time over which inquiries occur.
- **Re-establish your credit history if you have had problems.** Opening new accounts responsibly and paying them off on time will raise your score in the long term.
- **Note that it's OK to request and check your own credit report and your own FICO score.** This won't affect your score, as long as you order your credit report directly from the credit reporting agency or through an organization authorized to provide credit reports to consumers, like the myFICO service. For more information, see page 14.

4. New Credit

Are you taking on more debt?

Approximately 10% of your score is based on this category.

People tend to have more credit today and to shop for credit—via the Internet and other channels—more frequently than ever. Fair, Isaac scores reflect this fact. However, research shows that opening several credit accounts in a short period of time does represent greater risk—especially for people who do not have a long-established credit history.

Multiple credit requests also represent greater credit risk. However, FICO scores do a good job of distinguishing between a search for *many* new credit accounts and rate shopping for *one* new account.

Your score takes into account:

- **How many new accounts you have.** The score looks at how many new accounts there are by type of account (for example, how many newly opened credit cards you have). It also may look at how many of your accounts are new accounts.
- **How long it has been since you opened a new account.** Again, the score looks at this by type of account.
- **How many recent requests for credit you have made, as indicated by inquiries to the credit reporting agencies.** Inquiries remain on your credit report for two years, although FICO scores only consider inquiries from the last 12 months. The scores have been carefully designed to count only those inquiries that truly impact credit risk—see page 14 for details.
- **Length of time since credit report inquiries were made by lenders.**
- **Whether you have a good recent credit history, following past payment problems.** Re-establishing credit and making payments on time after a period of late payment behavior will help to raise a score over time.

5. Types of Credit in Use

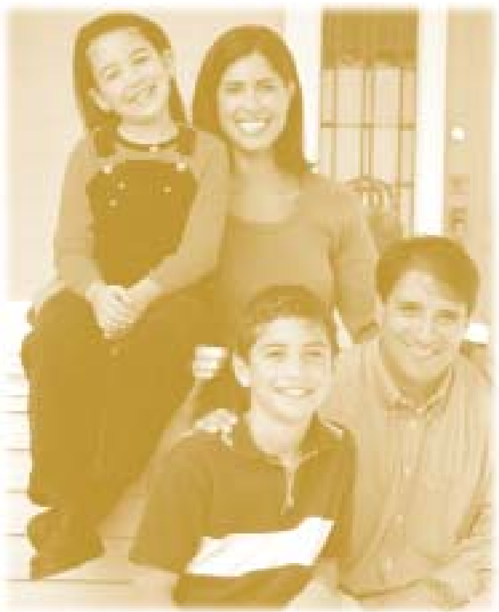
Is it a "healthy" mix?

Approximately 10% of your score is based on this category.

The score will consider your mix of credit cards, retail accounts, installment loans, finance company accounts and mortgage loans. It is *not* necessary to have one of each, and it is not a good idea to open credit accounts you don't intend to use. The credit mix usually won't be a key factor in determining your score—but it will be more important if your credit report does not have a lot of other information on which to base a score.

Your score takes into account:

- **What kinds of credit accounts you have, and how many of each.** The score also looks at the total number of accounts you have. For different credit profiles, how many is *too* many will vary.



✓ TIPS for Raising Your Score

- **Apply for and open new credit accounts only as needed.** Don't open accounts just to have a better credit mix—it probably won't raise your score.
- **Have credit cards—but manage them responsibly.** In general, having credit cards and installment loans (and making timely payments) will raise your score. People with no credit cards, for example, tend to be higher risk than people who have managed credit cards responsibly.
- **Note that closing an account doesn't make it go away.** A closed account will still show up on your credit report, and may be considered by the score.

Should I close old accounts to raise my score?

Generally, this doesn't work. In fact, it might lower your score. First of all, any late payments associated with old accounts won't disappear from your credit report if you close the account. Second, long-established accounts show you have a longer history of managing credit, which is a good thing. And third, having available credit that you don't use does not lower your score.

You may have reasons other than your score to shut down old credit card accounts that you don't use. But don't do it just to get a better score.

How the FICO Score Counts Inquiries

As explained in the last section, a search for new credit can mean greater credit risk. This is why the FICO score counts inquiries—requests a lender makes for your credit report or score when you apply for credit.

FICO scores consider inquiries very carefully, as not all inquiries are related to credit risk. There are three things to note here:

- **Inquiries don't affect scores that much.** For most people, one additional credit inquiry will take less than five points off their FICO score. However, inquiries can have a greater impact if you have few accounts or a short credit history. Large numbers of inquiries also mean greater risk: People with six inquiries or more on their credit reports are eight times more likely to declare bankruptcy than people with no inquiries on their reports.
- **Many kinds of inquiries aren't counted at all.** The score does not count it when you order your credit report or credit score from a credit reporting agency or the myFICO service. Also, the score does not count requests a lender has made for your credit report or score in order to make you a "pre-approved" credit offer, or to review your account with them, even though you may see these inquiries on your credit report. Requests that are marked as coming from employers are not counted either.
- **The score looks for "rate shopping."** Looking for a mortgage or an auto loan may cause multiple lenders to request your credit report, even though you're only looking for one loan. To compensate for this, the score counts multiple inquiries in any 14-day period as just one inquiry. In addition, the score ignores all inquiries made in the 30 days prior to scoring. So if you find a loan within 30 days, the inquiries won't affect your score while you're rate shopping.

Interpreting Your Score

When a lender receives your Fair, Isaac credit bureau risk score, up to four "score reasons" are also delivered. These are the top reasons why your score was not higher. If the lender rejects your request for credit, and your FICO score was part of the reason, these score reasons can help the lender tell you why your score wasn't higher.

These score reasons are more useful than the score itself in helping you determine whether your credit report might contain errors, and how you might improve your credit health. However, if you already have a high score (for example, in the mid-700s or higher) some of the reasons may not be very helpful, as they may be marginal factors related to the last three categories described previously (length of credit history, new credit and types of credit in use).

To see your own FICO score and reason codes with a detailed explanation on how you can improve the score over time, visit *www.myfico.com*.

What if I'm turned down for credit?

If you have been turned down for credit, the Equal Credit Opportunity Act (ECOA) gives you the right to obtain the reasons why within 30 days. You are also entitled to a free copy of your credit bureau report within 60 days, which you can request from the credit reporting agencies.

If the score was a primary part of the lender's decision, the lender will use the score reasons (see left) to explain why you didn't qualify for the credit. To get more specific information on what your score is and how you could improve it, go to *www.myfico.com*.

What is a good FICO score to get?

Since there's no one "score cutoff" used by all lenders, it's hard to say what a good score is outside the context of a particular lending decision. For example, one auto lender may offer lower interest rates to people with FICO scores above, say, 680; another lender may use 720, and so on. Your lender may be able to give you guidance on the criteria for a given credit product.

myFICO℠
The Score Lenders Use™

FICO® SCORE 707
FOR JOHN SMITH
ON OCTOBER 5, 2001

Your Credit Profile

The myFICO service can help you understand how lenders see your credit risk picture.

Checking Your Score

Since lenders check your score, it makes sense to see how lenders see you. It's easy to check your own FICO score, and to find out specific things you can do to raise it.

You can order your FICO score through online services developed by Fair, Isaac, in partnership with credit reporting agencies. Our score delivery services give you all the information you need to understand your score, the information it's based on, and ways to improve your credit health.

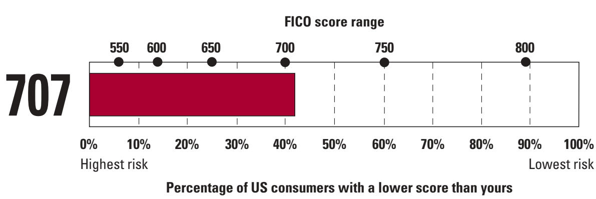
An important time to check your score is six months or so before a major purchase, such as a car or home loan. This gives you time to make sure your credit report information is right, correct it if it's not, and improve your score if necessary. In general, any time you are applying for credit, taking out a new loan or changing your credit mix is a good time to check your FICO score.

MANAGE YOUR CREDIT HEALTH

Improving your FICO score can help you:

- *Get better credit offers*
- *Lower your interest rates*
- *Speed up credit approvals*

The payoff from a better FICO score can be big. For example, with a 30-year fixed mortgage of $150,000, you could save approximately $131,000 over the life of the loan—or $365 on each monthly payment—by first improving your FICO score from a 550 to a 720.



ORDERING YOUR SCORE AND MORE

FICO score delivery services are available through many banks, financial services sites, credit reporting agencies and Fair, Isaac's myFICO site (*www.myfico.com*). These services include:

- Your current **FICO score**—the credit score lenders use to measure your credit risk.
- Your **credit report**, on which your FICO score is based.
- A **full explanation** of your score, the positive and negative factors behind it, and how lenders view your credit risk.
- A FICO **score simulator** you can use to see how specific actions, such as paying off all your card balances, would affect your score.
- **Specific tips** on what you can do to improve your FICO score over time.

The myFICO site also features in-depth information on FICO scores, including a full list of the score factors and sound advice for managing your credit health. In addition, you can see current information on the average interest rates for home and auto loans for different FICO score ranges.

BEFORE YOU BUY YOUR SCORE

Make sure you're buying your FICO score. Some businesses will sell or give you credit scores that are not FICO scores and may not be used by any lenders at all. These services may also give you credit management advice that does not apply to FICO scores and could actually hurt your credit standing with lenders.

The advice in this booklet and on *www.myfico.com* applies to FICO scores only, not to all scores. FICO scores are the scores most lenders use. Your FICO score is the score to know.

Check your score and learn more about scoring at *www.myfico.com*

Get the Facts About Credit Scores

Managing your credit health means knowing how your credit score works. This booklet answers your questions on credit scoring, including:

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The Effectiveness of Scoring on Low-to-Moderate-Income and High-Minority Area Populations

A Fair, Isaac Paper

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Introduction

Fair, Isaac pioneered the commercial development of statistically based credit decision systems, generally referred to as "credit scoring systems," starting in the late 1950s. Today, most major U.S. credit issuers rely on credit scoring systems to manage most or all of their consumer credit portfolios and now credit scoring is also becoming common in mortgage and small business lending. Credit scoring is one of the most commonly used methods of evaluating risk in the credit community. Credit scoring and the automated credit decision processes which it makes possible are part of making a large variety of credit products readily available to American consumers.

The first part of this paper will introduce the purpose of this paper and certain preliminary scoring concepts, followed by a brief analysis of some basic differences between credit scoring and judgmental decisions. After a brief overview of the primary fair lending laws impacting credit grantors in the United States, we will discuss the results of two case studies conducted by Fair, Isaac, followed by a brief conclusion tying the applicability of fair lending issues to the results of the two case studies. The first study used data on low-to-moderate-income applicants and the other used credit bureau data and census tract information in identifying and analyzing areas with high concentrations of minorities. Appendix A is a glossary of terms used in this discussion paper or in credit scoring generally.

Purposes

This discussion paper formally presents the results of two case studies conducted by Fair, Isaac at Fair, Isaac's InterACT '96 conference. Understanding the results of the case studies requires some background on the nature and purpose of credit scoring and specifically how credit scoring differs from individual judgment ("judgmental systems") or systems based on the application of defined rules.

Our goal was to use available data to address a number of questions about credit scoring that suggest credit scoring may raise negative fair lending concerns and may unlawfully discriminate against minorities. These questions were:

[1] Does credit scoring work on low-to-moderate-income (LMI) individuals and individuals residing in high-minority areas (HMAs)? In other words, does credit scoring rank-order LMI and HMA individuals' risk by score?

[2] Does credit scoring have a disproportionate negative impact on LMI individuals and individuals in HMAs?

[3] Does credit scoring work any differently on LMI and HMA individuals when compared to higher income (HI) individuals or those that do not reside in HMAs

(non-HMA)? In other words, are the odds-to-score relationships different among these populations?

[4] Are the factors that predict risk different for LMI and HMA individuals than for HI or non-HMA individuals?

[5] Are LMI and HMA individuals excluded from scorecard development populations?

[6] Would judgmental systems be a more predictive screen than credit scoring for LMI and HMA applicants? Which is more favorable to such applicants?

[7] (a) Would a scorecard developed specifically for HMA individuals be more predictive than a scorecard developed for the total population? (b) Would a scorecard developed specifically for HMA individuals be more predictive than the Fair, Isaac credit bureau scores?

This paper does not seek to advocate any political or public policy stance. We believe that those issues can be better addressed by open discussion, which could include the results of the case studies. Indeed, as described below, credit scoring is a means of assessing risk. It is a flexible enough tool to accommodate any reasonable public policy.

This paper is also not intended to cover all of the intricate details of credit scoring, but rather is intended to provide sufficient information to understand some of the pertinent fair lending concerns and the results of the two case studies. This paper is also not intended to set or recommend credit policy.

Concepts of credit scoring

Credit scoring is a statistical technology used to evaluate the degree of risk posed by a prospective borrower or existing customer. In developing a scoring system, the first step is to determine which pieces of information—known at the time a decision is made—correlate with "future" credit performance. Developing scoring systems requires the collection of historical data that represents both predictive information as well as the subsequent performance on the loan.

Predictive information consists of the universe of information that can be known at the time a credit decision is made, typically application information and credit bureau information. Performance information consists of information on the outcome of having made a decision to lend, such as whether the individual did or did not pay as agreed. Performance is usually assessed for a period of one-to-five years after the credit decision was made.

Since many of the factors that relate to future credit performance are likely to be correlated with each other, the weighting of various factors must be adjusted to take those relationships into account. Because of these correlations, factors that are predictive of credit performance on a stand-alone basis may not appear in the final scoring system, as they do not add any predictive value to that provided by the other factors which are already in the system.

In selecting the factors that will be scored and the points awarded to each answer, the goal of the developer is to find the combination that results in final scores that are best correlated with actual credit performance. This is accomplished through computer analysis of various possibilities; the number of required calculations is so large that it would be impractical if not impossible to perform manually.

To score an application, the points from each factor are added to produce a final score. In most systems, higher scores indicate better risks. For example, one out of every five applicants scoring 180 might be expected to become seriously delinquent, while at a score of 220 only one in 20 would be expected to perform poorly. The credit grantor sets a "cutoff" score based on the economics of the portfolio in question and accepts those applicants that score at or above the cutoff.

Application scorecards and credit bureau scorecards are the two most common types of scorecards used in screening new applicants. The key distinction between the two is that application scorecards consider both credit bureau information *and* information submitted on an application.

Over the last 25 years, credit scoring has become widely accepted in most kinds of consumer credit, because, by using scoring, a credit grantor can make credit available to more people at a lower cost than with other types of decision processes. When a creditor switches from judgmental decisions to scoring, it is common to see a 20 to 30% reduction in credit losses, or a 20 to 30% increase in the number of applicants accepted with no increase in the loss rate. In addition, the use of scoring allows for automated processing of applications, resulting in reduced processing costs and faster turnaround time, which also benefit consumers.

Comparing credit scoring systems to judgmental systems

Types of decision processes

Scoring is generally contrasted with subjective or judgmental decisions. Both types of decision processes have some common elements. Most importantly, both are based on the premise that—at least to a large extent—the future will resemble the past. In other words, new borrowers who are similar in certain important respects to those who have performed in a satisfactory manner in the past are likely to themselves prove to be good borrowers. Conversely, new borrowers who resemble prior borrowers whose performance was unsatisfactory are less likely to be good borrowers.

The distinguishing feature of most credit scoring models is that they rely on an exhaustive statistical analysis of actual credit experience to determine which factors should be considered in the credit decision, and the weight that should be accorded each factor.

Predicting individual behavior

Proponents of credit scoring explicitly recognize that it is impossible to predict individual behavior with certainty, but it *is* possible to make reasonably accurate predictions about the behavior of large groups of borrowers. A lender making a consumer credit decision is faced with predicting human behavior: Will this borrower repay this loan in a satisfactory manner, or not? Many of the factors affecting credit performance are outside the control of the borrower. A recession, layoff or serious illness can easily result in the best-intentioned borrower becoming seriously delinquent. The simple fact is that there is no way to predict the credit performance of *any individual* with absolute certainty: A crystal ball for creditors just doesn't exist.

Predicting aggregate behavior

What can be measured and predicted with reasonable accuracy is the level of risk—especially relative risk—presented by different *groups* of borrowers. By carefully analyzing all of the information known about a borrower at the time a credit decision is made, it is possible to determine not only which individual pieces of data are predictive of future performance, but which combinations and weightings result in the best overall predictor of credit performance. The scores produced by applying the resulting scorecard to subsequent borrowers permit the lender to determine the relative risk of different groups of borrowers—those scoring 200 are less risky than those scoring 180 but more risky than those scoring 220. But scores do not purport to say that *every* applicant scoring 200 or above will prove to be a satisfactory customer or that every applicant scoring 199 or below will become seriously delinquent. Nor does scoring determine what degree of risk is appropriate for a particular lender.

In the typical application scorecard development, 50 or 60 factors may be identified as having some predictive value on their own, and probably 8 to 12 variables will find their way into the final scorecard. If each variable has an average of only three possible values, the possible combinations still run to tens of thousands. It would be impossible for a subjective or judgmental decision process to weigh that much complex information.

Comparing the results of scoring and judgmental decisions

Scoring and judgment will not always produce the same decisions with respect to the same applicant. If the individual decisions were always the same, scoring couldn't produce the improvements lenders typically see. In addition, scoring decisions differ from most judgmental decisions in that scoring has built-in compensatory features. Judgmental systems are often a series of hurdles or "knock out" criteria. With scoring, a low score on one factor can be made up in other areas. Except for age (which cannot be used directly in a judgmental system), the characteristics in a scoring system are likely to be very similar to those which would be considered in judgmental decisions. Statistical analysis of the judgmental process consistently demonstrates this is true. The principal difference is in the weights accorded to each factor.

Legal Background

Overview

Fair lending addresses three types of discrimination. This section will first provide a brief overview of the three types of discrimination, then a more detailed discussion of disparate impact or "effects" test discrimination. Finally, we will compare how credit scoring and judgmental systems differ with respect to each type of discrimination.

Types of discrimination

The three types of discrimination are overt discrimination, disparate treatment and disparate impact:

[1] *Overt or blatant discrimination* means that decisions are explicitly based on some prohibited basis such as race or gender. It is an explicit expression of prejudice. This type of discrimination is a personnel management issues, not a marketing or risk management issue.

[2] *Disparate treatment* means that, even though there is no explicit use of a prohibited basis, applicants who are similarly qualified on all legitimate factors are nevertheless treated differently with respect to their race, gender, national origin or other prohibited basis. Disparate treatment forms the basis of virtually all publicized cases involving lender discrimination.

[3] *Disparate impact*, sometimes referred to as the "effects" test, means that a factor which is apparently neutral has a disproportionate negative effect on the qualified members of some protected class (a) without a sufficient business justification or (b) despite the existence of an equally effective but less discriminatory alternative. This theory was developed by the courts, primarily in employment discrimination cases. A classic example of an effects test factor is a minimum height requirement for certain jobs such as police officer or firefighter. Although neutral on its face, such a height requirement has the potential to disqualify a disproportionate number of women and so will be permitted only if it can be shown to be related to job performance.[1] To date, there are no published cases applying all of the elements of the "effects" test in the credit area. However, as noted in Regulation B[2], the legislative history of the Equal Credit Opportunity Act ("ECOA") indicates that Congress intended the "disparate impact" or "effects test" theory to be applied to credit as well as to employment.

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[1] See, for example, Dothard v. Rawlinson, 433 US. 321, 330 (1977).

[2] FRB Commentary to Regulation B, Section 202.6(a)(2).

The cases dealing with disparate impact discrimination have generally applied a three-step test. Each step represents a shifting of legal burdens between an employer and the party bringing the discrimination claim.

The first part of the test requires the plaintiff to show that the challenged factor has a "substantial"[3] disproportionate impact on a protected class. Making such a showing in credit cases is difficult because most, if not all, users of credit scoring systems are prohibited from requesting or recording race/ethnic origin data. The only exception to this prohibition is in the mortgage area, where the Home Mortgage Disclosure Act or HMDA requires the collection of information about each applicant's race, national origin and gender.

Under the U.S. Supreme Court's decision in *Wards Cove Packing vs. Atonio, 490 U.S. 642 (1989)*, the plaintiff must show that the practice in question has a disproportionate impact on the *qualified* members of the protected class. For example, the use of "own/rent" as a scorecard characteristic is frequently criticized on the grounds that, since some minority groups are more likely to rent than whites, such a characteristic must have a disparate impact on minorities. *Ward's Cove* requires a party bringing a disparate impact claim to show, as part of this initial burden of proof, that minority renters are less risky borrowers than non-minority renters.

If a plaintiff meets the burden of showing that a disparate impact exists, the second part of the test shifts the burden to the lender to demonstrate a business justification for the challenged factor. Both the Office of the Comptroller of the Currency (OCC)[4] and Federal Reserve Board[5] have indicated it constitutes a valid business justification if the criterion in question is demonstrably predictive of creditworthiness.

The third part of the test shifts the burden back to the plaintiff to show that there is an equally effective but less discriminatory alternative available, and that the creditor has refused to adopt that alternative.

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[3] Betsey v. Turtle Creek Assoc., 736 F.2d 983, 988 (1984).

[4] OCC's Examiner's Guide to Consumer Compliance (1993).

[5] FRB Regulation B, Section 202.6(a)(2).

Comparing judgment and scoring

With the exception of age, which may only be used in statistically based decision systems, the factors considered by a scoring system are likely to be very similar to those that would be used in a judgmental decision process. Thus, if one believes that certain factors in a scoring system raise fair lending concerns, going back to judgmental decisions is not likely to remove those factors from the process. However, due to the requirement of a business justification, returning to judgmental decisions could significantly reduce a lender's ability to defend those factors if challenged on a disparate impact basis.

Any disparate impact analysis involving credit scoring should clearly distinguish between a characteristic in a scorecard such as own/rent—which when analyzed in isolation may be perceived to have a disproportionate impact—and the impact of the scoring model as a whole. Indeed, it is often the case that too much emphasis is placed on analyzing individual criteria within a scorecard rather than the scorecard itself. Even if a particular factor may have a disproportionate impact on a protected class, the scorecard as a whole, because of its inherently compensatory nature, may be free of any such impact. This is in sharp contrast to many judgmental decision processes, which impose a series of "knock-out" rules where failure to achieve the requirements of any rule results in a denial of the credit request. In those cases, individual factors can more appropriately be analyzed in isolation.

Overt discrimination

For obvious reasons, lenders who use credit scoring as the sole basis for their decisions have in essence a safe harbor from claims of overt discrimination so long as the model does not contain a prohibited factor [6]. When used in this fashion, scoring serves as an effective management tool for preventing this most blatant form of discrimination. By comparison, judgmental systems which rely on the subjective evaluation of an applicant significantly reduce a lender's ability to prevent this type of discrimination.

Disparate treatment

A similar "safe harbor" exists for claims of disparate treatment as for claims of overt discrimination, since credit scoring models treat similarly situated applicants the same—by assigning them the same score. Judgmental decisions are more likely to result in disparate treatment because of the difficulty of rendering consistent decisions where there are numerous loan officers with different backgrounds, training, or levels of

[6] This analysis does not extend to credit scoring models that contain a prohibited characteristic in the scorecard. Application scorecards developed by Fair, Isaac do not include any characteristic which is a "prohibited basis" as defined by the ECOA.

experience. This problem is compounded with large institutions which may also have multiple offices in multiple locations.

Thus, one critical difference between credit scoring systems and judgmental systems is that, when used properly, credit scoring systems ensure that the credit decision process will result in decisions that "discriminate" solely on the basis of risk and not on a prohibited basis. It is for this reason that, as recently as the late 1970s, some lenders alleged to have been discriminating on a prohibited basis were required to enter into consent decrees that mandated their use of credit scoring models to prevent disparate treatment discrimination.

Disparate impact

Some consumer groups and regulators have recently raised concerns that credit scoring systems may have a disparate impact on protected classes—more specifically, that many of the factors contained in those models have a disparate impact on minorities. Most of that criticism, however, has centered on whether specific characteristics meet the first prong of the legal test for disparate impact: That is, does the factor in question have a disproportionate negative impact on minorities?

Thus far, there has been little data with which to answer this question. It is obvious that income, property, education and employment are not equally distributed by race/national origin (or gender), and so it is highly likely that many factors which are apparently related to creditworthiness will have an unequal impact by race/national origin (or gender). Thus, it is reasonable to expect that many rational credit criteria may have an unequal impact on minorities and women as compared to white males. The legal test for disparate impact recognizes these differences in both the employment area and the credit area by requiring both that such factors have a disproportionate impact on the *qualified* members of some protected class, and that they not be justified from a business standpoint. When compared to judgmental systems, it is only when the factors used in the credit decision—and the weight given each factor—have been statistically derived that there is any assurance that the credit grantor will be able to demonstrate the business justification needed to withstand an effects test challenge.

Whether there is a business justification is therefore likely to be the key issue in any disparate impact case. The advantage of using a statistically derived system over judgmental decisions is clear when it comes to demonstrating business justification or business necessity: The development statistics not only provide compelling justification for the use of a particular factor—that is, to assess creditworthiness—but also for the weight it receives in the decision process. If the system is designed to use the most predictive combination of factors available, it will be difficult if not impossible for someone to demonstrate that there is an equally effective alternative available. In the example above involving the characteristic own/rent, even if there were data showing minority renters are better risks than white renters, own/rent would still be a legal characteristic *if* there is a sufficient business justification for using it *and* there is no equally effective but less discriminatory alternative available. It should also be noted that any equally effective alternatives offered as being less discriminatory should be analyzed to ensure that they do not in turn have a disproportionate impact on members of protected classes other than the minority group initially affected by the challenged factor.

Low-to-Moderate-Income Scoring Study

Data used

Data from Fair, Isaac's pooled credit application database was used to study the impact of scoring on LMI applicants. This database contains characteristics taken from application forms and credit bureau reports gathered from tens of thousands of applicants at the time they applied for credit, and their subsequent payment performance[7]. The applicant information in this database was gathered from more than 20 lenders.

Direct installment loan applicants from 7/92 to 12/94 were isolated from the database, and a single scorecard, one designed to work on all income groups, was developed for that population. The characteristics considered in development of the scorecard included application and credit bureau characteristics, and Fair, Isaac's on-line credit bureau score.

Definition of low-to-moderate income

The first step in the study was to define "low-to-moderate-income" (LMI). The definition was based upon the total gross monthly income reported on the application form. This figure includes all of the household income reported on the application form, regardless of source.

In order to define LMI, we analyzed the distributions by income of applicants in the entire database, and the distributions by income for each individual lender. We selected a definition of LMI that would be less than half of the total applicant pool and less than half of the applicants for any individual lender. This was done to ensure that a definition arrived at globally would also be acceptable for each individual lender's subset of applicants.

Using that approach, we arrived at a definition of LMI of "less than $1,750 gross monthly income." The data showed that 1/3 of the entire pooled database, and between 1/5 to 1/2 of the applicants for each of the individual lenders, had gross income of less than $1,750 per month. For most of the individual lenders, the percentage of LMI applicants ranged between 25% and 35%.

In order to ensure that this approach yielded a reasonable definition of LMI, the gross monthly income figure of less than $1,750, or $21,000 per year, was compared to the

[7] The following rough performance definitions were used: "Bads" were those that went 90 or more days delinquent during the performance outcome period; "Goods" were those that were never were 60 days delinquent during this same period. The payment performance of rejected applicants was inferred using Fair, Isaac's proprietary statistical techniques.

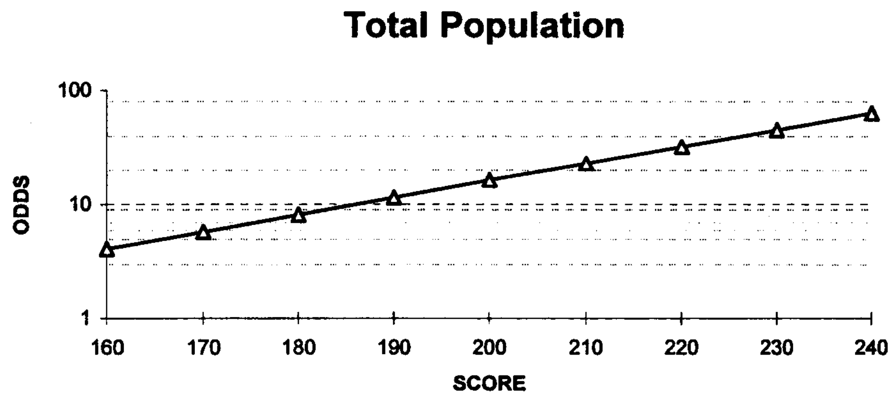
average poverty threshold for a family of four according to the 1990 U.S. Census. Adjusting for inflation[8] to match the time period when the applications were taken, the poverty level was roughly $1,220 per month, or $14,650 per year. $1,750 per month, or $21,000 per year, is about 45 % over that poverty level. This indicates that the approach used yielded a reasonable definition of LMI.

Odds vs. score comparisons

The first question investigated in the study was how the single scorecard developed on the entire database—one developed to assess risk for all income groups—would rank-order the risk of the LMI applicants.

As a starting point, Figure 1 contains the odds vs. score relationship of the scorecard on the whole population. As score increases, the odds—the ratio of the number of goods to number of bads in each score range—also increase. Fair, Isaac typically scales application scorecards such that with every increase of 20 points, the odds of satisfactory repayment double. In this case, at a score of 180, the odds are 8:1—8 goods for every 1 bad. At a score of 200, the odds increase to 16:1, and at a score of 220, the odds increase to 32:1.

Figure 1: Odds vs. score



[8] In 1989 the U.S. average poverty threshold for a family of four was $12,674 per year. The Consumer Price Indices for 1989, 1992, 1993 and 1994 were 126.1, 141.9, 145.8 and 149.7, respectively. Adjusting for inflation:

$12,674 * (141.9/126.1) = $14,262 in 12/1992

$12,674 * (145.8/126.1) = $14,654 in 12/1993

$12,674 * (149.7/126.1) = $15,046 in 12/1994

Applications were taken from 7/92 to 12/94 and the 1993 figure was used as an approximation for the period.

Figure 2 shows the odds vs. score relationship of the LMI applicants when scored using the single scorecard developed on the entire population. The data show a very similar risk ranking to that of the entire population: At a score of 180, the odds are 8:1, at 200, the odds are 15:1 and at 220, 29:1. In terms of points to double the odds, the general population scorecard doubles the odds of satisfactory repayment every 21 points for the LMI applicant population.

From the data illustrated in Figure 2, we concluded that a single scorecard developed on the entire population—one developed to assess risk for all income groups—effectively rank-orders LMI applicants by risk.

Figure 2: Odds vs. score

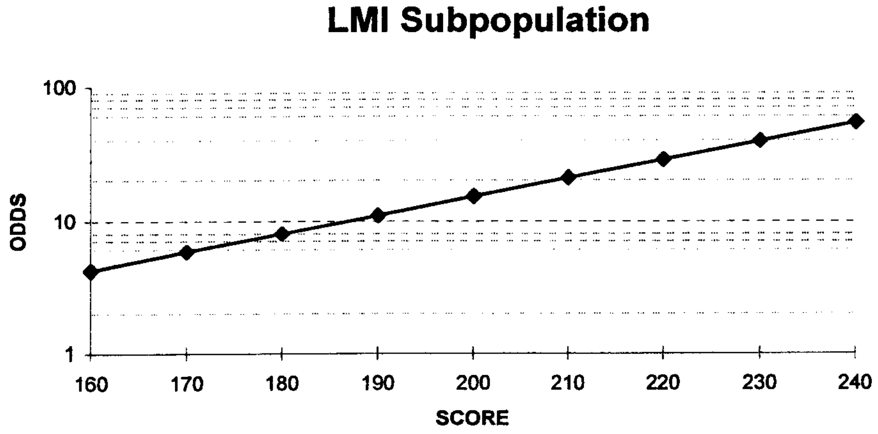
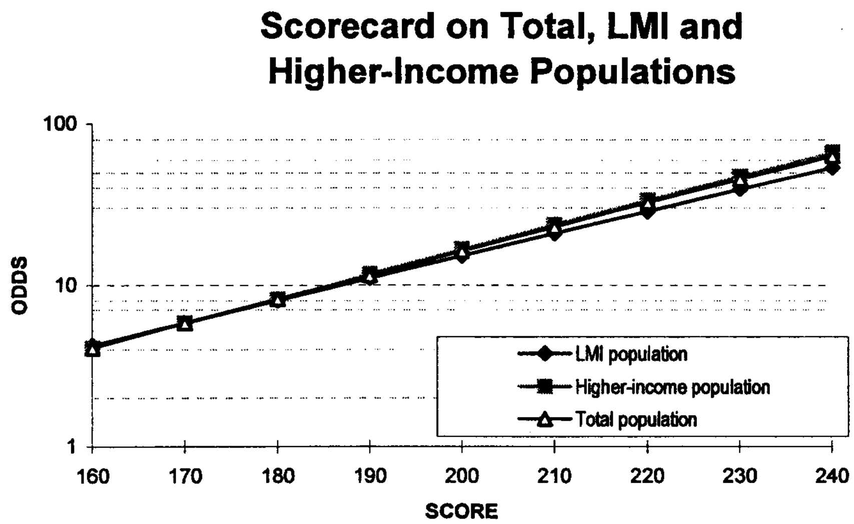


Figure 3 shows the odds vs. score relationships of the LMI population, the total population and the higher-income population. Higher-income applicants are all applicants not identified as LMI applicants. The odds vs. score relationships are very similar and, in particular, in the lower score ranges the differences are negligible. In the highest score ranges there is a slight difference between the LMI odds and the odds of the other populations. For example, in the highest score range—230 to 240—the data indicates that the LMI applicants at a given score present slightly greater risk.

Figure 3: Odds vs. score

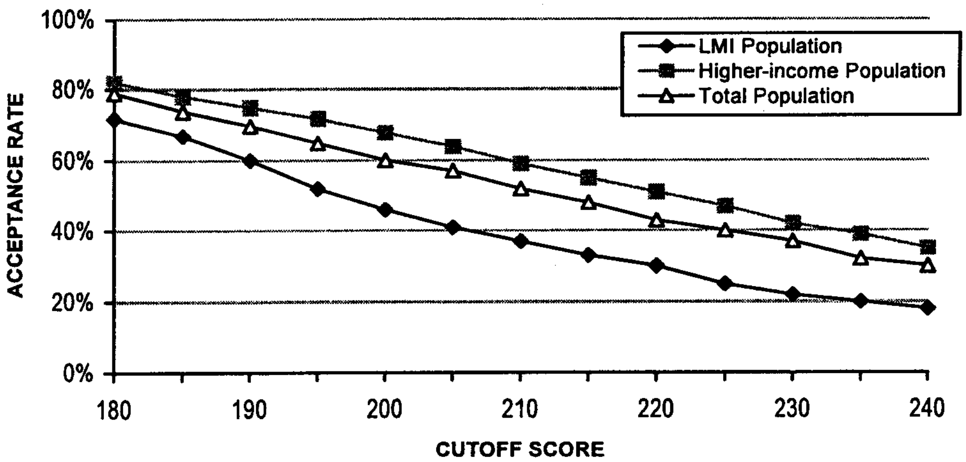


However, it is in the lower score ranges where attention should be focused. Many lenders set their cutoff score—the score at and above which they accept applicants and below which they decline applicants—around 200. Thus, applicants who score 230 to 240 are well above where a typical cutoff score would be set and they would all be accepted. Regardless of where the cutoff is set, a 5-point difference is small enough that we can conclude there is no substantive difference in the risk ranking among the various income groups, and that the same score indicates the same level of risk regardless of income level. To be certain, the differences that do exist consistently favor the LMI applicants.

Score distributions

Figure 4 contains the acceptance rates at various cutoff scores for the LMI, total and higher-income populations. The scorecard was scaled such that at a cutoff score of 200 the same percentage of applicants would be accepted as was accepted judgmentally in the development sample. In this study, the acceptance rate in the development sample was 60%—as shown on the graph, a cutoff score of 200 maintains that rate.

Figure 4: Acceptance rates by score



The LMI applicants as a whole score lower: At a cutoff score of 200, the acceptance rate for these applicants is 46%. The acceptance rate of the higher-income applicants at a cutoff score of 200 is 67%.

As shown previously, applicants at a given score, regardless of income, represent essentially the same level of risk. Therefore a lender consistently using this scoring system would be accepting the same risk-on-margin from either income group. The differences in the score distributions reflect differences in the overall risk of the two groups. In other words, the reason there are lower acceptance rates in the LMI applicant population is that, as a whole, lower-income applicants are riskier than higher-income applicants in this database. In this case, the overall odds of the LMI applicants are 9.4:1, or 9.4 goods for every 1 bad. For the higher-income applicants, the overall odds are 15.3:1, or 15.3 goods for every 1 bad. Total population odds are 12.7:1, or 12.7 goods for every 1 bad.

Population differences

We also studied, at the characteristic level, the differences between LMI and higher-income applicants. Characteristics contained in the scorecard were analyzed, as were candidate characteristics that did not enter the scorecard. Figure 5 contains the characteristics analyzed and their associated measure of difference between LMI and higher-income applicants at the attribute level.

- A population difference measure less than 0.100 indicates a negligible difference between the distributions.
- A population difference measure of 0.100 to 0.249 indicates a moderate difference between the distributions.
- A population difference measure greater than 0.250 indicates a large difference between the distributions.

Figure 5: Population differences between LMI and higher-income populations

APPLICATION CHARACTERISTICS	POPULATION DIFFERENCE	
Occupation Classification	0.550	
Age of Applicant	0.522	Large Differences
Residential Status	0.437	
Checking and Savings Account Reference	0.228	
Time With Present Employer	0.212	Moderate Differences
Bank Card and T+E Card References	0.181	
Bank Card Reference	0.170	
Time at Present Address	0.086	Negligible Differences
Personal Finance Company Loan Reference	0.007	

CREDIT BUREAU CHARACTERISTICS		
Number of Satisfactory Ratings	0.590	
Months Since Oldest Date Opened	0.457	
Debt Ratio From the Credit Bureau	0.386	Large Differences
Average Months In File	0.345	
Worst Rating From the Credit Bureau	0.344	
Percentage of Trade Lines With Balance	0.253	
Percentage of Trade Lines that are Installment	0.244	
Number of Bank/National Trade Lines With a Balance 75% or More of Credit Limit	0.218	
Number Installment Trade Lines With Balance	0.207	
Number of Revolving Trade Lines With Balance	0.204	
Percentage of Trade Lines Never Delinquent	0.200	
Revolving Balance to Limit Ratio	0.198	Moderate Differences
Installment Loan Balance to Loan Amount Ratio	0.139	
Maximum Delinquency Ever	0.133	
Maximum Delinquency or Public Record In the Last 12 months	0.125	
Number of Revolving Trade Lines 30+ Ever	0.110	
Months Since Most Recent 60+ Delinquency	0.103	
Number of Trade lines Opened in Last 12 Months	0.093	
Months Since Most Recent Date Opened	0.092	
Number of Major Derogatory Ratings	0.089	
Number of Minor Derogatory Ratings	0.086	Negligible Differences
Number of Trade lines 60+ Ever & Derog Public Record	0.078	
Number of Inquiries In the Last 6 Months	0.045	
Months Since Most Recent Inquiry	0.041	

Of particular interest is the analysis of the characteristic personal finance company references in Figure 5. This characteristic identifies whether or not an applicant has credit with a personal finance company, as indicated on the credit application.

A frequent criticism of some scoring systems relates to the use of personal finance company references as a characteristic in the scorecard. This criticism is based on the mistaken perception that low-income and minority borrowers are more frequent users of finance companies because they tend to have less access to traditional bank credit. The results of the LMI study showed that there was little to no difference in the distribution by attribute between the LMI and higher-income applicants for this characteristic. In fact, contrary to common belief, the higher-income applicants indicated that they had personal finance company references a slightly *greater* percentage of the time—11.8% of higher-income applicants in the research sample put on their application form that they had personal finance company references, compared to 9.2% of the LMI applicants. This characteristic is in the scorecard, and those with personal finance company references receive fewer points than those who do not. So, on average, the higher-income applicants score slightly *lower* on this characteristic than the LMI applicants.

Case study: Judgment vs. scoring of LMI applicants

The results of the previous case study show that using a single scorecard developed on the whole population to score LMI applicants is valid and provides a risk assessment consistent with that of the assessment on higher-income applicants. Although this is the case, a question still often posed is whether or not a judgmental screen on the LMI applicants would be more effective than scoring, or more beneficial to LMI applicants.

Data used

In order to answer this question, we surveyed the results from recent Fair, Isaac custom scorecard developments where the scorecard being developed was replacing a judgmental screen. We examined eight such developments:

- Four bankcard
- Three direct loan
- One indirect loan

Survey methodology

For the survey we defined an LMI applicant as one with less than $1,500 gross monthly income. This definition was used to again ensure that, for any individual lender, less than half of the applicants were defined as LMI.

In each of the databases surveyed, the LMI applicants were isolated and the performance—the acceptance rate and the resulting bad rate—of the judgmental screen on those applicants was observed. The custom application scorecard developed for the entire population was then used to score the LMI applicants. We then measured what the performance would have been if the scorecard had been used on the LMI applicants instead of a judgmental screen at the time they applied. We compared the scorecard's theoretical performance with the actual performance resulting from the judgmental screen in two ways:

[1] Using a cutoff score to maintain the judgmental screen's bad rate in order to compare acceptance rates; and

[2] Using a cutoff score to maintain the judgmental screen's prior acceptance rate in order to compare bad rates.

The results of these comparisons are shown in Figures 6 and 7.

Survey results

Figure 6: Strategy: Maintain bad rate; compare acceptance rates

DATABASE	BAD RATE	JUDGMENTAL ACCEPTANCE RATE	SCORING ACCEPTANCE RATE
Bankcard #1	10.9%	26%	76%
Bankcard #2	18.3%	24%	80%
Bankcard #3	2.3%	34%	67%
Bankcard #4	4.3%	14%	48%
Direct Loan #1	7.9%	76%	87%
Direct Loan #2	14.5%	37%	66%
Direct Loan #3	6.2%	54%	88%
Indirect Loan #1	7.4%	35%	63%

Figure 7: Strategy: Maintain acceptance rate; compare bad rates

DATABASE	ACCEPTANCE RATE	JUDGMENTAL BAD RATE	SCORING BAD RATE
Bankcard #1	26%	10.9%	5.1%
Bankcard #2	24%	18.3%	10.3%
Bankcard #3	34%	2.3%	1.4%
Bankcard #4	14%	4.3%	1.9%
Direct Loan #1	76%	7.9%	5.9%
Direct Loan #2	37%	14.5%	6.5%
Direct Loan #3	54%	6.2%	3.9%
Indirect Loan #1	35%	7.4%	2.9%

In every database surveyed, scoring would have provided a substantial improvement in the decision process compared to a judgmental screen.

The results of the judgmental screens, by themselves, deserve some comment. Note that there is no apparent relationship between the LMI acceptance rate and the LMI bad rates across the different databases. Thus the differences in LMI bad rates cannot be explained by different tolerance for risk across different lenders, by "tough" or lenient credit standards. Also, the bad rates for LMI applicants in some of these portfolios clearly would not have been tolerated for any length of time after being identified. If these lenders had not switched from judgment to scoring, it is very likely that some other action—such as imposition of a minimum income requirement—would have been taken to control losses in the lower income segments of these portfolios.

These results are theoretical in that they are based upon scorecard development databases, they include reject inference, and they assume perfect adherence to cutoff. These results are not based upon independent validations of booked accounts. Regardless, the direction and magnitude of the improvements provided by the scorecard indicate that even if the actual improvements in a real-world operating environment were significantly less than the theoretical improvements shown above, scoring would still provide a substantial improvement in performance over a judgmental screening process. Based on these results, for institutions seeking to affirmatively increase their extension of credit to minorities or LMI applicants, a scoring system offers a much more effective screen for doing so than judgmental decision making.

Case Study: The Effectiveness Of Credit Bureau Scores In High-Minority Areas

Data used

In performing this study, we used a sample of files from the Trans Union Corporation database—the same sample used by Fair, Isaac to develop the EMPIRICA® credit bureau score (EMPIRICA is a registered trademark of Trans Union Corporation). The data consisted of two credit reports for each consumer in the database: The earlier report was used for predictive information, the later report was used for performance information. On the earlier credit report, the EMPIRICA credit bureau score was generated. The latter credit report was used to determine the credit performance of the consumer in the two years following the score. This sample includes more than 800,000 pairs of credit reports, stratified such that it is representative of all the credit reports with trade lines in the credit bureau's file. Each of the credit reports includes a five-digit postal ZIP code associated with the consumer's residence.

Because direct race/national origin information is not available in this database, a separate source of U.S. Census data was used to identify ZIP codes in which a high percentage of minorities reside. Each consumer in the credit bureau database was then identified as to whether or not they reside (based on ZIP code) in a "high-minority area" (HMA). Since we do not identify minorities per se, but rather those individuals who reside in HMAs, the results of this study should be considered to reflect the socio-economic conditions in the different ZIP codes identified. The Census Bureau data indicate that the median income in the HMAs is only about two-thirds that in the rest of the population.

ZIP codes were defined as HMAs where Census data indicated that a certain percentage of blacks and Hispanics[9] reside—from as low as 40% to as high as 90%. The results presented in this document are based on an HMA defined as containing at least 70% black and/or Hispanic residents. However, similar results were observed for minority percentages ranging from 40 to 90%.

Representation of HMAs in the credit bureau data

Based on the Census data, residents of HMA ZIP codes account for 7.8% of the U.S. population of adults 18 years and over. In the credit bureau database, 6.7% of all the credit reports represented residents of HMAs. Consequently, although there is a slight

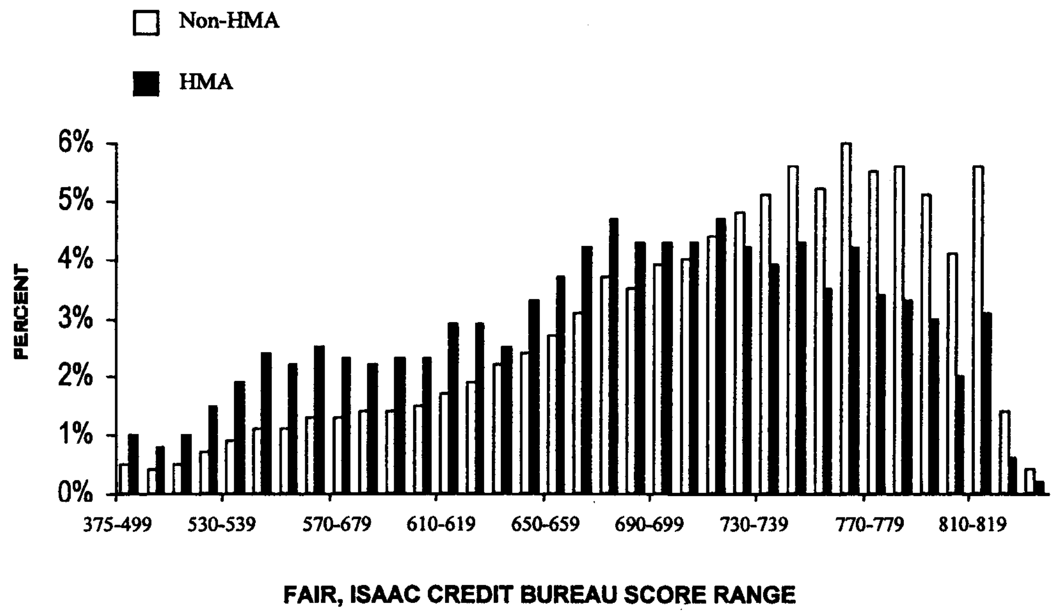
[9] The terminology and definition of racial groups are those used and defined by the U.S. Census Bureau.

under-representation of HMA residents in the credit bureau files, the data do not support the notion that HMA residents are "excluded" from the credit bureau data.

Score distributions

Figure 8 illustrates the difference in score distribution between the HMA population and the remainder of the population (non-HMA). High scores represent low risk of default, and low scores represent high risk. The HMA records score lower. This difference would result in a lower approval rate for the HMA population by any lender that relied solely on credit bureau score in approval decisions. For example, using a cutoff score of 620, 25.3% of the HMA population score below that threshold and would be declined, as compared to 13.8% of the non-HMA population.

Figure 8: Score distribution comparison



Population differences

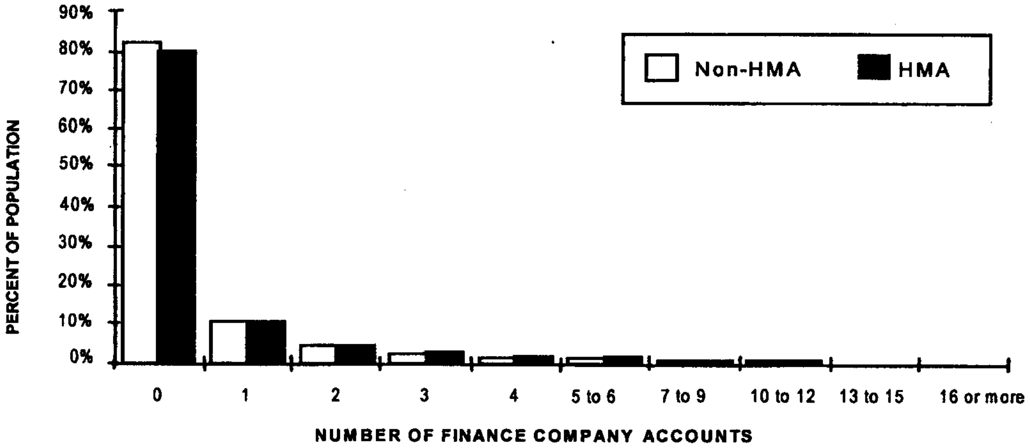
We studied which factors, or characteristics, differentiate these two populations. These factors are not necessarily considered in credit bureau or other types of scores; rather, we investigated the differences in credit reports between those who reside in HMAs and the rest of the credit population. Figure 9 lists characteristics and an index of their population difference, in descending order.

Figure 9: Population differences

CHARACTERISTICS	POPULATION DIFFERENCE
Revolving Debt Utilization	0.181
Number of Bankcards	0.127
Number of Recent Bankcard Openings	0.109
Average Revolving Balance	0.107
Length of Credit History	0.097
Number of Accounts with No Delinquency	0.089
Total Number of Accounts	0.085
Worst Delinquency	0.075
Number of Accounts Ever 90+	0.068
Amount Past Due	0.065
Months Since Most Recent Delinquency	0.063
Number of Home Loans	0.058
Number of Accounts with High Delinquency	0.057
Number of Recent 60+ Day Delinquencies	0.053
Average Balance	0.046
Number of Accounts Ever 30+	0.044
Installment Debt Utilization	0.038
Number of Recent Inquiries	0.020
Months Since Most Recent Collection	0.017
Months Since Most Recent Date Opened	0.011
Months Since Most Recent Public Record	0.011
Number of Recently Opened Accounts	0.010
Number of Finance Company Accounts	0.004

The results for the number of personal finance company trade lines were of particular interest. Note that this factor refers to the number of personal finance company trades that appear on the credit report (as opposed to the information in the LMI study, which refers to the finance company information volunteered on the application). A common concern is that those living in high-minority areas have less access to traditional bank credit, and thus are more likely to utilize finance company credit. The results in Figures 9 and 10 show that is not the case. The non-HMA population had more trade lines overall, but about the same number of finance company trades as the HMA. So, the *percentage* of finance company accounts, rather than the number of such accounts, is higher in the HMA. While Fair, Isaac credit bureau scorecards often use the *number* of finance company trade lines, the percentage of trade lines from a finance company is not a factor in any of the Fair, Isaac credit bureau scorecards.

Figure 10: Population difference for number of finance company accounts



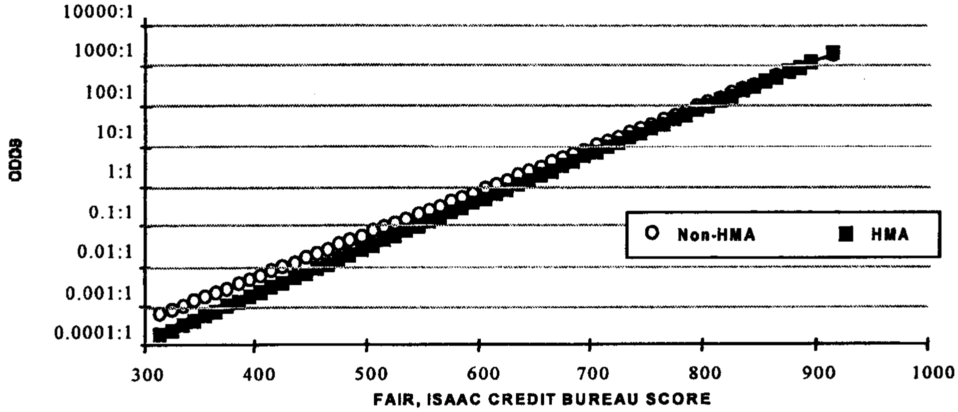
Odds vs. score comparisons

The remainder of this case study considers the future performance of those consumers in conjunction with the score and other information on the credit report as of the observation date. Categories of "good" and "bad"[10] were assigned to each credit report based on the performance indicated by the credit report in the two years after the scoring date.

Figure 11 shows the odds vs. score relationships for the HMA and non-HMA populations. For both populations, the odds vs. score lines show that scores are effective in rank-ordering future performance (i.e., the odds increase as the score increases).

[10] Approximate performance definitions: "Bads" were those that were 90 days or more delinquent on any type of credit, or claimed bankruptcy, in the two years after the scoring date. "Goods" exhibited no delinquency or had one isolated 30-day delinquency on the credit report during that period. All others are considered "indeterminates" and are not considered in odds calculation (although they are included in score distributions and other non-performance-related research).

Figure 11: Odds vs. score comparisons



Even though the credit bureau scores rank consumers by risk for both groups, the observed odds at a particular score were not equivalent for the two populations. We observed between a 5 and 40 point shift in scores at the same risk level[11]. The direction of this shift works to the benefit of the HMA population, in that the odds at any given score are slightly worse for the HMA population than for the rest of the population.

Development of a scorecard specifically for the high-minority population

In the last part of our analysis, we studied the predictors of performance for HMA populations as compared to the total population. In this part of the study we defined HMA as 90+% black and/or Hispanic, to highlight any population differences. Predictors for the HMA were observed, to determine whether they tend to be different from predictors for the total population.

Figure 12 shows the predictive value of factors on the HMA and non-HMA populations, in descending order of predictive value on the HMA population. Note that the ordering of the predictors is similar in both. Also note that there are no characteristics that are very predictive for one population, and not for the other.

[11] The magnitude of the odds vs. score shift depends on the score. At a typical operating range in the 600s, the observed shift is approximately 20 points.

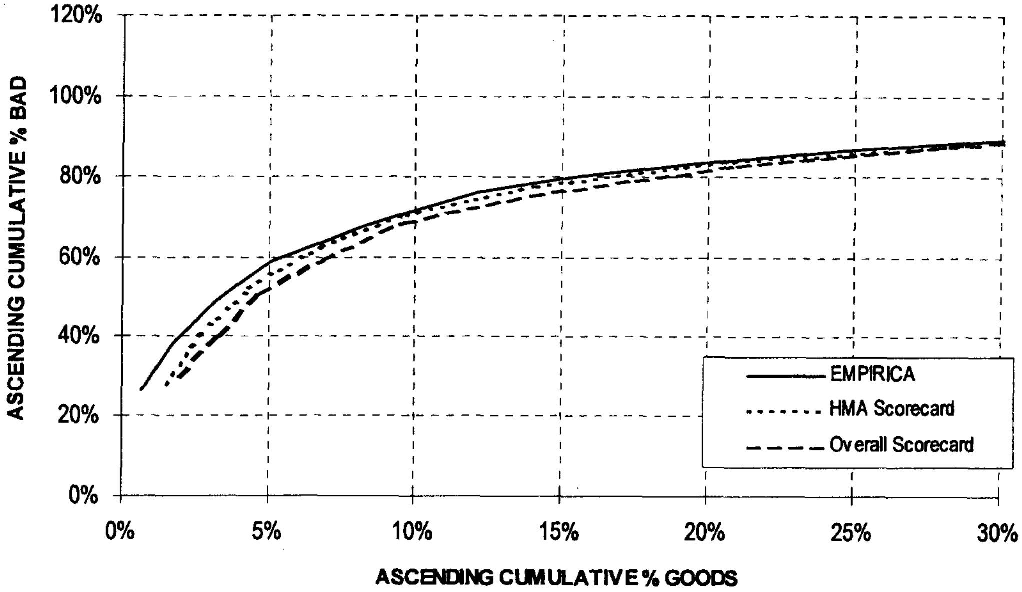
Figure 12: Comparison of predictors

CHARACTERISTICS	PREDICTIVE VALUE ON HMA	PREDICTIVE VALUE ON NON-HMA
Amount Past Due	1.996	1.886
Worst Delinquency	1.946	1.806
Months Since Most Recent Delinquency	1.622	1.797
Number of Accounts Ever 90+	1.593	1.347
Number of Recent 60+ Day Delinquencies	1.529	1.522
Number of Accounts Ever 30+	1.511	1.572
Revolving Debt Utilization	1.409	0.826
Number of Accounts with High Delinquency	0.927	0.962
Months Since Most Recent Collection	0.665	0.317
Average Revolving Balance	0.653	0.405
Average Balance	0.633	0.671
Length of Credit History	0.558	0.262
Months Since Most Recent Public Record	0.492	0.301
Installment Debt Utilization	0.409	0.510
Number of Recent Inquiries	0.293	0.371
Number of Accounts with No Delinquency	0.208	0.389
Number of Recently Opened Accounts	0.167	0.133
Number of Finance Company Accounts	0.154	0.076
Months Since Most Recent Date Opened	0.140	0.163
Number of Bankcards	0.111	0.056
Number of Recent Bankcard Openings	0.094	0.014
Total Number of Accounts	0.029	0.112
Number of Home Loans	0.008	0.027

Could a scorecard developed only on HMA data do a better job of predicting risk for HMA consumers? A scorecard was developed specifically for the HMA population (HMA Scorecard), and compared to the performance of a scorecard built for the total population (Overall Scorecard). Observing trade-off curves illustrates which system provides the most predictive power on the HMA group; the system that identifies the highest percentage of bads (scoring below each cutoff) for any chosen level of goods (scoring below the same cutoff) is the most predictive system. Figure 13 shows that the HMA Scorecard is slightly more predictive of risk than the Overall Scorecard on the HMA population. For example, at a score where 20% of HMA goods are identified, the HMA Scorecard identifies 82% of the bads, compared to 80% with the Overall Scorecard.

However, Figure 13 also shows that Fair, Isaac's multiple-scorecard credit bureau scoring system (represented by EMPIRICA) is a slightly better predictor of risk for HMA consumers than the HMA Scorecard, even though the Fair, Isaac credit bureau scores are built on data samples representing the total population. The Fair, Isaac credit bureau score systems at all three major U.S. bureaus contain 10 scorecards. These scorecards focus on different credit profiles to exploit the differences in predictors of each. One of the key factors that pulls a credit report into a different scorecard is the presence of a serious derogatory reference on the credit report. This helps explain why most of the improvement is in the lower score ranges; for example, at a score where 5% of the goods are identified, the Fair, Isaac credit bureau scorecard identifies 56% of the bads and the HMA Scorecard identifies 50%.

Figure 13: Good/bad trade-off curves--HMA population



These results show that Fair, Isaac credit bureau scores are both "fair" and effective when applied to HMA applicants. Segmentation of scorecards based upon credit profiles (for example, segmentation based on past credit payment history, regardless of race) outperformed the HMA-specific segmentation.

Conclusions

Our studies answered the initial research questions we posed:

[1] Does credit scoring work on LMI individuals and individuals residing in HMAs?

Our studies show that scoring is very predictive of risk for LMI applicants and applicants in HMAs.

[2] Does credit scoring have a disproportionate negative impact on LMI individuals and individuals in HMAs?

Any disparities in the risk-to-score relationship between the general population and LMI/HMA populations work in favor of LMI and HMA applicants. LMI and HMA populations may score lower overall, but this is not surprising, given that the uneven distribution of income, wealth, property and education is reflected in the credit risk of the LMI and HMA groups. Since most of the factors used in credit scoring systems are similar to those used in judgmental systems, any rational judgmental system of evaluating creditworthiness is likely to yield a similar, if not greater difference in acceptance rates between these groups and the rest of the population than will a scoring-based system. Moreover, the legal test for disparate impact acknowledges these population differences by requiring demonstrative evidence of disparate impact on the qualified members of a protected class, and by allowing a lender to demonstrate that there is a business justification for the use of even a characteristic that has such a disparate impact.

[3] Does credit scoring work any differently on LMI and HMA individuals when compared to higher-income individuals or those that do not reside in HMAs? In other words, are the odds-to-score relationships different among these populations?

Our research showed only minor differences in the odds-to-score relationships—differences that, as noted, favor LMI and HMA applicants.

[4] Are the factors that predict risk different for LMI and HMA individuals than for HI or Non-HMA individuals?

As indicated by Figures 5 and 12, there are some differences in the predictive strength of characteristics for LMI/HMA vs. HI/non-HMA populations, but these differences are not nearly so great as is sometimes claimed, and they do not involve some of the characteristics largely supposed to yield the greatest differences (e.g., number of personal finance company references).

[5] Are LMI and HMA individuals excluded from scorecard development populations?

Our research showed that the percentage of HMA individuals in the samples used to develop Fair, Isaac credit bureau scorecards nearly matches the percentage of HMA individuals in the general population. Because the characteristics of HMA residents seem to resemble those of LMI applicants, it is likely that this finding would hold true for LMI applicants.

[6] Would judgmental systems be a more predictive screen than credit scoring for LMI and HMA applicants? Which is more favorable to such applicants?

Credit scoring is a far more predictive screen for both the LMI and HMA applicants than is judgmental decision making. As indicated in Figure 6, a lender employing credit scoring could accept many more LMI applicants without raising their bad rate. Again, because the characteristics of HMA residents seem to resemble those of LMI applicants, it is likely that using scoring to evaluate minority applicants could produce the same improvements observed for LMI applicants.

[7] [a] Would a scorecard developed specifically for HMA individuals be more predictive than a scorecard developed for the total population?
[b] Would a scorecard developed specifically for HMA individuals be more predictive than the Fair, Isaac credit bureau scores?

[a] As revealed in Figure 11, a single scorecard developed specifically for HMA individuals outperformed a single scorecard developed specifically for the total population. However . . .

[b] The multiple-scorecard systems developed by Fair, Isaac and resident at the three main U.S. credit bureaus were proven to be more predictive than a single scorecard built for the HMA population.

Appendix A. Glossary of Scoring Terms

ACCEPTANCE RATE The percentage of applicants accepted. The acceptance rate varies by cutoff score.

$$\text{Acceptance Rate} = \frac{\text{\# of applicants accepted}}{\text{total \# of applicants}}$$

ATTRIBUTE One of the possible values of a characteristic.

BADS Accounts that have been seriously delinquent or have been charged off. The precise definition is determined by the credit grantor in custom scorecard developments.

BREAK-EVEN ODDS Odds at which losses due to delinquent or charged-off accounts balance profits from accounts paid on time.

CHARACTERISTIC A variable taken from an application, credit report or other source of information (e.g., "age," "income," "number of inquiries"). Characteristics have two or more attributes.

CREDIT BUREAU SCORES Scores based solely on credit bureau data available online from the major credit bureaus.

CUTOFF SCORE The score at and above which one decision is made (e.g., applicants are accepted) and below which a different decision is made (e.g., applicants are declined).

DIVERGENCE The measure of the ability of a scoring system to separate good accounts from bad accounts. For normally distributed scores:

$$\text{Divergence} = \frac{(mg - mb)^2}{1/2\,(dg^2 + db^2)}$$

where:
mg = mean of goods
mb = mean of bads
dg = standard deviation of goods
db = standard deviation of bads

GOODS Typically, seasoned accounts that have never been more than mildly delinquent. The precise definition is determined by the credit grantor.

INDETERMINATES Accounts that do not satisfy the definitions of good or bad.

INFORMATION VALUE The measure of the ability of a characteristic to separate good accounts from bad accounts.

$$\text{Information Value} = \sum_{i=1}^{n} (p_i - q_i)\ln\left(\frac{p_i}{q_i}\right)$$

where: p_i = percentage of all goods having attribute i
q_i = percentage of all bads having attribute i

ODDS A measure of the likelihood of success in a given event. Odds are the ratio of the number of successes to the number of failures for the event. In scoring terms, the odds represent the ratio of future "good" accounts to future "bad" accounts.

OVERRIDE A judgmental decision on a given application that is contrary to the scorecard logic. High-side overrides are applicants who score above the policy cutoff score but are declined; low-side overrides are applicants who score below cutoff but are accepted.

PERFORMANCE DATE The date performance data are observed in a scorecard development.

PERFORMANCE GROUP A categorization of applicants by performance. Typically accounts are categorized into the following groups: rejects, goods, bads, indeterminates and insufficient experience.

PERFORMANCE TRACKING Any set of ongoing procedures designed to ensure that a scoring system is performing as predicted.

POPULATION The body of applicants that a given scorecard is to be used on and/or that the development sample is gathered from.

POPULATION ODDS The ratio of all goods in a development population to all bads.

REJECT INFERENCE The process of statistically inferring the behavior of unbooked (rejected and/or uncashed) applicants. This allows for development of a scorecard that applies to all applicants, not just prior accepted applicants. Fair, Isaac employs a proprietary reject inference technique.

REJECTED APPLICATION The application form, credit report, and other information for an applicant denied credit by the credit grantor.

SAMPLING The gathering of a statistically representative cross-section of a credit grantor's applicant population (a sample) in order to determine the characteristics predictive of risk.

SCALING A mathematical process that transforms score weights into whole, positive numbers to simplify the scoring operation.

SCORE DISTRIBUTIONS Tables counting the number of applications in the development sample, and the proportion that are good and bad, by score range. Score distributions may be displayed as ascending or descending cumulative statistics.

SCORE The sum of score weights from characteristics from the application and from the credit bureau report or other external credit investigation. Also referred to as final score, credit score, or total score.

SCORE WEIGHT A numerical or point value attached to an attribute.

SCORECARD A tool comprised of a list of characteristics, each of which has two or more attributes, and a numeric score weight attached to each attribute. The score weights for an application are added to determine the total score.

SUB-POPULATION An identifiable fraction or subdivision of the population. (See Population.)

VALIDATION Any process that measures the validity of a statistical tool such as a scorecard.

WEIGHT OF EVIDENCE

A measure of the predictive strength of a given attribute of a characteristic.

$$\text{Weight of evidence} = \ln\left(\frac{p_i}{q_i}\right)$$

where: p_i = percentage of all goods having attribute i
q_i = percentage of all bads having attribute i

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In the course of a busy day, you may write a check at the grocery store, charge tickets to a ball game, rent a car, mail your tax returns, call home on your cell phone, order new checks, or apply for a credit card. Everyday transactions that you may never give a second thought to are an identity thief's bread and butter. Each of these transactions requires the sharing of personal information: your bank and credit card account numbers; your income, Social Security number and name, address and phone numbers, to name a few. While you can't prevent identity theft, you can minimize your risk by managing your personal information wisely.

Catching Identity Theft Early

Sometimes an ID thief can strike even when you've been very careful. One of the best ways to catch identity theft is to regularly check your credit record. Order your credit report from each of the three major credit bureaus each year and make sure all the information is correct. Also, follow up with creditors if your bills do not arrive on time. A missing credit card bill could mean an identity thief has taken over your credit card account and changed your billing address to cover his tracks.

- ID Theft Affidavit
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