AMERICAN ACADEMY *of* ACTUARIES

Subcommittee on Financial Institutions and Consumer Credit Committee on Financial Services United States House of Representatives

Hearing on "Fair Credit Reporting Act: How it Functions for Consumers and the Economy"

Statement of Walter C. Wright III, FCAS, MAAA Chairperson, Risk Classification Subcommittee American Academy of Actuaries

June 4, 2003

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INTRODUCTION

The Risk Classification Subcommittee of the American Academy of Actuaries appreciates the opportunity to provide comments on issues related to credit scoring and its use in insurance underwriting and ratemaking. Our subcommittee hopes these comments will be helpful as Congress considers related proposals. Our subcommittee is charged with assisting interested parties in evaluating actuarial practices related to the affordability and availability of insurance across all demographic classes and in risk classification in general.

This testimony briefly discusses overall risk classification and reviews often-referenced papers on the issue including a prominent credit scoring modeling company (Fair, Issac), an actuary (Monaghan), and the State of Virginia Insurance Bureau. This testimony is based primarily on a report (located at http://www.actuary.org/pdf/casualty/credit_dec02.pdf) that our subcommittee drafted at the request of the National Association of Insurance Commissioners (NAIC) in December of 2002. The NAIC has asked our subcommittee to review and report on additional papers such as the Alaska and Texas studies, and this report to the NAIC is slated for completion no later than their Fall 2003 Meeting.

ACTUARIAL STANDARDS CONCERNING RISK CLASSIFICATION

Insurance companies use individuals' credit histories in addition to other demographic information, histories of accidents and violations, and vehicle information as part of their underwriting and pricing process for automobile and homeowners insurance. The use of credit histories as part of the risk classification process has become widespread in recent years. Consumers and insurance regulators have expressed concern that the use of credit histories for personal lines of insurance may not be appropriate.

The subcommittee recognizes that risk classification systems, while vitally important, must not unfairly discriminate. We are interested in contributing our findings to any discussion of fair versus unfair discrimination in insurance underwriting practices and the appropriateness of using credit history. Members of the Academy rely on Actuarial Standard of Practice No. 12 (ASOP No. 12), *Concerning*

Risk Classification, for guidance regarding risk classification systems. Standards of practice serve to assure the public that actuaries are professionally accountable. At the same time, standards provide practicing actuaries with a basis for assuring that their work will conform to generally accepted principles and practices. ASOP No. 12 and virtually all the states require that risk classification not unfairly discriminate

ASOP No. 12 recognizes the importance of risk classification systems:

"In a voluntary market system, risk classification is vital to ensure the equity and financial soundness of the system. Economic incentives such as the avoidance of antiselection often have led to innovations and changes in risk classification systems. Risk classification has become more complex and refined, therefore promoting more equitable risk classification, and encouraging widespread availability of coverage."

ASOP No. 12 identifies four basic principles that should be present in any sound risk classification system:

1. The system should reflect cost and experience differences on the basis of relevant risk characteristics.
2. The system should be applied objectively and consistently.
3. The system should be practical, cost-effective, and responsive to change.
4. The system should minimize antiselection.

ASOP No. 12 addresses the elements of a risk classification system from an actuarial perspective, but not from a public policy perspective. The subcommittee recognizes that the four basic principles are *necessary* conditions for a sound risk classification system, but they are not necessarily *sufficient* conditions. Clearly, for example, a risk classification system would not be considered acceptable if law or regulation prohibited it. Like all effective underwriting tools, the use of credit scoring in insurance will have an adverse impact on some members of the community and a favorable impact on others.

HIGH-LEVEL SUMMARY OF THE PAPERS

The three papers we have reviewed are useful for obtaining an overview of credit-scoring issues. Summarizing these papers very briefly:

- The Fair, Isaac paper "Productiveness of Credit History for Insurance Loss-Ratio Relativities," is a comprehensive response to issues that have been raised by insurance regulators and others in regard to the use of credit history.
- The Monaghan paper, "The Impact of Personal Credit History on Loss Performance in Personal Lines," analyzes the effectiveness of using credit characteristics to predict future loss ratios for private passenger automobile and homeowners insurance.
- The Virginia Bureau of Insurance paper, "Use of Credit Reports in Underwriting" discusses the use of credit history in that state.

These three papers give a good multifaceted evaluation of the current regulatory and marketplace issues regarding the use of credit scores in risk classification. Each of the three papers is reviewed in more detail, below. For each paper, we first provide an overall summary of the paper, and then identify the major points and conclusions that are made in the paper, and then review and discuss these major points and conclusions.

PREDICTIVENESS OF CREDIT HISTORY FOR INSURANCE LOSS- RATIO RELATIVITIES

Fair, Isaac; 1999

See Appendix A for text of this paper

Summary Review of Paper

This study by a prominent provider of insurance scoring models provides a good description of why insurance companies use credit histories. It is a response to issues that have been raised by insurance regulators and others in regard to the use of credit history for insurance underwriting. It provides a comprehensive review of these issues, but does not provide any in-depth analysis or discussions of the underlying insurance scoring models. It has the following strengths and weaknesses:

Study's Major Points and Conclusions

1. The accuracy of credit data should not be a matter of concern.

   If credit data were widely inaccurate, scores also would be inaccurate. The fact that insurance scores are so predictive of insurance loss performance testifies to the overall accuracy of the credit information.

   Several studies are referenced that show very low error rates for credit data. In fact, there are much lower error rates than for motor vehicle reports (MVRs), which are readily accepted and routinely used for auto insurance.

2. The Fair Credit Reporting Act (FCRA) permits the use of consumer credit reports for underwriting insurance. It gives consumers certain protections, including notification requirements, free access to their credit reports, and in the case of an adverse action based on a consumer report, correction procedures.

3. Specific credit variables and model scores are highly effective at predicting insurance loss ratio relativities.

   The Fair, Issac study gives examples of five specific credit variables and how they are related to personal property and automobile insurance loss ratios. The credit information further separates insurance policies by loss ratio above and beyond the separation is provided by the other commonly used rating variables. The actual model scores also are very effective at predicting loss ratio relativities. Fair, Isaac commissioned Tillinghast-Towers Perrin to validate the relationship. (1996 paper, appended to NAIC white paper.) The general statistical techniques are well known but the exact models are proprietary.

4. Statistical models do not determine causality. Statistical techniques demonstrate statistical relationships, but do not determine causal relationships. But in other fields, such as medicine, the discoveries of statistical relationships have been considered valuable and useful, even without the establishment of causal relationships. One can speculate that those who manage their credit risk well may also manage their insurance risk well.

5. The Fair, Isaac scoring models are not unfairly discriminatory. In compliance with the Equal Credit Opportunity Act (ECOA) and the Fair Housing Act (FHA), the Fair, Isaac scoring models avoid the use of many factors, including: income, location, nationality, net worth, race, color, religion, and disability.

   A study by the American Insurance Association concluded that using insurance scores does not discriminate against low-income groups, and that insurance scores are not significantly correlated with income.

6. The use of Insurance Bureau scores (scores based on Fair, Isaac models) enables insurers to improve the speed, objectivity, and consistency of their underwriting.

   Insurance Bureau scores are used by many insurers in the United States and Canada. Insurance Bureau scores are widely available, so they enable insurers of all sizes to use credit information with efficiency, objectivity and consistency. Because they are objective, their use can eliminate subjective human judgment.

   Scores can be used for the following multiple purposes:

- Underwriting evaluation for various insurance programs; Sales management (for example, by monitoring the average scores by agent)
- Management information (for example, monitoring changes in average scores)

7. Credit scores, unlike Insurance Bureau scores, were developed to predict credit risk and are not appropriate for the purpose of predicting insurance risk.

Review and Discussion of Major Points and Conclusions

1. The accuracy of credit data should not be a matter of concern.

   This conclusion is based on studies by Arthur Andersen (for the Associated Credit Bureaus), TransUnion (a credit report company), and a comparison with the accuracy of motor vehicle records (MVRs), which was evaluated in a study by the Insurance Research Council.

   There are many ways to evaluate the accuracy of credit data and these studies are just a few. It is unclear in the TransUnion study, for example, how many important credit report inaccuracies might have gone undisputed.

   Further, the error rates measured by the credit data studies and the MVR study are not directly comparable. Fair, Isaac states "In view of the error rate of MVRs, the credit report error rate should not be an issue," but this seems to be too strong a conclusion.

2. FCRA permits the use of consumer credit reports for underwriting insurance, and gives consumers certain protections, including notification requirements, free access to their credit reports, and in the case of an adverse action (such as civil judgment, bankruptcy, tax liens) based on a consumer report, correction procedures. Evaluation of the legal ramifications of the FCRA is outside the scope of this review.

3. Specific credit variables and model scoring are effective at predicting insurance loss ratio relativities The Fair, Issac study provides many results (statistical relationships) showing that both individual credit characteristics and insurance scores are closely related to loss ratios. However, little or no in-depth data analysis is directly included in the paper, and therefore it is not possible to comment on the validity of these results. For example, Fair, Issac's conclusions regarding loss ratios are based on the implicit assumption that all other elements of the rating structure are correct, meaning that all groups of consumers would have identical loss ratios if it were not for their different credit scores. To the extent that there are overcharges and undercharges in the rating plans (due to factors other than credit rating), this could distort the indicated credit score differentials. There is also a potential

for distortion because not all companies use the same rating plan or have the same overall loss ratio. These possibilities would have been explored more carefully in a more in-depth study.

4. Statistical models do not determine causality. This is an appropriate conclusion. It should not be necessary to demonstrate causality. Actuarial Standard of Practice No. 12 states that causality cannot be required for risk classification systems. It is sometimes impossible or impractical to prove cause-and-effect relationships. Risk classes should be neither obscure nor irrelevant, but they need not exhibit a cause-and-effect relationship.

5. The Fair, Isaac scoring models are not unfairly discriminatory. The Risk Classification Subcommittee accepts Fair, Isaac's statement that its models do not use certain factors including income, location, nationality, net worth, race, religion, and disability. There is no way for the subcommittee to verify this statement without reviewing Fair, Isaac's models. However, this statement cannot be generalized to other models in use. Also, the paper does not address whether any of the credit variables used, or the overall insurance score, might be a surrogate or a proxy for any prohibited factor or factors. Our subcommittee has not reviewed the study by the American Insurance Association cited by Fair, Isaac.

6. The use of Insurance Bureau scores (scores based on Fair, Isaac models) enables insurers to improve the speed, objectivity, and consistency of their underwriting. The Insurance Bureau scores most likely enable insurers to improve their underwriting in this way, but no evidence is presented to indicate that insurers use the Insurance Bureau scores in an objective and consistent manner.

7. Credit scores, unlike Insurance Bureau scores, were developed to predict credit risk and are not appropriate for the purpose of predicting insurance risk. Although this was not a major point in the Fair, Isaac study, the distinction between credit (lending) scores and insurance scores is important. The study does not present any information about the relationship between credit scores and insurance scores.

THE IMPACT OF PERSONAL CREDIT HISTORY ON LOSS PERFORMANCE IN PERSONAL LINES

James E. Monaghan; 2000

See Appendix B for text of this paper.

Summary Review of Paper

The value of the Monahan paper is that it provides data and analysis that support why personal lines insurers consider credit scoring to be an important risk classification tool. The Monaghan study has the following strengths and weaknesses.

Study's Major Points and Conclusions

1. Eight credit information variables are identified that show strong power to predict loss ratios. This demonstrates correlation between certain credit information at the time a policy is written as new business, and future loss ratios.

   The eight credit information variables are:

- Amounts past due
- Derogatory public records (bankruptcies, tax liens, civil judgments, and so forth)
- Collection records (generated when an account is referred to a collection agency)
- Status of trade lines (a "trade line" is a credit account or loan account)
- Age of oldest trade line
- Non-promotional inquiry count (number of credit inquiries arising from activity or request of the consumer)
- Leverage ratio on revolving type accounts (the leverage ratio is the ratio of debt to account limits)
- Revolving account limits

2. The statistical models do not demonstrate causality.

Although the cause-and-effect relationships are speculative, there are reasonable causal links between credit characteristics and insurance risk.

Actuarial Standard of Practice No. 12 states that causality cannot be made a requirement for risk classification systems. It is sometimes impossible or impractical to prove cause-and-effect relationships. Risk classes should be neither obscure nor irrelevant, but they need not exhibit a cause-and-effect relationship.

The following list includes some examples of possible causal links between certain credit information and insurance loss experience:

- Maintenance: How responsibly one manages financial credit might also correspond to how one maintains and operates a car.
- Moral Hazard: "Moral hazard" refers to the possibility that some drivers might be less careful if they have insurance. Drivers who do not manage their financial credit responsibly might also be more likely to present a moral hazard.
- Claims Consciousness: Persons in certain financial situations might be more inclined to file claims.
- Fraud: Similarly, persons in certain financial situations might be more likely to be induced into fraud.
- Stress: Persons in certain financial situations might be more stressed.

It is possible that all of these and other factors create a cumulative effect.

3. Multivariate analysis was performed and presented which demonstrates that different credit profiles predict different loss ratios, even when other factors (such as driving record, age of driver, and so forth) are held constant.

   Credit characteristics were compared by type of rating territory (urban versus other) in several states. This demonstrated that the distribution of credit characteristics by type of territory is relatively uniform. In other words, urban territories had approximately the same percentage of risks with poor credit characteristics as did other territories. Similar results were found for other underwriting criteria, including: number of vehicles, number of drivers, residence type, residence stability, job stability, prior insurance, gender, and marital status.

Multivariate analysis also was performed to demonstrate that there are many credit variables that have independent relationships with loss ratios.

4. The study includes an analysis versus homeowners' insurance loss ratios, with similar results.

5. The issues regarding whether credit information should be used extend beyond loss performance:

- Questions remain about whether credit information should be applied to renewals, and if so, how often it should be re-checked. Should premium be changed solely due to credit information? Each evaluation creates an inquiry in the credit file.

- There is concern with using a classification variable that is "under the control of the insured." In this case, however, it is doubtful that insureds would manipulate the class plan because they already are affected by their credit histories in other ways.

- There is the need for a good measure of the accuracy of credit information. Insurers should inform customers of how to resolve inaccuracies, and then take into account any corrections.

- Privacy concerns need to be addressed when considering the use of credit history in personal lines of insurance. Unlike the use of accident history, for which the negligence of the insured can usually be determined, a poor credit history is not necessarily due to negligence on the part of the insured.

Review and Discussion of Major Points and Conclusions

The study is based on data and information for new auto policies written by one insurance company in 1993, and the earned premium and loss information for these policies from accident years 1993 through 1995. Credit information at new business time was matched with the experience data. Credit information was matched with premium and loss experience for 170,000 policies. Total premium volume was $394 million. Credit information had not been used during this historical period for rating or underwriting.

Only new business was studied. Though this study does not directly address renewal strategies, although there is no particular reason to think that the results would not generalize to renewal business. Credit information was collected only on one person, the named insured. As a result, the credit relationships might not be appropriate for recently married couples if each partner had different credit characteristics.

The author describes that drivers with past accidents and violations who have the best credit characteristics, have a lower overall loss ratio than do those good drivers who are in the "worst" group, as regards credit characteristics. In other words, he explains that for the purpose of forecasting future loss ratios, credit history is more important than past driving experience. However, the loss ratios of these two groups are probably not comparable because of the premium surcharges that would have applied to the drivers with past accidents and violations who are in the "best" credit group.

The author compares urban and non-urban territories and shows no clear-cut difference in distribution of credit information by type of territory. This point may be valid. From an actuarial point of view, however, there is no need to have similar distributions of credit characteristics by type of territory. The value of the use of credit history is that it enables the insurance company to more equitably rate drivers within any given territory.

The section of the paper that discusses the multivariate analysis is important because it demonstrates that the credit characteristics are adding predictive power above and beyond the existing variables. It also demonstrates that a large number of credit characteristics are adding predictive power, *independent* of one another.

USE OF CREDIT REPORTS IN UNDERWRITING

Virginia Bureau of Insurance (1999)

See Appendix C for Text

Summary Review of Study

This study by the Virginia Bureau of Insurance (1999) is important because it has been cited by the insurance industry as evidence that credit histories are not being used in order to discriminate based on income or race. Because the paper includes only a limited amount of the data, however, it is difficult for readers to assess the validity of the conclusions.

Study's Major Points and Conclusions

1. Approximately 50 percent of auto insurers and 60 percent of homeowners insurers responding to the Virginia Bureau of Insurance survey use some form of credit scoring with new business underwriting, representing 36 percent and 49 percent of the respective market shares in Virginia.

2. Of the insurers using credit history, roughly 30 percent may decline new business solely on credit history, and one percent may non-renew solely on credit history.

3. There is a statistical correlation between credit score and policy loss performance.

4. Credit scoring is an ineffective tool for "redlining" because income and race alone are not reliable predictors of credit score.

5. The level of consumer complaints involving the use of credit reports is very low (less than one percent of all complaints). However, the Virginia Bureau of Insurance is concerned that the number of complaints, new business declinations, and non-renewals will increase as more insurers use credit reports.

6. Almost two-thirds of agents (63 percent) responding to a bureau survey were in favor of a law prohibiting insurers from refusing to issue or renew policies due to adverse credit reports.

7. None of the credit variables used in the Fair, Isaac models appear to be unfairly discriminatory.

Review and Discussion of Major Points and Conclusions

1. Approximately 50 percent of auto insurers and 60 percent of homeowners insurers responding to the Virginia Bureau of Insurance survey use some form of credit scoring with new business underwriting, representing 36 percent and 49 percent of the respective market shares in Virginia. This conclusion was based on a survey of the following:

   A) Top 100 Virginia market share auto insurers (89 percent of the market responded).
   B) Top 100 Virginia market share homeowners' insurers (82 percent of the market responded).

   The conclusion is probably a reasonable estimate of what the market is doing. However, there may be a bias in responding. For example, companies using credit scoring as a potentially sole criterion for the acceptance or rejection of a potential policyholder may have tended to decline to respond. Also, since the actual survey is not part of the published paper, it is not possible to assess how to fully assess the responses. Also, it is difficult to project the findings to 2002, because companies have had more opportunity to respond to the marketplace and to decide how best to use credit history.

2. Of the insurers using credit history, roughly 30 percent may decline new business solely on credit history, and one percent may non-renew solely on credit history. (See comments regarding item 1.)

3. There is a statistical correlation between credit score and policy loss performance. This conclusion was based on company filings in which there was a proposal to use credit score as a factor in rating. The study includes no actual data, so it is not possible to comment on the quality of the supporting evidence. There were at least 50 survey respondents using credit history who apparently submitted filings with appropriate support for the use of credit history, indicates there is a correlation. The inclusion of summarized data seen by the bureau of insurance would have strengthened this study.

4. Credit scoring is an ineffective tool for "redlining" because income and race alone are not reliable predictors of credit score. This conclusion is based on the following:

A) TransUnion, Inc data apparently consisted of credit scores aggregated by Virginia ZIP codes and;
B) 1989 Census data by ZIP code apparently included average household income and racial mix.

The data is reviewed on an aggregate basis by ZIP codes, and there is no attempt to match the credit scores of individual consumers with their income and race. As with item #3, the paper does not include any of the supporting data, so it is not possible to comment directly on the conclusion. The level of consumer complaints involving the use of credit reports is very low (less than one percent of all complaints). However, the Virginia Bureau of Insurance is concerned that the number of complaints, new business declinations, and non-renewals will increase as more insurers use credit reports. This conclusion is based on telephone and written complaints received by the Bureau's Property and Casualty Consumer Services Section during a five-month period, March to August of 1999.

The implication is that the insurance buying public does not perceive a problem. Less than one percent of complaints seems low, but as the bureau indicates in the study, there is insufficient information to conclude whether or not this level will be maintained.
Furthermore, even if the level of complaint increases significantly, it will be difficult to assess what it means because using credit reports will, by design, adversely affect a significant number of consumers.

5. Nearly two-thirds of agents (63 percent) responding to a bureau survey were in favor of a law prohibiting insurers from refusing to issue or renew policies due to adverse credit reports.
This conclusion is based on a survey of 1,129 agents.

It is not clear that the 63 percent is representative of agents in total. Because of this there may be a greater tendency for the strongly opinionated to respond to the survey. For example, since it is not stated in the paper exactly how the survey was conducted, it is not known to what degree there was follow-up with the non-responding agents.

6. None of the credit variables used in the Fair, Isaac models appears to be unfairly discriminatory. The basis for this conclusion is not clear. There was at least one interview with representatives of

Fair, Isaac, and the study seems to suggest that the Bureau was allowed to see the actual list of credit variables used by Fair, Isaac.

It is not possible to verify this conclusion, because its basis is unclear. Further, the conclusion appears to apply only to Fair, Isaac models and there is no information regarding the variables used in other insurance scoring models.

Summary Review of Study

The Virginia Bureau of Insurance (1999) draws some significant conclusions about the use of credit history in the underwriting of auto and homeowners insurance in Virginia. These conclusions are based on data from rate filings and TransUnion, and several surveys implying reliability and thoroughness.

Because the paper includes only a limited amount of the data, however, it is difficult for readers to assess the validity of the conclusions. The inclusion of some summarized data displaying the correlation between credit score and loss performance, and data supporting the ZIP code analysis, would have strengthened the study.

CONCLUSION

Our subcommittee appreciates the opportunity to provide an actuarial perspective on these important issues and would be glad to provide you with any additional information that might be helpful..

APPENDIX A: PREDICTIVESNESS OF CREDIT SCORING FOR INSURANCE LOSS-RATIO RELATIVITIES

Fair, Issac

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.

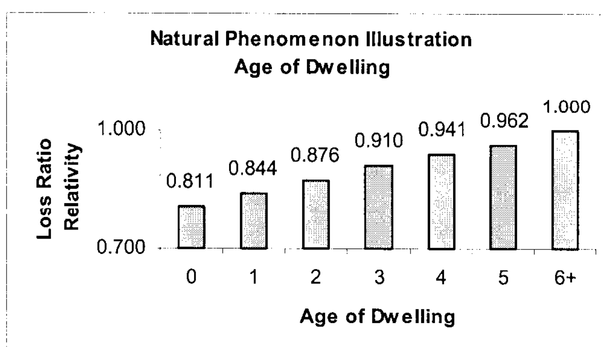
Terminology

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

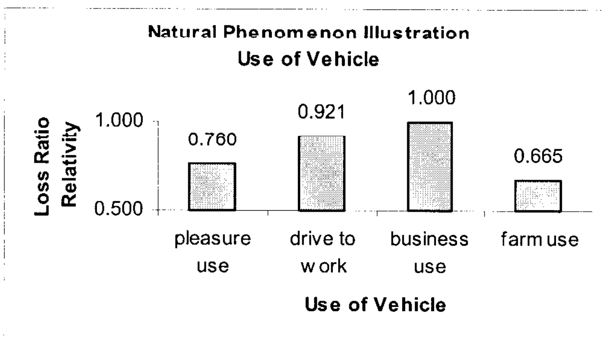
In current regulatory review practice, regulators review individual insurance underwriting programs by examining the correlation between the underwriting characteristics of policies and the loss ratios for those same policies. The examples below in Figures 1-3 are illustrative of that natural correlation.

FIGURE 1. AGE OF DWELLING VS. LOSS RATIO RELATIVITIES



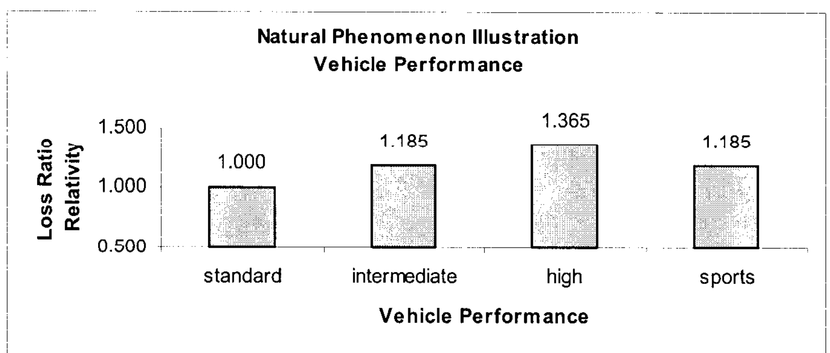
Loss ratio relativity was lowest for policies with new homes and increased as the homes got older.

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

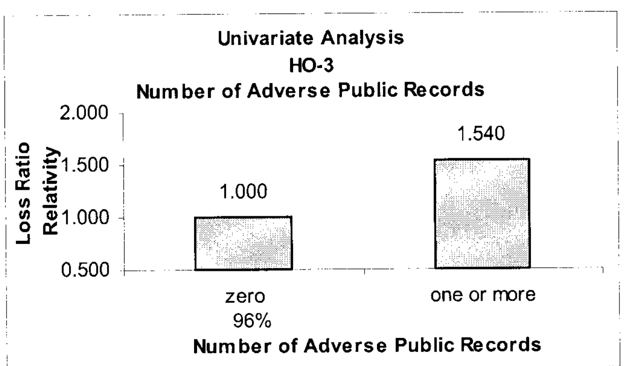
With the background of the discussion in the earlier sections on current underwriting review practices, the nature of credit report information, and the relationship between credit behavior and credit risk, it is clearer how some credit characteristics can correlate with insurance loss ratios, as illustrated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

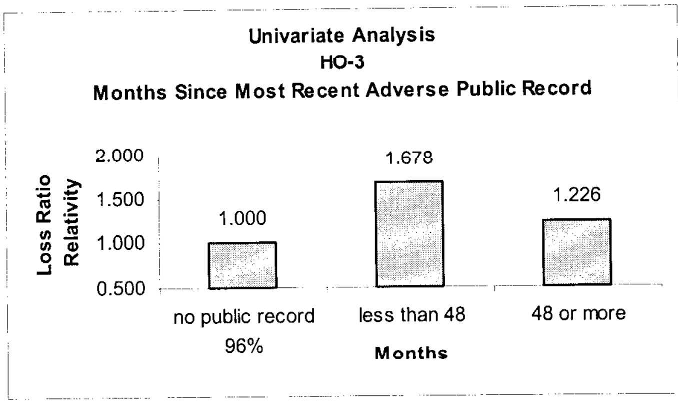
For personal property insurance—using a dataset of approximately 230,000 policies with claims, 1 million policies without claims and corresponding credit information on those policy holders taken from 11 archives of credit history from consumer credit bureaus—the relationship of five credit characteristics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

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



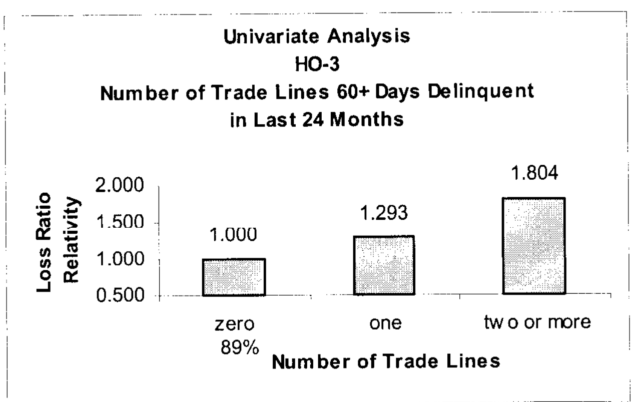
Of this population, 96% did not have any adverse public records. Of the remaining 4% having one or more adverse public records, loss ratio was 54% higher than those without any adverse public records.

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



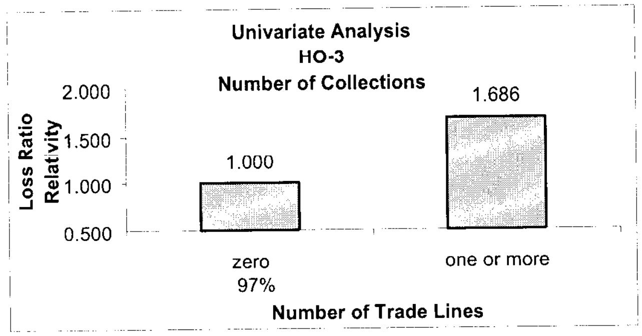
The same 96% of the population did not have any adverse public records. Of the remaining 4%, those having the most recent adverse public records (less than 48 months) were found to have 68% higher loss ratio than those without any adverse public records. Those having less recent adverse public records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



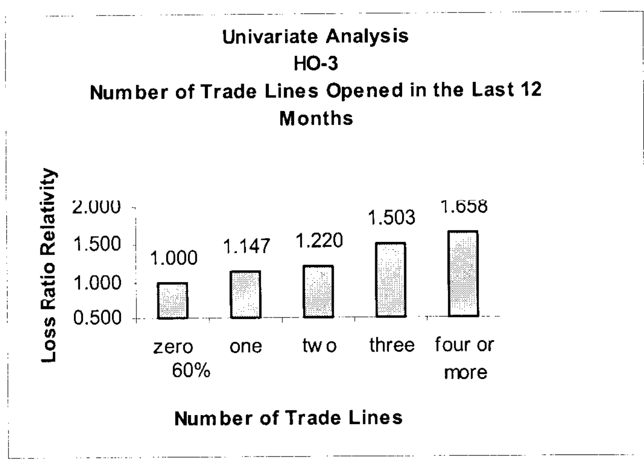
Of this population, 89% did not have any trade lines in delinquency for more than 60 days in the last two years. For people with one such delinquency, loss ratio was 29% higher than those without such delinquency. For those with two or more such delinquencies, loss ratio was 80% higher than those without.

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

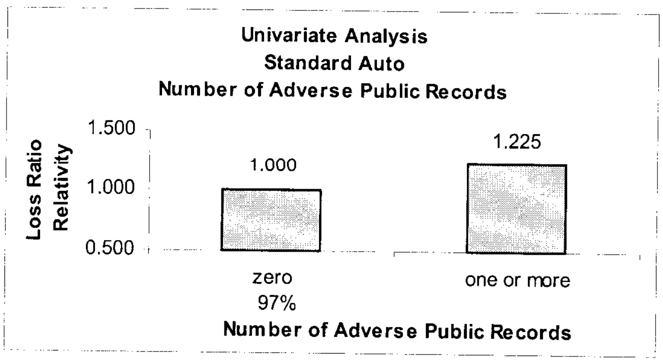


Of this population, 60% did not open any trade lines in the last year. People who opened one trade line in the last year had a loss ratio 15% higher on average than people who did not; two trade lines in the last two years, 22% higher; three trade lines, 50% higher; four or more trade lines, 66% higher.

Personal auto insurance

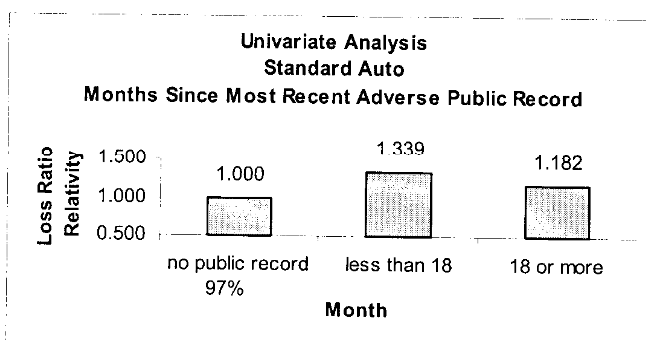
For personal auto—using a dataset of 350,000 policies with claims, 1 million policies without claims and corresponding credit information on those policy holders taken from six archives of credit history from consumer credit bureaus—the relationship of five credit characteristics to loss ratio relativities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

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



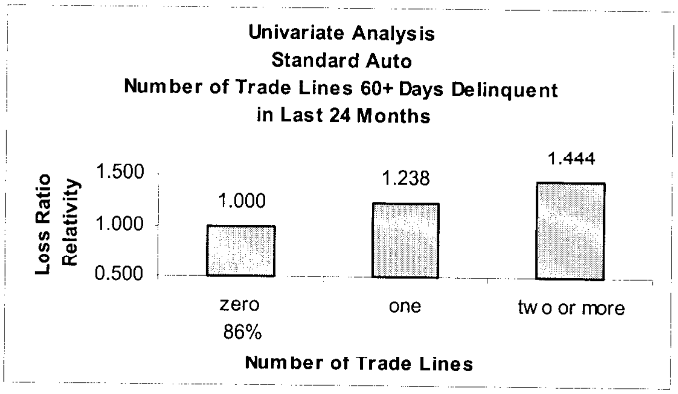
Of this population, 97% did not have any adverse public records. Of the remaining 3% that had one or more adverse public records, loss ratio was found to be 23% higher than those without any adverse public records.

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



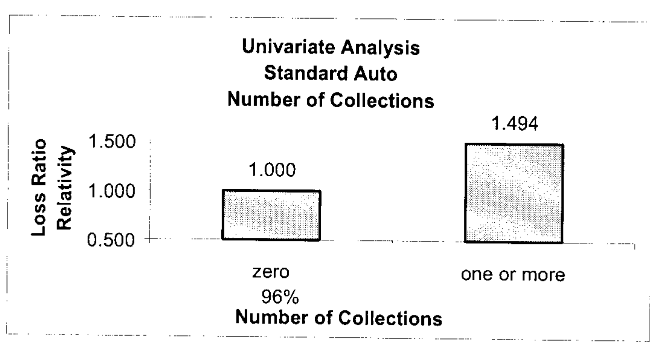
Again, 97% of the population did not have any adverse public records. Of the remaining 3%, those having the most recent adverse public records (less than 18 months) were found to have 34% higher loss ratio than those without any adverse public records. Those having less recent adverse public records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



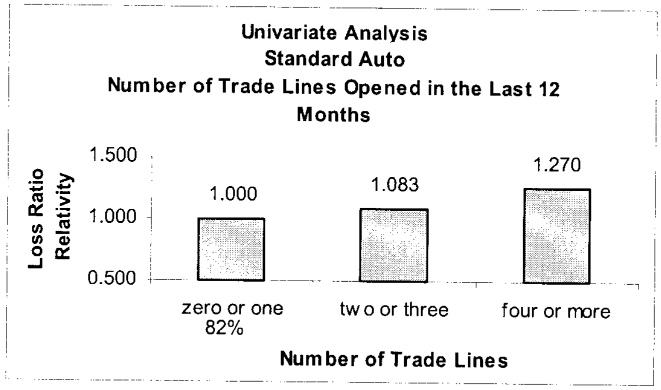
Of this population, 86% did not have any trade lines in delinquency for more than 60 days in the last two years. For people with one such delinquency, loss ratio was 24% higher than those without such delinquency. For those with two or more such delinquencies, loss ratio was 44% higher than those without.

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

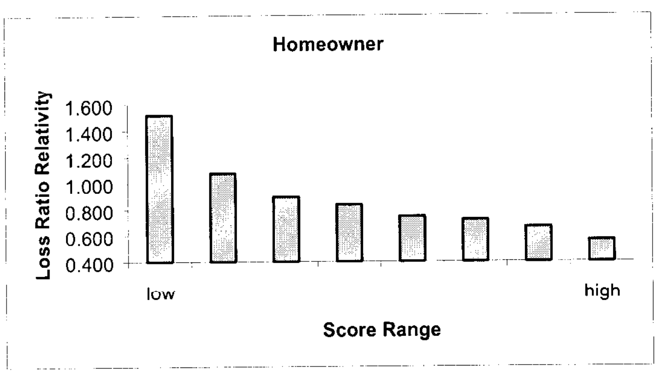
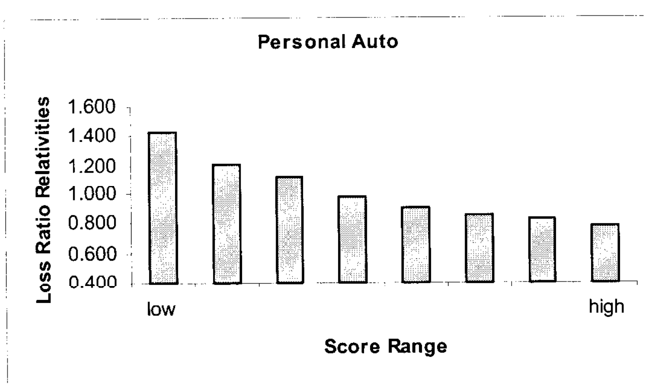


FIGURE 16. AUTO INSURANCE BUREAU SCORES VS. LOSS RATIO RELATIVITIES FOR PERSONAL AUTO POLICIES



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

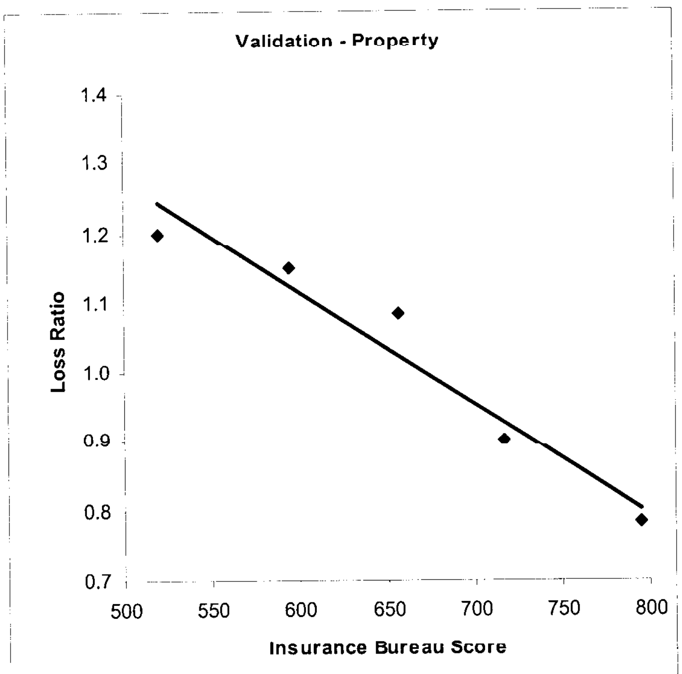
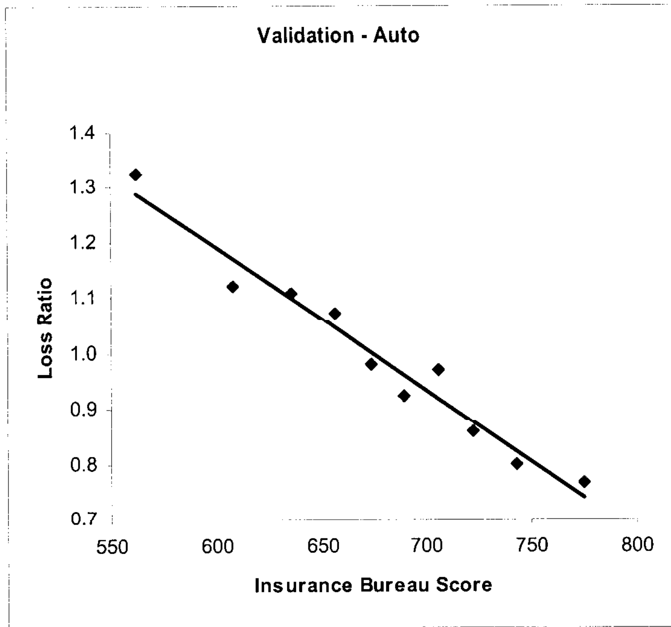


FIGURE 18. VALIDATION OF INSURANCE BUREAU SCORES VS. LOSS RATIO FOR PERSONAL AUTO INSURANCE



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.

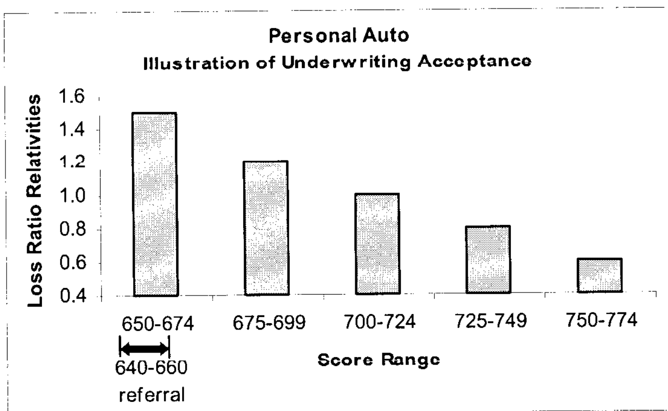
6. Use of insurance bureau scores

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



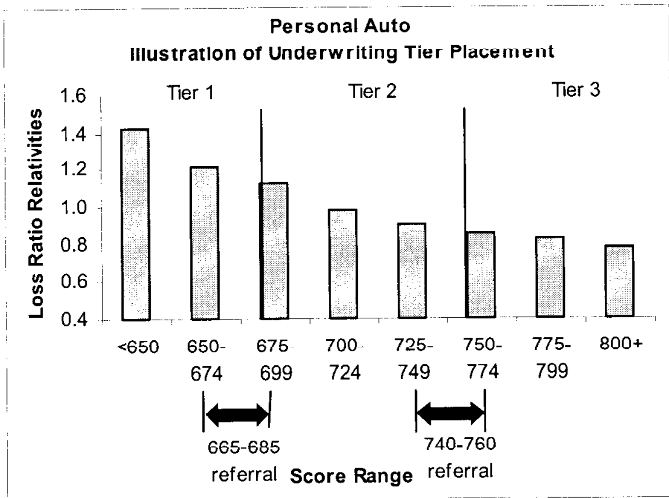
As an example, scores are appended to each policy of a personal auto program with losses developed for two to three years. Losses and premiums are totaled by predetermined score range. A possible result of insurance bureau scores vs. loss ratio relativities distribution is shown in Figure 19. The score 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

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

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

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"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

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10790WP 03/03 PDF

APPENDIX B: The Impact of Personal Credit History on Loss Performance in Personal Lines

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Introduction

At the time of this writing, a process of both education and debate is occurring with regard to the use of personal credit history in the underwriting or rating of personal lines insurance policies. The insurance industry, the NAIC, and other interested third parties are all involved in educating both themselves and each other on such issues as correlation, multivariate correlation, causality and the social or actuarial appropriateness of using this tool in either underwriting or rating. Although the scope of regulators is more finely focused on rating, the recent trend towards tier rating and the utilization of multiple rating companies by members of the insurance industry has blurred the distinction considerably between the two. The use of personal credit history in personal lines insurance has therefore, through its manifestation in underwriting, gone largely unnoticed until recent years. The rapid increase in its use has brought credit history to the forefront of debate in many jurisdictions, in addition to its use in quasi-rating schema.

The development and use of third-party scoring algorithms for credit evaluation, and the proprietary nature of such models, has made it difficult for regulators, companies, agents and customers to get a firm grasp of the underpinnings of automated risk evaluation based on credit history. Apparently, it is not only actuaries who occasionally take the position that "if I can't touch it, is it actually real?" The key issues under debate are the existence (or non-existence) of a correlation between past credit history and expected loss levels (and which variables are responsible for that correlation) and the establishment of causal links for such correlation. Both will be addressed here, although only the former can be statistically analyzed. Causality will be addressed on an informational (and necessarily subjective) basis. The key questions that will be addressed in this paper are:

1) Is there a correlation between credit history and expected personal lines loss performance?
2) If so, which specific criteria within a credit file are indicative of abnormal loss performance (favorable or unfavorable)?
3) If this correlation exists, is it merely a proxy, i.e., is the correlation actually due to other characteristics (which may already be underwritten for or against, or rated for)?
4) As a corollary to 3), are there dependencies between the impact of credit history on loss performance and other policyholder characteristics or rating variables?
5) What are the ramifications of utilizing such data for underwriting and/or ratemaking?

Research Database Construction

The data utilized in researching the relationships between credit history and private passenger automobile loss experience was assembled from several sources. All policies originally written during calendar year 1993 were first identified. Earned premiums for the calendar/accident years 1993 through 1995 were then appended for all coverages. The longest exposure period for any given policy is therefore 36 months, in the case where the policy was written on January 1st, 1993 and remained inforce through December 31st, 1995. All policies were included in the database, regardless of whether or not they remained inforce through the end of the experience period, making the shortest possible exposure period for any given policy one day. Hence policies are not homogenous in either length of exposure or in coverages afforded. Also of note is the fact that the company did not utilize credit information in underwriting or rating of policies during this time period.

Incurred losses were then added, where incurred loss was defined as the sum of paid losses, case reserves, supplemental reserves on case (which are established to cover adverse development on known losses), loss expenses and salvage and subrogation recoveries. These losses were evaluated as of June 30th, 1996 for the exposure period January 1st, 1993 through December 31st, 1995. Incurred losses during accident year 1993 therefore had 42 months of development, those during accident year 1994 were developed 30 months, and those during accident year 1995 were developed 18 months. All earned premium and incurred loss were determined at the policy level, i.e., accumulated for all vehicles insured on the policy at any time during the experience period and for all coverages afforded on those vehicles.

Data was then appended to each policy record that defined the underwriting and rating characteristics of the policy at the time of initial writing. This dataset contained such information as number of drivers, number of vehicles, prior accident and violation activity, state of residence, residence type and stability and prior insurance carrier information. Some of these variables certainly would have changed value during the experience period for many risks. In order to provide predictive value, information was compiled which related to the conditions in effect at the time of writing.

The dataset was sent to a national credit vendor to append archived credit histories for each match that could be found. These credit histories were retrieved from credit files archived at the time each policy was written (or at the nearest three-month interval). Each record was then stripped of any identifying information (i.e. policy number, name, address) in order to ensure compliance with the Fair Credit Reporting Act. This action permitted analysis of the data without knowledge of the identity of any individual risk. Again, in order to provide predictive value, information gathered was pertinent to the conditions in effect at the time each policy was originally written. The credit information added to the dataset contained all of the information in the insured's credit file. The original listing of policies contained approximately 270,000 records. Matches were obtained on approximately 170,000 of those. This "hit rate" is rather low; recall, however, that many of the policies were no longer actively insured by the company and address and other information could have been outdated.

Queries were then constructed and run against this database, accumulating earned premium and incurred loss during the experience period for various combinations of policy characteristics. In fact, thousands of such queries were run, evaluating the loss ratio and loss ratio relativity of given subsets of data relative to others and to the whole. These subsets each contained one or more variables from the two groups underwriting/rating characteristics and credit characteristics. The database had a grand total of $394 million in earned premiums for all records combined. The results of these queries, and the conclusions that could be drawn from them, shed light on the startling foundations of the credit scoring models: the individual credit characteristics. A data dictionary containing the description of all fields utilized in the results contained herein can be found in the Appendix.

Limitations and Difficulties

The construction of the database caused some inherent difficulties in interpretation and also rendered most traditional ratemaking methodologies unusable. The dataset was not compiled with the intent of applying ratemaking methods and principles. Since the process of risk selection occurs on a policy basis, the data was compiled to be utilized in that setting; loss ratio relativity is the only meaningful measure of performance expected to arise from these data.

The credit file utilized was associated with one individual, although many policies have more than one covered driver. This individual was the named insured. The named insured may or may not have been the individual involved in prior accident or violation events, and may or may not have been involved in subsequent losses during the experience period. This difficulty arises from the use of policy level data. The question remains unanswered as to what kind of loss experience one can expect from, for example, a married couple with significantly different credit histories (as can be expected with policies written on recently married persons).

Another difficulty encountered was determining the appropriate method of binning the data, particularly where the independent variable was of the continuous type (dollars, for example). Any data grouping of a continuous variable will have greater stability when larger bins are employed. Many different bin groupings were used in such cases, although only one will be shown here for each example.

Results of Data Queries

The database contained a large number of variables relating to underwriting characteristics, rating characteristics and credit information. Space limitations preclude presenting information about most of the queries that were run and results obtained. A sampling of this data will be reviewed and discussed. The first section will contain information about individual credit characteristics. All earned premium and incurred loss dollars will be shown in millions unless otherwise specified. The aggregate loss ratio for the entire database is 76.3%; this number is higher than average for the private passenger auto industry but recall this is premium and loss experience during the first (at most) 36 months of experience from a block of newly written policies. New business in general produces higher loss ratios than longer-tenured business.

1. *Amounts Past Due (APD)*

APD is defined as delinquent amounts that are uncollected as of the report date. This amount is the sum of all delinquent amounts on the credit file, regardless of how many accounts are delinquent. A scheduled payment must be at least 30 days late before it appears on the credit file as delinquent. Note that there is a significant amount of premium volume in the categories below $10. This is due to a logistical difficulty with the data: some records contained the value $0, others were blank. In order to run queries, the data must be uniformly formatted, yet there could have been statistically significant differences in results for "blank" versus $0. Therefore, all records with blanks were assigned a value of $1. The premium and loss dollars in the categories below $6-20 should be considered included with $0.

APD	Earned Premium	Incurred Loss	Loss Ratio	Relative Loss Ratio	Fitted Relative LR
$0	$ 257.7	$ 180.9	70.2%	0.92	
1-2	45.8	31.8	69.3%	0.91	1.03
3-5	6.5	4.9	75.9%	1.00	1.07
6-20	4.7	4.4	94.0%	1.23	1.11
21-50	5.5	4.8	87.5%	1.15	1.16
51-99	5.8	5.8	99.7%	1.31	1.19
100-199	7.7	7.3	95.9%	1.26	1.22
200-499	12.0	11.1	92.7%	1.22	1.25
500-999	10.2	10.9	107.2%	1.41	1.28
1K-2K	10.1	9.9	97.2%	1.27	1.31
2K-5K	12.5	12.6	100.5%	1.32	1.35
5K-10K	7.8	8.3	106.1%	1.39	1.38
10K +	7.7	7.6	99.8%	1.31	1.41
Total	$ 394.0	$ 300.4	76.3%	1.00	

A linear regression performed on loss ratio relativity vs. logarithm of APD generated a coefficient of 0.83. The t-statistic for 99.5% significance level with 10 degrees of freedom is 3.17; the t-stat for this dataset is 5.65. Thus the null hypothesis that slope of the regression is 0 is rejected with 99.5% certainty. A less statistical observation would be that loss ratio increases as the APD increases, but the change is very small compared to the large jump in loss ratio from around 70% for $0 to the mid-nineties at almost any value greater than $0. This is somewhat counter-intuitive, as one might speculate that small delinquencies should not have the same impact as large ones. Recall, however, that what is being measured is impact on loss ratio, not credit worthiness or any other characteristic. Since the causal links are not established, preconceived notions should be considered with skepticism.

2. *Derogatory Public Records (DPR)*

DPRs include such items as bankruptcies, federal, state or municipal tax liens, civil judgments and foreclosures. The presence of a DPR on a credit file also has significant impact on future loss performance. This should come as no surprise, as this variable is the one that has been utilized in the personal lines industry for the longest time and is the most widely accepted.

DPR	Earned Premium	Incurred Loss	Loss Ratio	Relative Loss Ratio	Fitted Relative LR
None	$ 358.6	$ 264.7	73.8%	0.97	1.04
1	22.4	21.6	96.5%	1.27	1.18
2	7.1	7.4	104.2%	1.37	1.33
3 or more	5.9	6.7	114.1%	1.50	1.54

Linear regression on number of DPR vs. relative loss ratio generated an R^2 value of 0.95. The loss ratio for all DPR that had an outstanding liability on the file of greater than $0 is 102.2%, (relativity = 1.34) and premium volume of $31.1. Although many will not be surprised that there is a correlation with this variable, the size of the difference in loss ratio may confirm the underlying reason for its historic use.

3. *Collection Records*

A collection record is generated when responsibility for collecting a delinquent account (or trade line as they are generally referred) is transferred to a collection agency In general, this occurs when a delinquency is more than 120 days past due. Collection records can, however, occur for delinquencies that are not associated with a trade line, i.e., in the case of a utility bill.

Collections	Earned Premium	Incurred Loss	Loss Ratio	Relative Loss Ratio	Fitted Relative LR
0	$ 364.6	$ 270.1	74.1%	0.97	1.05
1	19.0	18.5	97.5%	1.28	1.21
2	5.5	6.0	108.4%	1.42	1.37
3 or more	5.0	5.9	118.6%	1.56	1.61

R^2 value for the regression of number of collections vs. relative loss ratio is 0.96. The loss ratio for any collections with outstanding liability greater than $0 is 107.6% with a premium volume of $22.3. The results for this variable are very similar to those for DPR. Although there is increasing loss ratio for increasing number of collections, the largest jump in loss ratio occurs between 0 and 1.

4. *Status of Trade Lines*

Each trade line is given a rating based on its current status. A rating of 0 indicates no information is available, while a rating of 1 indicates that the most recent payment made was as agreed, or no more than 30 days past the payment due date. Status codes 2-5 are used to indicated trade lines where the most recent payment made was 30-59, 60-89, 90-119, or over 120 days past due, respectively. Codes 7-9 are used to denote such situations as accounts which are being paid under a wage earner plan, are in repossession, have been written off as bad debt, and others.

Condition	Earned Premium	Incurred Loss	Loss Ratio	Relative Loss Ratio
All trade lines not rated 2-5	$ 314.8	$ 227.3	72.2%	0.95
At least 1 trade line rated 2-5	79.2	73.1	92.3%	1.21

Condition	Earned Premium	Incurred Loss	Loss Ratio	Relative Loss Ratio
All trade lines not rated 7, 8 or 9	$ 334.1	$ 240.8	72.1%	0.95
1 or more trade line rated 7, 8, or 9	59.8	59.6	99.6%	1.31

If these two types of ratings are viewed exclusively, the following results are obtained:

All trade lines rated 1	$ 286.7	$ 198.8	69.3%	0.91
1 or more rated 2-5, none 7-9	47.5	42.1	88.6%	1.16
1 or more rated 7-9, none 2-5	28.1	28.5	101.5%	1.33
1 or more of each type	31.7	31.0	97.8%	1.28

When combining both types of trade line status, Note the difference between this variable and APD: APD refers to amounts that are currently delinquent, whereas status refers to the account evaluation based on the most recent payment made.

5. *Age of Oldest Trade Line*

This variable measures the time between the report date and the oldest date that any trade line was opened. Trade lines include more than just revolving-type accounts; home improvement loans, installment loans, car loans and mortgages are also considered trade lines. The years listed in the following table reflect the fact that the database involved policies written in 1993.

Year of Opening/ Age of Oldest Line	Earned Premium	Incurred Loss	Loss Ratio	Relative Loss Ratio	Fitted Loss Ratio Relativity
1963 & Prior (30+ yrs)	$ 9.6	$ 6.4	66.4%	0.87	0.79
1964-1968 (25-29 yrs)	24.4	14.7	60.2%	0.79	0.85
1969-1973 (20-24 yrs)	41.0	29.4	71.8%	0.94	0.91
1974-1978 (15-19 yrs)	68.3	48.9	71.5%	0.94	0.97
1979-1983 (10-14 yrs)	82.9	60.5	73.0%	0.96	1.03
1984 (9 years)	26.5	20.2	76.2%	1.00	1.07
1985 (8 years)	26.4	20.6	78.2%	1.03	1.08
1986 (7 years)	23.2	19.3	82.9%	1.09	1.09
1987 (6 years)	21.2	19.8	93.3%	1.22	1.10
1988 (5 years)	18.9	15.9	84.2%	1.10	1.11
1989 (4 years)	16.5	12.8	77.6%	1.02	1.13
1990 (3 years)	14.0	12.2	87.2%	1.14	1.14
1991 (2 years)	10.4	9.6	92.5%	1.21	1.15
1992 (1 year)	10.7	10.2	95.0%	1.25	1.16

The t-statistic for the dataset is (5.86); the t-stat for the 99.5% significance level for 12 degrees of freedom is (3.06), thus the null hypothesis that the slope of the regression is zero is rejected at the 99.5% confidence level. The linear regression on years since opening and relative loss ratio generated an R^2 value of 0.86. Here is a correlation that has drawn skepticism: are these results arising merely from the age of the insured, rather than the age of the oldest trade line? This question will be answered in the multivariate section using driver age data, but one can nevertheless deduce that if younger drivers are responsible for the poorer loss results in the lower section of this table, then the same results should be found in the class experience for those ages. This is not true for policies in this dataset, nor is it true for the insurance industry as a whole.

6. *Non-Promotional Inquiry Count*

A strong relationship was also found between loss ratio and non-promotional inquiry count. An inquiry is posted to an individual's credit history file any time that file is reviewed. Many such inquiries are made for direct mail marketing campaigns, which are not requested by the insured. These inquiries are excluded from consideration, and only those that arise from the activities and requests of the insured are included. Federal law prohibits the maintenance of inquiry records for longer than 24 months, at which point they are purged by the credit bureaus.

Number of Inquiries	Earned Premium	Incurred Loss	Loss Ratio	Relative Loss Ratio	Fitted Loss Ratio Relativity
0	$ 130.9	$ 92.9	71.0%	0.93	0.92
1	82.7	58.4	70.6%	0.93	0.96
2	55.1	40.9	74.2%	0.97	0.99
3	37.4	28.8	77.0%	1.01	1.03
4	24.9	20.8	83.4%	1.09	1.07
5	17.5	15.2	87.0%	1.14	1.11
6	12.0	9.7	80.6%	1.06	1.15
7	8.7	7.9	90.8%	1.19	1.18
8	6.0	5.3	87.7%	1.15	1.22
9	4.4	4.8	110.0%	1.44	1.26
10	3.2	3.2	100.1%	1.31	1.30
11-15	7.6	8.2	108.6%	1.42	1.41
16 or more	3.7	4.4	117.5%	1.54	1.60

The t-statistic is 9.51; the t-statistic for 11 degrees of freedom for the 99.5% significance level is 3.11. The correlation coefficient for the regression is 0.94. Once again, a single characteristic from an individual's financial management history has a surprisingly large and consistent impact on loss ratio, even in the smaller premium volume cells.

7. *Leverage Ratio on Revolving-Type Accounts*

This variable is calculated as the ratio of the sum of all revolving debt to the sum of all revolving account limits. Trade lines such as mortgages and installment loans are excluded due to the difference in the nature of such accounts. Since leverage ratio is a continuous-type variable, it was difficult to determine how to define data bins.

When the data was initially reviewed, it was found that the loss ratio relativity for leverage ratio = 0% was 1.04, while the relativities for leverage ratios below 10% were in the 0.75-0.90 range, and subsequently rose as leverage ratio increased. This anomaly occurred due to the fact that records with limits of $0 caused a zero divide, and were given a default leverage value of 0%. Therefore, the table displays a more detailed breakdown of records with 0% leverage, due to the marked difference that was evident in loss ratio impact where limits were low or zero.

Leverage Ratio	Revolving Limits	Earned Premium	Incurred Loss	Loss Ratio	Relative Loss Ratio	Fitted Loss Ratio Relativity
0%	$0	$ 20.3	$ 20.0	98.4%	1.29	
0%	$ 1 – 499	8.6	8.0	93.0%	1.22	
0%	$500 or more	35.8	23.2	64.9%	0.85	0.84
1-10%		91.6	58.9	64.3%	0.84	0.85
11-39%		91.6	65.0	70.9%	0.93	0.92
40-60%		41.8	31.5	75.2%	0.99	1.01
61-80%		30.5	24.8	81.2%	1.07	1.08
81-100%		24.6	21.7	88.1%	1.16	1.14
101% or more		49.0	47.3	96.6%	1.27	1.26

T-statistic for this dataset (excluding the low-limit, 0% leverage group) is 26.3, using weighted means of the leverage ratio ranges. The 99.5% confidence t-stat is 4.03. The R^2 value is 0.996. The practice of some insurance companies of utilizing the characteristic 'possession of a major credit card' as an underwriting criteria for company placement seems justifiable when the top segment of this table is considered. This depends of course on the average rate level of the writing company.

8. *Revolving Account Limits*

This variable is the denominator in the calculation of leverage ratio discussed previously. It is the sum of credit limits for all revolving-type trade lines on the report for a given individual.

Revolving Limits	Earned Premium	Incurred Loss	Loss Ratio	Relative Loss Ratio
$0	$ 41.5	$ 39.4	95%	1.25
$1 - $500	9.8	8.6	88	1.15
501-1000	13.0	12.5	96	1.26
1001-1500	12.0	10.3	86	1.13
1501-2000	11.2	10.8	96	1.26
2001-2500	10.0	8.1	81	1.06
2501-3500	18.8	15.3	81	1.07
3501-5000	26.0	20.6	79	1.04
5001-7500	36.2	28.2	78	1.02
7501-10 K	31.4	24.5	78	1.02
10 – 15 K	50.8	34.8	69	0.90
15 - 20 K	37.7	24.0	64	0.83
20 – 25 K	27.6	19.0	69	0.91
25 – 30 K	18.7	12.9	69	0.91
30 – 40 K	22.0	13.5	61	0.80
40 – 50 K	10.9	7.3	67	0.88
50 K +	16.4	10.7	65	0.85

Correlation coefficient for this regression is (0.78), using midpoints of the limit ranges. The first conclusion that could be drawn is that this correlation only duplicates the one already discussed in the leverage ratio section. This will be addressed in the multivariate section. Another conclusion that has been drawn is that this variable is directly correlated to personal income, and use of revolving limits in any underwriting or rating program is discriminatory towards lower income individuals (disparate impact). This may or may not be true; the data does not contain income information. It would be erroneous however, to assume that all people with low revolving limits are also low-income. Many people choose not to use credit; others may have substantial income but low revolving limits due to the fact that they cannot obtain such credit lines based on their past bill payment performance.

Many other individual variables were reviewed from the credit file. Some exhibited correlation to loss ratio at various significance levels, others had no such correlation. Those displayed thus far, however, show a systematic predictive power that requires explanation and understanding.

Causality

Explanation of these correlations, for the most part, cannot be found in the data assembled for this research. I would be remiss, however, if I did not at least attempt to set down those arguments which could be made suggesting reasonable causal links between an individual's bill paying history and expected loss experience for insured losses under a private passenger auto insurance policy.

Before listing such arguments, it is first appropriate to review the Actuarial Standards of Practice #12, entitled "Concerning Risk Classification". The relevant section is 5.2, which states the following:

> **5.2 Causality – Risk classification systems provide a framework of information which can be used to understand and project future costs. If a cause-and-effect relationship can be**

established, this tends to boost confidence that such information is useful in projecting future costs, and may produce some stability of results.

However, in financial security systems, it is often impossible or impractical to prove statistically any postulated cause-and-effect relationship. Causality cannot, therefore, be made a requirement for risk classification systems.

Often, the term "causality" is not used in a rigorous sense of cause and effect, but in a general sense, implying the existence of a plausible relationship between the characteristics of a class and the hazard for which financial security is provided. For example, living in a river valley would not by itself cause a flood insurance claim, but it does bear a reasonable relationship to the hazard insured against, and thus would be a reasonable basis for classification.

Risk classification characteristics should be neither obscure nor irrelevant to the protection provided, but they need not exhibit a cause-and-effect relationship.

Clearly, the operative word in this Standard of Practice is irrelevant, as the historical data in question is not obscure. Therefore, arguments must be put forth which, despite being speculative, are reasonable statements that a reasonable person would find relevant.

Why would an individual who has current or past difficulties with meeting financial obligations be expected to have above-average costs to an auto insurer? Since there is an administrative expense associated with the processing of insurance premiums and related transactions, it can be argued that subsequent lapses in the individual's payment history is a direct cost to the insurer. This cost would fall under the category of expenses, however. The focus here is loss costs.

Maintenance

The argument has already been made, and often, that auto insurers' underwriting practices are created for risk selection, and one characteristic that is viewed as favorable for selection is described in various quarters as "stability" or "responsibility". Few, however, could give an objective definition of how one could measure such a characteristic, but historically many customer characteristics have been utilized as an assumed proxy for this nebulous attribute, such as home ownership, marital status, number of vehicles, coverage and limits selected, etc. It is entirely possible that a person's current and historical management of debt is another indicator that could be utilized to identify this quality. If a person manages their financial affairs responsibly such that debts are paid on time, they may also take the same approach to the maintenance of other aspects of their lives, including their automobile. A vehicle kept in good working order and condition is less likely to be involved in an accident than one that is not, all other things being equal. Such an individual may also take greater care in operating that vehicle.

Morale Hazard

The CPCU textbook "Personal Insurance" defines morale hazard in the following way:

Morale hazard is a condition that exists when a person is less careful because of the existence of insurance. Morale hazard does not involve an intent to cause or exaggerate a loss. Instead, the insured becomes careless about potential losses because insurance is available. Leaving the keys in an unlocked car or allowing fire hazards to remain uncorrected are examples of morale hazard. Morale hazard results in additional losses that drive up the cost of insurance because of injuries and damage that could have been prevented."

The previous discussion of responsibility could lead to the argument that individuals who are careless in the management of finances also present a morale hazard in the area of automobile insurance.

Claims Consciousness

An insurer's loss experience measures dollars of loss which are paid on claims that are filed. The number of claims filed is less than the number of accidents that actually occur. Consider two risks that are identical in all ways (from an insurer's perspective) except for the fact that one manages their financial affairs much better than the other does. The risk who has a troubled financial history and condition is much more likely to be in debt and to a larger degree; the need for capital to satisfy financial obligations has a bearing on decisions made in many areas of his/her life. Suppose for example, that these two risks are both involved in an auto accident, involving no injuries, but causing property damage to their own vehicles which is some nominal amount (say, $100) more than the deductible. The risk whose financial condition is more sound has a disincentive to file the claim. It may impact his/her rates at the next renewal; the time and effort involved may not be even worth the compensation obtained. The risk with the poorer record of financial management has a greater incentive to file the claim and obtain the compensation, as it has greater value to that individual.

Fraud: Increased Severities

Continuing with these same two risks, consider now the situation in which the damage to property was much greater than the deductible; the vehicles each sustained damage measuring in the thousands of dollars. If an auto repair technician suggested a relatively easy way of recouping the deductible for the insured, or the benefits of padding the repair costs, the individual under the greater financial pressure would be more susceptible to acquiesce. This does *not*, however, imply that risks with poor bill-paying histories have any less integrity than other risks. Some people would never commit fraud on any level; others would do so with no need for provocation or encouragement; still others could be convinced to do so only under the proper conditions. This argument only implies that any individual who *could* be induced to participate in this level of fraud would be more likely to do so if they were under financial pressure from other sources.

Fraud. Increased Frequencies

The presence of severe financial pressure could also produce claims that would not have existed otherwise. There is some segment of the population that either does or could view the insurance mechanism as a financial opportunity. Fraudulent claims in the form of staged accidents, phantom claimants, phantom vehicles or arson are a way that an individual can extract funds from the insurance mechanism. Once again, this argument does not imply anything about the integrity of a risk with poor bill-paying history. What it does assert is that an individual with severe financial pressure could look to all possible sources of funds to alleviate that pressure. Therefore, any individual who was capable of committing this type of fraud is more likely to do so given the existence of that financial pressure compared to the absence of it.

Stress

The assumption is made here that individuals who are under financial pressure from debt exist under a greater level of stress than average. This stress could exist from the associated worries over future impact of financial condition. Individuals under such stress may be less focused on proper operation of a motor vehicle and make them more susceptible to accidents resulting from chance occurrences or distraction. It would be useful if there were some other condition which could produce this same level of stress, for which loss data was available, to strengthen the argument. A few currently coded customer characteristics could be considered candidates. One such variable is number of children under the age of 16. One must first make the assumption that risks with three or more children under the age of 16 have a higher level of stress than average. Whether or not one agrees with that probably depends on whether or not they are a parent! In any case, the loss ratio for such risks reviewed in a 1993 research study was over 20 points higher than average. Another possible variable candidate could be self-employed risks. The added responsibilities and worries of a small business owner could imply that their level of stress is higher than average. From that same 1993 study, self-employed risks had a loss ratio which was roughly 15% higher than average.

It is important to make note that this list is not suggested as a menu from which to select the one correct answer. It is likely that the impact on losses of financial management history is a cumulative impact of some or all of these situations, as well as others not listed here.

Multivariate Analysis: Underwriting Characteristics

There have been many assertions made, in the absence of data, about this relationship between loss experience and credit history. The following comes from the NAIC's "Credit Reports and Insurance Underwriting", dated December 14, 1996:

> **"There still is insufficient data to prove to all regulators' satisfaction whether credit history ... are or are not valid indicators ... independent multivariate analysis, a statistical method some regulators view as necessary, has not been performed." (p. 15) "Some regulators suggest that an unbiased and reasonably precise multivariate analysis is necessary to determine the actual rating factor.... They ask whether a person's credit history is truly correlated with future loss experience or whether it is a spurious correlation?" (p. 17)**

It is beyond the scope of this paper to determine whether or not the loss ratio method is appropriate to analyze this particular database. This method is questioned in the aforementioned NAIC report; the assertion is made that small errors in pricing for a number of rating factors could add up to a fairly significant overall pricing error, making loss ratios a biased measure. For purposes here, it is assumed that differences in relative loss ratio are due to differences in expected average loss costs after adjustments for individual premiums, and that this method is a reasonable way of measuring such differences when reviewing more than one variable simultaneously.

The utilization of the factors discussed earlier when performing multivariate queries tended to produce premium volumes in the individual cells which were smaller than desired for credible results. Strict credibility adjustments could not be performed, due to the fact that a) claim counts were not contained in the data and b) the premium and loss on each record arose from all coverages combined. In order to generate larger premium volumes, the credit variables were combined into four mutually exclusive profiles. These profiles were designed to achieve significant loss ratio differences and significant premium volumes described by each. Group A is defined by those characteristics producing the highest loss ratio, i.e., derogatory public records, collection records and large amounts past due. Group D is defined by those characteristics producing the lowest loss ratio, i.e. low leverage ratio, high age of oldest trade line, good account ratings, etc. The precise definitions of the four groups are contained in the appendix. These profiles will be used in this multivariate section for the sake of simplicity and brevity. Each individual credit characteristic was reviewed in conjunction with the underwriting and rating variables described herein. The variables discussed here are a sampling of all those reviewed; they were selected based on assumed relevance. The overall performance of these four profiles is as follows:

Group	Earned Premium	Incurred Loss	Loss Ratio	Loss Ratio Relativity
A	$ 74,279	75,333	101.4%	1.33
B	158,922	124,723	78.5%	1.03
C	69,043	47,681	69.1%	0.91
D	91,746	52,688	57.4%	0.75

Prior Driving Record

The loss performance of various prior driving record combinations is influenced by two significant factors: the underwriting practices of a given company and the experience modification system utilized in rating. Earned premium and incurred loss were aggregated for risks based on their prior accident and violation activity (in the three year period before they were originally written) and based on credit category (A-D):

Prior Driving Record	Group A Prem	LR	Group B Prem	LR	Group C Prem	LR	Group D Prem	LR	All Groups Prem	LR
No incidents	28.4	93%	66.0	71%	30.7	64%	45.8	53%	170.9	68.6%
1minor*	8.0	94%	17.3	68%	7.5	68%	8.4	50%	41.2	69.4%
1 at-fault accident	3.7	101%	7.7	74%	4.1	68%	5.9	65%	21.4	75.2%
1 non-fault acc.	6.6	109%	14.8	81%	7.3	70%	9.9	70%	38.7	80.7%
2 minors*	2.5	86%	6.0	59%	1.9	41%	2.4	43%	12.8	58.7%
2 incidents (any)	6.5	108%	13.5	96%	6.6	82%	7.9	64%	34.4	88.2%
All other (more Than 2 incidents)	18.6	114%	33.7	95%	10.8	83%	11.5	66%	74.6	93.1%

* *minor refers to a minor moving violation*

The favorable overall performance of the category '2 minor moving violations' can be attributed to both underwriting practice and experience modification surcharge system of the company from which this data was obtained. Of note here is the marked consistency of the loss ratio relationships across credit groups, regardless of prior driving record. Loss ratio relativities, calculated relative to each driving record sub-group, display this consistency:

Group	A	B	C	D	All Groups
No incidents	1.36	1.04	0.93	0.77	1.00
1minor moving violation	1.36	0.98	0.98	0.72	1.00
1 at-fault accident	1.35	0.99	0.90	0.87	1.00
1 non-fault accident	1.35	1.00	0.87	0.86	1.00
2 minor moving violations	1.47	1.01	0.69	0.74	1.00
2 incidents of any kind	1.23	1.08	0.93	0.73	1.00
All other (> 2 incidents)	1.22	1.01	0.89	0.70	1.00
Total	1.33	1.03	0.91	0.75	

Of particular note in this table is the wide difference in performance between clean driving record/poor credit history risks (93%) vs. poor driving record/good credit history risks (66%).

Age of Driver

It could be argued that the loss experience for poorer credit history risks is influenced by driver age distribution. If a disproportionate percentage of young drivers are contained in Group A, then credit history is merely substituting for age. However, as stated earlier, this would only be true if loss experience for younger drivers was adverse, which is not the case. There is a distributional difference in the four groups by age, but the loss experience relationships across credit groups is again robust:

Age of Driver 1	A Prem	LR	B Prem	LR	C Prem	LR	D Prem	LR	Total Prem	LR
< 25	$ 3.8	121%	$23.6	75%	$ 1.4	51%	$ 1.9	53%	$ 30.8	78%
25-34	21.1	103%	55.8	79%	22.6	66%	8 9	63%	108.4	80%
35-39	13.0	100%	21 8	81%	12.9	65%	13.0	54%	60.7	76%
40-44	12.4	109%	18.5	82%	10.4	76%	15.6	52%	57.0	79%
45-49	9.8	93%	14.6	83%	8.2	·76%	14.8	58%	47.4	76%
50-59	9.2	97%	14.4	78%	7.9	68%	16.5	53%	48.0	71%
60+	3.8	110%	8.3	75%	4.9	81%	20.0	67%	37.1	75%

Some of the individual cells in this table have significantly lower premium volumes than prior tables; they are shown nonetheless for completeness. Clearly, age of driver is not the cause of the poor loss experience in Group A.

Age of driver was also reviewed in conjunction with many of the individual credit variables. For example, the following is the cross-hatching of relative loss ratios for age of driver and non-promotional inquiry count:

Inquiry	Age of Driver 1 ⇒					
Count	Under 30	30-39	40-49	50-59	60+	Total
0-3	1.01	0.95	0.95	0.87	0.92	0.95
4-7	1.09	1.07	1.18	1.06	1.38	1.12
8-15	1.22	1.34	1.32	1.43	1.69	1.33
16+	1.48	1.88	1.25			1.56

(values are not shown for cells with premium volume less than $ 0.5 M)

The variable age of oldest trade line, reviewed earlier, could have a relationship to losses that is dependent upon age of operator. When these two variables were combined, the impact exhibited independence:

Age of Oldest	Age of Driver 1 ⇒								
Trade Line	26-30	31-35	36-40	41-45	46-50	51-55	56-60	60+	Total
< 7 years	1.15	1.23	1.19	1.43	1.25	1.19	1.44	1.15	1.15
7-9 years	1.02	1.03	1.01	1.20	0.96	1.07	0.87	0.92	1.05
10+ years	0.90	0.93	0.94	0.95	0.94	0.87	0.89	0.98	0.93

Classical Underwriting Profile

Historically, the underwriting function has identified and selected for various combinations of characteristics. The risk groups exhibited lower than average frequency of loss, which in the absence of premium adjustments, produced more profitable results. One such profile is the married, multicar, homeowner risk with clean driving record. In an effort to produce a favorable loss ratio within Group A, this characteristic was evaluated:

	Married multicar homeowner				All risks NOT married multicar homeowner			
Group	Clean Driving Record		All other		Clean Driving Record		All other	
A	$ 10.2	97%	10.6	102%	$ 27.8	92%	$ 25.6	113%
B	22.3	77%	20.2	85%	62.9	69%	53.4	88%
C	14.5	76%	13.5	76%	24.4	58%	16.7	74%
D	20.2	57%	16.0	58%	34.4	50%	21.2	70%
Total	67.3	74%	60.3	79%	149.5	67%	116.9	88%

Again, it is important to keep in mind that these results are heavily influenced by underwriting practice at the time of writing by a given company; this can influence column totals. The underwriting function, however, had no knowledge of the information that defines credit groups A-D, and the relationships across these groups are again consistent.

Rating Territory

A key concern voiced by regulators in at least a handful of states is the potentially disparate impact that the utilization of credit history in underwriting or rating could have on lower income urban risks. This paper will not address whether or not income levels in urban areas are in fact lower than suburban or rural areas. The issue of rating territory, however, was analyzed. Although rating territory was not a variable in the original database, subsequent state profiles were developed for inforce policies in order to determine distribution of risks by credit characteristics (again using the Groups A through D) in a sampling of states. The exposure distribution shown below exhibited no clear-cut disparate impact on urban territories when compared to non-urban territories:

State	Exposure Distribution Type	A	Group B	C	D
Connecticut	Urban	14%	32%	12%	42%
	All Other	13	29	13	46
	Total CT	13	30	12	45
New York	New York City	10	26	8	55
	Other urban	14	23	11	52
	All other	13	25	13	49
	Total NY	13	25	12	50
Ohio	Urban	14	20	12	54
	All other	10	19	16	54
	Total OH	11	20	15	54

Data is also available for many other underwriting characteristics, including number of vehicles, number of drivers, residence type, residence stability, job stability, prior insurance type, gender, marital status and many others. These characteristics were also queried against the individual credit variables, in addition to queries run against the four groups utilized above. The results were very similar. There were no variables that produced even roughly uniform results across the credit characteristics.

Multivariate Analysis: Credit Characteristics

Another group of variables that was analyzed is credit characteristics in combination with other credit characteristics. This is necessary to ensure that no dependencies or cross-correlations exist within these characteristics. As with the other analyses, this group contains many cross combinations that were reviewed; only a sampling will be discussed here.

Leverage and Revolving Limits

It was noted in single variable section that leverage ratio could be duplicating the impact of revolving account limits. When reviewing the numerator of leverage, revolving balances, it was found that there was virtually no relationship between that variable and loss ratio (R^2 value of 0.04). The array of loss ratio relativities (for all cells with premium greater than $ 0.5 M) for leverage ratio versus revolving limits shows the independence of their impacts:

		Leverage Ratios ⇒						
Revolv. Limits	Selected Midpoint	0% 0.00	0-50% 0.25	50-75% 0.625	75-100 0.875	100% + 1.20	All	Correl. Coefficient
$ 0	0	1.27	1.25			1.18	1.25	
1-999	500	1.02	1.01	1.35	1.38	1.34	1.21	0.87
1K-3K	2000	0.96	1.11	1.15	1.23	1.33	1.16	0.97
3K-5K	4000	0.78	0.99	1.04	1.19	1.34	1.05	0.98
5K-10K	7500	0.77	0.95	1.11	1.13	1.25	1.01	0.97
10K-25K	17500	0.78	0.83	1.09	1.07	1.07	0.88	0.88
25K +	35000	0.65	0.85	0.87	0.95	0.98	0.86	0.92
Total All		1.08	0.89	1.07	1.16	1.24	1.00	0.74
Correl Coefficient		-0.72	-0.74	-0.80	-0.90	-0.86	-0.87	

Note the consistency of the coefficients in both directions. This would not exist if one variable simply proxied for the other. In more general terms, risks with high leverage ratios have poorer loss performance than those with lower leverage ratios, regardless of limits; risks with low revolving limits have poorer loss performance than those with higher limits, regardless of leverage ratio.

Derogatory Public Records and Collections

Given the similarity of the distribution and loss results of these two characteristics, it might be expected that there is overlap between the two, i.e., individuals that exhibit one type of record commonly exhibit the other. This did not turn out to be the case:

DPR	Collections	Earned Premim	Loss Ratio	Loss Ratio Relativity
0	0	$ 339.2	72%	0.95
0	1	17.2	94%	1.23
1	0	13.7	96%	1.25
	Total 1any	30.9	95%	1.24
0	2	4.8	93%	1.22
1	1	3.1	88%	1.15
2	0	3.4	107%	1.41
	Total 2 any	11.2	96%	1.26
	Total 3 or more	12.6	117%	1.53

Each variable produced poor loss results regardless of whether or not the other variable was present. Both variables also had significant distributional volume.

Leverage Ratio and Inquiry Count

If the basis for the relationship between credit history and loss performance can be attributed to a more general characteristic, one might refer to that characteristic as financial stress, distress or duress. Since leverage ratio and high inquiry count can be expected to occur under such situations, it is reasonable to assume that there may be some overlap between these two variables also. As with the other multivariate combinations that are reviewed, it is important to keep in mind the distinction between distributional imbalance and loss ratio imbalance. In the driver age vs. credit group (A-D) table, there is a clear distributional imbalance, with older drivers being disproportionately represented in the best performing credit group. The loss ratio impact, however, remains consistent across credit groups and is not offset by the inclusion of age. This is also true to a lesser degree in the table of loss ratio relativities below: risks with higher leverage ratios are disproportionately represented in the higher inquiry count groupings, but the two-way impact on loss ratio remains:

Limits:	<500	>500			Leverage Ratio		
Inquiries	0%	0%	1-50%	50-75%	75-100%	100%+	Total
0	1.25	0.74	0.86	0.94	1.01	1.04	0.93
1-3	1.27	0.87	0.86	1.03	1.05	1.26	0.96
4-6	1.23	1.12	0.95	1.21	1.57	1.30	1.10
7-10	1.24		1.20	1.36	1.22	1.35	1.25
11+			1.18	1.28	1.54	1.99	1.46
Total	1.26	0.85	0.89	1.07	1.16	1.24	1.00

Trade Line Counts and Status

In addition to searching for variables that duplicated loss ratio impact within the credit characteristics, bivariate tables were reviewed to determine if some variables partially mitigated those impacts. For example, trade line status showed a strong impact earlier. One could argue that the impact of any trade line not rated 1 would diminish as the total number of trade lines increases. That is, if just one trade line is not in good standing, should that not have less significance for a risk with many trade lines, compared to one with only a few? The following table reveals that this appears not to be true generally:

Total Trade Lines	Total Rated 2 through 9	Earned Premium	Loss Ratio	Loss Ratio Relativity
1	0	$ 12.9	78%	1.02
	>0	3.3	116%	1.52
2	0	9.7	88%	1.15
	>0	6.2	103%	1.34
3	0	9.0	72%	0.94
	>0	8.1	93%	1.22
4	0	13.2	68%	0.89
	>0	5.1	90%	1.18
5	0	13.8	69%	0.91
	1	2.3	101%	1.32
	2 or more	3.0	104%	1.37
6	0	14.3	72%	0.94
	1	2.3	94%	1.23
	2 or more	3.1	117%	1.54
7-8	0	31.4	67%	0.88
	1	4.7	96%	1.26
	2	2.4	103%	1.36
	3 or more	4.3	105%	1.38
9-10	0	31.4	66%	0.87
	1	4.6	101%	1.33
	2-3	3.7	95%	1.25
	4-6	2.5	88%	1.16
	7 or more	0.5	134%	1.76
11-15	0	67.7	66%	0.86
	1	9.9	76%	0.99
	2-3	7.2	91%	1.19
	4-6	5.2	88%	1.15
	7 or more	2.3	106%	1.39
16 or more	0	75.6	69%	0.91
	1	13.5	89%	1.16
	2-3	8.5	82%	1.07
	4-6	5.5	99%	1.29
	7 or more	6.3	97%	1.27

Derogatory Public Records and Collections: Age and Amount

Another area of concern for both regulators and the insurance industry is the severity of a given event and its age. It is common practice for other variables, such as prior claims, to be evaluated differently based on their severity or amount paid. Thresholds are established to determine whether or not experience modification surcharges should apply in such cases. The age of a claim is also an important consideration in making underwriting decisions for private passenger auto applications. This concept is being applied to credit characteristics as well, as insurance companies apply different criteria to both age and amount when it comes to such items as DPRs and collections. The most commonly used vendor scoring algorithm also applies lesser weights to older events. This research database unfortunately was not large enough to have sufficient premium volumes in all the sub-groups, but those that have substantial weight indicate that severity and age may not be nearly as relevant factors as the existance of the record itself:

Age of Event	*Event=Collection* Premium	Loss Ratio	*Event=Derog.Public Record* Premium	Loss Ratio
Within 12 months	$ 5.8	110%	$ 7.6	103%
12-24 months	7.3	108%	7.5	93%
24-36 months	5.7	102%	6.1	107%
36-48 months	3.7	100%	4.7	106%
48-60 months	2.9	90%	3.6	111%
60-84 months	3.8	99%	5.9	92%
No collection records	364.7	74%	No DPR 358.9	74%

Amounts	*Event=Collection* Premium	Loss Ratio	*Event=Derog.Public Record* Premium	Loss Ratio
$0	$371.7	74%	$362.9	74%
$1 - $49	3.6	98%	6.9	95%
$50 - $99	3.7	102%	0.2	-
$100 - $499	9.6	106%	4.4	99%
$500 or more	5.4	120%	19.6	106%

Again, there were hundreds of other combinations of variables reviewed and analyzed; these have been provided as a sample. What has arisen is a significant number of variables within the credit history of an individual each of which has independent influence on private passenger auto loss experience. Such an environment lends itself most readily to a scoring-type mechanism, as the variables can be assigned independent weights that can be accumulated for an overall impact estimate for a given potential applicant. But the social and regulatory acceptability (or lack thereof) of these relationships has made it such that univariate scoring models are not viewed as the most favorable way of treating this particular set of data.

Other Impacts: Retention

One of the variables that was included in the research database was an indicator which designated whether or not a policy was still inforce at the end of the experience period, December 31st, 1995 (anywhere from 24 to 36 months since policy inception). The length of time that an auto policy remains inforce has a direct relationship to overall profitability, both from a loss and an expense standpoint. Characteristics that indicate better policy retention therefore indicate better expected experience over the lifetime of the policy.

The credit characteristics reviewed showed that in general, risks with better bill payment histories were retained at a higher rate than those with poorer bill paying histories. The reason for non-renewal was not available, therefore policies could have been no longer active due to a variety of reasons such as price shopping, underwriting cancellation, non-payment of premium, or any other reason for which a policy can normally cease to be inforce. The following table shows percentages of policies still inforce at the end of the experience period for various categories:

All policies	48%	Number of Inquiries = 0	51%
		1-3 inquiries	48%
Policies with no collection records	49%	4-6 inquiries	44%
One collection record	36%	7-10 inquiries	41%
2 or more collections	30%	11 or more inquiries	33%
No derogatory public records	49%		
One DPR	38%	Leverage = 0 ($0 limits)	33%
Two or more DPR	33%	=0 ($1-$500 limits)	39%
		= 0 (limits > $500)	51%
Amounts Past Due = $0	52%		
$1 - $20	52%	0% - 50%	53%
$21 - $100	40%	50% - 75%	47%
$101 - $499	36%	75% - 100%	44%
$500 or more	33%	100% or more	38%

It could appear as though the increase in losses and the deterioration of retention are two effects of the same cause. This is not the case, however, as the loss ratio variation by, for example, number of collections still exists within both subsets of policies: those that remained inforce at the end of the experience period and those that did not. The loss ratios for policies still inforce are 72%, 101% and 114% for risks with none, one, or two or more collections, respectively. The same values for policies that did not remain inforce throughout the experience period are 80%, 93% and 113% for risks with none, one, or two or more collections. This pattern is true for other variables as well. This is a second way in which credit history can impact loss experience.

Homeowners Line of Business

A database was constructed to analyze the impact of credit history on loss experience for the homeowners line of business. The procedure was nearly identical to that described above for the auto line of business, with the exception that the policies included were those originally written in policy years 1993 and 1994. In addition to obtaining the credit data at the time the policy was written, similar data was obtained on those same policies at later dates. This was done in an effort to determine what percentage of risks experience significant changes in their bill-paying profiles over time. Policies were not included in the study from other miscellaneous property lines such as renter, condominium, dwelling fire and landlord policies.

There are some differences in the two datasets. This homeowners database contains $120 million in earned premium and has an overall loss ratio of 64.1%, excluding catastrophe losses. The loss ratio is 79.2% with those catastrophe losses included. The experience period was extended to December 31, 1996 for the policies originally written in 1994, making the experience period 36 months for both policy years. For the majority of the writing period, 1/1/93 through 12/31/94, the company that wrote the policies did not use credit as an underwriting or rating tool. Approximately 10% of the policies were written after such a program was implemented in the underwriting area. During the experience period, all policies inforce were re-underwritten using credit score. While no action was taken directly due to the score, some policies received condition and maintenance reviews and had inspection reports ordered, if such reports were not ordered upon first issuance of the policy. Also, rating territory was included in this database from the outset.

There were striking similarities between the auto and home databases with regard to credit impact on loss experience. The most significant difference seemed to be that derogatory information on a credit report for a homeowners policy had a more severe impact on loss performance (Group A below). If premium and loss are aggregated according to the same Groups A through D as was done with the auto line of business, the results are as follows, with the auto experience displayed again for comparison (premiums are in millions and loss ratios exclude catastrophes for homeowners):

	Homeowners			***Auto***		
Group	Earned Premium	Loss Ratio	Loss Ratio Relativity	Earned Premium	Loss Ratio	Loss Ratio Relativity
A	$ 17.6	111.7%	1.74	$ 74.3	101.4%	1.33
B	41.4	66.5%	1.04	158.9	78.5%	1.03
C	11.9	54.5%	0.85	69.0	69.1%	0.91
D	49.1	47.4%	0.74	91.7	57.4%	0.75
Total	120.0	64.1%		394.0	76.3%	

The similarities between the loss ratio relativities for these profiles lends credence to the assertion that the impact of bill paying history on insured losses transcends line of business, and is not a characteristic attributable only to property policies and claims associated with them. Note that there is a much larger premium distribution in group D for homeowners, the best performing group. This could arise due to a variety of reasons. The same derogatory characteristics that make up Group A are considered in a loan or mortgage application, so a homeowners policy applicant has already (at some point) undergone a screening process based on credit history. The company's underwriting program during the experience period likely decreased the volume of group A policies in the cohort, increasing the proportional amount of Group D.

Individual Credit Variables

The review of individual variables will not be discussed in depth here, as many of the results were parallel with those obtained from the auto study. A handful of examples will be displayed. Compare these with the tables for auto on pages 3 through 5.

Amounts Past Due

APD	Earned Premium	Loss Ratio	Relative Loss Ratio
$0	$ 106.7	58.9%	0.92
$1 - $20	0.9	67.8%	1.06
$21 - $100	2.1	69.2%	1.08
$101-$500	3.5	100.0%	1.56
$501 +	6.8	124.9%	1.95

Collection Records

Number of Collections	Earned Premium	Loss Ratio	Relative Loss Ratio
0	$ 112.0	59.7%	0.93
1	5.2	125.3%	1.95
2+	2.9	124.9%	1.97

Derogatory Public Records

Number of DPRs	Earned Premium	Loss Ratio	Relative Loss Ratio
0	$ 105.4	57.7%	0.90
1	8.0	99.3%	1.55
2	3.0	122.5%	1.91
3+	3.6	125.1%	1.95

Age of Oldest Trade Line

Age in Years	Earned Premium	Loss Ratio	Relative Loss Ratio
< 1	$ 2.3	115.8%	1.81
2 – 3	3.0	68.7%	1.07
4 – 5	5.1	70.9%	1.11
6 – 7	8.3	77.6%	1.21
8-10	19.6	73.8%	1.15
11-15	26.6	60.5%	0.94
16-20	23.6	65.3%	1.02
21+	30.2	48.9%	0.76

Non-Promotional Inquiry Count

Number of Inquiries	Earned Premium	Loss Ratio	Relative Loss Ratio
0	$ 82.2	60.4%	0.94
1	19.5	59.5%	0.93
2	8.1	65.9%	1.03
3	4.1	84.2%	1.31
4-6	4.3	96.8%	1.51
7-10	1.3	106.7%	1.66
11+	0.5	261.2%	4.07

In nearly all characteristics reviewed, it was found that the range of the variable that was correlated with poorer loss experience produced more severe values for the homeowners line than for auto. The linear correlation coefficients for the above tables for loss ratio relativity were 0.95 for APD (0.78 for logarithm of APD versus loss ratio relativity), 0.81 for collection records, -0.74 for age of oldest trade line and 0.93 for non-promotional inquiry count.

Multivariate: Underwriting and Credit Combinations

As with the auto line of business, queries were run to produce premium and loss data for various combinations of risk characteristic and credit characteristic. For purposes of credibility, the credit characteristics were grouped into the same profiles shown above, Groups A through D. A sampling of those results are shown here.

Prior Loss History

At the time of application, an effort is made to determine if there were prior losses filed on the residence. This information arose either from a property CLUE (Comprehensive Loss Underwriting Exchange) report or from the interview with the applicant. Note that the loss ratio across credit levels is not that much different for risks with prior losses compared to those risks with no such prior losses. This is due to a) underwriting practice of the company writing the business and b) relatively less complete information in property CLUE than is present in the auto CLUE system and the state motor vehicle record histories combined.

	Risks with no prior losses			**Risks with at least 1 prior loss**		
Credit Group	Earned Premium	Loss Ratio	Relative Loss Ratio	Earned Premium	Loss Ratio	Relative Loss Ratio
A	$ 15.6	111.2%	1.73	$ 1.9	115.5%	1.80
B	37.7	66.7%	1.04	3.8	64.4%	1.00
C	11.0	56.2%	0.88	1.0	35.3%	0.55
D	43.6	45.7%	0.71	5.5	61.0%	0.95
Total	$ 107.9	63.6%	0.99	$ 12.2	68.6%	1.07

Town Class or Protection Class

Loss experience in the form of loss ratio relativities for credit groups A through D are evaluated within the various protection class designations and is shown below. Values are not shown for cells that possess a premium volume below $500,000.

Protection Class	*Credit Profile Group* A	B	C	D	Total
1	1.30	0.68		0.65	0.77
2	1.63	1.06	0.84	0.66	1.00
3	2.15	1.20	0.92	0.77	1.14
4	1.61	1.03	0.93	0.71	0.97
5	1.95	0.92	0.72	0.83	1.00
6	1.48	0.88	0.55	0.79	0.90
7		0.63	0.42	0.42	0.79
8		0.67		1.26	1.31
9		1.72		0.48	0.97
10					
Total	1.74	1.04	0.85	0.74	1.00

There is much more fluctuation for individual cells for this dataset compared to the auto line due to both the overall smaller premium volume and the greater volatility of homeowners losses. The consistency across the profile groups is still quite evident for various protection classes, and the relativities decrease monotonically wherever there is significant premium volume in the cells.

Liability Limits

During the two-year period of policy writing, the company wrote an approximately equal proportion of $100,000 and $300,000 liability limits on homeowners policies. A much smaller volume of premium was written with other limits of liability. The base premium was set based on the former limit, and the latter was offered as additional optional coverage.

	Liability Limit = $100,000			**Liability Limit = $300,000**		
Credit Profile Group	Earned Premium	Loss Ratio	Relative Loss Ratio	Earned Premium	Loss Ratio	Relative Loss Ratio
A	$ 9.7	115.5%	1.80	$ 6.4	100.3%	1.56
B	20.4	63.3%	0.99	17.5	70.4%	1.10
C	5.7	59.4%	0.93	5.2	48.4%	0.75
D	21.1	50.9%	0.79	23.2	43.7%	0.68
Total	$ 56.9	67.2%	1.05	$ 52.2	60.1%	0.94

Note the steady shift in distribution of premium between the two limits by group. The premium distribution of the $100,000 limit for the four groups (A through D) is 60%, 54%, 52% and 48%, respectively. Risks with poorer bill paying histories are more likely to choose the lower liability limit, even though the cost of this additional coverage was less than $10 in most cases.

Bill Mode

The two most common forms of payment of homeowners insurance premiums are direct bill, in which the policyholder pays the premium directly, or mortgagee bill, where the financial institution which holds the note on the property pays the premium.

	Direct Bill			Mortgagee Bill		
Credit Profile Group	Earned Premium	Loss Ratio	Relative Loss Ratio	Earned Premium	Loss Ratio	Relative Loss Ratio
A	$ 7.7	117.2%	1.83	$ 7.8	103.9%	1.62
B	19.9	69.5%	1.08	17.4	62.6%	0.98
C	5.3	56.7%	0.88	5.5	54.3%	0.85
D	27.7	46.8%	0.73	15.2	48.2%	0.75
Total	$ 60.6	64.0%	1.00	$ 46.0	63.9%	1.00

Rating Territory

As with the auto line, premiums and losses were aggregated by rating territory by assigning characteristic definitions to each rating territory, designating each territory as urban, suburban or rural. This designation was done by eye, without any objective definition of urban (such as population density); major urban areas were designated as such, satellite territories around urban areas and smaller population centers were referred to as suburban, and the remaining regions were called rural. Although there was little credibility when this data was reviewed at the state level, there was sufficient volume when premiums were accumulated by territory type across states. The credit-defined groups showed consistent impact on losses within each group, and there were only slight distributional differences. Only the largest 12 states were included in this query; these states made up roughly two-thirds of the premium volume of the entire sample.

	Urban		Suburban		Rural	
Credit Profile Group	Earned Premium	Relative Loss Ratio	Earned Premium	Relative Loss Ratio	Earned Premium	Relative Loss Ratio
A	$ 2.8	1.23	$ 7.3	1.99	$ 2.3	1.31
B	7.0	1.07	18.6	1.02	5.1	1.14
C	1.6	0.96	5.7	0.91	1.3	0.57
D	5.5	0.64	23.4	0.80	6.8	0.66
Total	$ 16.9	0.95	$ 54.9	1.04	$ 15.5	0.91

Motility

In order to understand the migration of risks from one credit profile to another over time, additional data was added to the homeowners database. Credit files from future dates were included, which were taken from archived records approximately 12 months after original writing date, and again at 48 months after the original writing date. For this discussion, the same four credit profiles will be used as in the above exhibits.

Group A, the poorest performing profile, was populated with 10,737 policies written in 1993. Of these, 84% still had Group A characteristics 12 months later, and 66% of those risks were still categorized as Group A 48 months later. 20% had migrated to Group B,and the remaining 14% to C and D. This is not surprising, given that 2 of the 3 criteria for Group A are maintained for many years on the credit file (derogatory public records and collections).

Group B was not as stable over time, significant portions of the population migrated in both directions. Of the original Group B in 1993, 67% were still in the group 12 months later, and 36% 48 months later. At that time, 31% had moved to D, 12% to group C, and 21% to A.

Group C was the least stable. Since this group is defined by better than average characteristics, it is not surprising that as those characteristics continue to improve, much of the distribution migrates to Group D. Only 50% of the group still had the Group C characteristics 12 months later, and only 11% at 48 months. 65% of the entire group migrated to Group D in four years. This is not surprising due to the fact that one of the differences between C and D is age of oldest trade line; for those risks that did not qualify as D, time can be the only factor necessary to cause a migration over the subsequent 3 year period. (Again, refer to the Appendix for exact Group definitions.)

Group D, the best performing group, showed the most stability. Risks with the best credit profiles are more likely to maintain those profiles over time. Of the 23,248 policies in this group, 87% still met the criteria for D 12 months later, and 78% met those criteria 48 months later.

This data was not collected on the original auto cohort, so the above data is for homeowners only. It does provide some indication about the necessity of updating the review of credit profile for the purpose of rating and/or underwriting.

Implications and Other Related Issues

The impact of credit history on expected loss performance is a major factor influencing whether or not this variable should be utilized in the rating of personal lines insurance premiums. There are, however, many other relevant issues that must be considered.

The credit history contains a large amount of data. The impact on loss performance has been measured in this study as if arising from a single variable, which is one particular accumulation of the credit data. There is of course an enormously large number of ways in which the data can be combined for this purpose of measurement. When the variables are inspected, individually, one finds that there are some that are historic, and cannot change until they are purged from the record (i.e., derogatory public records, collection records, inquiries and delinquent payments). Others contain information about current conditions, such as account status, current balances and limits, and overdue amounts. The method of combination of these variables will determine where the model falls in the responsiveness versus stability spectrum. This study has shown that both types have strong influences on loss performance. How they are combined is currently an open field for individual insurers' discretion. This study utilized a mutually exclusive profiling technique; scoring models can and do utilize a large number of variables, giving numeric weights to each individual characteristic which are then added to obtain a total. Either method can be accomplished using a wide range of variable counts.

An important gap in this study is the impact of credit history on loss performance for customers who have been insured with the same company for a number of years. Recall that the data was assembled from new policies written in a give policy year, and the subsequent three-year loss experience. This data cannot show if long-term customers who have similar credit characteristics are expected to have the same differences in loss performance. The creation of a rating factor based on credit history can affect renewal customers as well as new customers, yet there is currently no data publicly available to my knowledge that shows such relationships. Without such data, it would be speculative at best to assume that the relationships hold true regardless of tenure. Studies have shown that long-tenured customers produce far better loss experience than new customers. Opinions vary as to whether this is due more or less to two (or more) dominant factors which can cause such improvement: 1) the fact that longer term customers have more experience in operating a motor vehicle or maintaining a home, and 2) that the underwriting function of a given company will selectively non-renew poor performing risks, which could not be identified accurately in the underwriting process when the policies were originally written. The research done with this data has shown that longer-tenured customers tend to have better credit profiles than newer customers. This is one variable, policy tenure, that could be both distributionally and loss performance-linked to credit history.

The question as to how often the credit history needs to be reevaluated is also of concern. Although the motility information above indicates that there is a fair amount of stability over time for credit conditions, there is still significant change that occurs within such distributions. Each reevaluation will cause the creation of an additional inquiry record on the file. Although such inquiries should not be utilized for evaluation, there is no guarantee that all financial institutions and other users of credit data will ignore their existence. When such a reevaluation occurs, there is also the question as to which risks should experience premium adjustment. Is there reasonable justification for an individual risk to experience an increase in premium solely due to a change in a variable within the credit file? A different type of database construction technique would be required to answer such a question.

From an actuarial standpoint, questions arise concerning the nature of the variable. The literature is replete with admonitions concerning the use of variables that are, or can be, under the control of the insured. Although the historic variables are not under the control of the insured, certainly those that measure current conditions are. Worth considering, however, is the argument that such control is not nearly as relevant as other rating factors that are not utilized for this reason. An individual who has a poor history of timely bill payment, and is under a considerable debt load is already experiencing detrimental effects from these conditions. Such conditions are causing economic penalties in the form of monthly interest payment, or debt service, and can also result in higher interest rates charged for credit lines, installment loans and mortgage loans. There already exists a financial disincentive to maintain financial management habits that produce these conditions. Will a difference in auto or homeowners insurance premiums cause a change in such habits, where these other economic disincentives have not? It is likely, in my opinion, that the magnitude of the premium difference would not be as large as the sum of all other financial consequences of such a credit profile in most cases. This may mitigate the concern over the control the risk appears to have over the data contained in the credit file.

Another area of concern that is related to variable control is data accuracy. Reports as to the accuracy of credit history data vary widely depending upon the source. Credit bureau sources quote data accuracy values in the 99% to 100% range. Some consumer groups have quoted this number to be as low as 30% to 40%. This discrepancy is due to the way in which errors are measured. One could obtain the first result if errors were considered to exist only in cases where a) an adverse decision was made for a financial transaction, b) the customer inquired as to the credit data, c) discovered an error, d) contacted the creditor to correct the error, and e) the financial institution reversed the decision based on that correction. Dividing the number of such events by the entire credit warehouse would produce a very high level of accuracy. To produce the second, much lower values, one could simply count every possible error within the file, including seemingly irrelevant errors such as street name misspellings, and divide this count by the total number of records. Neither is a very good measure of data accuracy. For all parties concerned to get a true understanding of accuracy, a good method of measurement must be established. In any case, the utilization of credit history for rating requires the insurance industry to assist its customers by informing them of the method for resolving true inaccuracies on record, and taking those corrections into account through reevaluation.

An outstanding issue that will likely remain outstanding is causality. Although arguments were put forward earlier in this paper which attempted to link financial management responsibility and future expected loss levels, such arguments are unsupported, even if reasonable, speculation. The arguments of causality are generalized; in fact the difference between one rate level and another charged to a given individual could be different due to only one particular variable within the credit file. That individual may ask for an argument of causality pertaining only to the one characteristic that separates him or her from the next lower rate. Such questions may never be answered with statistical causality, even if the entire credit file (however that is aggregated) can be demonstrated to be causal in a way that goes beyond the mathematical correlations.

The issue of acceptance of credit history data in personal lines insurance has more obstacles than mere causality. The social and regulatory acceptance of such data in the rating of personal lines insurance may be restricted for other reasons. Arguments have already been made that indicate that some groups consider its use invasive, and that credit-based rating is a breach of privacy, regardless of its strength as a tool to reduce rate subsidies between risks. The auto line of business has considered past driving record to be a key factor in underwriting and rating. One key characteristic of prior accidents is negligence, i.e., whether the accident was the fault of the insured or not. It is natural for some people to immediately apply this concept to credit history as well. Credit files contain information about derogatory events that an individual may feel are perfectly explainable. Such explanations are commonplace in the area of mortgage financing, where an event is not considered if there is a suitable explanation for its existence in some cases. The key difference, however, is that the use of this data for rating or underwriting is not done for the purpose of credit worthiness. It is not done for the purposes of judging character, lifestyle, integrity or financial soundness. The purpose is to segregate risks by different levels of expected losses only, a point which may be difficult to communicate.

It may be easier to obtain regulatory acceptance comparted to social acceptance with regard to the use of credit history as a rating tool. The NAIC White Paper on the use of credit in underwriting, referred to earlier, makes several specific statements which indicate their deference to rating, rather than underwriting. The use of credit in rating requires the filing of a rating plan with supporting documentation. It permits inspection of content by both regulators and consumers. Such filing gives a regulatory body the evidence required to give valid statistical response to constituents who may call to inquire or register a complaint.

The data reviewed in this study produced clear evidence of a strong correlation between credit history and future loss performance. The understanding of this relationship, and its acceptance, have grown rapidly over the last few years. This understanding has come primarily in the form of scoring model results. Hopefully, this paper will serve as a starting point in an effort to place more detailed information from credit history, other than scoring models, and the relationship such data has to personal lines losses, in a public forum. This effort is necessary in order to promote greater understanding of the driving forces behind this relationship, and can only serve to improve the quality of discussion during future debates on the ways in which it will be utilized.

APPENDIX

1. Data Fields

Policy Variables included and reviewed:
State transfer indicator
Policy Tier
Original policy written month, day and year
Acive status indicator
Months of coverage
Writing company
Original producer code
Risk state
Vehicle type
Non-standard indicator
Number of vehicles
Number of operators
Number of potential operators
Payment plan
Residence stability
Residence code
Residence type
Number of years employed
Prior insurance code
Number of vehicles financed
For each driver:
  Age
  Gender
  Marital status
  Occupation code
  Number of years licensed
  Driving record: fault losses, non-fault losses, moving violations
  Comprehensive losses
Earned premium
Incurred losses

Variables included from National Credit File:
Trade Record: Subscriber code, date opened, high credit, date verified, date reported, date closed, date paid out, associated code, payment pattern, current balance, amount past due, account type, current manner of payment (status), credit limit, terms, maximum delinquency date, maximum delinquency amount, number of months 30-59 days past due, 60-89 days past due, 90+ days past due, loan type, dispute code, collateral field, duplicate indicator, account number, short subscriber name.
Inquiry Record: Subscriber code, inquiry date, type, loan type, loan amount.
Public Record: Date reported, amount, public record type, date paid, assets, liabilities, attorney, plaintiff, docket number.
Collection Record: Date reported, subscriber code, amount owed, status, date paid, creditor name.
Summary Record: Number of inquiries, trades, collections, public records, manner of payment totals for each status code.

2. Definitions of Credit Profiles Used in Exhibits

Group A: Existance of any of the following: Derogatory public record with liability amount >$0, collection record, or amount past due of $500 or more.

Group B: Does not meet any other group criteria.

Group C: No DPR or collection records, no APD; no trade lines with status codes other than 0 or 1, leverage ratio on revolving accounts less than 60%, age of oldest trade line at least 7 years.

Group D: Same as group C, plus nonpromotional inquiry count less than 4 and age of oldest trade line at least 10 years.

APPENDIX C: Use of Credit Reports in Underwriting

Virginia Bureau of Insurance

REPORT OF THE STATE CORPORATION COMMISSION'S BUREAU OF INSURANCE ON THE

USE OF CREDIT REPORTS IN UNDERWRITING

TO THE
SENATE COMMERCE AND LABOR COMMITTEE
OF THE GENERAL ASSEMBLY OF VIRGINIA

COMMONWEALTH OF VIRGINIA
RICHMOND
1999

COMMONWEALTH OF VIRGINIA

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STATE CORPORATION COMMISSION
BUREAU OF INSURANCE

December 22, 1999

TO: Members of the Senate Commerce and Labor Committee
of the General Assembly of Virginia

I am pleased to transmit this Report of the State Corporation Commission's Bureau of Insurance on the Use of Credit Reports in Underwriting.

This report was prepared at the request of the Senate Commerce and Labor Committee of the 1999 Session of the General Assembly of Virginia.

Respectfully submitted,

Alfred W. Gross
Commissioner of Insurance

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EXECUTIVE SUMMARY

During the 1999 Session of the Virginia General Assembly, the Senate Commerce and Labor Committee requested the State Corporation Commission's Bureau of Insurance (Bureau) to study the issue of whether insurers should be allowed to use credit reports in underwriting.

Several insurance industry surveys were conducted to obtain input from both insurers and agents. Based on the results of the Bureau's insurance company survey, about 30% of the private passenger automobile insurers and homeowners insurers licensed in Virginia indicated that they *refuse to issue* policies solely on the basis of an adverse credit report. Only 1% of the private passenger automobile insurers and homeowners insurers licensed in Virginia indicated that they *refuse to renew* policies solely on the basis of an adverse credit report. According to the results of the insurance agent survey, most agents are in favor of a law which would prohibit companies from refusing to issue and refusing to renew policies due to an adverse credit report.

Almost 50% of the private passenger automobile insurers that responded to the Bureau's survey and 60% of the homeowners insurers that responded to the Bureau's survey look at credit reports as part of their new business underwriting process. Some insurers look at the consumers' actual credit reports during the underwriting process. A few insurers have developed their own credit scoring models (i.e. a system of assigning a numeric value to a risk based on certain characteristics of a person's credit report and correlating it to insurance company premium and loss data). The majority of the insurance companies that underwrite based on credit history, however, rely on the scoring models developed by a third party vendor, such as Fair, Isaac and Company, Incorporated (Fair, Isaac). Fair, Isaac is a credit score modeler and has data showing that a correlation exists between credit scores and losses. However, Fair, Isaac has also indicated that credit scores should not be used as the sole criteria upon which to determine risk acceptability. According to Fair, Isaac, credit scores are intended to provide an additional tool in the underwriting process, not to replace other traditional underwriting factors such as prior losses and motor vehicle records.

Fair, Isaac provided the Bureau with data for the purpose of performing an analysis to determine whether a correlation exists between credit scores and population demographic data (e.g. income and race) identified by zip code. This analysis was prompted by comments from agents that the use of credit scores is actually a form of redlining. The Bureau analyzed the relationship between credit scores and income as well as the relationship between credit scores and race. Nothing in this analysis leads the Bureau to the conclusion that income or race alone is a reliable predictor of credit scores thus making the use of credit scoring an ineffective tool for redlining.

The Bureau's Property and Casualty Consumer Services Section receives approximately seven written complaints and phone calls a month from consumers pertaining to insurance companies' use of credit reports. These generally involve premium increases and policy terminations. This number represents less than 1% of the total number of written complaints and phone calls the Consumer Services Section receives from consumers each month.

There is a concern on the part of some consumer groups, such as The Fair Housing Council of Greater Washington, that the use of credit scores has a disparate impact on "protected classes" and that this creates a barrier to insurance. The Federal Home Loan Mortgage Corporation (Freddie Mac) also has conducted research that shows that minority borrowers are more likely than white borrowers to experience credit problems.

Virginia law requires insurance companies that are making an adverse underwriting decision based on a person's credit to provide the reason for the decision or advise the consumer of the right to obtain the reason. In addition, Virginia law establishes certain other requirements for companies that non-renew private passenger automobile and homeowners insurance policies due to an adverse credit report. Virginia law also prohibits insurance companies from using rates that are unfairly discriminatory. Consequently, when an insurer submits a rate filing in which credit scores are used as a rating factor, the Bureau requires the insurer to provide actuarial justification, and the filing is submitted to the Bureau's actuaries for review. In every case where insurers have proposed to use credit scoring as a rating factor and have been able to provide sufficient data to the Bureau's actuaries, the use of credit scoring has been found to be statistically correlated to losses.

Eleven states have addressed the use of credit reports in their laws. Some of these states prohibit the use of credit reports as the sole reason for terminating a policy. Some of the states, like Virginia, have established notification requirements for insurers that use credit reports in underwriting. A white paper published by the National Association of Insurance Commissioners (NAIC) on this subject recommended that insurers not be allowed to cancel or non-renew a policy solely due to adverse credit history even if credit reports are used in the initial underwriting stage. The NAIC white paper also recommended that the insurance industry educate the public about the use of credit reports in underwriting.

The Bureau has concerns about the long-term effect that the use of credit scores may have on Virginia consumers. As the number of insurers that use credit history as an underwriting tool increases, there may be an increase in the number of consumers that will be refused coverage, cancelled, non-renewed, or charged higher premiums due to their adverse credit history. Conversely, industry advocates of this practice argue that there may be an increase in the number of consumers that will obtain coverage at lower rates due to their good credit history.

The Bureau recommends that the insurance industry take steps to educate consumers about the use of credit scores in the underwriting process. Furthermore, the Bureau will continue to monitor the number of credit-related consumer complaints it receives as well as the number of companies that use credit scores in underwriting and rating. If the Bureau finds over time that a significantly greater number of companies are refusing to issue or refusing to renew coverage solely on the basis of an adverse credit history, the Bureau will consider proposing legislation to prohibit this practice.

INTRODUCTION

Legislative Request

During the 1999 Session of the Virginia General Assembly, the Senate Commerce and Labor Committee requested the State Corporation Commission's Bureau of Insurance (Bureau) to study the issue of whether insurers should be allowed to use credit reports in underwriting. Senate Bill No. 1321 would have prohibited insurers from declining to issue or refusing to renew homeowners insurance policies and private passenger automobile insurance policies solely because of credit information contained in a consumer report. Senate Bill No. 1321 was left in committee.

Methodology

The Bureau contacted the Professional Insurance Agents Association of Virginia and the District of Columbia, Inc. (PIA) and the Independent Insurance Agents of Virginia, Inc. (IIAV) to request assistance in conducting a survey of their member agents. The Bureau also conducted a survey of the top 100 writers of homeowners insurance in Virginia as well as the top 100 writers of private passenger automobile insurance in Virginia. In addition, the Bureau met with several agents to discuss their concerns over the use of credit reports in underwriting and also met with representatives from Fair, Isaac and Company, Incorporated (a credit score modeler) and an insurer (which uses its own scoring model) to discuss how factors are developed and weighted in their credit score models. Based on data provided by Fair, Isaac, the Bureau performed an analysis to determine whether there was a correlation between credit scores and population demographic data identified by zip code. The Bureau also obtained information from the National Association of Insurance Commissioners (NAIC), which recently conducted a survey of the other state insurance departments to determine whether any states had enacted legislation prohibiting the use of credit reports in underwriting. Finally, a review of the complaints received by the Bureau's Property and Casualty Consumer Services Section was conducted to determine how many complaints had been made by consumers pertaining to the use of credit reports.

BACKGROUND

Legislative History

In 1994, the Bureau proposed legislation that would have prohibited private passenger auto and homeowners insurers from non-renewing policies solely on the basis of a person's credit report. House Bill No. 220 was carried over to the following year. The final version of the bill, which was passed in 1995, amended §§ 38.2-2114 and 38.2-2212 of the Code of Virginia by establishing certain notification requirements for companies non-renewing private passenger auto and homeowners policies due to an adverse credit report.

Under the law, insurers are required to give a notice stating that the non-renewal is based on a consumer report, and the notice must provide the name and address of the institution reporting the credit information. The insurer must also advise the insured that he may obtain a free copy of the credit report and that he has 10 days to question the accuracy of the report. If the insured sends a written request questioning the credit report, the policy will remain in effect during the time the insurer is verifying the accuracy of the credit information. The law provides that a homeowners policy may not be non-renewed until 30 days after the accuracy of the credit report has been verified and communicated to the insured. Under a private passenger automobile insurance policy, the non-renewal may not become effective until 45 days after the accuracy of the credit report has been verified and communicated to the insured. The insured is required to respond to any company inquiry within 10 days of mailing. If the insured fails to cooperate, the insurer may terminate the investigation and non-renew the policy after providing 15 days written notice to the insured.

Federal Law

The Fair Credit Reporting Act (15 USCA § 1681), which was enacted in 1970, allows insurers to use credit reports in insurance underwriting. Disclosure to the consumer is not required unless an adverse action is being taken. At that time, the insurer must (i) give the consumer the name, address, and telephone number of the consumer reporting agency that made the report; (ii) inform the consumer of the right to obtain a free copy of the report; and (iii) inform the consumer of the right to dispute the accuracy of the report. Generally, credit reports may not include information on bankruptcies over ten years old or other adverse actions (such as judgements, liens, and collections) over seven years old.

Virginia Law

In addition to the notification requirements in §§ 38.2-2114 and 38.2-2212 noted above, subsection A of § 38.2-604 of the Code of Virginia states that insurers or agents must provide a written notice of insurance information practices to all applicants or policyholders in connection with insurance transactions. In the case of a new business application, this notice must be provided (i) at the time the policy is delivered if personal information is collected only from the applicant or public records or (ii) at the time the personal information is collected from another source. In the case of a policy renewal, the notice must be provided at each policy renewal unless (i) within the previous 24 months a notice has already been given or (ii) personal information is collected only from the policyholder or public records. Consequently, if insurers are obtaining credit reports, a written notice must be given to the consumer in accordance with § 38.2-604 of the Code of Virginia. Further, § 38.2-610 of the Code of Virginia states that, if a company makes an adverse underwriting decision based on a person's credit report, a written notice must be given to the consumer which either provides the reason for the adverse underwriting decision or advises the consumer of the right to obtain the reason.[1]

Some insurers use credit reports to price their business. This can be done using several different methods. One method is to place a person who, for example, has an excellent credit report in a preferred *company* which charges lower rates than other companies within the same group of affiliates. Another method would be to charge different rates within the same company using different *pricing tracks* or *tiers*. In this case, a person with an excellent credit report, for example, may be placed in a "preferred" tier where the price is lower than that of a "non-preferred" tier within the same company.

The use of pricing tiers is monitored by the Bureau pursuant to subsection A of § 38.2-1904 of the Code of Virginia which states that rates shall not be excessive, inadequate or unfairly discriminatory. Section 38.2-1904 further states that no rate shall be unfairly discriminatory if a different rate is charged for the same coverage and the rate differential (i) is based on sound actuarial principles or (ii) is related to actual or reasonably anticipated experience. Therefore, when an insurer submits a rate filing in which credit scores are used as a rating factor, the Bureau requires the insurer to provide actuarial justification, and the filing is submitted to the Bureau's actuaries for review. The Bureau also requires companies that use credit scores as a rating factor to re-underwrite each risk at renewal to make sure each risk is properly rated. The purpose of this requirement is to verify that companies are not engaging in unfair discrimination in their use of rates. Currently, the Bureau's files show that several companies are using credit scores as a rating factor. In every case where insurers have proposed to use credit scoring as a rating factor and have been able to provide sufficient data to the Bureau's actuaries, the use of credit scoring has been found to be statistically correlated to losses.

[1] The Bureau publishes automobile and homeowners consumer guides. Included in these guides is an explanation of consumers' rights with regard to insurers' use of credit reports.

AGENT SURVEY

Purpose of the Survey

The Bureau contacted the Professional Insurance Agents Association of Virginia and the District of Columbia, Inc. (PIA) and the Independent Insurance Agents of Virginia, Inc. (IIAV) to request assistance in conducting a survey of their member agents. The purpose of the survey was to determine whether agents were in favor of, or opposed to, a law prohibiting homeowners insurers and private passenger auto insurers from refusing to issue or refusing to renew policies due to an adverse credit report. Surveys were sent to 580 PIA members and to 549 IIAV members.

Survey Results

A total of 110 survey responses (19%) were received from the PIA, and a total of 158 survey responses (29%) were received from the IIAV. Of these, 65% of the PIA respondents and 61% of the IIAV respondents indicated that they were in favor of a law prohibiting homeowners insurers and private passenger automobile insurers from *refusing to issue* (new business) policies due to an adverse credit report. In addition, 70% of the PIA respondents and 77% of the IIAV respondents indicated that they were in favor of a law prohibiting homeowners insurers and private passenger automobile insurers from *refusing to renew* policies due to an adverse credit report.

When asked how many applicants had been turned down over the last year due to adverse credit information, the PIA respondents' answers ranged anywhere from "none" to "about 400" while the IIAV indicated that approximately 16% of their respondents' applicants were turned down due to adverse credit information. When asked how many insureds were non-renewed over the last year due to adverse credit information, the PIA respondents' answers ranged anywhere from "none" to "200" while the IIAV indicated that approximately 19% of their respondents' insureds were non-renewed due to adverse credit information.

When asked whether agents were opposed to insurers using credit information for rating purposes, 56% of the PIA respondents and 71% of the IIAV respondents said "yes."

Other Correspondence Received

In addition to the survey responses from the PIA and the IIAV, the Bureau received additional, unsolicited comments from 14 agencies. Each of these agencies, except one, expressed support (albeit, one expressed mixed support) for the use of credit reports in underwriting. The predominant theme among those expressing support was that credit scoring helps keep rates low for financially responsible insureds. The one agency that expressed opposition to the use of credit reports in underwriting provided an example of where one company was willing to write an insured's homeowners policy but would not write the auto policy at the same time simply due to the insured's credit report.

INSURANCE COMPANY SURVEYS

Purpose of the Surveys

The Bureau conducted two insurance company surveys. One was sent to the top 100 writers of homeowners insurance in Virginia (representing 99% of the market). The other survey was sent to the top 100 writers of private passenger automobile insurance in Virginia (representing 98% of the market). The purpose of the surveys was to determine (i) how many insurers use credit reports in new business and renewal business underwriting; (ii) how many insurers refuse to accept new business or non-renew existing business solely on the basis of an adverse credit report; (iii) whether insurers use their own credit scoring model or use a model developed by a third party vendor; (iv) whether insurers re-underwrite at renewal to determine if each risk continues to be properly placed or properly rated; and (v) how insurers categorize consumers who have little or no credit history.

Results of the Auto Survey

The Bureau received 106 responses to the private passenger automobile survey.[2] This number exceeded the total number of surveys sent out because the Bureau received responses from companies that were not in the top 100 writers but were affiliated with those that were in the top 100. The results of the survey are summarized below:

1. 50 companies (47% of the respondents) indicated that they use credit reports as part of their new business underwriting process.[3]
2. 29 companies (27% of the respondents) indicated that they would refuse to accept new business *solely* on the basis of an adverse credit report.[4]
3. 26 companies (25% of the respondents) indicated that they use credit reports as part of their renewal business underwriting process.[5]
4. 2 companies (2% of the respondents) indicated that they would non-renew *solely* on the basis of an adverse credit report.[6]
5. Of the companies that indicated that they use credit reports in underwriting, 31 use a scoring model developed by a third party vendor; 9 use a scoring model developed by their own company; and 11 look at credit reports but do not use a scoring model.

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[2] These companies represented 89% of the private passenger automobile insurance market in Virginia in 1998.

[3] These companies represented 36% of the private passenger automobile insurance market in Virginia in 1998.

[4] These companies represented 28% of the private passenger automobile insurance market in Virginia in 1998.

[5] These companies represented 8% of the private passenger automobile insurance market in Virginia in 1998.

[6] These companies represented 1% of the private passenger automobile insurance market in Virginia in 1998.

6. Of the companies that indicated that they use credit reports in underwriting, 20 said that they re-underwrite each risk at renewal to determine if the risk is still properly placed or properly rated.
7. When asked how applicants who have little or no credit history are underwritten, 4 companies indicated that they are underwritten as though they have an adverse credit report; 26 companies indicated that they are underwritten as though they have a good credit report; and 19 companies had other comments such as "no impact: these risks are treated neutrally" or "we look at each one on an individual basis."

Results of the Homeowners Survey

The Bureau received 102 responses to the homeowners survey.[7] This number exceeded the total number of surveys sent out because the Bureau received responses from companies that were not in the top 100 writers but were affiliated with those that were in the top 100. The results of the survey are summarized below:

1. 61 companies (60% of the respondents) indicated that they use credit reports as part of their new business underwriting process.[8]
2. 35 companies (34% of the respondents) indicated that they would refuse to accept new business _solely_ on the basis of an adverse credit report.[9]
3. 17 companies (17% of the respondents) indicated that they use credit reports as part of their renewal business underwriting process.[10]
4. 2 companies (2% of the respondents) indicated that they would non-renew _solely_ on the basis of an adverse credit report.[11]
5. Of the companies that indicated that they use credit reports in underwriting, 44 use a scoring model developed by a third party vendor; 17 look at credit reports but do not use a scoring model.
6. Of the companies that indicated that they use credit reports in underwriting, 8 said that they re-underwrite each risk at renewal to determine if the risk is still properly placed or properly rated.
7. When asked how applicants who have little or no credit history are underwritten, 2 companies indicated that they are underwritten as though they have an adverse credit report; 42 companies indicated that they are underwritten as though they have a good credit report; and 17 companies had other comments such as "each risk is individually underwritten based on overall characteristics" or "this is not considered positively or negatively."

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[7] These companies represented 82% of the homeowners insurance market in Virginia in 1998.
[8] These companies represented 49% of the homeowners insurance market in Virginia in 1998.
[9] These companies represented 29% of the homeowners insurance market in Virginia in 1998.
[10] These companies represented 20% of the homeowners insurance market in Virginia in 1998.
[11] These companies represented 1% of the homeowners insurance market in Virginia in 1998.

NAIC WHITE PAPER

NAIC Recommendations

The National Association of Insurance Commissioners (NAIC) conducted a study on the use of credit reports in underwriting. This study was completed in 1997. The NAIC's white paper recommended, among other things, that insurers should not be permitted to cancel or non-renew a policy solely due to an adverse credit history even if it initially underwrites the policy based solely on credit history. The white paper also recommended that the insurance industry should take steps to educate consumers about the scoring process. The white paper stated that companies should be able to decide whether or not to use credit history or whether to use a credit factor in rating but that credit information should be applied consistently within a company's book of business.[12]

Other States' Statutes

The NAIC's white paper summarized the other states' laws pertaining to the use of credit reports.

1. Arkansas prohibits auto insurers from refusing or continuing to insure risks based solely on knowledge of an insured's credit history.
2. Hawaii's laws state that an auto insurance rating plan cannot be based on a consumer's credit report.
3. Louisiana prohibits auto policies from being terminated due to a bankruptcy.
4. Montana laws state that auto and homeowners insurers may not refuse to insure, continue to insure, or charge a higher rate or limit the scope of coverage based solely on credit history unless related to the risk of the insured.
5. Other states, including Florida, Maine, New York, Oregon, Texas, Virginia, and Washington, have laws which (i) establish standards for using credit reports, (ii) establish notification requirements, or (iii) state that the use of the reports must be actuarially sound. [13]

Based on the Bureau's research, two other states have addressed the issue of credit scoring in their laws. Kentucky has a law which prohibits insurers from using credit history or the lack of credit history as the sole reason for declining or terminating a policy. Maryland has issued proposed regulations which include the following: (i) requiring the insurer to tell the consumer the exact reason for the adverse action and the means to obtain a copy of his credit report; (ii) requiring the insurer to file its credit criteria at the request of the commissioner; (iii) prohibiting an insurer from pulling a credit report due to a person's race, color, creed, sex or blindness; and (iv) prohibiting an insurer from pulling a credit report

[12] "Credit Reports and Insurance Underwriting," (Kansas City, MO: National Association of Insurance Commissioners, 1997), pp. 37 and 38.
[13] Ibid., pp. 31 and 32.

for one applicant or insured unless credit reports are pulled for all applicants or insureds.

ADDITIONAL RESEARCH

Meeting with Agents

The Bureau was requested by the patron of Senate Bill No. 1321 to meet with several agents to discuss their concerns over the use of credit reports in underwriting. The agents were asked to bring their concerned consumers. Four agents and the executive director of the PIA were in attendance. At the meeting, the agents indicated that the public is generally not aware that their credit will be checked when they apply for insurance coverage, and they are very surprised when they find out that a credit report has been run in order to determine insurance eligibility. Agents find it particularly hard to explain to a homeowner who has just qualified for a mortgage that he does not qualify for homeowners insurance. Agents are not given the specific reasons why the credit report is unacceptable; they are simply told that the applicant has adverse credit. The agents indicated that, at least with automobile insurance, they are able to find coverage with a company that charges higher rates. With homeowners insurance, however, they contend that there is no substandard or higher priced company in which to place risks with adverse credit.[14] It is the belief of the agents who attended the meeting that the use of credit reports is a form of redlining.

Company Meeting

The Bureau also met with an insurance company that uses its own scoring model to determine risk acceptability. This model was developed by the company rather than by an outside vendor. The purpose of the meeting was to determine what factors were used to develop the model and how the factors were weighted. The Bureau determined that there are no factors used in the model which appear to be unfairly discriminatory, such as age, sex, marital status, etc. The company indicated that it had been able to write more urban business since it began using credit scoring and that credit scoring had been able to lower the rates for 70% of its customers. The company's general manager also indicated that credit scores were not used to non-renew existing business. Furthermore, when asked whether insurance quotes by other insurance companies could negatively impact the consumer's score, the company indicated that, even though these showed up as inquiries on a person's credit report, they were disregarded and, consequently, they did not have an adverse impact on a person's credit score.

Meeting with Fair, Isaac

The Bureau met with a representative of Fair, Isaac and Company, Incorporated (Fair, Isaac) to discuss the company's scoring models. Fair, Isaac is a third-party vendor that develops scoring models for use by insurance companies and other financial institutions. The models take characteristics based

[14] There is nothing in Virginia insurance law that prohibits homeowners insurers from charging higher rates due to adverse credit reports.

on a person's credit report and formulate a score. According to Fair, Isaac, there is a statistical correlation between losses and the credit scores developed by any one of the models. More and more insurance companies are relying on the scores provided by Fair, Isaac to make a determination as to risk acceptability in both new and renewal auto and homeowners insurance business. Companies can choose the particular model (auto preferred, auto standard, auto substandard, homeowners, etc.) which represents the best fit for their books of business.

The primary purpose of the meeting with Fair, Isaac was to determine whether any of the factors used in the scoring models could be considered unfairly discriminatory (i.e. age, sex, marital status, race, color, creed, etc.). Based on the Bureau's review of the characteristics used in the scoring models, the Bureau concluded that none of the characteristics appear to be unfairly discriminatory. The factors used in the models developed by Fair, Isaac include the number of delinquencies, the number of months since the most recent delinquency, the number of trade lines open, the number of finance company accounts open, the number of adverse public record items (bankruptcies, judgements, liens, foreclosures), the number of months since the most recent adverse public record item, trade account balances, and the ratio of the trade account balance to the credit limit available on the trade account.

When asked whether credit reports should be used as the sole criteria upon which to determine risk acceptability, the representative from Fair, Isaac said that it was never Fair, Isaac's intention for insurance companies to use credit scores as the sole criteria in underwriting. In fact, the modeler does not support the sole use of credit reports in underwriting. It is Fair, Isaac's position that insurance companies should take into account other traditional underwriting factors (i.e. losses and motor vehicle records) as well as a person's credit score when making a determination as to risk acceptability. Credit scores were developed to save time and money and to provide an additional tool in the underwriting process. According to the Fair, Isaac representative, "each individual company's data is more predictive than credit data. Credit scores simply add more predictive value; it is a more powerful tool to use both."

When asked how insurance quotes from companies (which show up as inquiries on a credit report) were factored into the scoring models, the representative from Fair, Isaac said that these were not included in the models and did not affect a person's credit score. It was also noted that unsolicited inquiries (e.g. credit card solicitations in the mail) were not used in the calculation of a person's credit score.

At the request of several agents who are members of the PIA, the Bureau asked Fair, Isaac to compute a credit score, using several different models, for someone who had no history of late payments but who had incurred a great deal of debt. The Bureau's fictitious person had 10 years of credit and had no late payments, liens, judgements, foreclosures, or bankruptcies but had just purchased a house, had two car payments, and numerous credit cards with large balances on those credit cards in relation to the available credit on the credit cards. Fair, Isaac calculated the credit score for this person using four different models: a homeowners model, a preferred auto model, a standard auto model, and a non-standard auto model. Scores can range anywhere from 200s to 900s, with 900s being the better scores. The calculated scores are shown below.

Model	Score
Homeowners:	556
Preferred Auto:	507
Standard Auto:	587
Non-Standard Auto:	610

Each company that uses Fair, Isaac's scoring models may underwrite this risk differently, depending on the company's own individual underwriting criteria. For example, a company that requires a minimum score of 700 for its preferred auto program may decline this risk but may be willing to offer coverage at a higher rate in its standard or non-standard auto program.[15]

Finally, the Bureau asked Fair, Isaac if there were any statistics relating credit scores to zip codes since many agents had suggested that the use of credit scores was a form of redlining. Redlining refers to the practice of refusing to issue or refusing to renew insurance risks in a given geographic area. As a result of the Bureau's query, summary data from Trans Union (one of the major credit reporting agencies) was provided to the Bureau so that the Bureau could perform an analysis to determine whether there was a correlation between credit scores and population demographic data (e.g. income and race) identified by zip code.

Fair, Isaac provided the Bureau with the Trans Union data in a file containing the average credit score by zip code for Virginia zip codes containing more than 100 credit scores in the Trans Union database. There were 956 zip codes meeting this minimum number of credit score criteria. The average credit score for these zip codes was 701, with a median score of 702, and a minimum and maximum of 603 and 757, respectively. The Bureau matched average credit score by zip code to the 1989 Federal Census demographic data[16] by zip code and performed various regression analyses to determine if credit scores could be used to determine a person's income or race. A regression analysis measures the statistical significance of a set of dependent variables (credit scores) to a

[15] Insurance companies are not required to file their underwriting guidelines. Therefore, the Bureau does not know how each company would underwrite this particular risk based on these credit scores. For competitive reasons, the companies' use of credit scores is generally considered proprietary.

[16] This is the most recent census data available.

separate, independent variable (i.e. income or race) to determine if there is any correlation.

The Bureau analyzed the relationship between credit scores and income as well as the relationship between credit scores and race. Neither Fair, Isaac nor Trans Union collects data on income or race, thus requiring the Bureau to obtain this information from the 1989 Federal Census. Although the data obtained from Trans Union did not provide a one-to-one match between an individual's race, income, and credit score, this did not preclude the Bureau from analyzing whether correlations exist. Thus, average credit scores, median household incomes, and racial make-up by zip code were analyzed to obtain a general indication of correlation. Nothing in this analysis leads the Bureau to the conclusion that income or race alone is a reliable predictor of credit scores thus making the use of credit scoring an ineffective tool for redlining.

Information from the Credit Bureaus

There are the three major credit reporting agencies (Trans Union, Equifax, and Experian). These credit reporting agencies (also referred to as credit bureaus) collect information on consumers' debts and provide this information to subscribers. This information includes employment data, payment history, creditor inquiries (creditors who have requested a credit history in the past six months), and public record information (e.g. bankruptcies, tax liens, and foreclosures).[17]

The Bureau surveyed these three reporting agencies to determine how a person's credit report would be affected if he were shopping for insurance and had been quoted by several insurers that pulled his credit report. One credit reporting agency responded to the survey. This agency indicated that an inquiry would be posted to the credit report every time a person's credit history was assessed and that it would be identified as "Insurance Underwriting."

Other Research and Reports

According to research conducted by the Federal Home Loan Mortgage Corporation (Freddie Mac) and five of the nation's Historically Black Colleges and Universities, (i) having poor credit is a common problem in today's society; (ii) credit problems extend across income groups and are not unique to low-income families; and (iii) minority borrowers are more likely than white borrowers to experience credit problems.[18] Furthermore, according to a recent report released by The Fair Housing Council of Greater Washington, "It is highly probable that

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[17] "Credit Reports and Insurance Underwriting," pp. 26 and 27.

[18] "Freddie Mac & Historically Black Colleges & Universities Launch Multi-Million Dollar Initiative to Boost Minority Homeownership," Freddie Mac Press Release, September 21, 1999, http://www.freddiemac.com/news/archives1999/cceirel3.html (September 9, 1999).

credit scoring has a disparate impact on protected classes which creates barriers to having access to equitable insurance products."[19]

The report issued by The Fair Housing Council of Greater Washington also notes that the purpose of credit scoring is to assist in the underwriting process and to give the industry direction rather than be the sole determinant in the underwriting decision.[20] In an advisory released by the Federal National Mortgage Association (Fannie Mae), mortgage lenders were told to look at the factors which caused a bad credit score and not automatically disqualify someone simply due to a "below average" credit score.[21]

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[19] "The Fair Housing Index: An Audit of Race and National Origin Discrimination in the Greater Washington Apartment Rental Insurance Marketplace," (Washington, D.C.: The Fair Housing Council of Greater Washington, 1999), p. 7.
[20] Ibid.
[21] Kenneth Harney, "Mortgage Lenders Told to Look Beyond Credit Scores," Detroit Free Press, March 9, 1997, http://freep.com/realestate/money/qharney91.html (September 28, 1999).

CONSUMER COMPLAINTS

The Bureau reviewed the number and types of consumer complaints pertaining to the use of credit reports that had been received by the Property and Casualty Consumer Services Section over a five-month period extending from March of 1999 to August of 1999. During this time period, the Consumer Services Section averaged seven phone calls and written complaints a month pertaining to the use of credit reports. These involved homeowners and automobile insurance policies being terminated due to adverse credit as well as increases in premium due to adverse credit. These credit-related phone calls and written complaints represented less than 1% of the total number of phone calls and written complaints received by the Consumer Services Section during that time period.

CONCLUSION AND RECOMMENDATIONS

Based on the Bureau's findings, there appears to be concrete data indicating that a correlation exists between credit scores and losses. From this purely statistical perspective, therefore, the Bureau is unable to make a recommendation prohibiting the use of credit scores in the underwriting process. However, the Bureau has concerns about the long-term effect that the use of credit scores may have on Virginia consumers. As the number of insurers that use credit history as an underwriting tool increases, there may be an increase in the number of consumers that will be refused coverage, cancelled, non-renewed, or charged higher premiums due to their adverse credit history. Conversely, industry advocates of this practice argue that there may be an increase in the number of consumers that will obtain coverage at lower rates due to their good credit history.

As suggested in the white paper prepared by the National Association of Insurance Commissioners, the Bureau recommends that the insurance industry take steps to educate consumers about the use of credit scores in the underwriting process. Furthermore, the Bureau will continue to monitor the number of credit-related consumer complaints it receives as well as the number of companies that use credit scores in underwriting and rating. If the Bureau finds over time that a significantly greater number of companies are refusing to issue or refusing to renew coverage solely on the basis of an adverse credit history, the Bureau will consider proposing legislation to prohibit this practice.